REGIONAL PRICE VARIATIONS OF U.S. ALFALFA HAY

by

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STATEMENT BY AUTHOR

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Dr. Russell Tronstad Date

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ABSTRACT

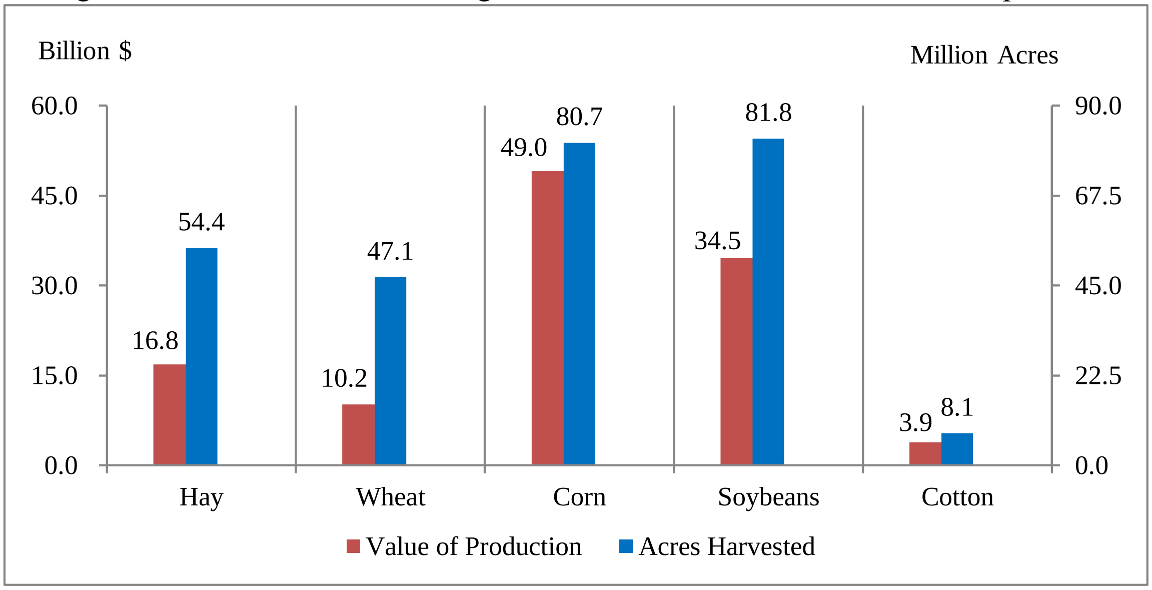
Alfalfa hay is one of the most important field crops in the United States, its regional price differences are driven by variations in quality, location, seasonality, and other features. This thesis investigates the impact of dairy cow inventories, lagged milk prices, corn prices, and alfalfa hay exports on alfalfa hay prices across regions and states utilizing a panel data. Furthermore, I analyze and depict a spatial economic distribution of alfalfa hay price variations with the support of SAS, ArcMap, and GeoDa. Results indicate that alfalfa hay exports are greatly contributing to higher alfalfa hay prices for the seven exporting states. Domestically, grain markets are highly linked to alfalfa hay markets and lagged milk prices as a derived demand have more influence than dairy cow inventories as a primary demand on alfalfa hay prices. Also, alfalfa hay prices are significantly and considerably different, and have positive spatial autocorrelation across states, following a consistent pattern with the lowest prices in the Midwest. Empirical evidence of this thesis may shed light on optimizing profit for dairy industries with an alternative ratio of crops and predicting when/where for hay industries to sell/buy alfalfa hay.

Keywords: alfalfa hay, dairy, exports, price differences, spatial economic pattern

CHAPTER 1. INTRODUCTION

As an important field crop of the United States (U.S.), hay is a commodity with a gross value of $16.8 billion in 2015, second only to corn and soybeans. Also, the 54.4 million acres of all hay harvested in 2015 enforces the importance of hay as a primary field crop of U.S., see figure 1 below. Alfalfa (*Medicago sativa*), also called lucerne, is commonly accepted as the most valued hay, one-third of hay acres (around 17.8 million acres) in U.S. were producing alfalfa in 2015, generating 8.7 billion dollars in sales (USDA-NASS, 2015). Alfalfa is a perennial crop that typically has a 3 to 4-year economic life with nutritional benefits to the soil by adding nitrogen (Putman et al., 2001). In some states, such as California, alfalfa is rotated with other crops like cotton, tomatoes, and small grains. Alfalfa is a water intensive crop and its profitability depends on water availability and cost (Russo, Green, and Homitt, 2008). Alfalfa hay is the main important for dairy cow rations, composing over 50% of a typical mix for dairy cows (Tejada, Kim, and Feuz 2015). Also, alfalfa hay is important for beef cattle, and horses to a less extent. Konyar and Knapp (1988) estimated that 65% of California's alfalfa hay is consumed by dairy cows, 18% is fed to beef cattle, and 17% is utilized by horses and other livestock.

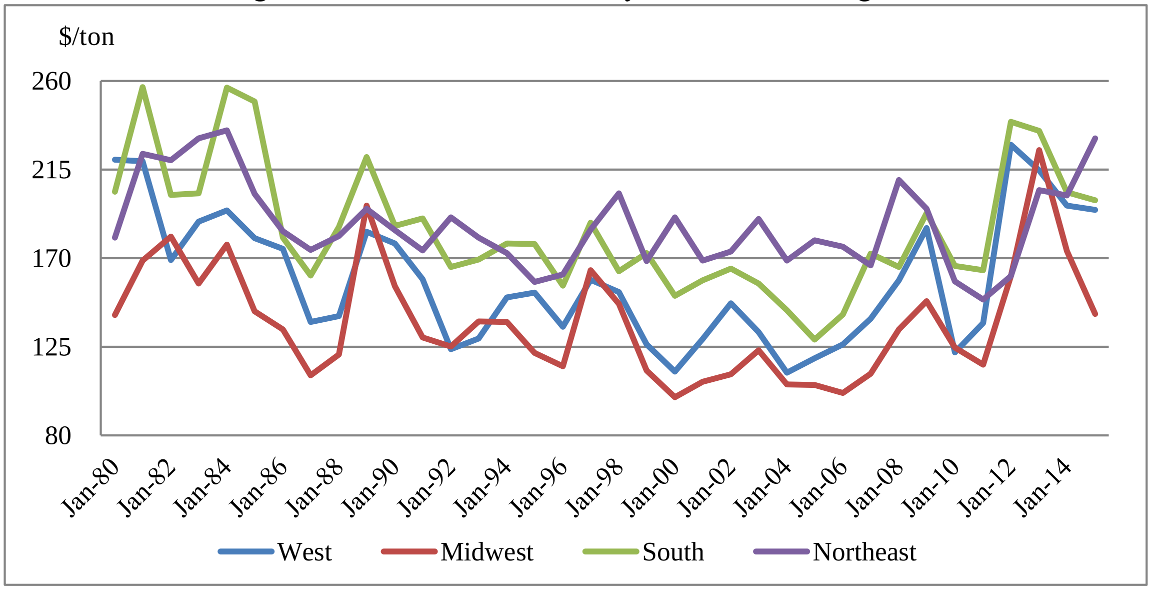
Figure 1. Gross Values and Acreages Harvested of U.S. Selected Field Crops, 2015



Source: USDA-NASS, 2015's $

Regional alfalfa hay prices (i.e. simple average of state-level prices by region) differ by up to one-hundred dollars per ton, depending on many factors related to regional demand and supply (see figures 28 and 29 in Appendix A) and the fact that alfalfa hay is relatively bulky to transport with high per pound shipping costs. However, alfalfa hay prices across regions do share a similar movement, see figure 2 below. January mean alfalfa hay prices are relatively higher than other months (see figure 26 in Appendix A) since alfalfa hay is usually harvested from March to October, depending on weather and location (Putman et al., 2001). Variations in alfalfa hay prices occur across locations and over time. Taking western alfalfa hay as an example, its mean price was almost ninety dollars lower than the Northeast in January of 2000 but exceeded the Northeast with an even higher price in January of 2011. Also, alfalfa hay prices in all regions showed increasing strength since 2004, partly because of the impact of emerging alfalfa hay exports (Putnam, Matthews, and Sumner, 2015).

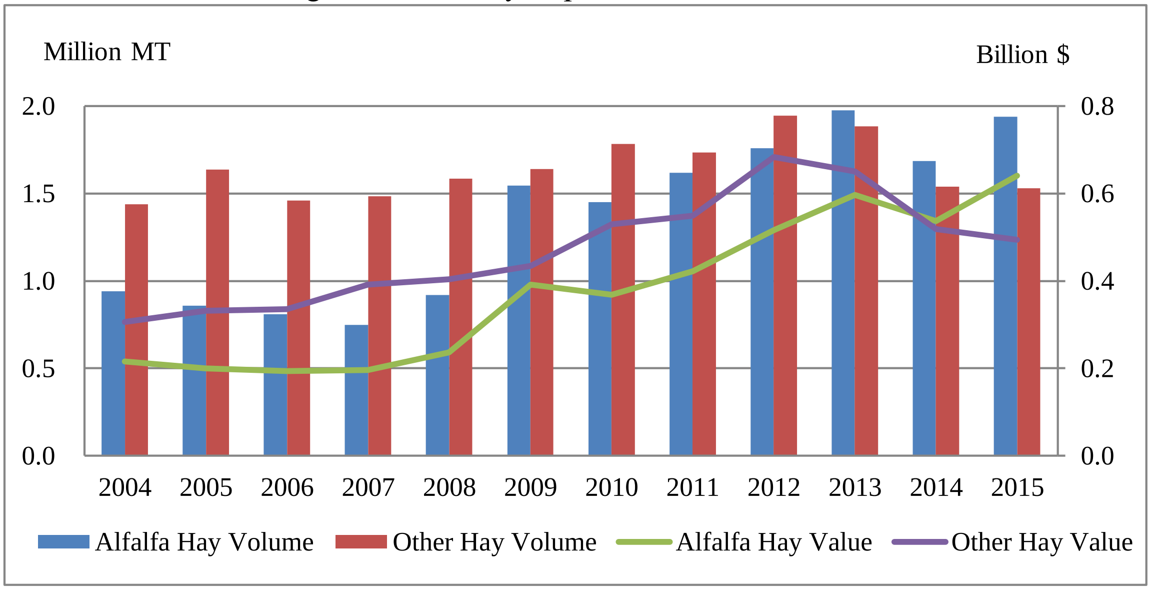
Figure 2. Jan. Mean Alfalfa Hay Prices across Regions



Source: USDA-NASS, 2015's $ (simple average of state-level prices by region)

Growing global demand for hay has fueled U.S. hay exports and contributed to higher alfalfa hay prices, as seen in figure 3 below. Export volumes of alfalfa hay are almost double from 2004 to 2015 while other hay export volumes have been quite stable. Alfalfa hay export volumes exceeded other hay in 2013, generating 0.64 billion dollars as gross values in 2015 (see figure 27 in Appendix A). 99% of alfalfa hay exports are from states in the West, mainly from Arizona, California, Idaho, Nevada, Oregon, Utah, and Washington (Putman, Matthews, and Sumner, 2013). In 2015, alfalfa hay export by volume from these seven western states accounted for 18.9% of their total alfalfa hay production and 3.6% of total U.S. alfalfa hay production, while other hay export volumes were 2.2% of total U.S. other hay production (USDA-NASS & USDA-FAS, 2015). Also, rising alfalfa hay prices have been led by increasing international demand and exports, such as emerging markets in China and the United Arab Emirates (UAE), plus mature markets such as Japan, South Korea, and Taiwan.

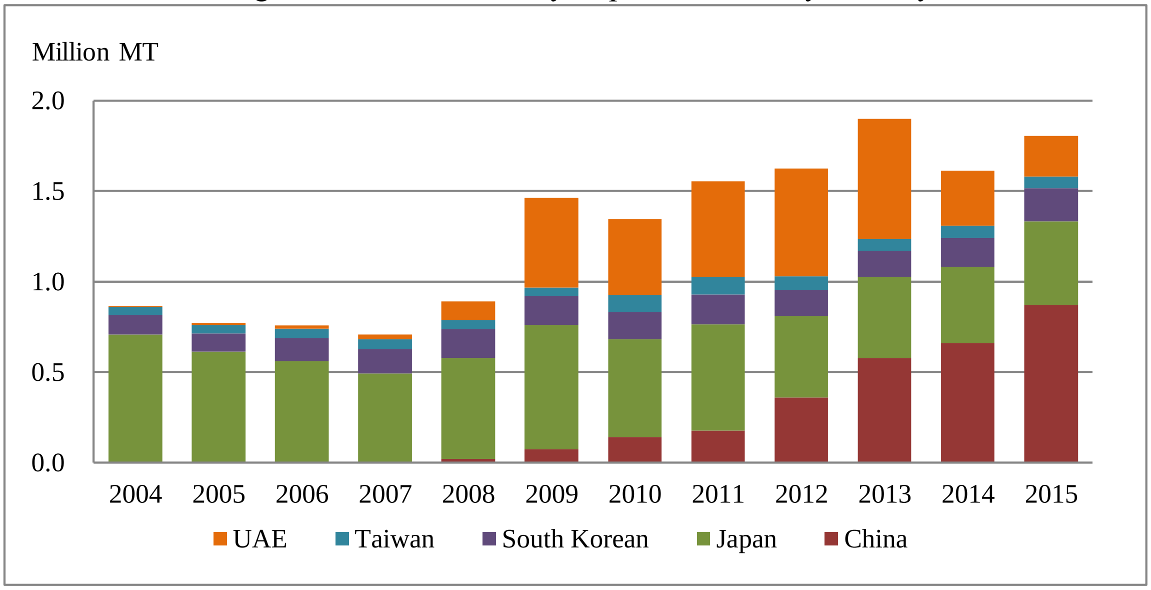
Figure 3. U.S. Hay Export Volumes and Values



Source: USDA-FAS, 2015's $, 1 MT=1.10 US ton

A rapid development of large corporate dairy farm projects in China and a prolonged drought in the United Arab Emirates (UAE) were the two main drivers behind higher U.S. hay exports in the last five years, see figure 4 below. In 2008, the People's Republic of China began to import hay to supplement its growing dairy industries and alfalfa hay demand from China alone has increased to 0.87 million metric tons (MT) in 2015, more than a four-fold increase from 2008, as shown in figure 4 below. Currently, China accounts for about 45% of total U.S. alfalfa hay exports. In 2008, government officials of the UAE banned the production of hay due to ground water conservation. Since water is a scarce commodity in the Middle East, forage production in Saudi Arabia will be completely phased out by 2016. Non-commercial and commercial livestock owners are being supported by UAE's forage imports.

Figure 4. U.S. Alfalfa Hay Export Volumes by Country



Source: USDA-FAS, 1 MT=1.10 US ton

Rabobank (2015) reports the prolonged drought in the western U.S. and increased competition for water from high-value permanent crops have led to a decline of approximately 300,000 acres of alfalfa hay—most of which were from California. Meanwhile, U.S. alfalfa hay exports are facing increased competition from Spain and Australia. Even though U.S. alfalfa hay exports are relatively weaker in 2014 and 2015, growing exports are expected to continue for the long-run due to the relatively high-quality of U.S. alfalfa hay compared to other countries.

Compared to other primary commodity crops, alfalfa hay has received relatively less aggregate U.S. market research on its price determinants and differences, few studies exist that address the impact of growing alfalfa hay exports either, even though alfalfa hay is gaining more economic prominence in terms of cash value and export volume.

Black and Clevenger (1984) state that “no published studies to forecast alfalfa hay prices were found. Although alfalfa hay is an important input in beef, dairy, and horse production, alfalfa hay price studies have scant attention in the literature." While a uniform quality standard was established in 1945 by the United States Department of Agriculture (USDA-AMS, 2002), and updated since then. The function of the national alfalfa hay market and countrywide marketing communication is relatively weak, and much of the trading relationship among farmers, dealers, and truckers remains the same today. Due to the availability of local hay directories and market information on the internet, information about alfalfa hay prices is more widely distributed than before, but few studies still exist.

One of the challenges associated with analyzing the price determinants and differences of alfalfa hay is that much alfalfa hay is grown and fed to animals on the same operation so that it never enters commercial hay markets. In addition, alfalfa hay is a very regional commodity due to its relatively low value per unit of volume or its bulkiness, compared to other commodities as shown in table 1 below. Data availability and overlooking of spatial attributes are hindering the market research of alfalfa hay.

Table 1. Relative Values and Shipping Costs of Selected Commodities, 2015

	Alfalfa Hay	**Wheat**	**Corn**	**Soybeans**	**Cotton**
U.S. Average Price	\$163.00/ton	\$5.00/bu.	\$3.60/bu.	\$8.80/bu.	¢62.20/lb.
Relative Values					
by weight (¢/lb.)	6.28	6.41	4.94	11.28	47.85
by volume (\$/ft^3)	0.78	3.59	2.59	6.33	14.08
Shipping Distance to Equal Farm Value of Commodity [a]					
ground miles	1,253.85	4,196.33	3,021.29	7,384.53	9,569.23
shipping method	truck	rail	rail	rail	truck

[a] Rail shipping cost of \$2.15/bu. for each 1,800 miles transported. Truck shipping cost of \$3.25 per loaded mile for a 50,000 lb. truckload.

Source: USDA-NASS & Tronstad and Aradhyula, 2003

In agricultural economics, commodities have important spatial attributes. Many types of research have been conducted using panel data since a panel data has the beauty of both time-series and cross-sectional information. However, immobile land, impactful weather, and political boundaries are often regionally explicit—location matters. According to the First Law of Geography, "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). To obtain a clear spatial economic pattern of U.S. alfalfa hay price variations, the recent development of spatial econometrics utilizing panel data is able to provide a better control for both spatial and temporal dependence for agricultural economists.

The objective of this thesis is to (1) quantify price determinants in alfalfa hay markets domestically and investigate the impact of alfalfa hay exports on the prices of U.S. alfalfa hay, and to (2) depict the spatial economic pattern of alfalfa hay prices by quantifying characteristics of spatial autocorrelation since prices of alfalfa hay considerably differ across locations.

Ordinary Least Squares (OLS) regression is used to examine determinants of alfalfa hay prices. A regression analysis utilizing panel data allows me to simultaneously take into account temporal and locational variations to obtain more robust and generalized results. A panel data set composed of 29 main alfalfa hay producing states was used. This data accounts for around 98% of U.S. alfalfa hay production with a maximum of a 36-year period from 1980 to 2015, using state monthly prices in January and July to match availability on all variables. To mainly estimate and quantify the influences from dairy markets like dairy cow inventories and lagged milk prices, corn prices, and alfalfa hay exports, the marginal analysis provides the response to price change and price elasticity. Furthermore, with a two-way fixed effects model controlling time and locations (region or states), I compared the results from pooled regression as well. Additionally, statistical tests address the existence of spatial autocorrelation and heteroscedasticity, so I introduced Geography Information System (GIS) methods to have a better understanding of spatial associations in alfalfa hay prices and illustrated a preliminary spatial economic pattern of alfalfa hay prices.

The remainder of the thesis is organized as follows. Chapter 2 provides a statement of the hypotheses that will be tested. Chapter 3 reviews some previous research on alfalfa hay markets. Chapter 4 shows the underlying theories of the models. Chapter 5 introduces the Ordinary Least Squares (OLS) regression and Exploratory Spatial Data Analysis (ESDA). Chapter 6 specifies the theoretical models. Chapter 7 describes the data characteristics, sources, and manipulation. Chapter 8 reports the pooled regression and two-way fixed effects models applied in this thesis. Chapter 9 presents the findings of spatial autocorrelation. Chapter 10 summarizes and discusses the findings, then concludes with implications.

CHAPTER 2. HYPOTHESES

This thesis estimates factors that influence regional prices within the 29 primary U.S. alfalfa hay producing states. Existing literature asserts that alfalfa hay plays an important role in livestock rations, especially dairy markets (i.e. Knapp and Konyar, 1990; Cann, 2014). Also, Sumner and Rosen-Molina (2011) found that alfalfa hay prices were not only closely related to milk prices but also highly linked with grain markets, such as corn. In agriculture, most crops share similar inputs like land, water, fertilizer, etc.. Corn for grains, as a classic example in feed grain markets, is treated as the leader in feed price movements. What's more, empirical studies have shown that acreage and prices of alfalfa hay are elastic to changes in various exogenous variables like the producer's cost index etc. (Knapp and Konyar, 1990). Thus, I expected changes in alfalfa hay prices to respond to changes in dairy cow inventories, lagged milk prices, and corn prices. In order to verify my expectation, the first null hypothesis is listed as follows.

1st H_0: No impacts of state-level dairy cow inventories, lagged milk prices, or corn prices on their respective state's alfalfa hay prices.

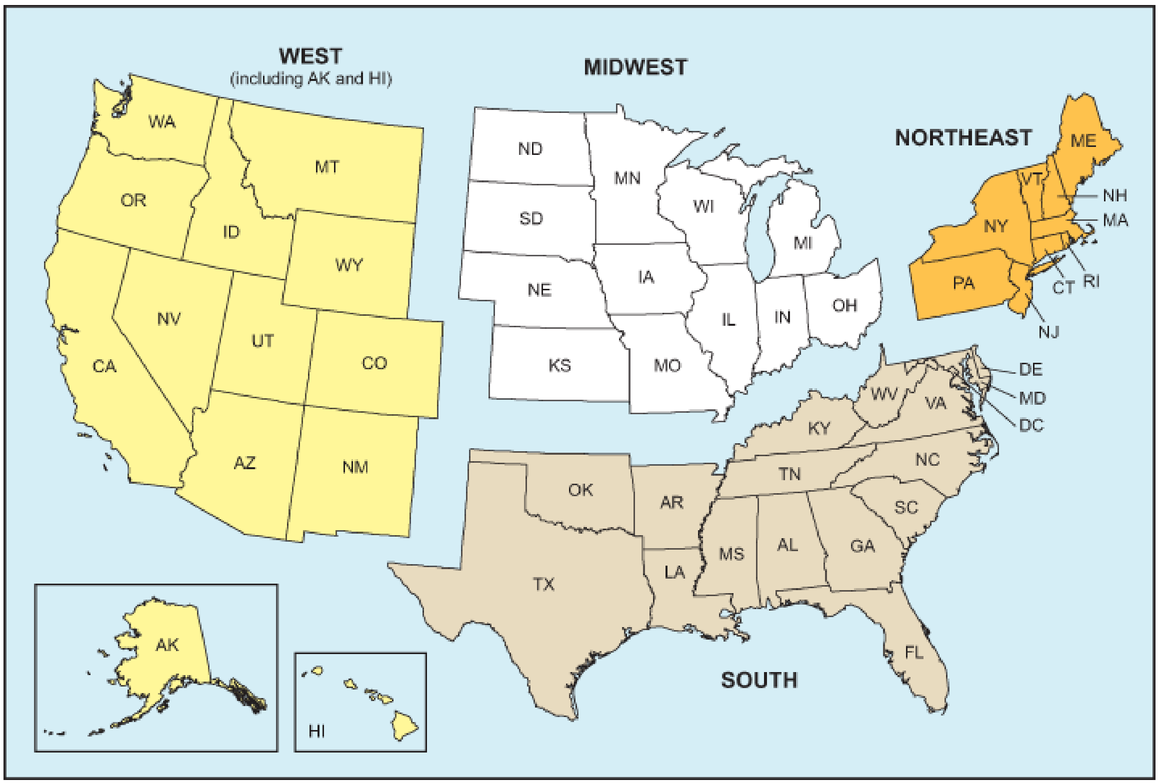
Fundamental changes like greater alfalfa hay exports have the potential to generate upward pressure on alfalfa hay prices. Thus, I also hypothesized that alfalfa hay exports have an impact on U.S. alfalfa hay prices. My second null hypothesis is.

