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Food Distribution Research Society

Journal of Food Distribution Research
Volume 52, Issue 2

Table of Contents

Regular Manuscripts

1 **Factors Influencing Tennessee Adults' Craft Hard Apple Cidery Visit Expenditures and Travel Distance** *Kimberly L. Jensen, David L. Hughes, Karen L. DeLong, Carlos O. Trejo-Pech, and Mackenzie B. Gill* 1–23

2 **Supermarket Pricing and Promotional Behavior: Evidence from the San Luis Obispo Market** *Richard J. Volpe, III, Nicole Tedjasaputra, Olivia Jackson, and Ryan Provost* 24–50

Invited Articles

4 **COVID-19 Trade Actions in the Agricultural and Food Sector** *Soojung Ahn and Sandro Steinbach* 51–75

5 **Low-Income Household Food Consumption Consequences of Rice Policy and Pandemic Impacts on Income and Price in Thailand** *Hoa T.K. Hoang, Wyatt Thompson, and Sanguk Kwon* 76–100

6 **Potential Impacts of Hard Infrastructure Development on Food and Agricultural Trade in North and Latin America** *Aaisha Al-Maamari and Amanda M. Countryman* 101–118

Journal of Food Distribution Research
Volume 52, Issue 2, pp. 1-23

Factors Influencing Tennessee Adults' Craft Hard Apple Cidery Visit Expenditures and Travel Distance

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Abstract

The craft hard apple cider industry is emerging in many areas of the United States, including Tennessee. Few studies exist regarding consumer preferences for visiting hard apple cider facilities (cideries). This study used a representative statewide survey of Tennessee alcoholic beverage consumers to examine their prior cidery visits, factors influencing cidery purchases, and expected expenditures and preferred travel distance to cideries. Most respondents had not visited a local cidery, but among those who had, most made hard apple cider purchases. Respondents stated they would travel about 61 miles to visit a cidery and spend about $38 annually while visiting cideries.

Keywords: hard cider, cidery, visitors, expenditures, travel, distance

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Background

Hard Cider Markets

Hard apple ciders have historic roots in American colonial culture (Smith and Lal, 2017) and have experienced a resurgence in popularity in the past decade. In 2019, the U.S. Alcohol and Tobacco Tax and Trade Bureau (ATTTB) reported production of 47.6 million gallons of bottled hard apple cider, compared with only 7.6 million gallons in 2010 (ATTTB, 2011, 2020). In addition, the number of cideries (facilities where cider is made) has grown rapidly across the United States, increasing to more than 800 in 2018, which is more than double the amount three years prior (Nurin, 2018).

Small craft ciders sold locally and regionally have gained a larger share of hard apple cider sales in the United States in recent years (The CiderJournal, 2017; Nurin, 2018).[1] Despite this rapid growth, little research exists regarding consumer preferences for hard apple ciders, visits to cideries, or preferences regarding cidery visits. This information is important because, for many cideries, on-site sales of hard apple ciders are an important component of their marketing strategy. In a survey of United States and Canada hard apple cideries, Snyder (2018) found that the majority of cideries are marketing their hard apple ciders on-site. In particular, among small-scale cider makers, about 60% sold hard apple ciders in their own tasting room by the glass and between 60%-70% sold bottles or cans at retail. Also, larger scale cideries were much more likely to use bottled/canned or kegged wholesale market outlets than were smaller scale cideries. Snyder's (2018) findings suggest craft cideries may be more reliant on sales at the cellar door compared with larger cideries. Hence, understanding influences on cidery visits and expenditures at cideries is of particular interest to smaller craft hard apple cider makers.

Roughly 40% of United States cideries are concentrated in just a few states (New York, California, Michigan, and Washington) (Conway, 2018). While other states have experienced less growth in their hard apple cider industry, they still have the potential for industry development based on promising hard cider apple growing conditions or significant tourism industries. For such areas where the cider industry is emerging, information about factors that may influence consumers' decisions regarding visiting a cidery is of particular interest. Examining consumer demographics and attitudes can help marketing efforts for cidery products and services. Information about the distance consumers would travel to a cidery can help with projecting market draw areas, while frequency of visits and expenditure information can assist with assessing potential market size for craft cideries in terms of sales.

Tennessee is an example of a state where small craft ciders are only recently emerging. The state only had seven cideries as of 2018. However, Tennessee lies within southern Appalachia, a region with a rich apple growing tradition (Veteto et al., 2011). Furthermore, tourism is an important contributor to the state's economy (Tennessee Department of Tourist Development, 2020). In 2019, the state's tourism expenditures were about $23 billion, and the state had 126 million domestic

[1] Some have suggested that craft hard apple ciders are those from smaller, independently owned facilities, making ciders pressed from fresh fruit not concentrates (CiderJournal, 2014).

person-stays. The state is home to 644 agritourism venues (USDA/NASS 2017). Tennessee has 70 wineries (TFWGA, 2020), 108 craft breweries (U.S. Brewer's Association, 2019), and 53 distilleries (American Distilling Institute, 2019).

Study Objectives

The purposes of this study were to ascertain alcoholic beverage consumers' past visits to hard apple cideries, factors influencing their decision to purchase hard apple ciders when visiting, and total cidery expenditures. Among those interested in visiting a cidery, factors that influence consumers' anticipated annual expenditures at cideries, and travel distance to a cidery were measured. These potential factors include demographics, alcoholic beverage expenditures and frequency of purchase, past hard cider purchases and cidery visits, preferences for amenities and services at cideries, and preferences for local foods.

Prior Studies of Cidery, Winery, and Brewery Visitors

Visitor Demographics

While prior studies of cidery visits are relatively few (Hughes and Wright, 2017; Smith and Lal, 2017), findings from studies of winery visits (Kolyesnikova and Dodd, 2008; Woods, Yang, and Nogueira, 2013; Stoddard and Clopton, 2014; Harrison, 2015; Lee, McCole, and Holecek, 2020) and brewery visits (Plummer et al. 2005; Kraftchick et al., 2014; Carr, Shin, and Severt, 2019) can also provide useful insights into factors influencing cidery visits and expenditures.

Results regarding the possible effects of gender on visiting a cidery, brewery, or winery have been mixed. Several studies have found that winery visitors were more likely to be female (Harrison, 2015; Lee, McCole, and Holecek, 2020). However, Woods, Yang, and Nogueira (2013) found that males were more likely to have made a visit to a local (in-state) winery within the past three years. Smith and Lal (2017) found that among cidery visitors, a larger percentage were female. However, studies of visitors to craft breweries have suggested that visitors tended to be composed of more males than females (Plummer et al., 2005; Kraftchick et al., 2014).

Mitchell and Hall (2006) profiled the typical winery visitor as 30-50 years old, while other studies have found the average winery visitor to be in their 40s (Geide, Harmon, and Baker, 2008; Stoddard and Clopton, 2014). Similarly, Kraftchick et al. (2014) and Plummer et al. (2005) both found that microbrewery visitors tended to be between 30 and 59 years old. Woods, Yang, and Nogueira (2013) found age to have a negative effect on the probability of respondents having made a visit to a local winery within the past three years, while Smith and Lal (2017) found that the majority of cidery visitors were under the age of 42.

In general, visitors to wineries, cideries, and craft breweries tend to have higher incomes and are college educated (Mitchell and Hall, 2006; Geide, Harmon, and Baker, 2008; Stoddard and Clopton, 2014; Harrison, 2015; Smith and Lal, 2017). Woods, Yang, and Nogueira (2013) found a nonlinear (positive, then negative) effect of income on the probability of respondents having visited a local winery within the past three years. They did not find significant effects of education level on the probability of winery visits. Furthermore, they did not find significant effects of income or education on the post-winery visit purchase of the local wine.

Several studies have suggested a negative relationship between winery visits and urban visitors. Woods, Yang, and Nogueira (2013) found that rural consumers were more likely to visit a winery than urban consumers. Smith and Lal (2017) found that the majority of the visitors, nearly 56%, came from in-state.

Woods, Harmon, and Nogueira (2013) found that preferences for buying local foods had a positive influence on the probability of respondents having made past visits to a local winery. Prior research has shown that Tennessee consumers' preferences for local foods positively influenced local muscadine wine and other local wine purchases (Everett et al., 2017, 2018).

Woods, Yang, and Nogueira (2013) linked winery visits to the frequency of wine purchases. Their results showed that among those who purchased wine at least once per week, about 61% had visited a local winery, but among those who purchased only once per year, only 38% had visited a local winery.

Several studies have also investigated drivers of visits to craft breweries (Plummer et al., 2005; Kraftchick et al., 2014; Carr, Shin, and Severt, 2019). Kraftchick et al. (2014) found that brewery visitors tended to be male, educated, and middle-aged. They found that the most important reasons for visiting the brewery were to taste new beer, experience the local beer, increase their beer knowledge, visit with family/friends, and to buy beer. They noted that about 82% of the brewery visitors surveyed were from in-state. Plummer et al. (2005) studied beer tourism in Canada associated with an ale trail. They found similar demographics among ale trail visitors as those found by Kraftchick et al. (2014) for craft brewery visitors. They found nearly 62% of visitors were male, with more than 60% falling between the ages of 30 and 59. Carr, Shin, and Seavert (2019) reported that brewery visitors who identified as microbrewery beer drinkers were more likely to visit microbreweries. This finding is suggestive of repeat purchase behaviors. Like Kraftchick et al. and Plummer et al., their data showed that microbrewery visitors tended to be of higher income (more than $40,000 annually), positing that this could be due to product costs. Carr, Shin, and Seavert (2019) also found, in examining factors that were important to visitors, that a strong sense of local identity was nearly as important to microbrewery visitors as beer taste/quality.

Travel Distance, Frequency of Visits, and Expenditures

Smith and Lal (2017) showed that for the cider product to be considered locally grown, 74.3% of the respondents stated it would need to be produced within 100 miles. Furthermore, more than 60% of the respondents said they had traveled under an hour to visit the cidery. Smith and Lal's (2017) findings were that visitors went to cideries, breweries, or wineries about one to three times per year, with 14% stating it was their first time visit, 42% visiting one to three times per year, and 27.2% visiting four to eight times per year. In a study of Virginia winery visitors, Harrison (2015) showed that the largest percentage of respondents had visited a local winery one to three times in the past year. Their results also showed that of those visiting wineries, 32.5% planned to spend

$25 or less, and about 47% planned to spend $25-$100 at the winery. Trechter, Hadley, and Parks (2008) surveyed wineries and cideries and found that the typical visitor was estimated to spend between $25 and $35 per visit. Woods et al. (2015) reported that local wine expenditures were most likely cited as less than $20 per month. They found fruit wine consumption had a positive effect on local wine expenditures, suggesting a possible linkage between preferences for fruit wines and local wines. Smith and Lal (2017) found that more than 70% of the respondents were first-time visitors to the cidery location, and 60% were first-time visitors to any cidery in the Hudson Valley region.

Relationship between Time and Travel in the Tourism Experience

As noted by Smith and Lal (2017), most visitors will either likely visit cideries on a day outing, or will make their cidery visit as part of a larger tourism trip. A small craft cidery in an emerging hard apple cider industry is not likely to be the primary reason for a multi-day tourist outing. In-state consumers are more likely to take a day trip to visit a cidery. Hence, costs incurred by cidery visitors are primarily from travel and expenditures on hard apple ciders at the cidery facility. Other agri-tourism research by Mellstrom and Murphy (2017) found that destination location is a strong influence on agritourism visits. They reported that single-day destinations near metropolitan areas tended to attract more visitors compared with destinations farther away. Their results are suggestive that agritourism visitors, for example those to cideries, may prefer venues that are perhaps far enough from metro areas to experience rural landscapes, but within driving distance for a day visit.

Travel costs include not only explicit expenditures (e.g., fuel) but also time (Prideaux, 2002). Travel to tourism sites is also determined by the situation of the traveler since higher income travelers may face higher opportunity costs of travel because of foregone earned income opportunities but also may have access to faster means of travel (Prideaux, 2002). On the other hand, some travelers may see getting to a tourism destination as part of the experience, especially if time devoted to the effort has a low opportunity cost. This relationship is particularly important since many households' work time has increased since the 1980s (Castells, 2000; Echtelt, Glebbeek, and Lindenberg, 2006).

Studies of the Visitor Perceptions of Overall Visit Experiences

A visitor to a cider-making facility may come to sample and purchase the product offered by the venue. However, they may also travel to the facility to experience the on-site amenities and the overall trip experience. Gomez and Kelley (2013) examined winery customer satisfaction with the tasting room experience. They found that wine knowledge and helpfulness of pourers, as well as speed of pours, influenced wine purchases. They also reported that food items for sale and sounds in the pouring room had little influence. A tasting room, however, is but one part of a winery tourist's experience. The term "winescape" has been used to describe the overall atmosphere associated with a winery experience, such as the vineyard and associated landscapes, facilities for tasting, winemaking facilities, etc. (Hall et al., 2000). Prior research has shown that while the primary motivations for wine tourists are to taste wines and purchase wines, other important motivations include learning more about wine, having a day out in rural setting, and experiencing the atmosphere (Bruwer and Alant, 2009; Bruwer and Lesschaeve, 2012; Back, Bufquin, and Park, 2018). Hence, not only would cidery visitors taste and buy hard apple ciders, but they would also visit to learn more about hard apple ciders, tour cider-making facilities, and perhaps enjoy a variety of other amenities associated with the cidery. Carmichael (2005) notes that both physical elements (such as wine tasting facilities) and services (such as tours) are important to the winery tourism visitor experience. McDonnell and Hall (2008) list several factors that may influence wine cellar visits, including outside attractiveness, inside attractiveness, ambience, staff, the product itself, merchandise, and brochures. Ratz and Dryer (2014) added guided visits/tours, seminars and courses, and culinary offerings as other factors influencing wine cellar visits. In their study, they found that wine quality was rated as most important, followed by service and advice, staff friendliness, and attractiveness of the region.

The term “beerscape” has also been used in reference to brewery atmosphere (Carr, Shin, and Seavert, 2019). Studies of microbrewery visitors’ preferences for beerscape attributes have focused on a variety of beers, embodiment of local culture, beer cost, and facilities. Missing from their beerscape is the notion of the facility visited being co-located with the crop used in making the beverage (barley and hops for beer, grapes for wine or apples for hard ciders) where it is produced. Hall et al. (2003) applied a similar context to food tourism, particularly where focused on local foods production and the ties to agricultural production, customs, and cuisines.

Due to the emerging nature of hard apple cideries in many regions, visitor perceptions of “ciderscapes” or the overall hard apple cidery visit experience are lacking. However, if the cideries are located on or nearby orchard land to produce the apples used in cider making, the venue takes on aspects of agri-tourism, where visitors might come to see apple orchards either located on the property or nearby. Research by Gao, Barbieri, and Valdivia (2014) on agri-tourism visitors found that landscape features associated with farms were important to visitors. Carpio, Wohlgenant, and Boonsaeng (2008) found that U.S. agri-tourism visitors tended to visit agri-tourism venues about 10 times annually at a cost of $88 per trip with an average distance traveled to the farm of 126 miles. They found that those who were older and lived in urban areas were less likely to have visited farms recreationally, whereas those who had young children in the household and larger household sizes were more likely to have visited. The number of recreational trips to farms was influenced negatively by trip cost and residing in an urban area. The number of trips was positively influenced by income, male gender, older age, and importance of the rural landscape.

Research Design: Survey Instrument, Data Collection, and Model

Survey Instrument and Data Collection

A panel of Tennessee residents aged 21 years or older who at least occasionally consumed alcohol was recruited by Qualtrics for this survey. The online survey was conducted by Qualtrics in July 2019. The sample was drawn using response quotas to represent Tennessee’s percentages of female (50.8%) and age categories (27.0% aged 21-34; 35.1% aged 35-54; and 37.9% aged 55 or older) (Census Bureau, 2019). Before the online survey was fielded, an online pretest with 50 responses was conducted, and the survey instrument was revised based upon these pretest results. A total of 1,261 Tennessee residents responded to the online survey. Appropriate human subjects protocols were followed and approved by the Institutional Review Board under UTK-IRB-17-03525-XM.

The survey instrument contained several sections, including questions about hard ciders, past cidery visits, interest in visiting a cider-making facility, travel distance, expenditures, cidery attributes, attitudes toward locally produced foods, and demographics. The survey instrument defined hard cider as cider made from apples that are fermented into an alcoholic beverage.

Regarding cidery visits, respondents were asked whether they had visited or would be interested in visiting a cidery in the future. Past cidery visitors were also asked about whether they purchased hard ciders and, if so, how much they spent. They were also asked about the importance of factors that influenced their decision to purchase ciders when they visited a cidery. These possible factors included cider taste, price, reputation, container types, expert advice, cidery visits before purchasing, samples before buying, ability to support a local business, the cider being made on-site, and the cider apples being grown on-site.

Those who had visited a cidery or were interested in doing so in the future were asked the farthest distance they would travel to visit a cidery, how many times a year they would visit, how much they would spend per visit on hard apple cider, and the importance of amenities and services on future hard apple cidery visits.

In addition, the respondents were asked their agreement with the importance of local foods. They were also asked about alcoholic beverage purchase frequency (i.e., beer, wine), willingness to try new beverage types and brands, and demographics and household characteristics.

To help identify amenities or services that might attract cidery visitors, several questions were asked about possible cidery services. Respondents were asked to rate the importance of visiting a cidery that had a tasting room, an apple orchard on-site, educational tours about how hard apple cider is made, cider on-site being offered for purchasing and consumption, live music or other special events, food and cider sample pairings being offered, and restaurants on-site or nearby. A copy of the survey instrument is available from the authors upon request.

Future Cidery Visits Model

In this study, two dependent variables are modeled for the i^{th} consumer, $\textit{Travel Distance}_i$ and $\textit{Annual Expenditures}_i$. In each case, the dependent variable is hypothesized to be influenced by a vector of respondent demographics, past cider purchases and cidery visits, alcoholic beverage purchases, expenditures, local foods attitudes, and preferences for services and amenities at hard apple cideries, $\boldsymbol{X}_i$. The equations can be expressed as:

$$i. \quad \textit{Travel Distance}_i = f(\boldsymbol{X}_i) \tag{1}$$

$$ii. \quad \textit{Annual Expenditures}_i = f(\boldsymbol{X}_i) \tag{2}$$

where $\mathbf{X}_i$ = (Female$_i$, College Graduate$_i$, Age$_i$, Age Squared$_i$, 2018 Household Income$_i$, Middle$_i$, West$_i$, Rural/Small Town$_i$, Suburb$_i$, Farm Background$_i$, Have Purchased Hard Cider$_i$, Have Visited Cidery$_i$, Purchase Local Foods$_i$,Weekly Beer Purchaser$_i$, Weekly Wine Purchaser$_i$, Alcohol Beverage Expend$_i$, Try New Types$_i$, Try New Brands$_i$, Tasting Room$_i$, Orchard$_i$, Educational Tours$_i$, Purchase and Consume$_i$, Events$_i$, Pairings$_i$, Restaurant$_i$). The definitions for each of these variables are contained in Table 1.

Table 1. Variable Names, Definitions, and Means for the Seemingly Unrelated Regression Model of Tennessee Consumers' Expected Travel Distance to Hard Apple Cideries and Expected Annual Hard Apple Cider Expenditures at Cideries

Variable Name	Definition	Mean (N = 1,055)
Dependent Variables		
Ln travel distance	Natural log of distance in miles would travel to visit a cidery (untransformed value)	3.842 (61.354)
Ln annual expenditures	Natural log of expected annual expenditures at cideries (untransformed value)	2.901 (38.461)
Explanatory Variables		
Female	1 if female, 0 otherwise	0.524
College graduate	1 if college graduate, 0 otherwise	0.432
Age	Age in years	47.427
Age squared	Age squared	2507.939
2018 household income	Household income for 2018 in $10,000	70.076
Middle	1 if located in Middle Tennessee, 0 otherwise	0.389
West	1 if " " West Tennessee, 0 otherwise	0.183
East	1 if " " East Tennessee, 0 otherwise (omitted)	0.428
Rural/small town	1 if reside in a rural area or small town, 0 otherwise	0.428
Suburb	1 if " " suburban area, 0 otherwise	0.438
Metro	1 if " " urban area, 0 otherwise (omitted)	0.134
Farm background	1 if have farm background, 0 otherwise	0.271
Have purchased hard cider	1 if have purchased hard cider before, 0 otherwise	0.643
Have visited cidery	1 if have visited cidery, 0 otherwise	0.188
Purchase local foods	Try to purchase local foods whenever possible, 1 = strongly disagree, …, 5 = strongly agree	4.068
Weekly beer purchaser	1 if purchase beer weekly, 0 otherwise	0.282
Weekly wine purchaser	1 if purchase wine weekly, 0 otherwise	0.187
Weekly alcoholic beverage Expend	Weekly alcoholic beverage expenditures in dollars	18.313
Try new brands	Likelihood of trying new brands of alcoholic beverages, 1=extremely unlikely, …., 5 = extremely likely	4.161
Try new types	Likelihood " " new types alcoholic beverages, 1 = extremely unlikely, …., 5 = extremely likely	4.017

Table 1. (continued)

Variable Name	Definition	Mean (N = 1,055)
	Importance of services to visiting a cidery (1 = not important at all, …5 = extremely important):	
Tasting Room	Tasting room	3.980
Orchard	Apple orchard on-site	3.518
Educational Tours	Educational tours about how hard apple cider is made	3.608
Purchase and Consume	Ability to purchase and consume on-site	3.851
Events	Live music or other special events	2.874
Pairings	Food and cider sample pairings offered	3.580
Restaurants	Restaurant on-site or nearby (within 15-minute drive)	3.413

A seemingly unrelated regression (SUR) model with correlated error terms is used (Greene, 2018). The model equations can be expressed as:

$$iii. \qquad Travel\ Distance_i = \boldsymbol{X_i \beta^{TD}} + \varepsilon_i^{TD} \tag{3}$$

$$iv. \qquad Annual\ Expenditures_i = \boldsymbol{X_i \beta^{YE}} + \varepsilon_i^{YE} \tag{4}$$

where $\boldsymbol{\beta^{TD}}$ and $\boldsymbol{\beta^{YE}}$ are vectors of parameters to be estimated and $\varepsilon_i^{TD}$and $\varepsilon_i^{YE}$are error terms. The correlations between the error terms are measured by $\rho_{TD,YE}$. The model is estimated in the Stata statistical software package, StataSE Version 16.0 (StataCorp, 2019). The conditional mixed process estimator with multilevel random effects and coefficients (CMP) algorithm is used to estimate the model.

The models are tested for multicollinearity among the explanatory variables using a Variance Inflation Factor (VIF) statistic, where a value exceeding 10 indicates multicollinearity (Chatterjee and Hadi, 1986) and the Condition Index (CI), where a value exceeding 30 indicates multicollinearity (Belsley, 1991). The models are also tested for heteroscedasticity using a Breusch-Pagan test (Breusch and Pagan, 1979).

Results

Of the 1,261 respondents, 103 (8.17%) had not visited a cidery in the past and had no interest in visiting a cidery in the future. About 10.71% had visited a cidery in the past, whereas 81.13% had not visited a cidery but were interested in doing so in the future. Smith and Lal (2017) found that about 70% were first-time visitors to the cideries where their surveys were conducted. The lower percentage of visitors in this study likely reflects the low number of cideries in the state. Among the 1,126 who had visited or had a future interest in visiting a hard apple cidery, a total of 1,055 answered all the questions to estimate the models as shown in Table 1.

Prior Cidery Visitors

Among those who had visited a cidery, notably 82.96% purchased hard apple cider when they visited the cidery. This finding could potentially suggest that if cideries attract visitors on-site, a large percentage of these visitors would make a hard apple cider purchase when at the facility. However, it should be noted that given the low numbers of cideries located in Tennessee, those who have visited a cidery in the state may be more cider-involved consumers than cidery visitors in states where many are located. As cidery numbers expand in Tennessee, the facilities may draw a wider range of visitors, and this percentage purchasing could be lower. Gomez and Kelley (2013) found that among winery visitors, about 95% said they had or would be buying wine after tasting. The lower rate among hard apple cidery visitors compared with winery visitors may in part be due to less familiarity with hard apple ciders than wines. Among those who had visited a cidery, the visitors indicated they had spent about $11.07 on average per visit.

Those who had visited a cidery were asked what factors were important influences on them choosing to spend money at the cidery, with 1 being not important at all, and 5 being extremely important. The mean ratings of importance of each factor are shown in Table 2. Means comparison *t*-tests were also calculated to evaluate which means were statistically different from each other at the 95% confidence level. Table 2 shows that among those who had visited a cidery in the past, the cider taste was the most important influence on purchasing decision. The importance rating for this factor was statistically greater than any of the other factors. This factor was followed in importance by being able to sample before you buy, good reputation of the ciders, and the chance to help support a local business. Statistically, the least important factor was that the hard cider apples were grown on-site. It should be noted that this reason was statistically less important than the cider being made on-site. If each of the reasons is compared with the importance of price, statistically, hard apple cider taste was rated as more important. However, cider apples being grown on-site was statistically rated as less important.

Table 2. Importance Ratings of Factors Influencing Hard Apple Cider Purchase Decisions at Tennessee Hard Apple Cideries Among Consumers Who Have Visited Tennessee Hard Apple Cideries in the Past

Factors Influencing Decision to Purchase Hard Apple Cider	**Mean Rating (1 = not at all important, …, 5 = extremely important) (N = 112)***	
Cider tastes good	4.375	
Sample before buy	3.991	b
Good reputation	3.875	b,c
Help support local business	3.866	b,c,d
Price	3.768	c,d,e
Cider is made on-site	3.705	c,d,e
Container types available on-site	3.679	d,e
On-site expert cider advice	3.670	d,e
Experience visiting cidery first	3.625	e
Apples grown on-site	3.313	

*Note: Like letters represent means that are not found to be statistically different at the 95% confidence level.

Future Cider Visits Travel Distance and Annual Expenditures

The means of the dependent and explanatory variables are presented in Table 1. Notably, the respondents would travel just over 61 miles on average to visit a cidery. This finding is similar to those by Smith and Lal (2017) and Woods, Yang, and Nogueira (2013). On average, the visitors expect to spend around \$38.46 per year. Note that this was about \$16.48 per visit with just over 2.3 visits per year. The annual visits finding is similar to Smith and Lal's (2017) findings regarding visits per year. The expenditure per visit (\$16.48) is lower than prior findings for the typical winery and cidery visitors' spending at least \$25 to \$35 (Trechter, Hadley, and Parks, 2008; Harrison, 2015); however, that number is higher than the \$11.07 that past visitors in this study indicated they had spent on prior visits. This discrepancy could suggest some potential overstatement of what people expect they would spend compared to what prior visitors indicated they actually spent. The number of anticipated annual visits is comparable to that found by Smith and Lal (2017) and Harrison (2015). In our study, about 64.3% of respondents had tried a hard apple cider previously. However, less than 11% of our respondents had visited a hard apple cidery in the past. This value is considerably lower than Smith and Lal's (2017) findings for visitors to Hudson Valley, New York, where 40% of cidery visitors had visited cideries in the region previously. This latter difference could, in part, be driven by the relatively small number of cideries in Tennessee compared with New York. Snyder (2016) found that about 16% of mid-Atlantic cider consumers purchase cider at tasting rooms. Approximately 40% indicated they would travel between 30 and 60 minutes to visit a new tasting room.[2]

The mean Likert ratings for possible cidery amenities are shown in Table 1. While *Tasting Rooms* received the highest Likert ratings at 3.98, having special *Events* received the lowest Likert rating at 2.87.

