Locational Advantage and the Impact of Scale: Comparing Local and Conventional Fruit and Vegetable Transportation Efficiencies

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Abstract

Fresh produce in the United States often travels thousands of miles in diesel operated semi-trucks before arriving to market. Under a high fuel cost scenario, the current low-cost, efficient supply chain could become a high cost organizational structure for US food distribution. Rising transportation costs of food sourced from distant locations may provide competitive opportunities for small- and mid-sized local producers if transportation costs are a smaller portion of their total costs. Farmers selling fresh produce in east Tennessee farmer markets are surveyed to obtain baseline information on their transportation energy use to deliver their products to market. Local farmer energy use is compared to three conventional transportation scenarios for fruits and vegetables grown in California, Texas, and Florida. Farmers within 25 miles of the market tend to have lower transportation fuel use per unit (*g/cwt.*) than the three conventional scenarios. However, farmers located farther from market often have inflated *g/cwt.* estimates due to small truckloads and low vehicle fuel economies.

An ordinary least squares (OLS) regression of local farmer truckload weights finds that by scaling-up their production and distribution, farmers can improve their transportation efficiencies. The OLS results are implemented in a sensitivity analysis that illustrates how local farmers' locational advantage in transportation varies with their production and distribution scales. A follow-up cluster analysis indicates that differences in scale accurately characterize the surveyed local farmers, and that the size of farmers' production, distribution, and marketing operations increases with their travel distance to market.

Local producers transporting their products more efficiently than the conventional system are better prepared to respond to high energy prices because either their production and distribution scales are large, or they are sufficiently close to market. While farmers selling fruits

and vegetables in local markets may be profitable due to the higher prices received for a differentiated product, improving in the area of transportation allows the local food network to take advantage of their proximity to consumer markets. A comparative analysis of conventional and local farmer transportation energy consumption indicates the robustness of the local food system in east Tennessee.

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Chapter I
Problem Identification and Explanation

A key resource powering contemporary agricultural production has been low cost fossil fuel energy. In recent years, the volatility of energy prices has given rise to acute scrutiny of the food sector's reliance on fossil-fuels and the fuel-food price relationship (Gilbert 2010; Saghaian 2010; Tegene 2009). Diesel fuel used in the transportation of agricultural products is especially important. Pimentel et al. (2008) cite that 5 percent of total energy use in the United States consists of food transportation and preparation. The link between rising fuel prices, higher transportation costs, and their impact on food prices at the retail level has also caught the attention of popular press (Wilde 2012). Agriculture is the leading industry in freight service utilization (Casavant et al. 2010). Long distance freight transportation by truck of fresh fruits and vegetables has intensified more rapidly compared to the mode of shipments of other agricultural commodities (Coyle et al. 2001). Canning et al. (2010) estimate that energy consumed by the transportation of fruits and vegetables is 10 and 12.6 percent, respectively, of the total energy used in their production. Along with relying on diesel fuel for truck operation, these perishable foods must be delicately handled and shipped using special packaging and diesel-operated refrigerated trucking (Ashby et al. 1995).

Much of the nation's fresh produce originates from western states and Mexico, where California is often cited as the dominant provider (Paggi et al. 2012). The 2007 Census of Agriculture (USDA 2007) indicates that California has the greatest share of marketed crop value in the United States, representing 11.4 percent of the total. Its temperate climate and fertile soils give California the competitive advantage in producing most high-valued, fresh market crops nearly all year (Sexton and Zhang 1995). Technological advances in the harvesting, handling, packaging and shipping sectors allow perishable fruit and vegetables to be hauled for thousands of miles before they reach their final destination (Coyle, Hall, and Ballenger 2001; Kaufman et al. 2000; Paggi et al. 2012).

The sector's dependence on diesel fuel makes this particular piece of the supply chain vulnerable to fuel price increases (Tester et al. 2012). Under a high fuel cost scenario, the current low cost, efficient supply network could become a high cost organizational structure for US food distribution (Casavant et al. 2010). Economic theory suggests that firms following cost-minimization behavior will strive to obtain their inputs, in this case fruits and vegetables, at the lowest price, holding other important factors such as product quality constant (Nicholson 2002). This concept is reflected in the business supply chain literature, as changes in retailer procurement locations when faced with rising marketing costs has received greater research attention (Acharya, Kagan, and Manfredo 2009). Sourcing produce from distant origins and relying on long distance truck shipments to distribute fruit and vegetables has been a successful strategy during periods of low energy prices (Hendrickson 2004). However, if this key input increases in cost, wholesalers and retailers facing higher marketing costs may alter their procurement strategies by adopting a regional sourcing strategy (Acharya, Kagan, and Manfredo 2009; Gosier et al. 2008).

Higher transportation costs of food sourced from distant locations may provide competitive opportunities for small- and mid-sized local producers if transportation costs are a smaller portion of their total costs (Gunter, Thilmany, and Sullins 2012). Local farms often use direct-to-consumer markets, such as farmer markets and community sustainable agriculture (CSA) as their main avenue to market fruits, vegetables, and other goods produced and sold regionally (Low and Vogel 2011). In the United States, direct-to-consumer sales increased by 49 percent between 2002 and 2007 (Martinez 2010). There is a larger number of small farms in the southeast United States compared to other parts of the nation (Ahearn 2013; USDA 2007). More specifically, in east Tennessee, rising consumer demand for locally produced agricultural goods is evident in the greater number of farmer markets and the burgeoning number of small- and mid-sized farms in operation (Hellwinckel et al. 2014).

However, transportation of locally grown food may be less efficient in terms of energy use per unit of product shipped than the conventional system due to economies-of-scale (Mariola 2008). Additionally, if local farmers in east Tennessee were to supply a more significant proportion of retailers' fresh produce inventory, a sourcing strategy in which individual farmers deliver their produce to different food markets and warehouses could be more energy intensive, and therefore, more costly than the conventional long distance supply chain. As noted by Hendrickson (2004) and Canning et al. (2010), local food production potentially has lower cost and energy usage, but delivering these foods to consumer markets should also be at least as efficient as the conventional distribution system if local farmers hope to insert their products into mainstream markets.

Understanding the degree to which farmers selling food locally in east Tennessee rely on non-renewable fossil fuels to ship goods to market would provide valuable baseline information on current energy consumption by local farmers to transport goods and instruct as to how the cost per unit of produce shipped for local food transportation compares to the marginal shipping costs of conventional, long distance transportation for similar products. Knowledge of local producers' energy use in transportation could help identify where local food distribution energy inefficiencies occur and how they may be improved.

Research Objectives

The primary objectives of this research are to:

- Obtain information on energy use of transporting locally grown products for sale in nearby markets in east Tennessee.
- Compare the transportation costs and energy uses of local producers with the transportation costs and energy uses of producers of similar crops using conventional, long distance sourcing practices.
- Determine optimal production and distribution scales for local farmers that achieve a per unit supply chain efficiency that is competitive with conventional agriculture food networks.

Chapter II
Literature Review

Research on the fuel use in food transportation has primarily focused on the energy requirements of transportation for conventional, long distance shipments of food items. Some food analysts are concerned with the energy, environmental, social, and economic implications of the increasing distance food travels (Paxton 1994; Heller and Keoleian 2003; Mundler and Rumpus 2012). In estimating the relative size of transportation energy, several researchers have estimated the fuel usage for every segment of the value chain of conventionally sourced food, from production to consumption, to measure the sector's CO_2 emissions and its potential contribution to global warming (Carlsson-Kanyama 1998; Mattsson 2002; Avetisyan 2013; Schlich and Fleissner 2005).

Life Cycle Analysis (LCA) is a tool commonly employed to estimate the total energy consumed during all stages of a product's life (Rebitzer et al. 2004). Agricultural products in particular are often analyzed using LCA methods because of the concern for agriculture's increasing dependency on non-renewable, price-volatile fossil fuels (Heller and Keoleian 2003). Roy et al. (2009) and Edwards-Jones et al. (2008) give evidence of the prevalence of LCA to investigate the energy intensity of the agricultural production system for different food groups, highlighting the myriad of life cycle analyses that have been conducted on different aspects of the food supply chain– some focusing on production (Nemecek et al. 2001; Haas et al. 2001), others narrowing their scope on a specific part of the food system, such as food distribution (Sonesson and Berlin 2003). Milà i Canals, Burnip, and Cowell (2006) utilize LCA to estimate total energy use and emissions from apple production in New Zealand orchards, excluding packaging and transportation. Cederberg and Mattsson (2000) use LCA methods to compare the energy demands and greenhouse gas emissions (GHGs) in organic and conventional milk production in Sweden, while Mattsson (2002) analyzes the factors that contribute most to energy consumption and emissions from organic potato production and distribution.

Many LCA studies focus on the energy consumed for long distance food transportation and the data are often compared with the energy consumed in local food transportation (Coley, Howard, and Winter 2009; Wallgren 2006; Sim et al. 2007; Jones 2002). Wallgren (2006) combines survey methods with the compilation of over 30 LCA studies to estimate the differences in fuel usage between conventional food transportation and locally grown food sold at a farmer market in Sweden. The author contends that fuel consumed for local food transportation is not significantly different to that of conventionally shipped food but that local food supply networks need to become more efficient. Sim et al. (2007) use LCA to estimate the energy consumption and CO_2 emissions from importing Kenyan runner beans, Chilean, Italian, and Brazilian gala apples, and Portuguese watercress to the United Kingdom and conclude that the fuel required for long distance transportation is greater than local distribution of these crops during the growing season. Pirog et al. (2001) determine whether local Iowan farmer cooperatives selling locally to supermarkets and participating in direct-sales venues such as farmer markets expend more fuel in transportation than the conventional supply chain. They find that conventional transportation of fruit and vegetables uses 4 to 17 times more fuel than the local distribution system (Pirog et al. 2001). Jones (2002) estimates that the energy reductions from locally grown apples versus importing the fruit to Britain varies from 0.7 to 4.5 Megajoules per kilogram (MJ/kg).

Other LCA studies, such as Blanke and Burdick (2005) are more holistic in their approach by opening their system boundaries to include transportation and other production stages, finding that producing and storing apples in Germany with controlled atmosphere storage requires 1.5 MJ/kg less energy than the energy needed to grow and import the same fruit from New Zealand. Heller and Keoleian (2011) estimate total fuel usage and GHG emissions from organic dairy production in the United States, concluding that the transportation of farm inputs and commodity distribution accounted for 29 percent of total energy. By locally sourcing certain materials, energy use from transportation would decrease by 7 percent (Heller and Keoleian 2011). In many cases, local food transportation has the potential to be as energy efficient per unit of output shipped as conventional, long distance food transportation. However, as Wallgren (2006) emphasizes, there is also a need to reduce local food transportation fuel usage. Mundler and Rumpus (2012) suggest that through product aggregation of local produce and a more organized supply chain structure, transportation fuel use for local food has potential energy saving benefits.

Some researchers find that conventional production and transportation systems experience economies-of-scale, and therefore, are more energy efficient per unit of produce shipped than a local food distribution network (Mariola 2008; Avetisyan, Hertel, and Sampson 2013; Schlich and Fleisnner 2005; Saunders, Barber, and Sorenson 2009; Coley, Howard, and Winter 2009). Using LCA methods, Saunders, Barber, and Sorenson (2009) calculate the energy usage from the production and transportation of New Zealand dairy products, lamb, and apples for export to the United Kingdom, and compare with the energy consumed if the importing country were to instead produce these same commodities for domestic consumption. The study finds that, because ocean barge transportation has high energy efficiencies per unit of product shipped, exporting to the United Kingdom would require 50 percent, 25 percent, and 10 percent less energy for dairy, lamb, and apples, respectively. Coley, Howard, and Winter (2009) use

LCA carbon accounting to conduct a case study comparing conventional, large-scale cold storage transportation and distribution of organic produce with a local supply chain in France. The authors determine that if a consumer travels more than 7.4 kilometres round-trip (4.6 miles), the conventional, long distance transportation system of fresh produce is more energy efficient because, although the total number of food miles is substantially lower for local food distribution systems, large-scale transportation requires less energy per unit of produce shipped (Coley, Howard, and Winter 2009).

Mariola (2008) signals the importance of considering the advantages of economies-of-scale in the large-scale transportation of produce, despite traveling, on average, over 1,500 miles from more distant locations such as California. Conventional, long distance shipping by truck hauls thousands of pounds of fruits and vegetables in a single load, thus the energy per unit of produce shipped is often minimal (Mariola 2008). King et al. (2010) carry out 15 case studies of different food distribution systems, including locally grown and direct-marketed, conventionally grown and long distance shipped, and a combination of local production using the supermarket distribution structure to sell its goods. The research team finds that while sourcing food locally results in less total food miles, the actual fuel consumed in local transportation is typically higher on a per unit basis because conventional supply chains transport larger volumes of produce. Small- and mid-sized local vendors bring less produce to market, and therefore, may have lower fuel use efficiencies despite traveling fewer miles to distribute their produce (Low and Vogel 2011). Similarly, Schlich and Fleissner (2005) estimate that orange juice concentrate produced and shipped from Brazil requires less energy per liter of juice than locally produced concentrate from apples grown in Germany because larger production and processing operations allow for energy savings due to economies-of-scale.

Born and Purcell (2006) argue against making the assumption that local food distribution is inherently less energy intensive than conventionally delivered food, as the reductions of energy usage from adopting a local food sourcing strategy may be negated by the competitive advantages in soil quality and climate. Similarly, Avetisyan, Hertel, and Sampson (2013) and Saunders, Barber, and Taylor (2006) stress the importance of considering more than fuel used during food transportation, as the comparative advantages of production may outweigh the benefits of less fuel consumption through a local transportation food distribution system. Desrochers and Shimizu (2008) relegate the "food miles" debate to a mere marketing scheme. Instead, Born and Purcell (2006) and Desrochers and Shimizu (2008), respectively, contend that the food distribution system has become more globalized in recent history because of its efficiencies in production and distribution and that food policy should favor the system that is most efficient.

Chapter III
Conceptual Framework

Competitive Advantages in Production

In agriculture, geography and climate are key factors in determining the productive activities that are suitable for a given region. US production of fruits and vegetables has become increasingly limited to certain geographic areas, namely California, Texas, and Florida because these states have a competitive advantage in fruit and vegetable production relative to farmers in other states. The geographical and climatological characteristics of these regions make year-round production of most fruits and vegetables on a large scale optimal (Lucier et al. 2006; Paggi et al. 2012; USDA 2012). California alone accounts for 65 and 48 percent of the nation's fruit and nut, and vegetable production, respectively, and is the nation's leading producer for nearly 80 crop and livestock commodities (USDA 2012).

A region with a comparative advantage in producing a good has an economic incentive to dedicate its resources to the production of that good (Nicholson 2002). The natural comparative advantage granted to geographical regions in states like California, Texas, and Florida in fruit and vegetable production creates agglomeration economies in these locations (Marshall 1920; Ohlin 1933; Isard and Peck 1954). The high concentration of farms growing fresh produce in one area stimulates the creation of industry-specific infrastructure, services, and technical skills that, in turn, benefit members in the regional industry cluster (McCann 2013). Specialization of the entire production process spurs the development of cost-reducing technologies that engender economies-of-scale, and thus, the competitive gap between producers in less productive geographic regions widens (Chandler et al. 2009).

The Role of Technology in Conventional Food Supply Chains

Transportation is a component of the fruit and vegetable supply chain that has experienced significant technological advances (Coyle, Hall, and Ballenger 2001; Kaufman et al. 2000; Paggi et al. 2012). Technological improvements have permitted more productive agricultural areas, though geographically separated from final consumer markets, to effectively exploit their competitive advantages and economies-of-scale by making viable a food supply chain that relies on long distance transportation (Wang et al. 2000; Coyle, Hall, and Ballenger 2001). North (1955) points out that much of the early history of California's economic development focuses on reducing shipping costs of the state's staple agricultural crops via technological advances in long distance transportation. In the United States, perishable produce is now hauled between 500 to 3000 miles before reaching consumers, using special packaging and controlled atmosphere shipping technology, both of which help maintain product freshness and minimize spoilage (Ashby et al. 1995; Huang 2004). Despite long travel distances for produce shipments, trucks hauling a fully loaded trailer achieve a high efficiency rate with respect to their fuel use per pound of produce hauled.

Ninety-four percent of fresh fruits and vegetables are transported via diesel operated semi-trucks (Casavant et al. 2010). Because truck operation depends on diesel fuel, transportation costs are often more volatile compared to the transportation costs of other agricultural goods (Lucier et al. 2006). Research concerned with the fuel dependency of conventional food transportation often cites direct-to-consumer products sold at nearby farmer markets or farmer stands as an opportunity to reduce the number of miles food travels, mitigate CO_2 emissions, and minimize the amount of fuel required to deliver fruits and vegetables to consumers (Pirog et al. 2001; Mundler and Rumpus 2012). If local farmers in east Tennessee require less fuel per pound of produce shipped than the conventional supply chain, rising fuel prices may present competitive opportunities for farmers marketing their fruits and vegetables locally. Local farmers less dependent on fuel for transportation are not as affected by fuel price increases. In theory, assuming that local farmers' and conventional farmers' costs of production net of transportation costs are equal, prices for fruits and vegetables distributed locally should increase by a smaller amount compared to produce shipped conventionally (Paggi et al. 2012). The economic intuition of the effect of rising fuel prices on transportation costs can be analyzed conceptually using a two region, supply-demand framework.

Inter-regional Trade and Transportation Costs

Following McCarthy (2001), for two geographically separated fruit and vegetable markets, say California (M_C) and east Tennessee (M_{ET}), homogenous baskets of fresh produce are grown and sold (Figure 1). Market equilibrium price in each region, M_C and M_{ET}, is p_C and p_{ET}, respectively. Both regions produce just enough baskets of produce to satisfy local demand. California has a comparative advantage in the production of fruit and vegetable baskets, and therefore, sells each produce basket at a lower price than east Tennessee farmers, where $p_{ET} > p_C$. Using trade theory presented by Roehner (1996), assuming zero transportation costs, the price difference between two geographically separated regions, $p_{ET} - p_C$, stimulates trade and specialization of production. At the market price, p_C, there is excess demand by consumers in M_{ET}. At the market price, p_{ET}, there is excess supply in M_C. Free-trade between the two production regions creates a third market, M_{Total}, in which consumers and producers from both regions compete to purchase and sell homogenous produce baskets, for which an equilibrium price, p_{Mkt}, is achieved.

The comparative advantage of California farmers in the production of fresh produce baskets incentivizes farmers in this region to specialize in fruit and vegetable production. Farmers' specialization attracts outside investment in areas related to the production of fruits and vegetables, and thus, further lowers production costs. Zero transportation costs allow for the delivery of their product to consumers in east Tennessee at a lower price than that offered by producers in M_{ET} (Chandler 2009; McCann 2013). Many east Tennessee farmers with less high quality land and shorter growing seasons cannot compete with the year-round, large-scale production of California fruit and vegetable farmers, and thus, dedicate their resources to another crop, industry, or profession (McCarthy 2001).

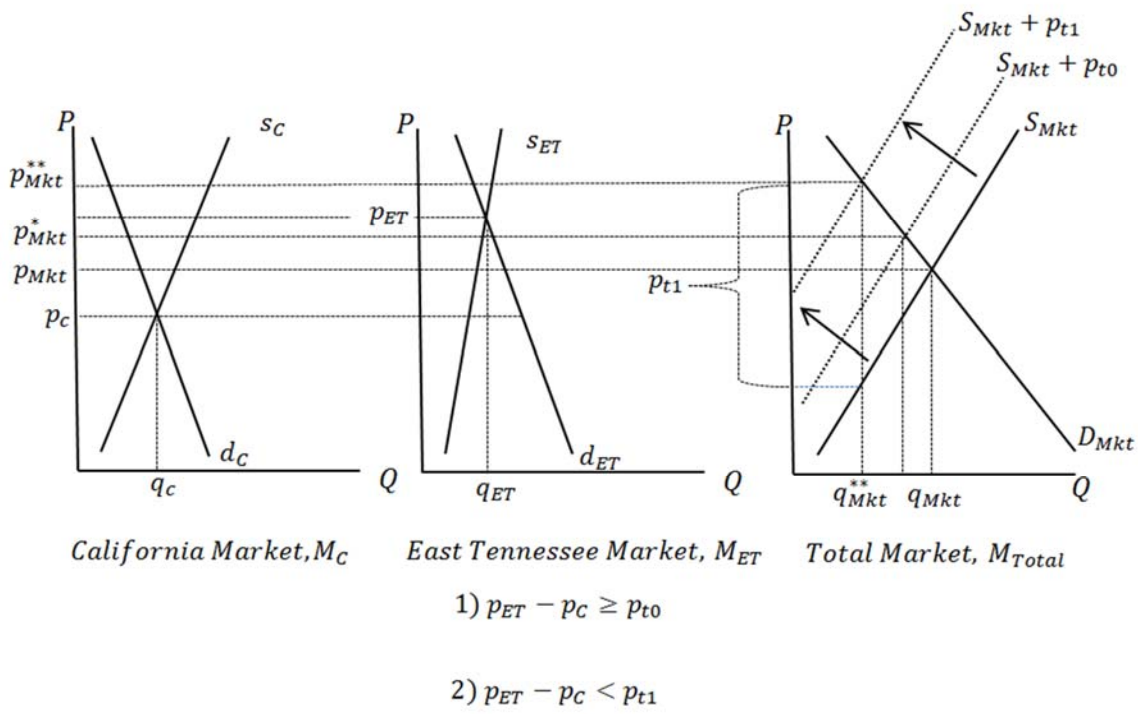

Figure 1. Inter-regional Market for Fresh Produce Baskets

The presence of transportation costs dampens California's competitive advantage, as farmers' cost functions now include an additional input cost,[1] which is passed on to consumers in the form of higher produce basket prices,

$$C = C(v,w,p_t,q)$$

where v is the per unit price of capital, w is the wage rate, p_t is the transportation rate, and q follows a Cobb-Douglas production function $q = f(k,l) = k^{\alpha}l^{\beta}$, where $\alpha+\beta > 1$ to reflect the increasing returns to scale of California farms (Samuelson 1952; McCarthy 2001; Nicholson 2002). Trade theory conceptualizes transportation costs as a tariff between two trading regions (Gehlhar 2000; Falvey 1976). Thus, the addition of transportation costs shifts the total market supply curve upward, creating a wedge between the producer and consumer prices. A higher equilibrium price, p^*_{Mkt}, and a lower quantity of fresh produce baskets are sold. Interregional trade continues in M_{Total} as long as the price differential between the production regions is greater than the cost to deliver the goods to the more distant market:

$$p_{ET} - p_C \geq p_{t0}$$

However, if transportation costs rise unexpectedly high due to fuel price volatility, for example, the transport rate could become greater than the California-east Tennessee price differential

$p_{ET} - p_C < p_{t1}$.

Trade between the two regions will not be economically viable. Although California producers still have a comparative advantage in the production of fresh produce baskets, significantly

[1] To narrow our focus on the effects of fuel price increases on food transportation, it is assumed that fuel is only used as an input for transportation. In reality, a fuel price increase would also increase the costs of production for California and Tennessee farmers, respectively. Such an increase would shift farmers' supply curves in both regions, and in turn, further shift the market supply curve upward.

higher transportation costs caused by shocks to fuel prices dissuade trade between the two regions (McCarthy 2001; Gehlhar 2000).

If California and east Tennessee farmers are assumed to have zero transportation costs in their home markets, the regional market supply curves for fresh produce baskets will be unaffected by the fuel price increase. The new M_{Total} equilibrium price that results after the second increase in transportation costs, p_{Mkt}^{**}, is greater than the east Tennessee market price, p_{ET}. In this scenario, east Tennessee farmers would have greater market opportunities to sell their produce baskets locally at competitive prices due to their relatively lower transportation costs.

Increasing Fuel Prices and Scale: An Application of Hotelling's Spatial Competition Model

An alternative framework that illustrates the potential marketing opportunities for east Tennessee farmers in a high fuel cost scenario and that explicitly incorporates the concepts of the comparative advantages in production and the low transportation costs of the conventional fruit and vegetable supply chain uses a competitive spatial model, first developed by Launhardt (1885) and later adopted by Hotelling (1929) and Palander (1935) (Fujita 2010). Assume the existence of a two-dimensional space in which farmers from California and east Tennessee produce and sell identical fruit and vegetable baskets (Figure 2) (McCann 2013). Let the horizontal axis represent distance and the vertical axis indicate product price. California farmers are located at point *CA*, while east Tennessee farmers are located at point *ET*, and therefore, are separated by distance *CA* – *ET*. Because California farmers have a natural productive advantage in growing fruits and vegetables relative to the east Tennessee farmers and experience increasing returns to production, the California market price for fresh produce baskets at *CA*, p_{CA}, is below the fresh produce basket price of the less efficient east Tennessee local farmers, whose price at ET is p_{ET}.