2nd H_0: No impact of alfalfa hay exports on U.S. alfalfa hay prices.

I also predicted alfalfa hay prices vary considerably across the U.S. regions, which are defined as West, Midwest, South, and Northeast as in figure 5 below. Similarly, price variations in alfalfa hay are also significant across states or within the same region for different states. Thus, the third null hypothesis is given below.

3rd H_0: No alfalfa hay price differences exist (1) across the four U.S. regions, (2) across 29 main alfalfa hay producing states, and (3) across states within the same region (see details of states included in chapter 7).

Figure 5. U.S. Regions Defined by State



Source: U.S. Census Bureau

Usually, agricultural economic activities have certain relations such as geography links within regions. Such relationships are distributed to prices of agricultural commodities due to certain geographical effects. For example, higher costs in land rental or water are transmitted in commodities with higher prices. In this thesis, I was interested in the existence of similar or dissimilar responses of alfalfa hay prices across U.S. regions or states. If so, how does a clustering or dispersing map look like? The last null hypothesis follows as:

4th H_0: No spatial autocorrelation is presented for U.S. alfalfa hay prices across regions or states.

To sum up, I tested the effects of dairy markets from dairy cow inventories and lagged milk prices, grain prices utilizing corn prices, and alfalfa hay exports on alfalfa hay prices. Also, I explored the spatial economic pattern of U.S. alfalfa hay prices.

CHAPTER 3. LITERATURE REVIEW

Even though alfalfa hay is a major field crop in the United States, especially in the western U.S., minimal economic research studies are available, compared to other major field crop commodities like corn, cotton, soybeans, and wheat. Part of this is due to the regional attributes of alfalfa hay, given it is a relatively bulky commodity. Existing alfalfa hay marketing research can be roughly divided into the three categories of (1) price forecasting, (2) market analysis, and (3) hay exports.

3.1 Price Forecasting

Blake and Clevenger (1984) forecasted alfalfa hay prices with linked annual and monthly models. They intended to help Mexico alfalfa hay producers ascertain a starting price for their crops before the first cutting of the year. Ordinary Least Square (OLS) regression was utilized based on a combined annual and monthly data set from 1960 to 1982. They estimated alfalfa hay production as a function of last year's acreage. To find May alfalfa hay prices, they combined production with April alfalfa hay prices, a corn futures contracts, and a time variable. They found that their predictions were relatively accurate and the price pattern was stable throughout the season. One limitation of their result is the inability of forecasting initial starting prices for the start of each season and subsequent monthly seasonal price patterns.

Blake and Catlett (1984) used corn futures to cross-hedge hay with monthly data from 1955 to 1981. They utilized prices of U.S. hay and New Mexico alfalfa hay in relation to the Chicago Board of Trade corn future prices in a multiple linear regression.

Their findings were (1) the optimal amount range of hedging forecasting for May corn futures contract is 38 to 47 tons per contract, and (2) the gross return for hay producers in the U.S. and New Mexico increase due to cross hedging hay with corn futures.

Konyar and Knapp (1988) used an Autoregressive Integrated Moving Average (ARIMA) model to estimate alfalfa hay acreage response, using a demand and price forecasting model with annual California data from 1945 to 1985. They found that alfalfa hay acreage and demand were inelastic to changes in competing crop prices, the cost of production, and prices of alfalfa hay. And cattle inventories were shown to be the single most important price determinant of alfalfa hay demand. The comparison of time-series to other structural econometric models showed that the latter ones performed better due to their theoretical structures, yet a lack of data limited its implication.

Sumner and Rosen-Molina (2011) forecasted U.S. alfalfa hay prices using the prices of milk and corn, in the context of global crop prices, using annual data from 1970 to 2010. They asserted that the prices of grains and milk would remain relatively high for a foreseeable future, due to a strong demand for meat and milk in a long-run. Based on a historical relationship, Sumner and Rosen-Molina projected high prices for alfalfa hay over the next decade since they found the prices of corn and milk to be highly related. However, very less insightful results of components affecting alfalfa hay prices were discussed in their paper.

3.2 Market Analysis

Konyar and Knapp (1990) estimated acreage response and an equilibrium model for 25 regions within the California alfalfa hay market, taking into account hay flows, hay consumption and production, and equilibrium prices. With annual data from 1945 to 1986, the model was tested by estimating parameters with data through 1982 and then generating a forecast for 1983 to 1986. They found that changes in alfalfa hay acreage were sensitive to production cost in the short-run and livestock feed costs in the long-run. Also, increased yield could negatively affect acreage. Lastly, alfalfa hay acreage was estimated to have a negative impact from a government program regarding water rates and cotton subsidies due to its water incentive attribute.

Tronstad and Aradhyula (2003) applied a multivariate Autoregressive Conditional Heteroskedastic (ARCH) process to three different quality levels of weekly data of alfalfa hay prices from 1983 to 2004 for Yuma, Arizona. They found the conditional and unconditional seasonality of variance to be quite different for all three hay qualities, even though they shared local supply and demand factors.

Bazen et al. (2008) modeled hay supply and demand for Tennessee using annual data with a range from 1966 to 2006. They estimated the supply function with rainfall, lagged hay acreage, the percentage change in row-crop acreage, as well as the prices of wheat, seed, and fertilizer. Factors modeled in the demand function were hay production, soybean prices, per capita income in Tennessee, a time trend, and December cattle inventories. They found small effects on hay prices from price inputs, weather, and changes in alternative crops prices because hay producers were usually cattle producers who harvested their own hay for maintaining reliable feed for cattle. They also found the Conservation Reserve Program (CRP) did not have a significant effect on hay prices and production.

Disersen (2008) developed a balance sheet model using monthly South Dakota alfalfa hay prices from 1976 to 2007. To better control for changes in alfalfa hay prices within and between marketing years, he estimated a supply function that includes expected alfalfa hay acreage based on last year's May and December alfalfa hay prices, and a time trend to account for yield increase. Also, he modeled demand using May and December alfalfa hay prices, May and December stocks, as well as fall and winter alfalfa hay use. He found that his inverse demand function explained more of the variation in alfalfa hay prices than the supply function.

Russo, Green, and Howitt (2008) provide estimates of the supply and demand elasticity for California's alfalfa hay utilizing annual data from 1970 to 2002. They found alfalfa hay prices to be inelastic with respect to acreage, but more elastic when ample water was available. Also, lower alfalfa hay yield and production may partly be due to the previous year's cotton prices and its own price risk respectively. Demand for alfalfa hay was positively related to dairy markets and negatively related to its own prices.

Cann (2014) investigated the structural change of the western alfalfa hay market and its effect on the western dairy industry with monthly data from 1980 to 2015, using the Chow test and an Integrated Farm System Model (IFSM) in simulating an average Utah dairy market. He found that the western hay market has undergone a structural change based on the regression results using demand and supply components such as alfalfa hay production, dairy cow inventories, etc. Profits of milk production would be increased, if the amount of alfalfa hay and corn silage was economically distributed.

3.3 Hay Exports

Gombos (2011) investigated the impact of a growing population and scarce resources on the emerging U.S. forage export industry from 2001 to 2010. Apart from mature markets in South Korea, Japan, and Taiwan, new markets were opening up in China and the Middle East. Given the competitions from other suppliers like Spain and Australia, they found that the dominant role for the western U.S. in forage export markets depended on having low production costs, reliable supply, and high quality.

Putnam, Matthews, and Sumner (2013) reported greater global hay demand coming mainly from China, the United Arab Emirates (UAE), and South Korea since the last decade, because of strong growth in dairy product demand, high quality, the reliability of the western hays, and water limitation. This phenomenon indicates that hay exports have become a fundamental part of hay markets in the West and are likely to become more important in the future.

Rabobank (2015) reported that nearly a doubling in alfalfa hay prices is largely contributed by a growing global demand for western U.S. hay exports from 1994 to 2015. Among the five main alfalfa hay importing countries, China and the United Arab Emirates (UAE) were the primary behind larger hay exports during the last five years.

Even though the U.S. was experiencing a price softening in 2015, a long-term trend indicated a continuously global high-quality forage and supported a higher price range.

Tejeda, Kim, and Feuz (2015) estimated a Vector Error Correction Model (VECM) using monthly average alfalfa hay prices for the seven western states (i.e. Arizona, California, Idaho, Nevada, Oregon, Utah, and Washington) starting from January 2000 to December 2014. They included the concentration and scale of dairy industries and the spatial differences in port distance for exports. They found a contemporaneous and dynamic price movement in the western hay markets. California was leading in western alfalfa hay markets while its neighboring states were sharing the transmitted price information, and were being affected by a shock due to hay exports.

While the literature available on the alfalfa hay market is not very extensive, it does provide lots of useful insights in market structure, such like the effects of (alfalfa) hay ending stocks, hay production, dairy and cattle inventories, prices of milk and beef cattle, alfalfa hay exports, commodity prices, and so on.

To obtain a better understanding of the U.S. alfalfa hay market, I focused on (1) the impact of grains or dairy markets on alfalfa hay prices, (2) the influence of alfalfa hay exports on its own price, (3) price variations of alfalfa hay across regions or states, and (4) the spatial autocorrelation of alfalfa hay prices.

Using state-level data for January and July from 1980-2015, I applied Ordinary Least Squares (OLS) regression that relies on the theory of demand and supply. Spatial econometrics has been widely adopted in the literature of agriculture (i.e. Zhang et al., 2007; Saizen, Maekawa, and Yamamura, 2010; Huang and Jiang, 2013; Tluczak, 2013). To obtain better geo-visual insights, I also utilized Exploratory Spatial Data Analysis (ESDA) to have a peer of spatial attributes for alfalfa hay markets. With the support of a geo-coded panel data, I observed some omitted results in OLS over time and space. A potential contribution of my thesis is to help market practitioners determine the price responses of alfalfa hay to state-level dairy industries or grain markets plus obtain an economic distribution of alfalfa hay prices in terms of spatial variations.

CHAPTER 4. THEORETICAL CONSIDERATIONS

4.1 Supply and Demand

Supply and demand theory originates from Adam Smith's invisible hand at work and is a milestone of economics. Graphically, market demand is presented as downward sloping line, reflecting an increasing quantity demanded when the corresponding commodity price goes down. Also, a downward trend implies diminishing utility that consumers receive from consuming additional units of a product. Likewise, market supply is generally shown as an upward sloping line because producers are willing to produce more of a product given a higher price when the additional cost of producing more goods is getting less. In a market equilibrium, where supply and demand intersect, consumers are willing to pay for an aggregate quantity that equals the price at which producers are willing to supply this equal quantity of product. Shifts in the quantity supplied (demanded) with corresponding price changes will yield a new market equilibrium, which is influenced by multiple factors endogenously and exogenously.

Alfalfa hay prices can also be described as a result of the free interplay of supply and demand. On the supply side, the production of alfalfa hay can be made up of the current year's production and carryovers from the previous year. Alfalfa hay production can be dissembled into acreage harvested and alfalfa hay yield. The alfalfa hay supply is primarily a function of livestock consumption, the prices of competing crops for land, and the prices of the products associated with these fed animals. Specifically, livestock consumption mainly comes from dairy cows, beef cattle, and other livestock like horses domestically, and exports (animals overseas) internationally. Competitive crops can be other grains such as corn. Derived demand can be prices of milk and feeder calves.

4.2 Competitive Market

Alfalfa hay markets are made up of multiple scales of individual hay sellers and buyers. At the aggregative level, the market equilibrium price is the response of the intersection of market supply and demand, there is not a single buyer or seller that can influence market price. Demand across the entire market becomes more inelastic while the individual firm's demand can be completely elastic. For instance, alfalfa hay supply from an individual farm cannot have an influence on alfalfa hay prices in the aggregate. However, when total alfalfa hay supply increases and market demand is weak, market prices will respond to the changes.

4.3 Derived Demand

Derived demand, generally understood as the demand placed on one good or service as a result of changes in the price for some other related good or service, is very common in agricultural markets. In each alfalfa hay market, alfalfa hay is demanded by the dairy and beef industries to generate milk and meat, which in turn are demanded by other related channels or the general public as inputs to generate other goods and services. The effect of derived demand on alfalfa hay can be significant since it is the most important and common feed in dairy industries. For example, when the prices of milk go down, that puts downward pressure on alfalfa hay markets since milk producers are less willing to pay as much as before to maintain their profit.

CHAPTER 5. EMPIRICAL METHODOLOGIES

5.1 Ordinary Least Squares (OLS) Regression

The method of Ordinary Least Squares (OLS) regression, is attributed to Carl Friedrich Gauss, a German mathematician. OLS regression generates coefficient estimates of an equation by minimizing the sum squared residuals or errors, which implies the estimated coefficients are best linear unbiased estimation (BLUE) with the smallest variance, given several critical assumptions below are satisfied (Gujarati, Porter, and Gunasekar, 2012).

5.1a *Assumptions*

Ordinary Least Squares (OLS) regression operates under five classical assumptions: 1) the model is linear in the parameters, with a correctly specified function form and corresponding error term, 2) all independent variables are uncorrelated with the error term, 3) the error term has a mean of zero, optimally with normal distribution for inference, 4) the variances of the error term are spherical, which means the error term has constant variances and they are uncorrelated with each other, 5) no independent variable is a perfect linear function of any other variable. Violating any of these assumptions may generate biased, inefficient, and/or less robust estimations.

Assumption 1 implies can be violated by omitted variables or an incorrect function form. The error term is designed to capture the effects of randomness and minor omitted variables, but not for the important components of dependent variables, since there is not a model to capture or quantify all factors existing in the production, consumption, and transfer of goods/services.

Assumption 2 specifies that the error term is unrelated to any independent variables in the model. It is often violated when an omitted variable exists and it is correlated to at least one variable in the model. As a result, the error term which captures this omitted factor will not be independent of the independent variable.

Assumption 3 states the mean value of error term should be zero. It implies that factors omitted in the model will be subsumed in the error term, which will not systematically affect the mean value of the dependent variable. In other words, the positive residual values cancel out the negative ones so that the average effect of the error term on the dependent variables is zero.

Assumption 4 says that the variances of the error term should be constant and have no autocorrelation. The constant variances of error are commonly known as homoscedasticity, meaning random variables in the sequence or vector have the same finite variance, while the opposite case is called heteroscedasticity, which is common in the cross-sectional data set. No autocorrelation or serial correlation could be violated if a positive error term is followed by another positive error term, or another way around, which is common for data with a time dimension.

Assumption 5 states no perfect correlation among independent variables. If it does, which is known as collinearity or multicollinearity. For instance, Ordinary Least Squares (OLS) regression cannot distinguish variables if the movement of one variable is mirrored by at least one other variable. Collinearity or multicollinearity is a matter of degree, not existence.

Assumptions 2, 3, and 4 are the foundations for a multiple-regression model. A linear model satisfying assumptions 2 and 3 can have unbiased results, but not necessarily efficient estimates. That is, the error term may not always have a normal distribution, which implies that both sides of distribution are approximately symmetrical and the distribution is fully defined by its mean and deviation. A normal distribution is much more likely to occur with a large data set. Other potential assumptions may also help in an application such as the number of observations should not be greater than the numbers of parameters to be estimated to avoid a perfect-fit or over-fit issue.

5.1b *Consequences of Violating Assumptions*

Several basic problems occur when the assumptions are violated, such as excluding a necessary variable, including an unnecessary variable, serial autocorrelation, heteroscedasticity, and multicollinearity. Failing to satisfy any of these assumptions may end up with biased or inconsistent estimators. Thus, a regression diagnostic is necessary to identify and solve the problems for an effective model.

The inclusion of an irrelevant variable does not affect the other variables' coefficient in a regression equation. However, it will reduce the adjusted R^2. This can happen when the theory associated with the model is not thoroughly vetted, the included irrelevant variables typically end up with insignificant coefficients.

Omitted variables can bias the estimated coefficients due to missing important or relevant information in a model theory. One typical sign of omitted variable bias is an unexpected sign on the estimated coefficients. Thus, it is necessary to examine the theory behind the estimation and previous literature on the subject.

Serial correlation of the errors frequently occurs in data with a time dimension, where there is a trend or pattern evident in the error term. Similarly, such correlation can contemporarily exist among all the entities observed in a data, known as spatial association or autocorrelation. While serial correlation doesn't necessarily cause biased estimators, it does affect the standard errors, which makes hypothesis testing unreliable. The Durbin-Watson (DW) test is a common way to identify the existence of serial correlation. In a panel data set, serial correlation is a more serious problem since some common adjustments of the standard errors may be invalid.

Heteroskedasticity, or variances of errors that vary over the entire range of observations, can also cause inefficient estimators due to biased standard errors and produce an unreliable hypothesis test. Various tests, such as the White test, can identify the issue of the inconstant variances of the error term. Yet, a more robust result relies on a better method such as Generalized Least Square (GLS) to make use of a non-spherical error term, which exists with heteroskedasticity or serial correlation in the error term.

The question of collinearity or multicollinearity becomes "How significant is it?". One clue of possible collinearity or multicollinearity occurs when variables are highly correlated with each other. The severity of correlation can be examined using Variance Inflation Factors (VIF) to determine whether the collinearity or multicollinearity is serious enough to warrant an action. Generally, variables with collinearity or multicollinearity are estimated with unexpected signs due to high standard errors.

Inference of them can be a problem too.

5.1c *Random Effects V.S. Fixed Effects*

Since a panel data generally has inherent features across time and observed units, a fixed effects model generally has better control of unobservable or omitted information in cross-sectional units and time. Random effects of the error term in pooled regression indicate there is no correlation between regressors and the error term. Thus, estimated coefficients in both fixed effects and random effects models are both consistent but the fixed effects model is inefficient. If the null hypothesis that the regressors are independent of error term can be rejected by the Hausman test, then the fixed effects model is consistent while the random effects model is not. Under the same null hypothesis, there should be no difference between the estimators if the classical assumptions hold.

5.2 Exploratory Spatial Data Analysis (ESDA)

Following Anselin (1998), Exploratory Spatial Data Analysis (ESDA) is a collection of techniques to describe and visualize spatial distributions, such as discovering the pattern of spatial association. One fundamental component of ESDA is spatial autocorrelation defined as a coincidence of (dis)similarity in values and locations. Spatial autocorrelation not only measures the spatial ordering of geographic data, but also the spatial covariance structure of spatial features. One usually assumes that agricultural economic activities have a relationship in a certain region, which influences commodities prices, information gap, and so on. Generally, negative spatial autocorrelation occurs when areal units tend to be surrounded by neighbors with very dissimilar values. By contrast, positive spatial autocorrelation occurs when high or low values of a random variable tend to be geographical clustered. Spatial autocorrelation employs formal statistical methods to measure the interdependence among nearby values in a geographic unit, to test a hypothesis about a spatial attribute of variables, and to illustrate spatial patterns. Analyzing the spatial economic pattern of alfalfa hay prices should enable us to better understand the characteristics of their distribution and transition and help alfalfa hay industries to derive useful insights. Hence, the technique of ESDA is applied, which serves to describe the spatial distribution (clusters, dispersion, or randomness) in terms of spatial association patterns such as global and local spatial autocorrelation (I and I_i).

5.2a *Spatial Weighting Matrix (W_{ij})*

In Exploratory Spatial Data Analysis (ESDA), both global and local spatial autocorrelation (I and I_i) are based on the introduction of a spatial weighting matrix (W_{ij}), which measures the interdependence of adjacent or neighboring values. Usually, a matrix is constructed to measure the association between different spatial features. The value of W_{ij} can be determined in contiguity or distance. The value of W_{ij} can be binary with $W_{ij} = 1$, if unit i and j share a common boundary, and $W_{ij} = 0$ if not. The distance between spatial features is also used to measure the spatial proximity of a pair of objects. A value of 1 will be assigned to W_{ij} when the distance is less than a predefined threshold, while $W_{ij}= 0$ if the distance between two spatial features is greater than the threshold.

A contiguity spatial weighting matrix is chosen due to the state-level data utilized. A spatial weighting matrix (generally symmetric) is normally defined as below:

$$W_{ij}=\begin{pmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & w_{nn} \end{pmatrix} \tag{1}$$

$$w_{ij} = \begin{cases} 1, \text{ region } i \text{ and region } j \text{ are adjacnet} \\ 0, \text{ if not} \end{cases} \tag{2}$$

Where n is the number of locations to be taken into account, W_{ij} is a n×n matrix, and w_{ij} stands for the elements of W_{ij}.

Also, there are many criteria for contiguity available such as rook, bishop, and queen contiguity, including a first or higher order. In this thesis, I applied a queen contiguity with the first order, which considers that two geographic units i and j are neighbors directly sharing a border in horizontal, vertical, or diagonal direction.

Usually, the spatial weighting matrix (W_{ij}) is row-standardized (i.e, scaled so that each row sums to 1, not symmetric). Row standardization is used to create proportional weights in cases where features have an unequal number of neighbors, increasing the influence of links from observations with few neighbors (O'Sullivan and Unwin, 2003).

5.2b *Spatial Autocorrelation*

Spatial autocorrelation is an important indicator for reflecting and describing some correlations within a phenomenon or attributes for a certain regional cell, the existence of spatial autocorrelation between neighboring locations can be assessed globally and locally (Huang and Jiang, 2014). There are several measurements used to examine spatial autocorrelation. The most two common measures are Geary's index (Geary's C) and Moran's Index (Moran's I). Both indices can be used to examine global and local spatial autocorrelation (I and I_i), and lead to similar conclusions, even though the coefficients of them do not provide the same information of spatial autocorrelation. Moran's I emphasizes the differences in values between the pairs of observations comparison rather than the covariance between the pairs. Hence, Moran's I is a more global measure and it is sensitive to extreme values, whereas Geary's C is more sensitive to differences in small neighborhoods. Moran's I is preferred in most cases since Moran's I is consistently more powerful than Geary's C (Tluczak, 2013), I chose Moran's I as a measure of spatial autocorrelation in this thesis.

5.2c *Permutation Test*

Before testing whether or not the measure of spatial autocorrelation is significantly different from zero, one favored approach is the random permutation test. A permutation test consists of randomly reassigning the attribute value to each cell and computing the Moran's I value each time, creating an empirical distribution of value I. In this thesis, I picked a permutation of 999 times for the original data set.

5.2d *Global Moran's I (I)*

Global spatial autocorrelation is used to examine and describe the spatial characteristics of attributes for a random variable (x) over an entire region, especially for detecting a cluster or dispersion. The global Moran's I (I) is defined as

$$I=\frac{n}{\sum_{i=1}^{n}(x_i-\bar{x})^2}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \quad (3)$$

Where n is the number of locations, $\bar{x}$ is the mean of $x_{i/j}$, which is the value at location i or j, and w_{ij} represents the elements of the spatial weighting matrix (W_{ij}).

The numerator of the second fraction is a covariance term. By calculating the product of two zones' different from the overall mean, it determines the extent to which they vary together. If both x_i and x_j lie on the same side of the mean (above or below), this product is positive; if one is above the mean and the other one is below, the product is negative. And the absolute size of the resulting value will depend on how close a value to the overall mean of the zone values. The spatial weighting matrix (W_{ij}) switches each possible covariance term on or off depending on the given criteria (contiguity or distance). Everything else in the formula normalizes the value of global Moran's I (I) relative to the number of zones being considered, the number of adjacencies in the problem, and the range of values in x.

