Examining Seasonality of Spatial Efficiency in the U.S. Fresh Broccoli Market: Implications for the Eastern Broccoli Industry

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Introduction

Broccoli is a major specialty crop in the U.S. with well-known nutritional benefits and a farm gate annual retail value of about $684 million (USDA 2012). Despite being consumed nationwide, production is located primarily in the West Coast, with more than 90% produced in California and 5% produced in Arizona (NASS 2012). The East Coast (i.e., Maine, New York, Kentucky, Virginia, Tennessee, North Carolina, South Carolina, Georgia and Florida) as a whole provides only approximately 4% of the total U.S. broccoli consumption (NASS 2012). More than 70% of California's broccoli production comes from the Salinas and Santa Maria areas (NASS 2012), which enjoy moderate weather conditions to grow and harvest broccoli year round. In contrast, in the East Coast, broccoli can only be harvested during certain seasons, depending on the production location (e.g. Florida's harvest is in the winter season and New York's harvest is in the summer season).

California's dominant position as a supplier of broccoli for the East Coast markets may face future unsustainability challenges, both economically and environmentally. The central valley, where Salinas and Santa Maria are located, is suffering increasing water scarcity due to intensive irrigation needs (Tanaka et al. 2006). Moreover, the long transportation distance from the West Coast to eastern markets not only produces considerable carbon emissions but may also results in higher prices due to increasing fuel costs (Weber and Matthews 2008). As consumers and retailers become more concerned about the environmental and social impact of food supply chains, they are demanding more locally- and regionally-grown food. To meet these demands, a consortium of broccoli industry stakeholders (including plant breeders, growers and marketers) are making efforts to expand the existing eastern broccoli industry to supply high-quality product year round (Atallah, Gómez, and Björkman 2014). This consortium is also making efforts to develop new broccoli varieties adaptable to eastern U.S growing conditions. To justify these efforts, it is important to assess the impacts of an expanding eastern broccoli industry on market performance.

When analyzing market performance of non-storable products such as vegetables, including broccoli, it is important to consider seasonality in production and transportation, because they cause price seasonality. For instance, although packer-shippers in California ship broccoli nationally year round, the peak harvest season in that region is in March, April and May, resulting in lower prices during these months. In addition, in the East Coast, different supply locations harvest broccoli in different seasons, contributing to further price seasonality. In addition to production seasonality, transportation costs also often exhibit seasonal patterns, with higher rates in the summer-fall season than in the winter-spring season. It is possible that the seasonal pattern will affect the market performance.

The degree of spatial market efficiency has been widely used to indicate market performance in various dimensions (Faminow and Benson 1990). A number of studies have examined the spatial market efficiency for multiple agricultural products (Baulch 1994; Goodwin and Schroeder 1991; Fackler and Goodwin 2002; Myers 2013). Most research to date focuses primarily on testing the spatial market efficiency of agricultural commodities such as rice, maize, wheat, among others. However, few studies have evaluated efficiency in fresh vegetables and fruits markets such as broccoli. An exception is Sexton, Kling and Carman (1991), which estimated the spatial efficiency of the U.S.

celery market. But the study considers the period 1985-1988 and the fruit and vegetable market has changed dramatically since then.

To fill this gap in the literature, we develop a switching regime model based on Sexton, Kling, and Carman (1991) to test the spatial efficiency in the U.S. fresh broccoli markets. We use weekly price data from one broccoli shipping point and ten demand locations, obtained from USDA's Agricultural Marketing Services covering the period from June 2008 to May 2013. To take seasonality into account, we also conduct the spatial efficiency analysis separately for the winter-spring season and for the summer-fall season.

Our results suggest that broccoli shipments from Santa Maria to West Coast and Midwestern demand locations operate mostly under the efficient arbitrage regime and there are no significant seasonal differences in spatial efficiency levels. In contrast, shipments to the majority of eastern demand locations exhibit considerable periods of market inefficiencies (gluts or shortages). Nevertheless, eastern markets are more efficient during the season when there is local and regional production. As a result, overall market efficiency could be improved if the eastern broccoli industry is able to supply product year round.

This paper proceeds as follows. First, we explore existing literature on market efficiency. The paper then describes the data and methodology used in our analysis. Next, we discuss results from the econometric models. Finally, we summarize and interpret our findings and discuss their implications for the broccoli industry.