Consumers are homogenously distributed across space and demand exactly one fresh produce basket per period, regardless of price (Eiselt and Laporte 1989). Because both regions produce the same fresh produce basket, consumers are indifferent in buying baskets from California and east Tennessee farmers, and thus, purchase from the producer with the lowest delivery price. To deliver their fresh produce baskets to consumers, California and east Tennessee farmers incur transportation costs, t_{CA} and t_{ET}, respectively. Transportation costs for both regions are a function of travel distance to market, economies-of-scale, and exogenously determined fuel prices. The slope of the transport cost function for California producers is flatter than the east Tennessee farmers, reflecting the California supply chain's efficiencies in transporting fresh produce baskets.

From Figure 2, it is apparent that California producers control most of the fruit and vegetable basket market, while the market area of east Tennessee farmers is limited to markets within short travel distance. Their low production costs and high transportation efficiencies allow California farmers to outcompete east Tennessee farmers in sales to consumer markets that are closer in distance to the east Tennessee farmers. Though east Tennessee producers have a locational advantage in delivering fruit and vegetable baskets to these nearby consumer markets, their small production and transportation scales constrain their market area. East Tennessee farmer profits are limited to area *abc* (Figure 2). However, a short term, exogenous rise in fuel prices in California could increase the transportation costs of produce baskets shipped from this region, and in turn, temporarily open marketing opportunities to east Tennessee farmers.[2] The

[2] Such a scenario is possible considering that California and east Tennessee fuel supplies primarily originate from different exporting countries (EIA 2015).

effect of increasing fuel prices is a simultaneous increase in production and transportation costs for California farmers, as fuel is used as an input in both production and transportation (Figure 3). The east Tennessee farmers see that their market area expands and that their profits from fruit and vegetable basket sales increase by area *abde*. On the other hand, if a fuel price increase were to affect both regions, the market area is unchanged, as production and transportation costs increase by the same amount for farmers in both regions (Figure 4).

In contrast to Hotelling's spatial competition model in which firms change location to gain monopoly power (McCann 2013), given the immobility of farmland, California and east Tennessee farmers cannot move their production location as a strategy to gain market area over their competition. On the other hand, assuming that the goals of farmers in both regions is profit maximization, California and east Tennessee farmers can respectively expand their market area by improving their production and transportation efficiencies, and in turn, reduce their production and transportation costs. Indeed, the contemporary conventional food supply chain is characterized by firms that lower their production and transportation costs in order to sell their products globally at a lower price than the same items grown locally. The small production and distribution scales of east Tennessee farmers constrain their competitiveness in conventional markets, forcing them to adopt niche marketing strategies. However, Hotelling's model suggests that, just as the California farmers have successfully reduced their production and transportation costs via increasing the size of their operations to generate economies-of-scale, farmers in east Tennessee can recuperate part of their local market by similarly scaling-up their production and transportation networks. In doing so, east Tennessee farmers can regain their competitive edge in the markets for which they have a locational advantage in transporting their fresh produce baskets. Figure 5 illustrates that by improving their transportation efficiencies and increasing their on-farm productivity, east Tennessee farmers flatten their transportation cost curves and reduce their production price to the California price level, $p_{CA} = p_{ET_1}$. Such a strategy expands the east Tennessee competitive market area and increases their profits by the areas *acdf* and *bcef*. Because the local food distribution system is still in its infancy relative to the long distance, conventional food supply chain, researchers often cite scaling-up the local food system's transportation network as an opportunity to capitalize on local farmers' proximity to mainstream consumer markets (King et al. 2010; Day-Farnsworth and Miller 2014). Therefore, while east Tennessee farmers could see greater marketing opportunities from an exogenous fuel price shock to the long distance, conventional transportation food network, the Hotelling spatial competition model suggests that east Tennessee farmers can alternatively recover market area by endogenously increasing their production and transportation scales, which in turn, improves their food distribution efficiencies.

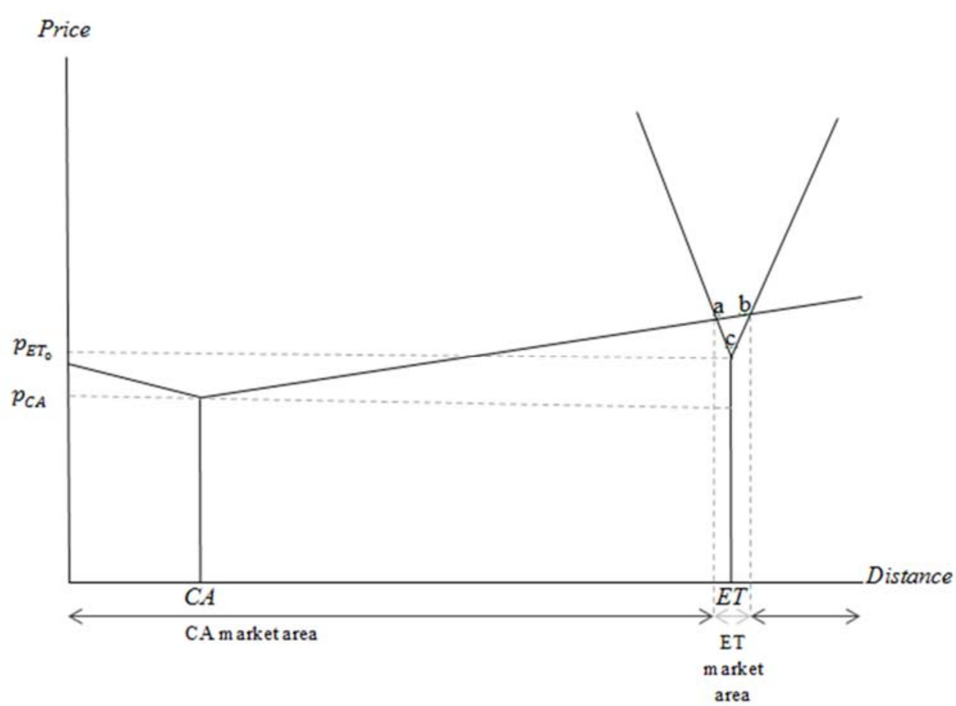

Figure 2. Hotelling spatial competition for two-region fresh produce basket market

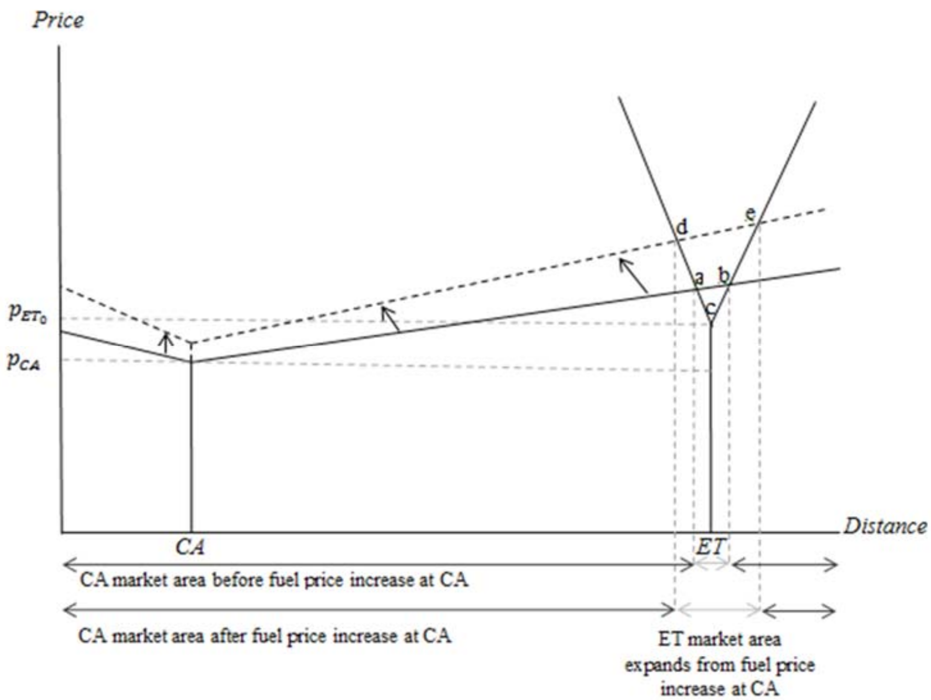

Figure 3. Market area effect of fuel price increase in California region

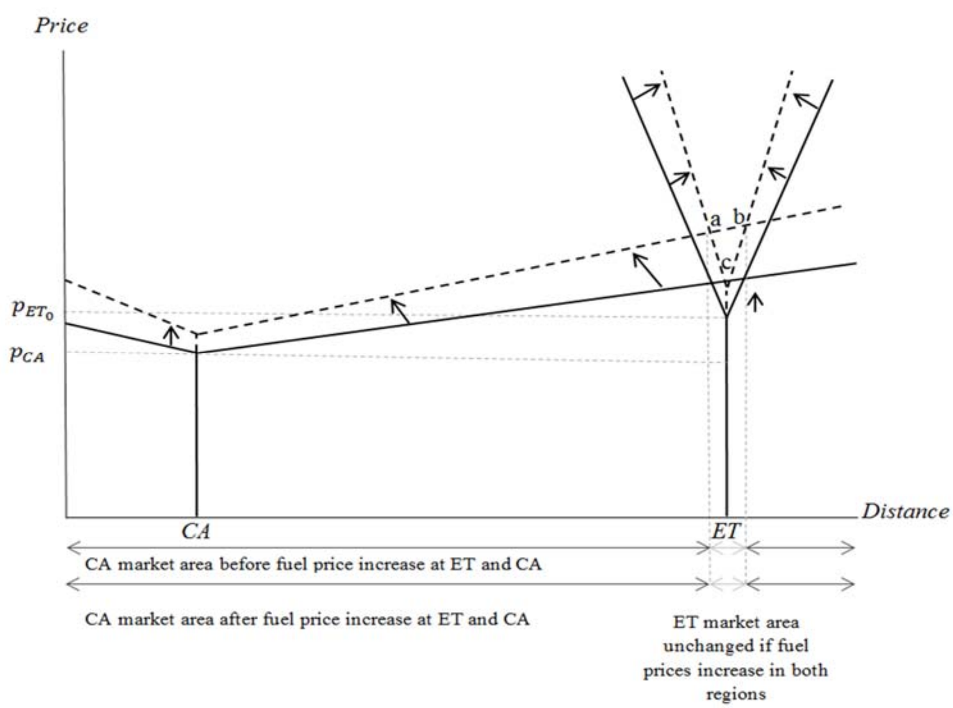

Figure 4. Market area effect of fuel price increase in both regions

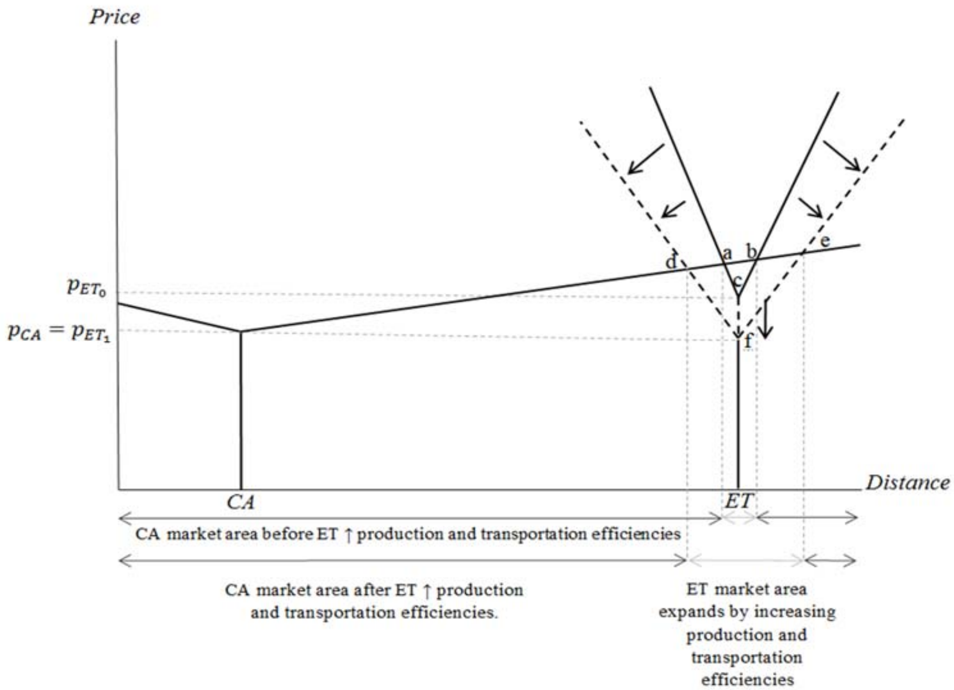

Figure 5. Market area effect of increase in production and transportation efficiencies by east Tennessee farmers

Chapter IV
Methods

While economic theory suggests that rising fuel costs can provide marketing opportunities to local farmers with a locational advantage in transportation, if local food distribution efficiency is inferior to the conventional supply chain, increasing fuel prices could potentially impact local food transportation more adversely than transporting fruits and vegetables over long distances. In order to obtain baseline information on the energy use of transporting locally grown produce for sale in nearby markets, a survey of farmers selling fruits and vegetables in direct-to-consumer local markets in east Tennessee was conducted.[3] A purposive, or judgment sample, was used to conduct the survey (Lohr 2009). Twenty-one of the 29 surveyed farmers were interviewed at the downtown farmer market in Knoxville, Tennessee. The remaining eight farmers were interviewed at other farmer markets in the Knox County area. The survey was conducted during the summer months of June, July, and August in 2014.[4] Farmers were interviewed during market hours. The survey was limited to farmers selling fresh produce.

There is still much to be investigated concerning local food markets and local food distribution (Martinez et al. 2010; Low and Vogel 2011; Day-Farnsworth and Miller 2014). Exploratory in-person surveys allow the acquisition of both quantitative and qualitative data. In formulating and conducting the local farmer transportation survey, research methods from life cycle analysis (LCA), transportation economics, and local food case-study literature (King, Hand, DiGiacomo 2013) were referenced. For LCA accounting, the research unit-of-interest

[3] A series of training modules were successfully completed by the researcher, and thereafter, the University of Tennessee's Institutional Review Board granted permission to carry out research involving human subjects.
[4] A sample survey is provided in the Appendix.

should be clearly defined (Rebitzer et al. 2004). In the case of collecting transportation fuel use information from local farmers, the primary functional unit of interest is the transportation fuel consumption per 100 pounds of produce delivered to market (cwt.), measured in gallons per cwt. (*g/cwt.*) for each surveyed farmer selling fresh produce.

Wallgren (2006) investigates local farmer fuel use for the transportation of fruits and vegetables to a farmer market in Sweden through in-person surveys. Her study's survey methods aid in developing the data collection techniques to investigate local farmer transportation fuel use. Additionally, meetings with East Tennessee Clean Fuels research staff helped determine other factors to consider when collecting transportation energy consumption information from local farmers (Personal Communication, May 13, 2014). Following Wallgren (2006), the survey collected farm addresses and a detailed description of the route taken to market, including any habitual stops, detours, additional deliveries, or side roads used during transit. With this information, the total distance traveled to the farmer market is estimated. The farmer's return travel distance was also included in the total distance calculation in order to account for the fuel consumption of partial and empty loads (Kaplin 2011). The total mileage was verified using Google Maps and Geographical Information Services (GIS). Unless otherwise noted, it was assumed that the farmer's only purpose for making the trip from their farm to the market was to sell his or her produce.

Information on farmer vehicle model, year, drivetrain, and fuel type was collected, along with the weight, in pounds, of the truckload shipment to the farmer market. In using LCA for their study of local food distribution systems, Mundler and Rumpus (2012) also identify the distance traveled, vehicle characteristics, and the truckload weight as the most relevant variables impacting transportation fuel use of local producers. Transportation economics research considers distance and quantity shipped, by volume and weight, as important variables influencing transportation costs (Moneta 1959; Friedlaender and Spady 1980; Wang et al. 2000; Hummels 2007).

The survey was administered during the peak growing months in which the heaviest fresh produce is marketed by local farmers, such as tomatoes, squash, melons, and root crops. Therefore, calculations for fuel use per cwt. shipped to market likely reflect a high-end estimate of local farmer truckload weights. If the farmer could not provide a reliable estimate of his or her truckload weight, the quantity was estimated by weighing the farm stand's different produce boxes, counting the total number of boxes, and multiplying quantities to derive the truckload weight per trip, an estimation technique utilized by Wallgren (2006). All other heavy cargo or energy consuming devices that impact total fuel use, such as campers, tables, tents, on-board freezers and coolers, containers, etc. were also accounted for in the final energy use calculations (Personal Communication, May 13, 2014). Figure 6 is a flow chart representation of the direct and indirect factors affecting local farmer transportation fuel use per unit.

Each farmer's vehicle fuel economy, measured in miles-per-gallon (MPG), is estimated through the US Department of Energy's vehicle fuel efficiency calculator at www.fueleconomy.gov. Farmer $i's$ fuel consumption per trip to market is calculated by:

$$\frac{\text{distance}_\text{i}\text{ (miles)}}{\text{mpg}_\text{i}} = \frac{\text{G}_\text{i}}{\text{trip}}\text{ (gallons per trip)}$$

where $distance_i$, the two-way distance traveled in miles by farmer i, is divided by mpg_i, farmer i's vehicle fuel economy, measured in miles per gallon, which yields G_i, total gallons of fuel consumed per trip by farmer i. To estimate transportation fuel use per cwt., G_i is divided by the farmer's estimated truckload weight and multiplied by 100 to obtain a one-hundred weight measurement:

$$\left(\frac{G_i}{truckload_i}\right) x\ 100\ \text{lbs.} = \frac{G_i}{cwt.}$$

where $truckload_i$ represents the truckload weight, in pounds, of fresh produce shipped to the market by farmer i. The term *g/cwt.* measures local farmer transportation fuel use efficiency in terms of the gallons of fuel consumed per cwt. transported to the market. Local farmer transportation fuel use per cwt. provides a baseline image of local food distribution efficiency. With this estimate, a better understanding of how travel distance to market, vehicle fuel economy (MPG), and truckload weight affect transportation energy use efficiencies is obtained. The estimate *g/cwt.* is the functional unit used to compare the transportation fuel use of local and conventional, long distance fruit and vegetable distribution systems.

Transportation fuel use estimates for conventional fruit and vegetable shipments rely on data sources provided by the USDA's Agricultural Marketing Services' (AMS) weekly truck rate reports for fresh produce, the Agricultural Refrigerated Truck Quarterly, and other food distribution studies (King et al. 2010; Casavant et al. 2010). AMS reports that conventional semi-trucks transporting fruits and vegetables haul 39,000 pounds of fresh produce, on average. The US Department of Transportation (2014) estimate that semi-trucks travel at approximately 5.7 miles per gallon (MPG). Other studies that have calculated conventional transportation fuel use assume that conventional semi-truck fuel economy ranges between 5.3 MPG to 6.1 MPG (Pirog et al. 2001; King et al. 2010; Paggi et al. 2012). The travel distance to market of three conventional scenarios are calculated by using shipping points from Palm Beach County, FL., Hidalgo County, TX., and San Joaquin Valley, CA., respectively. These three states rank in the top 10 in fruit and vegetable freight transportation by volume in the United States (USDA 2013). Each county grows a considerably large proportion of fruits and vegetables in their respective states (USDA 2012). California is the United States' dominant fruit and vegetable producer, accounting for over 30 percent of fresh produce truck shipments (USDA 2012).

The terminal market for all three conventional scenarios is Knoxville, TN., corresponding to the downtown farmer market location. Google Maps is used to approximate the total distance traveled from each shipping point to the terminal market. Distances for the Florida, Texas, and California shipping scenarios are 818, 1,333, and 2,338 miles, respectively. With estimates on travel distance, MPG, and truckload weight, transportation fuel use per cwt. of the conventional supply chain is obtained and compared with the local farmer fuel use estimates. A comparative analysis of the per unit transportation energy use of both food distribution systems serves as an indicator of whether local farmers' locational advantage in accessing nearby markets could open competitive opportunities over the conventional food supply chain in a high fuel cost scenario.

Because local food distribution systems are still evolving and conventional food supply chains have had more time to develop their scale efficiencies (Martinez et al. 2010; King, Gómez, and DiGiacomo 2010), US food system researchers investigating local food distribution often conclude that local, short distance food supply chains need to find an optimal scale to be at least as energy efficient as the conventional, large-scale distribution system (King et al. 2010; Day-Farnsworth and Miller 2014). Findings from the in-person survey of local farmers will allow for a better understanding of the local food distribution system in east Tennessee, and could provide farmers participating in direct-to-consumer markets with information as to how they could deliver their fruits and vegetables to consumers more efficiently. Additionally, the survey results can be useful to local and regional food policymakers hoping to improve the local food distribution system in east Tennessee.

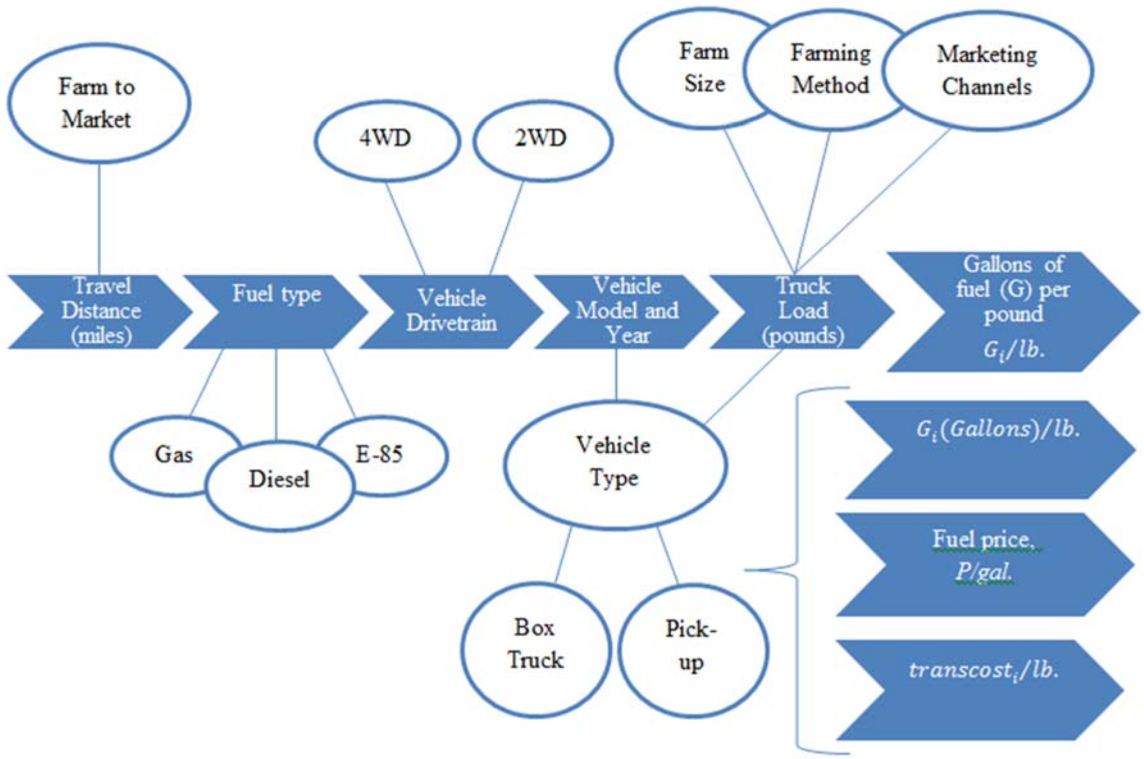

Figure 6. Local Farmer Transportation Energy Use Flow Chart

Chapter V
Comparing Local and Conventional Transportation Fuel Use Efficiencies

Transportation fuel use per 100 pounds of fruits and vegetables delivered to market (*g/cwt.*) is estimated for the 29 surveyed farmers and three conventional scenarios. Figure 7 shows the estimates of *g/cwt.* for each farmer compared with the conventional transportation supply chains. The estimates of *g/cwt.* for the conventional scenarios are labeled and highlighted to indicate the shipping origin.

Approximately 31 percent of the interviewed farmers' *g/cwt.* is below all three conventional transportation scenarios (Table 1). Twenty-one percent of the surveyed farmers' *g/cwt.* is less than the Texas and California thresholds, but require more transportation fuel per unit than the Florida scenario. Seventeen percent of the surveyed farmers' *g/cwt.* is below the California fuel use threshold, but consume more transportation fuel per unit than the Florida and Texas scenarios. Almost one-third of local farmer *g/cwt.* estimates are above the California threshold, indicating that these local farmers are less efficient in transportation than all three conventional scenarios. If local farmer *g/cwt.* is compared only with food shipped from California, 69 percent of the surveyed local farmers are at least as efficient in transporting their products to market as the conventional supply chain. However, if local farmer transportation efficiencies are only compared with fruits and vegetables sourced from Florida, the same proportion of the surveyed local farmers (69 percent) are above the threshold fuel use level for produce shipped from this state.

