ON THE MOO-VE: TESTING FOR SPATIAL AGGLOMERATION ECONOMIES IN THE U.S. DAIRY INDUSTRY

by

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Abstract

The geographic distribution and structure of the U.S. dairy industry have changed considerably during the last 30 years with larger herds representing an increasing proportion of the nation's overall dairy cow inventory and producing a greater share of the milk. Geographically, the migration of dairies from traditional production regions to states formerly unfamiliar with dairy production has transpired with the greatest increases in Federal Milk Marketing Order marketings occurring in California, Oregon, Washington, Idaho, Arizona, New Mexico, West Texas and Southwest Kansas since the 1980's. This study seeks to define the factors influencing the dairy location decision applying spatial econometric techniques.

To examine the effects of county-specific demographic, environmental, and market factors as well as to test for the influence of spatial agglomeration economies on the geographic distribution of the U.S. dairy industry, a spatially explicit, county-level model of the dairy production sector was developed. Quantities of milk marketed through the Federal Milk Marketing Order during the month of May for counties in 45 states during 1997 and 2002 were specified as a function of natural endowments, business climate, production resource availability, milk price, and market access. The model was estimated according to spatial autoregressive (spatially lagged dependent variable) and spatial Durbin (lagged dependent and independent variables) specifications accounting for the censored nature of the dependent variable and heteroskedastic errors. Based on RMSE, the spatial error model was selected to make out of sample predictions for 2004. The change in milk marketings between 1997 and 2002 was regressed on the 1997 independent variables using non-Tobit versions of the same models with limited success.

Results indicated a small but statistically significant presence of spatial agglomeration effects in the dairy industry in both 1997 and 2002 and revealed changes in the degrees of influence of several variables between the two periods examined. Population and the wages of agricultural workers became significant in 2002, while the elasticities of feed availability diminished, consistent with an increase in western-style

dairy production. Interestingly, the spatial parameter decreased from 0.052 in 1997 to 0.028 in 2002 suggesting spatial agglomeration economies had a diminishing role in determining the amount of milk marketed in a county.

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Dedication

To my wife, Audra, for her patience and encouragement throughout my graduate school and for continually convincing me I could accomplish this feat.

CHAPTER 1 - INTRODUCTION

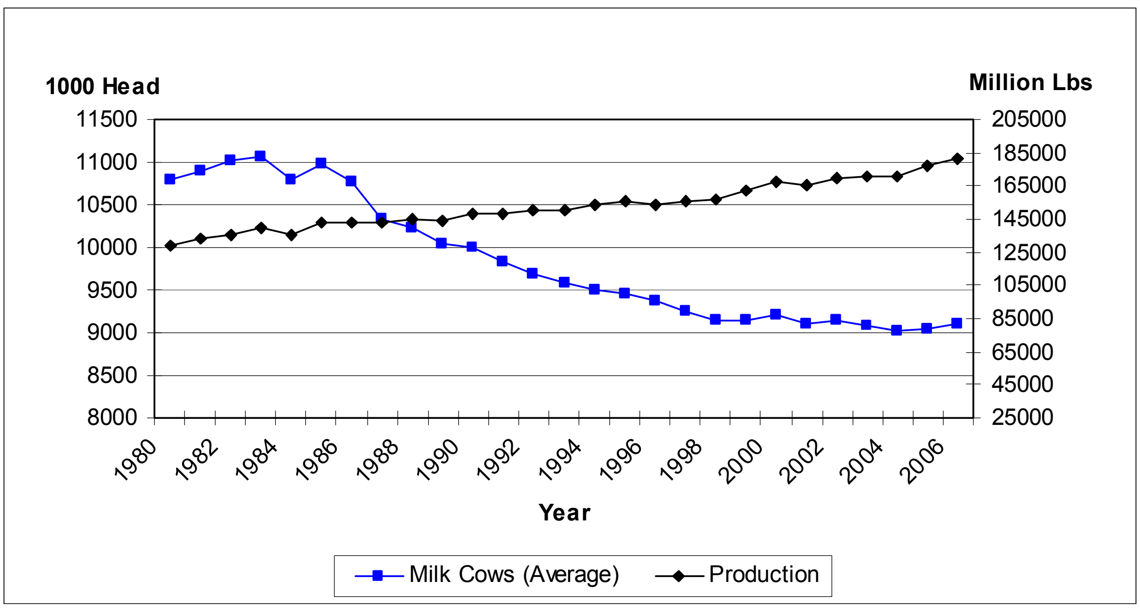
The U.S. dairy industry continues a structural and geographical transformation as the total U.S. herd size and number of farms decreases while regions generally considered non-traditional production regions are witnessing increases in cow inventories and milk production. There certainly appears to be underlying trends in animal agriculture and location specific factors that are enticing expansion and relocation of dairy operations in those areas. A focus of this thesis is to identify those factors using a regression technique and measure the changes in the magnitude of those effects in two periods. Additionally, the effects of spatial agglomeration that may arise from resource availability or market access, external economies generated by intra and inter industry presence in the region, and spillovers of technology or knowledge are hypothesized to have an impact on the changing distribution in the dairy industry. The specific objective of this thesis is to evaluate the presence of spatial agglomeration in the U.S. dairy industry and to construct a predictive model that considers the impact of agglomeration effects and traditional variables on the concentration and distribution of the industry using spatial econometric techniques.

The following sections will address the structural and geographic trends that have developed in the dairy sector during that last 30 years and review the commonly recognized motivations that influence the location decision. Chapter 2 will expand upon the concept of spatial agglomeration economies providing a survey of the literature regarding spatial agglomeration in industries including agriculture and the work that has been applied to geographic distribution in the dairy industry. Chapter 3 presents a location decision model and discussion of the data used in the estimations of models including hypothesized directional impacts of variables, while Chapter 4 presents the theoretical model and focuses on the specific spatial econometric methods. The results are subsequently revealed with discussion in Chapter 5 followed by the conclusions and recommendations for further research in Chapter 6.

1.1 Dairy Industry Trends

Dairy producers in the U.S. continue to produce greater quantities of milk with fewer cows on fewer farms as shown in Figures 1-1, 1-2, and 1-3. This has been accomplished by consistently increasing milk production per cow as dairy farms have become larger and more efficient. Led by advancements in genetics, nutrition, management, and technology, milk production per cow today has increased almost 60 percent from 1980 and has increased threefold since the 1950s (Miller and Blayney, 2006). Between 1980 and 2006, the number of dairy operations fell from 334,000 to 75,140 a decline of over 75 percent (Figure 1-2), but the majority of the attrition occurred among smaller operations while the number of large dairy farms (500 head or larger) has increased.

Figure 1-1 Total Milk Production and Herd Size in the U.S., 1980 - 2006



The trend towards larger farms is illustrated in Figure 1-4 showing the number of farms in several size categories in 1998, 2002, and 2006. The average herd size in the U.S. has more that quadrupled over a 40 year span and is currently about 111 cows, up from 32 in 1980 and 70 in 2000 (USDA NASS, 2007). Additionally, large farms continue to increase their share of total production as operations over 500 head produced 47 percent of the milk in 2006 compared with 39 percent in 2001 and 29 percent in 1997 (Miller and Blayney, 2006; USDA NASS, 2007). Figure 1-5 shows the percentage of milk produced on farms of various sizes for the years 1998 through 2004; note the continued increase in the proportion of milk produced on larger farms. Remarkably, the U.S. dairy sector continues to remain predominately in private hands as sole proprietorships or family partnerships and corporations account for approximately 84 percent of the ownership.