Literature Review

The nature of markets and their performance are of great interest to academic researchers, policy makers and practitioners. The degree of spatial market efficiency has been widely used to indicate market performance in various dimensions (Faminow and Benson 1990). For instance, the extent of market efficiency can have important implications for the competitiveness of markets (Sexton, Kling, and Carman 1991), the effectiveness of arbitrage (Carter and Hamilton 1989), the efficiency of pricing (Buccola 1983), and the overall operation efficiency of the market (Goodwin and Piggott 2001). Given that both agricultural production and consumption are often spatially dispersed, agricultural markets' efficiency levels are of special interest to researchers. Knowledge on the spatial market efficiency, can indicate whether agricultural products are distributed efficiently or misallocations (i.e., periods of gluts or shortages) exist.

Over the last few decades, a large amount of empirical research has measured the spatial market efficiency levels for different agricultural products using a variety of models and econometric methods (Fackler and Goodwin 2002). Fackler and Tastan (2008) provide a comprehensive summary of this literature. Most of these studies focus on storable commodities such as rice, maize, wheat, soybean, coffee, cattle and hogs. For example, Baulch (1994) examined the Philippines rice market; Benson and Faminow (1990) evaluated the Canadian market for hogs; Goodwin and Schroeder (1991) tested efficiency in the international wheat market and in the U.S. cattle market; Lee and Gómez (2013) investigated market efficiency in the international coffee market; Moser, Barrett, and Minten (2009) examined Madagascar's rice market; and Myers (2013) analyzed Malawi's maize markets, among others. However, little research has been conducted to investigate spatial efficiency in vegetable markets, despite their importance and high economic value. Exceptions include Sexton, Kling, and Carman (1991), who examined the U.S. fresh celery market, and Munir et al. (1997), who evaluated market efficiency in the Indonesian vegetable markets.

Among all these empirical studies on spatial market efficiency and market efficiency, there are two main frameworks commonly employed for statistical testing (Myers, Sexton, and Tomek 2010). The first is the (threshold) cointegration/error correction model (ECM), pioneered by Ravallion (1986) and further used by many researchers (e.g., Goodwin and Piggott 2001; Septhon 2003; Myers 2013). The second framework is the switching regime model, which was first applied to spatial price efficiency in agricultural commodities by Sexton Kling and Carman (1991), and subsequently extended by Baulch (1997), Barrett and Li (2002), Negassa and Myers (2007), and Butler and Moser (2010), among others. Although both frameworks can be used to test spatial market efficiency, each has its own advantages and limitations. In particular, the switching regime model is appropriate to estimate spatial efficiency when production is concentrated in few production locations and consumption is spread in multiple demand locations (Sexton, Kling and Carman 1991). In addition, the switching regime model can predict the probabilities that a given market falls in any of three regimes, namely efficient arbitrage, gluts or shortages regimes, relying on distributional assumptions of maximum likelihood estimates (Butler and Moser 2010). ECMs, for their part, are more appropriate to evaluate spatial efficiency when price series data are non-stationary and co-integrated (Goodwin and Piggott 2001; Meyer 2004). Therefore, to choose which of these two frameworks to use in spatial market analysis, depends on the research objectives as well as on and the characteristics of the market and the data.

Another important characteristic of agricultural markets is that they exhibit substantial seasonality in production and in transportation costs, which in turn can result in seasonal price patterns. In spite of its importance, most spatial efficiency studies of agricultural markets have ignored seasonality, which may lead to incorrect assessments of market efficiency (Zanias 1999). The effect of neglecting seasonality in spatial efficiency analysis may be small when it is about agricultural products that are easy to store (such as rice, maize, and soy) because storage can help mitigate product distribution misallocations and thus improve market efficiency. However, this effect may be significant when studying vegetable markets because they are highly perishable and need to be shipped to demand locations almost immediately after harvest.

There are several major existing studies that include both spatial market efficiency and seasonality in their analysis. Zanias (1999) examined the European Union soft wheat markets using a cointegration testing framework. Myers (2013) evaluated Malawi’s maize market using the threshold autoregression model (TAR). But none of them focused in vegetables and neither focused on the differences in spatial efficiency levels for different seasons. The exception is Sexton, Kling and Carman (1991), which studied the degree of spatial efficiency in the U.S. fresh celery market for different seasons. But vegetable markets have changes substantially since then (Saitone and Sexton 2012), warranting the need for additional assessment of market efficiency in vegetable markets.

