Factors Influencing Tomato Prices at Tennessee Farmers' Markets

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Selected Paper prepared for presentation at the Southern Agricultural Economics Association's 2018 Annual Meeting, Jacksonville, Florida, February 3-February 6, 2018

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 sales, increased by about 6% between 2007 and 2012, DTC sales did not change in this same time period. For those vendors still 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 prices. Specifically, we evaluated how factors such as weather, location, and consumer characteristics influence 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. A random effects panel data regression was used to evaluate the factors influencing tomato prices at Tennessee farmers' markets. Results suggest the factors influencing tomato prices at Tennessee farmers' markets are potential customers' age, household income, and seasonality.

Key Words: Tennessee Farmers' Markets, Tomato Prices, Random Effects Panel Data Regression

Area: Demand and Price Analysis, Food and Agricultural Marketing

JEL Code: Q10, Q13

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 2016, the USDA AMS reported 8,669 farmers' markets which is a 21% increase from 2011 (USDA AMS, Local Food Research and Development Division, 2017), but a lower increase than that between 2006 and 2011 (i.e., 63%). 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 the 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).

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). For those farms still using farmers' markets as their main marketing channel, a better understanding on how to attract consumers and price their products will probably influence their likelihood of survival under a more competitive environment. 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 prices at farmers' markets, particularly Tennessee farmers' markets prices. Specifically, we will evaluate how factors such as weather, location, 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.

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 et al., 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.

Govindasamy, 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 to be influential on their purchasing decisions. 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 consumers 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, 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 saving 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.

Similar to Sommer, Wing, and Aitkens, McGuirt et al. (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.

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, 2000). 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, 2000; Kemble et. al., 2017; Rutledge, Wills, and Bost, 1999;).

The different irrigation systems can help control variability of water availability through rainfall, and therefore the impact of precipitation on quality and supply of tomato production. Then, why do we include precipitation as a proxy of tomato quality and supply? Sources of water for some irrigation systems depend on rainfall patterns (Kemble, 2000). Additionally, even when using plasticulture and drip irrigation to grow tomatoes, excessive water through rainfall at later stages can affect tomato quality. 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.

Average weekly precipitation for each farmers' market location was gathered from the Nation Centers for Environmental Information (NCEI)[1]. 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.

Additionally, tomato supply and therefore tomato prices might be impacted by seasonal changes. While information is not available about weekly volume of tomatoes at the farmers' market, we expect more vendors selling tomatoes at the market when tomatoes are in harvesting season. Since there is an increase in supply during the harvest season we can expect the sign of

[1] https://www.ncei.noaa.gov/

seasonality to be negative. Therefore, during harvest season tomato prices are likely to be lower compare 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 have more awareness of health concerns and therefore be willing to pay more for fresh produce. 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.

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[2]. 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

[2] http://www.uky.edu/Ag/CCD/farmersmarket.html

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 use 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 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 use consumer demographics and household characteristics as reported in the 2013, 2014, and 2015 American Community Surveys by census tract[3]. 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 average consumer and household characteristics' values for all the census tracts associated with a specific farmers' market location. We include 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

We observed tomato prices at five farmers' markets over three market seasons and we have up to 43 weeks of price information because some farmers' markets did not report prices for all weeks. Because we are looking at cross sectional data over time this data set has a panel data structure (Greene, 2003). Specifically, we have an unbalanced panel data set. 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 (Woolridge, 2003). For example, if the reason why we have missing information on prices for some markets is associated with a sample selection problem then

[3] "**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.

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,…,M) is five and the maximum number of weeks available for a market (t =1,…,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 (Green, 2003). This approach can be specified as,

(1) $$y_t = \boldsymbol{x}'_t\boldsymbol{\beta} + \varepsilon_t,$$

where y_t is the midrange of tomato prices reported at farmers' markets during week t; $\boldsymbol{x}_t$ is an M x K matrix containing K explanatory variables potentially influencing tomato prices at M farmers' markets during week t; $\boldsymbol{\beta}$ are parameters associated with all explanatory variables included in $\boldsymbol{x}_t$; ε_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:

(2) $$E(\boldsymbol{x}'_t\varepsilon_t) = 0, t = 1,2, \dots \dots \dots \dots, T$$

(3) $$rank|\textstyle\sum_{t=1}^{T} E(\boldsymbol{x}'_t\, \boldsymbol{x}_t)| = K,$$

then pooled OLS consistently estimates $\boldsymbol{\beta}$ (Wooldridge, 2010)**.** Equation (3) implies that there could not be perfect linear dependency among explanatory variables. If in addition the following assumptions are met:

(4) $$E(\varepsilon_t^2 \boldsymbol{x}'_t \boldsymbol{x}_t) = \sigma^2 E(\boldsymbol{x}'_t \boldsymbol{x}_t), t = 1,2, \dots \dots \dots \dots, T$$

(5) $$E(\varepsilon_t \varepsilon_s \boldsymbol{x}_t \boldsymbol{x}_s) = 0, t \neq s, t, s = 1,2, \dots \dots \dots \dots, T \ ,$$

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 (4) implies homoscedasticity and equation (5) implies that the conditional covariances of errors across time are equal to zero.