The estimated SUR model for distance traveled and annual expenditure is shown in Table 3. The dependent variables were evaluated for non-normality and found to be skewed. Furthermore, Breusch-Pagan tests for heteroscedasticity were conducted for both the *Travel Distance* and *Annual Expenditures* models and were found to exhibit heteroscedasticity based on the Breusch-Pagan calculated statistics (χ^2 = 34.84, 1 df and χ^2 = 1,911.03, 1 df). A natural logarithm transformation of the dependent variables was then used in estimating the model to correct for these issues. The Breusch-Pagan test for heteroscedasticity was conducted after the natural log of the dependent variable was taken for *Travel Distance,* and heteroscedasticity was no longer found to be an issue. However, it remained for the *Annual Expenditures* model but at a reduced level. Therefore, robust estimators were used in the SUR model. As can be seen by the LLR Test against an intercept-only model, the estimated model is significant overall. Furthermore, the estimated correlation coefficient between the two equations (*Ln Travel Distance* and *Ln Annual Expenditures*) is significant, suggesting the use of the SUR approach is appropriate. To test for possible multicollinearity issues, variance inflation factor (VIF) and Condition Index analyses were conducted for the explanatory variables. The mean VIF was 5.12, which does not suggest serious issues with multicollinearity among the explanatory variables. Furthermore, the Condition

[2] A comparison of the respondent demographics with the Tennessee population is provided in Jensen et al. (2019).

Index was 18.57, which was below 30, and hence did not suggest multicollinearity to be a serious problem.

Table 3. Estimated Seemingly Unrelated Regression Model of Tennessee Consumers' Expected Travel Distance to and Annual Hard Apple Cider Expenditures at Tennessee Hard Apple Cideries and Estimated Effect of Variables on Percent Change in Expected Travel Distance to and Annual Expenditures at Tennessee Hard Apple Cideries

	Estimated Coefficients[a]		Effect on Percent Change in[b]	
Variable Name	**Log Travel Distance**	**Log Annual Expenditures**	**Travel Distance**	**Annual Expenditures**
Intercept	1.164***	1.224***		
Female	0.177***	-0.018	19.357***	-1.830
College graduate	0.085	-0.185***	8.888	-16.891***
Age	0.039***	-0.026*	3.979***	-2.538
Age squared	-0.000***	0.000**	-0.033***	0.029**
2018 household income	0.003***	0.002*	0.338***	0.153*
Middle	0.016	-0.150**	1.569	-13.958**
West	0.258***	-0.109	29.481***	-10.296
Rural/small town	0.320***	0.357***	37.651***	42.857***
Suburb	0.216***	0.143	24.154***	15.344
Farm background	0.072	0.077	7.480	8.032
Have purchased hard cider	0.136***	0.149**	14.596**	16.042*
Have visited cidery	-0.289***	0.274***	-25.084***	31.459**
Purchase local foods	0.027	0.076*	2.772	7.945*
Weekly beer purchaser	0.032	0.142*	3.287	15.211*
Weekly wine purchaser	-0.160**	0.088	-14.763***	9.234
Weekly alcoholic beverage expend	0.027***	0.012***	0.524***	1.232***
Try new brands	0.042	0.004	4.285	0.417
Try new types	0.029	0.149***	2.949	16.065***
Tasting room	0.026	0.033	2.601	3.360
Orchard	0.019	-0.060	1.884	-5.848
Pairings	0.018	-0.025	1.850	-2.512
Educational tours	0.088***	0.049	9.233***	4.988
Purchase and consume	-0.005	0.118***	-0.461	12.534***
Events	-0.032	0.049	-3.143	5.020
Restaurant	0.003	0.020	0.344	1.998
ρ_{TDYE}	0.163***			
LLR Test (df = 50) = 389.35***				
N = 1,055				

[a] ***denotes significance at α = .001, **denotes significance at α = .05, *denotes significance at α = .10.
[b] Standard errors were calculated using the Delta method (Oehlert, 1992) in STATA 16.0 Lincom module.

The estimated coefficients for the explanatory variables in the *Ln Travel Distance* and *Ln Annual Expenditures* models are shown in the second and third columns of Table 3. The estimated effect of a 1-unit change in each explanatory variable on the percentage change in the untransformed dependent variables (*Travel Distance* and *Annual Expenditures*) is shown in columns 4 and 5 of Table 3. These values are calculated as $(\exp(\beta_k) - 1) \times 100$ using the estimates in columns 2 and 3.

Several of the consumer demographic characteristics influenced *Travel Distance* and *Annual Expenditures*. Shown in column 4, compared with their male counterparts, female consumers would travel 19.4% farther to visit a cidery. This result is similar to prior studies that have found positive effects of female gender on winery or cidery visits (Harrison, 2015; Smith and Lal, 2017; Lee, McCole, and Holecek, 2020;). As can be seen in column 5, however, female gender (*Female*) did not significantly influence anticipated annual expenditures at cideries. Recent Nielsen statistics report that hard cider drinkers are about evenly split across genders (51% male and 49% female) (Newhart, 2019).

Being a college graduate (*College Graduate*) did not significantly influence the distance the respondent would travel to visit a cidery; however, college graduates indicated they would spend about 16.9% less at cideries in a year than those without a college degree. Although Woods, Yang, and Nogueira (2013) found no effect of income on post-winery purchases of local wines, this finding is somewhat surprising, as other studies have found that winery and cidery visitors tended to be college educated (Mitchell and Hall, 2006; Geide, Harmon, and Baker, 2008; Stoddard and Clopton, 2014; Harrison, 2015; Smith and Lal, 2017).

The results in Table 3 show household income (in 2018 thousand dollars) has positive and significant effects both on *Travel Distance* and on *Annual Expenditures*. As household income increases by \$10,000, the respondent indicated they would travel 0.34% farther and spend 0.15% more. Hence a \$100,000 increase in household income would result in 3.4% greater distance that the respondent would travel to visit a hard apple cidery and 1.5% greater hard cider expenditures annually. This finding is similar to prior research showing winery and cidery visitors to have higher incomes (Mitchell and Hall, 2006; Geide, Harmon, and Baker, 2008; Stoddard and Clopton, 2014; Harrison, 2015; Smith and Lal, 2017).

A squared term for *Age* was included in both equations, and the effect of *Age* on distance traveled and expenditures is calculated as $\frac{-\beta_{Age}}{2*\beta_{Age\ Squared}}$. In the case of *Travel Distance*, the coefficient sign on *Age* is positive, but the coefficient sign on *Age Squared* is negative (Table 3). Hence, age of respondent has a positive effect on travel distance up to a certain age (59.05 years) and then begins to diminish. The turning point of the effects of *Age* in *Annual Expenditures* is 44.83 years, with age having a negative effect up to that age, and then a positive effect. Combined, these results suggest that those who are more likely to travel farther and spend more money annually at cideries are in the 44-60 year old age category. They are similar to findings by Mitchell and Hall (2006). However, it is dissimilar to findings by Smith and Lal (2015) that the majority of cidery visitors were under age 42. According to 2018 statistics, about 25% of hard apple cider consumers are aged 30-49 years old (Statista, 2019).

Region within the state and urbanization of residence influenced *Travel Distance* and *Annual Expenditures* (Table 3). Compared with residents in the *East*, residents in the *West* were willing to travel 29.48% farther to visit a cidery. This finding may reflect differences in expectations about travel distances to cideries in the western part of the state. Consumers may be basing their expectations on where wineries, breweries, and distilleries are currently located, the majority of which are located in the middle or eastern parts of the state. In addition, according to the 2017 Census of Agriculture, Tennessee had 644 agritourism operations, but less than 25% of these are located in the western part of the state (USDA/NASS, 2017).

No significant effect on distance the respondent would travel to a cidery was found for Middle Tennessee. However, residents in the middle part of the state were willing to spend about 13.96% less annually at cideries than those in the East. Being a resident of a rural area or small town (*Rural/Small Town*) increased the distance the respondents would travel to visit a cidery by about 15.34%, compared with metro area respondents. Likewise, suburban residents would travel 24.15% more miles than metro area residents. These results may reflect the fact that more rural or suburban residents may expect to travel farther distances to services, such as cideries, than metro residents. Prior research has found that rural consumers were more likely to visit a winery than urban consumers (Woods, Yang, and Noguiera, 2013). Interestingly, residents of rural areas or small towns anticipated spending about 42.86% more annually than metro residents.

Having purchased hard apple cider (*Have Purchased Hard Cider*) before positively influenced both expected travel distance to cideries and annual expenditures (Table 3). Those who had purchased hard apple ciders before would travel 14.60% farther to visit a cider than those who had not, and they would spend about 16.04% more than those who had not. These findings could reflect revealed preferences and signal that once consumers have tried hard apple ciders, they may be more interested in traveling to cideries and purchasing local craft hard apple ciders while visiting them. This result could signal the importance of getting alcoholic beverage consumers to try hard apple ciders beyond the cidery door. Once a consumer has tried hard apple ciders, they are willing to travel farther and spend more once they are at cideries. However, to fully measure the effects of prior hard apple cider purchases on visits to hard apple cideries and on-site expenditures, additional research should include data from surveys of cidery visitors conducted on-site.

Surprisingly, the effects of having visited a cidery before (*Have Visited Cidery*) were mixed. Those who had visited a cidery previously were willing to travel 25.08% fewer miles; however, they anticipated spending 31.46% more than those who had not visited a cidery before. One possible explanation is that the novelty of visiting the cidery may hold the most effect on willingness to travel more miles to visit the facility. However, prior visitors may be more familiar with the product and willing to spend more on hard apple ciders when they do visit the cidery.

While those respondents who indicated they tried to purchase local foods whenever possible (*Purchase Local Foods*) were neither more or less likely to travel farther distances to visit a hard apple cidery; the preference for local foods positively influenced expected annual expenditures at hard apple cideries (Table 3). Each level of agreement that the respondent tried to purchase local foods when possible increased their expected annual cider expenditures by 7.94%. Hence, compared with a person who strongly disagreed that they tried to purchase local foods when possible, a person who strongly agreed with this statement indicated they would spend about 31.76% more on hard apple ciders at cideries annually. Preferences for local foods have been linked to preferences for local wines and beers in previous research (Woods, Yang, and Nogueira, 2013; Everett et al., 2017, 2018).

Weekly purchases of beer and wine (*Weekly Beer Purchaser, Weekly Wine Purchaser*) were included in the model to examine possibly complementary and substitution effects across beverages that might influence willingness to travel farther distances to visit cideries and annual expenditures at hard apple cideries. Findings regarding the effects of regular beer and wine purchases on distance travel and expected expenditures were mixed (Table 3). Weekly beer purchasers would spend 15.21% more annually on hard apple ciders at cideries compared with more infrequent beer purchasers. This result is suggestive of complementarity of craft beer and craft cider expenditures. Snyder's (2016) survey of cider consumers showed that about 41% most often drink beer when they select an alcoholic beverage. Interestingly, Snyder's (2016) study of hard apple cider makers found that 72% of cider makers were marketing to beer drinkers, but 90% were marketing to wine drinkers. In this study, while being a weekly wine purchaser had no effect on anticipated expenditures, it did influence the distance the respondents would travel to visit a cidery. Notably, if the respondent was a weekly wine purchaser, they would travel 14.76% fewer miles than those who are not weekly wine purchasers. While beyond the scope of this study, this finding could suggest that more wine-involved consumers would perhaps only be willing to travel shorter distances to visit hard apple cideries.

As expected, greater weekly alcoholic beverage expenditures (*Weekly Alcoholic Beverage Expend*) had a positive effect both on *Travel Distance* and *Annual Expenditures*. For each dollar spent per week on alcoholic beverages, the distance the respondents would travel to visit a hard apple cidery increased by 0.52%, and the amount they expected to spend on hard apple ciders at cideries increased by 1.23% (Table 3). Although greater willingness to try new brands of alcoholic beverages (*Try New Brands*) had no effect on *Travel Distance* or *Annual Expenditures*, greater willingness to try new types (*Try New Types*) positively influenced anticipated annual expenditures by 16.06%. This result, taken together with the positive effects of alcoholic beverage expenditures, may suggest that consumers who are greater alcoholic beverage spenders and who are willing to try new types of beverages will spend more on hard apple ciders at cideries.

Several questions were asked about the importance of services the cidery may offer in order to ascertain how cidery services may influence distance consumers would travel or their hard apple cider spending. Educational tours (*Tours*) about how the ciders are made positively influenced *Travel Distance* (9.23% for each level of importance of *Tours*) (Table 3). The importance of ability to purchase and consume hard apple ciders on-site (*Purchase and Consume*) positively influenced projected annual hard cider expenditures at cideries by 12.53% for each level of importance. Hence, these results suggest that information about facility tours and informational programs about how the cider is made can influence consumers to travel farther to cideries. Gao, Barbieri, and Valdivia (2014) suggest that agritourism venues can have natural features, agricultural features, and cultural features, with the latter resulting from the interaction between human activity and the environment, such as the value-added process associated with the making of hard apple ciders. However, the results also suggest that ability to consume and purchase cider on-site will increase cider expenditures. Visitors may be drawn by learning experiences on-site, whereas expenditures may be driven by ability to purchase and consume the product as part of and subsequent to a tour. Notably, Stoddard and Clopton (2014) found that returning winery visitors were more likely to place a greater emphasis on their ability to buy wine, whereas new winery visitors were more motivated by winery tours.

Conclusions, Discussion, and Implications

As in many other parts of the United States, Tennessee's hard apple cider industry is emerging and there are only a handful of cideries in the state. The state is well positioned to have a growing craft hard apple cider industry because much of the state is suitable for growing cider apples and Tennessee has a sizable tourism industry. In an emerging craft hard apple cider industry, cellar-door sales will comprise an important component of the small craft cideries' marketing. Hence, building a better understanding of influences on cidery visitorship and hard apple cider spending on-site provides information to facilitate industry growth.

The results from this study suggest that while few Tennessee alcoholic beverage consumers had visited a hard apple cidery, most visitors had purchased hard apple cider on-site, and there was considerable interest in visiting hard apple cideries in the future. Among those who had visited, cider taste held the most influence on purchasing hard apple ciders at the cidery. This finding reflects the importance of having tasting rooms and the ability to purchase hard apple cider on-site. However, least important was that the apples were grown on-site. This result could indicate a need for more information for hard apple cider consumers about history of the location and orchard and about local, heirloom, and other specialty apple varieties used in the hard apple ciders to build interest in purchasing ciders with apples grown onsite. However, it also seems to suggest that consumers might be as willing to purchase hard apple cider if the apples are not grown onsite and are instead purchased from local or regional apple growers. While our results showed that apples being grown on-site was less important to purchasing decisions than other attributes among those who had previously visited a cidery, additional research could investigate opinions about the importance of apples being grown on-site among those who have not yet visited a hard apple cidery but are interested in doing so in the future.

Among those who indicated they had visited or were interested in visiting a hard apple cidery in the future, factors influencing how far they would travel to visit a cidery and how much they anticipate spending at the cideries in a year were examined. Travel distance is of interest for assessing the market draw area for hard apple cideries. This study shows that, on average, in-state visitors would be willing to travel about 61 miles to visit a hard apple cidery. This result suggests that cideries should anticipate most of their in-state customer base will likely come from within about an hour's drive of their facility. In addition, visitors anticipate spending just over \$38.46 a year on hard apple ciders at cideries. A further break down of the expenditure variable reveals that this would occur over two to three visits per year, with visitors spending about \$16.50 per visit.

Additional future research regarding out-of-state visitor travel distance and expenditures could complement these estimates.

Household income had a positive effect both on distance visitors would travel and also on anticipated expenditures. This finding suggests that cideries might market to middle and higher-income consumers. The study results also suggest marketing ciders and cidery visits to alcoholic beverage consumers in the 44- to 60-year-old age group. Many of the demographics having a positive influence on distance traveled to and expenditures at craft hard apple cideries are similar to those found in studies of craft brewery visitors (Plummer et al., 2005; Kraftchick et al., 2014; Carr, Shin, and Severt, 2019). Furthermore, weekly beer purchasers were likely to spend more on hard apple ciders than less frequent beer purchasers. While beyond the scope of this study, these results suggest some potential synergy between craft brewery and craft cidery experiences and product expenditures. Interestingly, residence in a rural/small town positively influenced both expected travel distance to and expenditures at hard apple cideries. While it is likely that cideries should locate within an hour's drive of population centers, this result also suggests that consumers in smaller towns and suburbs may be willing to travel farther and also spend more than their metro counterparts.

Those who had purchased hard apple ciders in the past were both willing to travel farther to visit a cidery and also spend more on craft hard apple ciders. Hence, getting alcoholic beverage consumers to try hard apple ciders is likely to be an important contributor to them traveling to the cidery and spending more. Some craft cideries have been able to get hard apple ciders into craft brewpubs, on menus, and even in grocery stores. Marketing ciders beyond the cellar door to encourage consumers to try hard ciders can potentially help increase cidery visits and visitor expenditures.

Furthermore, the types of amenities offered by the cidery that attract visitors to travel farther distances differed from those that influenced their spending. While educational tours about how the cider is made would draw visitors to travel farther distances to come to the cidery, once there, ability to purchase and consume on-site would add to expenditures. The former result suggests that marketing of the cidery should include information about available tours at the facility. The latter result suggests that cideries should have facilities where consumers can sample and consume some of the hard cider they purchase at the cidery.

This study had several limitations. First, it represents a single snapshot in time. Second, with an emerging craft hard apple cider industry, many product development and marketing questions remain. For example, hard apple cider attribute preferences, such as preferences for packaging type, cider sweetness/dryness, sparkling/still, and other attributes. The effects of demographics on these preferences should be studied. Third, this study was limited to Tennessee consumers. Other regions with emerging craft hard apple cider industries should also be investigated. Furthermore, this study did not encompass surveys of visitors coming from out of state, which could be an important customer base for hard apple cideries, particularly in a state like Tennessee, where tourism is an important industry (Tennessee Department of Tourist Development, 2020). Consumer preferences for visiting cideries and purchasing locally hard apple ciders could vary across regions. For example, it might be expected that preferences for cidery visits and hard apple cider expenditures might differ across traditional apple production regions compared to those with periphery production. It is also important to note that because there are only a few cideries located in the state, part of this research focused on hypothetical or planned future cidery visit behaviors, rather than actual prior visits. As the industry grows, a confirmatory study among the cideries' actual visits and visitor expenditures on hard ciders at the cellar door would extend this research. Additional research might investigate how cidery visits relate to other alcohol beverage tourism since there are winery, brewery, and distillery tourist sites across the state.

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Supermarket Pricing and Promotional Behavior: Evidence from the San Luis Obispo Market

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Abstract

We collected price and promotional data from seven supermarkets operating in San Luis Obispo, CA, for one year, from 2017 to 2018. Using the data, we created a series of variables to measure prices and promotional activity. These variables were subjected to an exploratory regression analysis. The research uncovered a number of findings that help explain price variation in supermarkets and motivate future research. Average prices, price variation, promotional frequency, and promotional depth are all interrelated in important, and in some cases unexplored, ways.

Keywords: food prices food retail, pricing behavior, retail behavior

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Introduction

Supermarket pricing behavior is studied across multiple disciplines for diverse reasons. Retail food prices have direct implications for consumer welfare and the nature of price pass-through helps to shine light on the structure and functionality of the food supply chain. Many more examples abound throughout the fields of marketing, policy, and industrial organization. We seek to contribute to the literature on the empirical nature of supermarket pricing and promotional behavior, while raising questions to help motivate future research on the topic.

This study uses price and promotional data collected directly from seven supermarkets operating in San Luis Obispo, CA, to conduct a descriptive analysis of the degree to which price levels, promotional activity, and price variation are interrelated. We studied 30 distinct product categories in order to create a dataset that captures the meaningful variation within the supermarket. Product categories vary considerably in terms of their purchase penetration (the share of households purchasing items) and frequency (how often items are purchased) (Dhar, Hoch, and Kumar, 2001), as well as other factors such as the number of competing brands, storability, positioning in the supermarket, and promotional activity.

The variables of interest in the study are price levels, price variation, the price differences among national brands (NBs) and private labels (PLs) within product categories, and promotional frequency and depth. These variables partially comprise the so-called "marketing mix," or the key measurements of retailer marketing behavior and strategy.[1] We describe and discuss each in turn below. This study sought to measure how these factors vary across supermarket categories and the extent to which they are associated with one another. Each of these topics has been studied considerably, but they are typically not considered in conjunction with each other. The primary goal of our study was to provide broad insights into supermarket strategy and to inform future studies that seek to identify causal relationships connecting pricing and promotional behavior with store and category characteristics.

Food prices and variation therein are surely the two most studied aspects of retailer strategy. Our study is in the vein of Hosken and Reiffen (2004), Nakamura and Steinsson (2008), and Richards, Hamilton, and Allender (2016) in that we sought to measure and describe average food prices and price dispersion, rather than identify the determinants of these factors. Understanding and measuring retailer behavior via pricing provides insights into the study of price rigidity, input price pass-through, competitive action, and other aspects of retailer behavior.

The remainder of the paper proceeds as follows: We discuss a general background for supermarket pricing strategies, hypotheses that were evaluated in this study, the data collection process, the resulting dataset, and the stores visited for the study. We describe our methodology and present our results. We discuss our results and the extent to which our findings conformed to the hypotheses evaluated in this study. We conclude with the limitations of our study and ideas for future research.

[1]The marketing mix is typically said to include product placement, which is not a factor measured or included in our study.

Background

Nearly all supermarkets carry a mix of both NBs and PLs. The former are available in identical format across competing retailers, while the latter (also known as store brands) are marketed as being unique to the retailer at which they are being sold. The price difference between NBs and PLs within product categories are of interest for multiple reasons. This margin is often thought of as a measure of the relative quality of PLs, with wider NB/PL margins indicating stark quality differences and narrow margins indicating more comparable quality among products. Both Bontemps, Orozco, and Réquillart (2008) and Ward et al. (2002) studied the NB/PL margin as a measure of PL sales penetration and found that NB prices rise, on average, as PL market share increases. Volpe (2014) showed that the NB/PL margin varies with economic conditions, narrowing as average food prices rise. In an extensive review of the literature on PLs, Olbrich, Hundt, and Jansen (2016) recommend price gaps between NBs and PLs as one of the four most important research areas on PLs, looking forward.

Supermarkets set prices based on pricing strategies, and nearly all retailers use either high/low pricing (HLP), everyday low pricing (EDLP), or a combination of both (Ellickson and Misra, 2008). The key difference between the two is that the former relies on the use of promotions, or temporary and advertised price reductions. The academic literature on supermarket promotional activity is vast, with many studies seeking to measure the impact of promotions on sales and profitability. McColl, MacGilchrist, and Rafiq (2020)'s study is one recent example, demonstrating that promotions in large supermarkets often lead to cannibalization, or the increase in sales of one brand at the expense of others within product categories. Another is Budd et al. (2017), who used experimental design to demonstrate that promotions targeting healthy foods can increase the sales of these options. We followed the marketing literature (e.g., Bogomolova et al., 2015) and quantified promotional activity using frequency and depth. These are measured as the share of weeks that the items are on promotion and the percentage discount offered by promotions, respectively. Both of these measures have been studied in the context of their impacts on sales. However, little is known about how they interact with product characteristics or other aspects of retailer pricing strategy.

Hypotheses

While this study was exploratory in nature, extant economic and marketing research leads to a number of expectations with respect to associations among our marketing mix variables. The HLP strategy is associated with higher average prices (e.g., Bell and Lattin, 1998); therefore, we expected higher average shelf prices to be associated with promotional frequency and depth.

This phenomenon has been observed across stores and retail formats but, to our knowledge, has not been studied across products or categories. We expected promotional frequency and promotional depth to be inversely associated. Marketing scientists have shown that retailers and consumers alike perceive a tradeoff between promotions that are frequent and shallow and promotions that are infrequent and deep (Sivakumar, 1996; Sheehan, Hamilton, and Chellappa, 2019).

With respect to the NB/PL price differences, expectations were largely unclear in our setting. The bulk of the research on NB/PL competition and dynamics focuses on market share within product categories. Brüggemann, Olbrich, and Schultz (2020)'s study is a recent example of research in this arena that informs expectations for our purposes. The authors found that more NBs within categories, higher NB promotional activity, and lower NB prices were all associated with higher NB market share. Therefore, we expected that larger product categories and those with higher promotional frequency would be associated with higher NB/PL price differences, indicative of lower PL market share and potentially lower PL quality.

We expected both store size and category size to share associations with retail prices. Research on several fronts has shown that food prices are lower in larger stores and retail formats, likely due to efficiencies and scale (e.g., Chung and Myers, 1999; Saitone, Sexton, and Volpe, 2015). Thus, we expected that store size would be negatively associated with average prices. Very little empirical work has linked category size, as measured by shelf space, brand count, or product count, with food prices or promotional activity. Standard industrial organizational theory posits that product categories with more brands will see lower prices and increased promotional activity, as there is stronger competition for market share.

Finally, the literature on price rigidity offers some expectations with respect to the marketing mix. Much of the research on price variation and rigidity in food retail focuses on the impacts of upstream costs. Supermarkets face high menu costs (i.e., costs associated with changing prices). One of the advantages of the EDLP strategy is fewer price changes and, therefore, reduced menu costs (Levy et al., 1997). Thus, we expected that promotional activity, particularly promotional frequency, would be positively associated with price variation over time.

Data

A research team at Cal Poly collected price and promotional data directly from seven supermarkets in San Luis Obispo, CA, via weekly visits.[2] The stores included Vons, Ralphs, Smart and Final, Trader Joe's, Whole Foods, California (CA) Fresh Market, and Food 4 Less. The relative locations of the stores studied are shown in Figure 1. The average driving distance among the stores, examining them pairwise, is 2.63 miles. Vons and Ralphs are traditional supermarkets and are banners in national retail chains, owned by Albertsons and Kroger, respectively. Food 4 Less and Smart and Final are both warehouse format supermarkets, focusing on low prices and limited customer service. Trader Joe's is a limited assortment supermarket, selling its own PL brand nearly exclusively for most product categories. Whole Foods is a natural/gourmet supermarket, emphasizing fresh and organic foods and a high degree of customer service. It also features a limited availability of NBs. Finally, CA Fresh Market is a three-store independent grocer without a PL option in most product categories. The stores visited, as well as descriptive characteristics of these stores, are included in

[2]The research team consisted of six undergraduates, forming two teams of three each. One team collected price data from October 2017 through June 2018, then again from September 2018 through October 2018. The other team collected price data from June 2018 through September 2018. Within each team, one research assistant was assigned three stores to visit, while the other two were assigned two each. Each week, students visited their assigned stores unless travel or other obligations required team members to substitute for one another. One research assistant, Nicole Tedjasaputra, remained involved in the project and is a coauthor of the study.

Table 1. We also include demographic data, as drawn from the census tracts, to show that these stores operate in diverse environments, as defined by the nearby household characteristics.

Figure 1. Location of the Stores Included in the Analysis

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Table 1. Store Characteristics

Store	Square Footage[a]	Num. Registers	Num. Aisles	Pricing Strategy	Median HH Income[b]	Number of Households	Unemployment Rate
Trader Joe's	12,000	8	4	EDLP	$91,641	1,315	1.81%
Vons	45,000	11 (4 self-checkout)	11	HLP	$91,641	1,315	1.81%
Ralph's	45,000	7	21	HLP	$41,921	2,831	3.18%
CA Fresh Market	18,000	6	8	EDLP	$41,921	2,831	3.18%
Food 4 Less	50,000	10	15	HLP	$91,641	1,315	1.81%
Whole Foods	30,000	8	14	EDLP	$70,642	2,815	3.31%
Smart and Final	40,000	6	23	HLP	$40,292	1,832	5.63%

Notes: [a]These numbers are approximate and are based on estimates provided by employees. The authors are responsible for any errors. [b]Demographic data were drawn from the American Community Survey (ACS) 2016 5-year estimate. The unemployment rate is an estimate calculated as the number of unemployed persons over age 16, divided by the total number of persons over the age of 16.