To help fill the gap in the literature, we examine the spatial efficiency level in the U.S. fresh broccoli markets, using weekly price data from June 2008 to May 2013. Given that broccoli production and consumption are spatially dispersed and our tests result fail to reject that the broccoli price time series are stationary, we use the switching regime method in our analysis following Sexton, Kling and Carman (1991). Given that seasonality (in production and transport costs) is important to the broccoli supply chain, we also conduct two separate spatial efficiency analysis, one for the summer-fall season (June to November) and the other for the winter-spring season (December to May). This allows us to examine differences in spatial efficiency levels for different seasons and test whether market efficiency levels are improved during the season when local product is available. Our study is also relevant for other fruit and vegetable crops produced primarily in the West Coast and distributed nationally. Examples of such crops include carrots, celery, chicory, endive, grapes, strawberries, and lettuce.

Empirical Methods

We use a switching regime model following Sexton, Kling and Carman (1991) to assess the extent of market efficiency of the U.S. broccoli sector. The key premise of the model is that there are three regimes between a shipping point and a demand location: (a) the efficient arbitrage regime; (b) the shortage regime; and (c) the glut regime, depending on whether the price differences between the demand locations and shipping points equal, exceeds or fall below the corresponding transaction costs. The probabilities of the three market regimes are estimated as parameters, which can be used to assess the level of market efficiency.

Denote p_{it}^{S} as the price in the supply location *i* in time *t* and p_{jt}^{D} as the price in the demand location *j* ($j = 1, 2, 3, \dots, n$) in time *t*. In addition, let τ_{ijt} denote the transaction cost between the shipping point i and demand location j at time *t*. The transaction cost often includes transportation cost and other costs associated with the exchange. It is reasonable to assume that the transaction cost τ_{ijt} is a random variable with constant mean T_{ij} and that it has the following distribution:

(1) $\tau_{ijt} = T_{ij} + v_{ijt}, where\ v_{ijt} \sim N\left(0, \sigma_{ijv}^{2}\right),$

where v_{ijt} is the i.i.d. error term, *N* is the normal distribution, and σ_{ijv}^{2} is the variance of transaction cost in the market pair *(i, j)*. According to the law of one price, if markets are efficient (or fully integrated), then the following condition holds for each shipping point *i* at a given time period t:

(2) $\mathrm{p}_{it}^{S} = \mathrm{p}_{1t}^{D} - \tau_{i1t} = \mathrm{p}_{2t}^{D} - \tau_{i2t} = \cdots = \mathrm{p}_{nt}^{D} - \tau_{int}$

However, if there are product distribution misallocations due to such factors as shipment lags, imperfect information and risk factors, among others (Buccola 1983), then markets are deemed inefficient and there may be periodic gluts or shortages of product shipped to a give demand location *j*. In these cases, the equalities in Equation (2) will not hold for every t. To examine the existence of periodic gluts and shortages, let us define the price difference between shipping point i and demand location *j* as $R_{ijt} = p_{jt}^{D} - p_{it}^{S}$. Assume that the data generating process for R_{ijt} (we drop the subscript i and *j* for simplicity) as follows:

(3) $R_t = T + v_t + u_t,\ with\ probability\ \theta_1,$

(4) $R_t = T + v_t - u_t,\ with\ probability\ \theta_2,$

(5) $R_t = T + v_t, \qquad with\ probrobability\ 1 - \theta_1 - \theta_2,$

where u_t is a one-side, positive half-normal random variable with variance σ_u^2 and is independent of v_t. In this representation of R_{ijt}, Equation (3) identifies a regime of product shortages in demand locations; Equation (4) defines a regime of product gluts in demand locations; and Equation (5) defines a regime of efficient arbitrage (i.e., efficiency of markets or market spatial efficiency). Using the density of the sum of a normal random variable and a truncated normal random variable (Weinstein 1964), we can write the density functions for R_t in each of the three regimes as follows:

$$(6) \qquad f_{1t} = \left[\frac{2}{(\sigma_u^2+\sigma_v^2)^{1/2}}\right] \varphi \left[\frac{R_t-T}{(\sigma_u^2+\sigma_v^2)^{1/2}}\right] \left[1 - \Phi\left[\frac{-(R_t-T)\sigma_u/\sigma_v}{(\sigma_u^2+\sigma_v^2)^{1/2}}\right]\right],$$

$$(7) \qquad f_{2t} = \left[\frac{2}{(\sigma_u^2+\sigma_v^2)^{1/2}}\right] \varphi \left[\frac{R_t-T}{(\sigma_u^2+\sigma_v^2)^{1/2}}\right] \left[1 - \Phi\left[\frac{(R_t-T)\sigma_u/\sigma_v}{(\sigma_u^2+\sigma_v^2)^{1/2}}\right]\right],$$

$$(8) \qquad f_{3t} = \frac{1}{\sigma_v} \varphi \left[\frac{R_t-T}{\sigma_v}\right],$$

where $\varphi(\cdot)$ is the standard normal density function, and $\Phi(\cdot)$ is the standard normal cumulative distribution function. We use maximum likelihood estimation (MLE) to estimate the model. The likelihood function can be formulated as follows:

$$(9) \qquad L = \prod_{t=1}^{T} [\theta_1 f_{1t} + \theta_2 f_{2t} + (1 - \theta_1 - \theta_2) f_{3t}]$$

The unobserved transaction cost *T*, the probabilities for the shortages and gluts regimes θ_1 and θ_2, and the error parameters σ_v^2 and σ_u^2 can be estimated by maximizing the log of Equation (9). The probability for the efficient arbitrage regime can be subsequently calculated from the estimates of θ_1 and θ_2. The estimated parameters can indicate whether periodic product gluts or product shortages occur in various demand locations. Furthermore, to take seasonality into account, we separately estimate probabilities for the three regimes for the winter-spring season and for the summer-fall season. By doing this, we can find whether the market efficiency levels for the season when there is local production in the demand location differs from the season when there is no local supply. The differences in efficiency levels between seasons therefore indicate whether or not competition from local production improves market efficiency.

Data and Descriptive Statistics

Weekly broccoli prices for shipping points and demand locations were obtained from the Agricultural Marketing Service of the U.S. Department of Agriculture (AMS-USDA) covering the period from June 1, 2008 to May 31, 2013. The shipping point data we employ is from Santa Maria, which is the one of the two biggest broccoli producing suppliers in California. Salinas is the other major broccoli supplier in California, but shipments from Salinas to demand locations are generally missing between December and February. Santa Maria, on the other hand, has more stable month-to-moth broccoli shipments and is therefore more appropriate for the seasonality analysis. For demand locations, we employ terminal market prices for ten major U.S. metropolitan areas, including Los Angeles, Seattle, Chicago, Dallas, St. Louis, Boston, New York, Philadelphia, Atlanta, and Columbia. These cities are grouped as locations in the West Coast, Midwestern, Northeastern and Southern regions of the U.S. Figure 1 shows a map of Santa Maria (the shipping point) and the demand locations included in our analysis.

[Insert figure 1 here]

Table 1 shows the summary statistics for broccoli price data of both the shipping point and the demand locations. Prices are in terms of dollar per carton of broccoli crowns. Maximum and minimum price for each location are reported and we employ the average price in our analysis. As expected, the shipping point, Santa Maria, has the lowest broccoli mean price of $10.24 per carton. Prices for demand locations are generally higher than that of the shipping point but vary depending on their respective distance to the shipping point. Los Angeles, the closest demand location to Santa Maria, has the lowest terminal price of $14.3 per carton. Chicago and St. Louis in the Midwest have mean prices around $15.7 per carton, which are slightly higher than the price for Los Angeles. Cities located in the Northeast have even higher mean prices between $15.77 and $16.57 per carton but lower than the prices for Atlanta and Columbia in the Southeast, which have the highest mean prices of $18.64 and $19.18 per carton, respectively. It is clear that all locations experience volatile broccoli prices and have comparable standard deviations of around $3.87-$5.34 per carton over the study period.