Fixed effects and Random Effects Panel Data Regressions

We can disaggregate ε_t in (1) as $\varepsilon_t = c + \mu_t$, where μ_t is the idiosyncratic error and c is the time-invariant component of the error term. Therefore we can rewrite equation (1) as,

(6) $$y_{mt} = \boldsymbol{x}'_{mt}\boldsymbol{\beta} + c_m + \mu_{mt},$$

where $\boldsymbol{x}_{mt}$ 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 μ_{mt} or not we will have to use a fixed effects estimation or a random effect estimation approach for $\boldsymbol{\beta}$ (Wooldridge, 2002). If c_m is correlated with μ_{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 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 (2), (3), (4), and (5) 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 $\boldsymbol{x}_{mt}$ to decide whether a fixed effects or a random effects estimation approach should be used in this analysis. Specifically, if the random effects approach is selected for this analysis, it is suggested that for small sample unbalanced panel data sets, like one we are using in this study, we should use the Swany-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 Swany-Arora method is that the later uses a more elaborated adjustment for the estimated variance of μ_{mt} for small samples (STATA, 2017).

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,

$$H = (\hat{\beta}_F - \hat{\beta}_R)'(V_F - V_R)^{-1}(\hat{\beta}_F - \hat{\beta}_R), \tag{7}$$

where $\hat{\beta}_F$ and $\hat{\beta}_R$ are coefficient vectors from the fixed effects and random effects approaches, 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 $\boldsymbol{\beta}$**.** 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 (4) and (5). Therefore we can use a robust version of the Hausman test as presented in Cameron and Trivedi (2005),

(8) $$RH = (\hat{\beta}_F - \hat{\beta}_R)'(V_{\_BOOTSTRAPPED(\hat{\beta}_F - \hat{\beta}_R)})^{-1}(\hat{\beta}_F - \hat{\beta}_R),$$

where $V_{\_BOOTSTRAPPED(\hat{\beta}_F - \hat{\beta}_R)}$ is the covariance matrix of $\hat{\beta}_F - \hat{\beta}_R$ from the bootstrapped joint distribution.

Diagnostic Tests

The assumption presented in equation (3) is one of the conditions necessary to obtain consistent estimators of $\boldsymbol{\beta}$. 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 (Green, 2003). Multicollinearity is tested by utilizing Belsey, 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 (Belsey, 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 Woolridge's test for serial correlation will allow us to test for serial autocorrelation. The test uses the first differences method to obtain the residuals μ_{mt} by eliminating the time-invariant effects c_m and estimating $\boldsymbol{\beta}$ by regressing $y_{mt} - y_{mt-1}$ and $\boldsymbol{x}_{mt} - \boldsymbol{x}_{mt-1}$ (Drukker, 2003). From here, the residuals μ_{mt} are regressed on their lags to estimate the coefficients on the lagged residuals. Based on Wooldridge's findings that when μ_{mt} are not serially correlated then the correlation between μ_{mt} and μ_{mt-1} is equal to -0.5, this test concludes that when the coefficient from regressing μ_{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 $H_0\colon \sigma_c^2 = 0$, where σ_c^2 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 (4) is likely to be violated in the context of panel data sets. Therefore, we use a modified Wald test to test for groupwise heteroskedasticity in our panel data set (Baum, 2001; Green, 2003). This test can be specified as,

(9) $$V_m = T_m^{-1}(T_m - 1)^{-1} \sum_{t=1}^{T_m} (u_{mt}^2 - \hat{\sigma}_m^2)^2,$$

(10) $$W = \sum_{m=1}^{M} \frac{(\hat{\sigma}_m^2 - \sigma^2)^2}{V_m},$$

where M are the number of cross sectional units; $\hat{\sigma}_m^2 = T_m^{-1} \sum_{t=1}^{T_m} u_{mt}^2$ are estimates of the error variance of the mth cross sectional unit; σ^2 is the error variance for all m cross sectional units; T_m is the number of errors per mth cross sectional unit; and W has a $\chi^2(M)$ distribution.

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 p-value associated with the modified Wald test for groupwise heteroscedasticity (*p-value*= 0.000) indicates that we reject the null hypothesis of homoscedasticity in this regression model.