The estimates on transportation fuel use per cwt. provide a baseline image of the interviewed local farmer transportation energy use efficiencies. The results from the transportation fuel use comparisons show that there is a mix of efficient and less efficient food distribution operations. Because *g/cwt.* is measured using three components – distance to market, MPG, and truckload - *g/cwt.* varies according to the farmer's respective travel distance to market, vehicle fuel economy, and truckload weight. To understand how local farmer *g/cwt*. is related to these three transportation efficiency components, *g/cwt.* is analyzed with respect to each variable in two-dimensional Transportation Efficiency Plots.

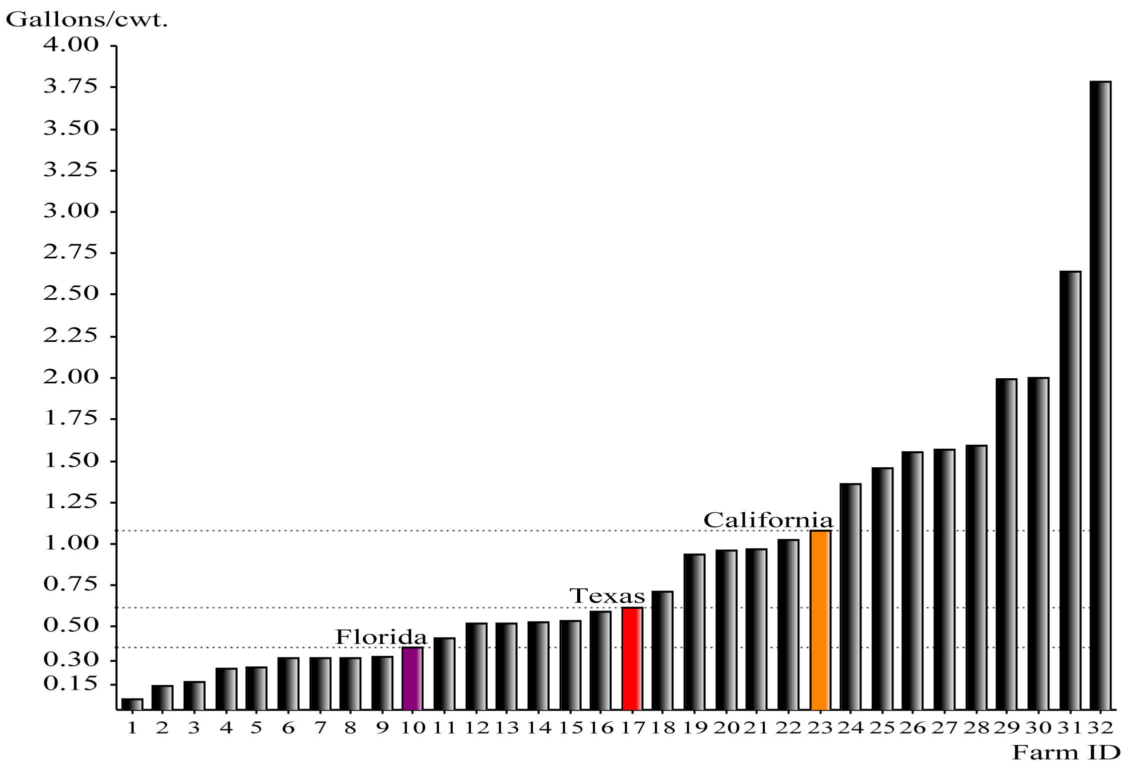

Figure 7. Local vs Conventional Transportation Fuel Use Efficiency

Table 1. Local Farmer Transportation Fuel Use Efficiency Compared to Conventional Scenarios

	Local farmers are more efficient than FL, TX, and CA	Local farmers are less efficient than FL, TX and CA	Local farmers are more efficient than TX and CA only	Local farmers are more efficient than CA only
Quantity	9	9	6	5
Percent	31%	31%	21%	17%

n=29 observations

Transportation Efficiency Plots

Distance to Market and g/cwt.

The Distance Efficiency Plots (Figures 8 and 9) show the relationship between local farmer *g/cwt.* and the two-way travel distance to market in miles. In Figure 8, the three horizontal lines indicate the *g/cwt.* estimates for the conventional transportation scenarios from Florida (bottom line), Texas (middle line), and California (top line). Figure 9 plots the same relationship using the natural log scale of distance. Figure 9 also includes the *g/cwt.* estimates of the three conventional scenarios.[5] In both plots, there is a positive relationship between *g/cwt.* and distance. Holding truckload weight and MPG constant, the farmer farthest from market will consume more gallons of fuel per trip. However, the scatter plots show that local farmer *g/cwt.* varies considerably as travel distance to market increases. The increasing variation is attributable to differences in farmers' truckload weights and vehicle fuel economies. Farmers traveling over 100 two-way miles to market with *g/cwt.* estimates below the California threshold transport

[5] Note that only the one-way distance is used in estimating *g/cwt.* of the three conventional scenarios, whereas the two-way distance is used for local farmer *g/cwt.*

larger truckloads compared to farmers traveling similar distances to market with *g/cwt.* above the California threshold.

On the right-hand side of Figure 8, two farmer transportation cases are highlighted to illustrate the sources of efficiency and inefficiency. The farmer with *g/cwt.* above the California threshold travels more than 150 two-way miles to market, and delivers 900 lbs. of produce using a 12 MPG vehicle. In contrast, the farmer with *g/cwt.* well below the California threshold also travels over 150 miles to market in a similarly low 13.5 MPG vehicle but has a significantly larger truckload weight over 1,500 lbs.

The variation in *g/cwt.* is less for farmers located within 50 two-way travel miles to market. Observations in this portion of the scatter plot display a clustering pattern. However, a farm's proximity to market does not guarantee a lower *g/cwt.* than conventional transportation systems. For an extreme case, consider the isolated observation in the upper left-hand side of the plot. This local producer's farm is located just 25 miles outside of the market, but the farmer uses a vehicle with low MPG and hauls less than 300 lbs. of produce to market. Thus, food miles are an insufficient indicator of local food chain efficiencies, and in particular when farmers have low truckload weights (200-300 lbs.) and poor vehicle fuel economy.

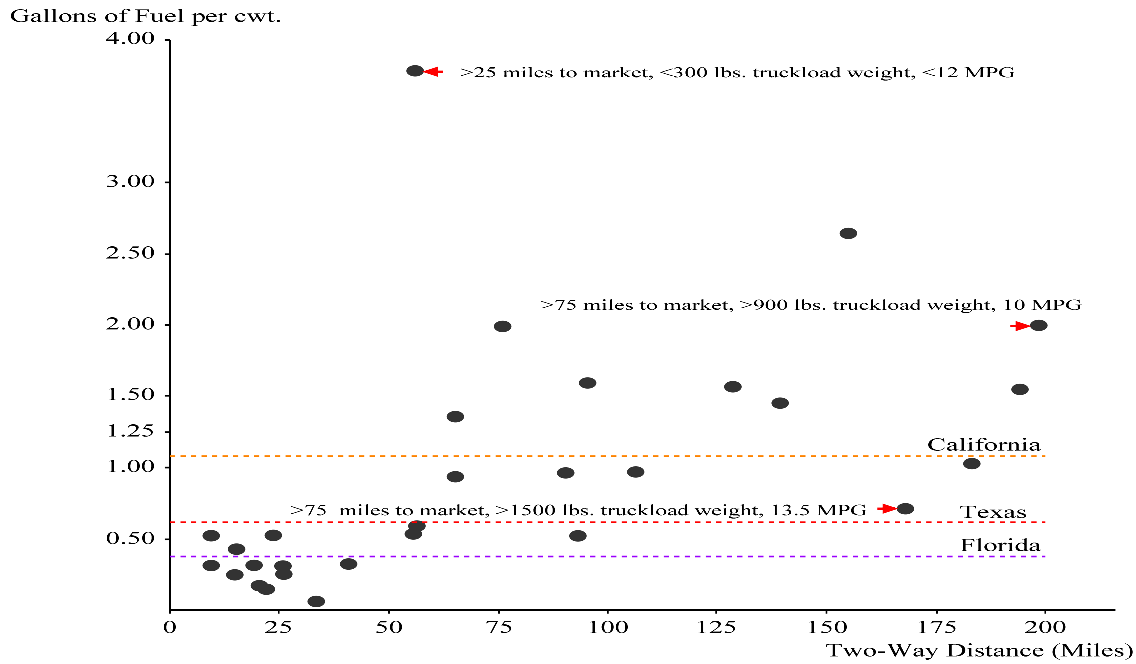

Figure 8. Transportation Efficiency Plot: Distance to Market and g/cwt.

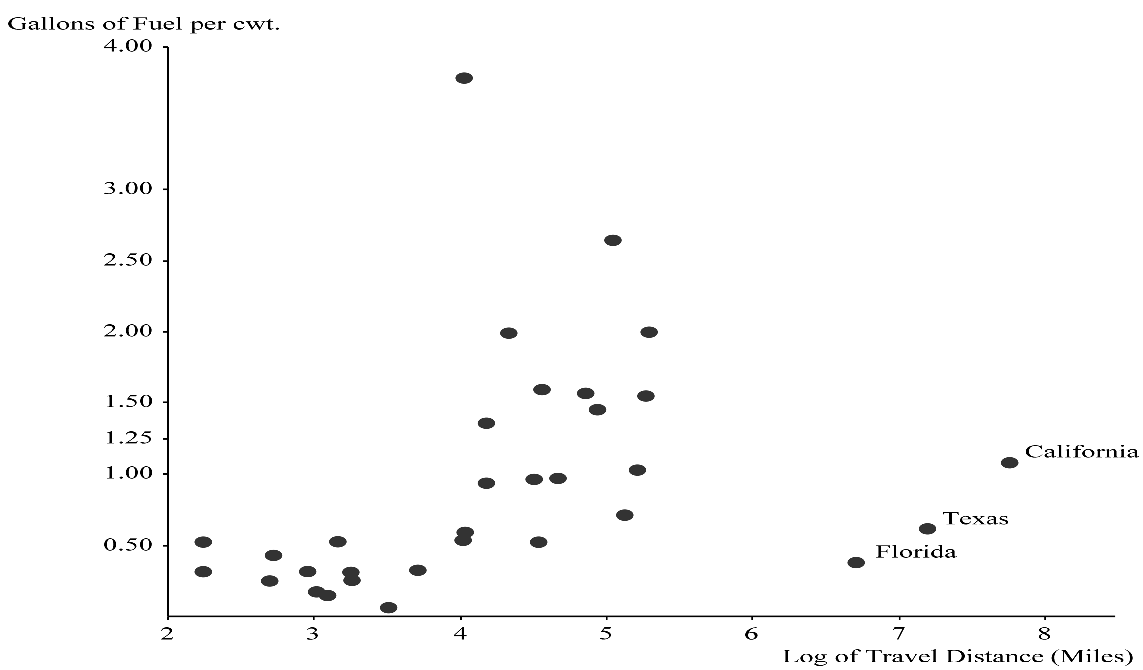

Figure 9. Transportation Efficiency Plot: Log of Distance to Market and g/cwt.

Comparing Local and Conventional Transportation Efficiencies by Travel Distance to Market

The Distance Efficiency Plots provide an alternative way of comparing local and conventional transportation fuel use efficiencies. By dividing farmers into 50 mile segments based on their two-way travel distances to market, Figure 10 indicates that all twelve farmers with travel distances below 50 miles have lower *g/cwt.* estimates than conventional transportation scenarios from Texas and California, while nine of the twelve farmers in this distance range transport their produce to market at least as efficiently as the Florida scenario. These farmers' transportation efficiencies are due primarily to their minimal travel distances to market and less to large truckloads. For example, the median truckload for farmers traveling less than 50 two-way miles to market is 588 lbs., approximately 23 percent below the average truckload weight of the surveyed farmers.

Local farmer competitiveness with conventional supply chains is mixed for farmers traveling between 51-100 two-way miles and over 100 two-way miles to market. Surveyed farmer *g/cwt.* estimates in these travel distance categories are all above the Florida threshold. Five of the nine farmers with two-way travel distances between 51-100 miles have *g/cwt.* estimates below the California threshold, while only three of the eight farmers traveling over 100 two-way miles have *g/cwt.* estimates below the California threshold. The three farmers with *g/cwt.* estimates below the California threshold compensate their longer travel miles with larger truckload weights. Local farmers farther from market can improve their transportation efficiencies by increasing their truckloads or by employing more fuel economic vehicles. However, improving vehicle MPG usually requires using a smaller vehicle, which in turn may constrain vehicle carrying capacity.

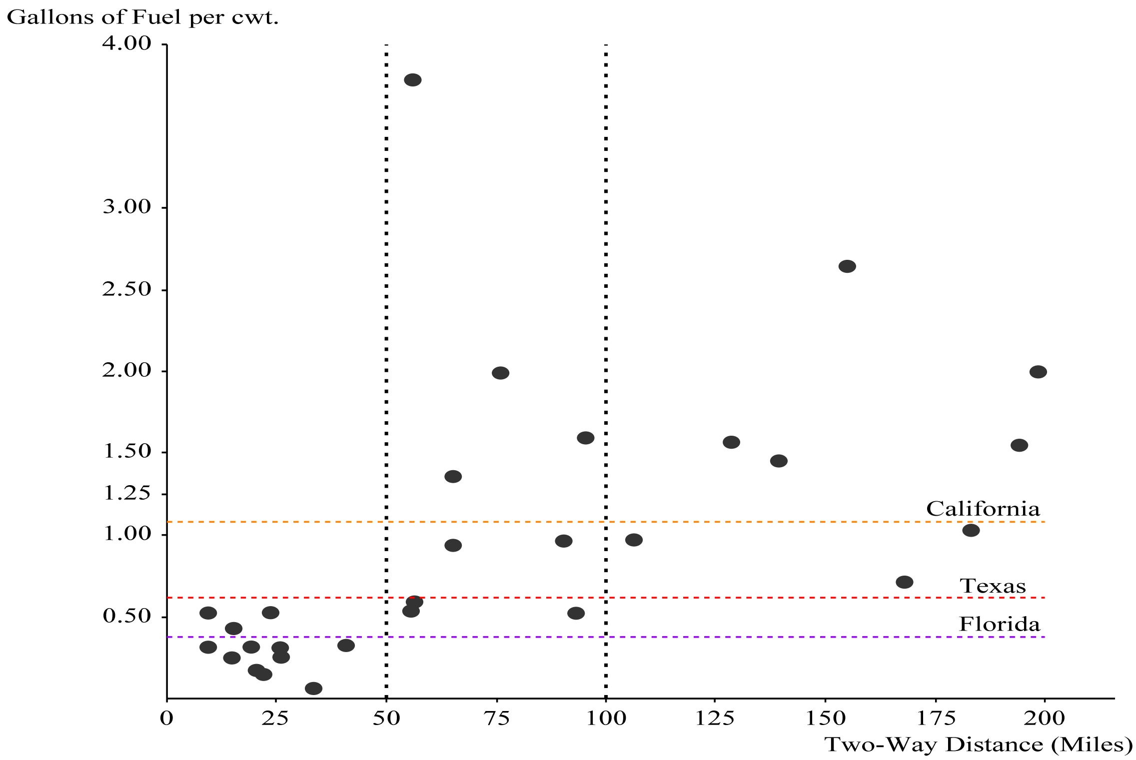

Figure 10. Comparing Local and Conventional Transportation Efficiencies by Travel Distance to Market

Truckload Weight and *g/cwt.*

The Truckload Efficiency Plots (Figures 11 and 12) show the relationship between *g/cwt.* and truckload weights of produce delivered to market. Figure 12 plots *g/cwt.* against the natural log of truckload weights. Given two farmers with equal travel distances and vehicle MPG, the farmer with the larger truckload will have lower *g/cwt*. Larger quantities of produce delivered to market reduces *g/cwt.* because transportation fuel use is spread over more units of product. Thus, on average, as truckload weight increases, *g/cwt.* is expected to fall. In the plots, the inverse relationship between *g/cwt.* and truckload weight is noted.

The Truckload Efficiency Plots help identify the relatively more efficient shipping operations due to differences in the surveyed farmer truckloads. Farmers in the lower left-hand portion of the plot have small truckload weights, but have *g/cwt.* estimates below all three conventional transportation thresholds. These farmers' low *g/cwt.* is due mostly to their minimal travel distance to market and high vehicle MPG. On both extremes of the efficiency plots, two special cases are noteworthy. In Figure 11, the point on the far upper-left represents a farmer that hauls less than 300 lbs. of produce to market. In addition to shipping a small truckload to market, the farmer travels over 50 two-way miles to market in a 10.5 MPG pick-up truck. Thus, the farmer's *g/cwt.* is significantly above the California threshold. In contrast, the farm on the lower right-hand side of Figure 11 hauls 4,050 lbs. of corn to market and is located less than 15 miles from market. In combining large truckloads with short travel distances local farmer fuel use efficiency can be significantly below the conventional transportation scenarios.

However, not all farmers with larger truckloads are competitive with conventional transportation. For example, one particular group of farmers has truckload weights ranging between 650-800 lbs., but their transportation fuel use is well above the California threshold (Figure 13). Despite larger truckloads, these farmers travel more than 100 two-way miles to market in 9-15 MPG vehicles. Given their respective travel miles, their truckload weights are too low to compensate the extra food miles. To contrast an inefficient case with an efficient case, a second farmer cluster is also identified in Figure 13. The farmers have truckload weights between 750-1200 lbs. However, all four farms are within 20 miles of market. Their vehicles are of varying fuel economy. Thus, one potential optimal transportation operation that is competitive with most conventional food supply chains is that farms within 20-25 miles of markets deliver truckloads at least as large as 750-800 lbs.

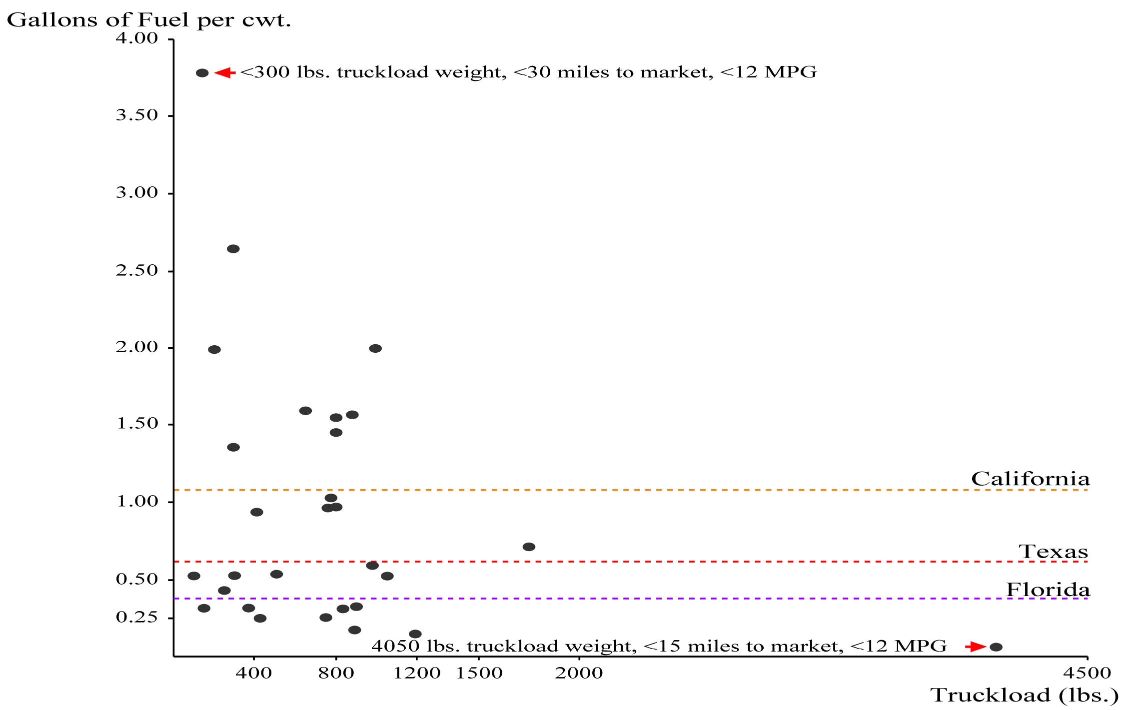

Figure 11. Transportation Efficiency Plot I: Truckload Weight and g/cwt.

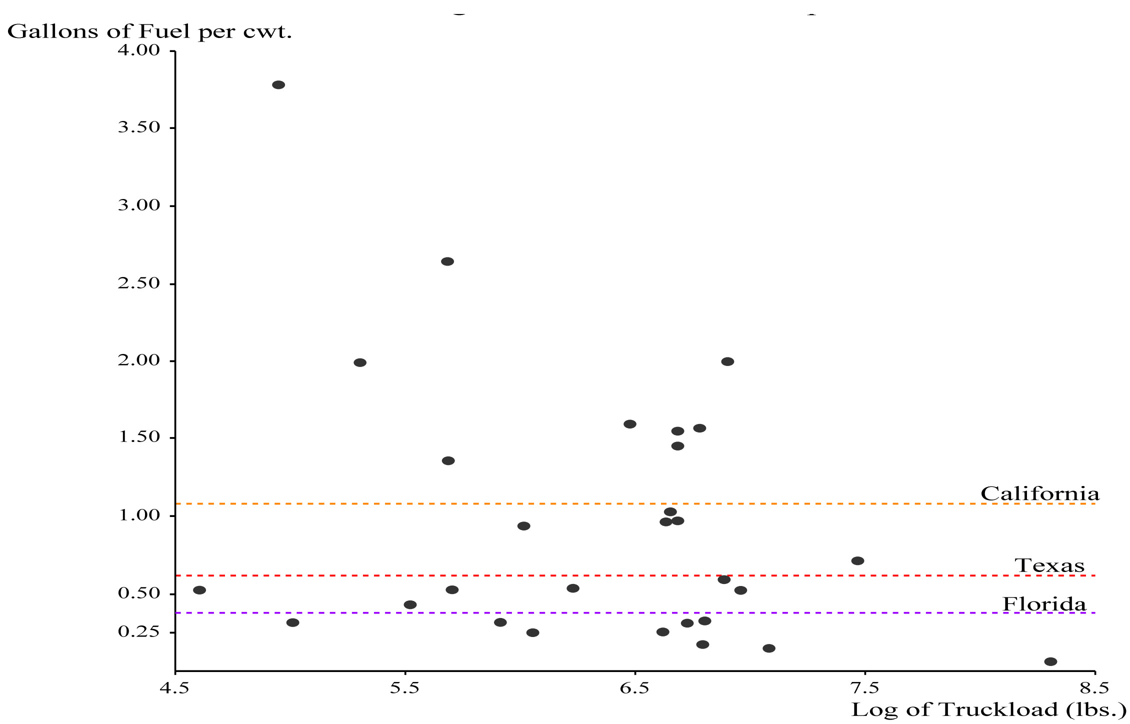

Figure 12. Transportation Efficiency Plot I: Log of Truckload Weight and g/cwt.

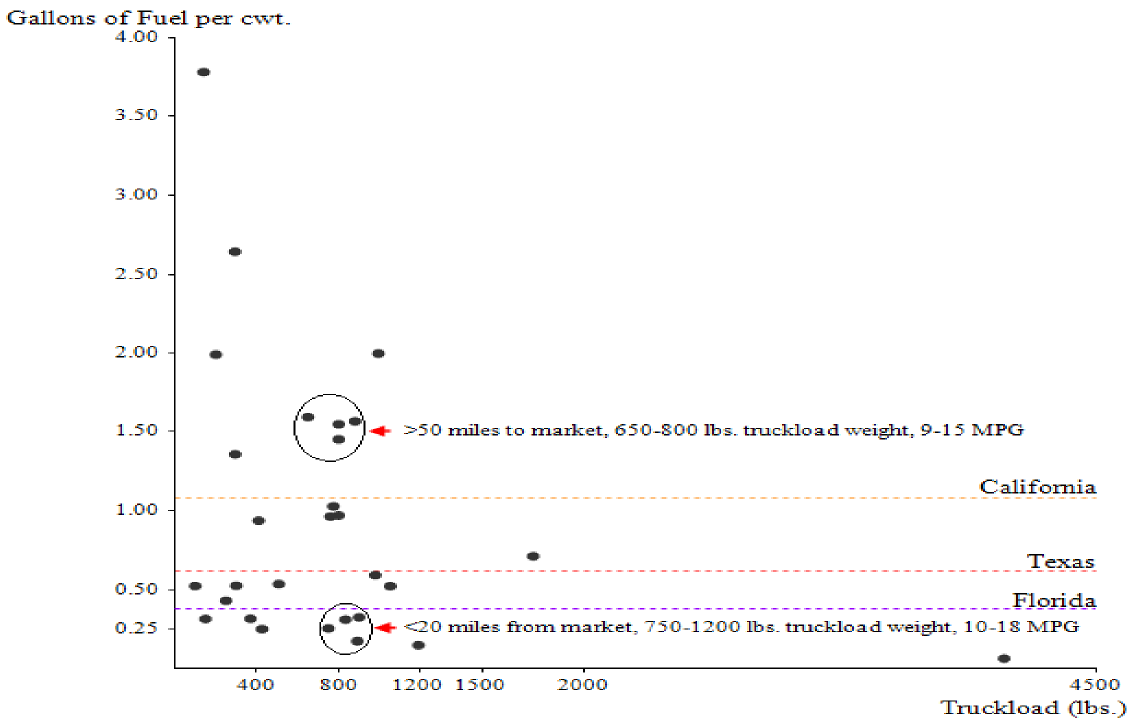

Figure 13. Transportation Efficiency Plot II: Truckload Weight and g/cwt.

