Factors Influencing Tomato Prices at Tennessee Farmers' Markets

Sarah Bellingham

University of Tennessee, sbellin2@vols.utk.edu
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I am submitting herewith a thesis written by Sarah Bellingham entitled "Factors Influencing Tomato Prices at Tennessee Farmers' Markets." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Agricultural and Resource Economics.

Margarita M. Velandia, Major Professor

We have read this thesis and recommend its acceptance:

Christopher N. Boyer, Chad M. Hellwinckel

Accepted for the Council:  
Dixie L. Thompson

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)
Factors Influencing Tomato Prices at Tennessee Farmers’ Markets

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Sarah Bellingham
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ABSTRACT

The number of farmers’ markets in the United States continue increasing but at a decreasing rate. Additionally, although the number of farms with direct to consumer (DTC) sales, including farmers’ markets, increased by about 6% between 2007 and 2012, DTC sales did not change in this same time period. For those vendors using farmers’ markets as their main marketing channel, a better understanding on how to price their products could influence their likelihood of survival under a more competitive environment. The main purpose of this study is to identify the factors influencing prices at farmers’ markets, particularly Tennessee farmers’ markets tomato prices. We evaluated how factors such as competition, weather, location, and consumer characteristics influence tomato prices at Tennessee farmers’ markets. First price formation at farmers’ markets is framed using various microeconomic models from perfect to imperfect competition. Specifically, some of the models explored could help explain the impact of vendor interaction on farmers’ markets prices. Then, a robust random effects panel data regression is used to evaluate the factors influencing tomato prices at Tennessee farmers’ markets. The midrange of weekly per pound tomato prices at Tennessee farmers’ markets between 2013 and 2015, household characteristics, and weather information were used for this analysis. Results from the regression analysis suggest the factors influencing tomato prices at Tennessee farmers’ markets were potential customers’ age and household income, and seasonality.
TABLE OF CONTENTS

CHAPTER 1: INTRODUCTION ............................................................................................................. 1
CHAPTER 2: LITERATURE REVIEW ................................................................................................. 4
Consumer Demographics and Purchasing Behavior at Farmers’ Markets................................. 4
Farmers’ Market vs. Other Marketing Channels’ Prices ................................................................. 7
Factors to Consider when Setting Prices at the Farmers’ Markets ............................................ 8
CHAPTER 3: CONCEPTUAL FRAMEWORK ..................................................................................... 9
Farmers’ Markets in a “Perfect Competition World” ..................................................................... 9
   How does the Establishment of Equilibrium Prices Look Like in a Perfect Competition
   Farmers’ Market Scenario in the Very Short Run? ................................................................... 9
   How does the Establishment of Equilibrium Prices Look Like in a Perfect Competition
   Farmers’ Market Scenario in the Short Run? ......................................................................... 10
How does the Establishment of Equilibrium Prices Look Like in a Perfect Competition
Farmers’ Markets Scenario in the Long Run? ............................................................................ 11
Farmers’ Market in an “Imperfect Competition” World ................................................................ 14
   Do Vendors in a Farmers’ Market act as a Cartel? ................................................................ 15
   Can We Adopt the Price Leadership Model to Illustrate How Prices are Formed at
   Farmers’ Markets? ..................................................................................................................... 16
   Does Product Differentiation Play a Role in Price Setting at a Farmers’ Market? ................. 17
Game Theory Models to Analyze Pricing at Farmers’ Markets .................................................... 18
   How Does Predatory Pricing Come into Play at a Farmers’ Market? .................................... 20
CHAPTER 4: EMPIRICAL MODEL .................................................................................................. 22
CHAPTER 5: METHODS AND PROCEDURES ............................................................................ 24
Data ........................................................................................................................................... 24
Factors Influencing Farmers’ Markets Prices: A Panel Data Regression Approach ...................... 26
Fixed Effects and Random Effects Panel Data Regressions ......................................................... 28
Diagnostic Tests .......................................................................................................................... 30
CHAPTER 6: RESULTS .................................................................................................................. 34
CHAPTER 7: CONCLUSIONS ......................................................................................................... 36
REFERENCES ............................................................................................................................... 39
APPENDIX .................................................................................................................................... 46
VITA ............................................................................................................................................. 53
LIST OF TABLES

Table 1. Description of Variables Included in the Regression Analysis ..................................47
Table 2. Descriptive Statistics for the Variables Across all Years, 2013, 2014, and 2015
(n=181) .................................................................................................................................47
Table 3. Descriptive Statistics for the Variables Used in the Regression Analysis for 2013,
2014, and 2015 Sorted by Location .....................................................................................48
Table 4. Results Comparing Robust OLS, Robust Fixed Effects, and Robust Random
Effects ....................................................................................................................................49
LIST OF FIGURES

Figure 1. Market Supply in the Short Run ................................................................. 50
Figure 2. The Three Cost Scenarios of Long-Run Equilibrium in a Perfect Competitive Market ............................................................................................................. 51
Figure 3. Model of Price Leadership Behavior ............................................................................. 52
CHAPTER 1: INTRODUCTION

Farmers’ markets are defined as two or more agricultural producers selling directly to the public at an established location (United States Department of Agriculture Agricultural Marketing Service (USDA AMS), 2017). In 2017, the USDA AMS reported 8,687 farmers’ markets, which is a 7% increase from 2012 (USDA AMS, Local Food Research and Development Division, 2017). This percentage increase is lower than that between 2008 and 2012 (i.e., 68% increase). According to the 2015 Local Food Marketing Practices Survey, there are a total of 41,156 operations selling products at the farmers’ markets with total sales of about $710 million (USDA National Agricultural Statistics Service (NASS), 2017).

The growth in sales dollars and number of farmers selling products through direct-to-consumer (DTC) market outlets, which includes farmers’ markets, have slowed in recent years. Although the number of farmers with DTC sales increased by about 5.5% between 2007 and 2012, there was no change in DTC sales in this same period. There could be several factors associated with this trend including the stagnation in the number of consumers buying local, increased availability of locally grown products at intermediate marketing channels (e.g., grocery stores), and/or some farmers relying on more cost effective and profitable market outlets to sell their locally grown products (Low et al., 2015). Ultimately, this is resulting in more competitive farmers’ markets in the United States. For those farms using farmers’ markets as their main marketing channel, research is needed on ways to attract consumers and price their products in order for these farmers to survive under a more competitive environment.

The ability of agricultural producers using farmers’ markets as a market outlet to enhance profits and guarantee their long-term economic viability could depend on their understanding of
cost of production and price information, adjustment to emerging consumer trends, and taking
advantage of new market opportunities (Tropp and Barham, 2008). Pricing products at farmers’
markets can be a complex process (Bruch and Ernst, 2011). Accurate information regarding cost
of production, competition, prices, and consumer preferences are important when setting prices
at farmers’ markets, but may not be available in some cases. Even if this information is available,
understanding how to use this information may be challenging for producers.

The main purpose of this study is to identify the factors influencing tomato prices at
Tennessee farmers’ markets. Specifically, we will evaluate how factors such as weather,
competition, seasonality, and consumer characteristics influence tomato (excluding grape and
cherry tomatoes) prices at Tennessee farmers’ markets. We chose tomato prices for this analysis
because tomatoes are a very popular item at the Tennessee farmers’ markets and a large
percentage of tomato producers use the same unit of sale for this item (i.e., per lb) facilitating the
collection and analysis of these data.

Information from this study is intended for agricultural producers to better understand
factors they should consider when pricing their products and therefore improve their pricing
strategies. Additionally, this information could be used by Extension personnel when developing
educational materials to help producers better assess information they need to incorporate when
pricing their products at farmers’ markets as well as identify best pricing strategies when using
this market outlet.