The authors visited each store once per week, on Tuesday, to ensure that price and promotional changes were captured in the week they occurred. The dataset includes 30 product categories. The categories were selected largely out of convenience. We consulted marketing literature and visited the stores in question to identify product categories that were available in identical or similar formats across all stores, were easily visible for the researchers to find, and spanned all of the major supermarket departments. For each category, we sought to record data on the leading NB (as determined by availability across all seven stores) and the store's comparable PL, if applicable in both cases. In some cases, it was not possible to measure NBs and PLs within categories. For example, Trader Joe's is a limited assortment supermarket with few to no NBs, and CA Fresh Market is an independent supermarket with relatively few PL offerings. For simplicity, we characterize all fresh produce as "bulk" and are unconcerned with brands, to the extent they are labeled for consumers. Table 2 summarizes the dataset according to product categories.

Table 2. Product Descriptions and Average Prices Across All Stores

Product Category	Brand	Avg Shelf Price	Avg Promo Price	Average NB/PL Difference
Soda (6-pack cans)	Coca-Cola	$2.05	$1.39	43.29%
	Private label	$1.32	$0.91	
Coffee (12 oz.)	Folgers	$7.56	$5.10	48.52%
	Private label	$4.61	$2.42	
Tuna (5 oz.)	Bumble Bee	$1.52	$1.11	17.24%
	Private label	$1.28	$1.13	
Cereal (12 oz.)	Cheerios	$4.15	$2.57	47.18%
	Private label	$2.57	$1.00	
Potato chips (8 oz.)	Lays	$3.24	$2.26	27.78%
	Private label	$2.54	$1.56	
Macaroni and cheese (7.25 oz.)	Kraft	$1.55	$1.13	63.04%
	Private label	$0.81	$0.76	
Pasta sauce (26 oz.)	Prego	$2.91	$2.03	34.54%
	Private label	$2.05	$1.16	
Peanut butter (16 oz.)	Jif	$3.55	$2.18	29.17%
	Private label	$2.65	$1.76	
Cookies (13 oz.)	Chips Ahoy	$3.27	$2.17	41.68%
	Private label	$2.14	$1.40	
Hazelnut spread (13 oz.)	Nutella	$4.82	$3.90	46.93%
	Private label	$2.99	N/A	

Table 2. (continued)

Product Category	Brand	Avg Shelf Price	Avg Promo Price	Average NB/PL Difference
Ketchup (20 oz.)	Heinz	$3.18	$2.09	50.61%
	Private label	$1.90	$1.42	
Pancake mix (40 oz.)	Bisquik	$3.69	$2.49	30.82%
	Private label	$2.47	$1.36	
Eggs (dozen)	Egglands	$3.53	$2.16	13.81%
	Private label	$3.07	$2.10	
Milk (gallon)	Alta Dena	$4.78	$3.51	32.28%
	Private label	$3.45	$2.37	
Almond milk (1/2 gal.)	Almond Breeze	$3.50	$2.51	5.84%
	Private label	$3.30	$2.14	
Orange juice (1/2 gal.)	Simply Orange	$4.38	$3.00	29.91%
	Private label	$3.24	$2.37	
Cheddar cheese (2 lb.)	Tillamook	$9.68	$6.62	31.51%
	Private label	$7.05	$4.27	
Butter (1 lb.)	Land O'Lakes	$5.98	$3.64	36.65%
	Private label	$4.17	$2.76	
Ice cream (1/2 gal.)	Breyers	$4.52	$3.90	29.56%
	Private label	$4.09	$2.22	
Frozen waffles (12.3 oz.)	Vans	$3.07	$2.17	31.44%
	Private label	$2.23	$1.52	
Frozen broccoli (10 oz.)	Birdseye	$2.75	$1.94	51.25%
	Private label	$1.63	$1.21	
Chicken breasts (1 lb.)	Foster Farms	$5.39	$2.58	28.38%
	Private label	$4.05	$1.33	
Bacon (1 lb.)	Oscar Mayer	$8.31	$4.89	35.84%
	Private label	$5.78	$2.99	
Ground turkey (1.25 lb.)	Jennie-O	$5.16	$2.37	14.80%
	Private label	$4.45	$2.37	
Fuji apples (1 lb.)	Bulk	$1.34	$1.07	
Russet potatoes (1 lb.)	Bulk	$1.00	$0.95	
Baby carrots (1 lb.)	Bulk	$1.50	$1.00	
Zucchini (1 lb.)	Bulk	$1.84	$1.26	
Romaine lettuce (head)	Bulk	$1.42	$0.95	
Bananas (1 lb.)	Bulk	$0.67	$0.54	

The research team collected the data over a one-year period, from October 2017 through October 2018. Each week, the shelf price was recorded, as well as a binary indicator reflecting whether the product in question was on promotion. If on promotion, the promotional price was also recorded.[3] Using the raw price and promotional data, we created the variables to be used in our analysis. These are reported and defined in Table 3, along with summary statistics. Most of the marketing mix variables are calculated using the primary price data, as collected by the authors. The authors estimated category size by measuring the length of the shelves within product categories and multiplying by the number of shelves. It does not take into account the depth of shelves and is, therefore, an estimate. Brand count is a count taken by the authors during store visits and does not include product variations within companies (e.g., flavor or package size differences by brand). Square footage is an estimate of the selling space, per store, and is based on estimates made by store employees, shared in conversation with the authors. We created the dummy variable for HLP pricing at the product level, rather than the store level. Ellickson and Misra (2008) studied more than 17,000 supermarkets and found that 38% of them used a combination of HLP and EDLP, meaning that pricing strategies vary by department or product categories. If a product has a promotional frequency of 10% or greater, it is classified as HLP in our dataset.[4]

[3]For Ralphs and Vons, shoppers are required to have membership cards, which are free to obtain, in order to redeem promotional prices.
[4]We experimented with 5% and 15% as thresholds as well, given that we could find no widely accepted point of delineation between HLP and EDLP in the literature. Using these alternate thresholds does not change the results.

Table 3. Summary Statistics and Variable Definitions

Variable	**Definition**	**Mean**	**Std Dev**	**Minimum**	**Maximum**
Average shelf price	The average weekly nonpromotional price, across all stores.	3.38	2.08	0.19	12.90
Normal shelf price	The normalized weekly average shelf price, calculated as the average shelf price divided by the average of all products' shelf prices, by store.	1.00	0.60	0.07	3.51
Coefficient of variation shelf price	The coefficient of variation of the shelf price, calculated as the standard deviation divided by the mean.	0.45	0.13	0.00	0.67
Average promotional price	The average weekly promotional price, across all stores. This is only reported during promotions and is blank otherwise.	2.99	1.76	0.49	10.15
Coeffience of variation promotional price	The coefficient of variation of the promo price, calculated as the standard deviation divided by the mean.	0.29	0.21	0.00	0.89
Promotional frequency	The share of weeks that a product was on promotion during the data collection period.	0.35	0.36	0.00	1.00
Promotional depth	The average percentage difference between the shelf price and the promotional price.	0.19	0.13	-0.55	0.57
NBPL shelf difference	The average percentage difference between national brand and private label shelf prices within product categories.	0.28	0.13	-0.03	0.57
Brand count	The estimated number of unique brands offered, by product category and store.	8.57	7.90	0.00	44.00

Table 3. (continued)

Variable	Definition	Mean	Std Dev	Minimum	Maximum
Category size	The estimated square footage of product categories, by store. This is calculated as the estimated length of product shelves by the number of shelves.	47.29	59.24	0.75	333.33
Square footage	The size of the stores visited for this study, as measured by retail space square footage, and estimated by store employees, in thousands.	36.84	12.41	12.00	50.00
Registers	The number of checkout aisles, or registers, by store. This includes self-checkout.	8.07	1.86	6.00	11.00
HLP	A dummy variable equal to 1 for store/product combinations that are on promotion more than 10% of the time, or follow the high-low pricing strategy.	0.55		0.00	1.00

As a starting point in our empirical analysis, we calculated averages for all variables by store. The results are reported in Table 4. The highest average shelf prices are at CA Fresh Market and the lowest are at Trader Joe's. However, the objective of this study was not to rank or categorize retailers according to average price levels. Comparing average prices for food baskets is problematic for multiple reasons. First, in the calculation of average prices, relatively more expensive items are given disproportionately more weight than cheaper items. Second, without purchase data, it is impossible to determine how well these prices reflect what prices consumers actually pay, on average. And finally, many of these comparisons are not exact across stores. For example, Trader Joe's sells only PLs, which are nearly always cheaper than NBs.

Table 4. Sample Means of Variables Included in Estimated Regressions by Store

Variable	California Fresh Market	Food 4 Less	Ralphs	Smart and Final	Trader Joe's	Vons	Whole Foods
Average shelf price	$3.99	$3.37	$3.17	$3.03	$2.66	$3.93	$3.50
Normal shelf price	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Coefficient of variation shelf price[a]	0.51	0.51	0.51	0.47	0.09	0.48	0.51
Average price	3.50	$2.76	$2.76	$2.72	N/A	$3.39	$2.69
Coefficent of variation promotional price	0.27	0.39	0.26	0.30	N/A	0.40	0.05
Promotional frequency	0.31	0.67	0.25	0.25	N/A	0.55	0.03
Promotional depth	0.22	0.23	0.19	0.14	N/A	0.18	0.22
NBPL shelf difference	N/A	0.27	0.32	0.28	N/A	0.24	0.25
Brand	11.46	6.35	11.17	8.17	1.54	10.04	8.51
Count category size	34.28	49.51	66.30	41.13	14.17	66.04	31.86

[a]CV is the coefficient of variation, measured as the standard deviation divided by the mean.

Shelf price variation is consistent across stores. The coefficient of variation (CV), which is the sample standard deviation divided by the sample mean, is equal to 0.51 for CA Fresh Market, Food 4 Less, Ralphs, and Whole Foods. It is only slightly less for Smart and Final and Vons. The CV is nearly zero for Trader Joe's, which practices strict EDLP and rarely changes prices. Therefore, excluding promotions, food prices in the sample varied similarly throughout the sample. This may reflect consistent responses by retailers to changes in market fundamentals and warrants further investigation.

Promotions were commonplace at five of the seven retailers in the sample. No promotions were observed at Trader Joe's during the data collection, and very few were observed at Whole Foods. However, the average product in the sample was on promotion 67% of the time at Food 4 Less and 55% of the time at Vons. We do not claim that our sample of products is accurately representative of the entire product mix at the respective stores, but it is worth noting that this intensity of promotional activity exceeds that measured by studies using scanner data (e.g., Hosken and Reiffen, 2004). At Ralphs, Smart and Final, and CA Fresh Market, the average product in the sample was on sale between 25%-31% of the time. On average, Smart and Final, which featured relatively low average shelf prices, had the lowest average promotional depth, at 14%. The deepest promotions were at Food 4 Less, with an average depth of 23%. Therefore, Food 4 Less engaged in the heaviest promotional activity out of all the sampled retailers.

The average NB/PL shelf price difference, in percentage terms, was also fairly consistent across stores. The difference ranged from 24% at Vons to 32% at Ralphs. The averages in the sample corroborate those of Volpe (2011), who measured the NB/PL price difference across hundreds of product categories for Safeway and Albertsons (before they merged) and found an average of 23%.

Finally, the sampled stores exhibit considerable variation with respect to average brand counts and category size. The data indicate that with more brands, category size increases, as expected. Trader Joe's, focusing primarily on its own PL, features fewer than two brands per sampled category, on average. Alternatively, CA Fresh Market, Ralphs, and Vons all average more than 10 brands per category. One motivating factor behind sampling a variety of stores and product categories is that elements of retail strategy and pricing behavior depend on the breadth and depth of product categories.

Given the exploratory and descriptive nature of this study, we calculated pairwise correlations for all of the continuous variables in our analysis. In doing so, we were able to examine whether the associations among our variables corroborate empirical evidence to date, and also identify potential elements of supermarket pricing and promotional behavior that is worth exploring in future research. We report the correlation coefficients for selected variables in Table 5.

Table 5. Correlation Coefficients for Selected Continuous Variables Included in the Estimated Regressions

	Avg Shelf Price	Normal Shelf Price	CV Shelf Price	Avg Promo Price	Promo Freq	Promo Depth	NBPL Shelf Dif	Brand Count	Category Size	Sq Footage	Registers
Average shelf price	1.00	0.97***	0.09	0.95***	0.27***	0.17**	0.00	-0.04	-0.15**	0.03	0.08
Normal shelf price		1.00	-0.02	0.93***	0.24***	0.17**	0.04	-0.09	-0.21**	0.00	0.00
Coefficient of variation shelf price			1.00	-0.11	-0.19**	0.15**	0.24**	0.13**	0.16**	0.27**	0.00
Average promotional price				1.00	0.17*	-0.12	0.02	-0.04	-0.19***	-0.07	0.07
Promotioal frequency					1.00	0.20***	0.00	0.01	0.24***	0.41***	0.27***
Promotional depth						1.00	0.02	-0.01	0.07	0.09	0.01
NBPL shelf difference							1.00	0.04	-0.08	0.05	-0.17*
Brand count								1.00	0.64***	0.24***	-0.05
Category size									1.00	0.29***	0.09
Square footage										1.00	0.46***
Registers											1.00

Note: ***Indicates that the Pearson correlation coefficient is significant at the 0.01 level, **at the 0.05 level, and *at the 0.10 level.

Some of the estimated correlation coefficients warrant discussion because of their statistical significance and magnitude. The promotional activity variables shared a number of intriguing correlations with other variables in the analysis. Throughout the discussion of correlations, we discuss only those coefficients that are statistically different from zero. As expected, all price measurements share very strong and significant positive correlations. That is, both nominal and normalized shelf prices, as well as promotional prices, are all strongly pairwise correlated, an observation with implications for regression specification design.

Promotional frequency is positively correlated with average and normalized shelf prices, as well as average promotional prices. Therefore, it seems that higher-priced items go on sale more frequently. Frequency is negatively correlated with the CV of shelf prices, which suggests that shelf price rigidity increases with promotional activity, implying that for some products, retailers adjust prices primarily through promotions. The correlations between average and normalized prices with promotional depth are weaker than those with frequency. Importantly, depth is positively correlated with the CV of shelf prices, suggesting some divergence with respect to retailers' use of timing versus depth for sales. Promotional frequency and depth share are positively correlated, which means that at least some products exhibit both deep and frequent promotions. Promotional frequency is positively associated with category size, register count, and store square footage, showing that promotional activity tends to be higher in larger categories and larger stores. Depth shares no significant correlations with category or store characteristics.

The NB/PL price difference shares a positive correlation with the CV for shelf prices. Therefore, on average, the price difference widens between NBs and PLs within product categories as shelf prices become more volatile, and vice versa. The NB/PL price difference is negatively correlated with the register count, meaning that, on average, NB and PL substitutes are priced somewhat closer to one another in larger stores.

The brand count and category size variables both share a number of associations in the data that reflect potential unexplored aspects of retailer strategy and the price-setting process. Not surprisingly, the two variables share a strong and positive correlation, showing that physically larger categories are likely to have more competing brands than smaller ones. Brand count is positively correlated with shelf price CV, meaning that prices change more often in categories with more brands. This may be a function of interbrand competition, including the aforementioned NBs and PLs. Brand count and category size are also positively correlated with square footage, suggesting an intuitive positive relationship between store size and product assortment. The correlation between category size and shelf price CV is also positive, though weaker. Category size is negatively correlated with average and normalized shelf prices, as well as average promotional prices. Taken together, the data suggest that supermarket categories with a greater number of products have lower shelf prices and more intense promotional activity, all of which may also relate to the nature of competition among brands.

As noted, we used both square footage and register count as related, but distinct, measures of store size. The two variables share a positive and significant correlation, but at 0.46, it is clear that larger store footprints do not always result in more registers. Stores exhibit variation in the size and efficiency of their registers and checkout lanes. Square footage is positively correlated with the CV of shelf prices, suggesting that prices vary more in larger stores, even in the absence of any promotional activity. This is consistent with the notion of cost efficiencies, or that menu costs are smaller in percentage terms for larger stores.

Methodology

To quantify associations among price and promotional variables, we employed a regression framework and estimated a series of ordinary least squares (OLS) regressions. Our goal in this framework was to investigate our hypotheses of interest described in the background section, estimate the magnitudes of associations, and assess significance when possible, not to claim or infer causality. Therefore, we employed a generalized regression model that describes each individual continuous variable of interest as a function of all others. To measure associations, marketing mix variables were modeled as

$$\begin{aligned} &Variable_{ij} \\ &= f(Norm\ Shelf\ Price_{ij}, Avg\ Shelf\ Price_{ij}, CV\ Shelf\ Price_{ij}, Avg\ Promo\ Price_{ij}, \\ &Promo\ Freq_{ij}, Promo\ Depth_{i}\ , Brand\ Count_{ij}, Category\ Size_{ij}, Sq\ Footage_{ij}, \\ &No.of\ Registers_{ij}, HLP_{ij}) + error_{ij} \end{aligned} \tag{1}$$

for product category i and brand j. The purpose of (1) is to measure associations among the full suite of marketing mix variables as well as category and store characteristics, while avoiding evident multicollinearity. Our empirical strategy was to estimate (1) for a the full series of variables of interest, maintaining the righthand side variables consistent, except for the one being used as the dependent variable for each estimation. We experimented with nested versions of (1) for most variables to assess the robustness of our findings, and these results are available from the authors upon request. The data were cleaned of potential outliers to correct any mistakes made in the data collection and entry processes. To account for potential heteroskedasticity, we used robust standard errors that are clustered by store. We calculated the variance inflation factors (VIFs) and conditional index numbers for each estimation of (1) to check for multicollinearity.[5] Average shelf price (Avg Shelf Price) was collinear with normal shelf price (Norm Shelf Price) and average promotional price (Avg Promo Price) in almost all estimated regression specifications of (1).

Model (1) includes store-level variables reported in Table 1. These include square footage (Sq Footage), number of registers (Registers), and high-low pricing (HLP). Recall that Sq Footage is an estimate drawn from conversations with store employees. Registers is a count of the checkout lanes, taken by the authors during data collection. HLP is the dummy calculated per product and

[5]There is no diagnostic measure agreed upon to investigate potential multicollinearity in OLS models. We employ two of the most common to develop consensus when investigating this potential issue in our estimations. The variance inflation factor is typically thought to represent serious multicollinearity at values of 10 or higher (O'Brien, 2007) .Condition index numbers indicate serious collinearity when two conditions are met-the condition index must be above the threshold of 30, and at least two explanatory variables must individually account for at least 90% of the total variance (Hair et al., 2013).

store combination. We also estimated (1) with store fixed effects, but our preferred estimation results include the store characteristics, as they provide superior model fit (as measured by the adjusted R-squared) in most cases and make our findings more generalizable. The number of aisles was found to be highly collinear with the number of registers in preliminary regressions, and we opted to include only regression using registers due to the heterogeneity of aisle size and length across stores. To assess model fit, we relied on the adjusted R-squared. We also calculated and reported the model F statistics.

Results

We present our regression results in two separate tables, partially to facilitate presentation, but also because we wished to separate the results that speak directly to the retail marketing mix from those that address price variation or rigidity. Given that we measured average prices in two distinct, but related, ways, we estimated (1) for each variable in the marketing mix twice, once using average shelf prices and once using normalized shelf prices. This process intended to lend robustness to the findings. Also, due to multicollinearity, it was never possible to include the average promotional price in (1). Table 6 reports selected regression results for OLS estimations of (1), with marketing mix variables measuring price levels and promotional activity.[6] The estimations on the NB and PL price shelf price differences (NBPL Shelf Dif) were limited in scope, because that variable could only be calculated for a limited number of stores and categories, depending on the availability of PLs. These estimations featured a sample size of 78 and resulted in only CV shelf price (CV Shelf Price) and register count being statistically significant. The correlation between CV Shelf Price and the NBPL price difference was one of the stronger pairwise correlations in the data. Nonetheless, it is important to note that the CV Shelf Price varies relatively little in our dataset. The adjusted R-squared and the F statistics associated with the NBPL Shelf Dif regressions suggest that our model specifications explain very little of the variation of NBPL Shelf Dif, despite having two statistically significant coefficients.

[6]We also experimented with estimating versions of (1) for multiple dependent variables in a system setting using seemingly unrelated regression (SUR). Given our limited sample size, SUR may have yielded efficiency gains in the estimation. However, the results were not qualitatively different from the OLS results. The SUR results are also available from the authors upon request.

Table 6. Regression Results on Prices and Promotions

	NBPL Shelf Dif	NBPL Shelf Dif	Norm Shelf Price	Avg Shelf Price	Promo Freq	Promo Freq	Promo Depth	Promo Depth
Intercept	-0.320	-0.334	2.074*	6.376*	-1.325***	-1.307***	-0.074	-0.061
	(0.287)	(0.330)	(1.123)	(3.951)	(0.459)	(0.459)	(0.227)	(0.227)
Average shelf price	0.005					0.008		0.008**
	(0.007)					(0.009)		(0.004)
Normal shelf price		0.019			0.034		0.033**	
		(0.023)			(0.031)		(0.015)	
Coefficient of variation shelf price	1.152**	1.165**	-1.995	-5.451	1.603*	1.581*	0.434	0.417
	(0.600)	(0.601)	(2.070)	(7.280)	(0.851)	(0.851)	(0.415)	(0.415)
Promotional frequency	0.053	0.051*	0.197	0.552			0.047	0.049
	(0.056)	(0.056)	(0.182)	(0.639)			(0.036)	(0.036)
Promotional depth	0.021	0.018	0.818**	2.648**	0.200	0.208		
	(0.139)	(0.140)	(0.371)	(1.307)	(0.155)	(0.155)		
Brand count	0.001	0.000	0.004	0.017	-0.002	-0.003	-0.002	-0.002
	(0.003)	(0.003)	(0.008)	(0.028)	(0.003)	(0.004)	(0.002)	(0.002)
Category size	0.000	0.000	-0.002**	-0.007*	0.001*	0.001*	0.001**	0.001**
	(0.000)	(0.000)	(0.001)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
Square footage	0.003	0.003	0.001	-0.040**	0.001	0.002	-0.001	-0.001
	(0.004)	(0.004)	(0.006)	(0.021)	(0.002)	(0.003)	(0.001)	(0.001)

Table 6. (continued)

	NBPL Shelf Dif	NBPL Shelf Dif	Norm Shelf Price	Avg Shelf Price	Promo Freq	Promo Freq	Promo Depth	Promo Depth
Registers	-0.018**	-0.017**	-0.026	0.133	0.058***	0.057***	0.007	0.005
	(0.008)	(0.008)	(0.028)	(0.100)	(0.011)	(0.011)	(0.006)	(0.006)
HLP	-0.032	-0.032	0.020	0.195	0.456****	0.457***	-0.009	-0.010
	(0.060)	(0.060)	(0.176)	(0.619)	(0.064)	(0.064)	(0.035)	(0.035)
N	78	78	184	184	184	184	184	184
Adj. R-sq.	0.036	0.039	0.017	0.039	0.417	0.416	0.050	0.046
Model F	1.32	1.34	1.40	1.93*	17.38***	17.29***	2.20**	2.10**

Notes: Robust standard errors in parentheses. Standard errors are clustered by store. *Coefficient is significant at the 0.10 level, **at the 0.05 level, and ***at the 0.01 level.

Relative to the NB/PL estimations, the results for (1) on normalized and average shelf prices, promotional frequency, and promotional depth all featured higher sample sizes, more explanatory power (as measured by the adjusted R-squared), and more statistically significant regression coefficients. For the most part, the significant coefficient estimates correspond to correlations from Table 4 that stood out as reflecting potentially meaningful associations. The OLS results for (1) with price variation, as measured by the CV for shelf prices (CV Shelf Price) and the CV for promotional prices (CV Promo Price), are reported in Table 7. As with the price level and promotional estimations presented in Table 6, these regressions feature multiple significant coefficient estimates, higher adjusted R-squared values, and more statistically significant model F statistics.

Table 7. Regression Results on Price Variation

	CV Shelf Price	**CV Shelf Price**	**CV PromoPrice**	**CV Promo Price**
Intercept	0.529***	0.528***	0.169***	0.169***
	(0.011)	(0.011)	(0.025)	(0.025)
Avgerage shelf price		-0.001		0.003
		(0.007)		(0.002)
Normal shelf price	-0.003		0.008	
	(0.003)		(0.007)	
Promotional	0.013*	0.012*	0.267***	0.266***
frequency	(0.007)	(0.007)	(0.016)	(0.015)
Promotional depth	0.014	0.013	-0.089***	-0.089***
	(0.014)	(0.014)	(0.032)	(0.033
Brand count	-0.002	-0.002	-0.000	-0.000
	(0.003)	(0.003)	(0.007)	(0.001)
Category size	-0.000	-0.000	0.001	0.000
	(0.003)	(0.003)	(0.009)	(0.001)
Square footage	-0.003	-0.003	0.001	0.001*
	(0.002)	(0.002)	(0.001)	(0.000)
Registers	-0.002	-0.000	-0.005**	-0.006**
	(0.001)	(0.001)	(0.002)	(0.002)
HLP	-0.031***	-0.032***	0.134***	0.134***
	(0.006)	(0.006)	(0.014)	(0.014)

Table 7. (continued)

	CV Shelf Price	CV Shelf Price	CV PromoPrice	CV Promo Price
N	184	184	184	184
Adj. R-sq.	0.134	0.132	0.814	0.815
Model F	4.53***	4.48***	101.45***	101.61***

Notes: Robust standard errors in parentheses. Standard errors are clustered by store. *Coefficient is significant at the 0.10 level, **at the 0.05 level, and ***at the 0.01 level.

Discussion

The OLS results suggest a number of potentially meaningful associations among price and promotional variables, which in turn may shed light on components of supermarket behavior and strategy. As discussed above, we calculated both the VIFs and condition index factors for all coefficients in all estimations of (1). The inclusion of any two price variables—average shelf price, average promotional price, or average normalized price—led to multicollinearity in all estimations, therefore we only include shelf or normalized prices separately.[7] We discuss our findings with respect to four sets of estimations of (1): those related to the NB/PL margin, those related to price levels, promotional frequency and depth, and, finally, price variation, as measured by the CV.

NB/PL Price Differences

Price variation measured as CV Shelf Price is found to be positive and significant in both estimations of (1) that feature NBPL Shelf Dif as the dependent variable. A marginal increase in shelf price variation is associated with an increase in the NB/PL margin, within categories, by 1.15 percentage points. Zhao (2006) found, in both a review of the literature and in his own study, that price dispersion within product categories is associated with both the degree of retail competition, as measured by store entry, and consumer heterogeneity. Recall, however, that our regression results suggest our model specifications weakly explain the variation in NBPL Shelf Dif, despite the statistical significance of the coefficient associated with price dispersion. As shown in Table 1, the supermarkets in our study operate in somewhat diverse socioeconomic conditions, despite all being in the same small city. In future research, competition may be approximated using measures, such as the Herfindahl-Hirschman Index (HHI), and shopper heterogeneity may be proxied using demographics. Moreover, studies such as that of Ward et al. (2002), have found that PL penetration and market share have implications for the NB/PL price difference within categories, and we are unable to measure market share or sales in this setting.

The register count is negatively and significantly associated with the NB/PL price difference. Thus, it seems that NBs and PLs are closer in price, on average, in larger format stores. This may reflect higher quality of PL products and established PLs at larger stores that are more comparable to NBs. This finding calls for more research on the relationships between store characteristics and market structure on NB and PL prices.

[7]The full set of multicollinearity results are available from the authors upon request.

Average and Normalized Prices

For both average and normalized shelf prices, we found that Promo Depth has a positive and statistically significant coefficient, while Category Size has a negative and statistically significant coefficient. The finding with respect to Promo Depth suggests that retailers offer larger discounts on relatively more expensive items in the supermarket. Jedidi, Mela, and Gupta (1999) showed that the long-run impact of promotions on sales tends to be negative, though the short-term sales increases can be significant. This finding is observationally consistent with the notion that retailers recognize this phenomenon and offer deeper promotions on more expensive items in order to advertise significant savings to consumers and to maximize the sales boost during promotions.