The global Moran's I (I) value ranges from -1 to 1. A positive value of I means nearby areas tend to be similar in attributes, a value which is closer to 1 implies a cluster appears more frequently and obviously. Likewise, a negative one indicates dissimilarity among areas, when the value gets closer to -1, the difference appears more remarkably. And a value equals to 0 presents an independent regional attribute indicating that no spatial autocorrelation exists, or the pattern is a random distribution.

The calculation of global Moran's I (I) is normally tested by the standardized asymptotic normality of statistic Z since a Z-score indicates whether or not I can reject the null hypothesis that there is no spatial association among the data. Usually, the Z-score is compared to a range of values for a particular confidence level. Generally speaking, the significance level of P = 0.05 for a 95% confidence interval. For example, a

Z-score would have to be lower than -1.96 or higher than +1.96 to be statistically significant at a 5% level.

$$Z(I)=\frac{I-E(I)}{\sqrt{Var(I)}} \tag{4}$$

Where $E(I)=-\frac{1}{n-1}$ (5) and $Var(I)=E(I^2)-E(I)^2$ (6)

5.2e *Local Moran's I (I_i)*

While global Moran's I (I) tends to average local variation, local Moran's I (I_i) refers to dividing the global measure into small regional units locally for identifying spatial autocorrelation. This tool identifies where a random variable x is extreme and geographically homogeneous, and specifically describes the locations of the cluster and scatter points in the regional space. A standard form of I_i is the Local Indicator of Spatial Association (LISA) proposed by Anselin (1995).

The value of a Local Indicator of Spatial Association (LISA) is computed as:

$$I_i=z_i \sum_{j\neq i}^{n} w_{ij} z_j \tag{7}$$

Where $z_{i/j}=(x-\bar{x})/s$ (8), n is the number of locations, $s=\sqrt{\frac{\sum_{j=1,j\neq i}^{n}(x_j-\bar{x})^2}{n-1}}$ (9), which is the standard deviation of x, and $z_{i/j}$ is the standard form of regional attributes, and w_{ij} represents the elements of the spatial weighting matrix (W_{ij})

The interpretation of the local Moran's I (I_i) is similar to the global one. If I get a negative value for I_i, I can conclude that a unit i is surrounded by neighboring units, which are different from each other in terms of tested attribute. In the case of a positive value, it implies that a similar attribute exists among the unit i's neighbors. Similar to the global Moran's I (I), the value of I_i also requires the Z-test, and the explanation is the same as above. The equation is shown as

$$Z(I_i)=\frac{I_i-E(I_i)}{\sqrt{Var(I_i)}} \tag{10}$$

Where $E(I_i)=-\frac{\sum_{j=1,j\neq i}^{n} w_{ij}}{n-1}$ (11) and $Var(I_i)=E(I_i^2)-E(I_i)^2$ (12)

In summary, the sum of all values of local Moran's I (I_i) is proportional to the value of the global Moran's I (I) using the same data. The relationship between I and I_i can be expressed as:

$$I=\frac{\sum_{i=1}^{n} I_i}{\sum_i^n \sum_{j,j\neq i}^{n} w_{ij}} \tag{13}$$

5.2f *Moran Scatter Plot and Clustering Map*

For reporting the global and local Moran's I (I and I_i) for measuring spatial autocorrelation, GeoDa (ArcMap) applies a Moran scatterplot for the global one and a clustering map for the local one. Generally, there are three possible outcomes, which are random, cluster, and dispersion. Randomness indicating failing to reject a null hypothesis that there is no spatial autocorrelation or the Moran's I is zero globally or locally. For clusters, there are two potential outcomes (H-H and L-L), For example, H-H investigated a geographic unit has a high attribute value associated with its neighboring units. Similarly, Dispersion (H-L and L-H) investigates that a geographic unit with high (low) attribute value is surrounded by neighbors with low (high) attribute values, which is indicating the occurrence of likely spatial outliers.

CHAPTER 6. THEORETICAL MODELS

This section describes econometric specifications within the framework of a pooled regression and two-way fixed effects model, also known as Least Square Dummy Variable (LSDV). With the expectation that alfalfa hay prices are linked to dairy industries' variables such as dairy cow inventories and lagged milk prices, the movement of corn prices in the feed market, and alfalfa hay exports. I also hypothesized there is a need to introduce region or state dummies to capture their heterogeneity for price differences in alfalfa hay markets. In a word, this paper is modeling the economic relationships between those factors and an economic pattern of alfalfa hay prices.

To estimate the prices of alfalfa hay, the important components that influence prices needed to be identified, as was outlined in chapter 4. First, alfalfa hay is an excellent forage for high-producing dairy cows since dairy cows efficiently use the high-level protein, calcium, and high-quality fiber in alfalfa hay for milking. Dairy cows can eat more alfalfa hay than grass hay due to the lower fiber content in alfalfa hay (Putman et al., 2001). Also, alfalfa hay is an important feed for feedlots cattle in the feeder stage. Thus, I included inventory numbers of dairy cows (heifers and milking cows) and fed cattle (including fed steers and heifers, as a proxy for beef cattle) domestically, as well as alfalfa hay exports internationally. Also, their corresponding derived demand is included with all milk and feeder calf prices. From the supply side, I included alfalfa hay production and all (alfalfa and other) hay ending stocks. Also, corn, alfalfa hay, and soybeans are common ingredients of a typical dairy ration. Thus, corn prices (for grain) were included since corn is a substitute commodity for alfalfa hay at the margin (see more details in chapter 7).

Model specifications are estimated based on an inversed demand function. Model 1 (see equation 9 below) regresses alfalfa hay prices on alfalfa hay production, all hay ending stocks, dairy cow inventories, fed cattle inventories, corn prices, lagged milk prices, lagged feeder calf prices, and alfalfa hay exports. Likewise, model 2 (see equation 10 below) is constructed as a double-log form (export volumes were assumed as zero prior to 2004 due to data unavailability, missing values were recoded as zero after log transformation) using same control variables, which provides the marginal effects in terms of price elasticity with respect to the independent variables. Models 3, 4, 5, and 6 (see equations 11, 12, 13, and 14 below) utilizing the same idea above with two-way fixed effects models, controls the effects of seasonality using a January dummy and heterogeneity of locations including regions and states. Also, expected signs for variables are listed in table 2 below. For instance, alfalfa hay prices are positively linked to dairy cows and fed cattle, and corn prices, while negatively relative to alfalfa hay production and all hay ending stocks.

Table 2. Definition and Expected Signs of Variables

Variable	Abbreviation	Unit	Period	Sign
Alfalfa Hay Prices	AHP	2015's $/ton	Jan.&Jul.	
Dairy Cow Inventories	DCI	1000 heads	Jan.&Jul.	+
Fed Cattle Inventories	FCI	1000 heads	Jan. for both	+
Milk Prices	MP	2015's $/cwt	Jan.&Jul.	+
Feeder Calf Prices	FCP	2015's $/cwt	Jan.&Jul.	+
Alfalfa Hay Production	AHPRO	1000 tons	annual for both	-
All Hay Ending Stocks	AHES	1000 tons	Dec.(Jan.)&May	-
Corn Prices	CP	2015's $/bu.	Jan. for both	+
Alfalfa Hay Exports	AHE	1000 metric tons	Jan. for both	+

Note: 1 cwt=100 lbs and 1 metric ton=1.1 US ton

Model 1：

$$AHP_{i\ t}=\beta_0+\beta_1*AHPRO_{i\ t-1}+\beta_2*AHES_{i\ t}+\beta_3*DCI_{i\ t}+\beta_4*FCI_{i\ t}+\beta_5*AHE_{i\ t}+\beta_6*MP_{i\ t-1}+\beta_7*FCP_{i\ t-1}+\beta_8*CP_{i\ t}+\varepsilon_{i\ t} \quad (9)$$

Model 2:

$$logAHP_{i\ t}=\beta_0'+\beta_1'*logAHPRO_{i\ t-1}+\beta_2'*logAHES_{i\ t}+\beta_3'*logDCI_{i\ t}+\beta_4'*logFCI_{i\ t}+\beta_5'*AHE_{i\ t}+\beta_6'*logMP_{i\ t-1}+\beta_7'*logFCP_{i\ t-1}+\beta_8'*logCP_{i\ t}+\varepsilon_{i\ t}' \quad (10)$$

Model 3:

$$AHP_{i\ t}=\theta_0+\theta_1*AHPRO_{i\ t-1}+\theta_2*AHES_{i\ t}+\theta_3*DCI_{i\ t}+\theta_4*FCI_{i\ t}+\theta_5*AHE_{i\ t}+\theta_6*MP_{i\ t-1}+\theta_7*FCP_{i\ t-1}+\theta_8*CP_{i\ t}+\theta_9*Jan._{i\ t}+\theta_{region}*Region\ \ Controls_{i\ t}+e_{i\ t} \quad (11)$$

Model 4:

$$logAHP_{i\ t}=\theta_0'+\theta_1'*logAHPRO_{i\ t-1}+\theta_2'*logAHES_{i\ t}+\theta_3'*logDCI_{i\ t}+\theta_4'*logFCI_{i\ t}+\theta_5'*AHE_{i\ t}+\theta_6'*logMP_{i\ t-1}+\theta_7'*logFCP_{i\ t-1}+\theta_8'*logCP_{i\ t}+\theta_9'*Jan._{i\ t}+\theta_{region}'*Region\ \ Controls_{i\ t}+e_{i\ t}' \quad (12)$$

Model 5:

$$AHP_{i\ t}=\gamma_0+\gamma_1*AHPRO_{i\ t-1}+\gamma_2*AHES_{i\ t}+\gamma_3*DCI_{i\ t}+\gamma_4*FCI_{i\ t}+\gamma_5*AHE_{i\ t}+\gamma_6*MP_{i\ t-1}+\gamma_7*FCP_{i\ t-1}+\gamma_8*CP_{i\ t}+\gamma_9*Jan._{i\ t}+\gamma_{state}*State\ \ Controls_{i\ t}+\mu_{i\ t} \quad (13)$$

Model 6:

$$logAHP_{i\ t}=\gamma_0'+\gamma_1'*logAHPRO_{i\ t-1}+\gamma_2'*logAHES_{i\ t}+\gamma_3'*logDCI_{i\ t}+\gamma_4'*logFCI_{i\ t}+\gamma_5'*AHE_{i\ t}+\gamma_6'*logMP_{i\ t-1}+\gamma_7'*logLFCP_{i\ t-1}+\gamma_8'*logCP_{i\ t}+\gamma_9'*Jan._{i\ t}+\gamma_{state}'*State\ \ Controls_{i\ t}+\mu_{i\ t}' \quad (14)$$

CHAPTER 7. DATA DESCRIPTION

Data is compiled on alfalfa hay prices, inventories of dairy cows and fed cattle, alfalfa hay production, all hay ending stocks, alfalfa hay exports, as well as prices of milk, feeder calves, and corn. The United States Department of Agriculture-National Agricultural Statistics Services (USDA-NASS) Quickstats database supplies the majority of the data used. This data set is also supplemented with data from the Livestock Marketing Information Center (LMIC) and the United States Department of Agriculture-Foreign Agricultural Services (USDA-FAS).

The purpose of organizing a panel data set is to measure components contributing to alfalfa hay prices across the 29 main alfalfa hay producing states. The data years range from 1980 to 2015, including January and July for most variables. The four U.S. regions and their respective states are included. Western regions include 11 states, which are Washington, Montana, Oregon, Idaho, Wyoming, California, Nevada, Utah, Colorado, Arizona, and New Mexico. Midwest region includes the 12 states, such as North Dakota, Minnesota, Wisconsin, South Dakota, Michigan, Nebraska, Iowa, Illinois, Indian, Ohio, Kansas, and Missouri. There are four states in the South, which includes Kentucky, Oklahoma, Texas, and Arkansas. Two states from the Northeast are included and are New York and Pennsylvania. These 29 states produce around 98% of U.S. alfalfa hay production.

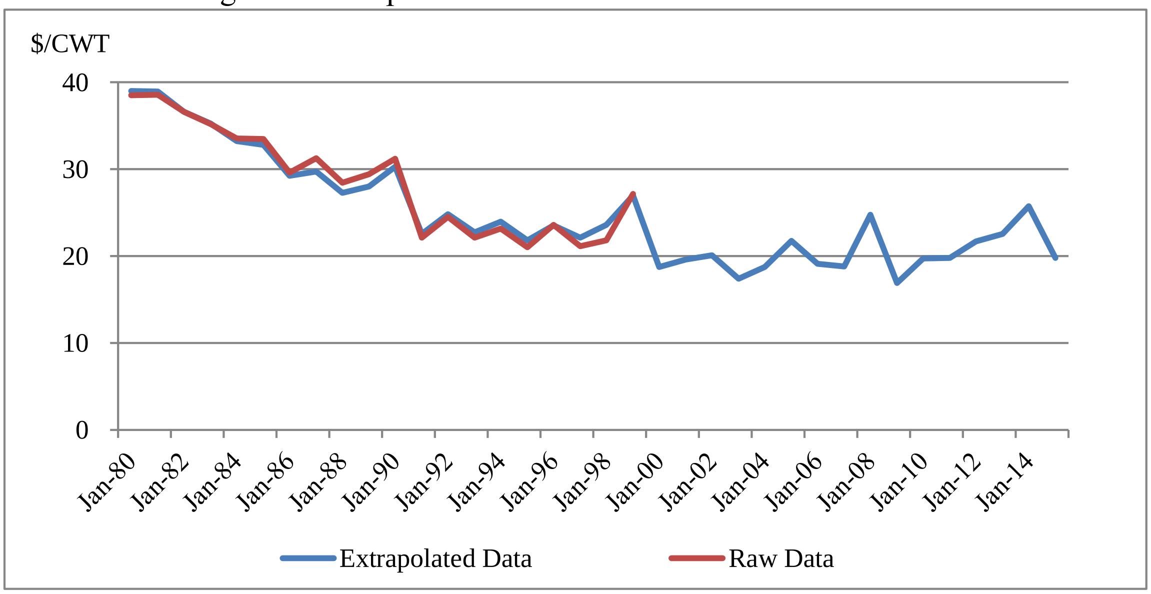
Monthly data was used because January and July data are the only two months available for fed cattle inventories. Because the July one is only estimated at the national level, I applied the January estimate for both months. Likewise, dairy cow inventories in January and July were used, but July data is not consistently available. Thus, I estimated July dairy cow inventories with quarterly data by calculating the simple mean of the second and third quarters each year. Prices of milk and feeder calves were lagged by one-year corresponding to January and July respectively as other literature did (Cann, 2014). Alfalfa hay production is only available annually and it was used twice both for both January and July, whereas all hay ending stocks are available for December (January sometimes) and May. The monthly corn price data has many missing years for states. Thus, I used market year corn prices for both January and July. Even though data of alfalfa hay exports are not available by state, yet there are total annual alfalfa hay export volumes for the seven western states including Arizona, California, Idaho, Nevada, Oregon, Utah, and Washington from 2004 to 2015. Alfalfa hay exports were taken as the simple average of total annual alfalfa hay export volumes for those seven western states by year.

Once the needed variables were identified and initial data was gathered from various sources, two problems became apparent. First, most variables were reported in January and July, except for annual alfalfa hay production and all hay ending stocks in December (January for some years) and May. The lagging effect should be taken into account for a meaningful theoretical model. Second, this panel data set contained 2,088 observations initially, including 29 states for 72 months from 1980 to 2015. However, missing data was a challenge. For example, Nevada has numerous missing observations for almost all variables. Other cases like prices of milk, corn, and feeder calves, as well as inventors of dairy cows and fed cattle, were randomly or systematically missing by year or month.

To fix the first problem, I used one-year lagged annual alfalfa hay production for both January and July within the same year. Also, one year was lagged for prices of milk and feeder calves in January and July respectively, i.e., one year lagging for January of 1981 is January of 1980. All hay ending stocks were a point in time estimate and were already lagged by one month at least for most observations so no more lagging was done.

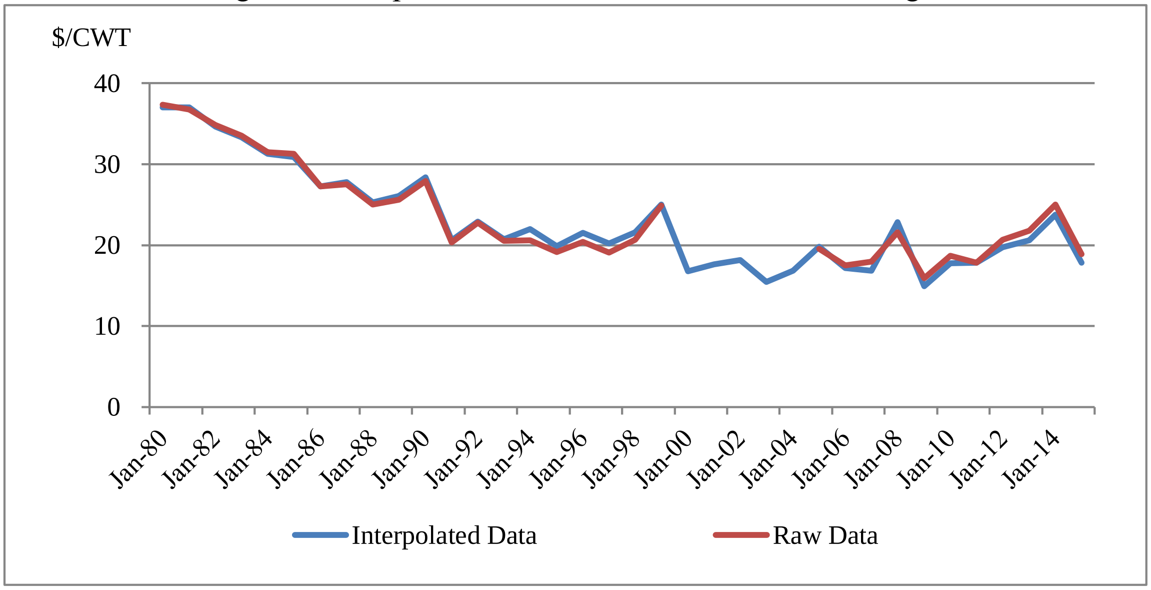
The second problem of missing values in explanatory variables was solved using three approaches. First, for those variables all missing for a state, such as corn price (market year prices) in Nevada, I chose to fill the gap with monthly national corn price using an expected basis. Second, for variables like fed cattle inventories where no July data was, January was used again for corresponding states since the numbers of fed cattle don't vary greatly within the same year. Likewise, dairy cow inventories didn't have July data. But given the quarterly data available for dairy cows, I estimated the July inventory using with the simple mean of the second and third quarters' dairy cow inventories. Third, for states with partly missing variables, I extrapolated or interpolated the date using the mean difference between monthly prices of state and nation. For instance, Arkansas didn't have data on milk prices after 1999, I calculated the difference between monthly prices of state and nation and subtracted the (positive) negative mean difference from the national monthly prices for those missing values. Since the national monthly price had no missing values, I then estimated all missing values for milk prices in Arkansas. A well-estimated data depends on whether there is a good fit with existing state prices in a line chart, see figures 6 and 7 below for examples. Also, other two criteria for judging whether the extrapolation or interpolation is a good or bad are displayed in Appendix B and estimation results without extrapolation or interpolation in Appendix C. The descriptive statistic summary is given in table 3 below.

Figure 6. Extrapolated Data for Jan. Milk Prices in Arkansas



Source: USDA-NASS, 2015’s $

Figure 7. Interpolated Data for Jan. Milk Prices in Oregon



Source: USDA-NASS, 2015's $

Table 3. Descriptive Statistics of Variables

Variable	Min.	Mean	Max.	Std. Dev.
AHP	52.30	150.17	350.74	44.29
DCI	3.80	286.04	1,892.00	377.42
AHPRO (lagged)	62.50	2,744.88	11,340.00	1,836.59
AHES	12.00	2,009.48	13,400.00	1,983.24
FCI	4.00	479.95	2,980.00	710.20
CP	2.11	4.55	9.64	1.42
MP (lagged)	10.33	22.56	39.98	5.78
FCP (lagged)	60.57	146.33	348.01	33.51
AHE	0.00	18.03	282.16	59.53

Note: N_{after}=1,803, delete observations with missing values for the data with data extrapolation or interpolation

CHAPTER 8. ESTIMATION RESULTS

This chapter discusses the regression results estimated for the U.S. alfalfa hay market and alfalfa hay exports on alfalfa hay prices. The coefficients, standard errors, t-statistics, and p-values (Heteroscedasticity Consistent) for each variable used in the pooled regression model and two-way fixed effects models with linear and double-log forms are reported.

First, the results of pooled regression models are presented for the first two null hypotheses, i.e. no impact of dairy industries (dairy cow inventories or lagged milk prices), corn prices on alfalfa hay prices, as well as no impact of alfalfa hay exports on alfalfa hay prices. The result of model 1 states dairy cow inventories, lagged milk prices, corn prices, and alfalfa hay exports all have positive and significant impacts on alfalfa hay prices, and the two null hypotheses can be rejected at a 1% level of significance, see table 4 below. Lagged milk prices as a derived demand seem to have more influence on alfalfa hay prices than dairy cow inventories as a primary demand, and the marginal effect of corn prices show a strong and positive correlation with alfalfa hay prices. Interestingly, the coefficient's magnitude of alfalfa hay exports is 0.14, which means on average, one thousand metric tons increased for alfalfa hay exports annually will lead to \$0.14 increased in its prices, holding other factors constant. In another word, given total annual U.S. alfalfa hay export volume increased from 0.94 million metric tons (2004) to 1.9 million metric tons (2015), alfalfa hay prices increased by around \$19 for the seven exporting states. Model 2 reports regression results in terms of elasticity, see table 5 below. It's more interesting that both null hypotheses are also rejected at a 1% level of significance, showing positive and high elasticity. For instance, the marginal effect of dairy cow inventories in model 1 is only 0.05, while its marginal effect as elasticity on alfalfa hay prices is 9%, indicating, on average, a 1% increase in dairy cow inventories can lead to a 9% increase in alfalfa hay prices holding other factors constant. Similarly, this result shows that prices of lagged milk (22%) and corn (28%) have more impacts on alfalfa hay prices than dairy cow inventories while alfalfa hay exports (3%) are less important in terms of elasticity. Last, for the null hypothesis that there is no correlation between independent variables and the error term, results of the Hausman test states that model 2 rejects the null hypothesis, so fixed effects exist in model 2. Thus, coefficients of model two are likely to be biased.