The next chapter will summarize previous literature directly and indirectly related to
farmers’ markets prices and those factors influencing how prices are determined at a farmers’
market setting. Chapter three will frame price formation at farmers’ markets using various
microeconomic models from perfect to imperfect competition. Specifically, this study will
explore how some of these models could help explain the impact of vendor interaction on farmers’ markets prices. In chapters four and five, we will describe the empirical and econometric models to be used to evaluate factors influencing tomato prices at Tennessee farmers’ markets. Finally, in chapters six and seven we will summarize regression results and address general conclusions and limitations of this study.
CHAPTER 2: LITERATURE REVIEW

Previous literature on U.S. farmers’ markets has focused mainly on consumer demographics and purchase behavior at this market outlet (Alonso and O’Neill, 2011; Govindassamy, Italia, and Adelaja, 2002; Gumirakiza, Curtis, Bosworth, 2014; McGarry, Spittler, and Ahern, 2005; Onianwa, Mojica, and Wheelock, 2006; Strobbe, 2016). Additionally, there are few studies that have compared farmers’ market prices or DTC market channels’ prices with other market outlets’ (e.g., supermarkets, supercenters) prices (Gunderson and Earl, 2010; Martinez, 2016; McGuirt, Jilcott, and Ammerman, 2011; Sommer, Wing, and Aitkens, 1980). Although, there are few Extension publications aiming to help producers understand how to price their products at farmers’ markets (Bruch and Ernst, 2011; Chase, 2008; Ernst, 2014), there are no studies evaluating the factors influencing farmers’ markets prices.

**Consumer Demographics and Purchasing Behavior at Farmers’ Markets**

Alonso and O’Neill (2011) studied farmers’ market visitor needs and wants at one farmers’ market located in a rural area and at one located in an urban area in Alabama. Visitors’ earnings seem to affect their expenditures at farmers’ markets, with visitors attending the urban farmers’ market having higher incomes and therefore higher spending levels at the market. Conversely, those attending the rural farmers’ market have lower incomes and therefore lower spending levels at the market. Additionally, those visitors at the market located in the rural area valued access to lower prices, access to products naturally grown (e.g., “natural” pesticide), and of high nutritional value, access to a space that allows socialization with the community. Overall, this study suggests that location may affect farmers’ markets visitors spending patterns as well as their motivations to visit and purchase products at these market outlets.
Govindaasamy, Italia, Adelaja (2002) used a survey of 336 New Jersey farmers’ market customers to identify attitudes, preferences, and characteristics of those who shop at farmers’ markets. Respondents’ demographics suggested the majority of farmers’ market shoppers to be 51 years old or older, female, having a household size of more than two, college graduates, white, and having an income of more than $40,000 a year. Among these respondents, most of them valued convenience, price, quality, and freshness when purchasing products at farmers’ markets. Additionally, a large percentage of respondents were interested in the location where the product was produced. Finally, when asked about prices at the farmers’ markets, the majority of respondents perceived prices at the farmers’ markets to be good.

Gumirakiza, Curtis, and Bosworth (2014) conducted in-person interviews of 1,488 randomly selected farmers’ market customers from 16 markets across Nevada and Utah to evaluate the characteristics, attitudes, and concerns that may affect the probability of visiting a and purchasing produce at a farmers’ market. Results from these interviews suggested that married females who visit farmers’ markets frequently, engage in home gardening, and perceive “agriculture open space” and “supporting local growers” as important were more likely to attend farmers’ markets primarily to purchase produce.

Using data from a survey of produce consumers in San Luis Obispo County, California, McGarry, Spittler, and Ahern (2005) compare consumer characteristics of those who shop at farmers’ markets and those who do not. They found age, income, and employment status to be similar between the two groups. However, married females with some post graduate education were more likely to shop at a farmers’ market. The farmers’ market consumers perceive the produce selection at this market outlet to be fresher, of higher quality, more likely to be locally grown, better for the environment, and more reasonably priced than produce in supermarkets.
Onianwa, Mojica, and Wheelock (2006) evaluated characteristics of consumers, views and preferences of consumers shopping at farmers’ markets, and differences in consumer views and preferences about farmers’ markets and supermarkets. They obtained data through face-to-face interviews of 222 randomly selected consumers at two farmers’ markets in Alabama. They found that a large percentage of those consumers attending these Alabama farmers’ markets were females, married, had above high school education, and had household incomes higher than $25,000 a year. Some of the attributes influencing consumer preference of farmers’ markets over supermarkets included freshness of products, price, products aspect, and access to variety of products.

Strobbe (2016) evaluated consumer spending patterns at farmers’ markets and the factors influencing those spending patterns using information from a survey of farmers’ markets consumers, conducted in 2011, at five farmers’ markets around the Metro Vancouver area in Canada. He found that location, shopping frequency (e.g., weekly, monthly, daily), type of products purchased (e.g., organic vs. non-organic), size of household, home ownership (e.g., owner vs. renters), level of education, and race were factors influencing consumer expenditure levels at farmers’ markets. In contrast, he found that food and market attributes have little or no impact on purchasing behavior. Once consumer demographics and other factors are taken into account, it seems that food and market attributes do not have a major influence on expenditure. We could infer that those factors affecting consumer spending patterns at farmers’ markets may also affect prices paid by consumers at these market-outlets.
Farmers’ Market vs. Other Marketing Channels’ Prices

Gunderson and Earl (2010) used a survey to collect quantitative and qualitative data to compare the prices and determine a relationship between farmers’ markets and nearby grocery stores’ prices. They measured the average cost savings experienced by customers at farmers’ markets and how these cost savings influence how produce is priced at farmers’ markets in Florida. The study suggested that vendor full time position and the difference between nearby grocery stores’ and farmers’ markets’ prices will influence the percentage cost savings experienced by a customer when buying products at farmers’ markets. Additionally, this study suggest that average grocery stores’ prices and average cost savings at farmers’ markets affect how produce prices are set at farmers’ markets.

Martinez (2016) used 2006 Nielsen Homescan data and a hedonic regression model to evaluate price differences between various marketing outlets including DTC, grocery stores and super centers. Results presented in this study suggest that factors that may influence prices at farmers’ markets include seasonality, geographic location, household income, age, and race of shoppers.

Sommer, Wing, and Aitkens (1980) evaluated potential savings realized by consumers at farmers’ markets and provided methods and data useful to other researchers interested in this type of analysis. They collected price information from all the vendors at 15 California farmers’ markets. They recorded both prices of a product on a per unit and a per weight basis for each identifiable item, where an identifiable item is a product identified by the vendor as a separate product (e.g., cherry tomatoes vs. salad tomatoes). They calculated average prices for all sellers for each identifiable item. Findings suggest that market location (i.e., small vs. larger cities) and seasonality may influence differences between farmers’ markets and supermarket prices for
some or all products. Therefore, we could infer from these findings that seasonality and location are some factors to consider when analyzing farmers’ markets prices.

Similarly, McGuirt, Jilcott, Ammerman (2011) evaluated the potential consumer savings at farmers’ markets by comparing farmers’ markets and supermarket prices in North Carolina. Produce prices were collected from the first 10 vendors upon entering a farmers’ market in 12 counties in North Carolina. Prices were converted to a per pound basis with the exception of corn and melons and an average price was calculated. Like Sommer, Wing, and Aitkens (2011) found significant differences in price savings by location (i.e., county). This study reinforces the importance of including location as a potential factor influencing farmers’ market prices.

**Factors to Consider when Setting Prices at the Farmers’ Markets**

As mentioned above, there are a few Extension publications available for producers to better understand how to price their products at farmers’ markets (Bruch and Ernst, 2011; Chase, 2008; Ernst 2014). These publications mentioned cost of production, competition, consumer values and preferences, and willingness to pay as factors to be considered when setting prices at farmers’ markets. Bruch and Ernst (2011) suggest that consumer age, gender, race, income, location, education, marital status, and household size are factors that could affect consumer purchasing behavior at farmers’ markets and therefore prices consumers are willing to pay at these market outlets. In general these publications can help us identify some factors that may affect prices at farmers’ markets.
CHAPTER 3: CONCEPTUAL FRAMEWORK

To better understand the factors influencing tomato prices at farmers’ markets, we first explore how prices are set in a farmers’ market setting. This section will explore different frameworks from the microeconomic theory that could help us understand the price formation process that takes place in the context of farmers’ markets.

Farmers’ Markets in a “Perfect Competition World”

In this section, we will begin analyzing prices and pricing decisions in the context of a farmers’ market using a perfect competition framework. We assume tomatoes are the only goods in the market. There are a few key assumptions in defining perfect competition: 1) a large number of producers participating in the market; 2) producers selling homogenous products; 3) profit maximizing producers; 4) price-taking producers who’s actions have no impact on prices; 5) perfect information for both consumers and producers attending farmers’ markets; and 6) there are no transaction costs. Defining the time period is also an essential component to consider when conducting price analysis in the perfect competition context (Nicholson and Snyder, 2012). Equilibrium price formation will be different when looking at the very short run (e.g., daily), short run (e.g., weekly), and the long run (e.g., an entire market season).