MPG and *g/cwt.*

Holding distance and truckload weight constant, the farmer with highest vehicle MPG will have lower transportation fuel use per unit of produce shipped. In observing the MPG Efficiency Plot (Figure 14), the inverse relationship between MPG and *g/cwt.* is observed but is somewhat less defined. At least two outlier transportation cases in the MPG Efficiency Plot have significant interpretative value. On the right-hand portion of the efficiency plot, two farmers' *g/cwt.* are well above the California threshold. In each case, farmer vehicle MPG is between 18-20 MPG, higher than most other farmer vehicles. However, the benefit of using more fuel economic vehicles is reduced substantially because both farmers ship less than 300 lbs. of fruits and vegetables to market. In addition, each farmer's travel distance to market is considerably

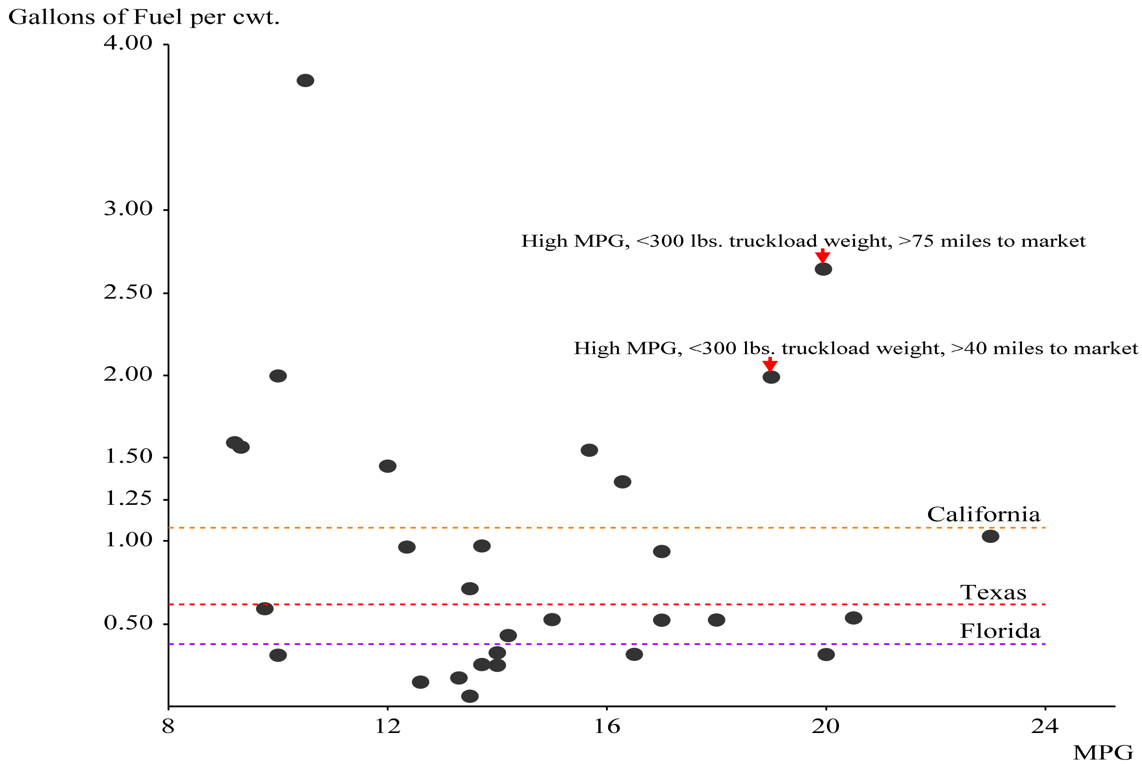

Figure 14. Transportation Efficiency Plot: MPG and g/cwt.

high given their small truckload weights. Although local farmer vehicles may have double or triple the fuel economy of conventional semi-trucks, if truckload weights of local farmers are only 300 lbs. and travel distance to market is more than 50 two-way miles to market, local farmer *g/cwt.* is often inferior to the conventional supply chain. If farms with fuel efficient vehicles and long travel distances can increase their truckload weights, transportation fuel use efficiencies will be similar to most conventional transportation scenarios. However, as stated above, because shipping 1,000-1,500 lbs. of produce typically entails using a larger vehicle of low vehicle fuel economy, such as a box truck, it may be infeasible to have high vehicle MPG and truckload weight simultaneously.

The Transportation Efficiency Plots help analyze how *g/cwt.* varies with distance to market, truckload weight, and MPG, and in evaluating efficient and inefficient transportation operations among the surveyed local farmers. Greater scrutiny of special cases instructs as to how local farmer transportation inefficiencies occur. Findings from comparing local and conventional transportation efficiencies and the Transportation Efficiency Plots corroborate the findings of Wallgren (2006), Mariola (2008), King et al. (2010), and Mundler and Rumpus (2012), all of whom suggest that the local food supply chain is often less efficient than conventional, large-scale food distribution due to the small transportation scales of local food supply chains. In their study comparing conventional, intermediate, and local food supply chains, King et al. (2010) conclude that conventionally transported food often uses less fuel per unit than locally grown and distributed food due to the economies-of-scale of conventional food supply chains. Yet, as was shown in the Hotelling Spatial Competition Model, despite hauling less weight, local farmers can still potentially distribute food more efficiently than the conventional supply chain if food miles are sufficiently low for local producers. Findings from the Transportation Efficiency Plots support the study by King et al. (2010) and the theoretical model of Hotelling (1929), as surveyed farmers with the shortest travel distances also tend to have lower *g/cwt.* In contrast, farmers farther from market are often not competitive with the three conventional transportation scenarios because their truckload weights are insufficient to make up for the added travel distance to market.

Chapter VI
The Impact of Scale: Modeling Truckload Deliveries to Market

There is growing interest in scaling-up local food production and distribution so that it has similar efficiencies to the conventional food supply chain (Day-Farnsworth et al. 2009; Bittner et al. 2011; Day-Farnsworth and Miller 2014). Day-Farnsworth and Miller (2014) affirm that several farmers delivering less-than-full truckloads to multiple locations is often less efficient than the conventional food distribution system. The authors discuss ways in which regional food distribution networks can obtain greater scale eficiencies. Some authors claim that local food supply chains need to improve significantly before they can compete with conventional food supply chain systems, especially if fuel prices were to rise in the future (King, Gómez, and DiGiacomo 2010).

While for a given farmer travel distance to a farmer market is exogenously determined, vehicle fuel economy (MPG) and truckload weight delivered to market are both transportation efficiency factors that are in the farmer’s control. In the case of truckload weight, variables related to scale, such as farm and vehicle size are expected to impact the amount of produce farmers deliver to the farmer market. Farmers hauling larger truckloads will have improved transportation fuel use efficiencies.

Case studies related to scaling-up local food distribution are most often oriented toward farm produce aggregation and establishing contractual relationships with local institutions, such as hospitals and schools, so that deliveries can be made on a consistent basis using larger vehicles (Day-Farnsworth et al. 2009; Diamond and Barham 2012; NOFAVT 2012). However, not all farmers are interested in product aggregation, and in such cases, local producers may need to increase their respective operation scales to improve their transportation fuel use efficiency.

Using the survey data collected on local farmers' transportation methods in delivering produce to nearby farmer markets, an ordinary least squares (OLS) regression model tests hypotheses on how farm and vehicle size affect truckload weight.

The variables for analysis and their description are provided in Table 2. The dependent variable, *truckload*, indicates the weight, in pounds, of mixed fruits and vegetables transported to the farmer market. The regression model uses five regressors. The variable, *acres*, refers to the number of acres planted in fruits and vegetables for sale at the local farmer market. *acres* is a scale variable describing production size and is hypothesized to have a positive effect on the quantity of produce delivered to market. The correlation between *acres* and the dependent variable, *truckload*, is 0.82.

Table 2. Variables for Truckload Weight OLS Model

Dependent Variable	Description
truckload	The truckload weight mixed fruits and vegetables shipped to the farmer market, measured in pounds (lbs.)
Covariates	
acres	The number of acres planted in fruits and vegetables for local food market sales
organic	Organic farming methods (yes=1) (i.e. USDA Certified Organic or Certified Natural Grown)
acresorg	Interaction term between *acres* and *organic*
boxtruck	Farmer delivers produce in a box truck (yes=1)
mktchannels	The number of marketing channels used per week

The binary variable, *organic*, controls for production practices and indicates whether a farmer uses organic or conventional farming methods, such as synthetic fertilizers and non-organically certified insecticides and pesticides. Preliminary data exploration shows that the average truckload size is larger among conventional farmers than for organic farmers, whose median truckloads are 800 and 508 pounds, respectively. The interaction term, *acresorg*, takes into account the difference in the effect that increases in farm size may have on conventional and organic farmers' truckload shipping weights.

The categorical variable, *boxtruck*, measures the impact on farmers' truckload weights when the farmer uses a box truck to transport fruits and vegetables to market. This binary variable models how scaling-up vehicle size affects the surveyed farmers' shipping weights, controlling for the other regressors. Median truckload size for *boxtruck* farms is 979 pounds, while median truckload weight for pick-up trucks is 418 pounds.

The last regressor in the OLS model is *mktchannels* and accounts for the number of marketing activities used per week (i.e. multiple farmer markets, CSA shares, on-site farm stands, restaurants and wholesale, pick-your-own). Farmers with local food sales tend to use more than one marketing channel for their fresh produce (Lawless et al. 1996; Uva 2002; LeRoux et al. 2010). Farms with multiple marketing strategies may be larger farms, and thus, have greater quantities of produce for sale at the farmer market. On the other hand, if a given farm has several marketing channels, it may use the farmer market as a way of promoting its other marketing activities, such as pick-your-own produce or sales to restaurants. In this case, the farm may bring less produce to market. Thus, the sign on the coefficient of this variable could either be positive or negative.

The linear regression is:

$$truckload_i = \beta_0 + \beta_1 acres_i + \beta_2 organic_i + \beta_3 acresorg_i + \beta_4 boxtruck_i + \beta_5 mktchannels_i + e_i$$

where β_0 is the intercept, β_2 to β_5 are the coefficients to be estimated, and e_i is the error term assumed to be independently and identically distributed (i.i.d) with a mean of zero and constant variance.

Model Results

The estimated model's coefficients, *t*-statistics, standard errors, p-values, and overall model significance are reported in Table 3. The Breusch-Pagan Test for heteroskedastic errors (Breusch and Pagan 1979) is not significant. The test result is also given in Table 3. Three of the five variables are statistically significant below $\alpha < .01$.

The production scale variable, *acres*, and the interaction term, *acresorg,* are respectively significant at the 1 percent level, indicating that there is a non-trivial difference in the marginal impact on truckload weights for an additional acre planted in fruits and vegetables among farmers using conventional and organic production methods. Controlling for vehicle type and marketing channels, an additional acre planted in fruits and vegetables for a conventional farmer (*organic* = 0) yields approximately 129 lbs. more produce shipped to market, on average. The marginal effect of *acres* on truckload weight for an organic farm (*organic* = 1) is approximately 9 lbs., 120 lbs. less than the marginal effect for conventional farmers.

The binary indicator variable, *organic*, is not significant. Because the coefficient on *acresorg* is negative, the difference in average truckload weights between the two farming methods diminishes as the number of acres planted in fruits and vegetables increases. For farms of 1.75 acres, the average truckload weight difference between conventional and organic farms is zero, holding *boxtruck* and *mktchannels* constant. Thus, organic farms with less than 1.75 acres of production ship more produce to market than the conventional farmers surveyed, *ceteris paribus*. For farms larger than 1.75 acres, local farmers using conventional production practices transport heavier truckloads to market, holding other variables constant (Figure 14). This result suggests that there may be diminishing returns to increasing farm size for the surveyed organic farmers compared to the interviewed farms using conventional farming practices. The marginal effect of *acres* on *truckload* increases at a greater rate for the conventional farmers interviewed. These results are consistent with the theoretical cost function from the Conceptual Framework, where California conventional farmers are assumed to have increasing returns to scale in production.

Table 3. Regression Output for Truckload Weight (lbs.) Regression

Variable	Coefficient	*t*-statistic (Standard error)	*P*-value
intercept	215.56	1.915 (112.54)	0.068
acres	128.67	10.623 (12.11)	0.0000
organic	209.65	1.503 (139.48)	0.146
acresorg	-119.65	-4.909 (24.37)	0.0000
boxtruck	574.81	4.892 (117.49)	0.0000
mktchannels	-30.95	-0.553 (55.96)	0.586

n=29
Standard Errors in Parentheses
R^2: 0.895, R^2 Adjusted: 0.8654, R^2 Press: 0.6822
F-Statistic (df: 5,23): 37.01
P-value: 0.0000
Breusch-Pagan Test for Heteroskedastic Errors: 1.4843
P-value: 0.9149
df: 5

Although *organic* is not statistically significant, a joint significance *F* test is carried out to test whether truckload shipments are the same among conventional and organic farmers when acres planted are equal in both farming groups. The null and alternative hypotheses, respectively, are:

$$\text{H}_0\text{: } \begin{pmatrix} \textit{organic} \\ \textit{acresorg} \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

$$\text{H}_A\text{: } \textit{organic or acresorg} \neq 0$$

The F statistic is 13.8 with numerator $df = 2$ and denominator $df = 23$ (Wooldridge 2012). This is above the F critical value (= 5.66) at the 1 percent significance level. Thus, truckload weights are different for organic and conventional farms of the same size. The result suggests that conventional farmers may have some production advantages over the organic growers of fruits and vegetables.

The binary indicator variable *boxtruck*, is statistically significant at the 1 percent significance level. Farmer vehicle type is an important variable in determining farmer truckload weight. Controlling for all other variables, a farmer using a box truck carries, on average, 575 lbs. more produce to market than a farmer using a pick-up truck in transportation. Thus, in order to improve east Tennessee local food transportation efficiencies, scaling-up vehicle sizes to allow for larger truckload shipments may have a considerable impact. To illustrate, a local producer that farms 4 acres in fruits and vegetables, uses conventional agricultural techniques, has two alternative marketing channels, but transports produce to the farmer market in a pick-up truck is expected to ship, on average, 668 lbs. of produce. If this same farmer were to own a box truck, truckload weight would nearly double to 1,243 lbs.

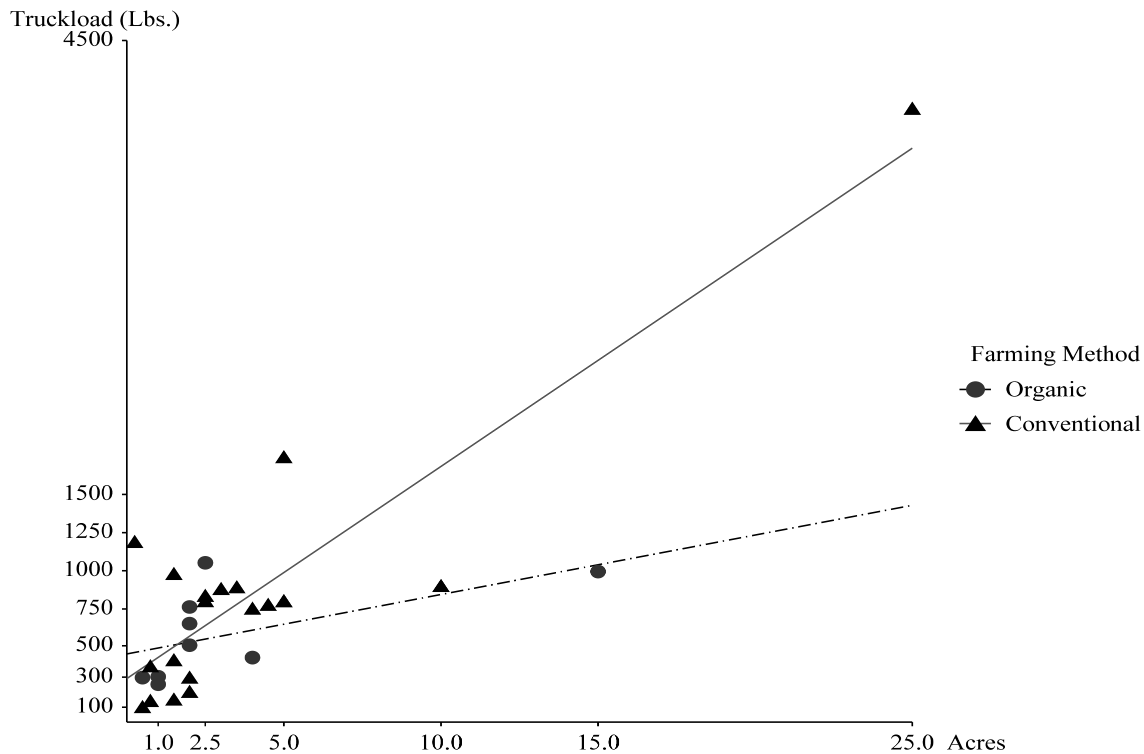

Figure 14. Truckload Weight and Acres Planted by Farming Method

Using a box truck alone does not necessarily enable a farm to transport larger loads to market. The production scale must also be adequately large to take advantage of the added carrying capacity. The average number of acres in fruit and vegetable production for the 9 farmers using a box truck is 6.25 acres, whereas the remaining 20 local producers with pick-up trucks plant 2.75 acres. The coefficient for *mktchannels*, which accounts for the number of different marketing activities that a farm participates in weekly, is not significant.

Discussion of Model

Because the sample is not random, the regression results cannot be used to make inferences about the broader population of farmers transporting food to local markets. The model only pertains to the 29 surveyed farmers. OLS is implemented as a supplementary analysis and to test hypotheses related to the interviewed farmers' truckload weights. The in-person format of the survey during market hours reduces the number of questions that can be formulated during an interview session.

The regression results show that organic farmers producing less than 1.75 acres of fruits and vegetables deliver larger truckloads to the farmer market compared to conventional farmers with the same farm size, *ceteris paribus*. However, as acreage in fruits and vegetables increases beyond 1.75 acres, the effect of *acres* is significantly larger for conventional farms compared to organic farms. To test whether the 1.75 acre point-estimate is different from zero, a nonlinear restriction is formed by taking the ratio of the coefficients corresponding to *organic* and *acresorg* (Gregory and Veall 1985):

$$H_0: \frac{\beta_2}{\beta_3} - 1.75 = 0$$

$$H_A: \frac{\beta_2}{\beta_3} - 1.75 \neq 0$$

The delta method is used obtain the point-estimate's standard error, and in turn, compute the *t*-statistic (Wooldridge 2010). At the 10 percent level, the 1.75 acre threshold is different than zero, $\frac{1.75}{0.990} = 1.769$. Because the OLS equation models truckload weight rather than production, further research investigating whether there is a relationship between acres and on-farm production of fruits and vegetables can help inform whether conventional farms are more productive than the organic farms as farm scale increases.

Due to the seasonality of production, transportation efficiency likely varies throughout the marketing year. Fruits and vegetables produced in the summer months are considerably bulkier compared to the lighter weight vegetable crops of the fall and spring. Therefore, in the summer, there may be considerable efficiency gains by using a vehicle with greater carrying capacity, as production tends to be at its peak during this time period. One question is whether the benefit of transporting produce in larger box trucks during the summer months has the same benefit during the early and late production cycles. Future research could investigate the nature of this seasonality and how it impacts local food transportation efficiencies.

Despite the issue of seasonality, the model provides a quantifiable example of the potential impact of scaling-up local food production. While some authors (Day-Farnsworth et al. 2009; Diamond and Barham 2012) refer to the significance of scaling-up the local food supply chain via farmer cooperatives and food hubs, in this study, the impact of increasing production and distribution scale is analyzed on the micro-setting for a single farm. The two scale variables, *acres* and *boxtruck*, which account for the influence of production and distribution scales on farmer truckload weights, both test significant and their respective coefficients are non-trivial in size. Therefore, the OLS results suggest that increasing farm and vehicle sizes can help improve local food transportation fuel use efficiency by increasing truckload weight.

Chapter VII
Comparative Advantage in Production vs Locational Advantage in Transportation

Local Food Transportation Sensitivity Analysis

Whereas fruit and vegetable farmers in distant geographic regions such as California have significant comparative advantages in production and higher transportation efficiencies due to economies-of-scale, farmers selling food locally have locational advantages in transporting their produce to market if their transportation costs per unit are lower than similar products delivered over long distances. Just as Hotelling's Competitive Spatial Model suggests that location alone can give marketing advantages to farmers selling food baskets in their most proximate market areas (McCann 2013), analysis of the surveyed east Tennessee farmers' *g/cwt.* has similarly indicated that farmers with the shortest travel distance tend to transport their products to market more efficiently than the conventional food supply chain, despite their relatively small truckloads. Additionally, the Hotelling framework indicates that if east Tennessee farmers can improve their production and transportation efficiencies, farmers can expand their market area, and thus, extend the geographical bounds of their locational advantage.

Using the truckload regression coefficients and average MPG estimates of farmers' vehicles, a sensitivity analysis is conducted to observe how variations in truckload and vehicle fuel economy affect local farmers' locational advantages in the delivery of fruits and vegetables to market. Given truckload weight and vehicle MPG, it is possible to observe the maximum travel distance to market before farmers lose their locational advantage in transportation over conventionally transported food in terms of fuel use per unit of produce shipped. A farm's travel distance threshold is the maximum travel distance to market before the local farmer's transportation fuel use per unit exceeds that of long distance, conventionally transported fruits and vegetables.

As indicated earlier, there is statistical evidence that the surveyed farmer truckload weights are associated with the number of acres planted in fruits and vegetables, farming method, vehicle size, and the number of alternative marketing channels the farmer uses per week. Similarly, vehicle fuel economy (MPG) is contingent on factors such as the vehicle year and model, fuel type, and drivetrain. In the sensitivity analysis, the production and distribution scale variables, farm size and vehicle type, are varied to show how the travel distance threshold changes when these parameters are varied.

Table 4 displays the estimated truckload weight and MPG for the three scenarios. Because nearly 70 percent of the surveyed farms use conventional farming methods in production, all three cases assume that the farmers use conventional farming practices. Aditionally, to simplify the scenario analyses, *mktchannels* in each scenario is fixed at the average of 2 marketing channels. Scenario 1 models the average farm using conventional farming practices and a pick-up truck for transportation. The scenario 1 farm plants 2.25 acres. Scenario 2 models the average local farmer using conventional farming methods that delivers produce to markets in box trucks. The scenario 2 farm plants 2.75 acres, slightly more than the scenario 1 farm. Lastly, the scenario 3 farm increases its production scale considerably relative to the first two scenarios. The third scenario models a farm with 6 acres in production and a box truck for transportation.

Farmer vehicle fuel economy (MPG) in each scenario is determined by categorizing farmer vehicles by vehicle type (pick-up or box-truck), drivetrain (2-WD or 4-WD) and fuel type (gas or diesel). Among the surveyed farmers using pick-up trucks and box trucks for transportation, the 2-WD, gas-operated pick-up and the the 2-WD, gas-operated box truck are the most frequently observed vehicles in their respective vehicle model groups. The average MPG estimates for both vehicle profiles are used in the scenario analysis. In scenario 1, the pick-up truck has a fuel economy of 18.6 MPG, whereas in scenarios 2 and 3, the box truck has a vehicle fuel economy fixed at 10.7 MPG.