Larger categories with more brands likely feature a greater degree of competition among brands. This notion is consistent with the finding that larger categories, as measured by square footage, are associated with lower shelf prices, and this conforms to our expectations. According to the estimation on average shelf prices, each additional square foot of shelf space is associated with a reduction in shelf price of almost a penny. The economic significance of this relationship, therefore, varies by product category. It would be worthwhile and interesting to use longitudinal data to study the impact of changes in category size, or brand count within categories, on shelf prices as an attempt to measure the competition effects on pricing within stores, rather than between stores.

Also, in line with our expectations, we found that square footage is negatively and significantly associated with average prices. Each additional 1,000 square feet of selling space is associated with a \$0.04 decrease in average prices. Therefore, while both store size and category size have inverse associations with shelf prices, store size seems to be economically more important.

Promotional Frequency and Depth

Our findings showed that the CV of shelf prices is positively and significantly associated with both promotional frequency and depth. That is, as shelf prices became more variable in the dataset, we observed more promotional activity. This conformed to our expectations, and it supports the idea that stores with heavy promotional activity change prices more often and are more accepting of menu costs.

Average prices are positively and significantly associated with Promo Depth. We did not find evidence that promotional frequency and depth are inversely related. It is likely that a number of product characteristics are associated with heavier promotional activity, in terms of both promotional depth and frequency. These may include storability and average times between purchases (Narasimhan, Neslin, and Sen, 1996) or product size, bulkiness, and hedonic nature of product prices (Felgate and Fearne, 2015).

Results showed that category size is positively and significantly associated with both Promo Freq and Promo Depth in all estimations, in line with our expectations. Therefore, as total shelf space increases within categories, promotional activity tends to increase. To our knowledge, this exploratory finding is novel. It may relate to our findings with respect to average prices and category size, as it is consistent with the notion that interbrand competition is stronger in larger categories. Larger categories may also feature more NB products from large manufacturers or distributors, which in turn may exhibit more promotional activity as a result of their larger marketing budgets. The magnitudes of these coefficients are small. For both frequency and depth, an increase in category size of 10 square feet is associated with an increase of approximately 1 percentage point. The association among category characteristics and retail prices and behavior is largely unexplored, beyond the principal elements of category management.

HLP is strongly and positively associated with promotional frequency, which is to be expected, given that promotional incidence is the defining characteristic of the HLP strategy. Interestingly, this coefficient is insignificant in the promotional depth estimations, further demonstrating a lack of association between promotional frequency and depth. In another finding that warrants further research, register count is positively and significantly associated with promotional frequency, implying that larger stores offer promotions more frequently, on average.

Price Variation

For the most part, we did not observe significant regression coefficients in the estimations on price variation. However, we observed a great disparity in model fit when comparing estimations of (1) for shelf price variation versus promotional price variation. The adjusted R-squared values for the CV Shelf Price estimations are about 0.13, but for CV Promo Price they are 0.81. This suggests that most of the shelf price variation is driven by upstream cost changes, which are not included in our study. But promotional frequency and depth, collectively, seem to explain the great majority of the variation in promotional prices. As noted above, researchers have studied price variation in a number of different ways in economic and marketing research. We separated shelf price variation from promotional price variation, and, therefore, did not examine the impact of promotional activity on price changes. We measured how prices, whether shelf or promotional, vary over time for product categories.

Promo Freq and Promo Depth emerged as the two most important variables associated with price variation. As promotional frequency increases, shelf price variation also increases. Therefore, products with more frequent promotions also see more frequent shelf price changes. This is holding HLP constant, which makes this point somewhat nuanced. On average, products exhibiting the HLP strategy see fewer price changes, as measured by the CV. However, marginal increases in promotional frequency are associated with greater shelf price variation. According to the regression results, promotional depth seems not to be associated with CV Shelf Price.

Both Promo Freq and Promo Depth seem to be associated with the CV of promotional prices. Taken together, the results indicate that products with higher promotional frequency (and in general, those abiding by HLP) see more variation in the sale prices offered. However, deeper promotions are more likely to yield promotional prices that vary little over time and are more predictable to consumers. The coefficient on Registers is also negative and significant, lending more evidence to the notion that store size is important for explaining promotional activity. We found that larger stores see less variation in the promotional prices offered.

Conclusions

We conducted an exploratory analysis of pricing and promotional behavior for supermarkets operating in San Luis Obispo, CA, using primary data collected. We used a reduced-form regression framework to identify significant associations among various variables that measured retailer behavior and, in many cases, strategy. In some cases, our results conform to previous research in marketing and economics. But in many cases, we raise questions that merit further research using larger datasets, greater longitude, and an identification strategy that can assess causation.

The most intriguing results from the study, in our view, are those pertaining to the nature of product categories and promotional behavior. Price and promotional activity are both related to category size in a number of significant ways, and it is possible that researchers have emphasized shopper or product characteristics in empirical research while overlooking or undervaluing category characteristics. Promotional activity has been studied extensively, but our findings indicate that there is more to be learned about the links between promotional activity, shelf prices, and store format. Category size, as measured by shelf space or brand count, seems fertile ground for empirical exploration into understanding how and why retailer behavior varies within supermarkets.

As an exploratory study focusing on a single market, our study was not without limitations. We were unable to observe either sales or upstream costs, meaning we could only measure how the marketing mix variables interrelated with one another. The products studied were selected largely based on convenience, given that they were available across different retailers and visible within stores. Without market share data, it is not clear that we always selected the "leading" national brand within categories. It is our hope that the findings of this study and the questions raised by the results spur more research using larger and more diverse datasets.

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COVID-19 Trade Actions in the Agricultural and Food Sector

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Abstract

This study investigated the determinants of trade actions in the agricultural and food sector related to the coronavirus pandemic. These emergency trade measures aimed to prevent the inflow of certain products and promote the import of others. We investigated the determinants of such measures using product-level trade action data for WTO members. Applying an instrumental variable approach that accounts for high-dimensional fixed effects, we found that trade actions relate negatively to the applied tariff level and the domestic pandemic severity. Countries implemented fewer trade facilitation actions considering increased domestic COVID-19 cases, but this was done more in response to spiking foreign case numbers.

Keywords: Coronavirus pandemic, trade actions, agricultural and food sector, control function approach, product level

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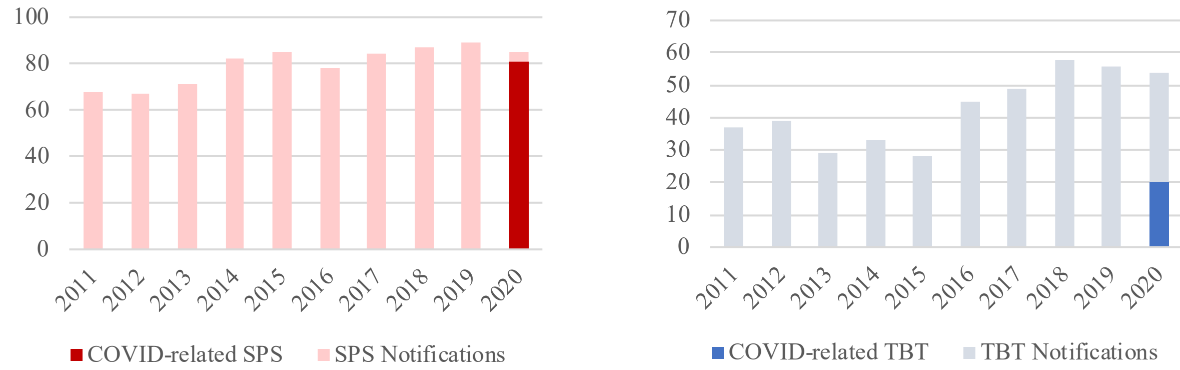
Introduction

As the coronavirus (COVID-19) pandemic began to spread in spring 2020, several countries implemented trade actions to reduce the virus's cross-border movement (Chen and Mao, 2020; Kerr, 2020). Because cross-border movement is a significant source of coronavirus spread, international trade was also affected (Adda, 2016). Non-tariff measures (NTMs) related to COVID-19 were initiated as emergency measures by 38 countries in 2020 (United Nations, World Trade Organization, 2021b). The first NTM notification to the World Trade Organization (WTO) banned the import of exotic species and decorative animals from China to the Russian Federation (United Nations, World Trade Organization, 2021b). Various other nations have taken similar measures to prevent the transmission of the virus by wild animals. The coronavirus pandemic caused a suspension of food production activities in several countries, and the production level was unable to keep up with demand (Aday and Aday, 2020). The decline in production resulted in supply shortages and higher prices for some food products (Peel, 2021). In response to this market failure, several countries notified the WTO of emergency measures, enabling them to adopt trade actions immediately, without the usual 60-day comment period or 6-month transition period before entry into force.

COVID-19-related NTMs were implemented to either restrict or facilitate trade, targeting mostly personal protective equipment, food, medical equipment, plant products, and live animals (United Nations, World Trade Organization, 2021b). Our study focused on the agricultural and food sector as it is closely related to human health and food security. This sector faced severe impacts from the pandemic because the global food system is highly integrated (Chen and Mao, 2020). Major NTMs in the agricultural and food sector are Sanitary and Phytosanitary (SPS) and Technical Barriers to Trade (TBT) measures. According to the United Nations Conference on Trade and Development (2019), SPS measures intend to protect human or animal health from risks by additives, contaminants, toxins, or disease-causing organisms in food. TBT refers to technical regulations and procedures for conformity assessment with technical rules and standards. Over the last decade, SPS and TBT measures have been on the rise. In 2020, the total number of SPS and TBT notifications decreased compared to those of the previous year, but the notifications are different from the previous years. As shown in Figure 1, more than 95% of the SPS notifications are related to COVID-19, which is not surprising considering that the pandemic is directly related to the health of humans and animals. About 40% of the TBT notifications in the agricultural and food sector were implemented under the emergency response to COVID-19. TBT is less likely to affect the agricultural and food industry than SPS, but it is closely related to food standards and technical regulations (United Nations, World Trade Organization, 2021a). The COVID-19-related TBTs include strengthening technical regulations and standards on imports, most of which were implemented to mitigate the existing rules and facilitate imports.



Source: Collected from WTO and calculated by the authors. Notes: The graphs show NTMs in the agricultural and food sector (HS01-24).

Figure 1. Number of General and COVID-19-related SPS and TBT Notifications

Somewhat counterintuitively, NTMs can promote trade by reducing asymmetric information and externalities through opening information on standard requirements (Xiong and Beghin, 2017; Gourdon, Stone, and van Tongeren, 2020). According to the WTO agreement, these measures should not be used as a source of restricting trade. Yet, despite this limitation, some researchers argue that NTMs technically substitute for tariffs in the free trade era (Looi Kee, Nicita, and Olarreaga, 2009). They can be utilized to protect the domestic market (de Almeida, da Cruz Vieira, and da Silva, 2012). The notifications to SPS and TBT agreements imposed as an emergency response to COVID-19 are different from those notifications before. Since this event was directly related to the health of humans and animals, most measures had a clear purpose, such as restricting or facilitating trade. Most studies investigating their impact on international trade or their determinants disregard the stated purpose of the NTM notification (Orefice, 2017; Santeramo and Lamonaca, 2019; Webb et al., 2020). There has been no research on the determinants of COVID-19-related NTMs taken considering the aim of each notification. To fill this gap, we analyzed the determinants of SPS and TBT in response to COVID-19 trade actions in the agricultural and food sector, considering their stated purpose when filing notification to WTO.

This paper presents findings from our analysis of COVID-19-related NTM determinants in the agricultural and food sector. We distinguished between trade-restricting and facilitating NTMs and constructed a balanced panel dataset for NTM actions at the 6-digit product level covering 55 countries for 2020. We added monthly information on MFN tariffs, trade flows, exchange rates, dietary supply, and new COVID-19 cases for each country and the world.[1] To assess the drivers of NTMs related to COVID-19, we estimated a high-dimensional count data regression model that controls for product and country heterogeneity, where we identified the parameters of interest with

[1]COVID-19 cases in the rest of the world can be regarded as a proxy for country awareness of the issue, which might force countries to take action.

the Poisson pseudo-maximum likelihood estimator (PML) (Silva and Tenreyro, 2011).[2] According to Silva and Tenreyro, the salient feature of Poisson PML is that it does not affect the performance of the estimator if the dependent variable has a large proportion of zeros. We accounted for potential endogeneity bias due to measurement error in the COVID-19 case with a control function approach adopted by generalizing the conditional Poisson model to an instrumental variable setting (Wooldridge, 2015). Our instruments were the 12-month lagged Gross Domestic Product (GDP) per capita, the agricultural employment rate, and agricultural GDP share. They correlate strongly with differences in diagnostic capabilities among countries and pass the weak instrument test. We then measured heterogeneity in the probability of implementing trade restricting and facilitating NTMs according to product categories. Our main coefficient of interest, COVID-19 cases, might have a country's inclination to report NTMs related to certain products, so we implemented a subanalysis for product heterogeneity.

Our IV estimates indicated a negative association among domestic COVID-19 cases and NTMs and a positive association for worldwide case numbers. These findings are driven mainly by a lower probability of trade-facilitating trade actions among countries with a significant increase in COVID-19 cases. We found that the worldwide propagation of the coronavirus pandemic related positively to the number of NTMs implemented. Depending on whether countries already implemented a COVID-19-related NTM, the probability of imposing further measures correlated negatively with the increasing number of domestic COVID-19 cases but positively with worldwide COVID-19 cases. We found no evidence for a heterogeneous effect on products of domestic COVID-19 cases and worldwide COVID-19 cases. The relationship was more pronounced for semiprocessed and bulk products than for aquaculture, horticulture, and processed products. Our results related to the work of Crivelli and Gröschl (2016) and Orefice (2017), who argue that SPS and TBT are more likely to be represented as trade barriers. However, we found that they are efficient measures for trade facilitation during an emergency. While at the beginning of the pandemic researchers worried about the trade restriction effect of NTMs (Chen and Mao, 2020; Organization for Economic Co-operation and Development, 2020), our results provide evidence that these concerns did not materialize as the effects of COVID-19 cases are correlated with facilitating trade in the agricultural and food sector.

The remainder of this paper is organized as follows. We first provide an overview of trade actions in the agricultural and food sector related to COVID-19, then introduce the empirical strategy and review data sources. The results and conclusion follow.

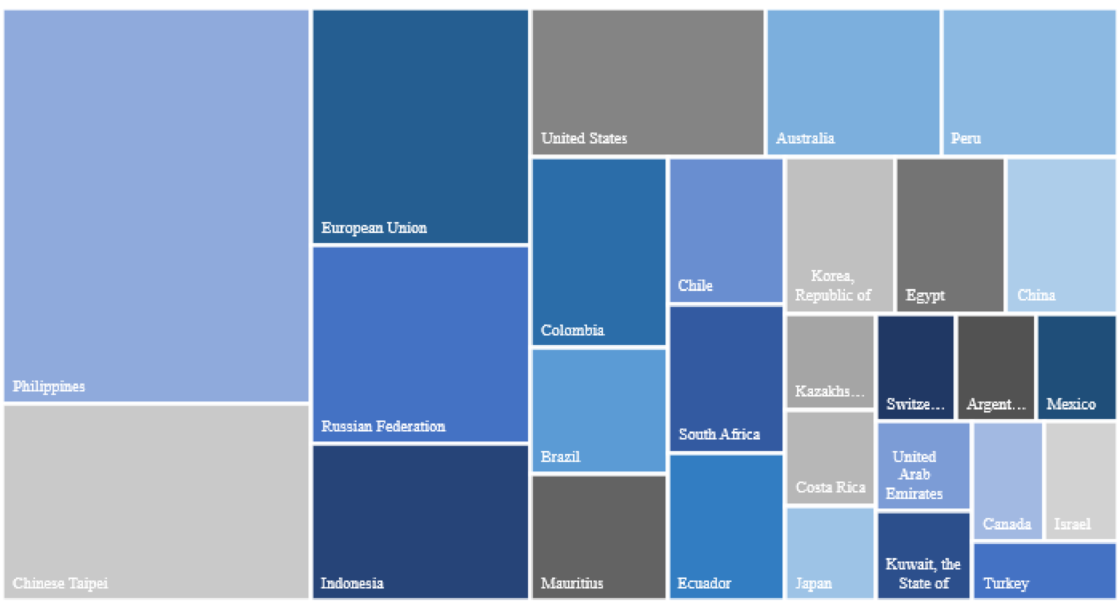
COVID-19-Related NTM in the Agricultural and Food Sector

In spring 2020, several governments reported SPS notifications to prevent the inflow of wild animals because they were known as potential hosts of viral infections. Among 101 notifications of SPS and TBT reported to the WTO for the purpose of COVID-19 emergency, 21 notifications

[2] "Pseudo" means maximizing a likelihood function with a group of probability distributions that do not necessarily contain the true distribution. Pseudo ML provides consistent and asymptotically normal estimators of parameters for the true distribution (Gourieroux, Monfort, and Trognon, 1984).

were regarding trade restriction, 80 of which were to facilitate agricultural and food trade.[3] As of December 31, 2020, 31 WTO members submitted SPS and TBT notifications in response to COVID-19. These were SPS and TBT notifications reported by several South American and African countries against the European Union.

Following the Russian Federation, which banned imports of exotic and decorative animals in February 2020, notices of import restrictions for various food products and animals from Kazakhstan, Indonesia, and Mauritius came out in March. Most of the SPS notifications in February and March related to import bans for China, Hong Kong, Italy, Iran, South Korea, Switzerland, and the European Union, where COVID-19 spread had increased rapidly during that period. After the pandemic declaration by the World Health Organization (United Nations, World Health Organization, 2020), most COVID-19-related SPS and TBT notifications were intended to facilitate trade rather than restrict trade. Countries subject to these NTMs also targeted all trading partners rather than limiting the focus to some countries. The Philippines reported the highest number of SPS and TBT notifications in the agricultural and food sector for 2020 (see Figure 2). Chinese Taipei (Taiwan), the European Union, the Russian Federation, Indonesia, and the United States followed in terms of NTMs. Most of these cases were revised notifications, including extending the application period for the same measures, or lifting the previous measures, and few countries reported other types of SPS or TBT measures.

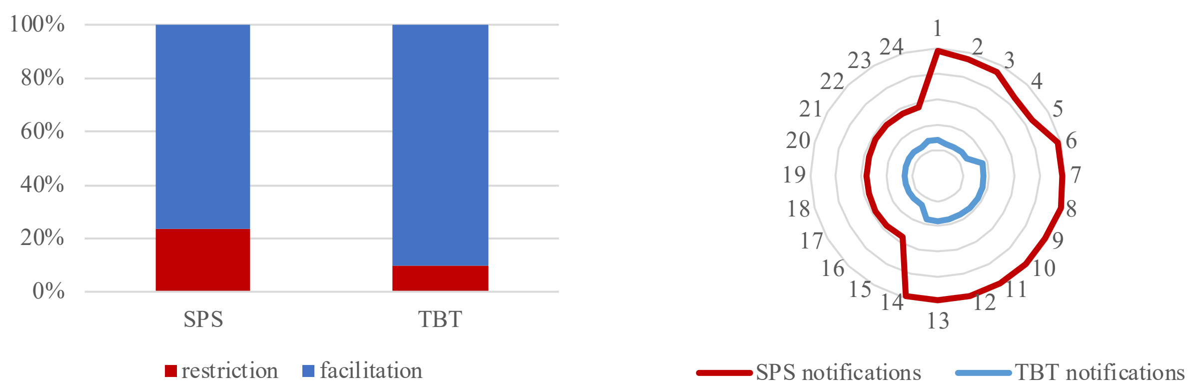


Notes: The figure shows NTMs in the agricultural and food sector (HS01-24). The box size for each country implies the proportion of NTM notifications related to the COVID-19 (SPS and TBT) in agricultural sector, 2020. The color of the box identifies the country.

Figure 2. Countries with the COVID-19-related SPS and TBT in the Agricultural Sector for 2020

[3]The purpose of notification is listed in most of the WTO documents as a category and if there is no indication, they are classified by referring to other notifications.

Most TBT notifications facilitate imports (see Figure 3 [a]). With the pandemic declaration, countries adopted lockdown orders, implying that there were restrictions on the movement of labor, which would have disrupted trade-related work. TBTs include the reduction of labeling requirements on certain food products, the change of maximum residue levels of agricultural products, and online verification of certificates. On the other hand, SPS notifications include more import restrictions than TBTs. Unlike the early stage of COVID-19-related SPSs, which were mostly import bans of wild animal products from China and the neighboring countries, they were about the requirement of COVID-19 testing of imported food and animal products. For instance, Indonesia, the United States, and South Korea notified that they strengthened additional inspection measures for meat products. In China's case, their notification included a requirement of COVID-19 testing for imported cold chain foods from certain producers in Ecuador. Some countries took SPS measures against a single country. The Philippines notified a temporary ban on poultry meat from Brazil and Chile and strengthened requirements for phytosanitary certificates on blueberries imported from Peru. The SPS notifications on the purpose of trade facilitation were similar to TBTs, with respect to alternative measures for the submission of certificates for food safety and sanitation. Some SPS notifications included lifting their former SPS measures that were used to restrict imports from other countries. Among the SPS and TBT measures implemented in the agricultural and food sector, 41.6% were applied to all products. The second-largest number of notifications was related to wild animals, fish, and meat products (see Figure 3 [b]). Even though most of the early notifications were concentrated on wild animals and meat products, the focus expanded in the second half of 2020 to include measures covering plants, fruits, and whole items. These characteristics of NTMs imply that the determinants of SPS and TBT may be different across product space and according to the stated purpose.



(a) Purpose of notifications (b) Product heterogenity

Source: Collected from WTO and calculated by the authors.
Note: The right figure shows a distribution of SPS and TBT notifications in 2020 according to HS2 code.

Figure 3. Heterogeneity of COVID-19 related SPS and TBT in Agricultural Sector for 2020

Methodology

Empirical Strategy

The baseline regression model investigates factors that correlate with the probability of implementing NTMs in response to the COVID-19 pandemic. We specify the count data regression model in its generalized form as follows:

$$\begin{aligned} NTM_{ikt} = \exp\Bigg(& \beta_1 \ln(1 + MFN_{ikt}) + \beta_2 \ln(Imports_{ikt-12}) + \beta_3 \ln(Exports_{ikt-12}) \\ & + \beta_4 \ln(Exchange\ Rate_{it-1}) + \beta_5 \ln(Dietary\ Supply_{it-12}) \\ & + \beta_6 \ln(COVID_{it-1}) + \beta_7 \ln\left(\sum_j COVID_{it-1}\right) + \gamma_i + \delta_k \Bigg) \varepsilon_{ikt} , \end{aligned} \tag{1}$$

where the dependent variable is the number of NTMs (SPS and TBT) imposed by country i on product k at time t. The baseline regression model includes the applied tariff level $\ln(1 + MFN_{ikt})$, the 12-month lagged imports $\ln(Imports_{ikt-12})$ and exports $\ln(Exports_{ikt-12})$, the one-month lagged exchange rate $\ln(Exchange\ Rate_{it-1})$ and the food supply level $\ln(Dietary\ Supply_{it-12})$. The variables $\ln(COVID_{it-1})$ and $\ln\left(\sum_j COVID_{it-1}\right)$ measure new COVID-19 cases in country i and in the rest of the world. We include country γ_i and product δ_k fixed effects to account for systematic differences in the implementation probability and indicate the multiplicative error term with ε_{ikt}.[4] The descriptive statistics of all variables are provided in Table 1.

[4]We excluded time fixed effects from the regression model because they would have prohibited us from measuring the impact of worldwide COVID-19 cases. This variable would be highly correlated with the time fixed effects.

Table 1. Summary Statistics of Variables

Dependent Variables	**N**	**Mean**	**SD**	**Min**	**Max**
NTM (Dummy)	1,356,240	0.380	0.485	0	1
Facilitation (Dummy)	1,356,240	0.373	0.483	0	1
Restriction (Dummy)	1,356,240	0.026	0.158	0	1
NTM (Cumulative)	1,356,240	0.804	1.312	0	12
Facilitation (Cumulative)	1,356,240	0.781	1.301	0	12
Restriction (Cumulative)	1,356,240	0.027	0.175	0	3
SPS (Dummy)	1,356,240	0.364	0.481	0	1
TBT (Dummy)	1,356,240	0.139	0.346	0	1
SPS (Cumulative)	1,356,240	0.687	1.108	0	12
TBT (Cumulative)	1,356,240	0.139	0.346	0	1
E (Sample)					
Control function					
NTM (Dummy)	1,356,240	0.380	0.485	0	1
Facilitation (Dummy)	1,318,104	0.383	0.486	0	1
Restriction (Dummy)	230,400	0.151	0.358	0	1
SPS (Dummy)	1,327,200	0.372	0.483	0	1
TBT (Dummy)	987,360	0.191	0.393	0	1
Control function conditional on NTM					
NTM (Dummy)	1,305,984	0.395	0.489	0	1
Facilitation (Dummy)	1,273,527	0.397	0.489	0	1
Restriction (Dummy)	168,801	0.205	0.404	0	1
Control function conditional on product					
NTM (Dummy)	1,356,240	0.380	0.485	0	1
Facilitation (Dummy)	1,318,104	0.383	0.486	0	1
Restriction (Dummy)	230,400	0.151	0.358	0	1
Explanatory variables					
Log (MFN +1)	1,356,240	1.065	1.270	0	8.007
Log (Export values), 12 months lag	1,356,240	5.119	6.056	0	22.332
Log (Import values), 12 months lag	1,356,240	6.503	6.297	0	22.162
Log (COVID-19 cases, home country), 1 month lag	1,356,240	3.422	4.590	0	15.319
Log (COVID-19 cases, rest of the world), 1 month lag	1,356,240	6.253	7.465	0	16.664
Log (Exchange rate), 1 month lag	1,356,240	1.986	2.001	0	9.672
Dietary supply, 12 months lag	1,356,240	124.018	28.490	0	152
Instruments					
Log (GDP per capita), 12 months lag	1,356,240	9.967	0.885	7.805	11.667
Agricultural employment rate, 12 months lag	1,356,240	8.348	8.938	0.060	32.140
Agricultural GDP (share of GDP), 12 months lag	1,356,240	3.247	2.914	0	13.128

Note: The medians for all NTM variables are zero.

We used the Poisson PML estimator to identify the relationship between COVID-19 case numbers and NTMs (Gong and Samaniego, 1981; Gourieroux, Monfort and Trognon, 1984).[5] The estimator is unbiased and consistent in the presence of heteroskedasticity. Even if the conditional variance is not proportional to the conditional mean, the estimator is still consistent (Wooldridge, 1999; Cameron and Pravin, 2013). Because the estimator does not make a specific assumption on the dispersion of the fitted values, we did not have to test for this aspect of the data. A further advantage of the Poisson PML estimator is that the scale of the dependent variable has no effect on the parameter estimates, which is a particular concern for the Negative Binomial PML estimator. If the conditional mean is correctly specified, the Poisson PML estimator yields parameter estimates that have a similar magnitude to the estimates of both the Gaussian and Negative Binomial PML estimators (Silva and Tenreyro, 2011). We accounted for high-dimensional fixed effects using the approach outlined in Correia, Guimarães, and Zylkin (2020). Because we suspected the presence of residual correlation at the HS-heading level (HS4), we addressed the potential heteroskedasticity and serial correlation in the error term using a robust variance estimator that accounts for clustering at the year-month level (Cameron and Miller, 2015).