How does the Establishment of Equilibrium Prices Look Like in a Perfect Competition Farmers’ Market Scenario in the Very Short Run?

The very short run in the context of farmers’ markets could represent one single day in the market (e.g., Saturday). Within a one day period there is no supply response meaning farmers cannot react to market conditions, as tomatoes brought to the market need to be sold at a price determined by the demand conditions on that specific day. Supply of tomatoes as well as the
number of vendors in the market are assumed to be fixed. This means that vendors are unable to increase or decrease the amount of tomatoes they brought that day to the market. Additionally, price will adjust in a way that all tomatoes brought to the market will be sold. In this case, the supply curve is a vertical line and the equilibrium price is the one at which customers are willing to buy all tomatoes available at the market. In the context of tomatoes sold at the farmers’ market under a perfect competition framework in the very short run, farmers want to get rid of their tomatoes regardless of price. This could happen when tomatoes are perishable to the point that if not sold on a specific market day they will lose their value. The very short run price analysis is not common, however, in the context of farmers’ markets where there are perishable goods that must be sold on a given day, this scenario may be important to be considered (Nicholson and Snyder, 2012).

*How does the Establishment of Equilibrium Prices Look Like in a Perfect Competition Farmers’ Market Scenario in the Short Run?*

The short run can be described as the period of time between one week and the next where vendors can use the knowledge they observed in the previous week to adjust their supply for the week after. Additionally, there are a fixed number of vendors selling tomatoes at the market but these vendors are able to adjust the volume of tomatoes they bring to the market from week to week. However, they may not be able to adjust overall tomato production. As opposed to other industries, agricultural production has to be planned before production season and cannot be adjusted easily. For example, if a farmer plants 100 tomato plants, it would be very difficult for the farmer to double production during harvesting season in order to adjust to demand conditions.
In the short run, while prices act as devices for rationing demand, they may also act as a signals for vendors to adjust supply or the volume of tomatoes brought to the market (Nicholson and Snyder, 2012). The decision of how many tomatoes to bring to the market is informed by the price received at the market the week before.

In the short run, the supply curve for an individual profit maximizing vendor, who is also a price taker, is equivalent to the positively sloped section of the marginal cost curve (Nicholson, 2002). In the short run, the total amount of tomatoes supplied to the market is the sum of tomatoes supplied by each vendor and it is described by the supply curve in Figure 1(c). Figure 1(c) results from the horizontal summation of the supply curves presented in Figures 1(a) and 1(b). The quantity $Q_1$ shown in Figure 1(c) is simply the summation of the quantities $q_1^A$ and $q_1^B$ supplied by vendor A and B at the price level $P_1$, respectively.

The price equilibrium in the short run solves the equation below,

(1) \[ Q_D(P^*, \alpha) = Q_S(P^*, \gamma), \]

where quantity supplied ($Q_S$) is equal to quantity demanded ($Q_D$). Both $Q_S$ and $Q_D$ are a function of the equilibrium price ($P^*$), but factors such as consumers’ income, prices of other goods in the market, or changes in consumer preferences could shift the demand curve ($\alpha$), and factors such as the price of inputs, changes in technology, or prices of other goods could shift the supply curve ($\gamma$). One implication of the market equilibrium condition in the short run for each individual vendor is that at the equilibrium price they earn a small profit because short run total average costs are covered (Nicholson and Snyder, 2012).

How does the Establishment of Equilibrium Prices Look Like in a Perfect Competition Farmers’ Markets Scenario in the Long Run?
In the context of farmers’ markets, the long run scenario could be understood as the period of time between one market season and the next where vendors can adjust the quantity of tomatoes supplied at the farmers’ market based on their previous market season experience. In this scenario, profit maximizing producers will supply tomatoes where price is equal to their long run marginal costs. Additionally, in the long run we introduce the entry and exit of new vendors into the market place.

As other producers outside the farmers’ market observe vendors making economic profits then they will have an incentive to participate in the farmers’ market. At the same time those farms having negative profits at the farmers’ market will stop selling tomatoes at the farmers’ market. In the perfectly competitive scenario it is assumed there are no special costs for entering or leaving farmers’ markets. With additional producers participating in the farmers’ market we will observe a rightward shift of the supply curve (Nicholson and Snyder, 2012). An example of new vendor entry in a market place is the one we observed at the Market Square farmers’ market\(^1\) in Knox County, where high prices attracted new vendors to participate in this market year after year.

A farmers’ market is in the competitive long run equilibrium when profit maximizing vendors have no incentive to enter or exit the market. When assessing pricing in the long run there are three scenarios we could evaluate: 1) constant-costs; 2) increasing costs; and 3) decreasing costs. These three scenarios are described by assumptions made regarding how the entry of new producers to the markets affect individual producers’ input costs. First we look at the case where entry and exit of vendors do not affect input costs. This case is also called the fix-cost industry. In this scenario, for example, new farmers producing and selling tomatoes at the market will not affect the price of inputs used in tomato production such as labor and fertilizer.

\(^{1}\) https://www.nourishknoxville.org/market-square-farmers-market/
The long-run equilibrium conditions for an individual farm states that price is equal to the long-run marginal costs and is also equal to the long run average costs. Since we are assuming all farms have identical cost curves, these conditions will apply for all farms participating in a farmers’ market in the long-run. Under these conditions farms are maximizing their profits. Additionally, under the above mentioned assumptions each farm experienced zero farm profits and therefore farms have no motivations to either enter or exit the farmers’ market. When assuming that new farms participating in the farmers’ market have no impact on individual farms’ input costs, the long-run total market supply \((L)\) is represented by a horizontal line at the equilibrium price (see Figure 2(a)). Therefore, changes in demand will have no impact on the market equilibrium price (Nicholson and Snyder, 2012).

The second scenario to be evaluated is when new producers entering the market will cause the average costs for individual producers to increase. In this scenario, it is assumed that producers currently producing and selling tomatoes at the farmers’ market will have to compete for inputs due to the increased competition for production inputs with the new entrants. As a result, this will increase the costs of inputs such as fertilizer and pesticides. As producers face increased input costs they will adjust to the new scenario determining a new long-run market supply \((L)\). This process will end up describing an upward sloping supply curve as presented in Figure 2(b) (Nicholson and Snyder, 2012).

Finally, the third cost scenario to be evaluated is the decreasing cost industry. This scenario implies that new farms entering the market will have a negative impact on input prices. In this scenario, for example, we could assume that more farmers producing tomatoes in a single area (e.g., a county) could increase the number of skilled labor in the area and therefore decrease
the cost of accessing skilled labor. In this scenario, the long-run supply curve (L) will have a negative slope as presented in Figure 2(c) (Nicholson and Snyder, 2012).

**Farmers’ Market in an “Imperfect Competition” World**

The previous section framed a farmers’ market in a “perfect competition world.” However, we should ask ourselves, how well does a farmers’ market fit the assumptions of perfect competition? In this section, we will begin exploring how a farmers’ market context violates the perfect competition assumptions and whether a farmers’ market better fits the assumptions of an imperfect competition framework.

The first assumption of perfect competition is that a large number of producers are participating in the market. However, in the farmers’ market context there could be limited space for vendors and therefore a fixed number of vendors are allowed to sell products in the market. While some farmers’ markets are larger than others, in general, vendors have to go through an application process the year before the farmers’ market season starts before they can set up a booth at the market. Therefore, it seems that in the context of farmers’ markets the first assumption of perfect competition is violated. Thus the evaluation of pricing under an oligopoly model where there are relatively few firms, may be a better fit for the analysis of pricing in a farmers’ market context (Nicholson and Snyder, 2012).

The second assumption under perfect competition is all farms are selling homogenous goods. This assumption could be held when analyzing pricing under a homogenous oligopoly. Additionally, this assumption could be relaxed by allowing farms to differentiate their product. For example, farmers could try to differentiate their products through quality and product advertising. In this study, we assume that in the farmers’ market setting consumers may look at
tomatoes as homogenous goods regardless of variety, with the exception of grape/cherry tomatoes. Nonetheless, it is important to note that although first time customers at farmers’ markets looking for tomatoes may perceive tomatoes as homogenous goods; regular customers may already have tasted tomatoes from various vendors and may have established preferences over other tomatoes sold from different vendors based on taste and/or the relationship they established with a specific vendor.