Table 4. AHP as a Function of the Following Variables in Model 1

Variable	Estimate	Std. Error	T-value	P-value
Intercept	95.40	4.27	22.32	<.0001
DCI	0.05	2.82×10^{-3}	19.25	<.0001
AHPRO (lagged)	-0.02	4.87×10^{-4}	-31.17	<.0001
AHES	-6.30×10^{-5}	3.71×10^{-4}	-0.17	0.86
FCI	5.97×10^{-3}	1.00×10^{-3}	6.15	<.0001
CP	8.08	0.63	12.74	<.0001
MP (lagged)	1.66	0.17	9.78	<.0001
FCP (lagged)	0.01	0.03	0.39	0.69
AHE	0.14	0.01	9.56	<.0001
Time Controls		No		
Location Controls		No		
Hausman Test		11.17 (P-value=0.19)		
R^2=0.51, Adjusted R^2=0.50, and F-value=229.10				

Table 5. logAHP as a Function of the Following Variables in Model 2

Variable	Estimate	Std. Error	T-value	P-value
Intercept	4.92	0.13	38.81	<.0001
logDCI	0.09	4.64×10^{-3}	18.43	<.0001
logAHPRO (lagged)	-0.20	8.24×10^{-3}	-24.19	<.0001
logAHES	-0.02	4.33×10^{-3}	-4.07	<.0001
logFCI	6.54×10^{-3}	3.67×10^{-3}	1.78	0.07
logCP	0.28	0.02	14.67	<.0001
logMP (lagged)	0.22	0.03	8.80	<.0001
logFCP (lagged)	0.01	0.03	0.48	0.63
logAHE	0.03	3.46×10^{-3}	9.61	<.0001
Time Controls		No		
Location Controls		No		
Hausman Test		32.07 (P-value<0.0001)		
R^2=0.52, Adjusted R^2=0.52, and F-value=244.69				

Regression diagnostics shows the data is heteroskedastic and autocorrelated using the White and Durbin-Watson tests. In model 1, given the null hypothesis i.e. there is no heteroscedasticity among the error term, the White test rejects it at the 1% level of significant with X^2=125.59 ~X^2_{44}. While the other null hypothesis i.e. there is no serial correlation among the error term, the Durbin-Watson test rejects it with a value of 1.46, implying there is a positive serial correlation. Likewise, model 2 with these two tests also rejects the two null hypotheses given the White test rejects the first null hypothesis at the 1% level of significant with X^2=107.67~X^2_{44} and the Durbin-Watson is 1.42. By introducing a fixed effects model and spatial autocorrelation, I expected more insights apart from impacts of component factors, more insights into the pattern of alfalfa hay prices is obtained by utilizing location dummies as a preliminary approach.

With control of region and time effects (January dummy), all variables I investigated remain positive at the 1% level of significance. The estimated coefficient of dairy cow inventories, lagged milk prices, and alfalfa hay exports are still significant and positive regardless of dollar values or elasticity almost in the same magnitudes while corn prices slightly decrease. However, all the results still indicate markets of dairy, grains, and alfalfa hay exports have a significant and positive impact on alfalfa hay prices across regions, see tables 6 and 7 below.

Table 6. AHP as a Function of the Following Variables in Model 3

Variable	Estimate	Std. Error	T-value	P-value
Intercept	87.70	4.72	18.58	<.0001
DCI	0.05	3.30×10^{-3}	14.86	<.0001
AHPRO (lagged)	-0.01	6.81×10^{-4}	-19.17	<.0001
AHES	-1.84×10^{-3}	5.73×10^{-4}	-3.22	1.30×10^{-3}
FCI	6.41×10^{-3}	1.05×10^{-3}	6.11	<.0001
CP	7.67	0.63	12.08	<.0001
MP (lagged)	1.57	0.17	9.40	<.0001
FCP (lagged)	0.03	0.03	1.04	0.30
AHE	0.13	0.02	8.56	<.0001
Jan.	8.79	2.10	4.18	<.0001
Time Controls		Yes		
Region Controls		Yes		
R^2=0.52, Adjusted R^2=0.51, and F-value=158.89				

Table 7. logAHP as a Function of the Following Variables in Model 4

Variable	Estimate	Std. Error	T-value	P-value
Intercept	4.91	0.13	35.82	<.0001
logDCI	0.09	5.36×10^{-3}	17.14	<.0001
logAHPRO (lagged)	-0.21	0.01	-18.37	<.0001
logAHES	-0.02	8.30×10^{-3}	-2.96	<.0001
logFCI	0.02	4.05×10^{-3}	4.77	3.20×10^{-3}
logCP	0.23	0.02	12.85	<.0001
logMP (lagged)	0.21	0.02	9.00	<.0001
logFCP (lagged)	0.03	0.03	1.35	0.18
logAHE	0.02	3.69×10^{-3}	6.13	<.0001
Jan.	0.07	0.02	4.25	<.0001
Time Controls		Yes		
Region Controls		Yes		
R^2=0.56, Adjusted R^2=0.56, and F-value=190.65				

A credible inference will be a problem when introducing state dummies dues to collinearity or multicollinearity. In models 5 and 6, dairy cow inventories consistently have a high Variance Inflation Factor (VIF), about 22 for both models. Thus, its estimated coefficients should be a concern due to larger standard errors. Generally, variables with high VIF end up with high standard errors, which leads to rejecting the null hypothesis that variables are statistically different from zero, even though they have unexpected signs. A solution for collinearity or multicollinearity is to focus more on the magnitude of t-values and check how sensitive the T-test is if collinearity or multicollinearity exists in a model.

with control of the state and time effects (January dummy), findings from model 5 and 6 are still quite similar with results above. Across main alfalfa hay producing states, dairy cow inventories, lagged milk prices, corn prices, and alfalfa hay exports all have a significant and positive impact on alfalfa hay prices see tables 8 and 9 below.

Table 8. AHP as a Function of the Following Variables in Model 5

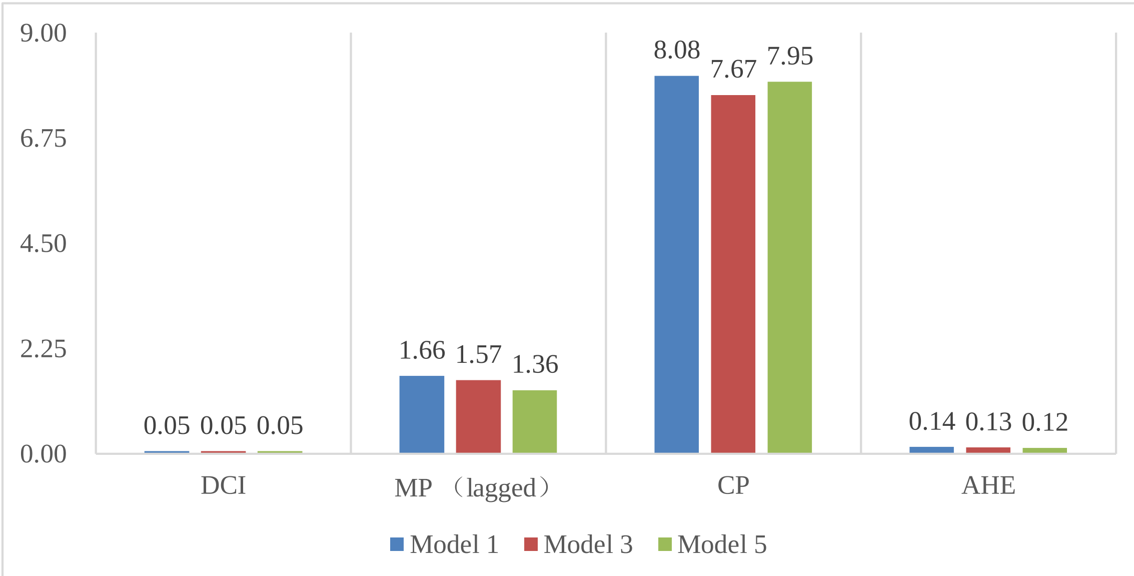
Variable	Estimate	Std. Error	T-value	P-value
Intercept	34.82	12.39	2.81	5.00×10^{-3}
DCI	0.05	9.40×10^{-3}	5.36	<.0001
AHPRO (lagged)	-0.01	1.32×10^{-3}	-8.77	<.0001
AHES	-9.70×10^{-4}	6.81×10^{-4}	-1.42	0.15
FCI	0.02	4.31×10^{-3}	3.54	4.00×10^{-4}
CP	7.95	0.59	13.59	<.0001
MP (lagged)	1.36	0.15	8.79	<.0001
FCP (lagged)	0.12	0.02	4.85	<.0001
AHE	0.12	0.02	7.82	<.0001
Jan.	7.03	2.18	3.23	1.30×10^{-3}
Time Controls		Yes		
State Controls		Yes		
R^2=0.63, Adjusted R^2=0.63, and F-value=82.2				

Table 9. logAHP as a Function of the Following Variables in Model 6

Variable	Estimate	Std. Error	T-value	P-value
Intercept	5.48	0.23	23.83	<.0001
logDCI	0.08	0.01	5.38	<.0001
logAHPRO (lagged)	-0.24	0.02	-10.79	<.0001
logAHES	-0.09	0.01	-6.65	<.0001
logFCI	-9.82×10^{-3}	0.02	-0.63	0.53
logCP	0.23	0.02	14.21	<.0001
logMP (lagged)	0.23	0.02	11.19	<.0001
logFCP (lagged)	0.09	0.02	3.98	<.0001
logAHE	0.03	3.67×10^{-5}	8.18	<.0001
Jan.	0.17	0.02	7.23	<.0001
Time Controls		Yes		
State Controls		Yes		
R^2=0.67, Adjusted R^2=0.67, and F-value=99.65				

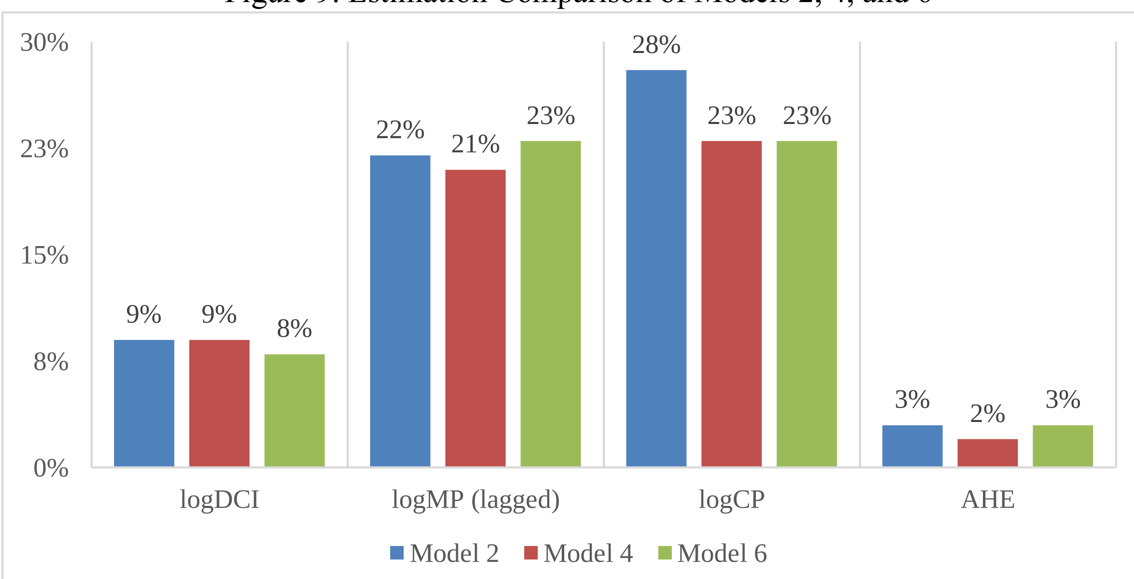
In summary, alfalfa hay prices are influenced by dairy cow inventories, lagged milk prices, corn prices, and alfalfa hay exports positively and significantly regardless of dollar value or elasticity. All the estimation coefficient of the variables I am interested at are quite robust through different approaches. Corn prices have the largest impact on alfalfa hay prices. Lagged milk prices have more impact than dairy cow inventories especially in terms of elasticity. Alfalfa hay exports greatly contribute to its prices, around 13% of the mean U.S alfalfa hay price ($19 out of $150 from tables 3 and 4) but less important in terms of elasticity.

Figure 8. Estimation Comparison of Models 1, 3, and 5



Note: $p<0.01$ for all

Figure 9. Estimation Comparison of Models 2, 4, and 6



Note: $p<0.01$ for all

To test the third null hypothesis, i.e. no alfalfa hay price differences (1) across the four U.S. regions (2) across 29 main alfalfa hay production states and (3) among states in the same region. Table 10 below shows the results of regional alfalfa hay price variations relative to the Midwest, where the null hypothesis that alfalfa hay prices in each region are not different from the Midwest (the first part of the third null hypothesis) can be rejected at a 1% level of significance, being consistent with figure 2 in chapter 1. The order of mean alfalfa hay prices by region is ranked as South, Northeast, West, and Midwest. On average, alfalfa hay prices of other regions are significantly and considerably different from the Midwest. For example, average alfalfa hay price in the South is significantly higher than the Midwest by $13.04 per ton while holding other variables constant, which is also consistent with the aggregate market structures of dairy and alfalfa hay. For instance, the South has relatively lower alfalfa hay production but its dairy industries have a great demand for alfalfa hay since it is the main feed for dairy cows, states like Texas is a good example. As a result, alfalfa hay prices in the South are driven up due to this unbalanced market equilibrium. However, table 11 below presents a different result in terms of elasticity. For example, the Northeast and West have a 16% and 11% more elastic impact on alfalfa hay prices compared to the Midwest, mainly caused by major domestic alfalfa hay demand and exports (see figures 28 and 29 in Appendix A).

Table 10. Estimation of Region Dummies in Model 3

Variable	Estimate	Std. Error	T-value	P-value
West	4.25	2.00	2.12	0.03
Northeast	10.51	4.09	2.57	0.01
South	13.04	2.92	4.47	<.0001

Note: Midwest as a reference ($131.39, mean)

Table 11. Estimation of Region Dummies in Model 4

Variable	Estimate	Std. Error	T-value	P-value
West	0.11	0.01	8.08	<.0001
Northeast	0.16	0.02	7.40	<.0001
South	0.02	0.02	1.00	0.32

Note: Midwest as a reference

Even though t-values for region dummies in table 10 above marginally reject the null hypothesis when using a different critical value ($\sqrt{\ln(1803)}$=2.73), I did find a similar pattern as the region case. Relative to Nebraska in the Midwest, states in South and Northeast have higher alfalfa hay prices, and states in Northeast and West have more elastic impacts. Most of the states are significantly different from Nebraska in models 5 and 6 (reject the second part of the third hypothesis, i.e. no alfalfa hay price differences across 29 main alfalfa hay production states), see tables 12 and 13 below. However, there are some outliers from this pattern. For instance, alfalfa hay prices in the West like New Mexico ($70.97 higher), Oregon ($55.20 higher), and Nevada ($53.71 higher), and Ohio ($75.33 higher) in the Midwest are all much higher than Nebraska. Similar findings in table13 but in smaller magnitudes. Thus, I rejected the third part of the third hypothesis, i.e. no alfalfa hay price differences among states for the same region. As a further step, spatial autocorrelation analysis conducted to investigate the alfalfa hay price pattern across states.

Table 12. Estimation of State Dummies in Model 5

Variable	Estimate	Std. Error	T-value	P-value
Arizona	30.96	9.84	3.15	1.70×10^{-3}
Arkansas	53.87	11.99	4.49	<.0001
California	38.99	14.21	2.74	6.10×10^{-3}
Colorado	41.55	7.04	5.90	<.0001
Idaho	46.43	9.30	4.99	<.0001
Illinois	33.39	9.63	3.47	5.00×10^{-4}
Indiana	24.52	11.70	2.10	0.04
Iowa	42.41	6.61	6.42	<.0001
Kansas	14.23	4.62	3.08	2.10×10^{-3}
Kentucky	59.72	10.95	5.46	<.0001
Michigan	28.49	10.18	2.80	5.20×10^{-3}
Minnesota	40.48	10.19	3.97	<.0001
Missouri	47.05	10.67	4.41	<.0001
New Mexico	70.97	10.54	6.74	<.0001
New York	17.04	13.08	1.30	0.19
North Dakota	10.63	9.91	1.07	0.28
Ohio	75.33	11.18	6.74	<.0001
Oklahoma	45.71	9.89	4.62	<.0001
Oregon	55.20	10.22	5.40	<.0001
Pennsylvania	62.08	12.01	5.17	<.0001
Texas	30.15	8.74	3.45	6.00×10^{-4}
Utah	26.46	10.23	2.59	9.80×10^{-3}
Washington	41.39	10.17	4.07	<.0001
Wisconsin	0.07	15.92	0.00	1.00
South Dakota	38.73	9.10	4.26	<.0001
Nevada	53.71	10.72	5.01	<.0001
Montana	34.01	9.78	3.48	5.00×10^{-4}
Wyoming	24.17	10.34	2.34	0.02

Note: Nebraska as a reference ($103.02, mean)

Table 13. Estimation of State Dummies in Model 6

Variable	Estimate	Std. Error	T-value	P-value
Arizona	-0.26	0.06	-4.02	<.0001
Arkansas	-0.53	0.12	-4.53	<.0001
California	0.20	0.06	3.42	4.00×10^{-4}
Colorado	0.17	0.04	4.18	<.0001
Idaho	0.10	0.05	2.08	0.04
Illinois	0.00	0.05	-0.03	0.98
Indiana	-0.18	0.07	-2.71	6.80×10^{-3}
Iowa	0.17	0.04	4.19	<.0001
Kansas	0.13	0.04	3.75	2.00×10^{-4}
Kentucky	0.02	0.09	0.27	0.78
Michigan	-0.05	0.06	-0.78	0.43
Minnesota	0.11	0.06	2.01	0.04
Missouri	0.06	0.07	0.87	0.39
New Mexico	0.04	0.06	0.65	0.52
New York	-0.02	0.09	-0.26	0.80
North Dakota	-0.18	0.06	-2.82	4.90×10^{-3}
Ohio	0.21	0.06	3.36	8.00×10^{-4}
Oklahoma	0.06	0.05	1.14	0.25
Oregon	0.07	0.06	1.08	0.28
Pennsylvania	0.20	0.07	2.76	5.90×10^{-4}
Texas	0.09	0.06	1.48	0.14
Utah	-0.12	0.07	-1.64	0.10
Washington	-0.01	0.06	-0.26	0.80
Wisconsin	-0.01	0.08	-0.13	0.90
South Dakota	0.06	0.05	1.23	0.22
Nevada	-0.01	0.09	-0.07	0.94
Montana	0.11	0.07	1.73	0.08
Wyoming	0.02	0.07	0.25	0.80

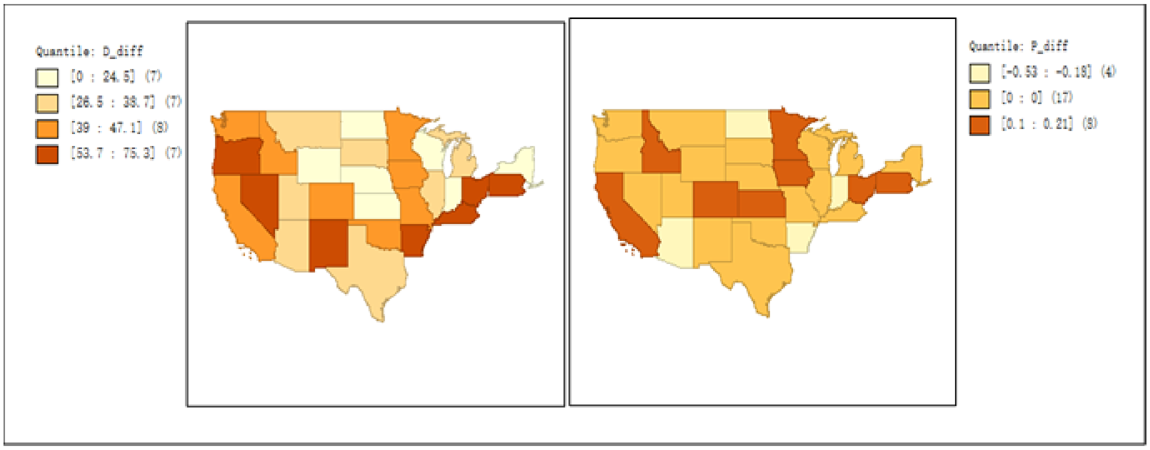
Note: Nebraska as a reference

CHAPTER 9. FINDINGS OF SPATIAL AUTOCORRELATION

Given the regression results of alfalfa hay price differences across U.S. regions and states, pattern analysis was conducted to verify the regression results and explore spatial attributes of alfalfa hay prices. Utilizing a U.S. shape file, ArcMap and GeoDa can geocode and geo-visualize the characteristics of alfalfa hay prices.

The estimations of state dummies from models 5 are 6 were geo-visualized in terms of price differences and elasticity differences for alfalfa hay, see figure 10 below. Relative to Nebraska, the map presents price differences (premiums) of alfalfa hay on the left-hand side, while the other map shows elasticity differences on the right-hand side. All the maps below only include 29 main alfalfa hay producing states, others states were taken off from the U.S. map. The areas with the lightest color in both labels include Nebraska, those states which are not significantly different from Nebraska, and those states which are and locate in the lowest quantile. Darker colors correspond to higher quantiles with the difference in alfalfa hay prices and elasticity relative to Nebraska. In terms of premium (left-hand side of figure 10), the lowest quintile is located in the Midwest, and it is surrounded by higher quantiles in other states when spreading out. What's more, this pattern is repeated year after year for alfalfa hay prices. Quantile Maps of Jan. (Jul.) alfalfa hay prices in 29 states were reported every five years since 1980 to 1995 since Indian and Arkansas had no report of alfalfa hay prices after 1995, see figures 10 to 14 below.

Figure 10. Quantile Maps of State Dummies Estimation in Models 5 and 6



Note: Nebraska as a reference ($103.02, mean) and p<0.05 for significance.