Figure 1-2 Number of Dairy Farms in the U.S., 1980 - 2006

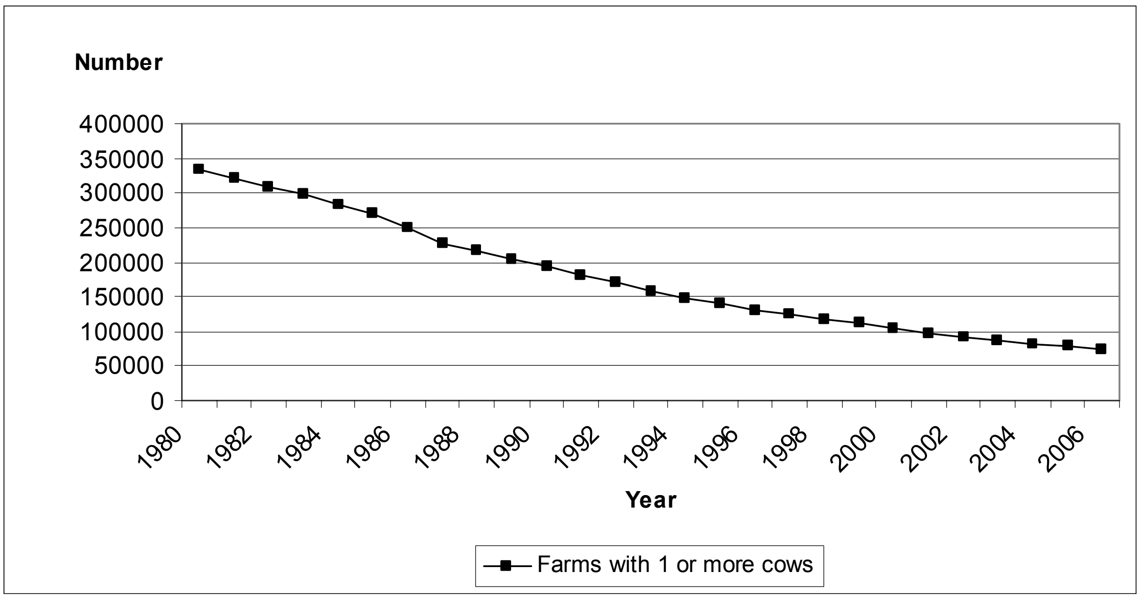


Figure 1-3 Milk Production on a Per Cow Basis, 1980 - 2006

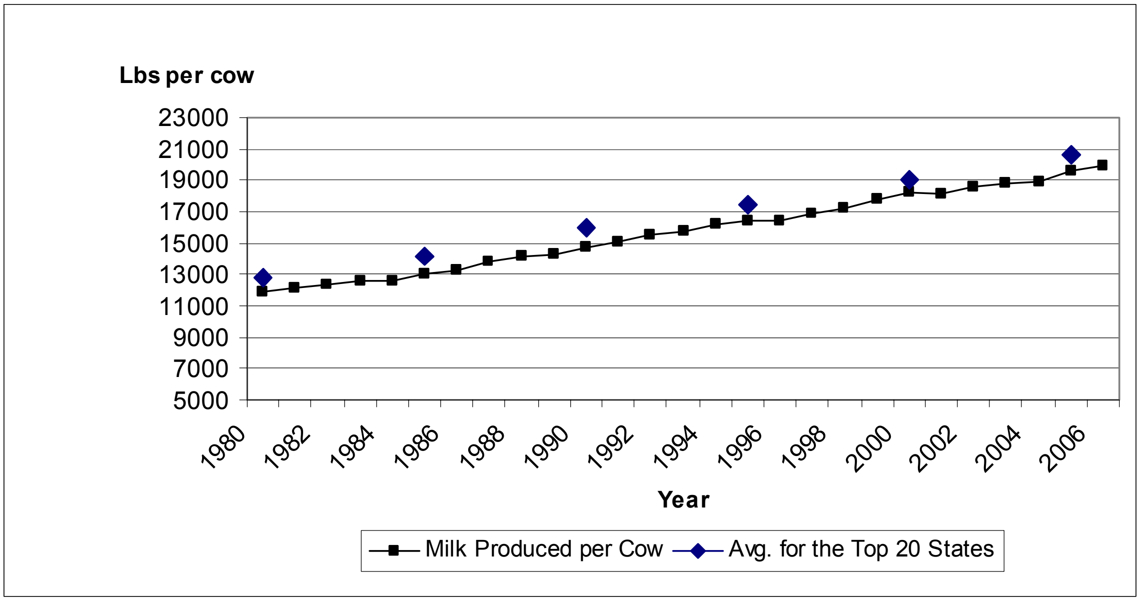


Figure 1-4 Number of Dairy Operations in Various Herd Size Classes

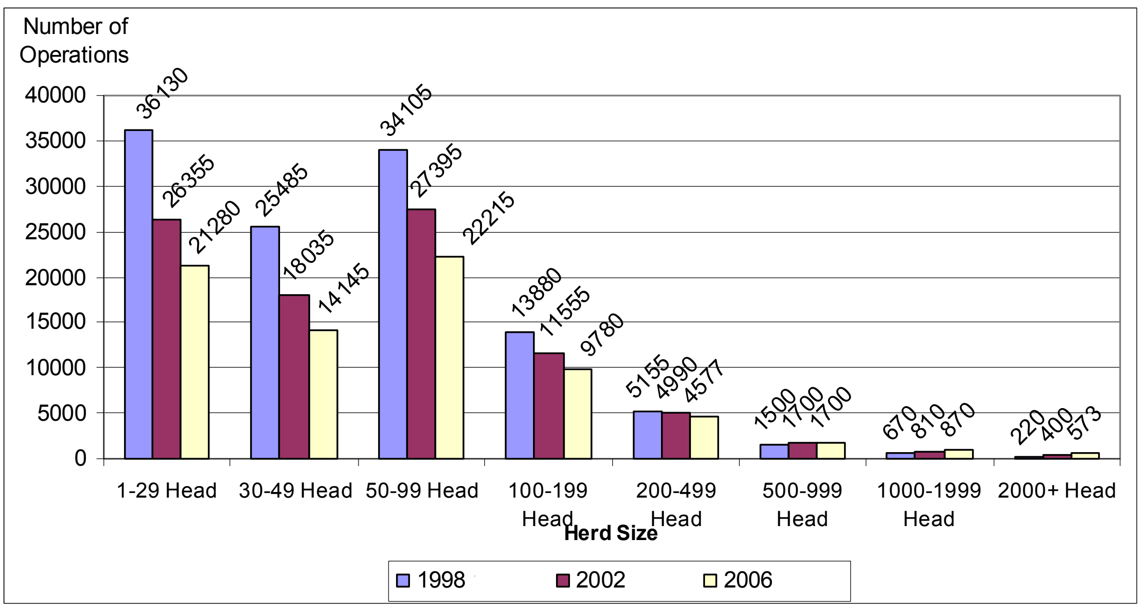
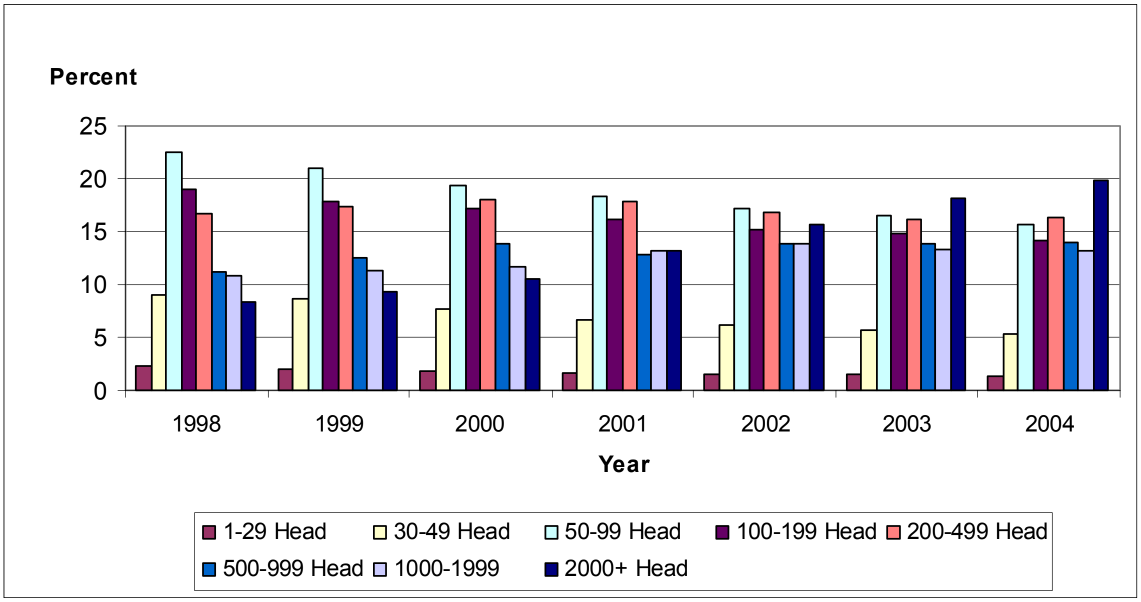