Only one model under a homogenous oligopoly framework assumes firms are price takers, the quasi-competitive model. All other models under this framework assume vendors recognize their level of production will affect the market price (Nicholson and Snyder, 2012). In the farmers’ markets context, vendors act as price setters and not price takers. Therefore in a farmers’ market context the perfect competition assumption suggesting vendors are price takers is violated.

*Do Vendors in a Farmers’ Market act as a Cartel?*

We can begin the discussion of producers as price setters in the context of a cartel model where producers realize their decisions have an effect on prices and no longer act as price takers (Nicholson, 2002). Those vendors would realize, as a group, they can affect the price and work together to manage their decisions in order to achieve monopoly profits (Nicholson, 2002). One important assumption in the cartel model is that vendors will coordinate the amount of output they will supply to the market and also determine how monopolistic profits generated will be shared among cartel members. Several problems can arise in the cartel model: 1) monopolistic decisions are considered illegal in the U.S.; 2) the cartel needs extensive information about market demand and marginal cost functions of those vendors who belong to the cartel; 3) the cartel solution is unstable (i.e., \( p > MC \)) as vendors have an incentive to continue producing
more. While we may believe some vendors at the farmers’ market work collectively as a group, we do not believe they control the volume of tomatoes being brought to the market to influence prices but rather agree on the sell price. Vendors who view themselves as equal in terms of products, costs of production and marketing, may agree on a price at the beginning of the season to avoid “price wars” and compete for customers based on quality and not prices. For example, a Tennessee vegetable producer selling produce at farmers’ markets said during an interview in July of 2017 “when I get to the market in the morning and I see that other farmers have identical products to me, we discuss and figure out what price we should all be selling at. It is not always the highest price but typically we figure out a good price between us. That way customers do not shop based on price between the farmers” (Agricultural & Resource Economics, Institute of Agriculture, University of Tennessee, 2017).

*Can We Adopt the Price Leadership Model to Illustrate How Prices are Formed at Farmers’ Markets?*

In the price leadership model it is assumed there is a sole leader who acts as a price setter on the outside of a group of quasi-competitive vendors (i.e., competitive fringe) in the marketplace. Here, the leader observes the market supply determined by the competitive fringe and the demand function the competitive fringe faces. The leader then determines its own demand curve by subtracting the supply the competitive fringe is willing to supply at the different price levels from the total demand. Using this demand curve the leader derives its marginal revenue. The leader will produce tomatoes at the level where marginal revenue ($MR$) is equal to marginal cost ($MC$), and the price will be determined by the demand faced by the leader at this level of production (see Figure 3). The competitive vendor group then acts as price taker
and supplies the quantity its profit maximizing condition allows them to supply at the price impose by the leader (Nicholson, 2002).

In the farmers’ market context, a price leadership model could partially explain how vendors set their prices, as we see groups of vendors selling tomatoes at the same price. However, we may not necessarily be dealing with a competitive fringe that initially has a higher price, but a group of vendors who do not know their own costs of production and therefore use other vendors’ prices as a reference to set their price. In this case this group trusts the leader’s price will cover their production and marketing costs as well.

*Does Product Differentiation Play a Role in Price Setting at a Farmers’ Market?*

All of the above mentioned models have assumed vendors produce and sell homogenous products (e.g., tomatoes) and therefore made customers indifferent about who they buy their products from (Nicholson, 2002). By allowing for product differentiation, we can relax the assumption of the law of one price\(^2\) to allow vendors to compete for price by establishing some kind of differentiation in their products from one another. Product differentiation at the farmers’ market may be seen through quality, taste, booth display, and even vendor-customer relationships. For example, previous literature suggests consumers at farmers’ markets value and are influenced by attributes such as quality and freshness (Govindasamy, Italia, Adelaja, 2002). Therefore, if vendors in the market are able to differentiate their products (e.g., tomatoes) based on these attributes, they may be able to set their prices at a higher level than their competitors.

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\(^2\) **Law of one Price** assumes a homogenous good is sold at the same price regardless of who buys it or which vendor sells it.
**Game Theory Models to Analyze Pricing at Farmers’ Markets**

A unique case of oligopolistic competition for price analysis is the conjectural variations model. This model allows for strategic interactions among firms. In a farmers’ market setting this approach could allow us to better understand the process behind price formation in this context. Game theory can be used to further analyze the strategic competition between vendors in a farmers’ market setting (Nicholson and Snyder, 2012).

In a farmers’ market setting vendors strategically compete for prices not quantities. Therefore, we will start by using a game theory model that specifically assumes firms strategically compete for prices to analyze price formation in a farmers’ market setting.

Price-setting oligopolies can provide us with a story about how farmers form their prices or make their price decisions in a farmers’ market setting (Allen and Hellwig, 1986).

We assume there are two profit maximizing farm businesses with the same cost per unit $c > 0$, producing perfect substitute products. At a specific time vendor $i$’s profit will be a function of its price and the other vendor’s price such that $\pi^i(p_i, p_j)$ (Maskin and Tirole, 1988), the market demand function in this scenario is set as $Q_D$ and the total profit function can be described as:

\[
\Pi(p) = (p - c)Q_D, \tag{2}
\]

where we assume this function is strictly concave (Maskin and Tirole, 1988). Following the assumptions described above each farm business’ profit function can be defined as

\[
\pi^i(p_i, p_j) = \begin{cases} 
\Pi^i(p_i), & \text{if } p_i < p_j, \\
\frac{\Pi^i(p_i)}{2}, & \text{if } p_i = p_j, \\
0, & \text{if } p_i > p_j
\end{cases} \tag{3}
\]
The first condition in equation (3) implies vendor $i$ will receive all market profits when setting its price below vendor $j$. The second condition in equation (3) shows that when vendor $i$ sets price equal to vendor $j$’s price, and equal to the cost per unit they will split the total market profits. Finally, the third condition in equation (3) implies vendor $i$ receives no profits when her/his price is higher than vendor $j$. Equation (3) implies that there is one Nash equilibrium $(p_i^*, p_j^*)$ where both vendors set their prices at their cost of production such that $p_i^* = p_j^* = c$. A Nash equilibrium is defined as a situation in which neither player (e.g., vendor) can improve her/his payoff (e.g., profit) by unilaterally changing strategies (Myerston, 1978). Thus when one vendor slightly undercuts the other vendor’s price there is no Nash equilibrium as the undercutting vendor would capture the entire market demand but at a profit loss per unit. Additionally, the Nash Equilibrium does not exist when one vendor increases their price above the other as they are only at best earning zero profits without any market share.

Usually, there are more than two vendors in a farmers’ market setting. Currently the national average number of vendors at a farmers’ market is five (USDA NASS, 2017). Therefore, we evaluate whether the Nash equilibrium discussed above will hold when there are more than two vendors in a farmers’ market setting. We will start with the case of three vendors. If vendor $i$ and $j$ hold their prices equal to $c$ and vendor $k$ sets her/his price $p_k > c$ then vendors $i$ and $j$ will split the total demand and therefore total market profit while vendor $k$ will receive zero profits. Vendor $k$ can improve profits by decreasing her/his price. If in an effort to gain part of the market total profit, vendors $i$ and $j$ raise their prices above $c$ but below $p_k$, they can still capture part of the demand and have strictly positive profits, therefore this is not a Nash equilibrium. If on the other hand $p_i = p_j = c$ and vendor $k$ sets her/his price below $c$, vendor $k$
will capture the entire market demand while losing money as she/he will not be able to cover
cost of production. In this situation vendor \( k \) can improve her/his profits by unilaterally changing
price strategies. Therefore for \( i = 3 \) the Nash Equilibrium will be \( p_i^* = p_j^* = p_k^* = c \). When
increasing the number of vendors in this farmers’ market setting we will obtain the same result,
therefore the Bertrand model Nash equilibrium described above will hold for the case where we
have more than three vendors in the market.