Table 4. Truckload and MPG Estimates by Varying Farm Size and Vehicle Type

Scenario	Number of Acres	Farming Method	Vehicle Type	Drivetrain and Fuel	Truckload (lbs.)	Average MPG
1	2.25	Conventional	Pick-up	2-WD, Gas	443	18.6
2	2.75	Conventional	Box Truck	2-WD, Gas	1082	10.7
3	6	Conventional	Box Truck	2-WD, Gas	1501	10.7

Sensitivity Analysis Results

By combining the estimates for truckload weight, MPG, and travel distance to market, estimates for transportation fuel use per cwt. are derived for each scenario. Figure 15 graphically represents the three scenario's two-way travel distance thresholds.[6] The line intersections denote the maximum travel distance to market beyond which local farmers consume more gallons of fuel per unit relative to conventionally transported food from Florida, Texas, and California. Delivering fresh produce from these locations requires 0.38 *g/cwt.*, 0.62 *g/cwt.*, and 1.08 *g/cwt.* for Florida, Texas, and California, respectively. These threshold levels are demarked by three colored dashed lines in Figure 15. The axis of Figure 15 represents the farm shipping point (i.e.

[6] Two-way travel distances are included in the local farmer *g/cwt.* estimates, whereas one-way travel distances are assumed for the three conventional scenarios (Kaplin 2011). Conventional semi-trucks transporting fruits and vegetables over long distances typically return with full truckloads of other products to maximize efficiency. The interviewed local farmers, on the other hand, did not report any backhaul activity.

the farm gate). As the farmer travels away from the farm gate, transportation mileage to deliver fruits and vegetables to market increases. As miles-to-market rises, larger quantities of fuel are needed to transport produce to market. The slope of the line in each scenario depends on the modeled farmer production and vehicle characteristics. The slopes flatten as production and transportation scales increase.

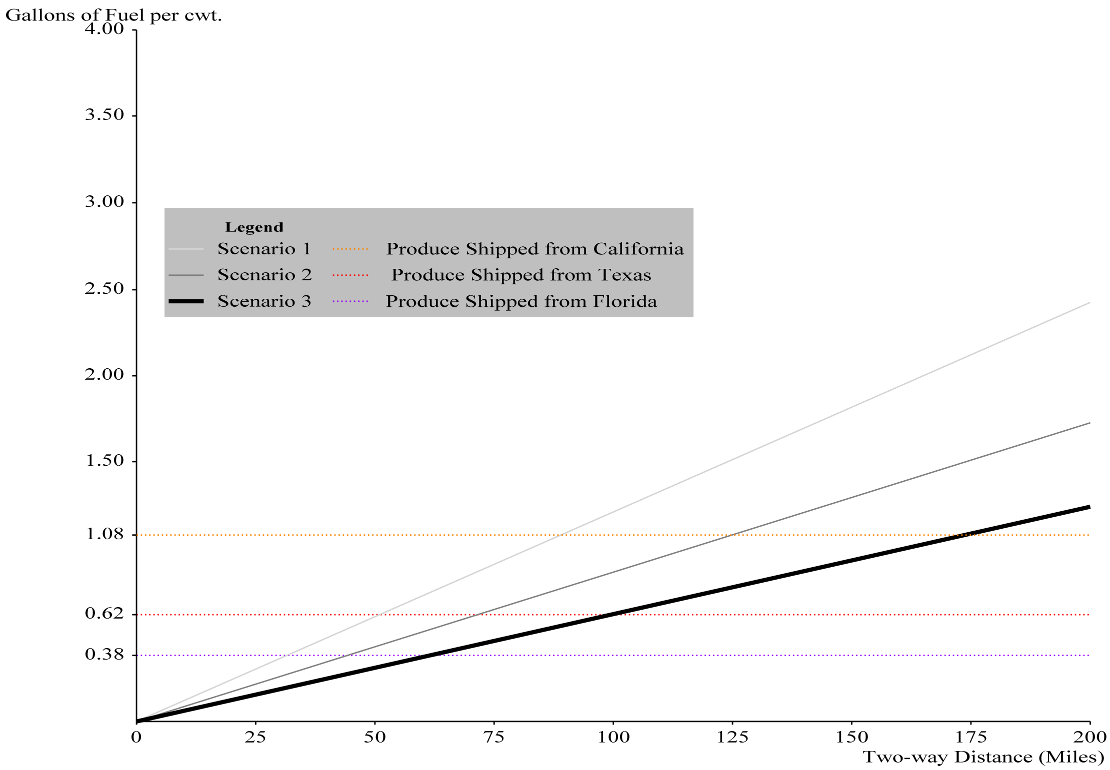

Figure 15. Travel Distance Thresholds

The farm in scenario 1 can travel the fewest miles before surpassing the travel distance thresholds of the three conventional transportation scenarios (Table 5). Acres planted in fruits and vegetables are relatively low (2.25 acres) and the farmer uses a pick-up truck to deliver produce. It follows that truckload weight is also low, 443 lbs. The small truckload is compensated somewhat by using a more fuel efficient vehicle relative to scenarios 2 and 3. The farmer can travel up to 15.5 (31), 25.5 (51), and 44 (88) one-way (two-way) miles and maintain a locational advantage in transportation over produce shipped from Florida, Texas, and California, respectively. The results from scenario 1 suggest that farms with small truckloads should use a more local marketing strategy– within 15-45 miles of their targeted market. In doing so, farmers with small scale production and transportation scales can maintain a locational advantage over most conventional food supply chains with respect to their transportation fuel use per unit.

Table 5. Scenario Results for One-Way and Two-Way Break-Even Travel Distance Thresholds

	Conventional Shipping Points Break-Even Mileage Marker					
	Florida (g/cwt. = 0.38)		Texas (g/cwt. = 0.62)		California (g/cwt. = 1.08)	
Scenario	One-Way	Two-Way	One-Way	Two-Way	One-Way	Two-Way
1	15.5	31	25.5	51	44	88
2	22	44	35.5	71	62.5	125
3	30	60	49.5	99	86	172

In scenario 2, acres planted in fruits and vegetables increase by 0.5 acres, from 2.25 to 2.75 acres. However, the farmer now uses a box truck for transportation. The farmer is able to haul a significantly larger truckload to market (1,082 lbs.) compared to scenario 1 because the farmer's carrying capacity has expanded. However, in using a larger vehicle, average fuel economy is reduced to 10.7 MPG. The farm in scenario 2 can travel up to 22 (44), 35.5 (71), and 62.5 (125) one-way (two-way) miles and maintain a locational advantage in transportation relative to produce shipped from Florida, Texas, and California, respectively. Comparing the threshold travel distance boundaries of scenarios 1 and 2, the break-even mileage marker is pushed out several miles in scenario 2. The farmer can travel an additional 18.5 miles (one-way) before eclipsing the travel distance threshold of conventional food produced and transported from California. Farms with the production and vehicle characteristics of the farmer in scenario 2 have a longer travel radius in which they can deliver their produce before *g/cwt.* exceeds conventional supply chain efficiency levels. In summary, scenario 2 shows that increasing truck size improves local food distribution efficiencies.

The third scenario considers a farm with scaled-up production and vehicle size. The farm plants 6 acres in fruits and vegetables and transports produce in a box truck. The farmer ships an estimated 1,501 lbs. of produce to market. By increasing its production and transportation scales, the farm in scenario 3 transports its produce almost twice as far as the farm in scenario 1 before its *g/cwt.* surpasses the travel distance thresholds of the three conventional scenarios. The farm in scenario 3 can travel 86 miles (one-way) from the farm gate to market before losing its locational advantage over produce imported from California. The farmer in scenario 1, on the other hand, can travel only 44 miles (one-way) before its *g/cwt.* exceeds the California threshold.

Just as the theoretical Hotelling Competitive Spatial Model (1929) shows that improving east Tennessee farmers' transportation efficiencies rotates their transportation cost curves downward, giving local farmers increased market area over their California competitors, results from the sensitivity analysis similarly show that by increasing farmers' truckloads, and in turn, transportation fuel use efficiencies, the competitive threshold travel distances are also extended. If the surveyed local farmers' production costs are assumed to be equal to conventional farmers' production costs, the sensitivity analysis closely represents the effect on local farmers' market area by improving their transportation efficiencies, as the only factor differentiating the final price consumers pay per cwt. of fruits and vegetables depends on local and conventional farmers' respective transportation fuel use efficiencies. However, as signaled in the Conceptual framework, a more realistic assumption is that conventional farmers have comparative advantages in production, and therefore, lower production costs, meaning that the threshold travel distances found in the sensitivity analysis may be somewhat inflated. Additionally, the analysis does not account for any potential changes in the final price paid by consumers as local farmers increase their transportation efficiencies. In the Hotelling Model, a downward rotation of east Tennessee farmers' transportation cost curves decreases the price of fresh produce baskets at and below the east Tennessee market area and increases east Tennessee farmer profit. The sensitivity analysis, on the other hand, makes no assumptions regarding the changes in producer welfare or in the alterations of local fruit and vegetable prices as local farmer transportation fuel use efficiency increases.

Geographical Mapping of the Travel Distance Thresholds

Figures 16, 17, and 18 provide a geographical representation of the travel distance thresholds of the three scenarios. The downtown farmer market in Knoxville, TN is designated as the terminal point for shipments of locally and conventionally grown produce. The triangles indicate the surveyed farm locations. The three colored areas of the maps represent competitive transportation zones (CTZs) from which the local farmer can ship products to market and have a locational advantage in transportation over at least one of the three long distance conventional supply chain scenarios. The size of the CTZ is determined by the modeled farmer's transportation efficiency, which is in turn affected by the respective truckload weight and vehicle MPG estimates presented in the scenario analyses. Therefore, each map is interpreted in light of the production and distribution scales used in the respective scenarios.

The purple-colored area signals the geographical space in which a farm can be located and consume less than or equal to 0.38 *g/cwt.*, the transportation fuel use threshold for fruits and vegetables shipped conventionally from Florida to the downtown market. Any farm located inside the purple CTZ with the same truckload weight and vehicle MPG estimates as the modeled farmer delivers fruits and vegetables to market at least as efficiently as the conventional transportation scenarios from Florida, Texas, and California. Similarly, the red CTZ indicates the geographical area in which a farm can ship its produce to market and use less than or equal to 0.62 *g/cwt.*, the transportation fuel use threshold for produce shipped from Texas to the downtown market. Farms located inside the red CTZ with identical truckload weights and vehicle MPG as the modeled farmer delivers produce to market at least as efficiently as conventionally transported food from Texas and California. The yellow CTZ demarks the geographical space in which the modeled farm can deliver produce to market and use less than or equal to 1.08 *g/cwt.*, which corresponds to the transportation fuel use efficiency for fresh produce shipped conventionally from California to the market center. If the farm is located outside of all three CTZs, the modeled farm's transportation fuel use exceeds the *g/cwt.* of the three conventional transportation scenarios.

Localized and Regionalized Marketing Strategies

Scenario 1 models the local farmer with a small farm size, pick-up truck, and truckload. For the small scale farmer, nine of the surveyed farms are located outside of all three CTZs. Although local farmers travel fewer miles to market relative to the travel distance of conventionally sourced produce, if the scale of production and distribution of local farmers is not sufficiently large, the geographical scope of local food's locational advantage in transportation is significantly reduced. Because the scenario 1 farm has small production and distribution scales, the travel distance to market must be low in order for the farmer's *g/cwt.* to not surpass the threshold fuel use levels of conventionally transported produce. Farms located roughly one county outside of the downtown market can compete on a transportation fuel use basis with produce shipped from California. Therefore, such small scale farms must have a highly localized marketing strategy to achieve comparable transportation efficiencies with conventional food distribution networks.

In scenarios 2 and 3, the production and distribution scales are increased, and in turn, farmers deliver larger truckloads of fresh produce to market. The increase in production and distribution scales allow local farmers to significantly expand the geographical range across which fresh produce can be delivered to the downtown market before *g/cwt.* exceeds the conventional transportation travel distance thresholds. Whereas only six farms in scenario 1 are located inside the purple CTZ, the number is increased to 10 and 14 farms in scenarios 2 and 3, respectively. In scenario 3, truckload weight increases to 1,501 lbs. and only one surveyed farm is excluded from the CTZs. Farms hauling more weight (i.e. 1,000-1,500 lbs.) can deliver their produce to market from two or three counties outside of the downtown market and maintain their locational advantage over conventional food supply chains. Scaled-up farmers have the opportunity to market fruits and vegetables in a more "regional" sense by traveling up to 86 one-way miles to market.

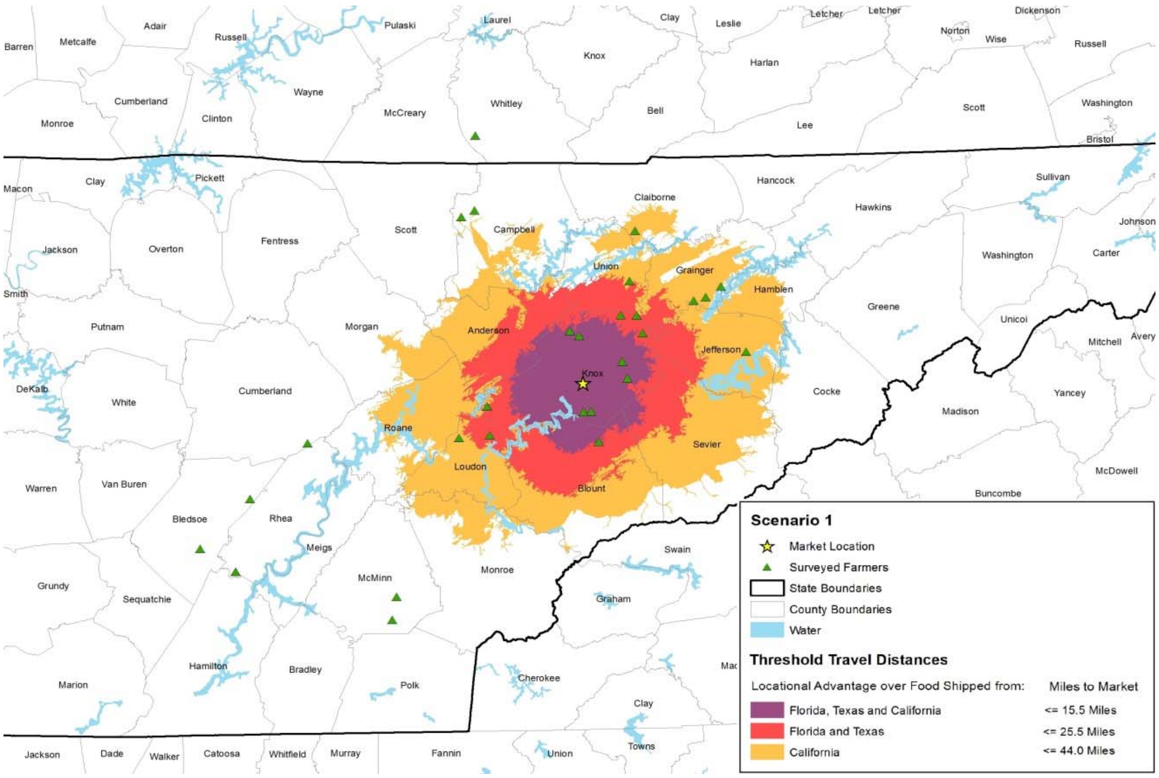

Figure 16. Scenario 1 Competitive Transportation Zones

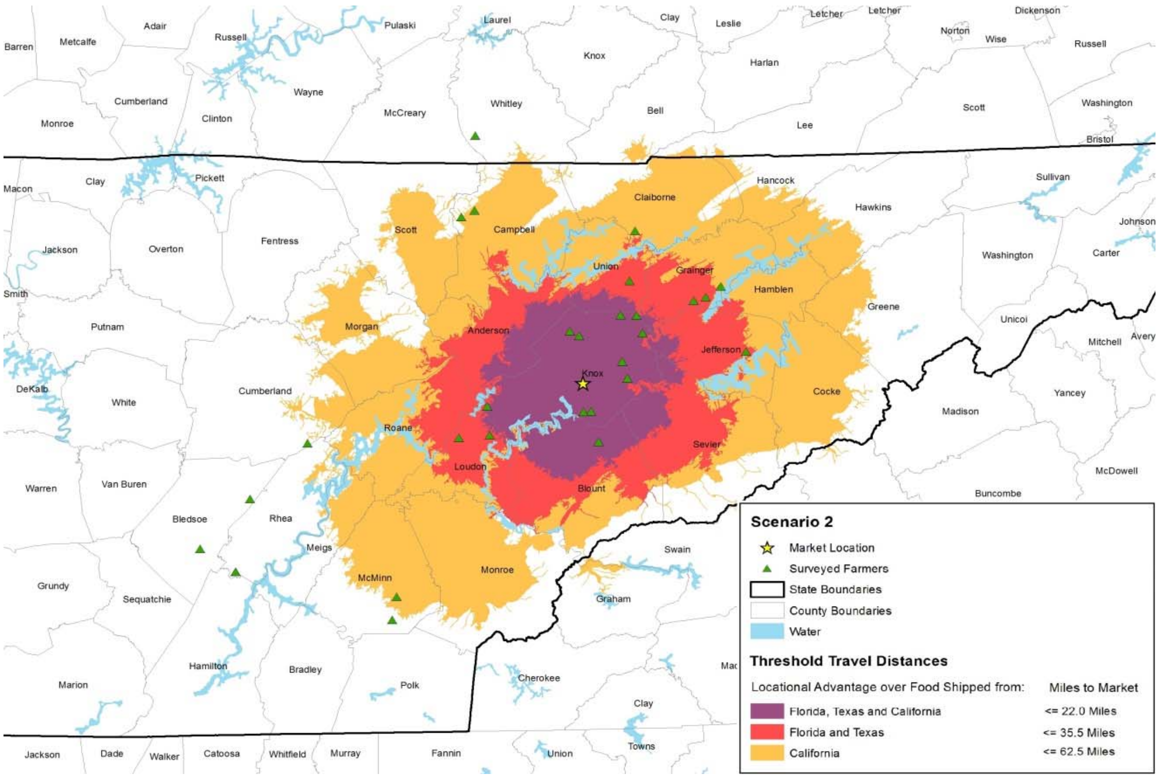

Figure 17. Scenario 2 Competitive Transportation Zones

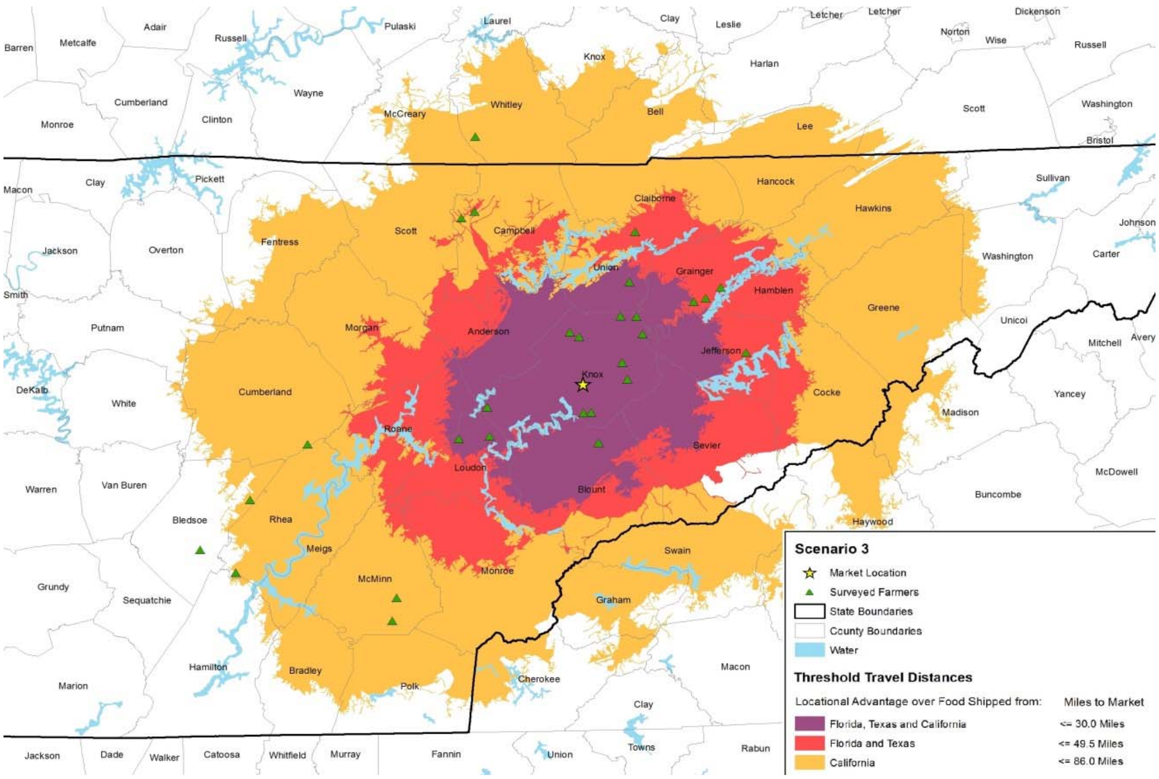

Figure 18. Scenario 3 Competitive Transportation Zones

Chapter VIII
Typology of Local Farmer Transportation Fuel Use Efficiencies

Cluster Analysis of Local Farmers

From the regression and sensitivity analyses, local farmer production and distribution scales are shown to impact transportation fuel use efficiencies. In particular, farm size (*acres*) and vehicle type (*boxtruck*) significantly affect farmer truckload weights. However, in driving a larger vehicle, such as a box truck, vehicle fuel economy is reduced. Therefore, the type of vehicle used by local farmers also alters MPG. Additionally, from Chapter V, the Distance Efficiency Plot highlights the positive relationship between local farmer transportation efficiencies and travel distance to market, where farmers traveling below 50 two-way miles have more efficient food distribution operations compared to farmers with longer travel miles to market. Therefore, all three components - travel distance, truckload weight, and MPG – as well as factors associated with these three components, such as production and distribution scales, must be considered jointly to study local food transportation efficiency and discuss how farmers can improve their distribution operations.

There is some interest in exploring how local food production and distribution is related to farm location (i.e. distance to market). In their local food study, Martinez et al. (2010) signal the need to investigate the relationship between farm size, farm location, product mix, and marketing channels. In order to analyze these relationships among the 29 surveyed farmers, an exploratory cluster analysis is conducted using variables related to farm location, production, and distribution scales, namely, travel distance to market, farm size, farming practices, vehicle type, and local food marketing participation. Cluster analysis provides a method of non-arbitrarily classifying the surveyed local farmers according to their farm location, production, and distribution scales and facilitates the evaluation of local farmer transportation fuel use efficiency with respect to the typology of each cluster. A description of the eight variables used for analysis is provided in Table 6.[7]

Table 6. Local Farmer Production and Distribution Variables for Cluster Analysis

Variable	Description
	Location
distance	The two-way travel distance, in miles, to the market.
	Production
organic	Binary variable: =1 if farmer uses certified organic or naturally grown farming methods; =0 otherwise
acres	The number of acres planted in fruits and vegetables for local food market sales
	Distribution
mpg	The estimated fuel economy of the farmer vehicle.
truckload	The estimated truckload weight, in pounds, of produce shipped to market.
boxtruck	Binary variable: =1 if farmer delivers produce using a box truck; =0 otherwise
mktchannels	The number of marketing channels used per week (e.g. CSA deliveries, wholesale/retail, pick-your-own, restaurant sales, etc.)
fmsmktswk	The number of farmers markets attended per week.

Cluster analysis[8] is performed using a two-stage cluster approach in which hierarchical clustering is followed by a non-hierarchical clustering technique to verify the cluster structure (Rencher 2003). In the first stage, several hierarchical clustering algorithms are implemented, though Ward's Method (Ward 1963) provides the clearest cluster structure. The clusters are then verified by the *k*-Means non-hierarchical clustering algorithm, where the cluster centroids from Ward's Method serve as initial seeds (MacQueen 1967; Johnson and Wichern 1992). A four cluster solution most effectively partitions the interviewed farmers into well-defined,

[7] Jolliffe (2002) justifies the mixed use of continuous and binary variables in PCA.

[8] Prior to cluster analysis, principal component analysis (PCA) is carried out on the correlation matrix of the eight variables. PCA standardizes the data into uncorrelated, linear combinations of the original variables with maximum variance. The unit-free principal component scores are more adaptable to cluster analysis, as the eight original variables are measured on varying scales. See Appendix C for a description of principal component analysis, cluster analysis, and the PCA output from this study.

homogenous groups. Mean profiles for each of the four clusters are given in Table 7. The first two principal component scores are plotted by cluster and shown in Figure 19.

Table 7. Local Farmer Mean Profiles for Production and Distribution Variables

Variable	Cluster 1 N = 16	Cluster 2 N = 6	Cluster 3 N = 6	Cluster 4 N = 1
distance (miles)	50.66	69.77	154.02	33.4
boxtruck*	0%	100%	33%	100%
mpg	16.17	10.54	14.70	13.5
acres	2.03	1.88	7	25
organic*	38%	33%	17%	0%
truckload (lbs.)	433.63	882.26	1003.17	4050
fmsmktswk	1.69	2.67	5.33	10
mktchannels	1.5	2	2.67	2

* Binary variables as a percentage of observations in the cluster.