Figure 1-5 U.S. Milk Production Percentages by Herd Size, 1998 - 2004



Blayney (2002) suggests several broad factors that have contributed to the structural change in milk production since World War II, those being adoption of technological innovations, change in the production system, and specialization. Among the technologies that have altered the nature of dairying are the increased mechanization of general farm operations and the milking process and greater advances in computer monitoring, as well as improvements in the design of animal housing, feeding, and milking parlors. Increased understanding of the animals' biological processes has allowed for improvements in feeding efficiency, and genetic engineering has produced rBST, a synthetic version of a naturally occurring hormone that boosts milk production, improving milk output per cow. Change in the production system has moved dairying from pasture-based milk production to confinement feeding, substituting feed rations grown on farm or purchased for open pasture grazing. Finally, the dairy farm has specialized from an agricultural operation with dairy as a sideline for home or community consumption to one that focuses solely on production of milk for the greatest portion of its profits (Blayney, 2002). Government policies on both the state and federal levels have undoubtedly influenced milk production as well. These changes have resulted in a more concentrated industry with increasing numbers of large farms and larger average herd sizes in all states.

From New York almost a century ago, to Wisconsin in 1914 and California in 1994, the leading dairy producing state has migrated first westward then to the Southwest following the population growth, lower priced land, and better production conditions (Stephenson, 1995). In the last three decades, the dairy industry has seen tremendous migration from areas of traditional production (i.e., the Upper Midwest, Great Lakes, and Northeast) to areas in the Southwest U.S. While in sheer numbers more dairy farms are still located in the traditional regions, 71 percent in 2000, those regions no longer hold the same level of dominance in terms of total herd size. A number of "western" states have moved into the top twenty rankings for milk production and animal inventory. Herath, Weersink, and Carpentier (2004) report that between 1975 and 2000, the Southeast region of the U.S. lost 50 percent of their cow inventory, while New England lost 33 percent, the Great Plains 43 percent, and the Mid-Atlantic states (including Delaware, Maryland, New Jersey, New York, and Pennsylvania) lost more than 20 percent. The Rocky Mountain and Far West regions, on the other hand, increased by 64 percent and 60 percent, respectively. Most importantly, the milk production per cow in the traditional areas lags well behind the per cow output of states in the western part of the country implying that some locations are considerably more suitable for dairy production than others (Miller and Blayney, 2006). Yavuz et al. (1996) generally recognized that supply factors including milk per cow and cows per farm are key factors influencing regional distribution of U.S. milk production.

There is ample evidence that the most prolific dairy producers have concentrated in certain states. As Table 1-1 points out, the top 20 milk producing states have remained relatively stable since 1985 with a noticeable increase in the rankings of states in the West and Southwest. However the share of overall milk production from those top 20 has continuously increased over the same period. In 2005, the top 10 milk producing states accounted for over 72 percent of total U.S. production, a five percent increase from the 1985 percentage (Mosheim and Lovell, 2006) while the top 20 states accounted for just over 88 percent. Moreover, the production in certain states is extremely concentrated geographically as well. For example, the top 10 *counties* in California produced 93 percent of the state's milk in 2005 and accounted for nearly 20 percent of the nation's milk. Furthermore, the top 5 accounted for 14 percent of the nation's milk (California Department of Food and Agriculture, 2005).

Table 1-1 Top 20 States by Milk Production, 1985 - 2005

	1985			1995			2000			2005		
	State	*Million Pounds*	*%[a]*	*State*	*Million Pounds*	*%[a]*	*State*	*Million Pounds*	*%[a]*	*State*	*Million Pounds*	*%[a]*
Rank	U.S.	143,021	~	U.S.	155,292	~	U.S.	167,393	~	U.S.	176,929	~
1	WI	24,700	17.3	CA	25,327	16.3	CA	32,245	19.3	CA	37,564	21.2
2	CA	16,762	11.7	WI	22,942	14.8	WI	23,259	13.9	WI	22,866	12.9
3	NY	11,732	8.2	NY	11,600	7.5	NY	11,921	7.1	NY	12,078	6.8
4	MN	10,835	7.6	PA	10,489	6.8	PA	11,156	6.7	PA	10,503	5.9
5	PA	9,983	7.0	MN	9,409	6.1	MN	9,493	5.7	ID	10,161	5.7
6	MI	5,568	3.9	TX	6,113	3.9	ID	7,223	4.3	MN	8,195	4.6
7	OH	4,870	3.4	MI	5,565	3.6	TX	5,743	3.4	NM	6,951	3.9
8	IA	4,058	2.8	WA	5,304	3.4	MI	5,705	3.4	MI	6,750	3.8
9	TX	3,968	2.8	OH	4,600	3.0	WA	5,593	3.3	TX	6,442	3.6
10	WA	3,750	2.6	ID	4,210	2.7	NM	5,236	3.1	WA	5,608	3.2
11	MO	2,870	2.0	IA	4,047	2.6	OH	4,461	2.7	OH	4,743	2.7
12	IL	2,721	1.9	NM	3,623	2.3	IA	3,934	2.4	IA	4,025	2.3
13	ID	2,421	1.7	MO	2,690	1.7	AZ	3,033	1.8	AZ	3,742	2.1
14	VT	2,410	1.7	VT	2,545	1.6	VT	2,683	1.6	IN	3,166	1.8
15	IN	2,358	1.7	IL	2,399	1.5	FL	2,463	1.5	VT	2,641	1.5
16	TN	2,235	1.6	FL	2,381	1.5	IN	2,419	1.5	CO	2,348	1.3
17	KY	2,222	1.6	AZ	2,230	1.4	MO	2,258	1.4	OR	2,284	1.3
18	VA	2,102	1.5	IN	2,214	1.4	IL	2,094	1.3	KS	2,276	1.3
19	FL	2,038	1.4	KY	2,020	1.3	CO	1,924	1.2	FL	2,273	1.3
20	NC	1,748	1.2	VA	1,950	1.3	VA	1,900	1.1	IL	1,958	1.1
	Top 20[b]	119,351	83.5	*Top 20[b]*	131,658	84.8	*Top 20[b]*	144,514	86.3	*Top 20[b]*	161,600	91.3

[a] Percent of the U.S. total. [b]Total of the top 20 states.

The states listed in Table 1-2 are those states with the most dairy cows in selected years from 1985 through 2005. Although it closely follows the amount of production, it is not a perfect match to Table 1-1.