A potential concern regarding the identification strategy relates to endogeneity caused by "measurement error" in the COVID-19 numbers (Kilani and Georgiou, 2020; Kisa and Kisa, 2020). First, only for those countries that reported COVID-19-related SPS and TBT notifications in 2020, we observed whether NTMs were imposed to facilitate or restrict trade. Second, COVID-19 case reporting and testing varies across countries and time, and the number of cases might be affected by various factors. Thus, this measurement error of the COVID-19 variables becomes part of the error term in the regression, creating an endogenous bias. Therefore, we are suspicious that the baseline results are biased due to this source of measurement error (Semykina and Wooldridge, 2010). To account for endogeneity concerns, we applied the control function approach, a two-step procedure developed by Heckman and Robb (1985). This procedure is adopted by generalizing the conditional Poisson model to an instrumental variable (IV) setting (Wooldridge, 2015). For the first stage, the instrumental variables are regressed on the endogenous variable (COVID-19 cases). In addition to the instruments, fixed effects for country and product and all covariates from the baseline specification were included in this linear regression. Our instruments included the 12-month lagged GDP per capita, the agricultural employment, and the agriculture GDP share. These log variables correlate strongly with COVID-19 case numbers and misreporting (Nguimkeu, Pierre, and Tadadjeu, 2021). Countries with high agricultural employment and agricultural GDP share, such as many developing countries, are likely to underreport COVID-19 cases because of inadequate diagnostic and reporting capabilities. Countries that have a higher income level are more likely to test for COVID-19, so the measurement error in the COVID-19 case is more elevated (Hasell et al., 2020). The descriptive statistics of the instrumental variables are provided in Table 1. For the second stage, the baseline specification is adjusted by including the first-stage

[5] Although we could also rely on the standard Poisson regression model to estimate the relationship, this estimator has two properties that could complicate the identification of the exchange rate volatility treatment effect. First, this regression is known to suffer from convergence problems which can result in spurious estimation results. Second, it is sensitive to numerical difficulties, which is a particular issue for regressions with high-dimensional fixed effects and highly disaggregated data (Silva and Tenreyro, 2011). Therefore, we used the PML estimator as it circumvents these cavities of the standard Poisson regression.

residuals in the regression specification. All parameters are identified with the Poisson PML estimator. Although a correct identification of the COVID-19 case number effects is ensured with the control function approach, it is necessary to adjust the standard errors for the estimation error in the first stage (Cameron and Miller, 2015). To account for this error, we applied a block-bootstrap procedure with replacement, randomly drawing 1,000 samples from the entire history of each country-product-pair (Gonçalves and Kilian, 2004).

Since the estimates from the first step are the same as the 2SLS estimates, one might wonder what difference it makes compared to the 2SLS. However, compared to the 2SLS approach, it produces a hypothetical heteroscedasticity-robust Hausman test, which implies that the COVID-19 variables become exogenous by including the residuals from the first stage (Wooldridge, 2015).

Data

The raw data on COVID-19-related NTMs came from the WTO's NTM database (United Nations, World Trade Organization, 2021a). We focused on SPS and TBT related to agricultural and food trade announced in 2020. There are 101 COVID-19-related SPS and TBT notifications, of which we used import-related NTMs implemented by countries for which detailed trade data were available for the study period. We classified these trade actions according to trade facilitation and restriction policies. Our final policy dataset included 86 SPS and TBT notifications imposed by 55 countries[6] on agricultural and food trade in 2020.[7]

We constructed a panel dataset for imports and exports at the country level for 2018 to 2019, based on tariff-line level trade data for 91 countries from the Global Trade Information Services (2021). Export and import data were disaggregated at the product level using the Harmonized System (HS) 6-digit code. Since we focused on agricultural and food trade, we included trade flows categorized in sections HS 01 to HS 24 for 55 countries. Tariff data came from the Tariff Analysis Online (United Nations, World Bank, 2021a). This dataset offered tariff-line duties by countries on specific goods based on the HS code system. We used MFN tariffs defined at the tariff-line level and imposed on imports from other WTO members, except when the country is part of a preferential trade agreement.

Monthly data on confirmed COVID-19 cases came from the Data Repository of the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (Dong, Du, and Gardner, 2020). Using daily COVID-19 cases, we calculated the lag of monthly cases for each country and the world. We included monthly exchange rate data from the International Financial Statistics (United Nations, International Monetary Fund, 2021). These exchange rates were based on national currency per U.S. dollar, period average, one of the most used as selected indicators. For the food security level, we used one of the food security indicators from FAOSTAT (United Nations, Food and Agricultural Organization, 2021). The FAO offers several indicators for each country, and among them, average dietary energy supply adequacy (normalized) is used for the

[6]The country list is provided in Table 2.
[7]Data for the European Union are disaggregated to individual countries (27 countries plus the United Kingdom). Kuwait and United Arab Emirates are excluded due to trade data limitations.

relation with the imposition of NTMs. We used a 1-year lagged term because a country with a low level of dietary supply might have decided to notify certain NTMs to facilitate trade. We included interaction terms for the heterogeneity analysis based on the Regmi et al. (2005) product classification. This classification categorizes agricultural and food products in aquaculture, primary bulk commodities, produce/horticulture, semiprocessed, and processed products. Instrumental variables, such as GDP per capita, agricultural employment, and agricultural GDP share, came from the World Development Indicator (United Nations, World Bank, 2021b). We constructed a 12-month lagged weighted average for all instrumental variables.

The summary statistics are presented in Table 1. Our dependent variables are distinguished in two ways, a dummy and a cumulative variable. The average number of NTMs indicates that our sample contained many zero NTMs. Based on the food dietary variable, we found that our sample countries tend to have a high food security level. Our instruments, GDP per capita, agricultural employment, and agricultural GDP share, indicate that most advanced economies are not heavily dependent on the agricultural sector, but the sample included various countries with high agricultural employment and GDP shares.

Table 2. Country List

Argentina	Japan
Australia	Kazakhstan
Austria	Latvia
Belgium	Lithuania
Brazil	Luxembourg
Bulgaria	Malta
Canada	Mauritius
Chile	Mexico
China	Netherlands
Colombia	Peru
Costa Rica	Philippines
Croatia	Poland
Cyprus	Portugal
Czech Republic	Romania
Denmark	Russia
Ecuador	Slovakia
Egypt	Slovenia
Estonia	South Africa
Finland	South Korea
France	Spain
Germany	Sweden
Greece	Switzerland
Hungary	Taiwan
Indonesia	Thailand
Ireland	Turkey
Israel	United States
Italy	

Results and Discussion

Baseline Results

Table 3 shows the baseline regression results for the determinants of COVID-19-related trade actions and compares the dummy with a cumulative outcome variable specification. MFN tariff rates matter for NTM all-purposes with different magnitude and direction of the estimated effects. Facilitating-purpose NTMs show a negative correlation with the tariff rate. For the positive relationships among tariffs and NTMs, our general results contrasted with Beverelli, Boffa, and Keck (2014), who found that tariff and NTMs are substitutes. This is caused by the fact that COVID-19 NTMs were imposed as emergency measures. Export values show a positive correlation with the NTMs, but the impact is low, and import values are statistically insignificant. The exchange rate affects restricting-purpose NTMs at the 1% significance level. An increase in exchange rates (a falling currency) leads to a higher likelihood of imposing NTMs for trade restrictions. The dietary supply level affects only restricting-purpose NTMs. The estimates indicate that a 1% increase in dietary supply level leads to a 56.5% decrease in NTM cases. These results are consistent with our initial hypothesis that countries with higher dietary supply levels have a lower probability of imposing NTMs for trade facilitation during the pandemic. The effects of COVID-19 cases vary across the type of dependent variables. When we considered NTMs as dummy variables, a 1% increase of domestic COVID-19 cases decreased the number of NTMs for trade facilitation by 9.3%, while the coefficients are insignificant for cumulative NTMs. On the other hand, the effect for COVID-19 cases in the rest of the world is high for both purposes of NTMs with similar effects and direction. Since all COVID-19 variables suffer from endogeneity concerns, we employed control function estimation methods and compared the results with the baseline results.

Table 3. Baseline Regression Model

	Dummy Variables			Cumulative Variables		
Dependent variables	**NTM**	**Facilitation**	**Restriction**	**NTM**	**Facilitation**	**Restriction**
Explanatory variables						
Log (MFN +1)	-0.005**	-0.005*	0.102***	-0.042***	-0.049***	0.095***
	(0.002)	(0.003)	(0.014)	(0.002)	(0.003)	(0.012)
Log (Export values), 12 months lag	0.000**	0.000**	0.004***	0.001***	0.002***	0.003***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Log (Import values), 12 months lag	0.000	0.000	-0.002	-0.001***	-0.001***	0.000
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.001)
Log (Exchange rate), 1 month lag	-0.017	0.037	-12.446***	-0.256***	-0.220*	-12.945***
	(0.148)	(0.163)	(1.711)	(0.118)	(0.126)	(1.651)
Dietary supply, 12 months lag	0.038	0.048	-0.833*	-0.069	-0.056	-0.546
	(0.107)	(0.132)	(0.482)	(0.073)	(0.084)	(0.463)
Log (COVID-19, home country), 1 month lag	-0.098***	-0.096***	0.047	-0.027	-0.026	0.048
	(0.026)	(0.026)	(0.038)	(0.031)	(0.031)	(0.037)
Log (COVID-19, rest of the world), 1 month lag	0.353***	0.353***	0.460***	0.436***	0.438***	0.453***
	(0.032)	(0.033)	(0.137)	(0.042)	(0.043)	(0.128)
Constant	-9.345	-10.662	95.098**	3.365	1.685	76.160**
	(13.167)	(16.268)	(39.104)	(8.595)	(10.130)	(38.832)
Pseudo R2	0.885	0.893	0.863	0.929	0.935	0.852
N	1,356,240	1,318,104	230,400	1,356,240	1,318,104	230,400

Notes: Standard errors are presented in parentheses with clustering at year-month level. Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level.

Control Function Estimates

We present the control function estimation results in Table 4. The upper part shows the second stage, and the lower part shows the first stage regression results. The F-statistics imply that our instruments passed the weak identification test, while the coefficient significance in the first stage and the residuals in the second stage indicate that the instrumental variables were relevant.

They are highly correlated with the two COVID-19 endogenous regressors. The control function estimates for the MFN tariffs have the same direction as the baseline regression model for all NTM purposes. The effect of export values is significant for restricting-purpose NTMs, while the coefficients for import values are insignificant. The exchange rate parameters show a similar magnitude and direction, as indicated in the baseline model. The dietary supply-level coefficient is significant for facilitating NTMs. This result implies that the higher a country's dietary supply level, the lower the likelihood of imposing facilitating-purpose NTMs, which is in line with our hypothesis on the role of dietary supply. We also found that a higher number of domestic COVID-19 cases related negatively to NTM notifications for trade facilitation, consistent with the results shown in the baseline model. An increase in the number of worldwide COVID-19 cases has a positive effect on facilitating and restricting NTMs, and these effects are more considerable than those in the baseline model.

Table 4. Control Function Estimation

	Dummy Variables		
Dependent variables	**NTM**	**Facilitation**	**Restriction**
Explanatory variables			
Log (MFN +1)	-0.008*	-0.008**	0.103***
	(0.004)	(0.004)	(0.025)
Log (export values), 12 months lag	0.000	0.000	0.004*
	(0.000)	(0.000)	(0.002)
Log (import values), 12 months lag	0.000	0.000	-0.002
	(0.000)	(0.000)	(0.002)
Log (exchange rate), 1 month lag	-0.400*	-0.349	-12.170***
	(0.328)	(0.361)	(3.300)
Dietary supply, 12 months lag	-0.289***	-0.260***	-0.813
	(0.065)	(0.062)	(0.482)
Log (COVID-19, home country), 1 month lag	-0.425***	-0.425***	0.146
	(0.101)	(0.093)	(0.793)
Log (COVID-19, rest of the world), 1 month lag	0.593***	0.593***	0.400
	(0.060)	(0.057)	(0.588)
Residual (COVID-19, home country)	0.332**	0.335***	-0.100
	(0.133)	(0.123)	(0.801)

Table 4. (continued)

	Dummy Variables		
Dependent variables	**NTM**	**Facilitation**	**Restriction**
Explanatory variables			
Residual (COVID-19, rest of the world)	-0.249***	-0.248***	0.050
	(0.066)	(0.063)	(0.440)
Constant	31.382***	27.751***	92.691
	(8.200)	(6.454)	(65.779)
Pseudo R2	0.889	0.896	0.841
N	1,356,240	1,318,104	230,400
Instruments	COVID-19, home	COVID-19, world	
Log (GDP per capita), 12 months lag	14.493	53.407***	
	(8.784)	(16.658)	
Agricultural employment rate, 12 months lag	-2.800***	-3.951***	
	(0.703)	(1.101)	
Agricultural GDP (percent of GDP), 12 months lag	-7.134***	-8.508***	
	(0.619)	(0.540)	
Constant	-392.488***	-1,034.764	
	(104.285)	(209.162)	
F-statistics	42.164	87.562	
Adjusted R^2	0.282	0.298	
N	1,356,240	1,356,240	

Notes: The lower part of the table indicates the instruments used in the first stage, and the upper part of the table shows the outcome of the second stage. Standard errors are presented in parentheses, with clustering at year-month level and 1,000 replications of bootstrapping. Single, double, and triple asterisks (*, **, ***) indicate [statistical] significance at the 10%, 5%, and 1% level.

Table 5 shows control function estimates conditional on COVID-19-related NTMs implemented earlier. The coefficients for MFN tariff rates and the trade values were insignificant, but the exchange rate coefficients correlated strongly with NTMs. We found that a 1% increase in the exchange rate is associated with a 0.97% decrease for restricting-purpose NTMs. Dietary supply level also becomes significant for both NTM types, implying that higher dietary supply level in a country correlates with COVID-19-related NTMs. The COVID-19 coefficients show similar magnitude, as indicated in the first control function, meaning that the number of COVID-19 cases is associated with implementing additional NTMs.

Table 5. Control Function Estimation Conditional on NTMs

		Dummy Variables		
Dependent variables		**NTM**	**Facilitation**	**Restriction**
Explanatory variables				
Log (MFN +1)		-0.004*	-0.004	-0.002
		(0.002)	(0.002)	(0.006)
Log (Export values), 12 months lag		0.000	0.000	0.000
		(0.000)	(0.000)	(0.001)
Log (Import values), 12 months lag		0.000	0.000	-0.001**
		(0.000)	(0.000)	(0.000)
Log (Exchange rate), 1 month lag		0.244	0.274	-3.612**
		(0.168)	(0.266)	(1.731)
Dietary supply, 12 months lag		-0.299***	-0.257***	-1.406***
		(0.048)	(0.049)	(0.305)
NTM (Dummy) X Log (COVID-19 cases, home country), 1 month lag				
	0	0	0	0
		(omitted)	(omitted)	(omitted)
	1	-0.515***	-0.522***	-0.374*
		(0.078)	(0.078)	(0.235)
NTM (Dummy) X Log (COVID-19 cases, rest of the world), 1 month lag				
	0	0	0	0
		(omitted)	(omitted)	(omitted)
	1	0.618***	0.623***	0.661***
		(0.055)	(0.056)	(0.160)
Residual (COVID-19 cases, home country)		0.398***	0.405***	0.304
		(0.111)	(0.112)	(0.235)
Residual (COVID-19 cases, rest of the world)		-0.261***	-0.264***	-0.205
		(0.064)	(0.064)	(0.114)
Constant		31.699***	26.336***	117.032***
		(6.575)	(6.198)	(30.977)
Pseudo R2		0.939	0.943	0.981
N		1,305,984	1,273,527	168,801

Notes: The instruments are presented in Table 4. Standard errors are presented in parentheses with clustering at year-month level and 1,000 replications of bootstrapping. Single, double, and triple asterisks (*, **, ***) indicate [statistical] significance at the 10%, 5%, and 1% level.

A comparison of the control function results for SPS and TBT is shown in Table 6. MFN tariff rates are positively correlated with SPS notification, but the effect is small, whereas the impact of MFN is negligible for TBT. A 1% increase in the exchange rate is associated with a 0.6% decrease in the likelihood of implementing a TBT. Exchange rates are also negatively correlated with both SPS and TBT, but the TBT effect is larger compared to that for SPS. The dietary supply level affects TBT more than SPS, implying that TBT measures are more likely to decrease the food security level. COVID-19 cases in the home country are associated with SPS but not with TBT, whereas those in the rest of the world tend to increase both SPS and TBT. These findings indicate that countries with an increasing number of COVID-19 cases domestically are more likely to respond with SPS notifications. The response to the growing number of foreign COVID-19 cases shows that both SPS and TBT are the trade actions of choice for most trade policymakers.

Table 6. Control Function Estimation on SPS and TBT

	Dummy Variables	
Dependent variables	**SPS**	**TBT**
Explanatory variables		
Log (MFN +1)	-0.010**	-0.006**
	(0.004)	(0.012)
Log (Export values), 12 months lag	0.000	0.002***
	(0.000)	(0.001)
Log (Import values), 12 months lag	0.000	0.001
	(0.000)	(0.001)
Log (Exchange rate), 1 month lag	-0.405*	-26.064***
	(0.338)	(8.043)
Dietary supply, 12 months lag	-0.312***	-0.779***
	(0.064)	(0.800)
Log (COVID-19 cases, country), 1 month lag	-0.428***	0.165
	(0.105)	(0.278)
Log (COVID-19 cases, rest of the world), 1 month lag	0.597***	0.552**
	(0.066)	(0.383)
Residual (COVID -19 cases, home country)	0.340**	-0.081
	(0.138)	(0.560)
Residual (COVID-19 cases, rest of the world)	-0.257***	0.198***
	(0.068)	(0.277)
Constant	34.287***	133.159***
	(8.015)	(109.376)
Pseudo R^2	0.878	0.868
N	1,327,200	987,360

Notes: The instruments are presented in Table 4. Standard errors are presented in parentheses with clustering at year-month level and 1,000 replications of bootstrapping. Single, double, and triple asterisks (*, **, ***) indicate [statistical] significance at the 10%, 5%, and 1% level.

Product Heterogeneity

Figure 4 summarizes control function estimates including interaction terms composed of product category and the COVID-19 variables. The corresponding coefficients and bootstrap standard errors are presented in Table 7. The interaction effects allowed us to investigate the product heterogeneity depending on the number of COVID-19 cases in the home country and the rest of the world. The estimates provide no evidence for differences in the product effects for domestic COVID-19 cases. The results indicate that trade facilitation NTMs have been imposed across all types of products. In the presence of increasing COVID-19 numbers in the rest of the world, all interaction terms are statistically significant. The interaction effects do not vary across product categories for facilitating-purpose NTMs, while some evidence of product heterogeneity is observed for restricting-purpose NTMs. Semiprocessed products tend to be correlated with restricting-purpose NTMs, followed by primary bulk commodities and processed products. Aquaculture and horticulture are less likely to affect the incidence of NTMs for trade restrictions than the other products. These estimation results allow us to conclude that product heterogeneity does not play a significant role for COVID-19-related NTMs.

Table 7. Product Heterogeneity in the COVID-Related NTMs

	Dummy Variables		
Dependent variables	**NTM**	**Facilitation**	**Restriction**
Explanatory variables			
Log (MFN +1)	-0.008**	-0.008**	0.099***
	(0.004)	(0.004)	(0.018)
Log (Export values), 12 months lag	0.000	0.000	0.004*
	(0.000)	(0.000)	(0.002)
Log (Import values), 12 months lag	0.000	0.000	-0.002
	(0.000)	(0.000)	(0.002)
Log (Exchange rate), 1 month lag	-0.415	-0.361	-11.566***
	(0.326)	(0.358)	(3.299)
Dietary supply, 12 months lag	-0.294***	-0.265***	-0.951
	(0.068)	(0.064)	(0.641)
Product X Log (COVID-19 cases, home country), 1 month lag			
Aquaculture	-0.436***	-0.433***	-0.048
	(0.101)	(0.094)	(0.744)
Primary Bulk Commodities	-0.430***	-0.427***	-0.066
	(0.103)	(0.095)	(14.641)
Horticulture	-0.435***	-0.432***	-0.048
	(0.101)	(0.093)	(0.740)
Semi-processed	-0.430***	-0.427***	-0.062
	(0.104)	(0.095)	(14.684)
Processed	-0.437***	-0.434***	-0.048
	(0.100)	(0.092)	(0.739)
Product X Log (COVID-19 cases, rest of the world), 1 month lag			
Aquaculture	0.581***	0.584***	0.421
	(0.059)	(0.057)	(0.504)
Primary bulk commodities	0.613***	0.606***	1.059
	(0.063)	(0.060)	(84.807)
Horticulture	0.608***	0.603***	0.677
	(0.064)	(0.061)	(0.508)
Semi-processed	0.613***	0.607***	1.108
	(0.063)	(0.060)	(85.123)
Processed	0.607***	0.601***	0.794
	(0.064)	(0.061)	(0.497)
Residual (COVID-19 cases, home country)	0.342**	0.341***	0.069
	(0.133)	(0.124)	(0.764)
Residual (COVID-19 cases, rest of the world)	-0.257***	-0.253***	-0.020
	(0.067)	(0.064)	(0.428)
Constant	32.077***	28.309***	99.998
	(8.484)	(8.131)	(95.591)
Pseudo R^2	0.890	0.897	0.870
N	1,356,240	1,318,104	230,400

Notes: The instruments are presented in Table 4. Standard errors are presented in parentheses with clustering at year-month level and 1,000 replications of bootstrapping. Single, double, and triple asterisks (*, **, ***) indicate [statistical] significance at the 10%, 5%, and 1% level.

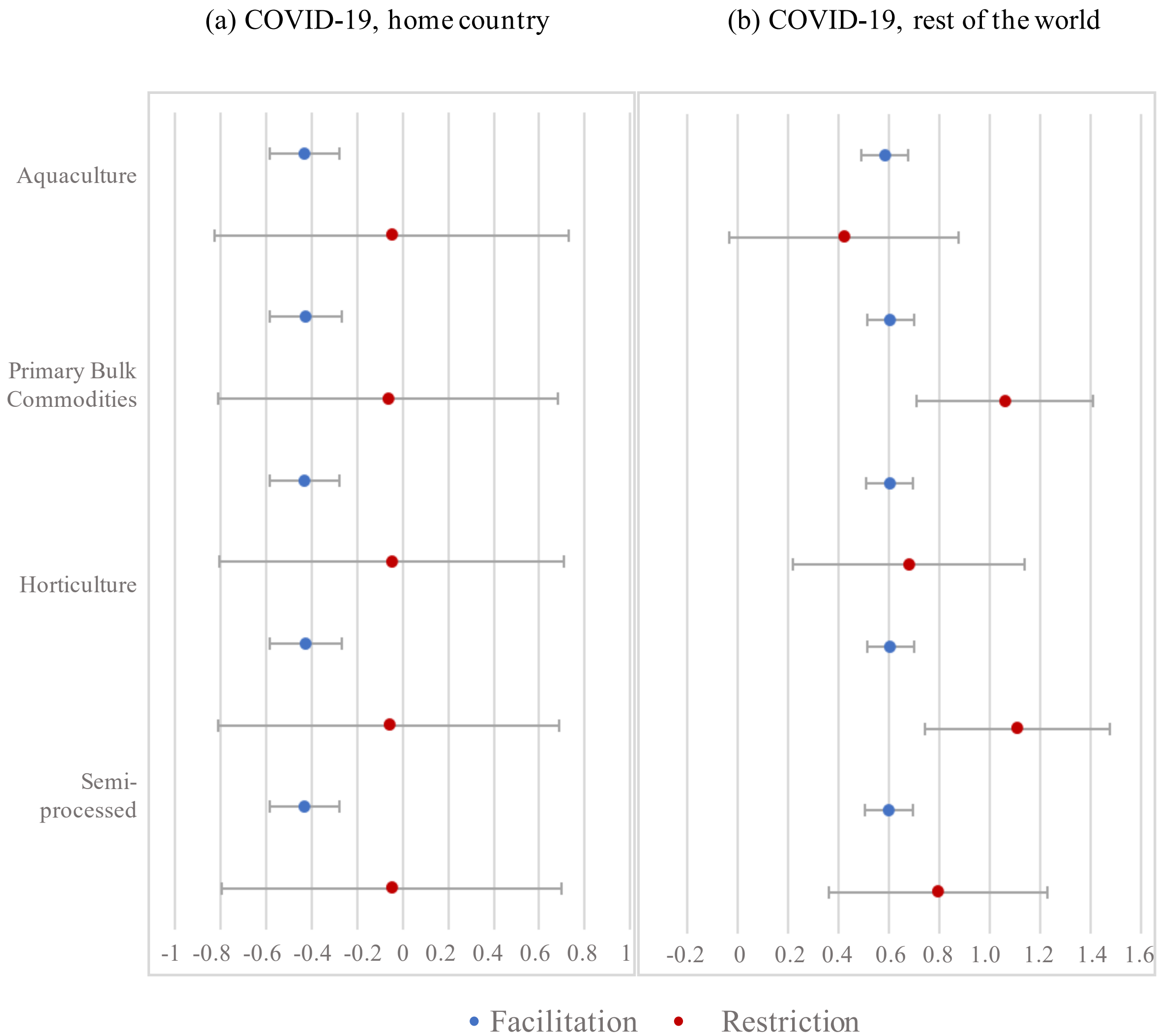


Figure 4. Product Heterogeneity of the COVID-related NTMs

Conclusion

This paper presents results of an analysis of the relationship between COVID-19 case numbers and NTMs in the agricultural and food sector implemented in response to the coronavirus pandemic. We estimated the association based on a product-level dataset on trade-restricting and facilitating-NTMs for 2020. Our count data regressions controlled for product and country fixed effects. We used a control function approach to account for endogeneity concerns caused by measurement error in the COVID-19 case numbers. Our IV estimates indicated a negative association between COVID-19 cases numbers and NTMs in the implementing country and a positive association for the rest of the world, which is an indication of countries' awareness on the pandemic circumstance. Our main findings were driven by a lower probability of trade-facilitating trade actions among countries with a significant increase in COVID-19 numbers. The effect on trade-restricting NTMs has the opposite sign but is statistically insignificant. We found that the further propagation of the coronavirus pandemic relates positively to the number of NTMs implemented. Depending on whether countries already implemented a COVID-19-related NTM, the probability to impose further measures correlates negatively with the number of COVID-19 cases in the country. Our results indicate that countries tend to impose COVID-19-related NTMs based on their dietary supply level for trade facilitation actions. We found limited evidence for a heterogeneous effect of COVID-19 cases in the home country on NTMs. Similar patterns can be observed for differences among SPS and TBT measures. These findings shed light on the role of COVID-19 trade actions by investigating factors that drive countries to implement NTMs during the coronavirus pandemic. Although NTMs are considered trade barriers (Crivelli and Gröschl, 2016; Orefice, 2017), they can be reasonable measures for trade facilitation during an emergency. At the beginning of the pandemic, policymakers were concerned about trade restrictions. Our findings show that the effects of COVID-19 numbers are more correlated with facilitating trade than restricting it in the agricultural and food sector. These results highlight the government's efforts to keep the supply chain running smoothly, especially in the presence of panic-buying during the early stages of the pandemic (Kerr, 2020).

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Low-Income Household Food Consumption Consequences of Rice Policy and Pandemic Impacts on Income and Price in Thailand

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Abstract

Using Thai household data, we estimated a demand system and analyzed the impacts of changes in rice prices and household income on food consumption, then used these results in four experiments. We found that a trade policy that attempts to reduce domestic prices benefits households in the higher income brackets while negatively affecting low-income, rice-producing households' food security. Results suggest that an agricultural policy with a view to support food security might have different, if not opposite, distributional impacts on targeted groups.

Keywords: food security, COVID-19, household-level analysis, demand estimation, rice policy, food policy, censored model, consumer economics

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Introduction

Thailand food security is perceived by some to be tied to rice market conditions, as exemplified by the rice pledging scheme in 2011 and the COVID-19 pandemic in 2020. The food security impacts of rice policies and external shocks are complicated by the interactions of prices, income of rice-producing and other households, and household behaviors. Assessment is further complicated by the likelihood of greater concern about the food purchases of low-income households relative to others. In this paper, we describe how we developed and applied an empirical model that can address these complications and related the findings to the circumstances of the poorest households.