Figure 11. Quantile Maps of Jan. AHP in 1980 and 1985 by State

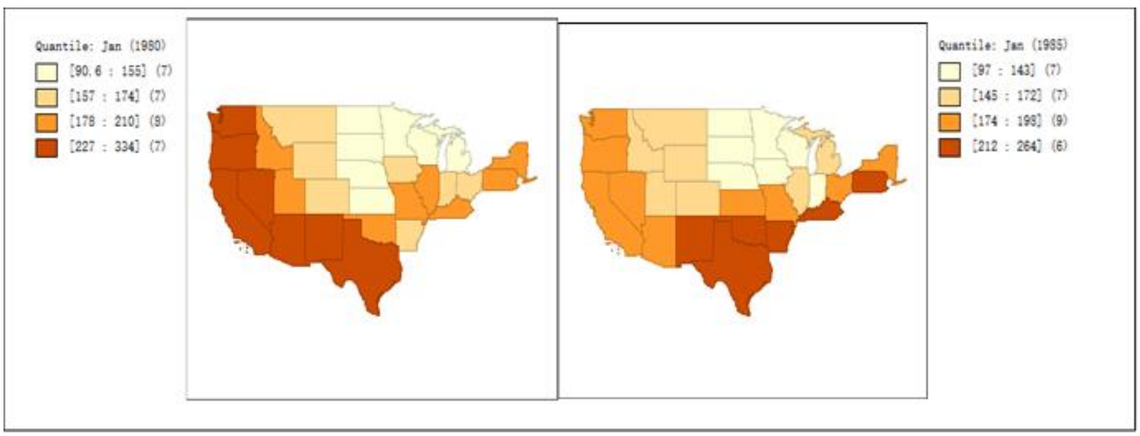


Figure 12. Quantile Maps of Jan. AHP in 1990 and 1995 by State

Figure 13. Quantile Maps of Jul. AHP in 1980 and 1985 by State

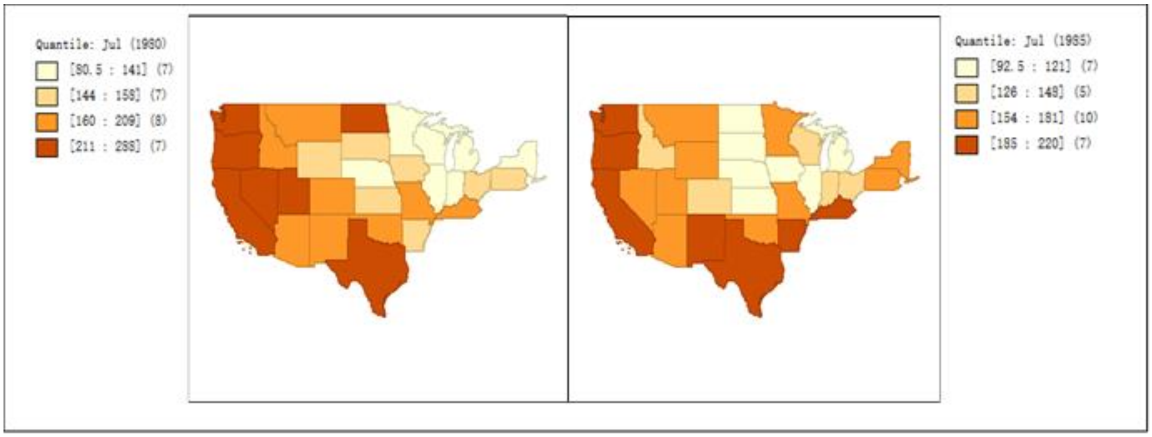
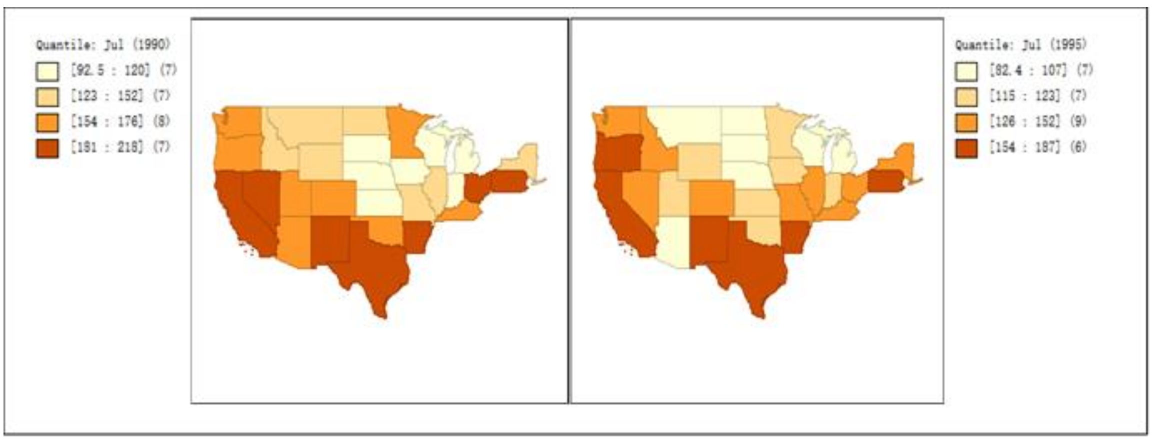


Figure 14. Quantile Maps of Jul. AHP in 1990 and 1995 by State



Considering a pattern analysis only with graphs may be arbitrary, I computed the global Moran's I (I) to quantify and verified the spatial attributes of alfalfa hay prices. As noted in chapter 5, there is a positive (negative) autocorrelation if the value of I is significantly different from zero and gets close to 1 or -1. In figure 15 below, I reported the neighbor counts for 29 states applying queen contiguity. Since Arkansas and Indiana didn't have reports for alfalfa hay prices after 1995, I calculated the values of I for 29 main alfalfa hay producing states from 1980 to 1995 for January and July. I-values, Z-scores, and P-values instead of using Moran scatterplot were reported in tables 14 and

15 below, figures 16 and 17 show a trend pattern of I-values by month. The values of I show that there is moderately positive spatial autocorrelation for alfalfa hay prices, and the mean global Moran's I in Jan (0.47) is higher than Jul one (0.39). However, the fluctuation in time trend is obvious and considerable with 0.66 as the highest and 0.12 as the lowest.

Figure 15. Neighbor Counts with Queen Contiguity

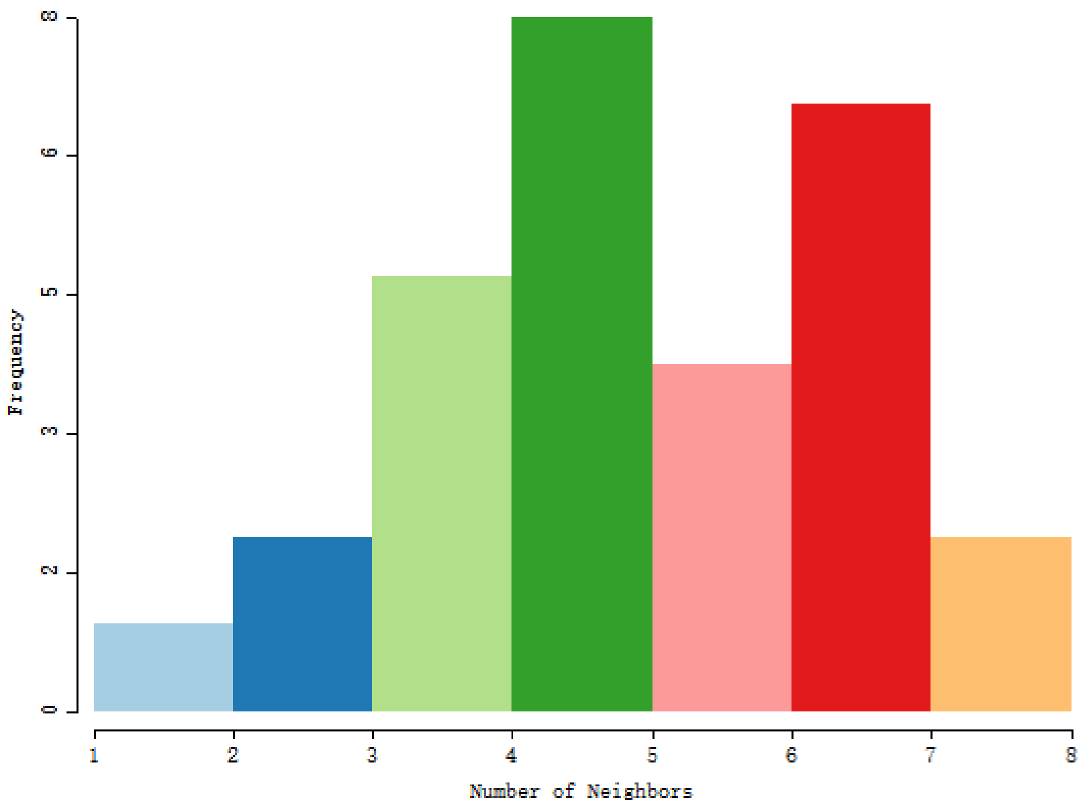
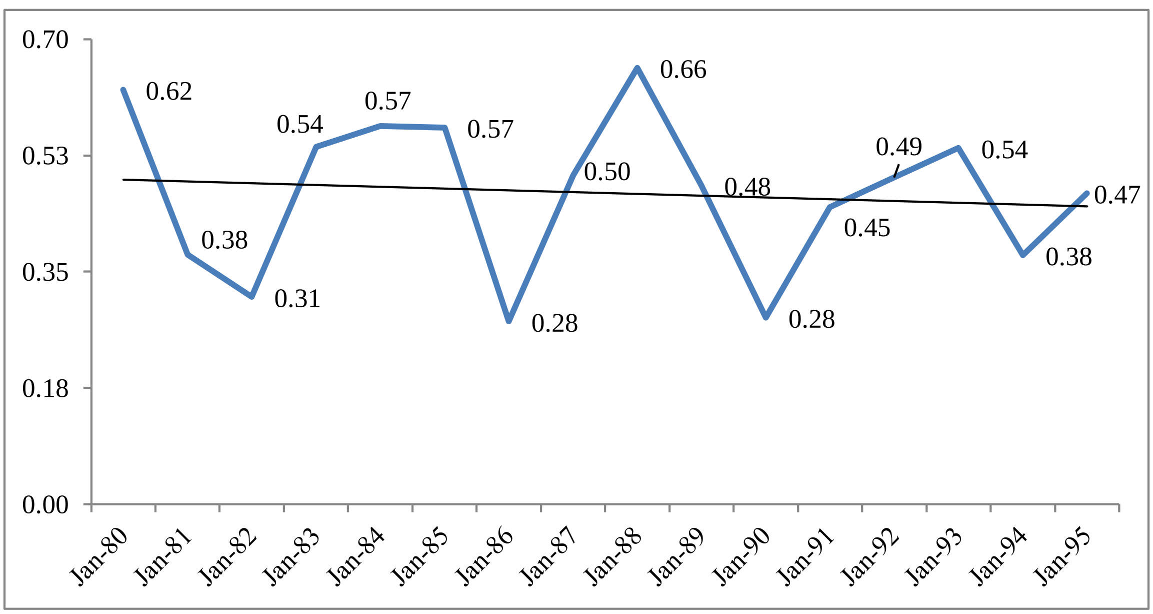


Table 14. Global Moran's I of Jan. AHP

	Global Moran's I	Z-score	P-value
Jan-80	0.62	5.40	<0.0001
Jan-81	0.38	3.29	9.90×10^{-4}
Jan-82	0.31	2.81	0.05
Jan-83	0.54	4.60	<0.0001
Jan-84	0.57	4.86	<0.0001
Jan-85	0.57	4.85	<0.0001
Jan-86	0.28	2.47	0.01
Jan-87	0.50	4.25	<0.0001
Jan-88	0.66	5.51	<0.0001
Jan-89	0.48	4.11	<0.0001
Jan-90	0.28	2.51	0.01
Jan-91	0.45	3.84	<0.0001
Jan-92	0.49	4.30	<0.0001
Jan-93	0.54	4.58	<0.0001
Jan-94	0.38	3.27	<0.0001
Jan-95	0.47	4.06	<0.0001

Note: mean I=0.47

Figure 16. Global Moran's I of Jan. AHP



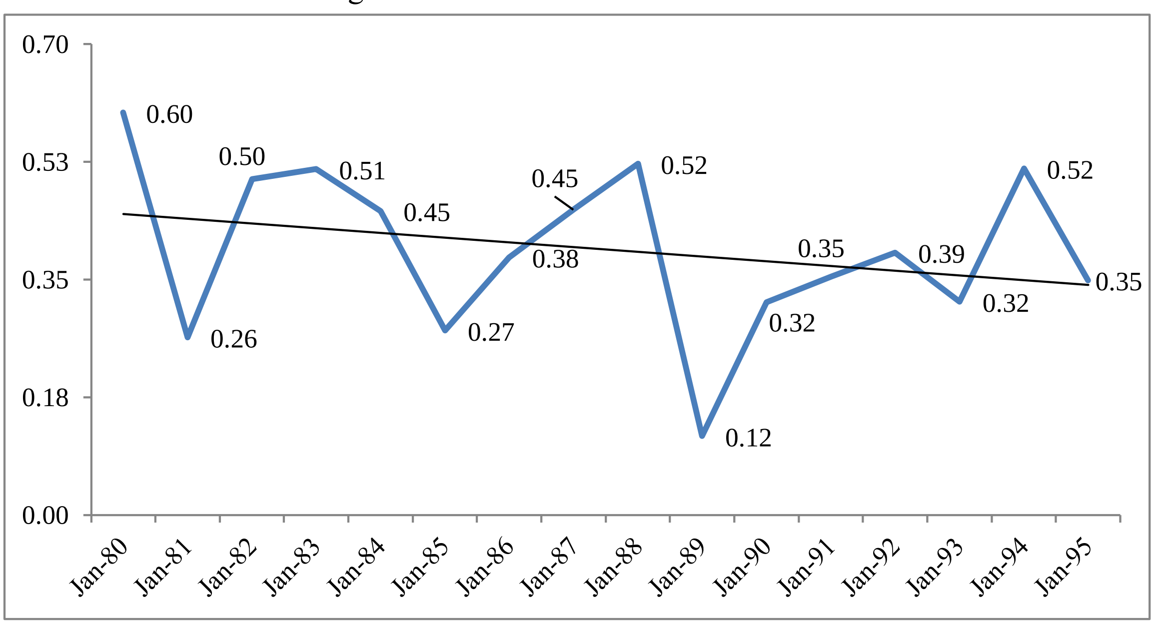
Note: Jan-82, Jan-86, and Jan-90 (p<0.05) & others (p<0.01)

Table 15. Global Moran's I of Jul. AHP

	Global Moran's I	Z-score	P-value
Jul-80	0.60	5.12	<0.0001
Jul-81	0.26	2.42	0.02
Jul-82	0.50	4.28	1.90×10^{-5}
Jul-83	0.51	4.40	<0.0001
Jul-84	0.45	3.93	<0.0001
Jul-85	0.27	2.47	0.01
Jul-86	0.38	3.35	8.10×10^{-4}
Jul-87	0.45	3.89	1.00×10^{-4}
Jul-88	0.52	4.84	<0.0001
Jul-89	0.12	1.50	0.13
Jul-90	0.32	2.80	5.20×10^{-3}
Jul-91	0.35	3.25	1.20×10^{-3}
Jul-92	0.39	3.50	4.70×10^{-3}
Jul-93	0.32	2.82	4.90×10^{-3}
Jul-94	0.52	4.40	1.10×10^{-4}
Jul-95	0.35	3.08	2.10×10^{-3}

Note: mean I=0.39

Figure 17. Global Moran's I of Jul. AHP



Note: Jul-89 (p>0.1), Jul-81 & Jul-85 (p<0.05), and others (p<0.01)

To better understand the pattern of alfalfa hay prices across states, local Moran's I (I_i) was applied for clustering analysis. As chapter 5 stated, a clustering pattern can be dissembled into (H-H), a unit with high value when surrounded by other units with similarly high values, and (L-L), a unit when the low value is clustered with the low-value units. An outlier can be (H-L) or (L-H), which is a unit surrounded by other units with statistically dissimilar values. With the support of I_i, I found there is also a low-value cluster in the Midwest, and the high-value clusters move around centering on the Midwest. Overall, this clustering pattern is consistent with the price pattern of alfalfa hay in figure 10 above. See figures 18 to 25 below since 1980 to 1995 with a 5-year interval.