Table 1-2 Top 20 States by Dairy Cow Numbers, 1985 - 2005

	1985			**1995**			**2000**			**2005**		
	State	*Million Head*	*%[a]*	*State*	*Million Head*	*%[a]*	*State*	*Million Head*	*%[a]*	*State*	*Million Head*	*%[a]*
Rank	U.S.	10,981	~	U.S.	9,466	~	U.S.	9,199	~	U.S.	9,043	~
1	WI	1,876	17.1	WI	1,490	15.7	CA	1,526	16.6	CA	1,755	19.4
2	CA	1,041	9.5	CA	1,294	13.7	WI	1,344	14.6	WI	1,236	13.7
3	NY	914	8.3	NY	703	7.4	NY	686	7.5	NY	648	7.2
4	MN	913	8.3	PA	636	6.7	PA	617	6.7	PA	561	6.2
5	PA	740	6.7	MN	592	6.3	MN	534	5.8	ID	455	5.0
6	MI	394	3.6	TX	401	4.2	TX	348	3.8	MN	453	5.0
7	OH	369	3.4	MI	326	3.4	ID	347	3.8	NM	328	3.6
8	IA	352	3.2	OH	289	3.1	MI	300	3.3	TX	320	3.5
9	TX	322	2.9	WA	264	2.8	OH	262	2.9	MI	312	3.5
10	MO	234	2.1	IA	251	2.7	NM	250	2.7	OH	270	3.0
11	KY	231	2.1	ID	232	2.5	WA	247	2.7	WA	241	2.7
12	IL	227	2.1	NM	191	2.0	IA	215	2.3	IA	195	2.2
13	WA	223	2.0	MO	190	2.0	FL	157	1.7	AZ	165	1.8
14	TN	210	1.9	FL	162	1.7	VT	156	1.7	IN	156	1.7
15	IN	192	1.8	KY	162	1.7	MO	154	1.7	VT	143	1.6
16	VT	188	1.7	VT	157	1.7	IN	146	1.6	FL	137	1.5
17	FL	173	1.6	IL	151	1.6	AZ	139	1.5	OR	121	1.3
18	ID	170	1.6	IN	144	1.5	KY	132	1.4	MO	117	1.3
19	VA	164	1.5	VA	129	1.4	IL	120	1.3	KS	111	1.2
20	SD	162	1.5	TN	127	1.3	VA	119	1.3	KY	106	1.2
	Top 20[b]	9,095	82.8	*Top 20[b]*	7,875	83.2	*Top 20[b]*	7,799	84.8	*Top 20[b]*	7,830	86.6

[a] Percent of the U.S. total. [b]Total of the top 20 states.

These statistics, though effective in illustrating the structural and geographical evolution of the sector, fail to explain the economic drivers behind the change. To understand the influence various factors may have in the decision to locate in a particular area, it is helpful to understand some of the regional differences and the types of operations that tend to exist in each region.

There are key differences between the farms constructed in the new dairy regions and those in more traditional areas. Stephenson (1995) and Peterson (2002) contrast the two types as a “traditional-style dairy” consisting of a smaller herd with comparatively more land holdings used for forage production versus the “Western-style dairy” that manages more cows and relies heavily on purchased feed. In this context the expansion efforts of a traditional dairy must contend with acquiring more land to produce feed while the western dairy can focus capital expenditures on specialized management or improved technology and simply purchase the additional feed required (Peterson and Dhuyvetter, 2001). To illustrate the size trend consider that in 1985 the average herd size in California was 200 cows, while in Idaho it was 40 and 48 in New Mexico. Currently, those numbers have soared to 763, 535, and 729, respectively. While herd size has increased in traditional states, too, the growth has not been as dramatic. Average herd size in Wisconsin is roughly 80 cows, while in Pennsylvania it is 63 with numbers having increased modestly from 46 and 35 over the same period (USDA NASS, 2007; Mosheim and Lovell, 2006).

Wolf (2003) points out that traditional areas face higher adjustment costs because of greater sunk costs than emerging regions. The opportunity to spread initial fixed costs over more animals explains why Western dairies are quicker to adopt new technologies and management techniques than dairies in the traditional areas. As such, Western dairies have taken advantage of favorable climates to utilize drylot production systems requiring less investment in building facilities than free-stall barns and less land than pasture-based systems. This approach accommodates increasing scale economies with larger herd size and reducing asset fixity, which further encourages more rapid adoption of new equipment designed for larger herds (Mosheim and Lovell, 2006). There is a positive relationship between the number of cows milked and production per cow due to larger dairies generally having greater access to capital to acquire new technologies and, once acquired, using the facilities and labor with greater efficiency (Garcia and Kalscheur, 2004). Peterson (2002) writes that much of the mobility in the dairy industry is credited to the increase in Western style production that favors the ability to relocate or expand more easily than traditional operations.

1.2 Factors Influencing the Geographic Location of Dairies

In the past, the perishability of milk and milk products required production to occur within a certain distance of the end consumer, giving rise to von Thünen-style production rings encircling urban areas where the milk was consumed and prices were determined by distance from market (Peterson, 2002). Today, government intervention in the milk pricing system combined with improvements in transportation and milk storability allow production to occur more remotely, as producers search for lower production costs and other amenities. Some traditional constraints such as climate and dependence on locally produced feedstuffs have also been minimized by advancements in facilities technology, irrigation, and management techniques (Herath, Weersink, and Carpentier, 2004). Milk is produced in each of the fifty states with the majority of counties having at least some production. Nonetheless, there are certain combinations of factors including natural endowments, market access, input and labor quality and availability, livestock infrastructure, and local business climate and policies that influence the location decision, resulting in regions that possess comparative advantage and support more intense production as discussed in the following sections.

1.2.1 Production Environment

A suitable climate and water availability affect every agricultural endeavor, and dairying is not exempt. Temperature and precipitation conditions dictate the type of housing facilities necessary to maintain consistent milk production and impact the availability and quality of locally produced feed (Wolf, 2003). Dairy animals are susceptible to heat stress especially in areas of high humidity, and excess rainfall in drylots can create muddy conditions increasing the occurrence of mastitis (Keown, Kononoff, and Grant, 2005). Water for animals to drink, waste management, and cooling in warmer climates, as well as for use in crop irrigation, if necessary, must be available in sufficient quantity (Peterson and Dhuyvetter, 2001). The moisture deficit (rate of evaporation minus rainfall) is greater in the semi-arid areas of the Southwest making the less capital intensive drylot system more feasible in those regions. In regions of higher rainfall, the risk of uncontrolled runoff can cause environmental compliance to be higher in drylot operations (Stokes and Gamroth, 1999). Soil type, topography, and climate also impact the agronomic value of the land and the cost of local feed production, while the climatic influence on feed quality is also considerable. Wolf (2003) reports that feed quality issues are more often problematic in feed produced on-farm, as it will likely be fed regardless of quality potentially decreasing milk production and farm profitability.

Dairy production involves the use of land and facilities, feed inputs, labor, initial animal purchases or replacement costs, and related services (veterinary, repair and upkeep) all of which may vary in cost and availability in different regions of the country. To minimize production costs it makes sense for dairies to locate in regions where these inputs are relatively less expensive. Peterson (2002) suggests that the costs for obtaining inputs and compliance with state or local regulations are more important than market access in the location decision. Advancements in technology and transportation have mitigated many of the constraints of natural environment and the necessity of locating near consumers, allowing dairies to pursue regions of lowest cost (Abdalla, Lanyon, and Hallberg, 1995). Table 1-2 compares the costs of production per hundredweight of milk across regions between 1993 and 1999, showing that the Pacific ($9.87) and Southern Plains ($11.07) regions have the lowest total variable production costs for those years while those in the Northeast ($12.50) and Southeast ($12.97) regions are the highest. A comparison of fixed costs shows similar results on the low end; the Pacific and Southern Plains are the lowest, while the Upper Midwest has fixed costs per hundredweight of $2.23 (USDA NASS, 2007). Blayney (2002) and Stephenson (2000) both cite less expensive land as a reason for dairies to move west, and there are some anecdotal claims that the same concern has contributed to an exodus of cows from California to the expanses of Texas, Kansas, Idaho, and New Mexico.