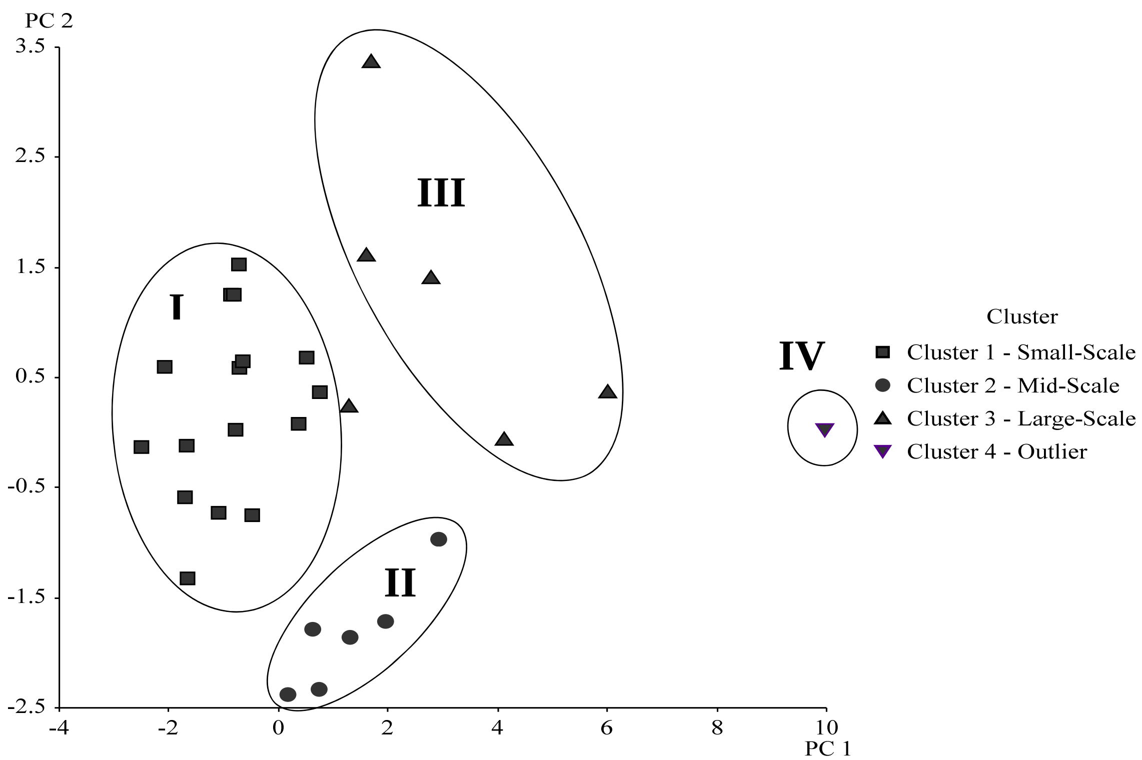

Figure 19. First Two Principal Component Scores by Cluster

Mean Profiles of Clusters

Cluster 1

Cluster 1 is the largest cluster, where approximately 55 percent of the interviewed farmers are clustered into this group. The average farm in cluster 1 travels 50.66 two-way miles to market, has small production and distribution scales, and uses few alternative marketing activities relative to the mean profiles of the other three clusters. Notably, all of the farmers in cluster 1 utilize a pick-up truck for transporting fresh produce to market. Because all 16 farmers use pick-up trucks for transportation, average vehicle MPG is high compared to the other clusters. The average number of acres planted in fruits and vegetables is 2.03 acres. Smaller farm and vehicle sizes of farmers in cluster 1 are associated with the lowest cluster average truckload weight. Farmer market participation (*fmsmktswk*), and alternative marketing channels (*mktchannels*) are also lowest of all four cluster averages. Approximately 38 percent of farmers (6 of the 16) use organic farming practices. Although this percentage is low, only 9 of the 29 interviewed farmers use organic farming methods. Thus, about 67 percent of the surveyed organic farms are in cluster 1.

Cluster 2

Farmers in cluster 2 travel 69.77 miles, approximately 19 more two-way miles to market relative to the cluster 1 average. Farmers in cluster 2 have similar farm sizes to those of cluster 1. Both groups average approximately 2 acres of fruit and vegetable production. Despite this relatively small production scale, cluster 2's distribution scale is large. In particular, all six farmers utilize a box truck to deliver their produce to market. By transporting produce in larger vehicles, average truckload weight is more than double the average truckload weight of cluster 1. However, in using a box truck for transportation, vehicle fuel economy is reduced. Average vehicle MPG is lowest of all clusters. As vehicle carrying capacity and truckload weights are increased, local food marketing activity also tends to rise. The average farm in cluster 2 participates in more farmer markets per week and uses slightly more marketing channels than farms in cluster 1. Two of the six farms in cluster 2 use organic farming practices.

Cluster 3

The average travel distance to market of cluster 3 farms is 154.02 miles, over three and two times greater the travel distances of clusters 1 and 2, respectively. With distance, farm size also increases. Cluster 3 farmers plant, on average, 7 acres of fruits and vegetables, approximately five more acres than farms in clusters 1 and 2. Whereas farmers in clusters 1 and 2 use only pick-up trucks or box trucks for transporting fresh produce, this is not the case for farms in cluster 3. Two of the six farms utilize a box truck, while the other four farms distribute their produce in pick-up trucks. Because of the mix in vehicle types, the average vehicle MPG of cluster 3 (14.7 MPG) is in between the higher fuel economy pick-up trucks and the low fuel economy box trucks of clusters 1 and 2, respectively. In expanding their production scale, the average farm in cluster 3 delivers more produce to market, averaging just over 1,000 lbs. of fruits and vegetables and has more local food marketing activity, where the average farm participates in approximately 5 farmer markets per week and utilizes almost 3 alternative local food marketing channels. Only one farm in cluster 3, the group with highest average farm size, uses organic farming practices, reflecting the fact that most of the surveyed organic farms are small in size.

Cluster 4: Outlier

Cluster 4 is a single-observation cluster, signaling the uniqueness of this particular producer and its contrast with the farms in clusters 1, 2, and 3. The most noteworthy characteristic of this farm is its truckload weight of 4,050 lbs. The interviewed farmers in clusters 1, 2, and 3 are highly diversified, growing and marketing a mixture of fruits and vegetables. Conversely, the cluster 4 farm specializes in producing sweet corn. In specializing, the farmer is able to plant a larger area of land, dedicating 25 acres to a single crop. Additionally, the farm matches its large production scale with a conformable mode of transportation, utilizing a box truck to deliver its corn to market. Finally, relative to other farmers, the outlier farm of cluster 4 relies more heavily on farmer market sales, participating in 10 farmer markets per week.

Relationship between Farm Location and Scale

In comparing the mean profiles of farmer clusters, there is a positive relationship between farm location, farm size, vehicle type, truckload weight, and local food marketing activity. Farms closest to market tend to have smaller production and distribution scales compared to farms farther from the market. The average farmer in clusters 1 and 2 plant a smaller number of acres in fruits and vegetables, while their average two-way travel distances to market are 50.66 and 69.77 miles, respectively. Cluster 3 farms average 7 acres in production, but their travel distance to market is 154.02 two-way miles. Local food marketing activity is more prevalent for farmers with longer travel distances to market. The average farm of the short distance cluster 1 participates in 1.69 farmer markets per week and uses 1.5 marketing channels. In contrast, the average farm of the long distance, large truckload cluster 3 participates in 5.33 farmer markets per week and uses 2.67 marketing channels.

As travel distance to market increases, farmers also tend to use larger vehicles to distribute their produce. Whereas the short distance farms of cluster 1 only use pick-up trucks for transportation, 90 percent of the surveyed farmers using box trucks belong to mid-distance and long distance clusters 2 and 3, respectively. When evaluating cluster truckload weights and vehicle MPG, the variable *boxtruck* has a strong discriminating effect on the clusters, as farmer vehicle type impacts both *mpg* and *truckload* directly. Pick-ups tend to have a higher fuel economy than box trucks but their carrying capacity is constrained. Therefore, while the average vehicle MPG is highest in cluster 1, the average truckload weight is significantly smaller (433 lbs.) compared to the other groups. In contrast, box trucks give cluster 2 farmers the extra carrying capacity to haul heavier loads of fruits and vegetables to market. The average truckload weight of farms in cluster 2 is nearly 900 lbs. - more than double the average truckload in cluster 1. However, vehicle fuel economy is low relative to cluster 1 pick-up truck farms, where cluster 2 farmer vehicles average 10.54 MPG. The influence of the variable *boxtruck* on *mpg* and *truckload* is less obvious for farmers in cluster 3, as vehicle types are mixed.

The distinction of each cluster structure allows for the classification of the surveyed farmers in terms of their farm locations, production, and distribution scales. To summarize, the overall mean profile for cluster 1 is characterized as "short distance, small-scale." Cluster 2 and 3 farms are identified as "mid-distance, mid-scale." and "long distance, large-scale", respectively. The single farm of cluster 4 is an outlier due to its truckload weight and unique production practices relative to the other farms. In order to show the four farmer typologies graphically, a three-dimensional scatter plot using *truckload, mpg,* and *distance* - the three dependent variables used in estimating local farmer transportation fuel use efficiency (*g/cwt.*) - is shown in Figure 16. The observations in the four clusters display little overlap, and the cluster centroids are quite separated.

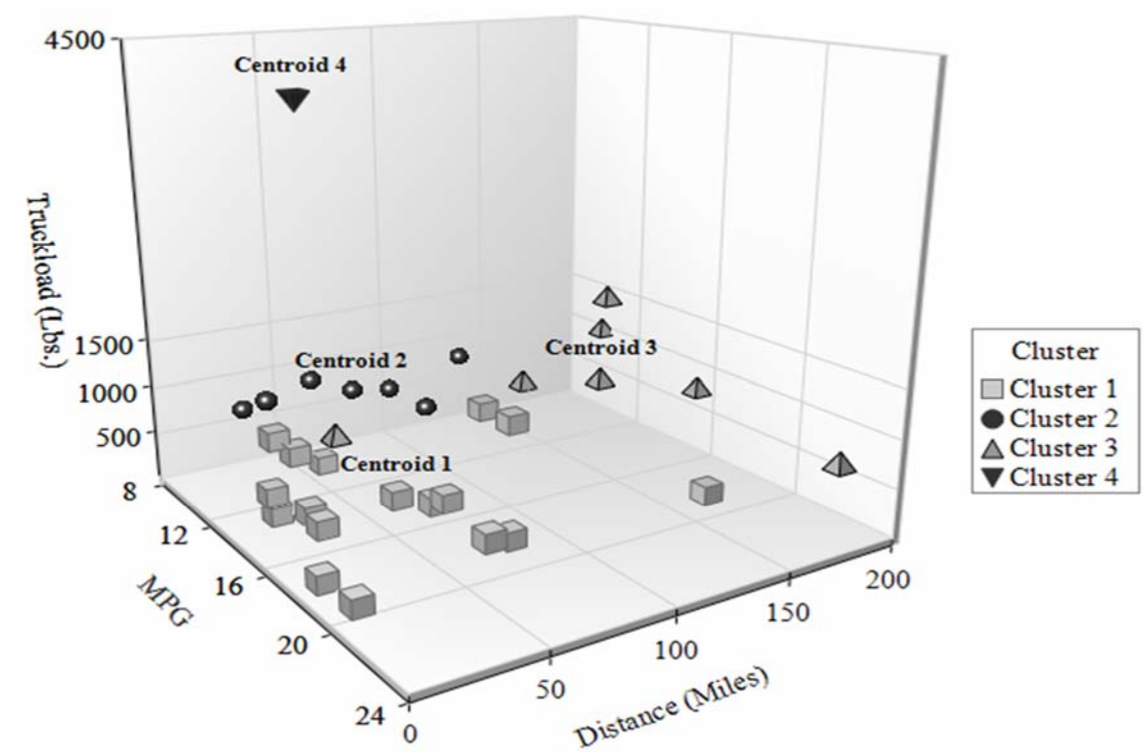

Figure 20. MPG, Truckload, and Travel Distance to Market by Cluster

Transportation Fuel Use Efficiency by Cluster

To observe how each group's transportation fuel use efficiency compares with the three conventional food supply chain scenarios, *g/cwt*. is calculated for the local farmer clusters using the cluster mean profiles of the variables *distance*, *mpg*, and *truckload* (Table. 8, Figure. 17). All four clusters have *g/cwt.* estimates below the California 1.08 *g/cwt.* threshold. Although the average farm of clusters 1, 2, and 3 have *g/cwt.* estimates below the California threshold, their respective *g/cwt.* surpass Texas and Florida's *g/cwt*. The outlier farm in cluster 4 has the highest transportation fuel use efficiency, using 18 times less fuel per cwt. than the California scenario. The farm's proximity to market and its 4,050 lbs. truckload yields a highly efficient transportation operation.

Clusters 1 and 2 have nearly the same transportation fuel use efficiency despite the latter group's distinct truckload weight advantage over cluster 1 (888.26 lbs. vs. 433.63 lbs.). The similarity in *g/cwt.* among the two clusters occurs because farmers in cluster 1 tend to travel short distances in fuel economic pick-up trucks yet haul less than 500 lbs. to market. In contrast, the average farm in cluster 2 travels somewhat longer distances to market using less fuel efficient box trucks but carries double the amount of produce compared to cluster 1. Therefore, the two clusters' average *g/cwt.* estimates are similar despite their differences in distance to market, production and distribution scales. The average farm in cluster 3 transports more fruits and vegetables to market than either cluster 1 or 2. However, given the cluster's longer average travel distance, *g/cwt*. is above the average *g/cwt.* of clusters 1 and 2.

These results again highlight that neither farm proximity nor large truckloads by themselves ensure that local producers have a locational advantage in transportation over conventional food supply chains. The average farm in cluster 1 is within 25 miles of the market and uses an efficient vehicle in transporting produce. However, by only carrying 433 lbs. of produce to market, the average cluster 1 farm loses its locational advantage in transportation over food shipped conventionally from Florida and Texas. On the other hand, the average farms of clusters 2 and 3 transport more weight to market by using larger vehicles and planting more fruit and vegetable acreage. Yet farmers in both groups tend to deliver their heavier truckloads over increasing travel distances to market. The cluster analysis further illustrates that local farmer transportation competitiveness with the conventional food supply chain requires that farmers take into account their travel distance to market, vehicle fuel economy, and truckload weight for their produce deliveries.

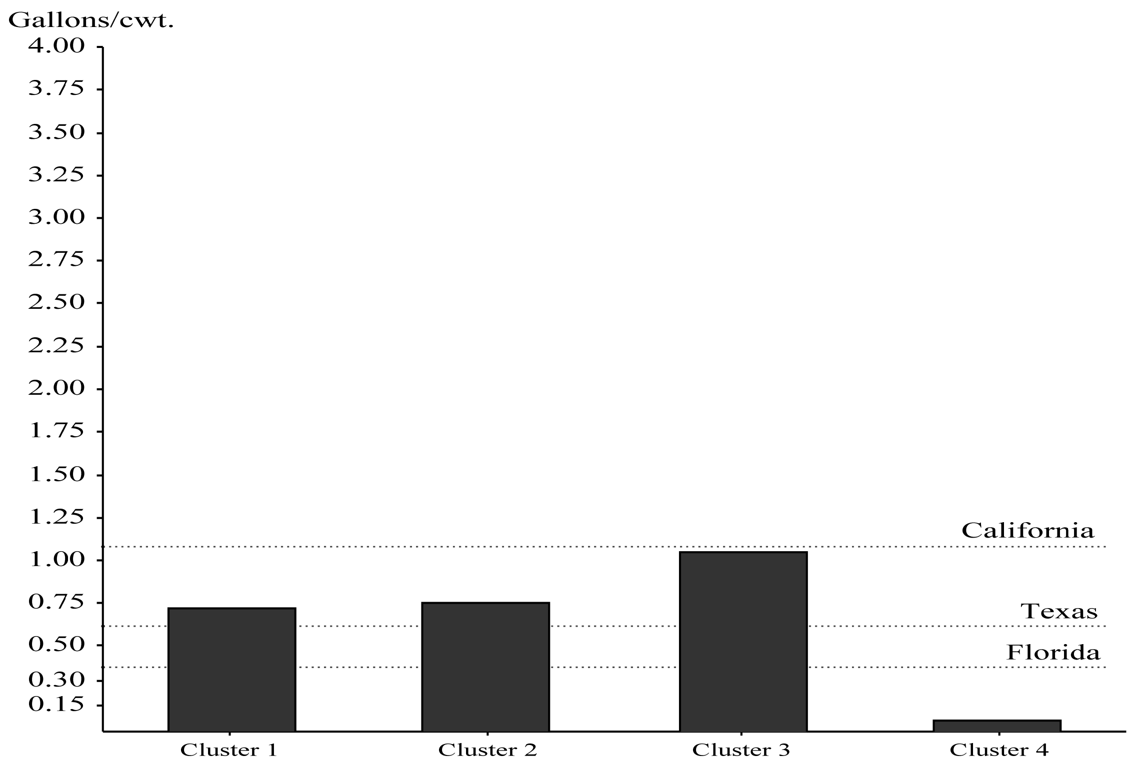

Figure 21. Transportation Fuel Use Efficiency by Cluster

Table 8. Local Farmer Transportation Fuel Use Efficiency by Cluster: Comparison with Conventional Scenarios

	Local Farmer Clusters				Conventional Scenarios		
	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Florida	Texas	California
g/cwt.	0.72	0.75	1.04	0.06	0.38	0.62	1.08

Chapter IX
Conclusions

US fruit and vegetable production has become increasingly concentrated in states such as California, Texas, and Florida due to their geographical and climatological comparative advantages in production (Lucier et al. 2006; Paggi et al. 2012; USDA 2012). These states' natural competitive advantages has led to the specialization of the entire production chain, enabling farmers in these regions to grow fruits and vegetables with increasing returns, while nearly eliminating competition from farmers in areas with fewer natural resource endowments (Isard 1951; Thisse 2009). Large-scale, specialized production is conveniently wedded with an efficient transportation network characterized by economies-of-scale. However, without relatively low transportation costs and technological advances that facilitate long distance food distribution, concentrating production of perishable food items in regions remote from most consumer markets would become less viable. Indeed, Glaeser and Kohlhase (2004) identify falling transportation costs related to technological innovation as a factor that has transformed the structure of the modern economy.

In his core-periphery model, Krugman (1990) develops a theoretical economic framework to help explain why industries concentrate in certain regions. Economies-of-scale and low transportation costs are two of the key parameters affecting industry agglomeration. Similarly, the scale economies associated with growing and transporting fruits and vegetables in only a few states like Florida, Texas, and California, coupled with low transportation costs, promotes the concentration of production in only the most optimal soil and climate conditions. High cost local farmers with less abundant fertile lands and seasonal production cycles are relegated to niche marketing strategies to sell their produce. Krugman (1990) points out, however, that there is a transportation cost threshold that determines industry convergence or divergence. Thus, in theory, if fuel prices were to rise sufficiently, transportation costs could become prohibitively high, reducing the incentive to concentrate fruit and vegetable supply chains in the more distant, low cost production regions. In turn, increasing transportation costs could open marketing opportunities to local farmers that have a locational advantage in delivering their fresh produce to nearby markets.

Yet, despite local farmers' proximity to markets, their transportation fuel use per unit (*g/cwt.*) is often greater than the per unit fuel use of shipping fruits and vegetables conventionally over thousands of miles. Compared to the *g/cwt.* for produce shipped from Florida, 20 of the 29 surveyed local farmers (69 percent) consume more fuel per unit in transporting their products to market. Relative to fruits and vegetables transported conventionally from California, a trip of nearly 2,500 miles to markets in Knoxville, TN, 9 of the 29 interviewed farmers (31 percent) require more *g/cwt.* even though their travel distances are significantly shorter.

Evaluation of the Transportation Efficiency Plots shows that farmers within 50 two-way miles of the market tend to have *g/cwt.* estimates below that of most conventional scenarios due mostly to their proximity to market and high vehicle fuel economies (MPG). As travel distance to market increases, balancing out the added travel miles with larger truckloads becomes essential if local farmers are to compete on a transportation fuel use basis with the conventional supply chain. These findings corroborate other local food transportation studies (Pirog et al. 2001; Wallgren 2006; King et al. 2010; Mundler and Rumpus 2012). Therefore, if there is indeed a transportation cost threshold that dissuades industry concentration and encourages a re-localization of an economic activity, as suggested by Krugman (1990), local farmers must at least begin to capitalize in the area of transportation, for which they potentially have a locational advantage.

Just as scale contributes to the efficiency of conventionally transported fruits and vegetables from Florida, Texas, and California, local farmer transportation efficiencies are also affected by farmers' relative production and transportation scales. The OLS regression on the surveyed local farmer truckload weights indicate that farm size, in terms of the number of acres planted in fruits and vegetables, and vehicle type (pick-up or box truck) have a statistically significant impact in determining the amount of fresh produce delivered to market. Controlling for all other variables, a farmer using a box truck carries 575 lbs. more product to market than a farmer using a pick-up truck in transportation. While most studies documenting the effects of scaling-up local food production and distribution provide qualitative analyses (Day-Farnsworth et al. 2009; Bittner et al. 2011; Day-Farnsworth and Miller 2014), results from the OLS regression yield local food analysts and policymakers with a quantitative baseline of the impacts of scaling-up local food networks.

Based on the Hotelling Competitive Spatial Model (1929), location can provide east Tennessee farmers marketing produce locally with a locational advantage over produce imported from the more distant production and shipping points. Additionally, the Hotelling model suggests that by increasing their production and transportation efficiencies, east Tennessee farmers can expand their market area. Using this theoretical framework and the scale coefficients from OLS, in particular *acres* and *boxtruck*, the transportation sensitivity analysis illustrates that as local farmers increase their production and distribution scales, the competitive transportation zones (CTZs) and the threshold travel distances expand - the point beyond which local farmers lose their locational advantage in transportation over conventionally transported food. Therefore, while large scale fruit and vegetable production and transportation greatly attribute to the low cost conventional food supply chain, it appears that factors of scale also play a key role in determining local farmers' locational advantage in transportation.

And while increasing the size of production and distribution operations of an individual farmer improves transportation fuel use efficiency, results from cluster analysis show that the surveyed local farmers can also be categorized in terms of scale, and that, on average, there is a positive relationship between local farmer production and distribution scales and their relative travel distance to market. Farmers traveling longer distances to market tend to have larger truckload weights, farm and vehicle sizes, and more local food marketing activity, while farmers traveling within 50 two-way miles are characterized by small pick-up trucks, truckload weights, and only one or two additional marketing channels. In many ways, the local farmer typology mirrors that of the conventional supply chain in that fresh produce hauled in from more distant regions uses larger production and transportation systems in order to achieve a high level of food distribution efficiency.

Because most local farmers in east Tennessee cannot feasibly produce the same quantities and at the same low cost as the specialized fruit and vegetable producers in states with natural competitive advantages in production, if local farmers are to capitalize on an exogenous shock to the conventional, long distance transportation system in the form of high fuel prices, local farmers must exploit their locational advantage by specializing in transportation. If conventionally grown fruits and vegetables are produced at a lower cost due to increasing returns, locally grown produce can be transported to market at a lower cost because of local farmers' relative proximity to consumer markets. Therefore, estimating and comparing local farmer transportation fuel use with conventional food supply chains helps indicate the robustness of the local food system in east Tennessee. As indicated in previous analyses, small truckloads lead to less efficient local food transportation unless farms are considerably close to the market. Just as Hotelling's model suggests, by increasing production and distribution scales, farmers can deliver their produce to market more efficiently, expand their competitive transportation thresholds, and make the local food system in east Tennessee more resilient to energy price fluctuations in the future. Local producers that transport their products more efficiently than the conventional system are more prepared to respond to high energy prices because either their production and distribution scales are sufficiently large, or they are sufficiently close to market to take advantage of the potential marketing opportunities. While the higher prices received for their differentiated product may enable local farmers to be profitable regardless of how their transportation fuel use efficiencies compare with the conventional supply chain, if local food is to become more than a niche market, improving in the area of transportation via scaling-up local farmer production and distribution may be a desirable goal for local farmers, consumers, and food policymakers.

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Appendices

Appendix A
Sample Survey

Fuel Use by Farmers at the Market Square Farmer's Market

Participation in the survey is voluntary, and you may refuse to respond to any question that you feel uncomfortable in answering. All responses are confidential. Farm and farmer names will not be used in the study.

1. What is the route used to bring your fruits and vegetables from your farm to the market? Do you consistently make any other stops or detours on your way to or from the market, such as to pick up produce from another farm or to make direct-to-consumer deliveries?