[Insert table 1 here]

To examine the seasonal difference in market efficiency levels, we separate the data into two parts: summer-fall (from June to November) and winter-spring (from December to May). The summary statistics for the separated data are reported in table 2. For Santa Maria, the shipping point, the mean price for the winter-spring season is $10.62 per carton, which is $0.76 higher than the summer-fall average price. Most demand locations located in the West Coast, in the Midwest and in the Southeast have higher average prices in the winter-spring season. For St. Louis and all Northeastern cities, there are no significant price differences between the winter-spring and summer-fall seasons. The reason could be that the higher winter-spring shipping prices also transmitted to these cities, but offset by higher transportation costs in the summer-fall season. The standard deviation of prices for Santa Maria in the winter-spring season is $4.55 per carton, which is also higher than that of the summer-fall season. This higher volatility in the shipping point in the winter-spring season appears to be transmitted to all demand locations.

[Insert table 2 here]

Results

Parameter estimates from Equation (9) without taking seasonality into account are reported in Table 3. The estimated probabilities of gluts, shortages and arbitrage efficient allow us to assess the level of market efficiency between Santa Maria and each demand location. These results are in line with our expectations. That is, broccoli shipments from Santa Maria to most West Coast and Midwestern cities (i.e. Los Angeles, Seattle, Chicago, and Dallas) operate primarily under efficient arbitrage regimes. Specifically, Dallas exhibits the highest market efficiency level, as efficient arbitrage has a probability of 81%, followed by Chicago with 79%, Los Angeles with 78%, and Seattle with 76%.

[Insert table 3]

In contrast, shipments to the majority of East Coast cities exhibit a higher probability for periods of market inefficiencies (i.e., gluts or shortages) than their Western and Midwestern counterparts. For example, the probabilities that markets are efficient between Santa Maria and Boston, New York, Philadelphia, and Columbia are only 34%, 57%, 22%, and 46%, respectively. It is also interesting to note that, for these markets, the estimated probabilities of gluts (θ_2) are all higher than the estimated probabilities of shortages (θ_1). These results suggest that Santa Maria often ships excess broccoli to these demand locations. The only exception in the East Coast is Atlanta, where the probability of efficient arbitrage is relatively high, reaching 70%. This may be due to the fact that Atlanta is supplied by Georgia and Florida in the winter season, which competes with broccoli shipped from Santa Maria during that season. Thus, our results suggest that competition from broccoli produced in Georgia and Florida may contribute to improved market efficiency in the Atlanta market.

The estimated transaction costs (which consist mostly of transportation cost) are in line with our expectations. That is, they tend increase with the relative distance to the shipping point, Santa Maria. Columbia exhibits the highest transaction cost of $9.49 per carton and Los Angeles has the lowest transaction cost of $3.62 per carton. It is important to note that transaction costs account for a significant portion of the price in demand locations located in the East Coast, ranging from 40% to 49.5% of terminal point prices. In addition, Northeastern demand locations exhibit lower transportation cost than their Southern counterparts even though they are located farther away from Santa Maria. This is because track rates for Southeastern locations are higher.

The above discussion suggests higher probability of market inefficiencies in East Coast demand locations. An important related question is whether or not these inefficiencies depend on the season. Given that our primary interest lies in whether or not broccoli production on the East Coast improves market efficiency, we also examine differences between the summer-fall season and the winter-fall season. We show parameter estimates from Equation (9) separating the sample into these two seasons in table 4. Our parameter estimates suggest that shipments from Santa Maria to most West Coast and Midwest demand locations operate under an efficient regime during both the winter-spring season and the summer-fall season. We find no significant seasonal patterns of market efficiency in these markets. The only exception is St. Louis, which has relatively lower probability of efficient arbitrage during the summer-fall season than in the winter-spring season (43% and 82%, respectively).

[Insert table 4]

In contrast, our results suggest that seasonality substantially affects market efficiency in the East Coast demand locations. In demand locations in the Northeast, for example, we find that the probability of efficient arbitrage is much smaller in the winter-spring season (ranging from 3% in Philadelphia to 47% in New York), when broccoli is not produced in this region. Conversely, in the summer-fall season, the probability of efficient arbitrage is much higher in the same region (ranging from 43% in Boston to 87% in New York).