Figure 18. Significance and Clustering Maps of Jan. AHP in 1980

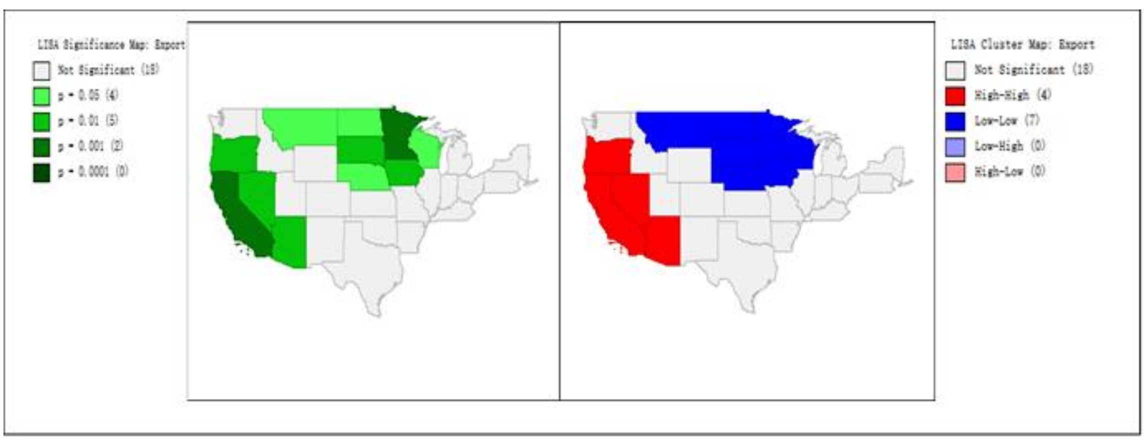


Figure 19. Significance and Clustering Maps of Jan. AHP in 1985

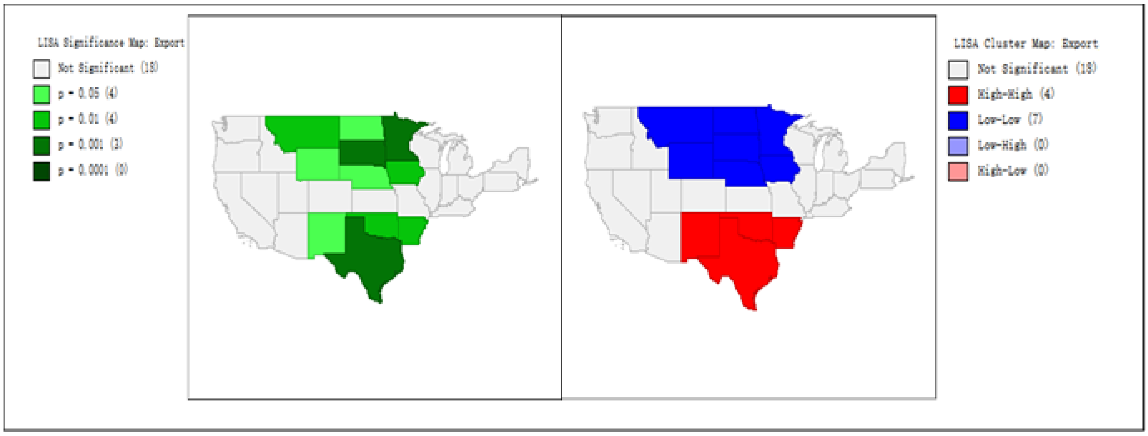


Figure 20. Significance and Clustering Maps of Jan. AHP in 1990

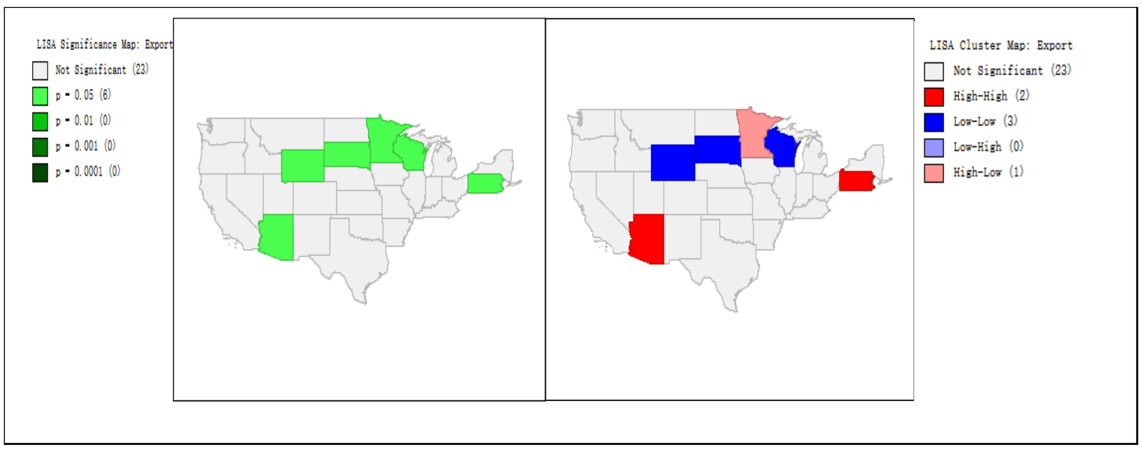


Figure 21. Significance and Clustering Maps of Jan. AHP in 1995

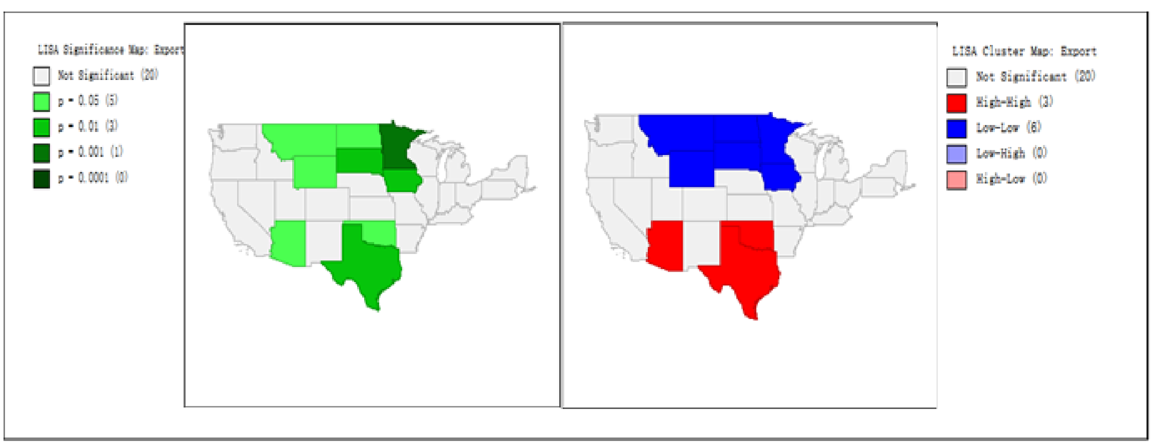


Figure 22. Significance and Clustering Maps of Jul. AHP in 1980

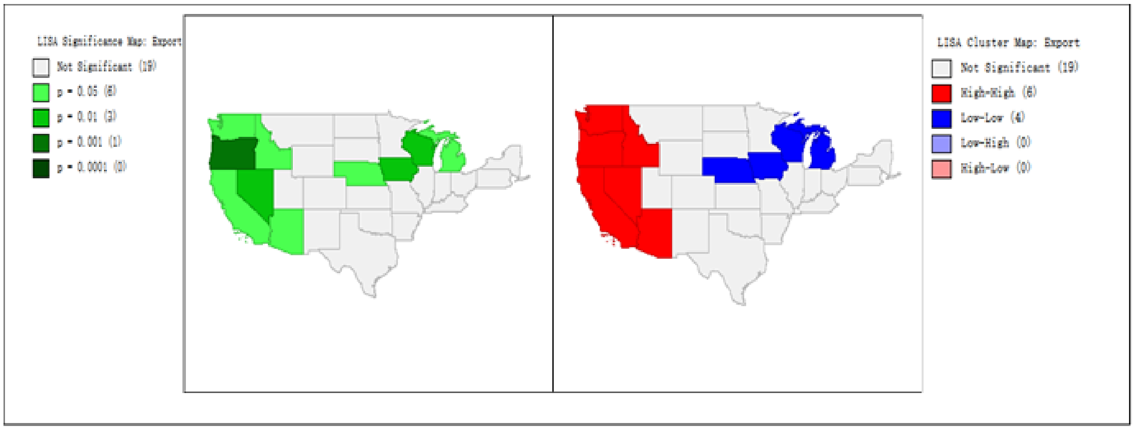


Figure 23. Significance and Clustering Maps of Jul. AHP in 1985

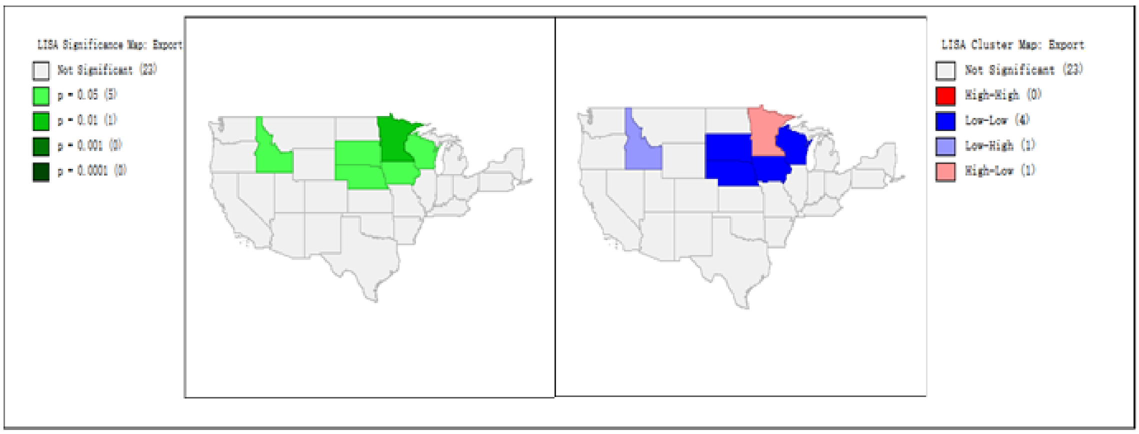


Figure 24. Significance and Clustering Maps of Jul. AHP in 1990

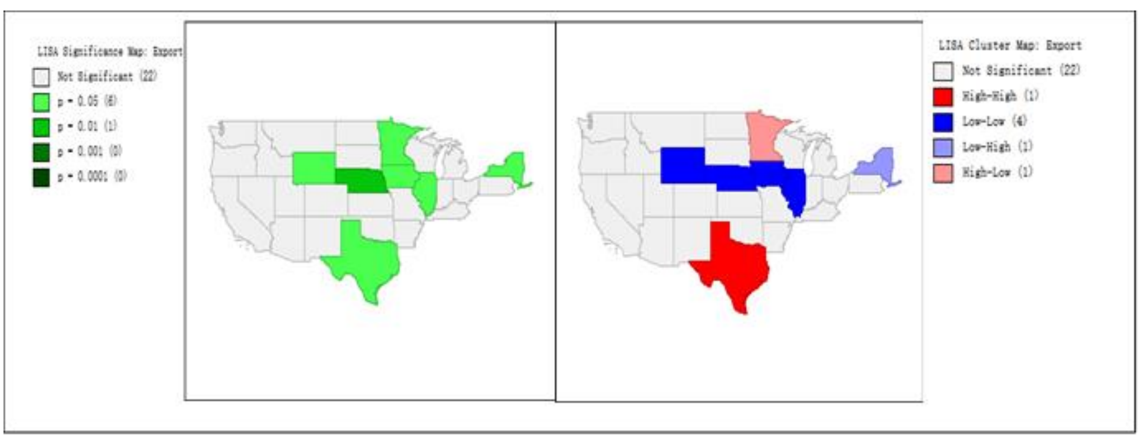
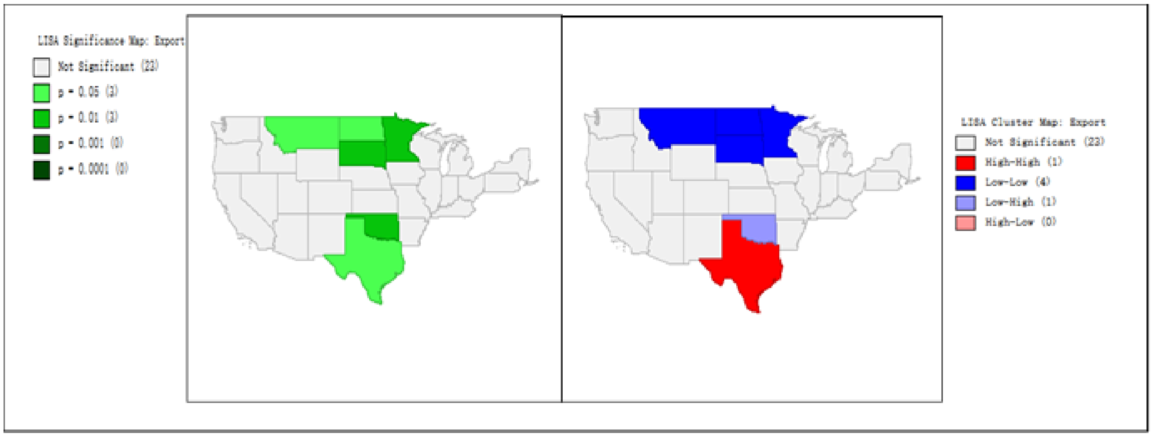


Figure 25. Significance and Clustering Maps of Jul. AHP in 1995



CHAPTER 10. DISCUSSION, CONCLUSIONS, AND IMPLICATIONS

This thesis examined how alfalfa hay prices (both in actual dollars and elasticity) are influenced by dairy industries from dairy cow inventories and lagged milk prices, grain markets such as corn prices, and alfalfa hay exports on alfalfa hay prices with other independent variables like fed cattle inventories, feeder calf prices, alfalfa hay production, and all hay ending stocks. Also, the spatial economic pattern of alfalfa hay prices among the United States was investigated, applying pooled regression models, two-way fixed effects models, and the method of spatial autocorrelation.

There are many data limitations in the U.S. alfalfa hay market. First, alfalfa hay export volumes and domestic hay flows within or across states were not included in since such data was generally unavailable. Also, some missing values among explanatory variables seemed to be a challenge as well. Fortunately, missing values could be reasonably filled in, and similar findings are yielded with regression using initial data, see Appendix C.

Several arguments regarding my data manipulation are listed below.First, I filled in the missing values for Nevada using national monthly price rather than national market year prices. However, considering state monthly corn prices were often missing (1/4 missing, all missing for some states and partly missing for some years) and variations in corn prices were small due to relatively low shipping costs, I thought this approach might work properly. Also, the argument for lagged price of milk, feeder calves, and alfalfa hay exports is that a one-year lag seems inconsistent with timing. However, a monthly lag for these two variables seems fairly close to yearly lagged values due to a lack of variations and forecasting is not part of this thesis. More arguments are regarding the quality of alfalfa hay export data since export volumes prior to 2004 are presumed as zero. However, all findings are quite robust with or without alfalfa hay export in regressions, even for a regression only including observation starting from 2004/ exporting states for all years/ exporting states starting from 2004. Last but not the least, the alfalfa hay prices in the seven western exporting states are not treated differently from other western states due to spatial autocorrelation.

The main findings from regression models empirically showed that alfalfa hay exports play a very critical role in alfalfa hay markets, it drove up alfalfa hay prices across states (around 13% of Avg. U.S. alfalfa hay price, \$19 out of \$150.17 from tables 3 and 4), due to a greater international demand from dairy industries and milk consumptions. What's more, lagged milk prices as a derived demand seem to have more impact than dairy cow inventories as a primary demand on alfalfa hay prices, potentially due to a higher fluctuation in milk prices than dairy cow inventories. For instance, since the last decade, the U.S. average annual all milk prices have fluctuated between \$12.18 to \$19.21 per hundredweight (cwt), a high fluctuation in terms of their nominal prices. Also, mean annual U.S. prices of all milk was showing a decreasing trend (USDA-NASS, 2010). However, relatively small coefficients estimated for dairy cow inventories and lagged milk prices (\$0.05 and \$1.60 respectively in table 4) imply that alfalfa hay prices are highly depending on quality across regions or states. Also, alfalfa hay prices are tied to corn prices ($8.08 in table 4), indicating higher corn prices yields higher alfalfa hay prices.

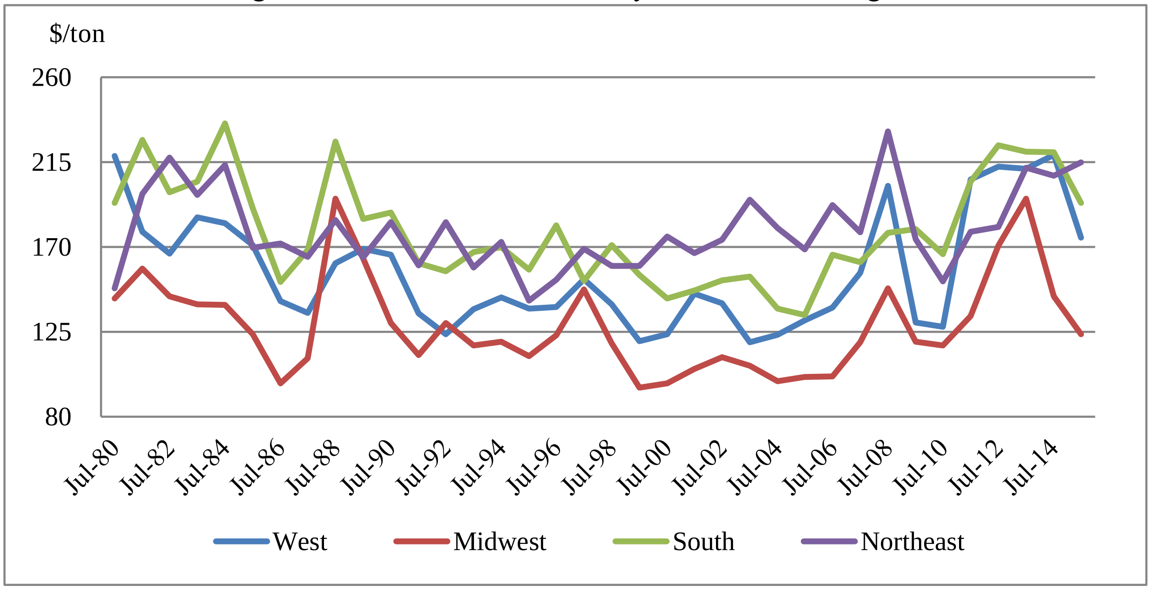
The second main finding is that alfalfa hay prices are statistically and considerably different across regions/states, also positively and spatially associated, with a low clustering in Midwest surrounded by a movable high clustering. Relative to the Midwest, average alfalfa hay prices in the South are the highest ($13.04 higher in table 10) on average, the Northeast comes in the second highest ($10.51 higher in table 10), and the West is the third ($4.25 higher in table 10). An economic pattern looks like this can be caused by differences in local demand and supply for alfalfa hay (see figures 28 and 29 in Appendix A). Also, across all 29 states, alfalfa hay prices behave significantly and consistently different from Nebraska, indicating a relatively consistent price difference pattern among regions. However, states (i.e. New Mexico and Ohio) with unusual high alfalfa hay prices, compared to their mean regional prices respectively, implying the existence of a spatial association in prices. As an outcome of conducting spatial autocorrelation, alfalfa hay prices are positively and moderately correlated in space, and there is a low clustering in the Midwest surrounded by another high clustering (states in West, South, Northeast), yet this high clustering is relatively changeable, potentially due to drought or other factors.

Implications of this thesis are more theoretical rather than practical since the major tasks of this thesis are to understand the marketing components influencing alfalfa hay markets and the economic pattern of alfalfa hay prices. The results from alfalfa hay exports and corn prices seem to support increasing alfalfa hay prices, but primary and derived demand seems to have a downward trend due to structural changes in dairy markets and relatively higher feed cost. Thus, an alternative ratio of feed components using other lower cost commodities likes corn silage and mixtures of grains may be the solution for optimizing profit for alfalfa hay and dairy industries. For instance, arbitrarily given an operation of feed ration (alfalfa hay to corn silage) 25/75, 50/50, or 75/25 respectively, a simulation approach can be conducted for an average state dairy to check which ratio generates the highest economic return. Secondly, a repeated price pattern of alfalfa hay seems to shed light on market decisions in producing, selling, buying, and storing alfalfa hay in the U.S. if the pattern is predictable. What's more, given less a less important finding that alfalfa hay price in January is at least $7 higher than July. An example of alfalfa hay price pattern is alfalfa hay sellers can make a better marketing decision such as when and where to sell alfalfa hay if a low/high clustering can be identified (predicted in advance) or storage cost can be evened. Potential future works can be (1) to estimate more reasonable alfalfa hay export volumes by state in a weighting approach to have a more accurate marginal effects of on alfalfa hay prices, (2) to improve the performance of models by having a better control of heteroscedasticity, serial correlation, and collinearity (multicollinearity), (3) to investigate what are the determinations of alfalfa hay price clustering pattern, and how do they cause the changes and movement of the clustering pattern.

APPENDIX A—SUPPLEMENTARY BACKGROUND

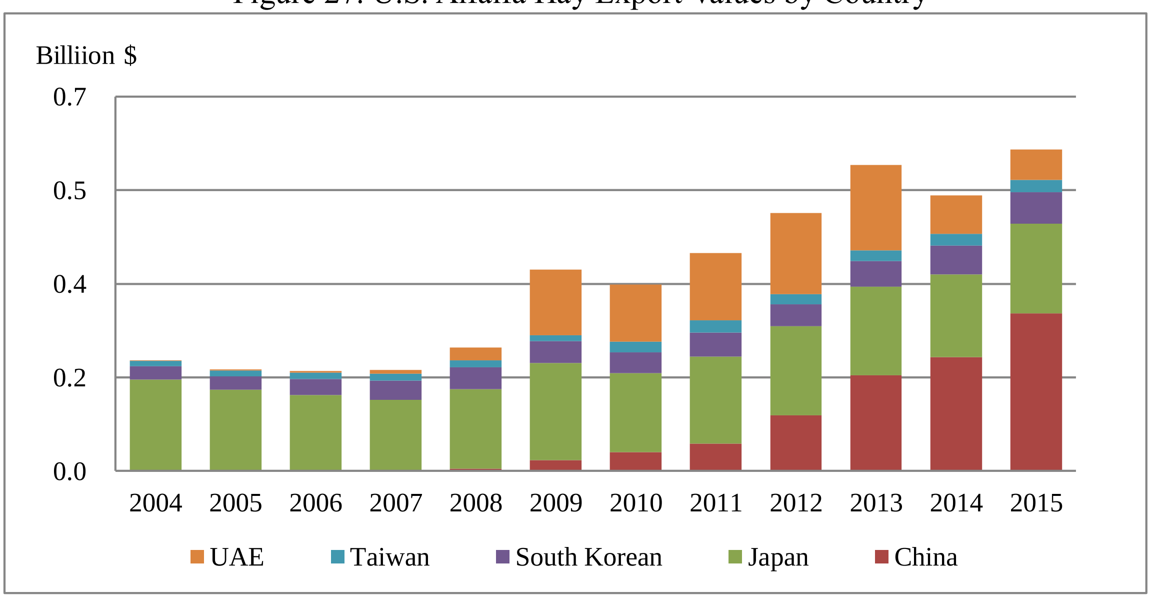
Appendix A includes other relevant background information of alfalfa hay markets.

Figure 26. Jul. Mean Alfalfa Hay Prices across Regions



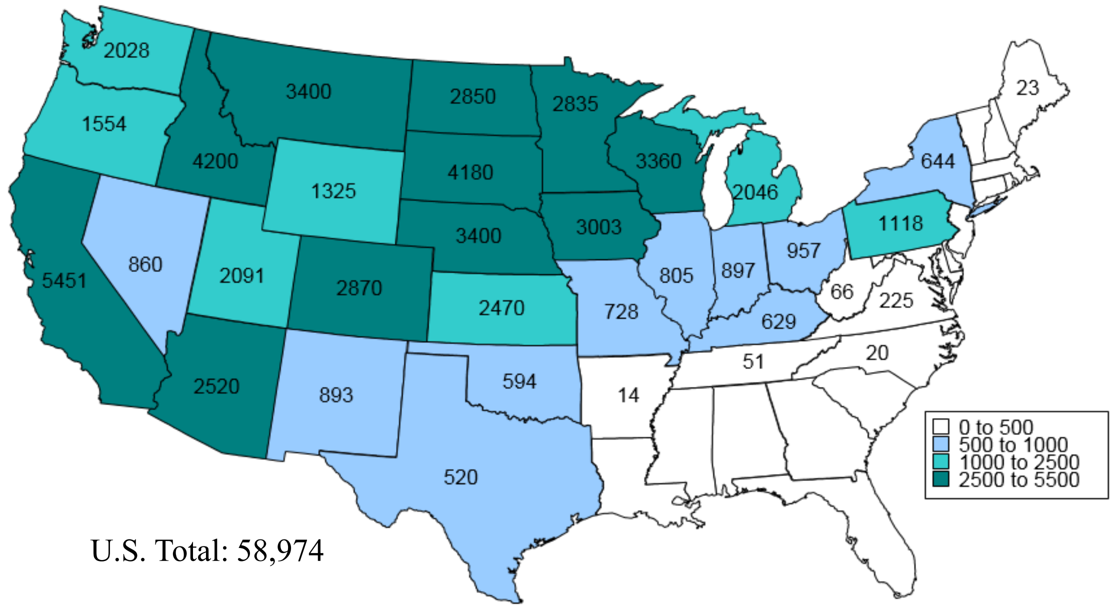
Source: USDA-NASS, 2015's $ (simple average of state-level prices by region)

Figure 27. U.S. Alfalfa Hay Export Values by Country



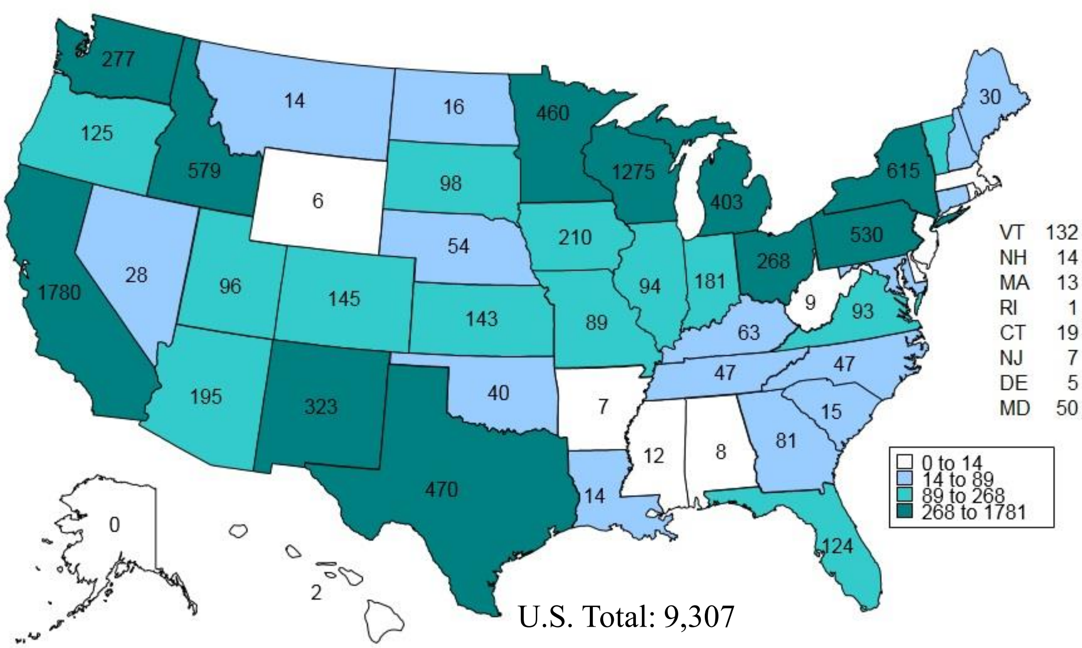
Source: USDA-FAS, 2015's $

Figure 28. U.S. Annual Alfalfa Hay Production (1000 Ton), 2015



Source: LMIC and USDA-NASS

Figure 29. U.S. Dairy Cow Inventories (1000 Head), January in 2015



Source: LMIC and USDA-NASS

APPENDIX B—DATA CONSIDERATIONS

Appendix B provides more details about Data Generating Process (DGP) and data cleaning.

According to United States Department of Agriculture (USDA), monthly prices are based on all sales of the commodity during the entire month, yet hay is based on the 5-day period centered on the 15th of the month. State-level commodity prices are estimated for months when at least 0.5% of the annual sales occur, weights for computing monthly U.S. average prices are based on estimated marketings during the month by state. Likewise, state marketing year prices are computed by weighting monthly prices and the estimated percentage of monthly sales during the market year. Animal and all hay stock inventories are based on sample survey procedures.

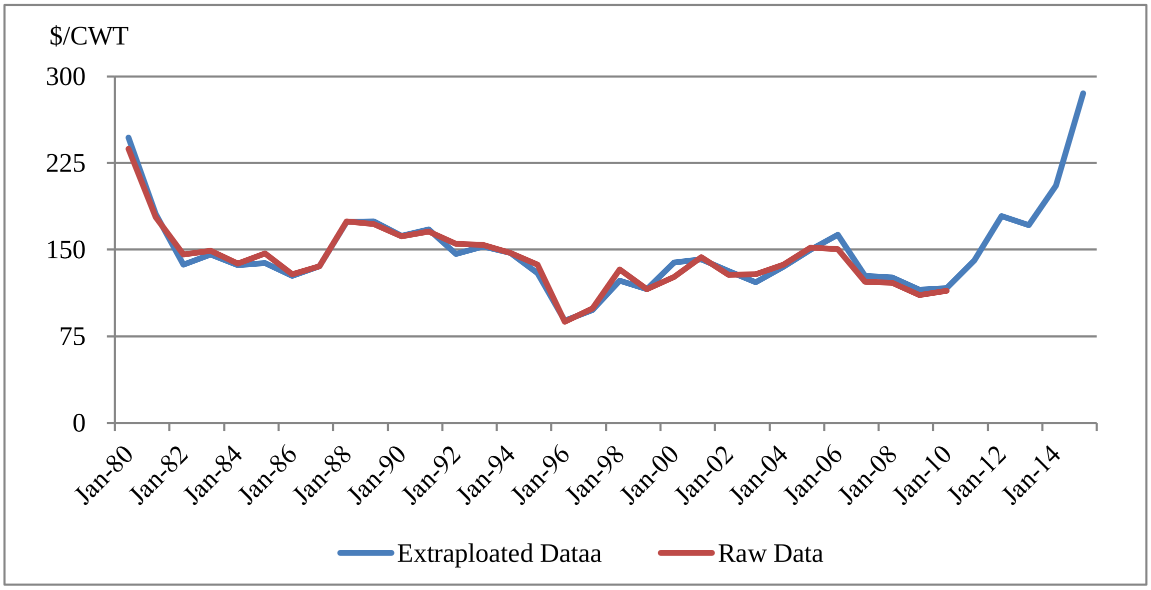
After data estimation for lagged prices of milk and feeder calves, I deleted all observations containing missing values in both data sets. Table 17 below shows that only lagged milk prices may be different from before by including estimated data, but it marginally rejects the null hypothesis using a standardized difference test. Dairy cow inventories, lagged alfalfa hay production, and alfalfa hay exports reject the null hypothesis as well. However, no data estimation was done to extrapolate or interpolate, and different means or variances computed for those variables were caused by the sample sizes containing different information. Thus, I chose the new and larger data set containing more information since it is relatively similar to the original data.