Although the Bertrand model described above may be the starting point to better
understand how vendors in a farmers’ market setting make pricing decisions, we have observed
that prices of similar products at farmers’ markets vary across vendors (University of Kentucky--
Center for Crop Diversification, 2017). Maybe a combination of product differentiation and price
leadership conditions may help us explain the price outcomes observed at farmers’ markets. In
the last section, we will explore one last model that may add value to the discussion above.

*How Does Predatory Pricing Come into Play at a Farmers’ Market?*

Predatory pricing occurs when one vendor sets her/his price at a very low level with the
motivation to encourage rivals to reevaluate their profitability in the future and ultimately drop
out of the market (Nicholson, 2002). In this model, vendors may set their price low in efforts to
signal to others that they have low cost of production even if it is not true. Additionally,
predatory vendors may utilize advertising and product differentiation to show rival vendors they
have economies of scale. In the context of farmers’ markets we see predatory pricing occurred
when producers using wholesale as their main marketing strategy decide to dump their surplus
production at wholesale prices at the farmers’ market. In this case, these wholesale vendors set
prices extremely low because they actually have very low cost of production due to the
economies of scale they achieve given their production size. Unlike the traditional predatory
pricing models, these wholesale vendors’ motivation is not to force other vendors out of the farmers’ market but to sell their surplus product. We also suspect there are other vendors that unintentionally set their prices very low because they do not know their cost of production, and although they are losing money on every unit they sell, they believe the only way to capture part of the market demand is lowering their prices.

As mentioned above a combination of the product differentiation, price leadership, and maybe predatory pricing may help us explain how vendors set their prices at farmers’ market. A common element across these frameworks, is that regardless of whether vendors take into account other vendors’ price decisions or not to set their prices, they are always competing for customers. Although not clear in the frameworks described above, it is important to note that demand, and therefore consumer preferences and their willingness to pay, play a major role in how vendors set their prices at farmers’ markets. We will use an econometric model in this study that will allow us to evaluate those factors influencing tomato prices at farmers’ markets, specifically those factors associated with demand and supply. Although, it would be ideal to capture the strategic interaction between vendors as a potential factor influencing prices at farmers’ markets, a proxy variable capturing this information is not available at the moment.
CHAPTER 4: EMPIRICAL MODEL

Product characteristics such as quality can influence prices paid for produce at farmers’ markets. Given that product quality and supply data is not available for this study, we used precipitation as a variable that could affect tomato quality and supply since tomato production is very sensitive to water availability at specific growing stages (i.e., early flowering, fruit set and enlargement) (Kemble and Sanders, 2000). Irrigation systems can help control rainfall shortages, reducing the impact of lack of rain on quality and supply of tomato production. However, excessive water in combination with other environmental conditions such as humidity and heat can help the development of pathogens that cause specific diseases affecting quality and supply of tomato production (Boyhan and Kelley, 2017; Kemble and Sanders, 2000; Kemble et al., 2017; Rutledge, Wills, and Bost, 1999). Thus, irrigation systems cannot impact supply shifts due to excessive rainfall. Greenhouse environments could control the impact of environmental factors on tomato production, nonetheless producers selling at farmers’ markets are traditionally small, generating approximately less than $20,000 per year in sales (USDA NASS, 2017), and therefore may not have the ability to make investments in greenhouse structures.

We averaged the daily precipitation as reported from various weather stations for each farmers’ market location (Nation Centers for Environmental Information NCEI³). Then we used this information to estimate average daily precipitation on a specific market week. The expected sign of this variable is unknown as water availability at specific stages could have a positive impact on tomato supply and quality but excessive water at later stages could have a negative impact on these two variables. The inclusion of this variable in the regression analysis allows us to control for quality as a potential variable influencing tomato prices.

³ https://www.ncei.noaa.gov/
Additionally, tomato prices might be impacted by seasonal changes. While information is not available about weekly volume of tomatoes at the farmers’ market, we expect that more vendors will be selling tomatoes at the market when tomatoes are in harvesting season. On average, peak harvesting season in Tennessee usually happens between July and August. Since there is an increase in supply during the harvest season, we can expect the sign of seasonality to be negative. Therefore, during harvest season tomato prices are likely to be lower compared to the rest of the growing season. This also implies that producers using season extension techniques that are able to supply tomatoes off-season maybe able to receive premium prices.

We believe in various regions of Tennessee older shoppers may be wanting to increase their consumption of fresh vegetables due to potential positive health benefits such as reducing the risk of chronic illnesses, and therefore would be willing to pay more for fresh produce (USDA MyPlate, 2016). We also hypothesized that shoppers with higher incomes will have a larger purchasing power and are able to pay higher prices at farmers’ markets. Therefore, age and household income are hypothesized to positively influence tomato prices at farmers’ markets.
CHAPTER 5: METHODS AND PROCEDURES

Data

The Center for Crop Diversification at the University of Kentucky started collecting prices at various farmers’ markets in Kentucky and posting weekly price reports on their website in 2004\(^4\). In 2013, the Department of Agricultural & Resource Economics at the University of Tennessee joined this effort and began collecting prices at various Tennessee farmers’ markets. The prices reported are weekly prices during the farmers’ market season.

In this study, we used tomato prices reported on a per pound basis at farmers’ markets in five Tennessee counties (i.e., Hamblen County, Jefferson County, Knox County, Marshall County, and Rutherford County) in 2013, 2014, and 2015. A total of 181 observations are included in our regression analysis. The minimum and maximum prices are reported at each market. Prices for all vendors are not reported to protect their identity and to minimize the time it takes for reporters to collect price data. Therefore, we used the midrange (i.e., the midpoint between the highest and lowest prices) as a measure of central tendency and a proxy of average prices (Rider, 1957). Because the midrange uses extreme values only it is greatly affected by these values, nonetheless tomato prices at Tennessee farmers’ markets have very small dispersion (see Tables 2 and 3) and therefore the midrange could be a good proxy of average prices. For example, if we have five vendors at a market selling tomatoes, two of them are selling tomatoes at $2 per lb, two vendors are selling tomatoes at $3 per lb, and there is one vendor selling tomatoes at $10 per lb, then the average (i.e., $4), median ($3), and midrange ($6) are going to be very different just because of the extreme value of $10 causing great dispersion. If on

\(^4\)http://www.uky.edu/Ag/CCD/farmersmarket.html
the other hand that last vendor is selling tomatoes at $3.5 per lb then average ($2.7), median ($3), and midrange ($2.75) prices are going to be very close.

We collected daily precipitation data by all reporting county stations to create an average weekly precipitation measurement in inches. With the exception of Jefferson County, all counties had a station reporting daily precipitation. To create a proxy for the precipitation variable for Jefferson County, one station from each bordering county is selected to create an average weekly precipitation measurement.

The seasonality variable in this study is a dummy variable used to identify when tomatoes are expected to be in full harvest, given normal production conditions. To determine the start of harvest season, an average number of days from transplant to harvest for various tomato varieties, excluding grape or cherry tomatoes, was calculated and then added to the average of the last frost date for all counties in this study (Bumgarner and Carver, 2016). Tomatoes can be expected to be harvested for eight or more weeks (Sams and Bates, 2005). To determine the end of the tomato harvest season, eight weeks were added to the beginning of the harvest season.

We used consumer demographics and household characteristics as reported in the 2013, 2014, and 2015 American Community Surveys by census tract. We selected consumer and household characteristics for the census tract where each farmers’ market is located, as well as information from those census tracts sharing boundaries with the selected census tract. Then we

---

5 “Census Tracts are small, relatively permanent statistical subdivisions of a county or equivalent entity that are updated by local participants prior to each decennial census as part of the Census Bureau's Participant Statistical Areas Program. Census tracts generally have a population size between 1,200 and 8,000 people, with an optimum size of 4,000 people. A census tract usually covers a contiguous area; however, the spatial size of census tracts varies widely depending on the density of settlement. Census tract boundaries are delineated with the intention of being maintained over a long time so that statistical comparisons can be made from census to census. Census tracts occasionally are split due to population growth or merged as a result of substantial population decline.” United States Census Bureau, 2016.
average consumer and household characteristics’ values for all the census tracts associated with a specific farmers’ market location. We included information from the census tract associated with each farmers’ market location as well as all census tracts surrounding this area as we assume consumers purchasing tomatoes at the farmers’ markets belong not only to a specific census tract but also surrounding areas.