The results for our Southeastern demand locations are opposite than those for the Northeastern cities. Table 4 indicates that, in Atlanta, the market is more efficient in the winter-spring season (67%) when there is broccoli supply from nearby regions such as Georgia and Florida. On the other hand, our results suggest that the probability of efficient arbitrage is zero in the summer-fall season for this city. The results are different for Columbia, even though this city is geographically close to Atlanta: our estimates indicate that the probabilities of efficient arbitrage in the winter-spring and summer-fall seasons are 43% and 59%, respectively. This may be due to the fact that North Carolina and South Carolina are able to supply broccoli to Columbia in the summer-fall season.

Our analysis of the influence of seasonality on market efficiency reveals other important aspects of the broccoli market in the East Coast. For example, we find that the probability of a glut regime tends to be higher than the probability of a shortage regime when local/regional supply is not available. This implies that Santa Maria may ship excess broccoli to these markets during the seasons when there is no local/regional production. Our results also indicate that transaction costs are not consistently higher in the summer-fall season despite the generally higher truck rates during these months. For example, the estimated transaction cost for Philadelphia in winter-spring season is $8.14 per carton, which is higher than the transactions cost in the summer-fall season for that city ($6.81 per carton). In addition, for Boston and New York, there are no seasonal differences in estimated transaction costs. This implies that other components of the transaction cost (different than transportation) in the winter-spring season may offset the lower truck rates.

Overall, these results suggest that markets in the East Coast tend to be more efficient during the seasons when local/regional product is available. Consequently, our findings support the hypothesis that expanding broccoli production in the East Coast may contribute to improved market efficiency.

Conclusion

In this paper, we employed a switching regime model to test for the spatial efficiency of broccoli markets between Santa Maria and various demand locations in the U.S., including cities located on the East Coast. We also examined differences in market efficiency levels between the summer-fall season and the winter-spring season. We employed Maximum Likelihood Estimators to derive the probabilities that a given market operates under three alternative regimes, namely efficient arbitrage, gluts and shortages.

We find that broccoli shipments from Santa Maria to Western and most Midwestern cities operate primarily under efficient regimes. Moreover, we find no seasonal differences in market efficiency levels in both Western and Midwestern cities. In contrast, shipments to the majority of East Coast demand locations exhibit higher probability periods of market inefficiencies. In cities located in the Northeast, markets tend to be more efficient in the summer-fall season; and in cities located in the Southeast, markets enjoy higher probabilities of efficient arbitrage in the winter-spring season. In other words, the seasons when local/regional supplies are available coincide with higher probabilities of having efficient markets.

These findings suggest that eastern markets are more efficient when there is local/regional competition due to broccoli production on the East Coast. As a result, overall market efficiency could be improved if the eastern broccoli industry is able to supply product year-round. Our results provide support to current efforts to develop varieties adapted to East Coast growing conditions and then extend the current harvest season to year round, which can contribute substantially to improve market efficiency in broccoli markets. In addition, an expanding East Coast broccoli industry can also help alleviate problems associated with increased water scarcity in California, can contribute to reduce the carbon emissions due to long distance transportation from California to the East Coast, and can meet the demand for local food and thus fostering local economic development.

Our study provides valuable insights to the analysis of market efficiency in specialty crops. Nevertheless it has several limitations that warrant future research. First, like most spatial analysis studies, price is the only variable that we use in this investigation. Future research can include shipment volume data and develop structural models to identify potential sources of market inefficiency. Second, we employed the wholesale prices at terminal markets reported to USDA in demand locations. Broccoli, like other vegetable crops, is being increasingly shipped directly to the warehouses of self-distributing retailers that operate regionally and even nationally. Most of these retailers have developed their own supply chain structures and the prices they pay to packer-shippers may not correspond exactly to the terminal prices reported to USDA. Consequently, future studies may use syndicated data (e.g., IRI scanner data) to incorporate these supply chains market efficiency analysis. Finally, our econometric model assumes that transaction costs are constant over the study period. Future research should develop statistical tests (using longer price data series) to test the validity of this assumption.