Table 16. Missing Counts and Percentage of Variables, Before and After

Variable	n miss (before)	n miss (after)	n miss % (before)	n miss % (after)
AHP	80	80	3.83%	3.83%
DCI	55	55	2.63%	2.63%
AHES	none	none	none	none
AHPRO	none	none	none	none
FCI	28	28	1.34%	1.34%
CP	72	none	3.45%	none
AHE	none	none	none	none
MP	523	none	25.05%	none
FCP	480	91	22.99%	4.36%

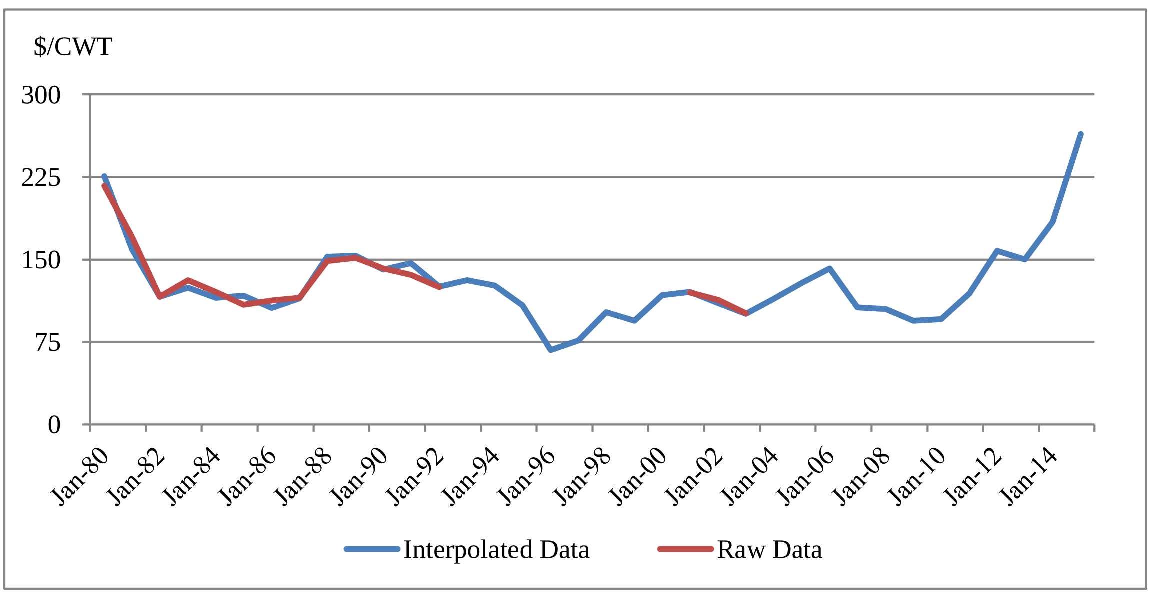
Note: N=2,088, before and after filling up the missing values

Figure 30. Extrapolated Data for Jan. Feeder Calf Prices in Arizona



Source: USDA-NASS, 2015's $

Figure 31. Interpolated Data for Jan. Feeder Calf Prices in Indiana



Source: USDA-NASS, 2015's $

Table 17. Tests for Differences in Variables after Data Estimation

Variable	T-test	Std. Diff.(%)	Ratio of Variance
AHP	-1.55	-4.11	1.18
DCI	-6.37	-17.28	0.83
AHPRO (lagged)	-3.05	-8.28	0.84
AHES	-1.02	-2.73	1.04
FCI	-0.72	-1.93	1.06
CP	0.19	0.51	1.04
MP (lagged)	-4.25	-11.47	0.91
FCP (lagged)	0.36	0.98	0.96
AHE	6.49	16.32	3.28

Note: N_{before}=1,126 and N_{after}=1,803, N_{before}/N_{after} means sample size after deleting observations with missing values for the data without/with data extrapolation or interpolation.

APPENDIX C—ESTIMATION RESULTS WITH INITIAL DATA

Appendix C reports descriptive statics and all regression results using the data without extrapolation or interpolation, given its sample size is 1,126.

Issues of heteroscedasticity, autocorrelation, and collinearity (multicollinearity) still exist. In model 1, we have X^2=98.96 $\sim X^2_{44}$ for the White test and 1.50 for the Durbin-Watson test. Similarly, in model 2, we also have X^2=115.48 $\sim X^2_{44}$ for the White test and 1.41 for the Durbin-Watson test. Also, in models 5 and 6, dairy cow inventories consistently have a high Variance Inflation Factor (VIF), at least 27 for both models.

Table 18. Descriptive Statistics of Variables (Before)

Variable	Min.	Mean	Max.	Std. Dev.
AHP	55.49	152.64	350.74	40.73
DCI	48.50	382.93	1892.00	414.60
AHPRO (lagged)	62.50	2,969.79	11,340.00	2,002.00
AHES	27.00	2,085.15	13,400.00	1,942.83
FCI	9.00	4,99.044	2,980.00	688.57
CP	2.26	4.54	9.64	1.40
MP (lagged)	11.06	23.52	39.98	6.044
FCP (lagged)	62.26	145.86	348.012	34.13
AHE	0.00	6.93	220.98	32.87

Note: N_{before}=1,126, delete observations with missing values for the data without data extrapolation or interpolation

Table 19. AHP as a Function of the Following Variables in Model 1 (Before)

Variable	Estimate	Std. Error	T-value	P-value
Intercept	110.60	5.29	20.92	<.0001
DCI	0.05	3.36×10^{-3}	14.20	<.0001
AHPRO (lagged)	-0.01	5.80×10^{-4}	-23.65	<.0001
AHES	2.46×10^{-4}	4.50×10^{-4}	0.54	0.59
FCI	2.85×10^{-3}	1.12×10^{-3}	2.54	0.01
CP	8.68	0.81	10.71	<.0001
MP (lagged)	1.48	0.20	7.38	<.0001
FCP (lagged)	-0.08	0.03	-2.63	8.50×10^{-3}
AHE	0.04	0.03	1.30	0.19
Time Controls		No		
Location Controls		No		
Hausman Test		12.66 (P-value=0.12)		
R^2=0.45, Adjusted R^2=0.44, and F-value=113.62				

Table 20. logAHP as a Function of the Following Variables in Model 2 (Before)

Variable	Estimate	Std. Error	T-value	P-value
Intercept	5.32	0.16	34.25	<.0001
logDCI	0.11	$7.93{\times}10^{-3}$	14.43	<.0001
logAHPRO (lagged)	-0.19	$8.96{\times}10^{-3}$	-21.11	<.0001
logAHES	$-8.80{\times}10^{-3}$	$5.14{\times}10^{-3}$	-1.71	0.09
logFCI	0.01	$4.10{\times}10^{-3}$	2.81	$5.10{\times}10^{-3}$
logCP	0.31	0.02	12.47	<.0001
logMP (lagged)	0.19	0.03	6.18	<.0001
logFCP (lagged)	-0.11	0.03	-3.61	$3.00{\times}10^{-4}$
logAHE	0.01	$5.77{\times}10^{-3}$	1.96	0.05
Time Controls		No		
Location Controls		No		
Hausman Test		11.56 (P-value=0.17)		
R^2=0.47, Adjusted R^2=0.47, and F-value=124.63				

Table 21. AHP as a Function of the Following Variables in Model 3 (Before)

Variable	Estimate	Std. Error	T-value	P-value
Intercept	100.71	5.55	18.14	<.0001
DCI	0.04	$4.00{\times}10^{-3}$	10.24	<.0001
AHPRO (lagged)	-0.01	$8.10{\times}10^{-4}$	-13.69	<.0001
AHES	$-1.69{\times}10^{-3}$	$7.40{\times}10^{-4}$	-2.30	0.02
FCI	$3.52{\times}10^{-3}$	$1.20{\times}10^{-3}$	2.93	$3.50{\times}10^{-3}$
CP	7.31	0.80	9.17	<.0001
MP (lagged)	1.42	0.19	7.34	<.0001
FCP (lagged)	-0.06	0.03	-1.76	0.08
AHE	$4.33{\times}10^{-3}$	0.03	0.14	0.89
Jan.	10.97	2.68	4.10	<.0001
Time Controls		Yes		
Region Controls		Yes		
R^2=0.48, Adjusted R^2=0.47, and F-value=85.10				

Table 22. logAHP as a Function of the Following Variables in Model 4 (Before)

Variable	Estimate	Std. Error	T-value	P-value
Intercept	5.26	0.16	32.24	<.0001
logDCI	0.11	0.01	12.27	<.0001
logAHPRO (lagged)	-0.18	0.01	-14.63	<.0001
logAHES	-0.04	0.01	-4	<.0001
logFCI	0.02	4.00×10^{-3}	5.41	<.0001
logCP	0.24	0.02	10.12	<.0001
logMP (lagged)	0.21	0.03	7.4	<.0001
logFCP (lagged)	-0.08	0.03	-2.65	8.00×10^{-3}
logAHE	1.40×10^{-3}	0.01	-0.23	0.81
Jan.	0.11	0.02	5.44	<.0001
Time Controls		Yes		
Region Controls		Yes		
R^2=0.52, Adjusted R^2=0.52, and F-value=102.04				

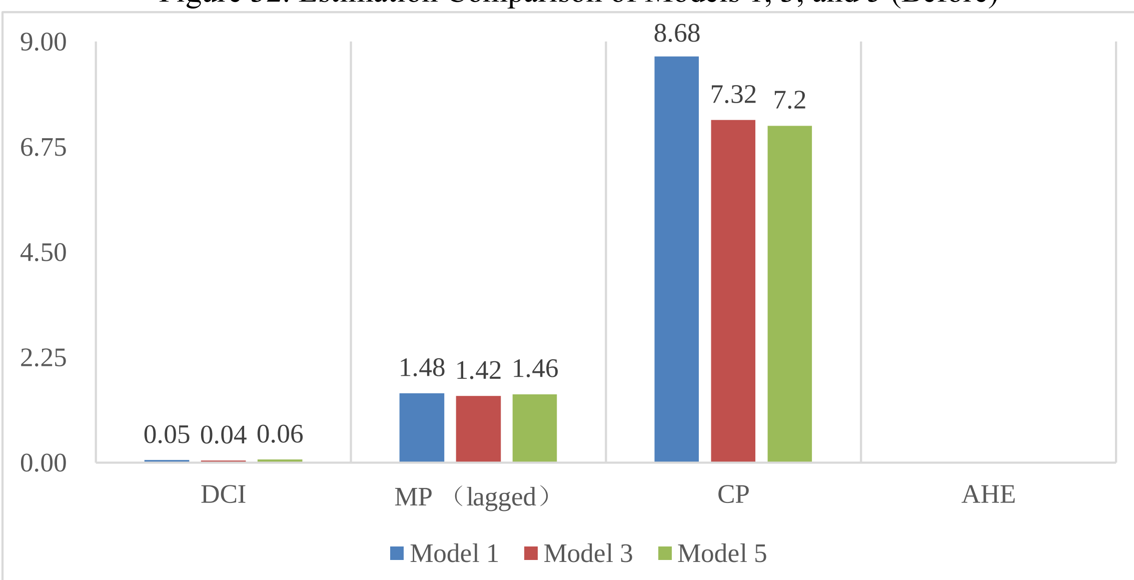
Table 23. AHP as a Function of the Following Variables in Model 5 (Before)

Variable	Estimate	Std. Error	T-value	P-value
Intercept	43.80	13.98	3.13	1.80×10^{-3}
DCI	0.06	0.01	4.80	<.0001
AHPRO (lagged)	-8.59×10^{-3}	1.65×10^{-3}	-5.21	<.0001
AHES	-1.16×10^{-3}	8.34×10^{-4}	-1.39	0.17
FCI	9.96×10^{-3}	4.96×10^{-3}	2.01	0.05
CP	7.20	0.72	10.00	<.0001
MP (lagged)	1.46	0.19	7.66	<.0001
FCP (lagged)	0.04	0.03	1.21	0.23
AHE	-0.01	0.04	-0.39	0.70
Jan.	9.76	2.75	3.54	4.00×10^{-4}
Time Controls		Yes		
State Controls		Yes		
R^2=0.62, Adjusted R^2=0.60, and F-value=52.87				

Table 24. logAHP as a Function of the Following Variables in Model 6 (Before)

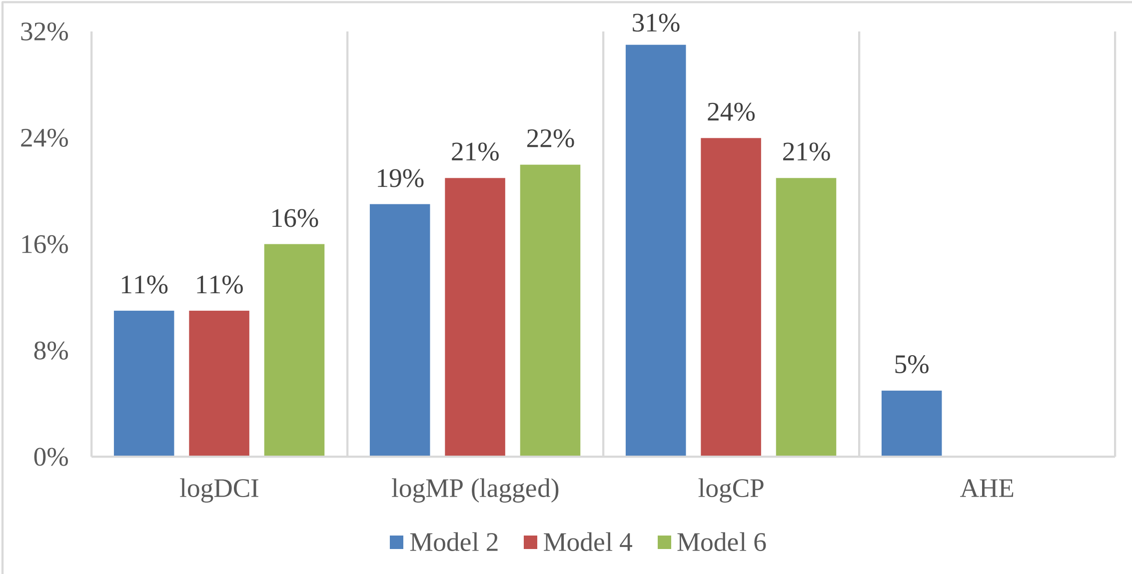
Variable	Estimate	Std. Error	T-value	P-value
Intercept	5.17	0.27	19.47	<.0001
logDCI	0.16	0.03	6.08	<.0001
logAHPRO (lagged)	-0.18	0.03	-5.78	<.0001
logHES	-0.08	0.02	-5.04	<.0001
logFCI	-0.04	0.02	-1.84	0.06
logCP	0.21	0.02	10.11	<.0001
logMP (lagged)	0.21	0.03	8.59	<.0001
logFCP (lagged)	0.01	0.03	0.48	0.63
logAHE	3.35×10^{-3}	0.01	0.54	0.59
Jan.	0.17	0.03	6.16	<.0001
Time Controls		Yes		
State Controls		Yes		
R^2=0.65, Adjusted R^2=0.64, and F-value=61.77				

Figure 32. Estimation Comparison of Models 1, 3, and 5 (Before)



Note: AHE (p>0.1) and others (p<0.01)

Figure 33. Estimation Comparison of Models 2, 4, and 6 (Before)



Note: AHE (p>0.05) in model 2 but not in models 4 & 6 and others (p<0.01)

Table 25. Estimation of Region Dummies in Model 3 (Before)

Variable	Estimate	Std. Error	T-value	P-value
West	10.58	2.41	4.38	<.0001
Northeast	16.36	4.29	3.82	1.00×10^{-4}
South	16.82	3.33	5.06	<.0001

Note: Midwest as a reference ($135.70, mean)

Table 26. Estimation of Region Dummies in Model 4 (Before)

Variable	Estimate	Std. Error	T-value	P-value
West	0.09	0.02	5.31	<.0001
Northeast	0.16	0.02	6.92	<.0001
South	0.05	0.02	2.06	0.04

Note: Midwest as a reference

Table 27. Estimation of State Dummies in Model 5 (Before)

Variable	Estimate	Std. Error	T-value	P-value
Arizona	34.59	11.57	2.99	2.90×10^{-3}
Arkansas	55.82	13.33	4.19	<.0001
California	20.93	16.19	1.29	0.20
Colorado	32.61	7.36	4.43	<.0001
Idaho	38.81	10.23	3.79	2.00×10^{-4}
Illinois	30.96	10.74	2.88	4.00×10^{-3}
Indiana	23.95	13.62	1.76	0.08
Iowa	33.11	6.87	4.82	<.0001
Kansas	12.63	4.87	2.59	9.60×10^{-3}
Kentucky	55.39	12.53	4.42	<.0001
Michigan	18.42	11.33	1.63	0.10
Minnesota	24.85	11.59	2.14	0.03
Missouri	39.84	12.12	3.29	1.00×10^{-3}
New Mexico	64.92	12.41	5.23	<.0001
New York	9.86	15.69	0.63	0.53
North Dakota	9.42	11.44	0.82	0.41
Ohio	71.27	12.72	5.60	<.0001
Oklahoma	45.93	11.57	3.97	<.0001
Oregon	56.25	11.31	4.97	<.0001
Pennsylvania	56.18	14.32	3.92	<.0001
Texas	40.72	11.02	3.69	2.00×10^{-4}
Utah	28.01	11.47	2.44	0.01
Washington	34.46	12.12	2.84	4.60×10^{-3}
Wisconsin	-20.67	18.51	-1.12	0.26

Note: Nebraska as a reference ($102.01, mean)

Table 28. Estimation of State Dummies in Model 6 (Before)

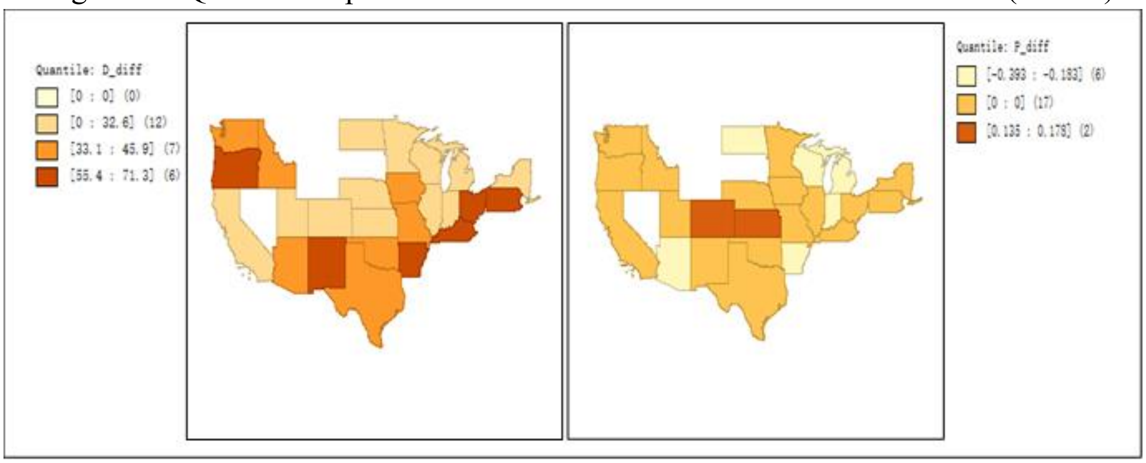
Variable	Estimate	Std. Error	T-value	P-value
Arizona	-0.20	0.09	-2.28	0.02
Arkansas	-0.39	0.16	-2.44	0.02
California	-0.05	0.10	-0.51	0.61
Colorado	0.18	0.04	4.01	<.0001
Idaho	-0.01	0.07	-0.17	0.86
Illinois	-0.02	0.07	-0.33	0.74
Indiana	-0.18	0.09	-2.01	0.04
Iowa	0.07	0.05	1.31	0.19
Kansas	0.14	0.04	3.34	9.00×10^{-4}
Kentucky	-0.07	0.13	-0.52	0.60
Michigan	-0.20	0.09	-2.25	0.02
Minnesota	-0.10	0.09	-1.13	0.26
Missouri	-0.02	0.10	-0.20	0.84
New Mexico	-0.04	0.10	-0.40	0.69
New York	-0.29	0.15	-1.87	0.06
North Dakota	-0.21	0.09	-2.31	0.02
Ohio	0.12	0.09	1.37	0.17
Oklahoma	0.11	0.07	1.61	0.11
Oregon	0.07	0.09	0.83	0.41
Pennsylvania	0.01	0.12	0.09	0.93
Texas	0.14	0.09	1.60	0.11
Utah	-0.10	0.10	-0.94	0.35
Washington	-0.10	0.09	-1.15	0.25
Wisconsin	-0.31	0.12	-2.54	0.01

Note: Nebraska as a reference

APPENDIX D—SUPPLEMENTARY GIS FINDINGS

Appendix D presents the results of global and local Moran's I (I and I_i) for 27 states, excluding Arkansas and Indian, since these two states didn't have a report for alfalfa hay prices after 1995. Other states were excluded from the U.S. map. Also, 1989 and 1991 were excluded due to missing alfalfa hay prices for Wisconsin. What's more, the results of the year 1980 to 1995 will not be reported here since they are almost identical with chapter 9.

Figure 34. Quantile Maps of State Dummies Estimation in Models 5 and 6 (Before)



Note: Nebraska as a reference ($102.01, mean) and p<0.05 for significance and 25 states included as table 28 indicates above.

Figure 35. Quantile Maps of Jan. AHP in 2000 and 2005 by State (27 States)

Figure 36. Quantile Maps of Jan. AHP in 2010 and 2015 by State (27 States)

Figure 37. Quantile Maps of Jul. AHP in 2000 and 2005 by State (27 States)

Figure 38. Quantile Maps of Jul. AHP in 2010 and 2015 by State (27 States)

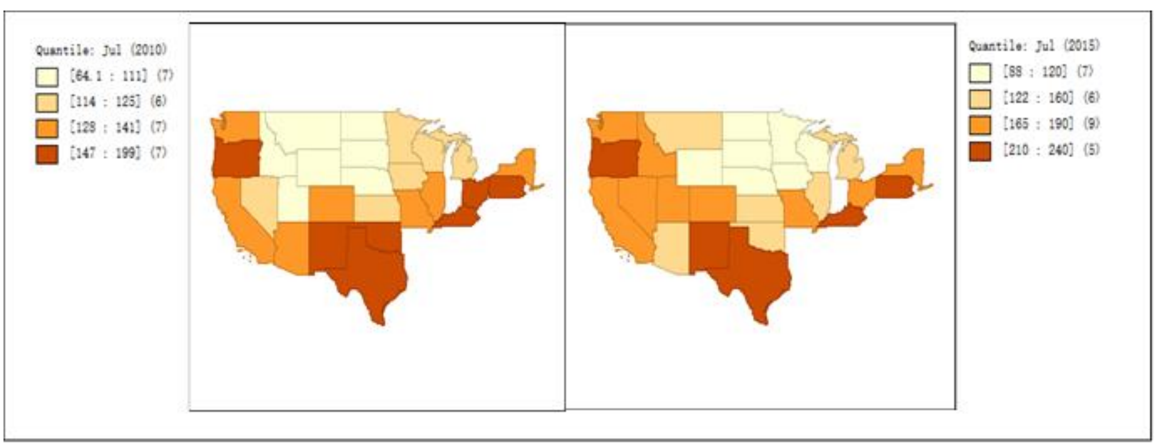


Figure 39. Neighbor Counts with Queen Contiguity (27 States)