**Factors Influencing Farmers’ Markets Prices: A Panel Data Regression Approach**

Because we are looking at cross sectional data over time, we have an unbalanced panel data set (Greene, 2003). An unbalanced panel data set can create some problems when the reason for the panel data to be unbalanced is correlated with the error term (Wooldridge, 2003). For example, if the reason why we have missing information on prices for some markets is associated with a sample selection problem then parameter estimates will be biased. However, in the case of our data set, prices are only missing due to the reporters being unavailable to report prices during some weeks. Furthermore, the data set can be defined as a long panel since the number of markets ($m = 1, \ldots, M$) is five and the maximum number of weeks available for a market ($t = 1, \ldots, T$) is 43 (Cameron and Trivedi, 2010).

The most basic approach to be used in evaluating those factors influencing tomato prices at farmers’ markets is a pooled ordinary least squares (OLS) regression (Greene, 2003). This approach can be specified as,

$$ y_t = x'_t \beta + \varepsilon_t, $$
where \( y_t \) is the midrange of tomato prices reported at farmers’ markets during week \( t \); \( x_t \) is an \( M \times K \) matrix containing \( K \) explanatory variables potentially influencing tomato prices at \( M \) farmers’ markets during week \( t \); \( \beta \) are parameters associated with all explanatory variables included in \( x_t \); \( \varepsilon_t \) is the error term. We omit the subscript associated with cross section observations (i.e., markets) for simplicity but will include it when indicating a specific cross section observation. If the following assumptions are met:

\[
E(x_t'\varepsilon_t) = 0, \quad t = 1,2, ..., T
\]

\[
\text{rank} |\sum_{t=1}^{T} E(x_t'x_t)| = K,
\]

then pooled OLS consistently estimates \( \beta \) (Wooldridge, 2010). Equation (5) implies that there could not be perfect linear dependency among explanatory variables. If in addition the following assumptions are met:

\[
E(\varepsilon_t^2x_t'x_t) = \sigma^2E(x_t'x_t), t = 1,2, ..., T
\]

\[
E(\varepsilon_t\varepsilon_s|x_tx_s) = 0, \quad t \neq s, t,s = 1,2, ..., T ,
\]

then simple OLS variance estimators from the pooled OLS regression are valid to evaluate statistical significance of individual parameters and overall significance of the regression model (Wooldridge, 2010). Equation (7) implies homoscedasticity and equation (8) implies that the conditional covariance of errors across time are equal to zero.
**Fixed Effects and Random Effects Panel Data Regressions**

We can disaggregate $\varepsilon_t$ in (1) as $\varepsilon_t = c + \mu_t$, where $\mu_t$ is the a vector of idiosyncratic errors and $c$ is a vector of time-invariant components of the error term of all markets. Therefore we can rewrite equation (4) as,

$$y_{mt} = x'_{mt}\beta + c_m + \mu_{mt},$$

where $x_{mt}$ is now 1 x $K$, and for this analysis, contains variables that change across $m$ and $t$. Depending on whether $c_m$ is correlated with $\mu_{mt}$ or not we will have to use a fixed effects estimation or a random effect estimation approach for $\beta$ (Wooldridge, 2002). If $c_m$ is correlated with $\mu_{mt}$ then a fixed effects estimation approach is appropriate otherwise a random effects estimation should be used.

It is likely there are time-invariant unobserved variables influencing prices at farmers’ markets such as information associated with vendor’s marketing strategies, vendor interaction, and producer-consumer interactions that influence how producers set prices at farmers’ markets, and prices ultimately paid by consumers at this market outlet. Nonetheless, we will need to first test whether the regression model actually contains an unobserved time-invariant effect $c_m$. If the assumptions presented in equations (5), (6), (7), and (8) are met and there is no presence of an unobserved time invariant effect, the pooled OLS regression approach is efficient and all statistics associated with this approach are asymptotically valid (Wooldridge, 2002).

If indeed the regression model contains an unobserved time-invariant component, we will need to test whether this component is correlated with $x_{mt}$ to decide whether a fixed effects or a random effects estimation approach should be used in this analysis.
When using the random effects approach the data is transformed by a value of $\hat{\theta}$ as shown below

$$
(y_{mt} - \hat{\theta} \bar{y}_m) = (x_{mt} - \hat{\theta} \bar{x}_m)\beta + (1 - \hat{\theta} )c_m + (\mu_{mt} - \hat{\theta} \bar{\mu}_m),
$$

where $\bar{y}_m = \sum_t \frac{y_{mt}}{T_m}$, $\bar{x}_m = \sum_t \frac{x_{mt}}{T_m}$, $\bar{\mu}_m = \sum_t \frac{\mu_{mt}}{T_m}$, and $T_m$ is the maximum number of weeks price data is available per market and $\hat{\theta}$ can be defined as $\hat{\theta}_m = 1 - \sqrt{\frac{\tilde{\sigma}_c^2}{T_m \tilde{\sigma}_c^2 + \sigma_e^2}}$,

where, $\tilde{\sigma}_c^2 = \frac{\sum_{i=1}^M \sum_{t=1}^{T_m} e_{mt}^2}{N - M - K + 1}$, $e_{mt} = (y_{mt} - \bar{y}_m - \bar{y}) - (x_{mt} - \bar{x}_m - \bar{x})\hat{\beta}_w$, $\hat{\beta}_w$ is the estimated $\beta$ obtained from the within estimation approach, $N = \sum_m T_m$, and $M$ is the number of markets in the sample, $\bar{y} = \frac{\sum_m \sum_t y_{mt}}{mT_m}$, $\bar{x} = \frac{\sum_m \sum_t x_{mt}}{mT_m}$, and $\sigma_c^2$ is the variance of the time invariant component (STATA, 2017). If $\sigma_c^2 = 0$, implying that $c_m$ is equal to zero, then $\hat{\theta}_m = 0$ and then equation (9) can be estimated using an OLS regression.

If the random effects approach is selected for this analysis, it is suggested that for small sample unbalanced panel data sets, like the one we are using in this study, we should use the Swamy-Arora method (Swamy and Arora, 1972) for estimating the error variance components (STATA, 2017). The only difference between the random effects estimation method and the Swamy-Arora method is that the later uses a more elaborated adjustment for the estimated variance of $c_m$ for small samples (STATA, 2017).

The difference between the two estimation methods is how $\tilde{\sigma}_c^2$ is calculated. Equation (11) shows the default calculation for $\tilde{\sigma}_c^2$ when using the random effects estimation approach,
(11) \[ \hat{\sigma}_{ct}^2 = \max\left\{0, \frac{SSR_b}{N-K} - \frac{\hat{\sigma}_e^2}{r}\right\}, \]

where \( T = \frac{M}{\sum_{m=1}^{M} T_m}, SSR_b = \sum_{m=1}^{M} \left( \bar{y}_m - \bar{x}_m \hat{\beta}_b \right)^2, \hat{\beta}_b \) is the coefficient obtained from the between regression estimation. Equation (12) shows how \( \hat{\sigma}_{cSA}^2 \) is calculated when using the Swamy-Arora method,

(12) \[ \hat{\sigma}_{cSA}^2 = \max\left\{0, \frac{SSR_b^* - (M-K)\hat{\sigma}_e^2}{N-tr}\right\}, \]

where \( SSR_b^* = \sum_{m=1}^{M} T_m \left( \bar{y}_m - \bar{x}_m \hat{\beta}_b \right)^2, tr = trace\{(X'PX)^{-1}X'ZZ'X\}, X \) is the \( N \times K \) matrix of covariates, \( P = diag \left\{ \left( \frac{1}{T_m} \right) \right\}, \tau_m \) is a \( T_m \times 1 \) vector of ones, and \( Z = diag[\tau_m] \)

(STATA, 2017).

Recall \( \hat{\sigma}_{ct}^2 \) or \( \hat{\sigma}_{cSA}^2 \) can not be negative therefore, STATA forces them to be 0, when the estimate of \( \hat{\sigma}_e^2 \) is negative. When \( \theta \) is very small or zero, we can expect to see parameters that are very similar to those in the OLS estimation as the data is not being transformed or it is only slightly transformed.