Table 1-3 Average Milk Production Costs and Returns for Six Regions, 1993 - 1999

	Northeast	**Southeast**	**Upper Midwest**	**Corn Belt**	**Southern Plains**	*Pacific*
Total Variable Cost	$12.50	$12.97	$11.27	$12.05	$11.07	$9.87
Total Fixed Cost	$1.75	$1.60	$2.23	$1.59	$1.23	$1.11
Total Cost	**$14.25**	**14.57**	**$13.50**	**$13.64**	**$12.30**	**$10.98**
Total Gross Value of Production	$15.53	$17.62	$15.48	$15.46	$15.44	$14.20
Gross Value of Production Less Cash Expenses	**$1.27**	**$3.04**	**$1.98**	**$1.83**	**$3.14**	**$3.22**

Source: Data from USDA ERS, 2007

The most important cost of production is feed with alfalfa hay, corn silage, and corn grain comprising the greatest share of feed rations. Feed costs represent about 37 percent of the total cost per hundredweight of milk produced on a farm with high per cow production and feed quality is a strong component of milk production (Dhuyvetter et al., 2000). Because of its higher water content, silage involves greater transportation costs than corn or alfalfa hay. Hay is bulkier than corn and thus has a higher transportation cost than corn. As dairy herd sizes increase, the amount of feed that must be purchased from outside the farm increases, while in regions where the dairy industry is growing rapidly, there may be a need to import feed from greater distances increasing transportation cost. A logical assumption is that the amount of feed commodities produced in a county would affect the intensity of dairy production in that county. Larger operations also demand more labor than a farm family can provide on their own so wage rates for agricultural labor and availability of local labor may also influence the decision on where to build or expand a dairy.

There is ample anecdotal evidence that expanding urban development into regions once inhabited by dairy farms is increasing land values, environmental compliance costs, and the occurrence of conflicts between dairy production or expansion efforts and residential populations (Anderson and Outlaw, 2004; Smith et al., 2006). As communities expand, there is less available land for animal facilities and feed production, and often the new citizens are less understanding and accommodating of the peculiar inconveniences often associated with agriculture resulting in negative production externalities that can drive dairy producers to relocate or leave production altogether. Such public pressures would also seem an effective deterrent to entry by new businesses into the dairy industry in those regions.

Some organizations and communities in rural areas are actively recruiting dairy operations in efforts to revitalize what are often suffering rural economies by providing opportunities for local labor and support services. These recruitment efforts may include tax relief or reduced costs for service (water or electricity) as allurements in addition to the natural endowments or economic attractions of the region. Recent survey research by Eberle et al. (2004) at the University of Illinois indicate that recruitment efforts play minimal roles and are often overshadowed by other influences in attracting dairies to a region. Still, groups like Western Kansas Rural Economic Development Alliance in Kansas, and similar organizations in Texas, South Dakota and Nebraska are actively promoting the virtues of their communities for dairying to have a role in the development of agglomeration economies.

Agglomeration economies, or thick market effects, are positive spillovers associated with greater concentrations of intra-industry (other dairies) or inter-industry (other livestock facilities) activity within a region (Cohen and Morrison-Paul, 2004). This may result from improved access to input suppliers or output markets and associated lower transaction costs, greater diffusion of production-related knowledge and technology, or industry supporting infrastructures, technical services, and business environments in a certain region. For example, as an area gains more dairies, crop producers may have an increased incentive in the form of guaranteed markets to produce consistent quantities of high quality feed in turn providing lower feed costs and reliable supplies for existing dairies and encouraging expansion of the industry. Conversely, thin market effects could be felt if too many dairies entered the area causing a reduction in feed availability (Cohen and Morrison-Paul, 2004). These spatially dependent, external and internal industry shift factors are an important dimension to consider when evaluating production concentration and location decisions in the dairy industry. There may also be spatial components active in determining the relationships between the independent variables considered in the modeling procedure. The theory and nature of spatial agglomeration economies will be discussed in greater detail in the literature review.

As mentioned earlier, many technologies have changed the process of milk production in the U.S., but they have also contributed to the location of production as well. Artificial insemination techniques have increased access to superior genetic lines to producers across the country and improved overall herd quality (Smith and Brouk, 2000). The advent of bulk tank storage occurred as dairies in California were being built to accommodate the larger herd sizes necessary to justify the additional investment in an on-farm cooler. It took dairies in traditional regions decades to catch up with herd sizes that would justify bulk tank storage, while producers in the West enjoyed greater economies of scale (Stephenson, 1995). As raw milk quality, bulk handling, and refrigeration methods have improved, the reduced costs of transporting milk greater distances for longer periods has eroded the advantages of local production, allowing producers flexibility in deciding to locate in areas of lower cost production (Stillman et al., 1995). For example, processing plants in the Southeast, where climate is a detriment to milk production, regularly ship large quantities of milk from as far away as Wisconsin (Schoening, 2006). Lower transportation costs also increase the distance inputs may profitably travel allowing dairies to locate farther away from traditional input producing regions.

1.2.2 Market and Consumption Trends

The demand for dairy products is very inelastic estimated at -0.16 for milk and -0.37 for cheese, indicating that small changes in price have little effect on consumer demand for milk and milk products (Schmit and Kaiser, 2002). Processed milk products have greater demand elasticities because they are more easily transported and less perishable than raw fluid milk (LaFrance, 2004). In 2004, 36 percent of milk utilization was for fluid milk products, much less than the 50 percent utilization twenty years earlier. Utilization for cheese nearly doubled in the same timeframe, accounting for 52 percent of milk usage in 2004. Finally, new uses for milk components (lactose, casein, and other proteins) are providing new markets for raw milk (Miller and Blayney, 2006).

While the per capita and overall consumption of all milk products increased each year from 1990 to 2001, the growth has been small and was not shared across all sectors of the industry. Most dairy consumption now occurs through processed food or in meals eaten away from home causing per capita consumption of fluid milk to decline slowly since the 1970s. Bailey (2002) explains that "fluid milk has not remained competitive with other beverages in terms of packaging, convenience, or advertising," (p. 4) and that consumer trends, including a shift away from breakfast and related foods, are also responsible. Whole milk consumption has fallen dramatically, but increased low fat and skim milk consumption has counteracted this to some degree, as consumers choose low-fat foods in their diets. Butter and ice cream consumption has remained fairly flat, while yogurt consumption has increased but accounts for less than 1 percent of the market (LaDue, Gloy, and Cuykendall, 2003). The demand for cheese, on the other hand, has more than doubled since 1980, following consumers' preferences for fast food, pizza, ethnic foods heavy in cheese, and other easy-to-prepare frozen foods (Blayney, 2006; Bailey, 2002). Additionally, it has been suggested that an aging American palate combined with greater expendable income has contributed to the increase in the amount of "fine" cheese consumed. There is some evidence that the fast food market is peaking and that cheese fatigue is setting in, giving rise to concerns that growth in this sector will no longer offset continued losses of fluid milk consumption. These trends have implications for the types of milk processing facilities being built and where they choose to locate influencing the quantities of milk produced within the footprint of that facility.

Future demand for dairy products will depend on a number of factors including new product development, advertising, health benefits, changing ethnic populations, and competition from other beverages. As those elements wax and wane in influence, the market for dairy products will change prices and profitability in the dairy sector, but not equally for all producers thereby altering the face and distribution of production. As mentioned earlier, increases in cheese consumption by Americans has been the driving force behind the dairy industry since the 1980s, while the consumption of fluid milk and other milk products has fallen or remained fairly flat. Dobson and Christ (2000) report that cheese manufacturing plants have followed milk production west. This trend, coupled with the aging processing plants in the Upper Midwest, continues to push dairy expansion to the western and southwestern regions to capture competitive advantages there. Peterson and Dhuyvetter (2001) postulate that establishing processing capacity may motivate increased production in the region to ensure that demand is met.

The U.S. dairy industry from 1980 through the present has become more concentrated in both fluid and manufactured milk product sectors. The numbers of processors in many facets of the industry have decreased as consolidation among the largest firms has occurred. A driving force in this consolidation has been the increased power of supermarket chains and Wal-Mart who often prefer to be supplied by a few suppliers with larger quantities at lower prices. Additionally lower transportation costs and extended shelf life of products have reduced the need for regionally located plants in favor of greater economies of scale characteristic of larger plants farther away from the markets (LaDue, Gloy, and Cuykendall, 2003; Dobson and Christ, 2000).