2. What is the model type and year of the vehicle(s) used to transport your produce to the market?

- Model Type
- Year

3. What type of fuel does the vehicle(s) used to transport your produce require?
   a. Gas
   b. Diesel
   c. E85

4. Is your vehicle 2WD or 4WD?

5. On average, how many pounds (or boxes, cartons, bags, or other unit) of produce do you bring to the market? What percentage of the produce delivered to market is sold? What do you do with the unsold produce?

6. Do you sell produce at other farmer's markets? If yes, what are the names and locations of these farmer's markets? Do you use the same vehicle? Do you carry the same amount of produce?

7. Do you sell produce to local retailers, wholesalers, restaurants, CSA, etc.?

8. To what extent would you say that transportation costs affect the prices of your produce at the market:

Don’t Know	Not at all	Somewhat	Significantly	Very Significantly

9. How important are the following characteristics to your choice to sell produce at the Downtown Knoxville Market's Square Farmer's Market?

Characteristic	**Not at all**				**Extremely Important**
Size of market (number of customers)	1	2	3	4	5
Higher price for produce	1	2	3	4	5
Proximity (in distance) to market	1	2	3	4	5
Tradition (long history of participating in this market)	1	2	3	4	5
Farm/Business exposure for other potential markets or customers	1	2	3	4	5
Small entrance fee	1	2	3	4	5
Other: ______________________________	1	2	3	4	5

10. Are there farmer's markets in which you choose to not participate that are closer in distance to your farm than the Market's Square Farmer's Market?
    Yes / No
    If yes, how important are the following factors to your decision not to participate in those markets that are closer to your farm?

Decision Factor	**Not at all**				**Extremely Important**
Lack of time/labor/resources to harvest, prepare, and ship to other market(s)	1	2	3	4	5
Not enough produce to sell at multiple markets	1	2	3	4	5
Smaller market (fewer customers)	1	2	3	4	5
Conflicting days with larger, more popular markets	1	2	3	4	5
Conflicting days with personal activities	1	2	3	4	5
Other: ______________________________	1	2	3	4	5

11. Which of the following best describes how you set your prices for a particular day at the market?

A. To cover the costs of production and transportation
B. Look at supermarket produce prices
C. Look at other farmers' produce prices in the market
D. Other (explain)

12. How would you respond to a 100% increase in the price of fuel?

A. Stop farming because of higher production and transportation costs
B. Participate in fewer markets
C. Buy a more energy efficient vehicle for transportation
D. Cooperate with neighboring farmers to transport your goods
E. Other (explain)

13. How do your fertilize crops?

14. How do you control for weeds and pests?

15. How many acres in fruit and vegetable production do you have?

Appendix B
Local Farmer Survey Results

Descriptive Statistics on Local Food Transportation

Table 9 contains descriptive statistics of the non-categorical survey data collected from local farmers marketing fresh produce in east Tennessee. A description of each variable is given in Table 10. The average two-way travel distance to market is 75.4 miles, while the median two-way travel distance is 56.40 miles. The median may be a more accurate estimate of the sample average, as farmer travel distances considerably above average distort the sample mean estimate. Approximately 41 percent of the interviewed farmers travel between 0-24 one-way miles to deliver produce to market (Figure 18). Thirty-one percent travel between 25-49 one-way miles, while the remaining 27 percent travel between 50-100 two-way miles.

Low and Vogel (2011) use data from the Agricultural Research Management Survey (ARMS) and report that the average distance traveled by farmers marketing their produce in local markets is 30.7 miles. Doubling this distance to take into account the return travel of the farmers' trips yields an average two-way travel distance of 61.4 miles. Table 11 provides findings from other studies with respect to farmer travel distance to local markets. The average travel distance of the interviewed local farmers participating in farmer markets in east Tennessee are similar to other studies.

The average and median local farmer truckload weight of fruits and vegetables shipped to market is 768.98 lbs. and 760.30 lbs., respectively. The average truckload weight of fruit and vegetables delivered to markets varies seasonally. Because the survey is carried out during the peak growing months for warm weather crops, from July through August, the surveyed farmers' truckload weights may be high-end estimates. In the fall and spring, truckload weight declines, as farmers primarily market cool weather green leaf crops. Because transportation fuel use efficiency is measured as the transportation fuel use per unit of produce shipped to market (*g/cwt.*), local farmer distribution efficiencies likely diminish in the spring and fall months, as truckload weights decrease seasonally.

The average vehicle model year of the surveyed farmers is 2001. Vehicle models range from 1987 to 2012. The average vehicle gets 14.7 MPG, though local farmer vehicle fuel economy varies from 9 to 23 MPG. The average local farmer consumes 6 gallons of fuel per farmer market trip. Using the LCA techniques outlined in the Methods section, average local farmer *g/cwt.* is estimated. On average, local farmers use 0.96 gallons of fuel per 100 lbs. (cwt.) of produce delivered to market. The average is skewed somewhat, as farmers with *g/cwt.* estimates significantly above average bias the sample mean upward. The median *g/cwt*. of 0.56 may be a more accurate descriptor of the average.

Table 12 contains the mean and median estimates for local farmer *g/cwt.* and the three conventional transportation scenarios. Comparing local and conventional transportation fuel use efficiency is sensitive to the shipping point assumed in the conventional scenarios and whether the mean or median *g/cwt.* is used as the baseline for local farmer fuel efficiency. If the local farmer mean *g/cwt.* is used, then local food distribution is only marginally more efficient than produce shipped from California. However, if the median *g/cwt.* is assumed, then local food distribution is almost two times as efficient as produce imported from California and is also more efficient than fruits and vegetables shipped from Texas.

The average acreage in production of fruits and vegetables for the surveyed local farmers is 3.81 acres, while the median is 2 acres, though some farmers plant significantly more than the average. Particularly, farmers specializing in only a few crops, such as those that grow and market only fruit or corn, respectively, tend to plant larger areas of land. Farmers with more diversified production have smaller farming scales. There is a large spread between the minimum and maximum number of acres planted, 0.25 and 25 acres, respectively.

Farmers with local food sales tend to utilize more than one marketing channel for their fresh produce. On average, the surveyed farmers participate in approximately 3 farmer markets per week, while 62 percent of farmers participate in more than one farmer market per week (Table 13, Figure 19). The maximum number of farmer markets attended for a given week is 10 markets. Many of the surveyed farmers participate in several markets on the same day using different vehicles and drivers. Several farmers participate in multiple farmer markets, sell CSA shares, operate farm stands, market to restaurants and wholesalers, and have pick-your-own produce options on the farm. The average farmer uses almost 2 local food marketing channels per week.

Through a series of local farmer interviews, Lawless et al. (1996) highlight the myriad of marketing activities in which small farms participate to boost farm income. In a case-study of diversified fruit and vegetable farmers, LeRoux et al. (2010) indicate that small farms may combine direct-to-consumer marketing strategies, such as farmer markets, with high-volume marketing strategies, such as wholesale, to reduce the risks of both marketing channels. In a survey of 122 local farmers in New York, Uva (2002) finds that farmers participate, on average, in 2.3 retail marketing activities per week and 1.7 direct-to-consumer marketing channels. Farmers participate in 2.3 farmers markets per week. The east Tennessee local farmers interviewed for this study use a similar number of farmer markets and marketing channels to sell their produce.

Table 9. Descriptive Statistics of Surveyed Local Farmers

Variable	Mean	Median	Min.	Max.	Standard Error
distance (miles)	75.40	56.40	9.4	198.5	11.18
truckload (lbs.)	768.98	760.30	100	4050	136.40
year	2001	2002	1987	2012	1.08
mpg	14.61	14	9.21	23	0.68
boxtruck	0.31	0	0	1	0.087
gallons	5.56	4	0.47	19.85	0.90
g/cwt.	.9586	.59	0.061	3.782	0.16
acres	3.81	2	0.25	25	0.94
organic	0.31	0	0	1	0.087
farmmkts.	2.93	2	1	10	0.44
mktchannels	1.86	2	0	4	0.18

n=29 observations

Table 10. Description of Variables

Variable	Description
distance (miles)	Travel distance, in miles, to transport local farmer produce to and from market.
truckload (lbs.)	The truckload weight mixed fruits and vegetables shipped to the farmer market, measured in pounds (lbs.)
year	Local farmer vehicle model year.
mpg	Local farmer vehicle fuel economy, measured in miles per gallon (MPG).
boxtruck	Binary variable: =1 if farmer delivers produce using a box truck; =0 otherwise
gallons	Gallons of fuel per trip to market
g/cwt.	Gallons of fuel per one-hundred pounds of produce shipped to market.
acres	Number of acres planted in fruits and vegetables for local food market sales.
organic	Binary variable: =1 if farmer uses certified organic or naturally grown farming methods; =0 otherwise
farmmkts.	Number of farmer markets attended per week.
mktchannels	Number of marketing channels used per week.

Table 11. Average Travel Distance to Markets from Other Farmer's Market Studies

Authors	Distance to Farmer's Market
Govindasamy et al. (1998) Location of study: New Jersey	Mean: 27 miles (distance to nearest market) Range for nearest market: 1-70 miles Mean: 42 miles (distance to furthest market) Range for furthest market: 5-75 miles
Åsebø et al. (2007) Location of study: Norway	Mean: 49 miles
Brown et al. (2007) Place of study: West Virginia	Mean: 19.53 miles; Min.: 4.50 Max: 54.50 Range: 10-19 miles 6% of respondents: >50 miles
Kremer and DeLiberty (2011) Location of study: Philadelphia	Mean: 61 miles; Range: 21-60 miles
Low and Vogel (2011) Location of study: United States; ARMS Survey Data	Mean: 30.7 miles Median: 15 miles Max.: 275 miles
Wallgren (2006)	Min: 15 km. (9 miles) Max: 250 km. (155 miles)
Knoxville Area Farmers' Markets (2014)	Mean: 37.70 miles Median: 28.2 miles S.D.: 30.11 Min.: 4.7 miles Max.: 99.25

Table 12. Average Transportation Fuel Efficiency of Surveyed Local Farmers Compared to Conventional Transportation Scenarios

Local *g/cwt.* (Mean)	Local *g/cwt.* (Median)	Conventional *g/cwt.* (California)	Conventional *g/cwt.* (Texas)	Conventional *g/cwt.* (Florida)
.9586	.590	1.079	.615	.378

Table 13. Local Farmer Participation in Multiple Farmer Markets per Week

Indicator	Quantity	Percentage
Single Market	11	38%
Multiple Markets	18	62%

n=29 observations

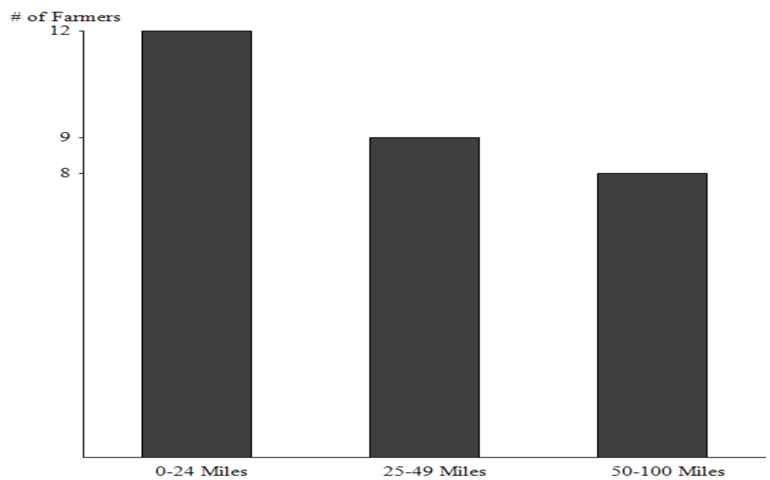

Figure 22. Local Farmers by Travel Distance to Market

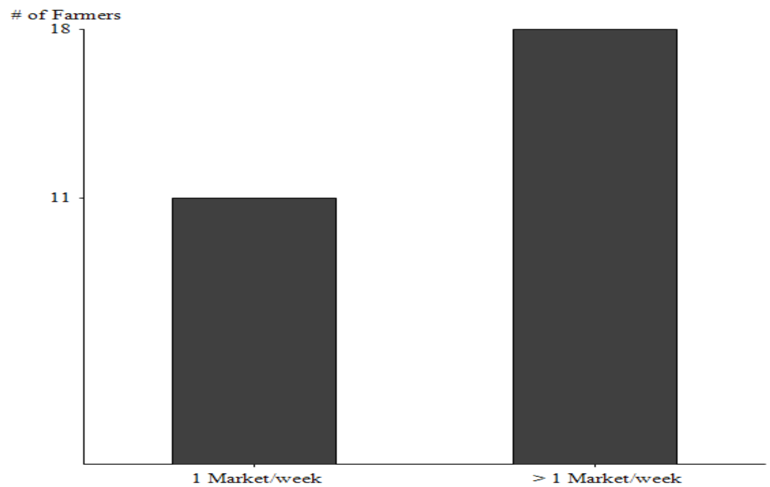

Figure 23. Local Farmer Participation in Multiple Farmer Markets per Week

Local Farmer Transportation Characteristics

The interviewed farmers provide information regarding their vehicle model type, fuel type, drivetrain, and year. Table 14 and its accompanying bar chart (Figure 20) show the different vehicle models utilized by farmers. The models Ford, Chevy, and Dodge comprise approximately 76 percent of the vehicle model types. Three fuel types are considered in the local farmer survey: gas, diesel, and E-85. However, none of the interviewed farmer vehicles run on E-85. Approximately 69 percent of farmers utilize gas-powered vehicles, while the remaining 31 percent use diesel operated vehicles (Table 15, Figure 21).

Fifty-nine percent of farmer vehicles are 2-WD while the remaining 41 percent drive 4-WD vehicles (Table 16, Figure 22). 4-WD vehicles are more powerful in terms of their hauling capacity, but may be more energy intensive in terms of MPG. Farmer vehicles are categorized by type (Table 17, Figure 23). ‘Pick-up’ refers to flatbed trucks without additional cargo attachments to the vehicle. ‘Box truck’ refers small- and mid-sized delivery trucks. Twenty of the 29 survey participant vehicles are pick-up trucks, while the remaining nine vehicles are box trucks.

Table 14. Local Farmer Vehicle Models

Vehicle Model	Quantity	Percentage
Ford	9	31%
Chevy	7	24%
Dodge	6	21%
Toyota	3	10%
GMC	1	3%
Isuzu	1	3%
Nissan	1	3%
Volkswagon	1	3%

n=29 observations

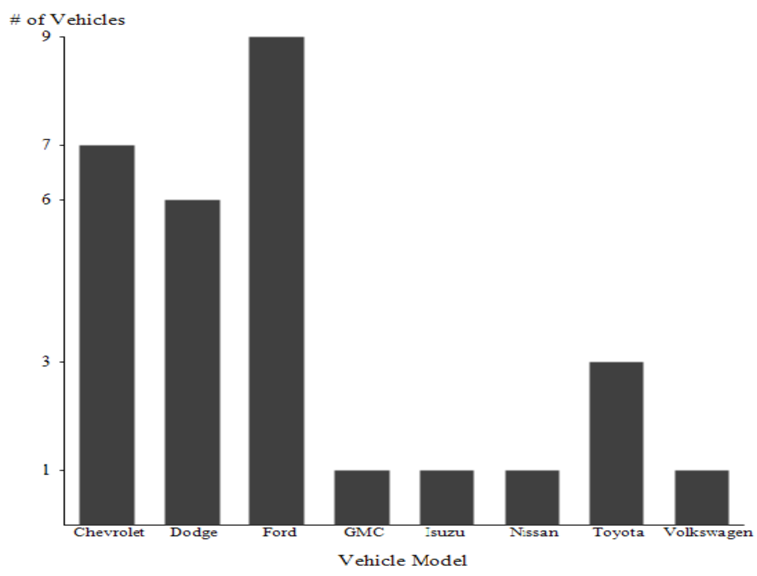

Figure 24. Local Farmer Vehicle Models

Table 15. Local Farmer Vehicle Fuel Types

Fuel Type	Quantity	Percentage
Gas	20	69%
Diesel	9	31%

n=29 observations

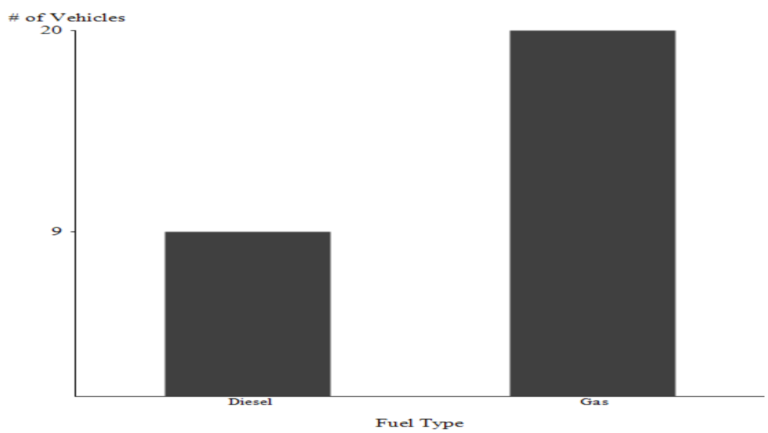

Figure 25. Local Farmer Vehicle Fuel Types

Table 16. Local Farmer Vehicle Drivetrains

Drivetrain	Quantity	Percentage
2-WD	17	59%
4-WD	12	41%

n=29 observations

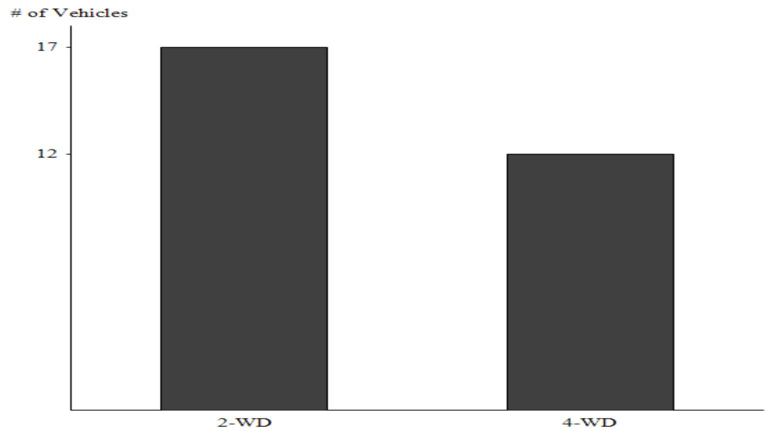

Figure 26. Local Farmer Vehicle Drivetrains

Table 17. Local Farmer Vehicle Types

Type	Quantity	Percentage
Pick-up	20	69%
Box truck	9	31%

n=29 observations

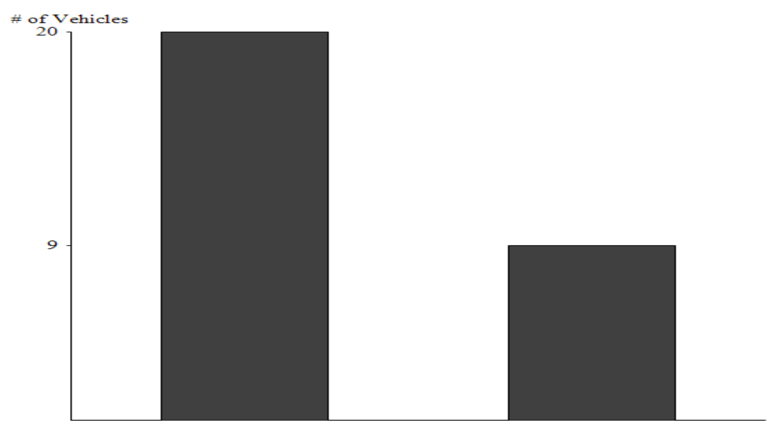

Figure 27. Local Farmer Vehicle Types

Marketing Activities of Local Farmers
Weekly Farmer Market Activity

The surveyed farmers rely heavily on weekly farmer markets in the east Tennessee region to market their produce. As indicated above, a little over 60 percent of farmers participate in at least 2 markets per week during the market season. On average, farmers participate in 3 farmer markets per week. The maximum number of markets attended per week is ten. Eleven of the 29 farmers participate in one farmer market per week.

There is a positive relationship between acres planted in fruits and vegetables and farmer market participation (Figure 24). The vertical axis simultaneously indicates acres and farmer market participation per week. Farms with low acreage in fruits and vegetables attend fewer markets per week, while farmers with higher acreage participate in more farmer markets. With the exception of two or three farms, farmer market activity and production acres are quite related. The average ratio of acres to markets is 1.3, meaning that for every 1.3 acres planted in fruits and vegetables the typical farmer attends one farmer market. Farm 10 participates in seven farmer markets per week, yet only reports 1.5 acres in fruit and vegetable production. However, this farmer also produces and sells meat and this could attribute to the farm's high farmer market activity.

From a food miles perspective, the surveyed farmers, as a group, travel at least as many miles as most conventional transportation food supply chains. The interviewed farmers sell produce at a total of 85 farmer markets in the east Tennessee region, travel 5,870 two-way miles, and consume 468 gallons of fuel per week. A conventional semi-truck shipment of fruits and vegetables from California to supermarkets in Knoxville, TN travels approximately 2,300 miles and consumes 410 gallons, 68 gallons less than the local estimate, suggesting that local food distribution may be just as fossil fuel dependent as the conventional food supply chain. Of course, if more than one trip from the conventional supply chain is made per week, the conventional food supply chain could be considerably more fuel dependent than these numbers indicate. Nevertheless, these figures are consistent with Desrochers and Shimizu's (2008) argument that the classic food miles argument in favor of local food is often illegitimate.

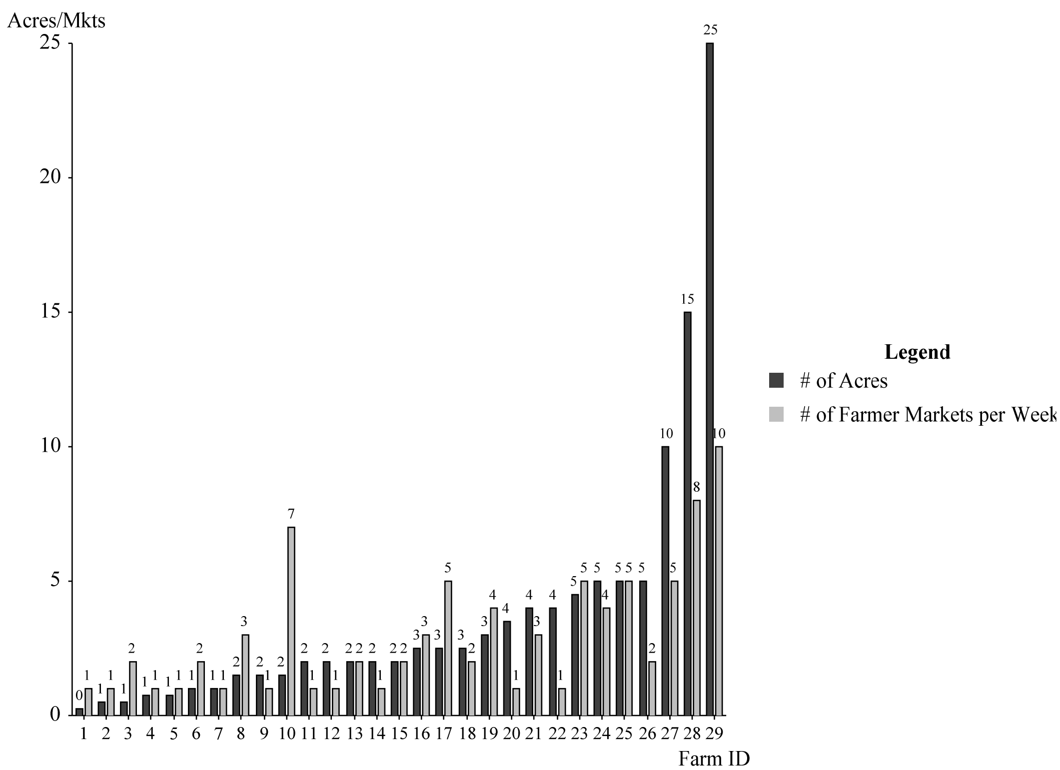

Figure 28. Acres and Farmer Market Participation per Week

The Role of Transportation Costs and Fuel Prices in Farmer Market Pricing and Decision Making

In two separate survey questions, the farmer market participants are asked:

Question 1: *To what extent would you say that transportation costs affect the prices of your produce at the market?*

Question 2: *How would you respond to a 100% increase in the price of fuel?*

Table 18 contains the tabulated responses for both questions. By adding the responses of the first two columns of the table and dividing by the total number of observations (25/29), 86 percent of the interviewed farmers express that transportation costs either do not affect or affect only somewhat their produce prices. The remaining 14 percent of farmers (4/29) state that transportation costs affect their produce prices either significantly or very significantly. Transportation costs, therefore, may play a small role in local farmer production costs, as most survey participants state that transportation costs have a small effect on their produce prices.