**Diagnostic Tests**

The assumption presented in equation (6) is one of the conditions necessary to obtain consistent estimators of \( \beta \). This assumption implies no perfect linear dependency among explanatory variables or no multicollinearity. Evidence of multicollinearity can inflate the parameter estimates variance causing an inaccurate interpretation of the results (Greene, 2003). Multicollinearity is tested by utilizing Belsley, Kuh, and Welsch (1980) collinearity diagnostic
procedure. A matrix of condition indexes reflecting the “conditioning” of a matrix of explanatory variables is estimated. The condition number is the largest condition index. A condition number of 30 or higher indicates there may be collinearity problems that need to be addressed (Belsley, 1991).

Serial autocorrelation is likely to be present when working with long panel data sets (Cameron and Trivedi, 2010). When $M$ is small and $T \rightarrow \infty$ the presence of autocorrelation within market locations can biased standard errors (Drukker, 2003). The use of the Wooldridge’s test for serial correlation will allow us to test for serial autocorrelation. The test uses the first differences method to obtain the residuals $\mu_{mt}$ by eliminating the time-invariant effects $c_m$ and estimating $\beta$ by regressing $y_{mt} - y_{mt-1}$ and $x_{mt} - x_{mt-1}$ (Drukker, 2003). From here, the residuals $\mu_{mt}$ are regressed on their lags to estimate the coefficients on the lagged residuals. Based on Wooldridge’s findings that when $\mu_{mt}$ are not serially correlated then the correlation between $\mu_{mt}$ and $\mu_{mt-1}$ is equal to -0.5, this test concludes that when the coefficient from regressing $\mu_{mt}$ on their lags is equal to -0.5 there is no serial correlation (Drukker, 2003).

The Breusch and Pagan Lagrangian multiplier test checks for the existence of an unobserved time invariant effect. The null hypothesis $H_0: \sigma^2_c = 0$, where $\sigma^2_c$ is the variance of $c_m$, implies the absence of an unobserved effect or that $c_m$ is always equal to zero (STATA, 2017; Wooldridge, 2002).

The assumption presented in (7) is likely to be violated in the context of panel data sets. Therefore, we used a modified Wald test to test for groupwise heteroskedasticity in our panel data set (Baum, 2001; Greene, 2003). This test can be specified as,

\begin{equation}
V_m = T_m^{-1}(T_m - 1)^{-1} \sum_{t=1}^{T_m} (e^2_{mt} - \bar{e}^2_m)^2,
\end{equation}
\[
W = \sum_{m=1}^{M} \frac{(\hat{\sigma}_m^2 - \sigma^2)^2}{v_m},
\]

\[\sigma^2_m = T_m^{-1} \sum_{t=1}^{T_m} \varepsilon_{mt}^2\] are estimates of the error variance of the \(m\)th cross sectional unit; \(\sigma^2\) is the error variance for all \(m\) cross sectional units; \(W\) has a \(\chi^2(M)\) distribution under the null hypothesis of a common variance \(\sigma^2\).

The Hausman test could be used to choose between the random effects and the fixed effects estimation approaches. The Hausman test could be specified as,

\[
H = (\hat{\beta}_F - \hat{\beta}_R)'(V_F - V_R)^{-1}(\hat{\beta}_F - \hat{\beta}_R),
\]

where \(\hat{\beta}_F\) and \(\hat{\beta}_R\) are vectors of coefficients from the fixed effects and random effects estimations, respectively; and \(V_F\) and \(V_R\) are the covariance matrixes of the fixed effects and random effects estimators, respectively. Under the null hypothesis the random effects estimator is indeed an efficient and consistent estimator of \(\beta\). If the null hypothesis is true, there should not be systematic differences between the fixed effects and the random effects estimators (Cameron and Trivedi, 2010). One of the limitations of the Hausman test is the restriction that the random effects estimator is fully efficient under the null hypothesis. This implies that the Hausman test could not be used in the presence of heteroscedasticity and serial correlation or the violation of the assumptions presented in equations (7) and (8). Therefore we can use a robust version of the Hausman test as presented in Cameron and Trivedi (2005).
\[
R_H = (\hat{\beta}_F - \hat{\beta}_R)'(V_{\text{BOOTSTRAPPED}(\hat{\beta}_F - \hat{\beta}_R)})^{-1}(\hat{\beta}_F - \hat{\beta}_R),
\]

where \(V_{\text{BOOTSTRAPPED}(\hat{\beta}_F - \hat{\beta}_R)}\) is the covariance matrix of \(\hat{\beta}_F - \hat{\beta}_R\) from the bootstrapped joint distribution.
CHAPTER 6: RESULTS

Table 1 presents the definitions of the variables included in the regression estimation. Some variables were rescaled to facilitate the interpretation from the regression results. Table 2 reports descriptive statistics for all market locations combining all years. Additionally, Table 3 aggregates the descriptive statistics by market location.

The condition number associated with all independent variables included in our regression analysis is 7.35 indicating no collinearity problems in our regression model. The Wald test for groupwise heteroscedasticity \((p\text{-}value = 0.000)\) indicates that we reject the null hypothesis of homoscedasticity in this regression model. Furthermore, the Wooldridge test for serial correlation suggest the null hypothesis of no first order autocorrelation cannot be rejected at the 10\% level. Therefore, we do not have to control or correct for serial autocorrelation in our regression model.

The Breusch and Pagan Lagrangian multiplier test for random effects suggests the rejection of \(H_0: \sigma_f^2 = 0\) an therefore \(c_m\) is not equal to zero (STATA, 2017). Results from the robust Hausman test suggest the difference in the coefficients in the fixed effects and random effects are not systematic, suggesting the random effects is the appropriate approach to be used. Therefore the random effects regression with robust standard errors is used to evaluate the factors influencing tomato prices at Tennessee farmers’ markets. Specifically we used the Swamy-Arora method for estimating the error variance components of the random effects regression.

Table 4 presents the parameter estimates, robust standard errors, and a goodness of fit measure for the pooled OLS, fixed effects, and random effects panel data regressions for
comparison purposes. When comparing parameter magnitudes and significance level across regression approaches it seems the pooled OLS and random effects regressions were very similar. In contrast, both magnitude and significance of parameters for the fixed effects regression are very different when compared to the random effects regression. For example, the parameter associated with household income has a negative sign and is not significant in the fixed effects model but the random effects regression results suggest household income has a significant and positive effect on tomato prices.

The results indicate the overall robust random effects regression is significant at the 1% level. The factors influencing tomato midrange prices were age, household income, seasonality, and precipitation. The parameter estimates for household income and seasonality were both significant at the 1% level while the parameter estimates for age and precipitation were significant only at the 10% level. Midrange prices were expected to increase by $0.09 and $0.03 per lb with an increase in one year in average age and an increase in $1,000 in the average median household income, respectively. In contrast, tomato midrange prices were expected to decrease by $0.29 per lb when tomatoes are in season. The parameter estimate for the precipitation variable was significant at the 10% level but was small in magnitude, suggesting no measurable effect of precipitation on tomato prices.

Overall, regression results from our random effects model suggest the factors influencing tomato prices at Tennessee farmers’ markets are age, household income, and seasonality.
CHAPTER 7: CONCLUSIONS

In this study, we evaluated the factors influencing tomato prices at Tennessee farmers’ markets. We first frame pricing decisions in the context of farmers’ markets using various models from the microeconomic theory. We specifically identified the models of product differentiation, predatory pricing, and price leadership as potential models that could help explain how prices are formed at farmers’ markets. While we are unable to identify one model that effectively explains all price trends we observed at farmers’ markets, there is a common element across these three models, and it is that vendors are always competing for customers regardless of whether they take into account other vendors’ price decisions or not when setting their own prices. Therefore demand, consumer preferences and their willingness to pay, play a major role in how vendors set their prices at farmers’ markets.

We also used a random effects regression to evaluate those factors influencing tomato prices at farmers’ markets, specifically those factors associated with demand and supply. We did not include variables capturing the strategic interaction between vendors as a potential factor influencing prices at farmers’ markets because a proxy variable capturing this information was not available when we conducted this study. Results from a random effects regression suggested consumer demographics (i.e. age and household income) and seasonality are factors influencing tomato prices at farmers’ markets. Knowing that areas with older and higher income consumers lead to higher tomato prices could help producers decide which farmers’ markets to attend and the level of prices they can set their fresh produce for. Additionally, knowing prices will be lower when products are in season may encourage producers to adopt season extension techniques (e.g. high tunnels).
Overall, this study’s results provide information for vendors at farmers’ markets about factors they should consider when setting prices at farmers’ markets. With the information presented in this study, vendors should be able to improve upon their current pricing strategies. Furthermore, Extension personnel can use the results from this study to create educational materials to help vendors incorporate this information into pricing strategies and provide resources that can justify for producers to obtain financial support to adopt season extension technologies.