Thailand launched a rice policy in 2011 to support the domestic rice price by purchasing stocks partly in the name of food security, but this policy collapsed in 2014 and took the government with it (Permani and Vanzetti, 2016). This apparent failure might seem to run afoul of expectations that a stable food grain price policy could support economic development of farmers and contribute to stability more broadly (Addison, Ghoshray, and Stamatogiannis, 2016). This favorable view of price stabilizing policies might be reassessed by estimating the market effects of trade policy and state-trading that might be used to achieve price stability (Hoang and Meyers, 2015). Indeed, high food prices benefit net producers of food commodities but can negatively affect food security, especially in rural areas (Ferreira et al., 2013; Ha et al., 2015). Whatever the state of scientific investigation, price increases might be seen by policy makers as an element of or even a synonym for stabilizing prices, as the government of Thailand at that time seemed to believe, given the policy change.

The second shock to Thai rice markets, income, and food security is a global pandemic with and without the likely impacts of a hypothetical rice trade restriction. COVID-19 has introduced unprecedented effects on the global economy. Since the onset of the pandemic, the government of Thailand has taken various measures to contain the spread of the virus including lockdowns and curfews since March 2020. The food service and tourism industry were hard hit as restaurants and hotels closed, and international travel was banned (USDA-FAS, 2020). By July 2020, a number of fiscal policies and social protection measures had been issued by the Thai government in an attempt to mitigate the adverse impacts of the pandemic (Gentilini et al., 2020), which included record COVID-19 response packages totaling 12.9% of GDP (The World Bank, 2020). Rice farmers and the poorest households are presumably among the sociodemographic groups that are most vulnerable and hardest hit by this pandemic. To assess the trade-off of a policy that attempts to tame high staple prices, we examined a hypothetical trade restriction where the Thai government restricts its rice exports so as to halve the domestic rice price increase.

The focus of our study was to examine the confounding impacts of price and income change on the lowest-income households in Thailand. Deaton (1989) found evidence that rice price increases might favor middle-income households, not poor households, helping motivate scientists to estimate household-level impacts of commodity price increases. Studies have applied some elements of Deaton's framework to recent cases or married equilibrium model output to household-level indicators (OECD, 2007; Arndt et al., 2008; Coxhead, Linh, and Tam, 2012;

Badolo and Traoré, 2015). Household-level data have been widely used to measure the impacts of agricultural policies, often with a focus on household welfare impacts rather than consumption. For example, Balié, Minot, and Valera (2021) calculated the welfare impacts of the rice tariffication policy in the Philippines using the price change simulated by a partial equilibrium model together with expenditure and elasticities estimated from 2015 household survey data. Using 2008 household data for Côte d'Ivoire, Dimova and Gbakou (2013) concluded that a price increase is a welfare gain for poor rural households but a loss for middle-income urban households. Hasan (2017) found that a sharp rice price increase is a welfare loss for the poor in Bangladesh, but the impacts on poverty seem to lessen for households that are engaged in rice farming. In a cross-country study using household level data, Zezza et al. (2008) concluded that the poor are hardest hit by a price shock. In the case of Ethiopia particularly, Uregia, Desta, and Rashid (2012) also found that net-cereal sellers and some net-cereal buyers benefit from price shocks due to their ability to diversify to other foods and off-farm activities.

Some studies of household food expenditure data have attempted to either advance estimation and application methods with better techniques, in particular through censoring (Bilgic and Yen, 2014; Lazaro, Sam, and Thompson, 2017), using models to project future food demand (Valin et al., 2014) or measuring the impact of price and income shocks on household consumption and food security (Savadogo and Brandt, 1988; OECD, 2017; Hoang, 2018). Our study was able to combine the relevant innovations by accounting for censoring while analyzing the impacts on household-level consumption and food security.

In the present study, we estimated a censored demand system that represents Thai household food purchases as functions of price and total expenditures. We calculated how Thai rice price policies affected the prices and income, then estimated food quantity effects with a focus on households of the lowest income quintile. Our results relate directly to the impact of Thailand's rice policy and COVID-19 on food security of poor rice producers, poor consumers who do not sell rice, and others. A strength of this application is the ability to use the estimated economic parameters to conduct *a priori* analysis. The impacts of COVID-19 on household food security around the world are yet to be fully understood even though policy makers scrambled to respond to the pandemic as it took place; events outpaced scientific assessment in peer-reviewed articles. Here, we developed and applied an approach that can help the public understand the impacts of the pandemic on poor households that potentially face food insecurity.

The broader implications are clear. In terms of policy, evidence suggests that middle-income countries around the world tend to intervene in agricultural commodity markets if they can afford to do so (Anderson and Valenzuela, 2008; Anderson, Rausser, and Swinnen, 2013), at least some of which might be intended to improve food security. However, a justification for interventions that target prices on the grounds of improving food security is uncertain. Global food security policies that increase price support might be justified as a means to increase poor farmer income, yet they can diminish food security of other poor households for whom staple food consumption accounts for a substantial share of income. Our results highlight these trade-offs in an important case of a key country in the global rice market. The information is more widely useful for readers and policy makers who consider market interventions that change food commodity prices as a panacea for food security. We found no evidence that this direction of research and policy would result in easy answers to the challenges of food security.

The paper is organized as follows: Section 2 describes the data used, theory relating to censored demand system estimation, and scenario assumptions. Section 3 provides the estimated elasticities and simulation results. The last section discusses policy implications and concludes with some suggestions for future research.

Estimation Strategy

Data and Method

We used the public version of the Household Socio-Economic Survey (HSES) data conducted by the National Statistical Office of Thailand in 2014 for the analysis. HSES is a nationwide quantitative survey and is conducted on an annual basis. Delays in releasing HSES data cause studies that focused on Thailand to use samples that are nearly a decade old when the research article was published (Tiwasing, Dawson, and Garrod, 2018; Manajit, Samutachak, and Voelker, 2020; Wongmonta, 2020). While we used the latest data available to us, there is a risk that changes in preferences since then could affect our results. Our final sample included 42,670 households with detailed sociodemographic information, including whether a household is engaged in rice farming.

Unfortunately, this data set merged all cereal consumption into one aggregated group that includes rice, wheat, and other cereals; other foods were aggregated into 14 different groups. For this reason, it was impossible for us to know the exact rice consumption in each household. Rice, however, remains the dominant staple in Thailand (FAO, 2019). Therefore, we expected that changes in rice prices would be mirrored in cereal prices, and vice versa.

We regrouped food consumption into 6 broad groups: (i) cereals, (ii) meats, poultry, fish, and other seafood, (iii) vegetables, nuts, and fruits, (iv) milk, milk products, eggs, and sugar, (v) oils and fats, and (vi) food away from home (FAFH) and other miscellaneous foods. The sixth group includes the remaining food items, except for tobacco products. (These group names are sometimes abbreviated in subsequent text, tables, and figures to conserve space.) It should be noted that in our data set the cereal group only measures food-at-home (FAH) and excludes FAFH consumption due to the difficulty in extracting cereals from the FAFH aggregate.

We then added non-food consumption as a composite *numeraire* good to represent all other goods and services that a household consumed. Therefore, with this demand system, we allocated all expenditures, not just food expenditures, and elasticities were directly estimated. This demand system is supposed to provide unbiased measures of welfare and unconditional predictions of demand responses (Zhen et al., 2014).

The quadratic almost ideal demand system (QUAIDS) has a form as follows:

$$w_{ih} = \alpha_i + \sum_{j=1}^{n} \gamma_{ij}\, lnp_j + \beta_i ln\left[\frac{m}{a(\boldsymbol{p})}\right] + \frac{\lambda_i}{b(\boldsymbol{p})}\left\{ln\left[\frac{m}{a(\boldsymbol{p})}\right]\right\}^2 + \mathcal{E}_{ih} \qquad (1)$$

where w_{ih} is the commodity i's budget share of household h derived from price, quantity and total expenditure, $w_i = p_i q_i / m$ and satisfies the constraint $\sum_{i=1}^{n} w_i = 1$, n is the number of commodities in the system, p_i is the price of commodity i, m is per capita total expenditure; $a(\boldsymbol{p})$ and $b(\boldsymbol{p})$ are the price indices, $\boldsymbol{p}$ is the vector of prices; α, β, γ, and λ are parameters to be estimated; $\mathcal{E}_{ih}$ is a random error term.

Price indices are defined below:

$$lna(\boldsymbol{p}) = \alpha_0 + \sum_{n=1}^{n} \alpha_i\, lnp_i + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \gamma_{ij}\, lnp_i\, lnp_j \qquad (2)$$

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

All parameters need to satisfy the adding-up condition, homogeneity condition, and Slutsky symmetry restriction:

Adding-up: $\sum_{i=1}^{n} \alpha_i = 1, \sum_{i=1}^{n} \beta_i = \sum_{i=1}^{n} \gamma_{ij} = 0,$

Homogeneity: $\sum_{i=1}^{n} \gamma_{ij} = 0\ \forall\ j,$

Symmetry: $\gamma_{ij} = \gamma_{ji}\ \forall\ i \neq j.$

The main focus of our study is cereal consumption among poor households, who spend a significant share of their income on staple foods. Fluctuations in the prices of cereals are expected to greatly affect these households' food security status. All else equal, an increase in income could give a household's food purchasing power a boost, though it is uncertain how income and price counteract if a household faces a trade-off between higher income and higher prices at the same time. This question is what our study attempted to answer.

Descriptive statistics of the food consumption, price, and sociodemographic variables used for the demand system estimation are presented in Table 1. Notably, more than 70% of households in the sample were engaged in agriculture, forestry, and fishing, of which 13% were engaged in rice farming activities. Using income per capita data, we divided the sample into quintiles with the lowest quintile representing households within the bottom 20% of the income distribution.

Table 1. Variable Definition and Sample Statistics (Sample Size = 42,670)

Variable	Unit	Mean	Standard Deviation
Unit price-cereals	THB/kg	34.6	9.4
Unit price-meats and fish	THB/kg	119.3	24.7
Unit price-vegetables, fruits, and nuts	THB/kg	52.6	21.0
Unit price-milk and sugar	THB/kg	78.5	34.9
Unit price-oils and fats	THB/kg	50.1	9.2
Index price-others	Index	109.0	43.0
Index price-nonfood	Index	0.4	0.1
Income per capita	THB/kg	70,880.5	45,023.7
Size of the household	Person	3.0	1.6
Age of the HH head	Year	53.6	14.8
Number of kids 5 years old and younger	Person	0.2	0.4
Number of adults 60 years old and older	Person	0.6	0.8
Educational level of the household head			
Pre-primary or below		6%	
Primary		59%	
Secondary		21%	
Postsecondary		3%	
Bachelor's degree		9%	
Graduate study		2%	
Head of the household is male		38%	
Head of the household is married		32%	
Residing in urban areas		39%	
Engaged in agriculture, forestry and fishing		71%	
Engaged in rice farming activities		13%	

Source: Authors' calculations using Thailand's Household Socioeconomic Survey 2014.

Table 2 presents budget shares and quantity consumed by income quintile. The lowest quintile households spent 10.4% of their budget on cereals, which is 5 times more than the highest quintile. Food, in general, accounts for more than half of the lowest quintile households' expenditures, whereas it is less than one-third for the highest income households. In terms of consumption, the poorest households consumed less food than other groups, although households of the second quintile actually had the highest level of cereal consumption. This is not surprising as cereals and grains are the basic food for poor and very poor households, whereas they may be inferior goods to those at higher income levels.

Table 2. Budget Share and Consumption by Income Quintile

	Full Sample	**Lowest Quintile**	**Second Quintile**	**Middle Quintile**	**Fourth Quintile**	**Highest Quintile**
Budget share						
Cereals	6.4%	10.4%	7.2%	5.3%	3.5%	2.0%
Meats and fish	8.7%	12.3%	10.4%	8.5%	6.3%	3.8%
Vegetables, fruits, and nuts	5.4%	6.4%	5.9%	5.2%	4.2%	3.0%
Milk and sugar	3.8%	4.6%	3.9%	3.3%	2.7%	1.8%
Oils and fats	0.6%	0.7%	0.6%	0.5%	0.4%	0.2%
FAFH and other foods	18.3%	14.4%	15.9%	16.9%	18.0%	16.8%
Nonfood	56.9%	46.3%	51.4%	56.2%	61.5%	70.9%
Quantity (kg/person)*						
Cereals	99.8	92.5	95.3	90.7	80.6	70.9
Meats and fish	41.8	30.3	38.7	41.4	41.3	41.1
Vegetables, fruits, and nuts	68.7	40.1	53.1	59.4	64.3	78.0
Milk and sugar	30.5	17.7	22.7	25.5	28.2	32.8
Oils and fats	6.5	4.0	5.2	6.0	6.0	6.0
FAFH and other foods	123.7	43.0	67.7	93.6	129.9	196.8
Nonfood	113.8	30.0	52.1	79.9	124.4	243.9

Source: Authors' calculations using Thailand's Household Socioeconomic Survey 2014. Quantity indices for FAFH and nonfood groups.

Price Endogeneity and Censored Demand System

Since unit prices are derived from expenditure and quantity, there is a possibility for an endogeneity issue due to the presence of total expenditure in the demand system. Following Hoang (2018), we impute the missing prices and correct the implied unit prices for quality variations using the communal mean price method. Unit price is first regressed on the mean unit price at the communal level, household budget share for food away from home, and a vector of household demographic variables. The residual from that equation was added to the communal mean unit price to obtain the quality-adjusted prices at the household level.

Like any other household data sets, we are not immune to the problem of households with zero expenditures (censoring). These households did not report consumption of one or more than one aggregated food groups. The highest rate of zero consumption in our data set is 9.7% (Table 3).

Table 3. Percentage of Zero Consumption for Each Group

	Non-consuming households (%)
Cereals	3.2
Meats and fish	9.7
Vegetables, fruits, and nuts	1.1
Milk and sugar	3.1
Oils and fats	8.6
FAFH and other foods	0.0
Nonfood	0.0

Source: Authors' calculations using Thailand's Household Socio-Economic Survey 2014.

Therefore, we followed Lazaro et al. (2017) to estimate a censored demand system using a 2-step approach. Although we had fewer incidence of zero expenditures than that study, perhaps owing to different levels of aggregation and scope of included goods, we are not aware of any lower bound Lazaro, Sam, and Thompson (2017) propose for the share of observations with zero expenditures. We can make a similar comparison to Dong, Gould, and Kaiser (2004) in that we have a smaller share of zero values in our data, but they also do not seem to set a threshold below which a censored demand is suspect. Yen, Lin, and Smallwood (2003) suggest not to use probit estimation if the share of zero expenditures in the sample falls below 5%. Two of the seven categories in this study exceed that threshold (Table 3). In a 2-step process, the first step involves a probit regression for each censored group. (In our case, we only estimated the first stage for the first five groups. The last two groups, FAFH and non-food, do not have the zero-expenditure problem). In the second step, we estimated a censored QUAIDS model using the first-step results and *nlsur* procedure in Stata version 14.2. Details of the probit estimation and demand equations are provided below.

At the first stage, we estimated the probability of a household h buying a commodity i by the probit model as follows:

$$d_{ih} = I(\boldsymbol{z}'_{\boldsymbol{ih}}\boldsymbol{\delta_i} + v_{ih} > 0) \tag{4}$$

where d_{ih} is a binary variable which is one if commodity i is consumed by household h and zero otherwise, $\boldsymbol{z}'_{\boldsymbol{ih}}$ is a vector of socio-demographic variables, $\boldsymbol{\delta_i}$ is a vector of parameter for observable variables, and v_{ih} is a normally distributed error term.

At the second stage, we estimated the commodity i's budget share of household h, w_{ih}. Assume that the two error terms $\mathcal{E}_{ih}$ and v_{ih} follow a bivariate normal distribution, w_{ih} in the censored QUAIDS can be written as:

$$w_{ih} = \Phi(z'_{\boldsymbol{ih}}\delta_i)(\alpha_i + \sum_{j=1}^{n}\gamma_{ij}\, lnp_j + \beta_i ln\left[\frac{m}{a(\boldsymbol{p})}\right] + \frac{\lambda_i}{b(\boldsymbol{p})}\left\{ln\left[\frac{m}{a(\boldsymbol{p})}\right]\right\}^2 + \theta_{ih}\frac{\varphi(z'_{\boldsymbol{ih}}\delta_i)}{\Phi(z'_{\boldsymbol{ih}}\delta_i)}) + \zeta_{ih} \tag{5}$$

where ζ_{ih} is a commodity-specific error term with zero mean, and $\Phi(.)$ and $\varphi(.)$ are cumulative and standard normal density distribution functions, respectively. We calculated the inverse Mills ratio and used it as a weight in the demand estimation to correct for non-response households. The ratio is calculated as:

$\frac{\varphi(z'_{ih}\delta_i)}{\Phi(z'_{ih}\delta_i)}$, $i = 1, \ldots\ldots$, n.

We then computed uncompensated expenditure and price elasticities corresponding to the estimated parameters for the system of equations (2), (3), and (5) from the equations (6) and (7). The average expenditure elasticity of good i across household h is

$$\eta_i = 1 + \mathrm{E}(\frac{\Phi(z'_{ih}\hat{\delta}_i)}{\hat{w}_{ih}})(\beta_i + \frac{2\lambda_i}{b(\boldsymbol{p})}\left\{ln\left[\frac{m}{a(\boldsymbol{p})}\right]\right\}). \quad (6)$$

The average uncompensated price elasticity of good i with respect to price of good j across household h is

$$e_{ij} = \mathrm{E}(\frac{\Phi(\boldsymbol{z}'_{ih}\hat{\boldsymbol{\delta}}_i)}{\hat{w}_{ih}})(\gamma_{ij} - (\beta_i + \frac{2\lambda_i}{b(\boldsymbol{p})}\left\{ln\left[\frac{m}{a(\boldsymbol{p})}\right]\right\})(\alpha_j + \sum_{k=1}^{n}\gamma_{jk}lnp_k) - \frac{\lambda_i\beta_i}{b(\boldsymbol{p})}\left\{ln\left[\frac{m}{a(\boldsymbol{p})}\right]\right\}^2). \quad (7)$$

As for the omitted group, we followed Lazaro et al. (2017) to recover its expenditure elasticity and the remaining uncompensated elasticities using Engel and Cournot aggregations, i.e.

$\sum_{i=1}^{n} w_i\, e_{ij} = 1$, and

$\sum_{i=1}^{n} w_i\, e_{ij} + w_j = 0$, respectively.

Finally, we computed bootstrapped standard errors from 50 replications of our data.

Scenarios

We proposed two different scenarios to estimate the impacts of policy and market shocks on household food security. The first scenario reflected on the Thai government's pledging scheme in 2011. The second scenario analyzed the likely, directional impacts of the COVID-19 pandemic with and without market intervention to mitigate the rice price change.

We estimated baseline values by using the model to estimate demands at actual price and total expenditure values. By doing this, we eliminated any noises that came from the model's errors. An expected issue in shocking a demand system is that if the change in budget share for some groups is significantly large, the model may force budget shares to zero or below in order to preserve the adding-up condition (i.e., total budget shares must sum to 1). Fortunately, this issue tends to happen to households at the very high level of expenditure, which were not the main focus of our study.

The Rice Pledging Scheme

In 2011, the Thai government introduced the price support program (also called the price pledging scheme), which promised to pay Thai rice farmers twice the market price. This program was designed as a price support policy to help Thai farmers avoid selling their crops during the harvest seasons when prices tend to be low (USDA, FAS, 2017). When the program was discontinued in 2014, it had incurred a loss of about $21.5 billion in total, as the government bought rice at higher prices but later sold it at a much lower price, let alone other operating costs (Permani and Vanzetti, 2016). Whereas the country had been one of the largest exporters in the thinly traded world rice market, Thailand's rice exports also plummeted, causing the world price to increase significantly in 2011 (FAO, 2012).

To understand the extent of the Thai government's rice policy on rice prices and rice farmers' income, we rely on Permani and Vanzetti (2016) for their analysis of the impacts of the rice pledging scheme during the 2011–2013 period. Using a partial equilibrium model that reflects the global rice supply and demand dynamics, they estimated the welfare impacts of the rice policy based on three different scenario assumptions about price change and the government's stockholding schemes. The program, in general, is a welfare loss for the Thai consumers and a welfare gain for the Thai farmers. Among six different scenarios that were the combinations of the pledging scheme with and without stock purchase and stock sell-off, we chose Scenario B as our reference because, according to those authors, this scenario best reflects what implementation mechanisms the Thai government adopted in reality (Permani and Vanzetti, 2016, Table 5, p. 280). Scenario B assumes two actions: (i) rice farmers sell rice to the Thai government at the policy price that is set 50% above the market price, and (ii) the government buys 5 million tons of rice annually during this period. In this scenario, the domestic price increases from $567 per metric ton to $837, or by 48%. Consumer surplus decreases by $2.6 billion, and producer surplus increases by $5.8 billion.

Converting Scenario B results from Permani and Vanzetti (2016) to domestic currency, we estimated an increase of about 8.8 Thai bahts (THB) per kilogram of rice. We applied this fixed price increase as a proxy for the cereal price shock for all households. Using this fixed producer-to-consumer margin, we assumed that poor households experience a larger impact of the price shock, as the increase represents a larger percent of the base price.

Similarly, we divided the producer surplus by the number of rice farming households in Thailand (roughly 12 million farmers) to estimate the average change in net returns per household. Comparing the average effect on returns with the mean income of rice farming households in HSES, we estimated an increase of about 25% in income for rice-farming households as a result of the rice policy. Based on these calculations, we used two simulations to measure the impacts of the rice policy on Thai households.

We shocked the cereal price and total expenditure variables in the demand system, holding everything else constant. This condition also means that households react to the rice price increase by reallocating their food budget without changing their preferences for different types of foods.

We then compared the simulated quantity changes for each food group and by each quintile with the corresponding base values.

The COVID-19 Pandemic and a Hypothetical Trade Policy

The wholesale prices of rice in Thailand increased by 7.8% on a year-over-year basis as the pandemic took hold (Bank of Thailand, 2021). In addition, the Thai economy contracted by 7.1% in 2020 (IMF, 2021). Little is known about the true effects of the pandemic on food markets, consumers, producers, and the economy as a whole. Nevertheless, we based our hypothetical assumptions on this information about price and income. Adding to the complexity of COVID-19, we tested the implications in the event that the Thai government were to intervene in the market to reduce the rice price increase by half. This hypothetical policy case might reflect some combination of rice export restrictions and renewed stock holding.

Scenario assumptions for the pandemic impacts without a rice policy response call for a 7.8% increase in rice price and a 7.1% reduction in household expenditures overall, with rice-producing household expenditures rising by 7.0% on average (Table 4). We assumed a direct link from income changes to total expenditure changes. For rice-producing household total expenditures, we relied on estimates of the rice-pledging policy effect on the income of these households, as given earlier, and assumed that a change in rice prices would have a similar impact on rice farmers' income on average. Thus, we calculated a conversion factor that is the percent change in rice-producing household per percent change in rice prices. The average value of the conversion factor is 0.9, which means that if rice prices increase by 1%, then we expect that rice farmers' income (and expenditures) would increase by 0.9%. Since we calculated this at the household level and based this relationship on the information of the earlier policy scenario, each household's conversion factor is slightly different.

Table 4. COVID-19 and Policy Assumptions

	COVID-19 without Trade Policy Response	**COVID-19 with Trade Policy Response**
Rice price	+7.8%	+3.9%
Income of all households including rice farming households	-7.1%	-7.1%
Income of households that are engaged in rice farming	+7.0%	+3.5%

Source: Authors' calculations.

Results

First- and Second-Stage Estimation Results

Table 5 reports parameter estimates with bootstrapped standard errors. Table 6 presents the own-price and expenditure elasticity estimates for the lowest income quintile. Full elasticity estimates are provided in Table 7. All estimates are reported at their median values. For brevity, we focus our discussion on the results for low-income households in Table 6. We find that except for nonfood, all other goods, meaning all foods, are inelastic with regard to their own price with magnitudes ranging from −0.60 to −0.82. The total expenditure elasticity for cereals is very inelastic (0.06) but positive. Animal product groups, including meats, fish, oils, and fats, are less inelastic with respect to total expenditure than cereals, milk, and sugar. FAFH and nonfood total expenditure elasticities are larger than 1. If total expenditure elasticities are considered proxies for income elasticities, our results are consistent with past findings that low-income households' basic cereals demand is relatively inelastic with respect to income, while their FAFH and nonfood demands are relatively elastic.

Scenario Results

Impacts of the Rice Pledging Scheme

We applied three simulations to compare the impacts of price and income effects in this scenario compared to the base case. Simulation 1 assumes cereal prices increase by 8.8 THB per kilogram for all households in the sample. Simulation 2 assumes rice farmers' income increases by 25%. Simulation 3 combines both simulations 1 and 2. Table 8 shows the results for our focus group—the lowest income quintile. In Simulation 1, which only accounts for an increase in cereal prices, households increase their budget share for cereals by 0.84 percentage points on average in response to higher staple prices while reducing their budgets for meats and fish, FAFH, and especially nonfood items. In terms of quantity, households reduce their food consumption overall. Cereal consumption is hardest hit with a decrease by 16.3%, as the increase in budget share (as well as expenditure) is insufficient to offset the increase in cereal prices.

In Simulation 2, which assumes an increase in rice farmers' income, the budget shares for FAFH and nonfood increase while those of other groups slightly decrease. It should be noted that food expenditures still increase in absolute terms for those with decreased budget shares since the increase in income more than offsets the percent decrease in the share. What we observe is an increase in consumption overall.

Table 5. Nonlinear AIDS Parameter Estimate

Category	Cereals	Meats and Fish	Vegetables, Fruits, and Nuts	Milk and Sugar	Oils and Fats	FAFH and Other Foods
γ (price coefficient)						
Cereals	0.0055***					
	(0.0011)					
Meats and fish	-0.0146***	0.0334***				
	(0.0010)	(0.0012)				
Vegetables, fruits, and nuts	-0.0026***	-0.0026***	0.0120***			
	(0.0007)	(0.0005)	(0.0003)			
Milk and sugar	-0.0100***	-0.0081***	-0.0028***	0.0159***		
	(0.0006)	(0.0005)	(0.0002)	(0.0004)		
Oils and fats	-0.0014***	-0.0007***	0.0005***	-0.0008***	0.0034***	
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
FAFH and other foods	-0.0016	-0.0186***	-0.0111***	-0.0031***	-0.0010***	0.0640***
	(0.0012)	(0.0007)	(0.0005)	(0.0006)	(0.0001)	(0.0017)
α	0.4381***	0.2222***	0.1331***	0.1633***	0.0125***	-0.0871***
	(0.0066)	(0.0092)	(0.0056)	(0.0051)	(0.0011)	(0.0103)
β (expenditure coefficient)	-0.1142***	-0.0145***	-0.0047*	-0.0353***	-0.0006	0.0724***
	(0.0025)	(0.0046)	(0.0026)	(0.0021)	(0.0004)	(0.0057)
λ (squared expenditure coefficient)	0.0065***	-0.0052***	-0.0021***	0.0019***	-0.0004***	-0.0083***
	(0.0003)	(0.0006)	(0.0003)	(0.0002)	(0.0000)	(0.0008)
θ (inverse Mills ratios)	0.0901***	0.0718***	0.0806***	-0.0856***	0.0062***	
	(0.0024)	(0.0024)	(0.0048)	(0.0024)	(0.0002)	

Note: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level. Bootstrapped standard errors (in parentheses) are reported instead of standard errors generated from the observed data. Source: Authors' calculations.