The 1980's and 1990's witnessed an increase in share of milk marketed through dairy cooperatives while the overall number of cooperatives fell by 48 percent through both attrition and consolidation (Dobson and Christ, 2000). Dairy cooperatives have, for the most part, remained out of fluid milk processing but do have considerable influence in cheese, butter, and milk component manufacturing. In 1997, cooperatives sold 61 percent of the butter, 40 percent of the natural cheese, and 76 percent of nonfat dry milk (Manchester and Blayney, 2001). Because the dairy cooperatives are owned and controlled by their farmer members, their decision making process is different than private industry regarding location, capacity, and value added manufacturing. The cooperatives also provide significant bargaining power in negotiating over-order pricing for the members and can jointly market their products under antitrust exemption under the 1922 Capper-Volstead Act (USDA RBCDS, 1985). The changing distribution and composition of the processing component of the dairy industry will continue to impact the rate at which the spatial distribution of milk production changes.

International trade has been and continues to be a small portion of U.S. milk production. With the exception of skim milk powder, U.S. exports of dairy products remain small and uncompetitive with international products from the EU or New Zealand. Since 1993, the U.S. has consistently held a negative dairy trade balance (Jesse and Dobson, 2006). Import quotas have helped restrict milk and dairy product imports into the U.S., with casein (a milk protein component) being the major exception. The international market is expected to continue having a minimal impact on domestic production. Yet, there is increasing foreign investment in domestic processing and marketing (Dobson and Christ, 2000).

Stephenson (1995) identified population growth as the primary factor influencing demand patterns and a key reason the dairy industry has migrated westward during the last 50 years. Stillman et al. (1995) allows that population shift is a contributing factor, but asserts that other factors such as input costs, climate, availability of quality forage and labor, and "the opportunity to specialize strictly in managing and milking cows" (p. 6) have played a greater role in motivating the movement in recent decades. Since milk must pass through at least one processing facility on its way to the consumer, the number of processors in a region may be correlated with production levels. Some livestock sectors (hogs and beef) are significantly influenced by the location of processing plants (Roe, Irwin, and Sharp, 2002; Pagano and Abdalla, 1994). Peterson (2002) and Herath, Weersink, and Carpentier (2004) found market access to have a positive effect on the growth of dairying in a region. At the same time, improvements in milk quality and the ability to preserve freshness during transport have reduced the necessity of producing in close proximity to concentrated markets, as mentioned above.

1.2.3 Government Policy

State and federal government policies influence dairy production decisions including location through three general channels. Government establishes rules and procedures to ensure the safety of food products and to minimize potential negative environmental impacts associated with animal agriculture. For producers, compliance costs vary both by broad geographic region and by characteristics specific to the individual production sites. The USDA's implementation and periodic adjustment of various price support mechanisms and marketing orders during the past 70 years have also contributed to dairy profitability and firm entry or exit in various regions. Finally, the federal government has, at times, found it necessary to enact specific legislation to reduce milk production quantities through manipulation of the U.S. herd size or payments to producers for limiting production therein affecting the composition of the industry through buyouts and voluntary reduction programs.

1.2.3a Production Regulations

Large confined animal feeding operations (CAFO) are perceived as sources of water and air pollution, but the degree to which they are regulated varies widely by state and sometimes within the states themselves. The amount of manure produced and volume of water required for animal health and sanitation increases with dairy size, while soil type and proximity to surface water can increase the cost of preventative measures necessary to keep waste runoff from polluting those sources. Even within a particular state, local concern over odor and heavy truck traffic, in addition to the potential for water quality problems, can create additional compliance costs or lengthen the time necessary to obtain approval for expansion or construction of a dairy.

It has been suggested by Osei and Lakshminarayan (1996), Metcalfe (2000), Herath, Weersink, and Carpentier (2004), and Isik (2004) among others that livestock operations are attracted to states with lower regulatory standards. The states with less stringent environmental regulations create "pollution havens" which would attract CAFOs from more heavily regulated states thereby increasing livestock production in those regions. However, comparing state regulations across time is difficult and imprecise as regional differences across the country impact the type of regulations necessary or practical in the area. There have also been studies that have found an unexpected positive correlation between regulation and production growth, suggesting the relationship between the two is only vaguely understood and inspiring questions of causality.

The government programs to support milk price, regulate marketing and, at times, restrict production through voluntary herd reduction or limiting output have created situations where profitability was removed from dependence on traditional economic factors. Two specific efforts, the Dairy Termination Program and Milk Diversion Program are discussed here. Although both occurred prior to the timeframe considered in this thesis, their impact on the decision to remain in, exit, or exit and re-enter the dairy industry is not negligible.

In 1984-85, the Milk Diversion Program (MDP) paid farmers $10 per hundredweight for reducing their milk marketings up to 30 percent. Though it reduced quantities marketed drastically in the year following inception, the MDP's long term effectiveness was poor (Winter, 1993). The Dairy Termination Program (DTP) was authorized by Congress under the 1985 Food and Security Act to accomplish the same goal by authorizing the USDA to accept bids from dairy producers to eliminate their entire herd and remain out of the dairy industry for a five year period. Between April 1, 1986 and September 30, 1987, about 1 million producing cows from 14,000 selected bids were slaughtered or exported; roughly 9 percent of the 1985 U.S. herd. The U.S. General Accounting Office (Winter, 1993) reported that the DTP temporarily reduced production capacity and eased the transition to lower support prices. However, between 1980 and 1985, replacement heifer numbers in the U.S. dairy herd increased from about 25 heifers per 100 head of producing cows to just under 50. "The result was that total milk production actually increased by about 1.5 percent during the paid termination program, almost certainly the result of rational expectations on the part of dairy producers regarding the coming dairy herd buyout program." (LaFrance, 2004, p. 5). As suggested by Rahelizatovo and Gillespie (1999), the program did encourage less efficient operators to leave production, and it is reasonable to assume that this exodus occurred heavily in areas that were not as favorable to dairy production, perhaps increasing the pace of relocation and concentration in the industry. These programs were forerunners to more recent industry-led efforts like Cooperatives Working Together (CWT), which provides incentive for herd retirement and export of butter and cheese to further support dairy prices (DPAA, 2006).

1.2.3b Milk Pricing in the United States

The current system of milk pricing in the United States has evolved to accommodate the complexity of milk production and distribution across the country while the means of production and distribution themselves are constantly changing. According to economic theory, the system should balance milk supply with demand, but the unique physical characteristics of milk and changes in the method of assigning value to milk based on composition have resulted in a confusing system indeed. The three tools the government uses to manage dairy prices include the federal marketing order system, the dairy price support program, and trade policies of import barriers and export subsidies. The marketing order system and determination of producer prices is addressed first.

The Federal Milk Marketing Orders

The dairy industry has been heavily regulated since 1935 when federal milk marketing orders (FMMO) dividing the nation into marketing regions were established under the Agricultural Marketing Agreement Act (Manchester and Blayney, 2001). The purpose of this system was to establish an orderly marketing system for raw, fluid grade milk and ensure an adequate supply of fluid milk for beverage consumption (Wolf, 2003). Federal orders regulate only Grade A (fluid grade) milk, but about 95 percent of the milk produced in the U.S. currently meets this standard (Stillman et al., 1995). Two core concepts underlying the function of the FMMO system are *classified pricing*, meaning that milk is priced based upon its "class" or end use, and *revenue pooling*, where all producers in an order receive the same minimum "blend" or "uniform price" (Miller and Blayney, 2006).