While this study provides some information about the factors influencing prices consumers pay at Tennessee farmers’ markets, there are still limitations to this study. Much of this study is limited to the data collected through the farmers’ markets price reports. For example, we do not have information on the product characteristics, volume of sales, number of vendors or consumers at the market, or ability to identify wholesale vendors. Nonetheless, this study gives ideas on how to start building a data set that combines primary and secondary data to evaluate factors influencing prices at farmers’ markets, when resources to collect additional primary data at farmers’ markets are limited.

Additionally, the results from this study suggest that the long term sustainability of farmers’ markets located in areas of low household incomes is threatened because producers will have to price their products based on consumer willingness to pay which in these areas tends to be low. If producers have to set low prices for their products to satisfy demand even if they are not covering their production and marketing costs then they will have to stop selling at the market at some point in time. If vendors exit the market due to negative profitability then the market will have to close. Nonetheless, there are some vendors that seem not be profit maximizers and they sell produce at a loss because they do not depend on the income generated
from the farmers’ markets. These vendors participate in these markets because of the social interaction with customers and other vendors or because they want to provide healthy foods to their communities not because they want to make a profit.

In future research it would be important to try to incorporate information regarding the influence of strategic interaction between vendors when evaluating those factors influencing produce prices at farmers’ markets. In general, additional research is necessary to better understand the factors influencing prices at farmers’ markets, and also identify effective and non-effective pricing strategies at farmers’ markets.
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APPENDIX
### Table 1. Description of Variables Included in the Regression Analysis

<table>
<thead>
<tr>
<th>Variable</th>
<th>Variable Name</th>
<th>Variable Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>TOMATO_P</td>
<td>Midrange of Weekly Price</td>
<td>Average of the highest and lowest weekly tomato price per pound</td>
</tr>
<tr>
<td>AGE</td>
<td>Average Median Age</td>
<td>Average median age of census tracts included in the analysis</td>
</tr>
<tr>
<td>HHI1000</td>
<td>Median Household Income</td>
<td>Average median household income in dollars of census tracts included in the analysis divided by 1000 = 1 if the market week is within the eight weeks of harvest season given a standard production season environment, 0 otherwise</td>
</tr>
<tr>
<td>SEASONALITY</td>
<td>Seasonality</td>
<td>The average of daily precipitation observations in inches of the reporting stations in a county in the week the market occurred multiplied by 100</td>
</tr>
<tr>
<td>PALLWEEK100</td>
<td>Average Weekly Precipitation</td>
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</tbody>
</table>

### Table 2. Descriptive Statistics for the Variables Across all Years, 2013, 2014, and 2015 (n=181)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>TOMATO_P</td>
<td>2.0433</td>
<td>0.6340</td>
<td>1.000</td>
<td>3.5000</td>
</tr>
<tr>
<td>AGE</td>
<td>38.2853</td>
<td>3.4207</td>
<td>33.9375</td>
<td>45.1833</td>
</tr>
<tr>
<td>HHI1000</td>
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<td>18.4689</td>
<td>42.2936</td>
<td>100.0563</td>
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<td>SEASONALITY</td>
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<td>15.0062</td>
<td>0.0000</td>
<td>94.3167</td>
</tr>
<tr>
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<td>Variables</td>
<td>Mean</td>
<td>Standard Deviation</td>
<td>Min</td>
</tr>
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<td>-----------</td>
<td>------</td>
<td>--------------------</td>
<td>-----</td>
</tr>
<tr>
<td>Hamblen (n=36)</td>
<td>TOMATO_P</td>
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<td>0.2322</td>
<td>1.5000</td>
</tr>
<tr>
<td></td>
<td>AGE</td>
<td>39.4056</td>
<td>0.7191</td>
<td>38.5000</td>
</tr>
<tr>
<td></td>
<td>HHI1000</td>
<td>45.5685</td>
<td>2.1092</td>
<td>42.2937</td>
</tr>
<tr>
<td></td>
<td>SEASONALITY</td>
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<td>0.5071</td>
<td>0.0000</td>
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<tr>
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<td>PALLWEEK100</td>
<td>16.7003</td>
<td>11.0875</td>
<td>0.1429</td>
</tr>
<tr>
<td>Jefferson (n=28)</td>
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<td>2.6067</td>
<td>0.4785</td>
<td>1.5000</td>
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<tr>
<td></td>
<td>AGE</td>
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<td>0.7709</td>
<td>43.0500</td>
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<tr>
<td></td>
<td>HHI1000</td>
<td>50.9342</td>
<td>0.9324</td>
<td>50.0938</td>
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<td>PALLWEEK100</td>
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<td>9.9466</td>
<td>0.2000</td>
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<tr>
<td>Knox (n=35)</td>
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<tr>
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<td>AGE</td>
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<td>34.5625</td>
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<td>2.2749</td>
<td>94.7780</td>
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<td>0.5021</td>
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<td>18.4786</td>
<td>0.4250</td>
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<tr>
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<td>55.2349</td>
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<td>0.5025</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>PALLWEEK100</td>
<td>12.9882</td>
<td>16.9918</td>
<td>0.0000</td>
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<tr>
<td>Rutherford (n=39)</td>
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<td>0.6159</td>
<td>1.1250</td>
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<td>0.4676</td>
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<td>PALLWEEK100</td>
<td>15.6473</td>
<td>15.1392</td>
<td>0.0534</td>
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<tr>
<td>Variable</td>
<td>Robust OLS</td>
<td>Robust Fixed Effects</td>
<td>Robust Random Effects</td>
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<tr>
<td>---------------</td>
<td>------------</td>
<td>----------------------</td>
<td>-----------------------</td>
<td></td>
</tr>
<tr>
<td>AGE</td>
<td>0.0936***</td>
<td>0.0962</td>
<td>0.0937*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0178)</td>
<td>(0.0698)</td>
<td>(0.0553)</td>
<td></td>
</tr>
<tr>
<td>HHI1000</td>
<td>0.0270***</td>
<td>-0.0004</td>
<td>0.0270***</td>
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</tr>
<tr>
<td></td>
<td>(0.0019)</td>
<td>(0.0204)</td>
<td>(0.0045)</td>
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</tr>
<tr>
<td>SEASONALITY</td>
<td>-0.2899***</td>
<td>-0.2730</td>
<td>-0.2898***</td>
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</tr>
<tr>
<td></td>
<td>(0.0746)</td>
<td>(0.0693)</td>
<td>(0.0763)</td>
<td></td>
</tr>
<tr>
<td>PALLWEEK100</td>
<td>0.0031</td>
<td>0.0021</td>
<td>0.0031*</td>
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</tr>
<tr>
<td></td>
<td>(0.0026)</td>
<td>(0.0014)</td>
<td>(0.0018)</td>
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<tr>
<td>CONSTANT</td>
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<td>-3.1917</td>
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<td></td>
<td>(0.7831)</td>
<td>(3.9277)</td>
<td>(2.2227)</td>
<td></td>
</tr>
</tbody>
</table>

**F STAT**     | 93.27***   | 251.7900***          | 879.1200***           

*; **; *** represent statistical significance at the 10%, 5%, and 1% levels, respectively
Figure 1. Market Supply in the Short Run
Figure 2. The Three Cost Scenarios of Long-Run Equilibrium in a Perfect Competitive Market

(a) Cost Case 1: Constant Cost
(b) Cost Case 2: Increasing Cost
(c) Cost Case 3: Decreasing Cost
Figure 3. Model of Price Leadership Behavior
VITA

Sarah Bellingham was born to Bruce and LuAnne Bellingham in Hamilton, Ohio. She went on to study Agriculture Business at Murray State University in the Fall of 2013. She began her Master’s studies at the University of Tennessee-Knoxville where she graduated in May 2018 in the area of Agricultural Economics.