Table 6. Uncompensated Price and Expenditure Elasticity Estimates for the Lowest Quintile

	Cereals	**Meats and Fish**	**Vegetables, Fruits, and Nuts**	**Milk and Sugar**	**Oils and Fats**	**FAFH and Other Foods**	**Nonfood**	**Expenditure Elasticity**
Cereals	-0.6258***	0.0649***	0.0734***	0.0386***	-0.0008	0.0628***	0.4515***	0.0636***
	(0.0059)	(0.0079)	(0.0043)	(0.0046)	(0.0009)	(0.0060)	(0.0115)	(0.0206)
Meats and fish	-0.0787***	-0.7221***	-0.0099*	-0.0487***	-0.0040***	-0.1350***	0.1092***	0.8889***
	(0.0077)	(0.0098)	(0.0051)	(0.0035)	(0.0011)	(0.0070)	(0.0112)	(0.0296)
Vegetables, fruits, and nuts	-0.0169**	-0.0248***	-0.8217***	-0.0325***	0.0077***	-0.1539***	0.1092***	0.9328***
	(0.0068)	(0.0088)	(0.0053)	(0.0043)	(0.0012)	(0.0081)	(0.0121)	(0.0312)
Milk and sugar	0.0125	-0.0248*	0.0069	-0.6511***	-0.0066**	-0.0079	0.2792**	0.3933
	(0.0127)	(0.0133)	(0.0066)	(0.1532)	(0.0031)	(0.0231)	(0.1293)	(0.3035)
Oils and fats	-0.1460***	-0.0681***	0.0631***	-0.0848***	-0.5997***	-0.1148***	0.0171	0.9331***
	(0.0123)	(0.0179)	(0.0102)	(0.0077)	(0.0159)	(0.0128)	(0.0223)	(0.0479)
FAFH and other foods	-0.1374	-0.1890	-0.1036	-0.0704	-0.0108	-0.6571	-0.2550	1.4231
	(0.3346)	(0.4919)	(0.2642)	(0.1770)	(0.0283)	(0.9924)	(0.6684)	(0.9720)
Nonfood	0.0175	-0.0046	0.0018	-0.0034	-0.0026	-0.0708	-1.0489***	1.0498***
	(0.1216)	(0.1788)	(0.0959)	(0.0666)	(0.0103)	(0.3612)	(0.2420)	(0.0143)

Note: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level. Bootstrapped standard errors (in parentheses) are reported instead of standard errors generated from the observed data. Source: Authors' calculations.

Table 7. Uncompensated Expenditure and Price Elasticity Estimates

	Cereals	**Meats and Fish**	**Vegetables, Fruits, and Nuts**	**Milk and Sugar**	**Oils and Fats**	**FAFH and Other Foods**	**Nonfood**	**Expenditure Elasticity**
Cereals	-0.3812	0.1041	0.1205	0.0598	-0.0017	0.1177	0.7500	-0.7732
	(2.5597)	(0.3062)	(0.4990)	(0.2529)	(0.0196)	(0.8002)	(3.0943)	(7.4880)
Meats and fish	-0.1046**	-0.6322***	-0.0133	-0.0648**	-0.0053***	-0.1773***	0.1400**	0.8527***
	(0.0416)	(0.1365)	(0.0093)	(0.0275)	(0.0028)	(0.0679)	(0.0630)	(0.0776)
Vegetables, fruits and nuts	-0.0215**	-0.0315**	-0.7749***	-0.0412***	0.0097***	-0.1936***	0.1400***	0.9151***
	(0.0099)	(0.013)	(0.0483)	(0.0088)	(0.0031)	(0.0407)	(0.0403)	(0.0546)
Milk and sugar	0.0157	-0.0391	0.0089	-0.4889	-0.0098	-0.0058	0.4100	0.1087
	(0.4295)	(0.2745)	(0.1756)	(0.2628)	(1.1977)	(0.3320)	(0.0613)	(0.1276)
Oils and fats	-0.1936	-0.0905	0.0835	-0.1126	-0.4698	-0.1513	0.0200	0.9114***
	(0.1281)	(0.0630)	(0.0681)	(0.0808)	(0.3758)	(0.1154)	(0.0613)	(0.1099)
FAFH and other foods	-0.1271*	-0.1748*	-0.0961*	-0.0646*	-0.0099***	-0.6832*	-0.2400	1.3940***
	(0.0671)	(0.0987)	(0.0533)	(0.0353)	(0.0057)	(0.198)	(0.1349)	(0.1982)
Nonfood	0.0175	-0.0046	0.0018	-0.0033	-0.0026	-0.0708	-1.0500***	1.1701***
	(0.2891)	(0.0499)	(0.0584)	(0.157)	(0.0128)	(0.1148)	(0.3828)	(0.0122)

Note: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level. Bootstrapped standard errors (in parentheses) are reported instead of standard errors generated from the observed data. Source: Authors' calculations.

Table 8. Impacts of the Rice Pledging Policy on the Lowest Income Quintile

		Base	Simulation 1	Simulation 2	Simulation 3	Simulation 1	Simulation 2	Simulation 3
Budget share							Percentage point change	
Cereals	Percent	10.6	11.5	10.3	11.1	0.84	-0.37	0.48
Meats and fish	Percent	12.7	12.6	12.4	12.3	-0.11	-0.24	-0.35
Vegetables, fruits, and nuts	Percent	6.9	7.0	6.9	6.9	0.03	-0.09	-0.06
Milk and sugar	Percent	5.7	5.7	5.6	5.5	-0.04	-0.13	-0.17
Oils and fats	Percent	0.8	0.8	0.8	0.8	-0.02	-0.02	-0.04
FAFH and other foods	Percent	17.1	16.7	17.2	16.6	-0.37	0.08	-0.53
Nonfood	Percent	46.4	46.0	47.1	47.0	-0.35	0.71	0.60
Quantity							Percent change	
Cereals	kg/person	97.0	81.2	98.7	82.8	-16.3%	1.7%	-14.7%
Meats and fish	kg/person	31.8	31.5	32.8	32.5	-0.9%	3.1%	2.2%
Vegetables, fruits, and nuts	kg/person	43.0	43.2	44.9	45.1	0.5%	4.3%	4.8%
Milk and sugar	kg/person	21.6	21.4	22.2	22.1	-0.6%	3.2%	2.5%
Oils and fats	kg/person	4.6	4.5	4.8	4.7	-2.6%	3.1%	0.4%
FAFH and other foods	Index	52.3	51.1	55.5	53.5	-2.2%	6.1%	2.3%
Nonfood	Index	30.5	30.3	32.6	32.6	-0.7%	6.8%	6.6%

Note: Simulation 1 assumes cereal prices increase by 8.8 THB per kilogram for all households in the sample. Simulation 2 assumes rice farmers' income and total expenditures increase by 25%. Simulation 3 combines both Simulations 1 and 2. Source: Authors' calculations.

Combining both negative price and positive income effects, we observed that households in the poorest quintile respond by increasing their budget for cereals, though this is not enough to offset the increase in prices. Cereal consumption, thus, reduces by 14.7% on average. Rice-producing households, which account for about 1 in every 4 households in this income bracket, also reduce their cereal consumption but to a lesser extent due to the offsetting income effect induced by the policy. Overall, the impacts on other categories of food and nonfood consumption are positive but smaller in absolute terms than in Simulation 2.

Impacts of COVID-19 and a Hypothetical Trade Policy

The first set of results estimates the impacts without any trade policy response (Table 9). Overall, higher cereal prices coupled with a decline in income cause low-income households to reduce their overall consumption, with the largest changes being FAFH (7.3%), followed by nonfood (7.1%) and cereals (6.8%). Comparing results for rice-farming and non-rice-farming households of the lowest income bracket, we found that those who are not engaged in rice farming are harder hit by the price increase because they do not benefit from the income boost induced by a higher price (Table 10). For both types of households in this income bracket, cereal consumption quantity is reduced at the higher price, but the greater value of rice sales mitigates some of this drop for rice-producing households. For such households, however, a large part of the income increase appears to go to buy non-cereal items, and the income effect in this case is more apparent when comparing quantities of other goods that they buy relative to the quantities purchased by low-income households that do not benefit from higher valued rice sales.

Adding a hypothetical trade response policy that cuts rice prices by half, we first compared the impacts on consumption across income quintile (Table 11). All else equal, such a trade policy increases cereal consumption for all households, with the largest impact on the lowest income households. On the flip side, a lower rice price means lower income for rice-farming households, which account for about a quarter of the lowest quintile and about one-fifth of the second lowest quintile. The negative income effects induce some decreases in consumption of other goods for these households. Households in the higher income ranks tend to benefit from the trade response overall.

Table 9. Impacts of COVID-19 without Trade Policy Response on the Lowest Income Quintile

		Base	Simulation 1	Simulation 2	Simulation 3	Simulation 1	Simulation 2	Simulation 3
Budget share							Percentage point change	
Cereals	Percent	10.6	10.9	11.0	11.3	0.3	0.4	0.7
Meats and fish	Percent	12.7	12.6	12.9	12.9	-0.1	0.2	0.2
Vegetables, fruits, and nuts	Percent	6.9	7.0	7.0	7.1	0.1	0.1	0.2
Milk and sugar	Percent	5.7	5.7	5.8	5.8	0.0	0.1	0.1
Oils and fats	Percent	0.8	0.8	0.8	0.8	0.0	0.0	0.0
FAFH and other foods	Percent	17.1	17.0	17.0	16.8	-0.1	-0.1	-0.3
Nonfood	Percent	46.4	46.3	45.5	45.5	-0.1	-0.9	-0.9
Quantity							Percent change	
Cereals	kg/person	97.0	92.1	95.4	90.4	-5.0%	-1.7%	-6.8%
Meats and fish	kg/person	31.8	31.7	30.7	30.6	-0.3%	-3.6%	-3.8%
Vegetables, fruits, and nuts	kg/person	43.0	43.1	41.3	41.3	0.1%	-4.1%	-4.0%
Milk and sugar	kg/person	21.6	21.5	20.9	20.9	-0.2%	-3.1%	-3.2%
Oils and fats	kg/person	4.6	4.6	4.5	4.4	-0.7%	-3.7%	-4.4%
FAFH and other foods	Index	52.3	51.9	49.0	48.5	-0.7%	-6.3%	-7.3%
Nonfood	Index	30.5	30.5	28.4	28.4	-0.2%	-7.1%	-7.1%

Note: Simulation 1 assumes cereal prices increase by 7.8%. Simulation 2 assumes rice farming household income and total expenditure decrease by 7.1%. Simulation 3 combines both Simulations 1 and 2. Source: Authors' calculations.

Table 10. Impacts of COVID-19 without Trade Policy Response on Rice- and Non-Rice-Farming Groups

		Rice-Farming and Poor			Non-Rice-Farming and Poor		
Quantity		**Base**	**COVID-19 Scenario**		**Base**	**COVID-19 Scenario**	
				Change from base			Change from base
Cereals	kg/person	96.4	91.3	-5.3%	97.25	90.2	-7.3%
Meats and fish	kg/person	32.0	31.8	-0.7%	31.73	30.2	-4.9%
Vegetables, fruits, and nuts	kg/person	45.2	45.0	-0.4%	42.3	40.1	-5.3%
Milk and sugar	kg/person	21.3	21.2	-0.7%	21.66	20.7	-4.3%
Oils and fats	kg/person	4.6	4.5	-1.9%	4.651	4.4	-5.5%
FAFH and other food	Index	52.4	51.5	-1.7%	52.14	47.5	-8.9%
Nonfood	Index	29.8	29.6	-0.9%	30.73	27.9	-9.2%
Number of households		2,157			6,377		

Source: Authors' calculations.

Table 11. Impacts of a Trade Response in the Event of COVID-19 by Income Quintile

Food Group	Unit	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Cereals	kg/person	2.3%	2.2%	1.9%	1.4%	0.04%
Meats and fish	kg/person	-0.3%	-0.1%	0.0%	0.1%	0.3%
Vegetables, fruits, and nuts	kg/person	-0.6%	-0.5%	-0.3%	-0.2%	-0.1%
Milk and sugar	kg/person	-0.5%	-0.2%	0.0%	0.2%	0.2%
Oils and fats	kg/person	-0.2%	0.1%	0.3%	0.5%	0.9%
FAFH and other food	Index	-0.2%	-0.2%	0.1%	0.3%	0.4%
Nonfood	Index	-1.2%	-0.6%	-0.5%	-0.3%	-0.2%

Source: Authors' calculations.

The impacts on rice-farming households' food consumption, in particular, is presented in Figure 1. As said, due to the dual nature of being both rice producers and consumers, the market intervention has as a negative effect on rice-producing household income relative to COVID without a trade policy response. The net effect of the pandemic on trade policy response for rice-farming households is a rice price that the limited income growth is insufficient to offset, as before, if judged in terms of cereal consumption alone. However, some of the potentially important effects are seen in negative spill-overs of the trade policy response to other goods caused by the combination of income and cross-price effect, with larger reduction in non-cereal consumption, especially nonfood items, compared to the COVID pandemic without trade policy response.

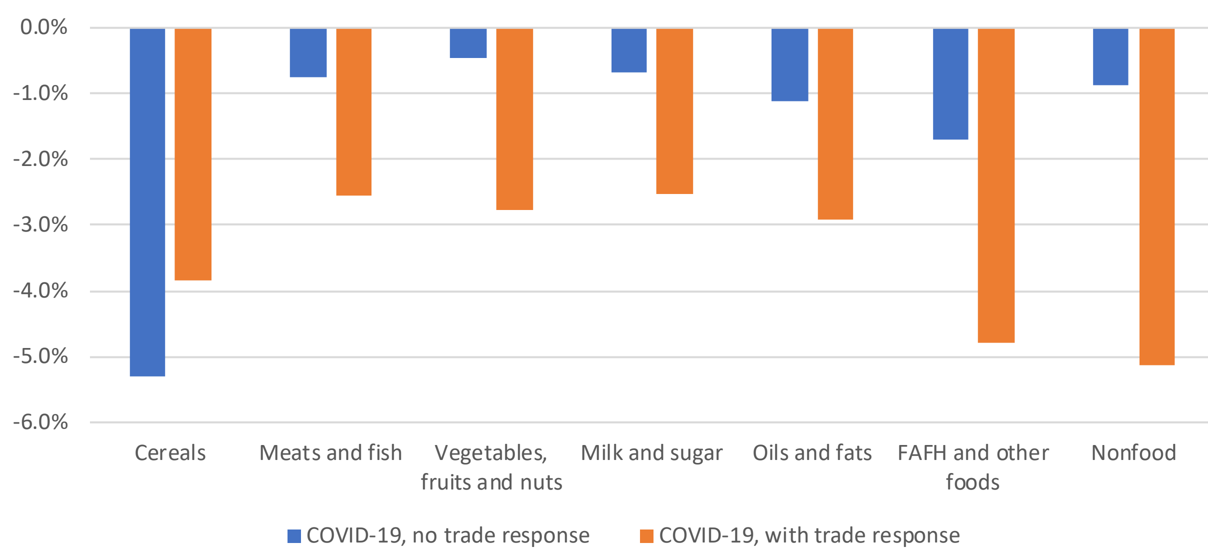

Figure 1. Changes in Consumption by the Lowest Income Households that Are Engaged in Rice Farming

Policy Implications and Conclusions

Evidence suggests that middle-income and developing countries turn to agricultural commodity market interventions as a policy instrument to achieve policy goals (Anderson and Valenzuela, 2008; Anderson et al., 2013), presumably including improving food security and managing crises when budget constraints limit other policy options. One outcome of the price surge of the last decade was a newfound reliance by many countries on direct intervention to constrain the market price increases in the name of food security (Demeke, Pangrazio, and Maetz, 2009). Taking Thailand as a case study, we used Thai household data to estimate food demands, adjust prices and expenditures to represent the impacts of the rice market interventions, and quantify the impacts, particularly on rice-producing households and poor households.

Thailand's rice pledging policy is recognized as an important case. This major rice-producing country introduced a policy to increase rice prices through stock-buying. The program resulted in higher income to rice producers and higher domestic prices to rice consumers. Consumers respond to the higher price by decreasing grain purchases. To some extent, the price impact is offset by a combination of reduced consumption of some foods to free up funds to buy higher priced grains and increased consumption of substitute foods. The net effect is a 14.7% decrease in cereal consumption on average for households whose income is not affected by the policy experiencing a negative impact on their food security overall.

We applied our method to estimate how income and price impacts suggested by Thailand's experience during the COVID-19 pandemic affect food security along this same dimension, to which we added an experiment to test the impacts of a hypothetical trade policy response. By exploiting our household representation and estimated market and income effects, we estimated selected pandemic price and income impacts on the poorest households of the country. These households try to preserve cereal consumption despite the income and price impacts of the pandemic, but still lose almost 7% of consumption, or about 24 days of cereal use in a year. This focus on maintaining staple consumption comes at the expense of other foods, with low-income households sacrificing 3%-7% of other foods, or 12 to 27 days' worth of use. A hypothetical trade measure that attempts to halve the domestic cereal price increase during the pandemic helps mitigate the impacts on many households while adversely affecting poor rice farming households' food security. Owing to the combination of price sensitivity, income sensitivity, and sizes of price and income effects of the trade measure, rice-producing households' food security is negatively affected to a larger extent relative to the impact of COVID-19 without a trade policy.

This study did not speak to all dimensions of food security, all policy makers' concerns, or all aspects of a pandemic, of course. It would require additional research to investigate intra-household consumption patterns or intra-annual price and income variations, to give two important examples. Pandemic impacts observed in 2020 go well beyond income and price shocks. Nevertheless, policy makers who have turned to agricultural policy with a view to support food security might do so again during the pandemic without waiting for a scientific study to provide information. For the case studied here and other countries that are in similar circumstances, namely looking for quick options to address a crisis yet perhaps with limited options apart from commodity trade or stock policies, our results are germane. The method and findings of the work above demonstrate the interactions of price-based policies and shocks with income effects in terms of their impacts on food consumption and security of the poorest households. Such findings can speak to certain outcomes of policy mechanisms during a crisis as severe as a global pandemic or as commonplace as widely used agricultural policy instruments.

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Infrastructure and Agricultural Trade in North and Latin America

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Abstract

This research investigated the impact of hard infrastructure on food and agricultural trade among North and Latin American countries. We employed a modified gravity model of trade for food and agricultural imports to measure the potential impact of the quality of hard infrastructure on the prevalence and patterns of agricultural trade. Results suggest that the development of hard infrastructure by investing in new projects or renewing existing network systems can increase agricultural trade volume and enhance trade performance among North and Latin American countries.

Key words: international trade, agriculture, infrastructure

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Introduction

Continued emphasis has been placed on trade barriers that restrict bilateral trade of food and agricultural products by both developed and developing countries. Although some countries have shown substantial growth in food and agricultural trade over the past 20 years, large portions of the developing world are still behind, often from either bilateral tariff or non-tariff barriers that impedes international trade. Lee and Swagel (1995) evaluated trade flows and trade barriers across countries and argue that import competition by weak industries and poor countries are threatened more by tariff and nontariff measures in addition to other trade costs, as compared to rich countries. Trade barriers include policy measures, trade facilitation and geographic factors, information and time costs, transport costs, and other transaction costs (Anderson and van Wincoop, 2004; Hummels, 2007). Trade policy measures, such as applied tariffs, have been reduced or eliminated over the last 20 years for agricultural products (Anderson, 2004). For example, in 2000, the United States imposed a 25.91% tariff on food imported from Brazil. This rate was effectively reduced to 9.37% in 2018 (World Bank, 2018). However, given the noticeable reduction in tariff rates, the volume of agricultural trade is still relatively low in some low-income countries. For example, in 2000, Brazil imported $20.79 million of food products from Mexico at 18.97% applied tariff rate; however, the imports of food products by Brazil from Mexico was 51.46 million in 2018, given a tariff rate decline to 7.38% (World Bank, 2018). This low level of bilateral trade may be explained by other non-tariff measures such as transportation and shipment costs. Transport costs can influence food product trade, and it can affect the access to central and international markets, thereby restricting trade flows (Bougheas, Demetriades, and Morgenroth, 1999; Limao and Venables, 2001; Clark, Dollare, and Micco, 2004; Behar and Venables, 2010). Transport costs can be determined by transaction and shipment costs, quality of infrastructure, and geographic variables, such as distance, common border, and whether a country is an island or landlocked. Infrastructure, geographic factors, and distance between countries are important in determining transport costs and trade patterns, as they implicitly represent shipment and travel costs (Limao and Venables, 2001; Behar and Venables, 2010). One potential geographic disadvantage for a country is if its geographic location increases the transport costs to move goods within or across the borders of countries. Many agricultural commodities are assumed to be bulky and perishable, which may increase transportation and freight costs. Given that infrastructure and distance are two determinants of transport costs, this study investigated how changes in the quality of hard infrastructure affect trade flows of food and agricultural products, while accounting for the distance across trading countries in North and Latin America.

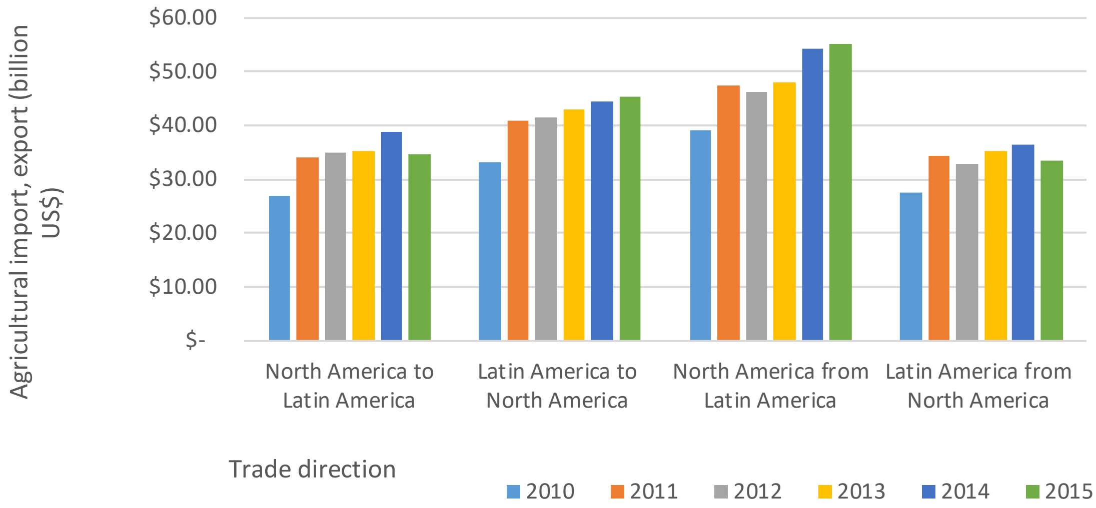
This manuscript focuses on hard infrastructure, which comprises all types of physical networks, such as roads, railroads, ports, and airports, the hard network system that enables physical connections within countries and across international borders. Physical infrastructure has a salient role in determining the cost of transportation that producers incur to move goods to local or international markets; thus, improving the quality of physical networks across the country and at the border may be one effective strategy to overcome distance and other geographic disadvantages and decrease transport costs. Therefore, the main objective of this study was to estimate the effect of the quality of hard infrastructure on agricultural bilateral trade volumes given other factors influencing the quantity traded, such as different tariff rates imposed by importing countries, distance and contiguity between trade partners, and differing income levels of each country. Also, the study investigated the unique contribution of each mode of transport infrastructure, including roads, railroads, ports, and airports on agricultural trade volume. A modified gravity model of trade was used to address the impact of infrastructure quality on bilateral trade among selected North and Latin American countries[1] for a 9-year period, 2006-2014. Where zero trade flows have been omitted by many past studies, this research accounts for zero trade flows in the analysis using the Poisson Pseudo Maximum Likelihood estimation method.

Agricultural Trade in North and Latin America

The United States, Canada, Argentina, and Brazil are key exporters and importers of food and agricultural products. The main forces that influence agricultural trade, in general, are changes in global food supply and demand, changes in agricultural commodity prices, countries' specific government regulations to protect agricultural trade, and direct or indirect domestic support to enhance domestic agricultural production (U.S. Department of Agriculture, 2017). The demand for food products derived by the increase in global population and income growth resulted in the increase of U.S. food export volume by more than $30 billion from 1991 to 2015 (World Bank, 2017).

Agricultural trade among North American and Latin American countries from 2010-2015 are compared in Figure 1. The total agricultural import value for North America from Latin America increased substantially from 2010 to 2015. Meanwhile, the total export levels for North America from Latin America and the imports of Latin America from North America fluctuated over the six years with a decline of roughly $3 billion from 2014 to 2015.

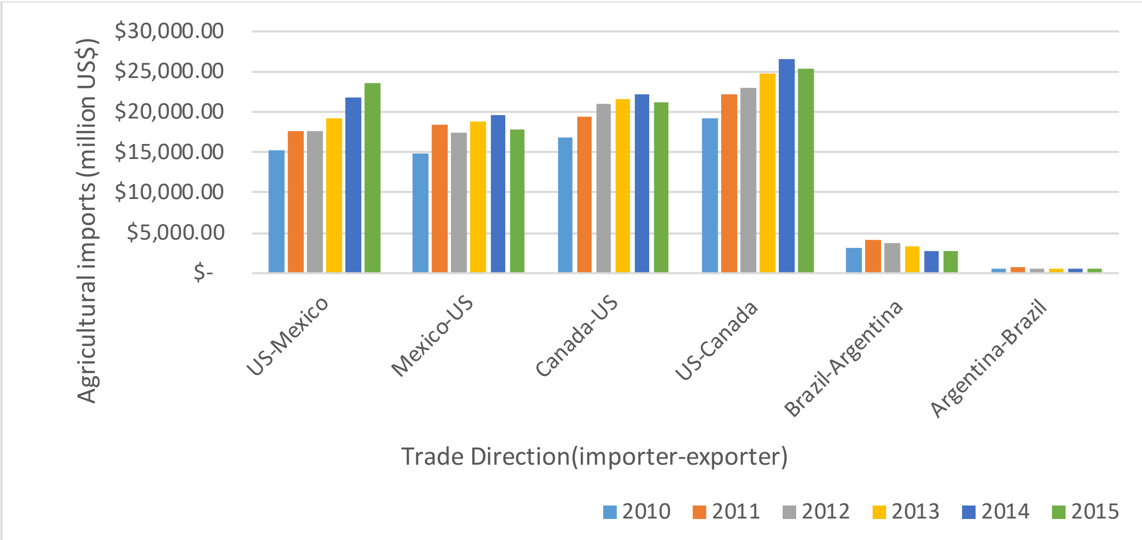
[1]North America includes the United States, Canada, and Mexico. The Latin America region includes South America (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Guyana, Paraguay, Peru, Suriname, Uruguay, and Venezuela), Central America (Belize, Costa Rica, El Salvador, Guatemala, Nicaragua, and Panama), and the Caribbean (Antigua and Barbuda, Bahamas, Barbados, Cuba, Dominica, Dominican Republic, Grenada, Haiti, Jamaica, St. Kitts and Nevis, St. Lucia, St. Vincent and Grenadines, and Trinidad and Tobago).



Data Source: World Integrated Trade Solution (World Bank, 2017), 2010-2015

Figure 1: Agricultural Trade Pattterns in North and Latin America 2010-2015

Agricultural trade patterns of selected countries from North and Latin America are represented in Figure 2. Countries are presented to show the difference in agricultural trade levels between developed and developing countries. The level of agricultural imports to the United States from Canada is the highest in volume as it gradually increased from about 19 trillion U.S. dollars in 2010 to 26 trillion U.S. dollars in 2014. Compared to Canada and the United States, Argentina's imports from Brazil are relatively low even though they share a common border and are members of the same regional trade agreement. In contrast, agricultural trade between Mexico and the United States increased during the period from 2010 to 2015. The volume of agricultural imports to the United States from Mexico was more than 20 billion U.S. dollars in 2015 compared to 15 billion in 2010. Thus, the difference in agricultural trade among regions or countries can be attributed to the different factors that determine the direction and volume of trade, which include tariff and non-tariff measures.