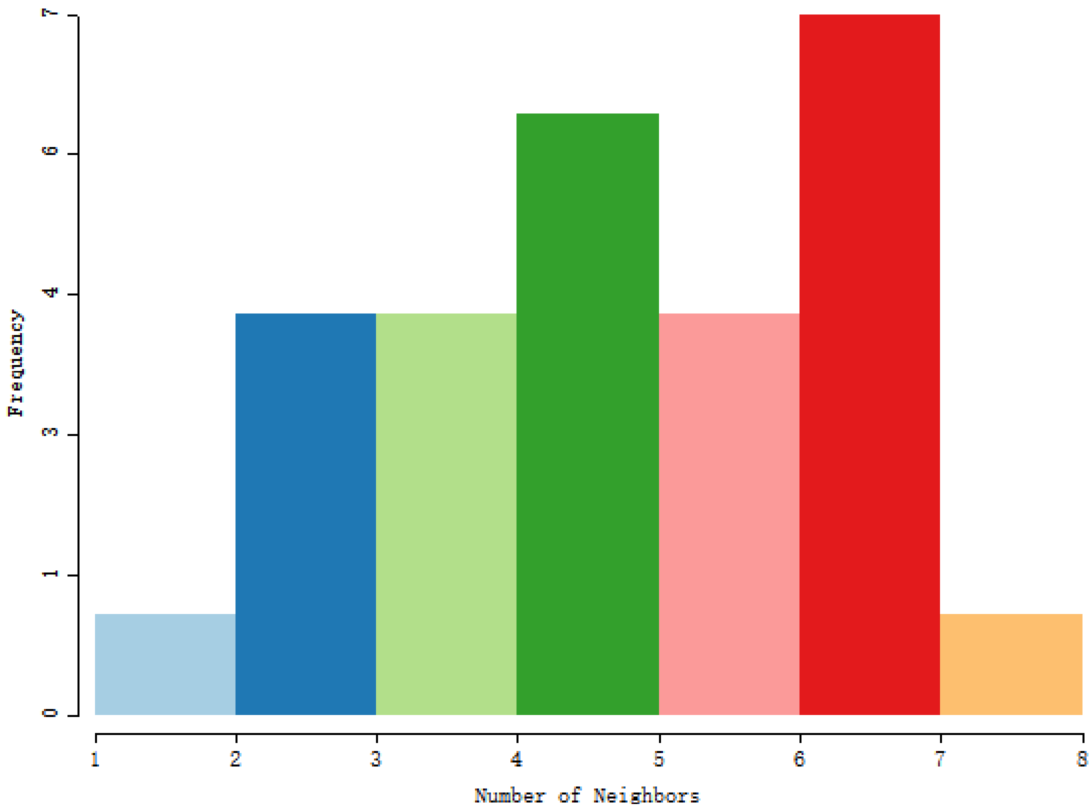
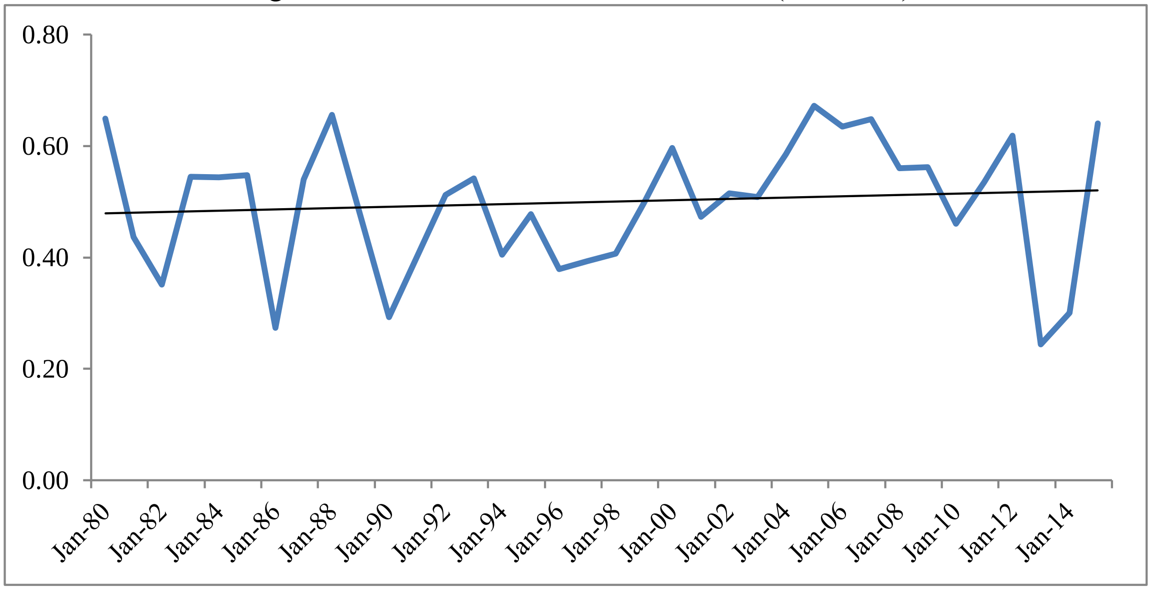


Table 29. Global Moran's I of Jan. AHP (27 States)

	Global Moran's I	Z-score	P-value
Jan-80	0.65	5.24	<0.0001
Jan-81	0.44	3.54	4.10×10^{-4}
Jan-82	0.35	2.93	3.30×10^{-3}
Jan-83	0.55	4.36	<0.0001
Jan-84	0.54	4.37	<0.0001
Jan-85	0.55	4.42	<0.0001
Jan-86	0.27	2.32	0.02
Jan-87	0.54	4.32	<0.0001
Jan-88	0.66	5.14	<0.0001
Jan-90	0.29	2.50	<0.0001
Jan-92	0.51	0.01	<0.0001
Jan-93	0.54	4.36	<0.0001
Jan-94	0.41	3.30	9.70×10^{-4}
Jan-95	0.48	3.90	<0.0001
Jan-96	0.38	3.10	1.90×10^{-3}
Jan-97	0.39	3.42	6.40×10^{-4}
Jan-98	0.41	3.43	6.00×10^{-4}
Jan-99	0.50	4.08	<0.0001
Jan-00	0.60	4.79	<0.0001
Jan-01	0.47	3.90	<0.0001
Jan-02	0.52	4.19	<0.0001
Jan-03	0.51	4.19	<0.0001
Jan-04	0.59	4.74	<0.0001
Jan-05	0.67	5.37	<0.0001
Jan-06	0.64	5.05	<0.0001
Jan-07	0.65	5.16	<0.0001
Jan-08	0.56	4.68	<0.0001
Jan-09	0.56	4.67	<0.0001
Jan-10	0.46	3.79	1.50×10^{-4}
Jan-11	0.54	4.30	<0.0001
Jan-12	0.62	4.89	<0.0001
Jan-13	0.24	2.18	0.03
Jan-14	0.30	2.66	0.08
Jan-15	0.64	5.00	<0.0001

Note: Mean I=0.50

Figure 40. Global Moran's I of Jan. AHP (27 States)



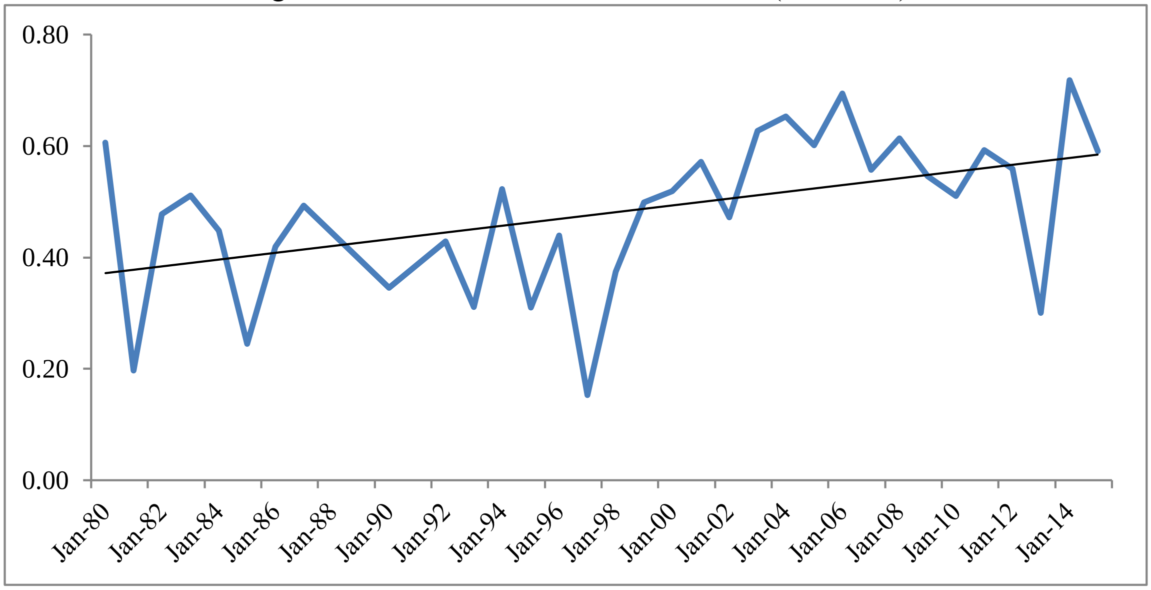
Note: Jan-14 ($p<0.1$), Jan-86 & Jan-13 ($p<0.05$), and others ($p<0.01$)

Table 30. Global Moran’s I of Jul. AHP (27 States)

	Global Moran's I	Z-score	P-value
Jul-80	0.61	4.85	<0.0001
Jul-81	0.20	1.78	0.08
Jul-82	0.48	3.86	1.10×10^{-4}
Jul-83	0.51	4.09	<0.0001
Jul-84	0.45	3.65	2.60×10^{-4}
Jul-85	0.25	2.12	0.03
Jul-86	0.42	3.41	6.50×10^{-4}
Jul-87	0.49	3.93	<0.0001
Jul-88	0.44	4.90	<0.0001
Jul-90	0.35	2.86	4.20×10^{-3}
Jul-92	0.43	3.64	2.70×10^{-4}
Jul-93	0.31	2.61	9.00×10^{-3}
Jul-94	0.52	4.18	<0.0001
Jul-95	0.31	2.59	9.50×10^{-3}
Jul-96	0.44	3.57	3.60×10^{-4}
Jul-97	0.15	1.49	0.14
Jul-98	0.37	3.12	1.80×10^{-3}
Jul-99	0.50	4.02	<0.0001
Jul-00	0.52	4.16	<0.0001
Jul-01	0.57	4.59	<0.0001
Jul-02	0.47	3.88	1.10×10^{-4}
Jul-03	0.63	5.05	<0.0001
Jul-04	0.65	5.19	<0.0001
Jul-05	0.60	4.76	<0.0001
Jul-06	0.69	5.47	<0.0001
Jul-07	0.56	4.46	<0.0001
Jul-08	0.61	4.86	<0.0001
Jul-09	0.55	4.39	<0.0001
Jul-10	0.51	4.14	<0.0001
Jul-11	0.59	4.66	<0.0001
Jul-12	0.56	4.52	<0.0001
Jul-13	0.30	2.64	8.30×10^{-3}
Jul-14	0.72	5.63	<0.0001
Jul-15	0.59	4.67	<0.0001

Note: Mean I=0.48

Figure 41. Global Moran's I of Jul. AHP (27 States)



Note: Jul-97 (p>0.1), Jul-81 (p<0.1), Jul-85 (p<0.05), and others (p<0.01)

Figure 42. Significance and Clustering Maps of Jan. AHP in 2000

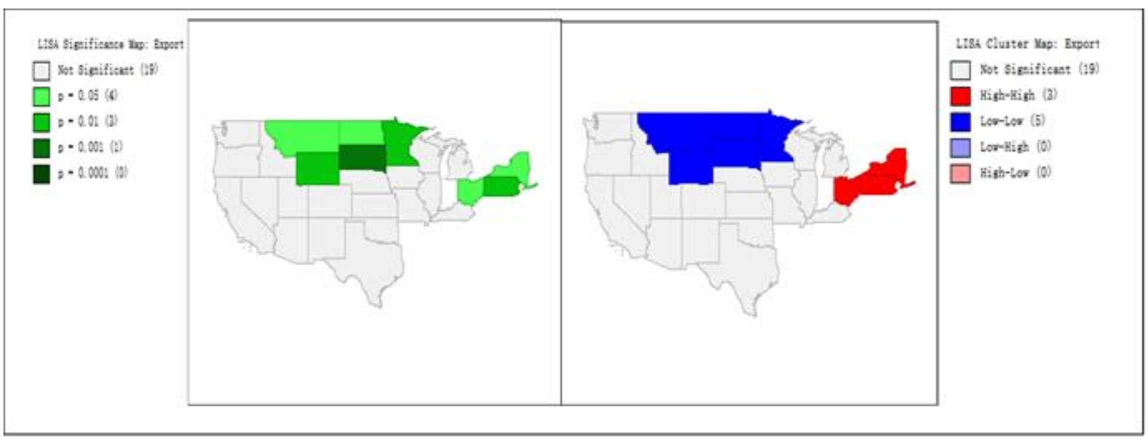


Figure 43. Significance and Clustering Maps of Jan. AHP in 2005

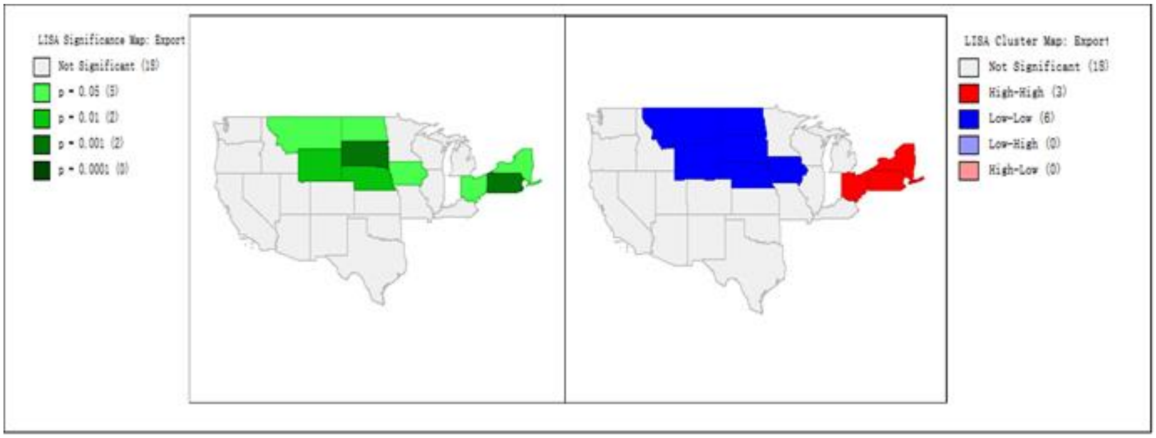


Figure 44. Significance and Clustering Maps of Jan. AHP in 2010

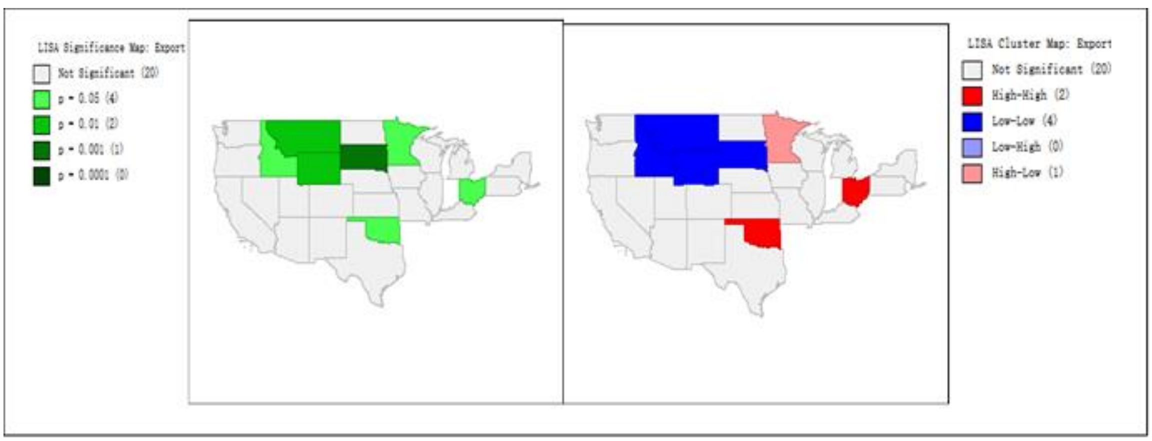


Figure 45. Significance and Clustering Maps of Jan. AHP in 2015

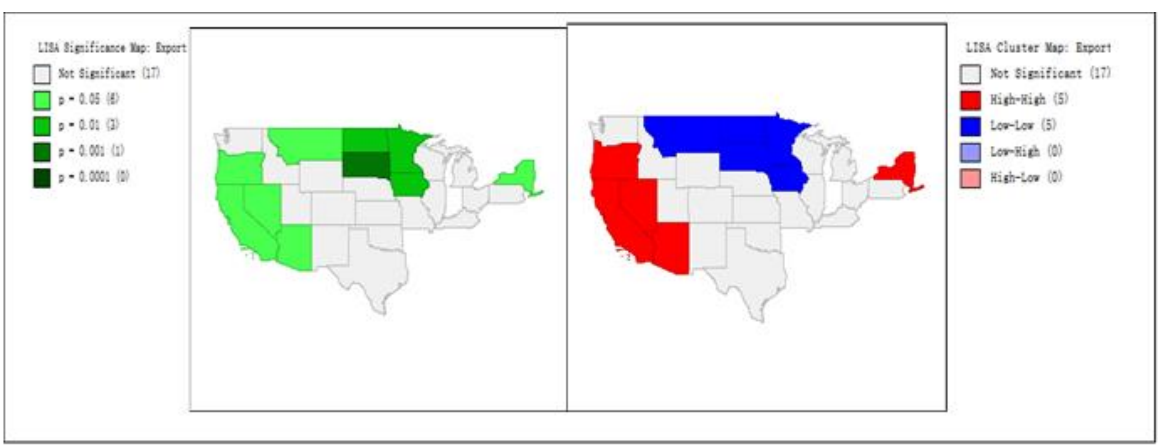


Figure 46. Significance and Clustering Maps of Jul. AHP in 2000

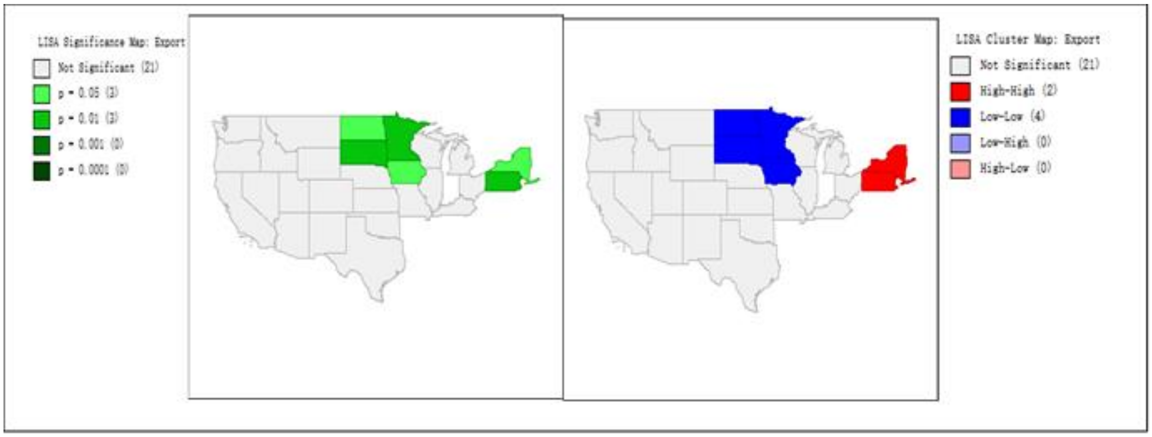


Figure 47. Significance and Clustering Maps of Jul. AHP in 2005

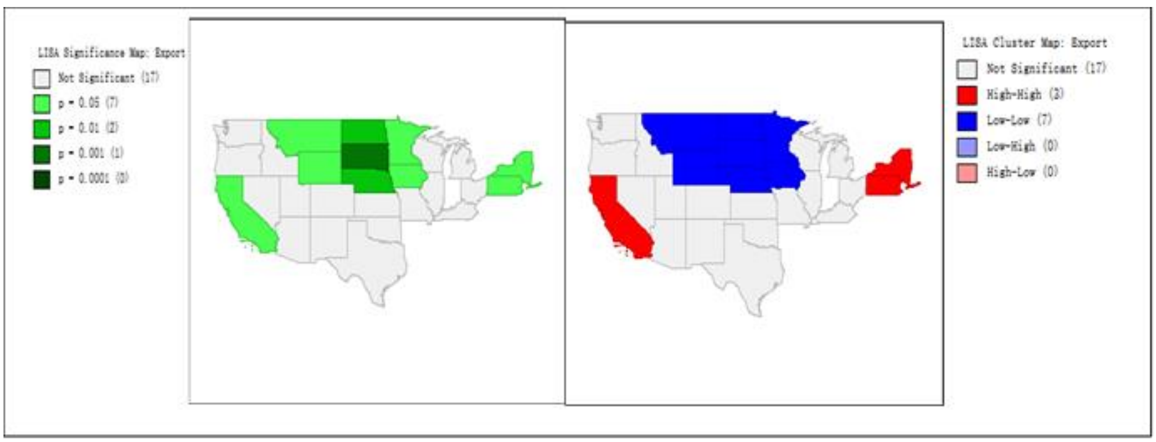


Figure 48. Significance and Clustering Maps of Jul. AHP in 2010

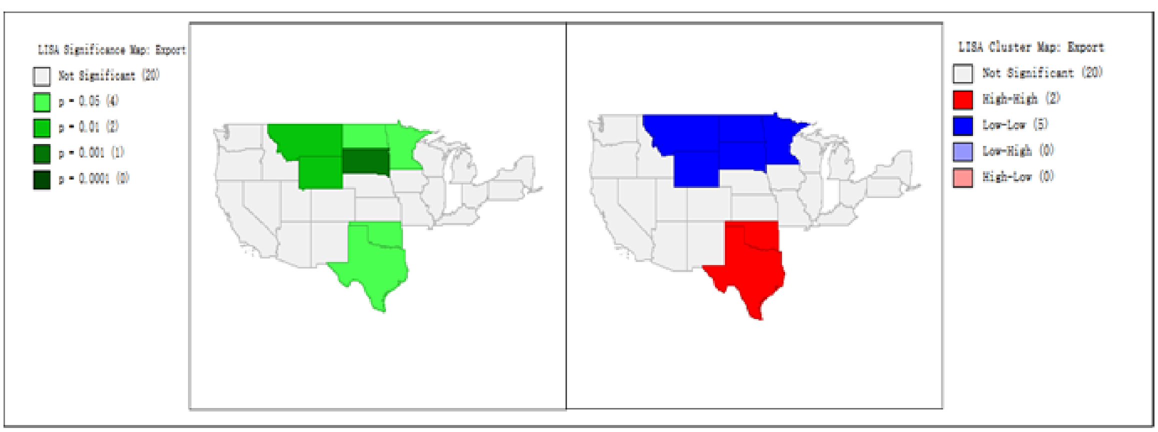
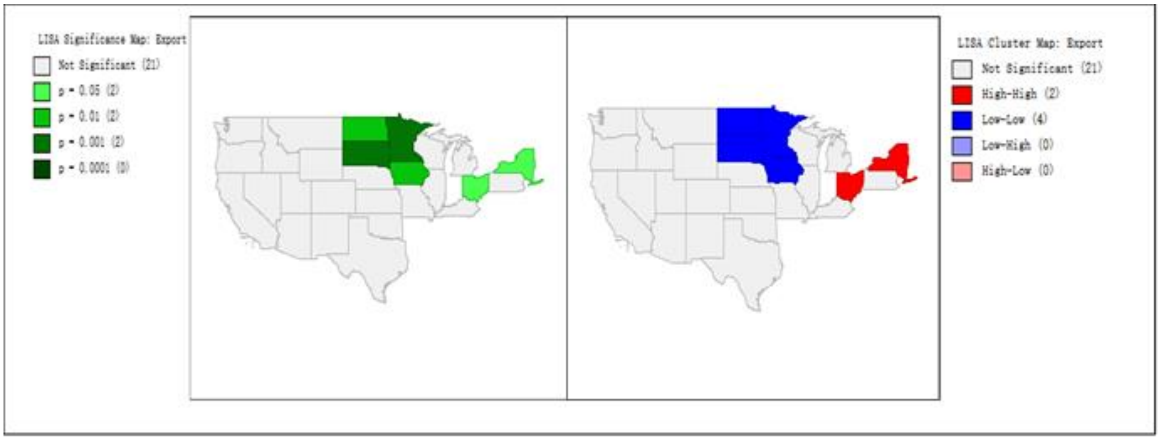


Figure 49. Significance and Clustering Maps of Jul. AHP in 2015



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