The four classes of milk and their usage are:

Class I: Beverage consumption,

Class II: Soft manufactured products such as ice cream, yogurt, cottage cheese,

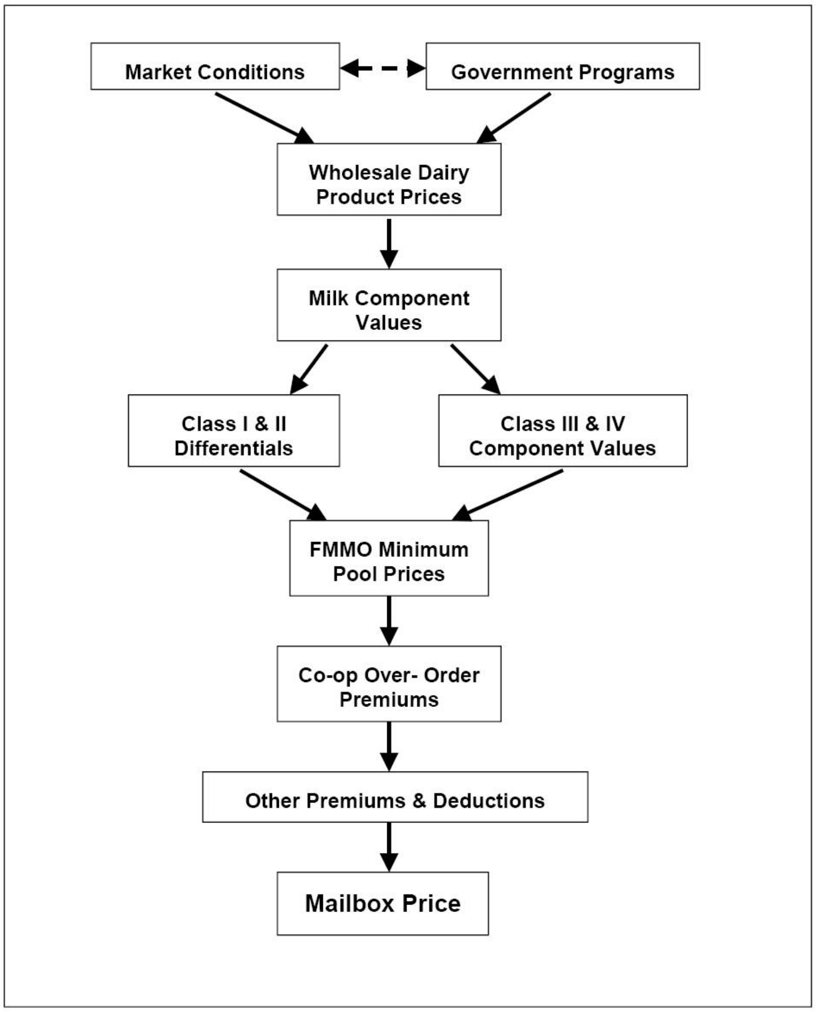
Class III: Hard cheeses and cream cheese, and

Class IV: Butter and non-fat dry milk.

The price formula for each class considers market conditions on the national and local levels and is based on wholesale prices for Class III and IV dairy products. Class I milk maintains a higher price than other classes reflecting the supply challenges and transportation costs of fluid milk. The class prices are announced monthly by the Agricultural Marketing Service (AMS) and each order adjusts its own minimum prices according to a predetermined Class I differential assigned to it (Miller and Blayney, 2006).

The class prices are not the prices paid to producers, however. Instead, under revenue pooling, a weighted average price based upon the minimum class prices and the actual product utilization of all milk classes in the order is calculated as a basis for minimum payments to producers. This is termed the blend or uniform price, and FMMO auditors periodically check processors to ensure that this pricing program is followed (Benson, 2001). Because more than 80 percent of all milk is marketed through cooperatives, this blend price generally represents the minimum price paid to cooperatives that in turn pass along a mailbox price to their members once premiums are paid and hauling and marketing fees are assessed, as depicted in Figure 1-6. The class prices and blend prices are established minimums; market conditions often result in higher prices paid for milk (Miller and Blayney, 2006; Manchester and Blayney, 2001).

Figure 1-6 Pricing Structure for Determining Mailbox Price

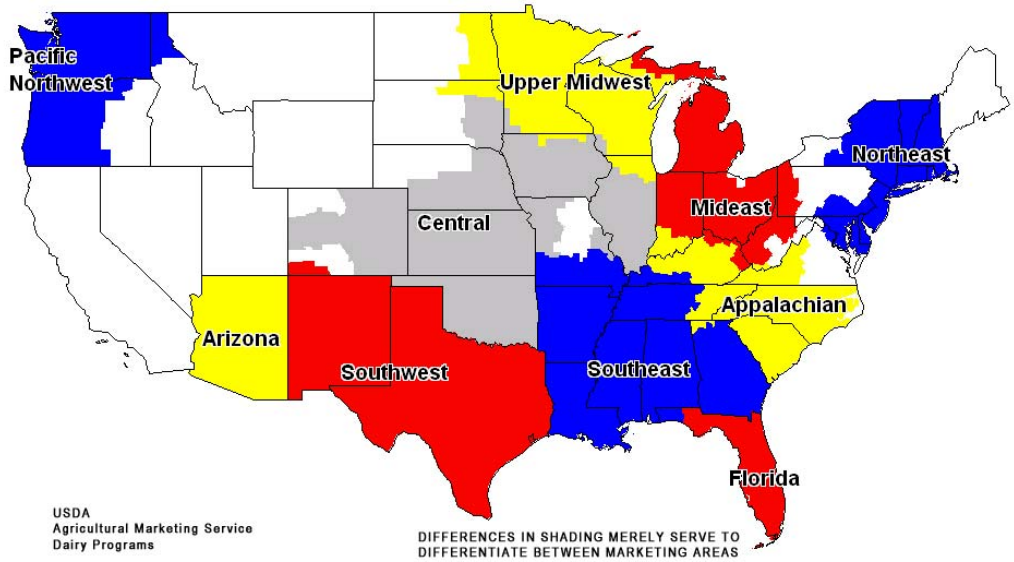


The FMMO system regulates the minimum price that first handlers (processors and manufacturers) must pay for Grade A milk but does not regulate the utilization decisions. Therefore FMMOs do not set a minimum price for producers. Instead the utilization ratios of milk by processors determines the blend price, which is paid to all producers or their cooperatives in the order. Cooperatives or similar producer associations have also been successful in many areas in negotiating over-order premiums that are paid in excess of the blend price. These encourage local production that, despite the greater cost to processors, is still cheaper than importing milk from other regions. Additionally there are premiums or discounts that can be assigned to milk prices at both the producer to cooperative and cooperative to processor levels based on volume, consistent delivery, component characteristics (butterfat, somatic cell count, protein, and other solids), and production methods (organic or rBST free), but these price adjustments and over order premiums are not regulated under the order system (Manchester and Blayney, 2001; Schoening, 2006).

The FMMO was reformed in January 2000 reducing the number of orders from 34 to 11 to better align the federal orders with the actual distribution areas of fluid milk handlers (Jesse and Cropp, 2000). In 2004, the Western order voluntarily dissolved leaving 10 federally regulated orders. California operates its own state order that is similarly structured in relation to the federal system and AMS reports a separate mailbox price for that state. Other states such as Montana, Nevada, and Pennsylvania have state marketing agencies and mechanisms that offer premiums to their producers but the administration of such programs is inconsistent across states and generally does not impact tremendous volumes of milk (Schoening, 2006). Benson (2001) states that the reality of milk movement across state and order lines causes the pricing effects of the FMMO system, over-order premiums, and support prices to be felt by producers not directly under FMMO regulation. In 2004, 61 percent of U.S. milk was marketed through the FMMO system and, when including state-level marketing orders, this percentage climbs to over 80 percent (Miller and Blayney, 2006). Limiting the classification further to only Grade A milk, 95 percent is marketed through the FMMO (Peterson, 2002).

Figure 1-7 below shows the currently established milk marketing orders including the withdrawal of the Western order in 2004. Maps representing the 2000 reforms and pre-reform orders from 1998 can be viewed in Appendices F and G, respectively.