Source: World Integrated Trade Solution (World Bank, 2017), 2010-2015.

Figure 2. Total Agricultural Imports, 2010-2015

Quality of Physical Infrastructure

Infrastructure variables have been represented by a weighted average quality index in the gravity model of trade to reflect the level of infrastructure quality in a country. The indices are valued from 1 to 7, where 1 represents the lowest quality, and 7 is the highest quality, using country data provided by the Global Competitiveness Reports 2006-2014 (Schwab, 2014). In general, for ground networks, the lowest quality hard infrastructure, with index values of 1, refers to routes which are normally without any construction and maintenance and are unpaved or gravel roads and railroads with bad conditions. Low-quality ground networks are common in most developing countries and oftentimes in rural areas of developed nations. For ports, low-quality ports are assumed to be small in size with old and degraded facilities and institutions and small-sized vessels. They have higher turnaround times for ships, ship to nearby countries, and serve a relatively low number of customers around the world. High-quality hard infrastructure, with index values of 7, comprises paved and smooth roads that connect cities and rural areas in the country with no vehicle congestion or traffic. High-quality ports can support large vessels that can carry large, heavy-weight cargo and are located in an accessible coastal border of a country. They have good and new storage facilities, minimal congestion, and they provide quicker services to customers with less costs to all parties. They also provide easier access to railroads, roads, and highways to move cargo on the interstates or to inland cities. Brazil is an example of an important agricultural exporter and importer with low to medium overall hard infrastructure quality, with a weighted average quality index value of 3.9 in 2014. On the other hand, the United States is an example of a highly developed country with good overall hard infrastructure, with a weighted average quality index value of 5.7 in 2014.

Literature Review

Cross-country variation in transport costs can largely impact the trade volumes. Transport costs include the cost of handling and shipping containers, insurance charges, inventories, and other fees related to finishing paper work and delay of shipment across borders (Anderson and van Wincoop, 2004). However, it is not easy to quantify the value of transport costs, especially for the opportunity costs associated with shipment delay. Kurmanalieva (2006) employed transport density to measure transport costs by using the minimum distance between two countries as an approximation for the transport density, as the shortest travel path is assumed to be used more by traders. Limao and Venables (2001) used three different ways to measure transport cost values, including shipping costs data, CIF/FOB ratio,[2] and gravity model of trade. They utilized data for 103 economies to assess the influence of infrastructure and transport costs on bilateral trade. Findings indicated that being a landlocked country increases shipping and transport expenses by about 55% higher than a coastal country, at the median. The authors included own country infrastructure, partner, and transit country infrastructure with other geographic factors to analyze the impact of transport costs on trade volume. Conclusions indicate that own country infrastructure, partner infrastructure, and transit country infrastructure significantly affect trade volume with an elasticity of 1.32, 1.11, and 0.60, respectively. On the other hand, Behar and Venables (2010) address how a change in transport costs might impact international trade and what might be the determinants of the transport costs. The authors suggest that transport costs are determined by a set of variables, including distance and geography of a country, quality of infrastructure, trade facilitation, freight and fuel costs, and transport technology.

Hummels (2007) investigated why world trade of all goods has increased by more than 3,000 million tons (about $9 million) from 1980 to 2004. Hummels (2007) argues that one important possible reason for the increase in international trade volume is the reduction in transport costs and development in transportation and physical infrastructure. The author suggested that the importance of transport costs can be evaluated relative to the value of trade, relative to other trade barriers (i.e., tariff), or relative to change in prices of goods. Dillon and Barrett (2016) provide empirical evidence for the role of infrastructure and transportation costs in determining local market conditions, including internal and external exchange of the products. The authors explored price transmission from global market to local markets for oil and maize, allowing transport and fuel costs to influence maize prices, and suggest that international shocks to global product prices, including transport costs, can transmit to local market prices. Given the importance of transport costs in determining the volume of trade and the direction or travel route for trade, we implicitly reflect the impacts of transportation costs on bilateral trade following Behar and Venables (2010); Clark, Dollare, and Micco (2004); Limao and Venables (2001); and Nordas and Piermartini (2004)

[2]CIF/FOB represents Cost, Insurance, and Freight (CIF) and Free on Board (FOB), which give an estimate of border prices of importing and exporting countries. CIF prices are reported by the importing country, which estimates the cost of imports. FOB prices are reported by exporting country, and they refer to costs of shipping the products abroad from exporting borders (see Limao and Venables, 2001). CIF/FOB data are provided by IMF's Direction of Trade Statistics.

using the determinants of transport costs (i.e., distance, common border, and quality of infrastructure) in the gravity model of trade.

Improving trade facilitation and infrastructure are considered important way to enhance international trade flows. A study by Portugal-Perez and Wilson (2011) used trade data for 101 countries to estimate the impact of hard and soft infrastructure on the export volume of developing countries. In the empirical model, the authors used indices and indicators to represent the quality of physical infrastructure for ports, airports, roads, and railroads infrastructure, and used business environment and transport efficiency as measures for soft infrastructure. Results showed that improving physical infrastructure and business environments have large impacts on increasing export value.

Shepherd (2016) addresses the relationship between trade facilitation, infrastructure, and network connectivity for Sub-Saharan Africa (SSA) and other global and regional value chains. Shepherd used network analysis of value-added trade for agricultural, textile, and clothing sectors for 189 countries for years 1996 and 2011 to estimate value chain connectivity measures. The findings show that there is a large gap in trade of agricultural, textile, and clothing between SSA and other developing regions, the Pacific and East Asia. The author suggests that the enhancement of trade facilitation and infrastructure can improve trade flows and better connect SSA with global and regional value chains.

Another study by Wilson, Mann, and Otsuki (2004) evaluated the effects of port efficiency, customs, regulations, and service infrastructure on trade flows of manufacturing products. The authors show that trade volumes are positively influenced by the four measures of trade facilitation, with the largest impact being port efficiency. Mirza (2009) confirms that the gains to trading countries exceed the capital costs of investing in border infrastructure reforms in Sub-Saharan Africa with a benefit-cost ratio of 3.9%. Mirza (2009) also discusses that while infrastructure development projects require a substantial amount of capital and resources, the literature supports that improving hard and soft infrastructure can result in a comparative advantage for national and international trading pairs through the reduction of transport and shipment costs.

Investment in physical infrastructure and other trade facilitation can decrease transportation costs, specifically for low-income countries, which increases agricultural trade. Korinek and Sourdin (2010) used a gravity model and data on maritime transport costs to assess the impact of maritime shipping costs on the trade of aggregated and disaggregated agricultural goods. Results show that maritime freight costs represent more than 10% of the total cost for most agricultural product imports. Further, findings indicate that a reduction in transport costs, while controlling for shipping distance, can increase agricultural imports. Other studies also investigated the role of infrastructure on agricultural trade and suggest that good quantity and quality infrastructure in both rural and urban areas can enable agricultural and food product access to national and international markets (Felloni et al., 2001; Park, 2005; Ismail and Mahyideen, 2015).

Agricultural commodities are more commonly shipped by railroads and roads within the country, as this is known to have a cost advantage compared to air and sea transport. However, shipments to the global market are affected heavily by transaction costs at borders and the distance between countries. Thus, this study evaluated the relationship between food and agricultural trade and quality of roads, railroads, ports, and airports. Much of the literature that addresses the role of trade facilitation on international trade theoretically or empirically applies the standard gravity model of trade. The gravity model of trade was used for the first time by Jan Tinbergen in 1962. The basic traditional model includes variables such as the country's income level, distance, and other dummy variables (e.g., contiguity, common language, colonial history, free trade agreement). Later, the gravity model of trade was modified to include different economic forces that may enhance or restrict bilateral trade flows. The modeling approach was expanded to explain the variation in bilateral trade by including trade facilitation and infrastructure as non-policy barriers to trade (Limao and Venables, 2001; Anderson and Wincoop, 2004; Clark, Dollare, and Micco, 2004; Nordas and Piermartini, 2004; Francois and Manchin, 2007; Behar and Venables, 2010).

Data and Estimation

Data and Variables

We used a panel of aggregated agricultural bilateral trade data for 25 selected North and Latin American countries from 2006 to 2014.[3] Data on imports for food, animal, and vegetable sectors were collected for all possible pairs of the 25 countries in the sample. Then, the aggregation of the three sectors was used to represent the total aggregated agricultural sector. The data on import values and weighted tariff rates were collected from the World Integrated Trade Solution (World Bank, 2017). GDP, as a proxy for income, was obtained from the World Development Indicators Database. Data on distance, common language, and common border dummy variables were taken from the CEPII Database (CEPII, 2017). Data on preferential trade agreements were collected from the Foreign Trade Information System (SICE, 2017) and World Trade Organization (WTO, 2017). Transportation infrastructure indices were employed to represent the quality of hard infrastructure in the model and were obtained from the Global Competitiveness Reports from 2006-2014 (Schwab, 2014), which were provided by the World Economic Forum and Executive Opinion Survey. The data on infrastructure were represented in terms of weighted average quality, indices valued from 1 to 7, where 1 refers to a country with extremely underdeveloped infrastructure and 7 refers to a country with well-developed infrastructure, on average within the country. The data for Executive Opinion Survey was collected from 150 institutions around the world that have a partnership with the World Economic Forum. The Global Competitiveness Report specifies infrastructure as one of the basic requirements that fosters productivity and enhances economic growth. Accordingly, we included the overall hard infrastructure variable in the model with four modes of transport infrastructure comprised of the quality of roads, railroads, ports, and airports.

The World Integrated Trade Solution data show that several country pairs have zero trade flows or import values that have not been reported. We assumed that the observations with missing

[3] Sample countries are selected based on the availability of infrastructure indices data. We restricted our sample to 2006-2014, because most countries in the sample did not report import values for 2015, and there are many zero trade observations for most of the country pairs for years before 2006.

import values are zero trade flows as shown in the literature (Santos Silva and Tenreyro, 2006; Helpman, Melitz, and Rubinstein, 2008; Baldwin and Harrigan, 2011; Francois and Manchin, 2013). Moreover, data on applied bilateral tariff rates have not been consistently reported for some pairings. Therefore, we calculated missing values for applied tariff rates using a weighted average tariff rate formula.[4] On the other hand, there are a few infrastructure indices that are not reported by the Global Competitiveness Reports. We calculated the missing data using interpolation by considering the indices' trends over the most recent two years of available data.

Table 1 shows the comparison of transport infrastructure indices for the year 2014 for the representative sample countries that have either maximum or minimum index value in each index category. The United States has the highest quality of overall transport infrastructure among North and Latin America for 2014, with an index value equal to 5.82 for overall infrastructure, 6.1 for airports, 5.7 for roads, and 4.9 for railroads. While the minimum quality of overall transport infrastructure is for Venezuela, Panama has the highest quality of ports infrastructure among the sample countries for the year 2014. Countries with no railroads have a quality index value equal to zero.

Table 1. Comparison of Hard Infrastructure Indices among Selected North and Latin American Countries in 2014

	Median	**Minimum**	**Maximum**
Transport infrastructure index (1-7)	3.98 Brazil	2.65 Venezuela	5.82 United States
Roads index (1-7)	3.7 Guatemala and Jamaica	2.5 Paraguay	5.7 United States
Railroads index (1-7)	1.9 Costa Rica and Suriname	0.00 Trinidad and Tobago and Barbados	4.9 United States
Port index (1-7)	4.2 Trinidad and Tobago	2 Bolivia	6.3 Panama
Airport index (1-7)	4.1 Colombia and Guatemala	2.6 Paraguay	6.1 United States

Data source: World Economic Forum, Global Competitiveness Report, 2014.

Empirical Model

Following past literature, we modified the same basic traditional gravity model of trade to investigate the impact of infrastructure quality on agricultural bilateral trade flows. The model specification in terms of the Cobb-Douglas form is the following:

[4] Weighted average tariff rate for year t = ((tariff rate of year(t-1)* import value of year(t-1))+(tariff rate of year(t-2)* import value of year(t-2))/(import value of year(t-1)+ import value of year(t-2)). This formula provides a straightforward approach to calculate the missing import-tariff weighted averages; however, this method has possible limitations as it can underweight high tariffs.

$$M_{ijt} = \alpha_0\, GDP_{it}^{\beta_1}\, GDP_{jt}^{\beta_2}\, D_{ijt}^{\beta_3} CB_{ijt}^{\beta_4} LG_{ijt}^{\beta_5} PTA_{ijt}^{\beta_6} (1+\tau_{ijt})^{\beta_7} INF_{it}^{\beta_8}\, INF_{jt}^{\beta_9}\, \varepsilon_{ijt} \tag{1}$$

Taking the logarithm of the equation results in the following model:

$$\begin{aligned} ln\, M_{ijt} = \beta_0 + \beta_1\, ln\, GDP_{it} + \beta_2\, ln\, GDP_{jt} + \beta_3\, ln\, D_{ijt} + \beta_4 CB_{ijt} + \beta_5 CL_{ijt} + \beta_6 PTA_{ijt} \\ + \beta_7\, ln\left(1+\tau_{ijt}\right) + \beta_8\, ln\, INF_{it} + \beta_9\, ln\, INF_{jt} + \mu_{ijt} \end{aligned} \tag{2}$$

Where i and j represents importing and exporting countries, respectively, M_{ijt} is the value of agricultural imports from country *i* to country *j* in thousands of U.S. dollars, *GDP* is gross domestic product in millions of U.S. dollars. D_{ijt} represents the distance between importing and exporting countries measured in kilometers. *CB*, *CL*, and *PTA* are dummy variables for common border, common language, and preferential trade agreement, respectively. The dummy variables equal 1 if the country pairs share a common border, speak a common language, or have a free trade agreement, and zero otherwise. τ_{ijt} is the weighted average effectively applied bilateral tariff rate. *INF* represents importer and exporter infrastructure indices corresponded to the quality of infrastructure. *INF* measures 5 different indices consisting of overall hard infrastructure, roads, railroads, ports, and airports. Finally, μ_{ijt} is the random error term.

Estimating the Gravity Model of Trade

It is often the case that certain country pairs do not trade with each other at all or for some timeframe. Therefore, we observed zero import values in agricultural trade data for some country pairs, especially when considering highly disaggregated products. Since the log of zero is undefined for log-linear models, zero trade observations become a problem when estimating the gravity model of trade using an Ordinary Least Squares (OLS) estimator. Many studies in this area argue that estimating the gravity model of trade while omitting zero trade observations results in a loss of important trade information and biased estimates (Linders and de Groot, 2006; Gómez-Herrera, 2013; Martin and Pham, 2015). Accordingly, the literature suggests that zero trade flows should be included in the model to deal with different empirical estimation problems (Linders and de Groot, 2006; Helpman, Melitz, and Rubinstein, 2008; Gómez-Herrera, 2013; Martin and Pham, 2015). The Heckman estimator, Tobit estimator, and Poisson Pseudo Maximum Likelihood (PPML) and Gamma Pseudo Maximum Likelihood (GPML) are examples of estimation methods that have been widely used to deal with zero trade values. This research employed a PPML estimation method to account for zero trade flows when estimating the impact of the quality of hard infrastructure on the import volume of annual agricultural trade. The PPML estimator is known to account for heteroskedasticity (Santos Silva and Tenreyro, 2006), can take advantage of the information contained in the zero trade flows, ensures that the gravity fixed effects are identical to their corresponding structural terms (Arvis and Shepherd, 2013; Fally, 2015), and results in unbiased as well as consistent estimators (Santos Silva and Tenreyro, 2006; Francois and Manchin, 2013; Gómez-Herrera, 2013).

PPML uses the level of trade values rather than the log of trade, and the interpretation of the estimated coefficients can represent simple elasticities. Santos Silva and Tenreyro (2006) specify the PPML model in terms of a constant elasticity of substitution (CES) form:

$$y_{ijt} = \exp\left(x_{ijt}\beta\right) \epsilon_{ijt} \tag{3}$$

where y_{ijt} is the import value; x_{ijt} is a vector of explanatory variables, β is the coefficient of explanatory variables, and ϵ_{ijt} is the error term, where $\left(\epsilon_{ijt}|x\right) = 1$. Taking the first-order conditions to solve for β, results in the following form:

$$\sum_{i=1}^{N}\left[y_{ijt} - \exp\,(x_{ijt}\hat{\beta})\right] x_{ijt} = 0 \tag{4}$$

This specification is estimated while assuming that the conditional variance is constant, and that the conditional variance is proportional to the conditional mean.[5] We estimated the model including all variables specified in equation 2 with the addition of importer and exporter time-varying fixed effects and exporter-importer time-invariant fixed effects.

With the PPML estimation method, our gravity model can be represented by the following form:

$$\begin{aligned} M_{ijt} = \beta_0 &+ \beta_1\, ln\, GDP_{it} + \beta_2\, ln\, GDP_{jt} + \beta_3\, ln\, D_{ijt} + \beta_4 CB_{ijt} + \beta_5 CL_{ijt} + \beta_6 PTA_{ijt} \\ &+ \beta_7\, ln\left(1+\tau_{ijt}\right) + \beta_8\, ln\, INF_{it} + \beta_9\, ln\, INF_{jt} + \beta_{10} \sum D_i + \beta_{11} \sum D_j \\ &+ \beta_{12} \sum \gamma_{ijt} + \mu_{ijt} \end{aligned} \tag{5}$$

where D_i (D_j) are the dummy variables of importing (exporting) countries, and γ_{ijt} is the time-varying fixed effects for a given trade pair in year t. In this study, we estimated 6 models, the basic model, and then 5 models each, including the basic model variables with the separate addition of infrastructure indices to the basic model (overall infrastructure, roads, railroads, ports, and airports).

We included time-varying fixed effects in the model to account for changes in trade costs and price indices between trading countries, which controls for country-specific multilateral resistance terms. Anderson and van Wincoop (2003) argue that omitting multilateral resistance terms from the gravity model of trade can result in biased estimates. However, Harrigan (1996) and Hummels (1999) used exporter and importer fixed effects in the gravity equation as a solution for omitting trade multilateral resistance terms. Feenstra (2002) argues that using either the fixed effects approach or multilateral resistance terms in the gravity model results in consistent estimates even though explicit multilateral resistance terms can result in more efficient estimates.

[5] This assumption says that $E(y_{ijt}|x)=\exp(x_{ijt}\beta) \propto V(y_{ijt}|x)$ (see Santos Silva and Tenreyro, 2006; para. 645.)

Empirical Results and Discussion

This section presents the results of the Poisson Pseudo Maximum Likelihood (PPML) estimated coefficients for the gravity model of agricultural trade. For each of the estimated gravity equations, we report 6 regressions, one for the basic model, one for the overall hard infrastructure index, and regression results for each mode of transport infrastructure, including roads, railroads, ports, and airports. The first column in Table 2 shows the estimated coefficients for the basic model. All the estimated coefficients are statistically significant except GDP estimates for exporting country. The estimated coefficient for the distance variable negatively influences agricultural import flows. A 1% reduction in the distance traveled would increase agricultural imports by approximately 0.7%, suggesting that a shorter travel route is expected to increase bilateral trade value. The coefficient of the common language variable has unexpected sign. This can be explained by the large number of zeros between trade partners that do not share a common language, or by other country pairs that have positive trade value but do not share a common language, which could result in a negative estimated coefficient for the common language variable.

The other five columns in Table 2 present the estimated coefficients for the quality of the four modes of physical infrastructure indices along with the overall hard infrastructure index. The quality of physical infrastructure has a positive impact on agricultural trade volume for both exporter and importer. Nevertheless, the estimated coefficient of exporters' transport infrastructure has a larger impact on trade flows than importers' transport infrastructure. This finding could be due to the higher costs that are incurred by producers in exporting countries while moving agricultural commodities from farm gates or processing factories to exporting borders, whereas importers ship the commodities from importing borders to domestic market centers. Hard infrastructure is assumed to be of higher quality in market centers compared to rural and agricultural areas. The estimated coefficients suggest that improving the quality of exporter and importer hard infrastructure by 10% is expected to increase agricultural trade flows by 8.9% and 5.4%, respectively. This means that investments in all physical infrastructure networks, including roads, railroads, ports, and airports, by reforming existing facilities and/or constructing new physical network systems are expected to lead to increased trade. Even though the results show that improving hard infrastructure positively influences agricultural bilateral trade, the advantages from such developments may differ from country to country based on the volume of agricultural trade, direction of bilateral trade, and the influence of other incentives on agricultural trade flows (e.g,. GDP level, low tariff rate, etc.).

Among the four indicators of hard infrastructure, the importers' and the exporters' ports index have the largest effects on the bilateral trade flows. This result is consistent with the finding by Nordas and Piermartini (2004), where they conclude that port infrastructure has the largest impact on bilateral trade, among all indicators of infrastructure. These large impacts can explain the importance of improving ports for countries that depend on sea transportation of agricultural commodities, especially for countries that do not share common land borders and use sea shipments for trading goods. Therefore, the investments in port infrastructure enhancement are assumed to have a large impact in agricultural bilateral trade among sample countries, given that all North and Latin American countries are coastal countries except Bolivia and Paraguay.

For roads infrastructure, the results imply that improving importer and exporter roads by 10% are expected to enhance agricultural trade flows by about 7.2% and 4.9%, respectively. Results indicate that most of the sample countries, especially among Latin American countries, depend heavily on road networks for agricultural bilateral trade because they share a common land border. Railroad indices have the smallest impacts on agricultural imports in the sample. The results suggest that improving the quality of importer and exporter railroads by 10% would increase trade volume by approximately 2.2% and 2.4%, respectively. This low impact could be due to the low quality of railroads in developing countries included in the study or because some countries have no railroad infrastructure (i.e., Barbados and Trinidad and Tobago).

Table 2. Hard Infrastructure Impacts on Agricultural Bilateral Trade, PPML Estimates

	Basic Model	**Infrastructure**	**Roads**	**Railroads**	**Ports**	**Airports**
Bilateral tariff rate	-0.1018***	-0.0976***	-0.1022***	-0.0878***	-0.0956***	-0.1021***
	(0.0254)	(0.0271)	(0.0251)	(0.0235)	(0.0256)	(0.0250)
GDP importer	1.6122***	2.0858***	1.5587***	1.7612***	1.9247***	1.5830***
	(0.3603)	(0.4336)	(0.4012)	(0.4017)	(0.3831)	(0.3612)
GDP exporter	0.3058	0.1352	0.1903	0.2174	0.1496	0.3366
	(0.3385)	(0.4159)	(0.3712)	(0.3535)	(0.3998)	(0.3438)
Distance	-0.6875***	-0.6879***	-0.6875***	-0.7672***	-0.6879***	-0.6874***
	(0.0514)	(0.0514)	(0.0515)	(0.0567)	(0.0513)	(0.0513)
PTA	0.7089***	0.7100***	0.7088***	0.6951***	0.7104***	0.7088***
	(0.0601)	(0.0599)	(0.0602)	(0.0604)	(0.0599)	(0.0600)
Common Language	-0.8130***	-0.8177***	-0.8130***	-1.1082***	-0.8189***	-0.8128***
	(0.1199)	(0.1201)	(0.1197)	(0.1375)	(0.1202)	(0.1197)
Common Border	0.7088***	0.7114***	0.7085***	0.6967***	0.7126***	0.7087***
	(0.0715)	(0.0717)	(0.0712)	(0.0692)	(0.0716)	(0.0711)
Infrastructure importer		0.5410**				
		(0.2330)				
Infrastructure exporter		0.8924***				
		(0.2246)				
Roads importer			0.7201***			
			(0.2451)			
Roads exporter			0.4886**			
			(0.2011)			
Railroads importer				0.2179**		
				(0.0865)		

Table 2. (continued)

	Basic Model	Infrastructure	Roads	Railroads	Ports	Airports
Railroads exporter				0.2403***		
				(0.0852)		
Ports importer					0.7655***	
					(0.2246)	
Ports exporter					0.6484***	
					(0.2026)	
Airports importer						0.7451***
						(0.2559)
Airports exporter						0.4301*
						(0.2465)
Constant	-6.4574	-9.4901	-4.7868	-6.1373	-8.0174	-6.6660
	(5.1961)	(6.4702)	(5.8633)	(5.7506)	(5.8281)	(5.1865)
Observations	4950	4950	4950	4185	4950	4950
Importer FE	Yes	Yes	Yes	Yes	Yes	Yes
Exporter FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.95	0.95	0.95	0.95	0.95	0.95
Wald chi2	71558.60	75297.45	70950.54	81440.44	75459.33	73028.04
Prob > chi2	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001

Source: Authors' estimates using Poisson Pseudo Maximum Likelihood (PPML) estimation.
Notes: All variables are in terms of log except the dummy variables; numbers in the parentheses are robust check standard error; the model estimated with addition of country dummy variables and time fixed effects; single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level.

Conclusion

Poor and inadequate quality network systems can be an impediment to international agricultural trade, which may increase transportation costs of food and agricultural shipments. Even though the quality of hard infrastructure varies across countries, the development of good quality physical infrastructure is expected to benefit both developing and developed countries by reducing transportation costs and positively influencing agricultural bilateral trade. This study estimated the impact of hard infrastructure on agricultural trade volumes. We employed a modified gravity model of trade using the Poisson Pseudo Maximum Likelihood estimator to understand the effects of the quality of physical infrastructure on agricultural bilateral trade among North and Latin American countries.

We found that the quality of physical infrastructure is positively related to agricultural bilateral trade. Results suggest that a 10% improvement in the quality of hard infrastructure is expected to increase agricultural trade by approximately 8.9% for exporting countries and by 5.4% for importing countries. The quality of roads and ports infrastructure has similar and large effects on agricultural bilateral trade. Port infrastructure is important for total agricultural trade because most of the sample countries are coastal and ship most products via water transport. Similarly, roads are important for food and agricultural product trade given that some countries in North and Latin America share an inland common border, such as the United States and Mexico, and Brazil and Colombia.

Poor-quality hard networks could be attributed to the intensive use of a transportation system over time without upgrading the damaged networks or adding new transportation systems. In addition, some countries experience different crises or natural disasters, which could lead to the deterioration of some physical infrastructure in the country at a given time. Improving the physical networks would require a substantial increase in project funding. However, increased investment in such projects may reduce delays and traffic in the roads and highway system and reduce maintenance costs for all modes of transport. Countries with low- to medium-quality ground networks, such as Suriname, Paraguay, Honduras, Guatemala, Costa Rica, and Brazil, may benefit from investing in repairing and expanding existing networks and building additional roads and railroads to expand the transportation capacity in each country. However, countries with high-quality hard infrastructure index values of 5 to 7, such as Canada and the United States, may also benefit from repairing and reforming existing physical networks while concentrating investment funds on railroads and roads, as they already have high-quality ports and airport systems.

Thus, the development of hard infrastructure for both exporting and importing countries is important to increase quantities traded, lower shipment costs, and help producers in rural areas have better access to domestic and international markets. This study only focused on assessing the impact of the quality of physical networks on trade flows. However, future research is warranted to evaluate and compare the costs of improving each transport mode relative to the benefits of increased agricultural trade, as countries may benefit from concentrating investment projects in developing the modes that are used more commonly to trade across the country and at the border. As results show, the large positive impact of the estimated results for ports indices suggests that it may be worthwhile to invest in developing port infrastructure from both importer and exporter perspectives, as this may result in increasing agricultural trade volumes for trading countries. In general, investments in hard infrastructure are expected to increase agricultural trade in both developed and developing countries. Even though developed countries have historically supported high-quality and well-developed networks, overall, there may be a deterioration of some hard infrastructure facilities over time in specific areas around the country where physical infrastructure is intensively used for transportation. Therefore, investments in improving roads, railroads, airports, and ports, or building new network systems are essential as one method that may increase trade of agricultural commodities between North and Latin American countries.

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