Table 18. Relationship Between Farmer Responses to 100% Fuel Price Increase and the Role of Transportation Costs on Produce Prices

	Extent that transportation costs affect produce prices				
Response to 100% Fuel Price Increase	Not at all	Somewhat	Significantly	Very Significantly	Total
Increase Prices	9	7	1	1	18
Other*	6	3	1	1	11
Total	15	10	2	2	29

*Other response possibilities included: Stop farming because of higher production costs, participate in fewer markets, use a more fuel efficient vehicle, cooperate with nearby farmers to transport produce.

However, when answering the question, "How would you respond to a 100% increase in the price of fuel?," 64 percent (16/25) of the farmers responding "Not at all" and "Somewhat" to question 1, also indicate that their reaction would be to increase their produce prices. In total, 62 percent of the interviewed farmers indicate that their reaction to a 100 percent increase in fuel prices would be to increase fruit and vegetable prices. These results imply that the surveyed farmers are somewhat sensitive to increasing fuel prices, but perhaps not due to transportation costs, as more than half stated that they would increase their produce prices in order to recover from a doubling of energy prices. Their response could be related to the observation that when energy prices increase, the costs of goods tend to rise in conjunction.

Aside from increasing their fruit and vegetable prices, farmers express that they would alter their behavior in a variety of ways if faced with a 100 percent increase in fuel prices. Due to the heterogeneity of responses, "Other" in Table 18 aggregates these diverse answers for table simplicity. However, these alternative responses are discussed in greater detail here. The second most common fuel price increase response is to cooperate with neighboring farmers to transport goods, where four farmers show interest in this option. Two farmers state that they would stop farming due to higher production and transportation costs. One farmer mentions that he would adjust to higher fuel prices by expanding his on-farm sales, such as through farm stands and agritourism. Two farmers with short two-way travel distances to market, 9.6 and 15.2 miles, respectively, state that fuel price increases would not affect their farming decisions because their transportation to market is minimal.

There may be some relationship between farmer responses to a hypothetical fuel price increase and farmer travel distance to market. Farmers with longer travel distances to market have higher transportation costs per trip, and thus, may be more likely to react to a 100 percent increase in fuel prices by raising their produce prices. Among the farmers with two-way travel distances greater than 50 miles, approximately 71 percent state that they would increase their fruit and vegetable prices if fuel prices were to increase 100 percent. The average two-way distance to market for farmers whose response is to increase produce prices when faced with higher fuel prices is 92 miles, whereas the average two-way distance among the farmers whose response is "Other" is 53 miles.

Farmer Market Pricing

Local food is often recognized as a niche market, distinct from conventional fruit and vegetable markets. Produce purchased locally typically demands a higher price because of the added value attributed to local food items such as product freshness and quality (Diamond and Barham 2012; Little et al. 2010). Understanding that local foods are differentiated from conventional produce, farmer market participants may charge higher prices for their fruits and vegetables, as consumer willingness-to-pay is considerably higher for locally grown fruits and vegetables (Carpio and Isengildina-Massa 2009). While farmer market produce often costs more than conventional supermarket produce, it is of interest to understand how farmers determine their fruit and vegetable prices at the market. In particular, are prices linked to production costs or do farmers use conventional fruit and vegetable prices as a reference to mark-up their prices? Hence, farmers are asked:

- *Which of the following best describes how you set your prices for a particular day at the market?*

Fifty-nine percent of farmers base their prices on other farmers' produce prices (Table 19). This price setting may be a way to avoid pricing competition among the market participants, and thereby lose the price premiums of selling local produce. During the period of market interviews, it is noted that price competition between market participants is a polemic issue. Several producers express aversion toward farmers that price their produce significantly below the average market price. This is especially the case for more perishable crops such as tomatoes, peppers, okra, and sweet corn. One vendor of okra was asked by neighboring farm stands to increase his price because the farmer's current price was too low compared to other farm stands.

Table 19. Farmer Responses: How Prices are Set at the Farmer Market

Option	Count	Percent
To cover production costs	5	17%
Look at supermarket prices	7	24%
Look at other farmers' prices in the market	17	59%
Total	29	100%

Approximately 24 percent of farmers use supermarket prices to set their prices. Several farmers, for example, obtain a baseline measure of the consumer's willingness-to-pay for local food by checking prices periodically at nearby specialty supermarkets that carry organic and local produce. The remaining 16 percent of the surveyed farmers base their farmer market prices the market of shortest travel distance. Thus, question #10 instructs on the factors that dissuade farmers from selling at markets with presumably lower transportation costs.

on their production and marketing costs. Thus, local farmers are price takers in that they use conventional supermarkets to help determine competitive prices of their produce. However, local farmers also have a certain degree of flexibility in setting their prices because of their differentiated product.

Marketing Strategies of Local Farmers

Question #9 of the survey asks farmers to rank the importance of six farmer market characteristics in influencing their decision to sell produce at the farmer market, where a 1-5 Likert scale is employed (1 - Not important at all , 5 - Extremely important). The characteristic of most interest with respect to transportation fuel use is "Proximity to Market." Geraci and Prewo (1977) state that the distance traveled to market is often used as a proxy variable to represent the cost of transportation. Therefore, if transportation costs are deemed important to local farmer production costs, it is hypothesized that farmers located closest to market will rank of higher importance "Proximity to Market" than farmers traveling greater distances to market. Figure 25 shows that this hypothesis may have some validity, where most farmers giving "Proximity to Market" a 4 or 5 on the Likert scale travel less than 50 two-way miles market. Overall, the "Size of Market" is ranked as the most important factor in deciding to sell produce at the farmer market (Table 20).

In question #10 of the survey, local farmers are asked whether they choose to not sell produce at markets closer to their farm than the market in which they participate. If the farmer responds "Yes", he or she is asked to rank the factors that impact their decision to not sell fruits and vegetables at the more nearby market. Assuming that travel distance and transportation costs are related (Hummels 2007) the least cost transportation option to deliver produce to market is

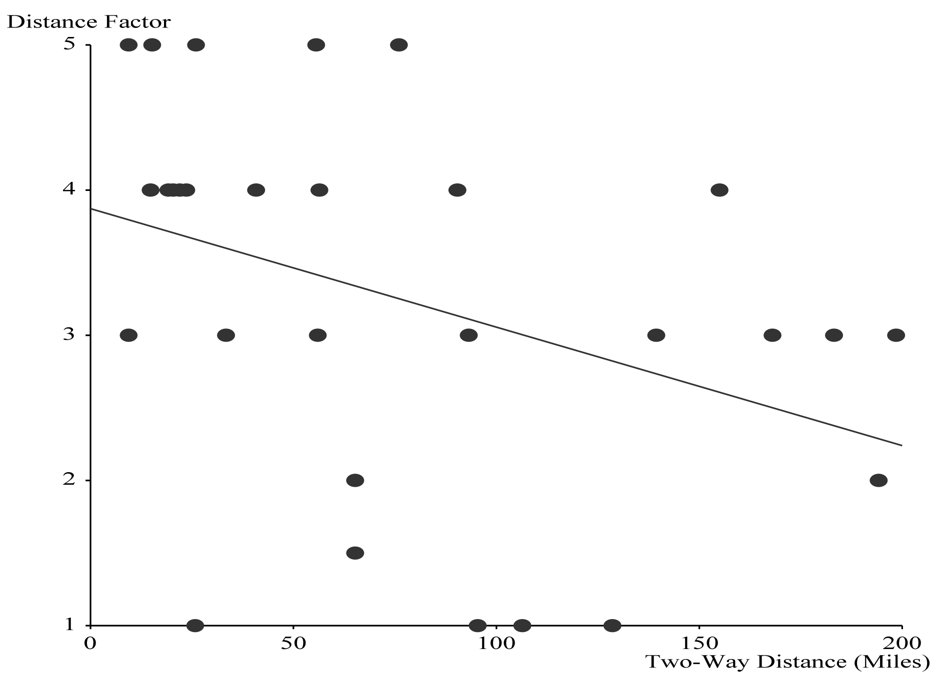

Figure 29. Comparing Travel Distance with Importance Given to Proximity to Market

Of the 29 interviewed farmers, 18 answered "Yes" with respect to not participating in closer farmer markets. "Smaller market (fewer customers)" is given most importance with a mean of 4.3 and a median of 5 (Table 21). The other decision factors are given minimal importance.

Table 20. Farmer Market Characteristics

Characteristic	Mean	Median
Size of Market	4.6	5
Higher Price of Produce	3.4	4
Proximity to Market	3.7	3
Market Tradition	3.0	3
Farm/Business Exposure	3.3	4
Entrance Fee	2.5	3

n=29 observations
Likert Scale 1-5: Not important at all=1, Extremely Important=5

These results imply that farmers' main criterion for not participating in markets closer to their farm is due to the lack of demand at these markets. If the farmer's sales at market cannot at least cover the harvesting and marketing costs to sell produce at the market, the farmer will choose not to sell his or her produce, regardless of the farm's proximity to market. Farmers with longer travel distances to market tended to respond "Yes". Farmers traveling more miles to the downtown market may be located in smaller towns whose farmer markets have a limited number of consumers.

Table 21. Decision Factors to Not Participate in Most Nearby Market

Decision Factor	Mean	Median
Lack of time/labor/resources to harvest, prepare, and ship to other market(s)	3	3
Not enough produce to sell at multiple markets	2.1	1.5
Smaller market (fewer customers)	4.3	5
Conflicting days with larger, more popular markets	2.5	1.25
Conflicting days with personal activities	1.3	1
Other	-	-

n=18 of 29 observations
Likert Scale 1-5: Not important at all=1, Extremely Important=5

Appendix C
Principal Component Analysis (PCA) and Cluster Analysis

Background

Principal Component Analysis (PCA) is a multivariate technique that maximizes the variance of a linear combination of the original variables (Jolliffe 2002). Following Rencher and Christensen (2012), the data structure is an *n x p* matrix, where *n* is the number of observations and *p* is the number of variables. The eigenvectors and eigenvalues of the *p x p* sample covariance matrix, **S**, are found by the function

$$(\mathbf{S} - \lambda\mathbf{I})\mathbf{a} = \mathbf{0}\ .$$

From this equation, *p* eigenvalues and eigenvectors are calculated, where λ_i denotes the eigenvalue that corresponds to the eigenvector, $\mathbf{a_i}$. The largest eigenvalue, λ_1, belongs to the eigenvector, $\mathbf{a_1}$, that, when combined with the *p* original variables, forms the linear combination with maximal variance. The second largest eigenvalue,λ_2, corresponds to the eigenvector, $\mathbf{a_2}$, that forms the linear combination of original variables accounting for the second largest amount of variance. The smallest eigenvalue,λ_p, corresponds to the eigenvector $\mathbf{a_p}$, and accounts for the linear combination with smallest maximum variance. The size of the eigenvalue, therefore, indicates the proportion of variance accounted for by each eigenvector. The sum of the eigenvalues is equal to the total variance of the data.

$$\sum_{i=1}^{p} \lambda_i = \sum_{i=1}^{p} \mathrm{var}(x_i) \ .$$

PCA is often used as a dimension reduction device in multivariate settings where a large percentage of the data's variance is represented by the first q linear combinations of variables, where $q < p$, without losing important information of the data structure (Everitt and Dunn 1991; Jolliffe and Morgan 1992; Wood 2009). The q linear combinations are called principal components and are expressed by

$$\mathbf{z_i} = \mathbf{A}\mathbf{y_i} \ ,$$

where $\mathbf{y_i}$ is the centered observation vector $\mathbf{y_i} - \bar{\mathbf{y}}$ multiplied by **A**, the $q\ x\ p$ matrix of eigenvectors, $\mathbf{a}_\mathbf{i}'$. Following Rencher and Christensen (2012) the eigenvector matrix **A**, is orthogonal and normalized so that, $\mathbf{a}_\mathbf{i}'\mathbf{a_j} = 0$ and $\mathbf{a}_\mathbf{i}'\mathbf{a}_\mathrm{i} = 1$ for $i \neq j$. In multiplying $\mathbf{y_i}$ by the orthogonal eigenvector matrix, the axes are rotated and the principal components are thereby uncorrelated, $\mathrm{cov}\left(z_i, z_j\right) = 0$ for $i \neq j$. The orthogonal matrix, **A**, diagonalizes the sample covariance matrix, **S**, such that $\mathbf{S_z} = \mathbf{ASA}'$.

Principal component analysis can also be carried out using the correlation matrix, **R**, where extracting the principal components of **R** is similar to the procedures for **S** (Rencher and Christensen 2012).. When the variables are measured on different scales, the correlation matrix is often preferred to avoid bias in the principal components (Everitt and Dunn 1991). If **S** is utilized and the variables are not measured on the same scale, the first few components may be dominated by the variables with greatest variability (Jolliffe 2002). With **R**, the variance and covariance are standardized so that the data is scale invariant.

While PCA is often implemented as a data exploration device, the technique is also useful in obtaining input for further statistical analyses (Jolliffe 2002). Cluster analysis is one particular multivariate technique that is commonly used in conjunction with PCA (Dillon and Goldstein 1984; Everitt and Dunn 1991). The aim of cluster analysis is to find the natural groupings of observations so that the observations with similar characteristics are grouped together, and the *k* different clusters are distinct from each other (Hand et al. 2001; Kaufman and Rousseeuw 2009). Unless all variables are recorded using the same units, the data must be either standardized or transformed prior to performing cluster analysis to facilitate the formation of clusters (Kaufman and Rousseeuw 2009). The principal component scores are unit-less, uncorrelated, and standardized to have a mean of zero and unit variance (Gan et al. 2007; Hand et al. 2001). Therefore, if the first few principal components account for a high percentage of the data's variance, cluster analysis can be carried out using the first q component scores with minimal loss of information (Ding and He 2004).

The most frequently employed method of clustering (dis)similar observation vectors is by distance measurements, such as the Euclidean distance

$$d\left(\mathbf{x}_i, \mathbf{x}_j\right) = \sqrt{(\mathbf{x}_i - \mathbf{x}_j)'(\mathbf{x}_i - \mathbf{x}_j)}\ .$$

Thus, observation vectors with similar characteristics will have smaller distances compared to observations with distinct characteristics, whose distances will be larger (Härdle and Simar 2007). While different clustering methods vary by their criteria in defining and forming groups, most clustering algorithms utilize some type of distance measurement to determine clusters (Rencher and Christensen 2012).

Among clustering methods are hierarchical (agglomerative and divisive) and non-hierarchical techniques (Gan et al. 2007). Agglomerative hierarchical clustering, for example, begins by placing each observation into its own cluster, and thereafter, iteratively groups the most similar observations into clusters until all *n* observations form one large cluster. Examples of hierarchical algorithms are single-linkage, complete-linkage, average-linkage, centroid, median, and Ward's method (Murtagh 1983).

Non-hierarchical methods, such as *k*-means, require the specification of the number of clusters prior to analysis (Kaufman and Rousseeuw 2009). Using an initial seed vector for each pre-specified cluster, all *n* observations are grouped into the nearest seed based on the Euclidean distance. Thereafter, the initial seed vectors are recalculated and replaced by the new cluster centroids. In this step, observations may relocate to the cluster in which it is closest to the group centroid. This process is iterated until the *n* observations cannot be relocated to a nearer cluster (Pena et al. 1999; Gan et al. 2007; Härdle and Simar 2007; Rencher and Christensen 2012).

Hierarchical and non-hierarchical clustering methods have their advantages and disadvantages (Härdle and Simar 2007). Several authors have recommended trying a number of clustering techniques on the same data in order to find the cluster structure that makes the most sense to the researcher (Jolliffe et al. 1986; Rosenberg and Turvey 1991; Kaufman and Rousseeuw 2009; Jain et al. 1999). Two disadvantages of hierarchical clustering are that the technique does not allow for the relocation of observations once they are placed in an initial cluster, and that cluster results can vary depending on the clustering algorithm chosen (Gan et al. 2007; Kaufman and Rousseeuw 2009). The setback of non-hierarchical clustering is that there can be a certain degree of arbitrariness in choosing the number of clusters for analysis and the beginning seed values (Pena et al. 1999). Several authors propose a two-stage cluster analysis in which the first stage consists of a preliminary hierarchical clustering method to find the initial number of *k* groups. The second stage uses the cluster centroids from hierarchical clustering as input for a second-stage non-hierarchical clustering method (Milligan 1980; Fisher 1995; Lu et al. 2008; Rencher and Christensen 2012).

Cluster analysis has been used to find typologies among farms and farmers in numerous agricultural applications (Rosenberg and Turvey 1991; Bernhardt et al. 1996; Makhura et al. 1998; Solano et al. 2001; Milán et al. 2003; Usai et al. 2006; Pardos et al. 2008). Pardos et al. (2008) and Milán et al. (2003) employ PCA followed by cluster analysis to classify sheep farms based on their different production practices and economic profitability. Solano et al. (2001) use socio-economic survey data to classify Costa Rican dairy farms via PCA and cluster analysis. Majumdar et al. (2008) find three groups of family forest owners in the southeast United States by applying PCA and cluster analysis to US Forest Service survey data.

Bernhardt et al. (1996) implement cluster analysis as a means of finding an objective characterization of conventional and alternative farming systems using socio-economic and environmental data. Makhura et al. (1998) utilize cluster analysis to classify South African farmer commercialization practices into seven homogenous groups, while Rosenberg and Turvey (1991) use cluster analysis to find swine producer profiles in Ontario, Canada. In both studies, the authors signal the utility of cluster analysis in helping policymakers make more informed decisions in determining the types of resources and assistance that each farmer group may need.

Correlation Matrix (R) of Local Farmer Production and Distribution Variables

The correlation matrix (**R**) is provided in Table 22. The relationships observed in **R** are often reflected in the principal components. Analysis of this matrix prior to conducting PCA facilitates the interpretation of the factor scores. There are several moderate-high correlations among the variables. The variable *distance* is quite correlated with *fmsmktswk* and *mktchannels,* whose correlation coefficients are 0.60 and 0.33, respectively, suggesting that farmers farther from the market tend to participate in more marketing activities than farmers located relatively close to market. Farmers located in areas with low population densities may have fewer alternative marketing opportunities in their nearest town, and thus, travel to more distant farmer and wholesale markets to distribute their products. *boxtruck* is negatively correlated with *mpg* (-0.61), reflecting the inverse relationship between vehicle size and vehicle fuel economy. Larger box trucks are generally less fuel efficient than smaller pick-up trucks. Conversely, *boxtruck* and *truckload* have a strong positive relationship. Farmers using bigger vehicles have more carrying capacity to haul fruits and vegetables. *acres* is highly correlated with *truckload* and *fmsmktswk* and is moderately correlated with *mktchannels*. Farmers with more acreage in fruits and vegetables generate more produce, haul larger truckloads to market and use several marketing channels to sell their products. *fmsmktswk* and *mktchannels* are somewhat correlated (0.45), indicating that farmers with more weekly farmer market activity are also combining these direct marketing sales with other activities, such as wholesale/retail, CSA shares, farm stands, etc.

Table 22. Correlation Matrix for Principal Component Analysis

Variable	distance	box truck	mpg	acres	organic	truckload	fmsmktswk	mktchannels
distance	1	0.22	0.02	0.24	0.02	0.30	0.60	0.33
boxtruck	0.22	1	-0.61	0.17	0.09	0.55	0.22	0.22
mpg	0.02	-0.61	1	-0.21	0.01	-0.36	-0.12	0.08
acres	0.24	0.17	-0.21	1	-0.09	0.69	0.68	0.37
organic	0.02	0.09	0.01	-0.09	1	-0.10	-0.26	0.19
truckload	0.30	0.55	-0.36	0.69	-0.10	1	0.62	0.34
fmsmktswk	0.60	0.22	-0.12	0.68	-0.26	0.62	1	0.45
mktchannels	0.33	0.22	0.08	0.37	0.19	0.34	0.45	1

Analysis of Principal Components

Prior to cluster analysis, principal component analysis (PCA) is carried out on the correlation matrix of the eight variables. PCA standardizes the data into uncorrelated, linear combinations of the original variables with maximum variance. The unit-free principal component scores are more adaptable to cluster analysis, as the eight original variables are measured on varying scales.

The eigenvalues and eigenvalue scree plot from the PCA are provided in Table 23 and Figure 26, respectively. Because the principal components will serve as input to cluster analysis, only the first 5 principal components are retained, accounting for a pre-specified 90 percent minimum variance (Everitt and Dunn 1991). The fifth eigenvalue is 0.56, which is above the 0.50 threshold used by Weigel and Rekaya (2000) in their implementation of PCA as a data transformation technique for cluster analysis.

As a precursor to cluster analysis, the first few principal components are evaluated for potentially meaningful interrelationships among the local farmer transportation variables (Everitt and Dunn 1991) (Table 24). When all or several elements have high, positive coefficients for the first PC, the component is often described to be a measurement of size. In PC 1, the variables *distance, boxtruck*, *acres*, *truckload*, *fmsmktswk*, and *mktchannels* have moderate to high, positive coefficients and are contrasted with *mpg* and *organic*, whose weights are negative. This suggests that there may be some inverse relationship between farmers' production, distribution, and marketing scales and their farm locations, farming practices, and vehicle types. PC 1 is labeled as a descriptor of production and distribution scale.

Table 23. Eigenvalues of Principal Component Analysis

PC	Eigenvalue	Individual Percent	Cumulative Percent
1	3.19	39.9	39.9
2	1.51	18.91	58.81
3	1.21	15.13	73.94
4	0.81	10.15	84.09
5	0.56	7.03	91.11
6	0.38	4.8	95.91
7	0.17	2.15	98.06
8	0.16	1.94	100

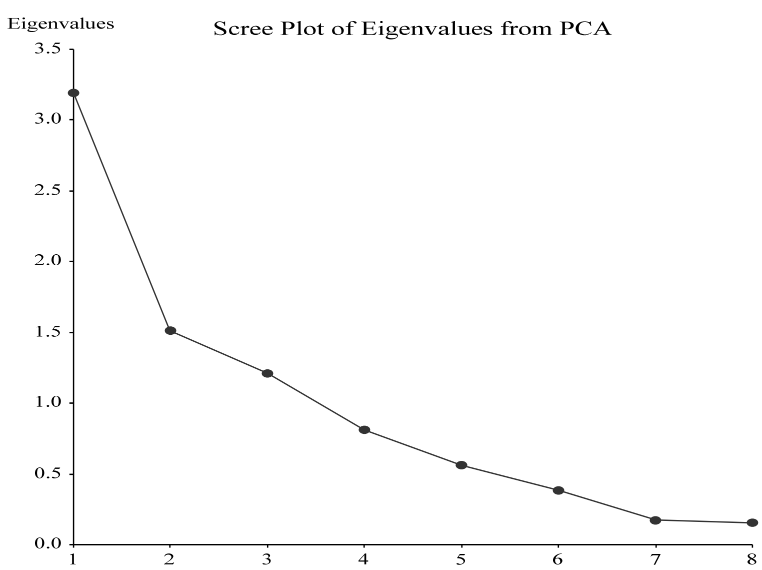

Figure 30. Scree Plot of Eigenvalues from PCA

PC 2 contrasts vehicle fuel economy with vehicle type, as *mpg* and *boxtruck* have high, positive and negative coefficients, respectively. This reflects the inverse relationship between these two variables. PC 2, therefore, may account mostly for the variation in farmer vehicle fuel economy (MPG). The largest weights for variables in PC 3 correspond to *organic* and *mktchannels*, both of which are negative, indicating that there may be a relationship between farming practices and marketing activity among the interviewed farmers. PC 4 contrasts *acres* with *distance*, suggesting that there may be considerable differences between the size of farms and their location relative to the market.

Table 24. Eigenvectors of the First Five Eigenvalues

Variable	PC 1	PC 2	PC 3	PC 4	PC 5
distance	0.569	0.361	-0.195	-0.657	0.222
boxtruck	0.578	-0.648	-0.202	-0.230	-0.246
mpg	-0.397	0.807	-0.099	0.048	-0.100
acres	0.776	0.155	0.167	0.467	0.255
organic	-0.096	-0.133	-0.897	0.181	0.356
truckload	0.860	-0.156	0.108	0.185	0.030
fmsmktswk	0.845	0.350	0.185	-0.092	0.074
mktchannels	0.558	0.350	-0.494	0.179	-0.494

Vita

Charles Cate Grigsby-Calage conducted this research as a Research Graduate Assistant from 2013 to 2015. He graduated in May 2015 with a Master's degree in Agricultural & Resource Economics from the University of Tennessee.