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Figure 1. Map of supply and demand locations

Table 1. Summary Statistics for weekly broccoli price data

Markets	N	Mean Price[a]	Standard Deviation
Shipping point			
Santa Maria	260	10.24	4.16
Terminal markets			
West-Coast Cities			
Los Angeles	260	14.30	4.52
Seattle	260	17.07	5.34
Midwestern Cities			
Chicago	260	15.61	4.49
Dallas	260	17.15	4.48
St. Louis	254	15.80	3.87
Northeastern Cities			
Boston	253	16.20	4.34
New York	238	16.57	4.24
Philadelphia	259	15.77	4.02
Southern Cities			
Atlanta	259	18.64	4.67
Columbia	236	19.18	3.97

a: Unit: dollar per 20 lb carton.

Table 2. Summary Statistics for separated weekly broccoli price data

Markets	Winter-Spring			Summer-Fall		
	N	Mean price	Standard deviation	N	Mean price	Standard deviation
Shipping point						
Santa Maria	130	10.62	4.55	130	9.86	3.70
Terminal markets						
West-Coast Cities						
Los Angeles	130	15.10	5.01	130	13.49	3.82
Seattle	130	18.04	6.27	130	16.09	3.99
Midwestern Cities						
Chicago	130	15.68	5.22	130	15.53	3.64
Dallas	130	17.52	4.94	130	16.77	3.96
St. Louis	124	15.79	4.16	130	15.81	3.57
Northeastern Cities						
Boston	128	16.29	4.99	125	16.11	3.56
New York	118	16.24	4.67	120	16.90	3.76
Philadelphia	129	15.75	4.79	130	15.78	3.10
Southern Cities						
Atlanta	129	19.03	5.43	130	18.24	3.73
Columbia	114	19.58	4.68	122	18.80	3.13

Table 3. Parameter Estimates for Spatial Efficiency in U.S. Fresh Broccoli Markets

Markets	T^a	σ_u^2	σ_v^2	θ_1 (Shortage)	θ_2 (Glut)	$1-\theta_1-\theta_2$ (Efficient)	Log likelihood	N	*T* as % of mean price
West-Coast Cities									
Los Angeles	3.62	8.82	1.66	0.20	0.02	0.78	-510.21	260	25.35%
	(23.20)[b]	(2.57)	(5.23)	(2.26)	(0.88)				
Seattle	5.79	41.40	9.82	0.22	0.02	0.76	-737.96	260	33.94%
	(12.46)	(2.42)	(4.83)	(1.84)	(0.83)				
Midwestern Cities									
Chicago	5.27	9.80	2.96	0.12	0.09	0.79	-571.97	260	33.74%
	(25.39)	(2.10)	(4.23)	(1.29)	(1.30)				
Dallas	6.47	16.03	5.14	0.16	0.03	0.81	-631.89	260	37.72%
	(18.68)	(1.24)	(4.08)	(1.02)	(0.48)				
St. Louis	6.05	8.18	0.83	0.22	0.37	0.40	-563.57	254	38.29%
	(31.57)	(6.04)	(2.68)	(3.70)	(4.85)				
Northeastern Cities									
Boston	6.64	11.18	1.08	0.20	0.46	0.34	-609.82	253	41.01%
	(23.60)	(5.57)	(2.32)	(3.72)	(4.65)				
New York	6.91	17.67	3.36	0.11	0.32	0.57	-605.03	238	41.70%
	(19.89)	(4.10)	(3.32)	(2.07)	(2.79)				
Philadelphia	7.27	12.06	0.63	0.08	0.70	0.22	-604.23	259	46.11%
	(22.25)	(8.16)	(2.00)	(3.20)	(6.38)				
Southern Cities									
Atlanta	8.13	12.93	3.01	0.19	0.11	0.70	-604.02	259	43.62%
	(31.91)	(1.97)	(3.64)	(1.52)	(1.59)				
Columbia	9.49	19.17	2.70	0.20	0.34	0.46	-623.25	236	49.50%
	(26.52)	(4.34)	(2.61)	(3.13)	(3.17)				

a: Transaction cost.
b: t-value in parentless.