The p-value associated with the Woolridge 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 $H_0\colon \sigma_c^2 = 0$ 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 Swany-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 are 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. Results suggest the factors influencing tomato midrange prices are age, household income, seasonality, and precipitation. The parameter estimates for household income and seasonality are both significant at the 1% level while the parameter estimates for age and precipitation are significant only at the 10% level. Midrange prices are expected to increase by $0.09 and $0.03 with an increase in one year in average age and an increase in $1000 in the average median household income, respectively. In contrast, tomato midrange prices are expected to decrease by $0.29 when tomatoes are in season. The parameter estimate associated with the precipitation variable is not only slightly significant but very small in magnitude, suggesting no 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.

Conclusions

In this study, we evaluated the factors influencing tomato prices at Tennessee farmers' markets. Through a random effects regression approach, we found consumer demographics (i.e. age and household income) and seasonality to be the factors influencing these prices.

Specifically, knowing that areas with older population and higher income households lead to higher fresh produce prices could help producers decide which farmers' market to attend and the level of prices they can set for their fresh produce. 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 identifying wholesale vendors. Nonetheless, this study gives ideas on how to start building a data set that combines primary and secondary information to evaluate factors influencing prices at farmers' markets, when resources to collect additional primary data at farmers' markets are limited. Additional research could provide more information on the factors influencing prices, given data availability.

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Table 1. Description of Variables Included in the Regression Analysis

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

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

Variable	Mean	Standard Deviation	Min	Max
TOMATO_P	2.0433	0.6340	1.000	3.5000
AGE	38.2853	3.4207	33.9375	45.1833
HHI1000	63.7619	18.4689	42.2936	100.0563
SEASONALITY	0.4641	0.5001	0.0000	1.0000
PALLWEEK100	15.8545	15.0062	0.0000	94.3167

Table 3. Descriptive Statistics for the Variables Used in the Regression Analysis for 2013, 2014, and 2015 Sorted by Location

	Variables	Mean	Standard Deviation	Min	Max
Hamblen (n=36)	TOMATO_P	1.7604	0.2322	1.5000	2.2500
	AGE	39.4056	0.7191	38.5000	40.2000
	HHI1000	45.5685	2.1092	42.2937	47.3545
	SEASONALITY	0.5000	0.5071	0.000	1.0000
	PALLWEEK100	16.7003	11.0875	0.1429	42.4062
Jefferson (n=28)	TOMATO_P	2.6067	0.4785	1.5000	3.5000
	AGE	43.8143	0.7709	43.0500	45.1833
	HHI1000	50.9342	0.9324	50.0938	52.9623
	SEASONALITY	0.5357	0.5079	0.0000	1.0000
	PALLWEEK100	14.0865	9.9466	0.2000	47.0000
Knox (n=35)	TOMATO_P	2.7179	0.2632	2.1250	3.1250
	AGE	35.1479	0.4627	34.5625	35.5875
	HHI1000	97.9981	2.2749	94.7780	100.0563
	SEASONALITY	0.4286	0.5021	0.0000	1.0000
	PALLWEEK100	20.1513	18.4786	0.4250	73.2424
Marshall (n=43)	TOMATO_P	1.4186	0.2629	1.0000	2.5000
	AGE	40.0793	0.2428	39.7818	40.3364
	HHI1000	55.7042	0.6459	55.2349	56.6966
	SEASONALITY	0.5581	0.5025	0.0000	1.0000
	PALLWEEK100	12.9882	16.9918	0.0000	1.0000
Rutherford (n=39)	TOMATO_P	1.9833	0.6159	1.1250	3.0000
	AGE	34.1192	0.1937	33.9375	34.4500
	HHI1000	67.9249	0.5307	67.6625	69.0446
	SEASONALITY	0.3077	0.4676	0.0000	1.0000
	PALLWEEK100	15.6473	15.1392	0.0534	60.5267

Table 4. Results Comparing Robust OLS, Robust Fixed Effects, and Robust Random Effects

Variable	Robust OLS	Robust Fixed Effects	Robust Random Effects
AGE	0.0936***	0.0962	0.0937*
	(0.0178)	(0.0698)	(0.0553)
HHI1000	0.0270***	-0.0004	0.0270***
	(0.0019)	(0.0204)	(0.0045)
SEASONALITY	-0.2899***	-0.2730	-0.2898***
	(0.0746)	(0.0693)	(0.0763)
PALLWEEK100	0.0031	0.0021	0.0031
	(0.0026)	(0.0014)	(0.0018)**
CONSTANT	-3.1906	-1.5182	-3.1917
	(0.7831)	(3.9277)	(2.2227)
F STAT	93.27***	251.7900***	879.1200***

*,**,*** represent statistical significance at the 10%, 5%, and 1% levels, respectively