Table 4. Seasonal Parameter Estimates for Spatial Efficiency in U.S. Fresh Broccoli Markets

Markets	Season[a]	T	σ_u^2	σ_v^2	θ_1 (Shortage)	θ_2 (Glut)	$1-\theta_1-\theta_2$ (Efficient)	Log likelihood	N	T as % of mean price
West-Coast Cities										
Los Angeles	Winter	4.16	11.43	2.40	0.16	0.04	0.79	-277.24	130	27.51%
		(13.31)	(0.75)	(2.68)	(0.79)	(0.56)				
	Summer	3.31	3.97	1.12	0.20	0.00	0.80	-217.73	130	24.51%
		(12.52)	(0.90)	(2.29)	(0.73)	(0.00)				
Seattle	Winter	6.43	47.58	15.74	0.20	0.02	0.78	-391.14	130	35.65%
		(6.27)	(0.93)	(2.65)	(0.73)	(0.32)				
	Summer	5.28	28.18	6.27	0.22	0.00	0.78	-336.60	130	32.82%
		(9.85)	(1.59)	(2.35)	(1.31)	(0.00)				
Midwestern Cities										
Chicago	Winter	4.38	11.60	3.72	0.25	0.00	0.75	-298.36	130	27.95%
		(8.11)	(1.03)	(2.38)	(0.86)	(0.00)				
	Summer	5.72	20.26	2.44	0.02	0.05	0.93	-261.66	130	36.85%
		(32.45)	(0.18)	(2.82)	(0.12)	(0.60)				
Dallas	Winter	5.99	16.70	7.67	0.28	0.00	0.72	-340.89	130	34.19%
		(5.07)	(0.84)	(1.49)	(0.52)	(0.00)				
	Summer	6.66	11.79	3.42	0.09	0.00	0.91	-278.41	130	39.72%
		(17.83)	(0.39)	(2.95)	(0.41)	(0.00)				
St. Louis	Winter	5.15	18.67	3.69	0.15	0.03	0.82	-288.30	124	32.61%
		(15.04)	(1.02)	(3.38)	(1.05)	(0.52)				
	Summer	6.02	6.79	0.58	0.27	0.30	0.43	-271.14	130	38.08%
		(31.01)	(4.05)	(2.17)	(3.23)	(3.47)				

a: "Winter" here stands for "Winter-Spring" and "Summer" here stands for "Summer-Fall".

Table 4. Seasonal Parameter Estimates for Spatial Efficiency in U.S. Fresh Broccoli Markets (Continued)

Markets	**Season**	***T***	σ_u^2	σ_v^2	θ_1 **(Shortage)**	θ_2 **(Glut)**	$1-\theta_1-\theta_2$ **(Efficient)**	**Log likelihood**	**Obs.**	***T* as % of mean price**
Northeastern Cities										
Boston	Winter	6.66	12.93	1.00	0.21	0.57	0.22	-324.54	128	40.85%
		(11.46)	(4.62)	(1.20)	(2.72)	(3.34)				
	Summer	6.66	8.42	1.09	0.20	0.37	0.43	-280.18	125	41.32%
		(19.75)	(2.97)	(1.80)	(2.26)	(2.53)				
New York	Winter	6.75	18.51	2.88	0.09	0.44	0.47	-304.34	118	41.55%
		(11.38)	(3.27)	(2.06)	(1.42)	(2.41)				
	Summer	6.77	28.45	5.27	0.08	0.05	0.87	-294.58	120	40.03%
		(22.21)	(0.81)	(3.33)	(0.84)	(0.56)				
Philadelphia	Winter	8.14	17.53	0.03	0.05	0.92	0.03	-307.18	129	51.67%
		(29.83)	(6.56)	(0.63)	(2.48)	(13.14)				
	Summer	6.81	10.31	0.97	0.11	0.44	0.46	-288.48	130	43.14%
		(24.77)	(4.29)	(2.50)	(2.23)	(3.53)				
Southern Cities										
Atlanta	Winter	7.52	15.43	4.90	0.31	0.02	0.67	-321.74	129	39.50%
		(8.74)	(1.22)	(2.06)	(0.82)	(0.27)				
	Summer	10.28	7.52	0.55	0.05	0.95	0.00	-272.60	130	56.35%
		(8.17)	(3.42)	(1.05)	(0.92)	(2.18)				
Columbia	Winter	8.74	22.77	4.77	0.30	0.27	0.43	-322.24	114	44.66%
		(10.52)	(2.36)	(1.42)	(1.51)	(1.70)				
	Summer	9.55	15.54	2.25	0.14	0.27	0.59	-294.25	122	50.79%
		(28.87)	(2.38)	(2.53)	(2.21)	(1.91)				