Figure 1-7 Federal Milk Marketing Order, 2006



<u>Milk Price Support Program.</u>

The Dairy Price Support Program (DPSP) has been in existence since 1949 and authorizes the Commodity Credit Corporation (CCC) of the USDA to provide a floor price for storable, wholesale dairy products including butter, non-fat dry milk, and cheddar cheese by purchasing unlimited quantities offered for sale at specified prices (Price, 2004). This allows the DPSP to artificially floor the wholesale price for processed dairy products which in turn affects the Class III and IV prices that determine other class prices and subsequently blend prices for producers. The DPSP also includes a *make allowance* in its purchase price intended to cover manufacturing costs of the products purchased by the CCC so that the price returned to farmers meets the target level. Since 1989, the farm price has exceeded the desired support level, and export subsidies have occasionally been used primarily for the removal of excess supply (Miller and Blayney, 2006).

The Dairy Export Incentive Program (DEIP) was enacted to create markets for U.S. dairy products in regions where subsidized exports from other countries made the U.S. product unable to compete. World Trade Organization restrictions have limited the utilization of DEIP since 1995, although before that time it indirectly influenced milk price by removing product from domestic markets.

Two voluntary producer programs in the 1980s provided payments to producers who reduced production under the Milk Diversion Program or exited the industry for five years under the Dairy Termination Program but were not in effect during the period of this study. Direct payments were established under the 2002 Farm Act and the Milk Income Loss Contract (MILC) program provides monthly payments to producers based on current production when milk price falls below a certain level. Like the direct payments, MILC's effective period follows the period of this study but would have an impact on future studies of the dairy industry.

CHAPTER 2 - LITERATURE REVIEW

Recently there has been a growth in the application of spatial econometrics to economic geography and industry location. This section outlines briefly the justification for considering spatial effects in a firm's location decision as described by LeSage (1999b) and provides a discussion of several authors' work in the application of spatial econometrics. Past literature on the determinants of the geographic distribution of the agricultural industries and factors influencing dairy production decisions is also reviewed.

2.1 Theory of Spatial Agglomeration

Spatial agglomeration theory recognizes the existence of inherent advantages and economic motivations prompting firms to locate in clusters. These advantages may include an abundance of specialized inputs and related production resources, knowledge spillovers from other nearby firms in the same industry, or simple transportation cost savings realized by locating near input suppliers or demand markets (Cohen and Morrison-Paul, 2004). Presented in a simple form, O'Sullivan (2003) writes that "the general mechanism underlying agglomeration economies may be stated as: by locating close to one another, firms can produce at a lower cost." These positive spatial spillovers, or agglomeration economies, are also referred to as "thick market effects," where production is more efficient or cost effective when it is spatially concentrated (Ciccone and Hall, 1996). By representing the productivity impacts of these spatial effects as shifts of a production or cost function, their "firm-external" nature is revealed. Expanded production not only allows internal economies of scale to push the cost curve downward, but external cost economies associated with neighboring industries or firms augment that effect when firms are concentrated in a region where agglomeration economies exist (Cohen and Morrison-Paul, 2004). Conversely, there are also "thin market effects" that negatively impact the production economies experienced by firms in a particular regions that may result from market competition or negative externalities that exist in that area (Ciccone and Hall, 1996).

Agglomeration economies might also occur because distance and location are indeed relevant factors in determining the concentration or intensity of activity in a given region as postulated by the spatial agglomeration theory. This concept was addressed by von Thünen's concentric rings determining land usage around urban areas based on the trade-off of land rents and transportation costs, and Alfred Marshall's recognition of the importance of external geographic economies to firm performance (Fujita, Krugman, and Venables, 2000).

Agriculture and the livestock industry in particular face conditions that drive producers towards consolidation and concentration in areas where the lowest production costs can be achieved. That production relies on available inputs, services, and markets that can be shared more efficiently when firms are clustered in a region that accommodates those needs. There are many plausible reasons where such a situation may arise in the dairy industry including access to high quality feed, availability of labor with necessary skill requirements, existing infrastructure to support intensive livestock production, or even the ability to obtain permission and begin construction without facing stringent environmental restrictions or local opposition that add time and cost to the endeavor. The likelihood that these conditions exist in clusters of counties add a spatial element to determining where production is likely to increase and where it may be on the decline.

Industrialization and the impact of technology on specialization in animal agriculture have been identified as key elements in mitigating the influence of natural endowments and regional comparative advantages and allowing greater industry mobility in pursuit of cost minimization and profit maximization (Abdalla, Lanyon, and Hallberg, 1995). In general, animal agriculture has undergone a shift towards greater concentration on fewer, but larger, farms and, in the dairy and swine industries particularly, production has expanded heavily in states that were not previously considered traditional production areas. Some reasonable explanatory efforts for the concentrated migration include economic responses to the presence of certain natural endowments in those areas or technologies that have diminished their necessity in others, as well as differences in production costs, access to processing facilities, the flight towards pollution havens, and a reaction to the existence of agglomeration economies that originated in spatially clustered production areas. With the emerging popularity of spatial econometric techniques, researchers in agriculture have increasingly sought to determine the presence of agglomeration economies in the livestock industry and its component sectors.

2.2 Empirical Tests of Spatial Agglomeration

Until recently economic literature was devoid of studies that considered the spatial effects on economic activities despite early theoretical work that such influences did exist. The computational ability combined with routines devised by Anselin (1988), LeSage (1999a, 1999b), and Pace and Barry (1998) among others have provided researches with practical tools to test for and estimate spatial effects using econometrics.

LeSage (1999b) presents two problems associated with sample data that exhibit a spatial component; there is spatial dependence among the observations and, second, spatial heterogeneity causes the relationships between observations to vary across space. This unstable relationship between data points is counter to Gauss-Markov assumptions that a singular linear relationship with constant variance exists and the explanatory variables are fixed in repeated sampling, leading to inconsistent coefficient estimates when using OLS. This spatial dependence among n observations of y can be represented as

$$y_i = f(y_j), \quad i = 1, \dots, n \quad j \neq i.$$

The dependence occurs because data collection might reflect measurement error associated with spatially defined units such as zip codes, counties, and school districts and "the division boundaries fail to accurately portray the nature of the underlying process generating the sample data" (LeSage, 1999b, p. 3) or because distance and location have a significant impact on the economic activities in a region as suggested by spatial agglomeration theory.

In a general form, a spatial autoregressive model with spatial autocorrelation in the lagged dependent variable only (SAR) can be written:

$$y = \rho W y + X\beta + \varepsilon \tag{1}$$
$$\varepsilon \sim N(0,\sigma^2 I_n),$$

where y is an n x 1 vector of cross-sectional dependent variables, X represents an n x k matrix of explanatory variables, β is an n x 1 vector of coefficient parameters, and ε is an n x 1 vector of residuals identically and independently distributed with a mean of zero and variance of σ^2, where I_n is an n x n identity matrix. The ρ parameter is the coefficient of spatial lag multiplied by the n x n spatial weight matrix (W) and the dependent y providing a *spatial lag* of the dependent variable. Cohen and Morrison-Paul (2004) compare the spatial lag effect to temporal autocorrelation adjustments except that spatial linkages rather than time linkages are represented via lags for geographic location at any point in time. If the ρ parameter is set equal to zero (no spatial autocorrelation), then the dependent variable is specified as a function of the traditional explanatory variables, their coefficients, and the error term.

Alternative specifications for the basic spatial model above account for spatial autocorrelation in the other terms in the equation or in their combinations. For example, if autocorrelation appears in the errors instead of the lagged dependent variable, the model is referred to as a spatial error model (SEM) where u becomes the error term subject to the spatial lag parameter λ.

$$\mathrm{y} = X\beta + u \tag{2}$$
$$u = \lambda W u + \varepsilon$$
$$\varepsilon \sim N(0,\sigma^2 I_n).$$

If the autocorrelation appears in the independent variable matrix, it is termed a spatial cross-regressive model (SCM) as suggested by Roberts, Angerz, and McCombie (2005):

$$\mathrm{y} = X\beta + \rho W X + \varepsilon \tag{3}$$
$$\varepsilon \sim N(0,\sigma^2 I_n).$$

When both the dependent variable and errors exhibit spatial autocorrelation, the model becomes a mixed spatial autocorrelation (SAC) and is defined as:

$$\mathrm{y} = \rho W_1 \mathrm{y} + X\beta + u \tag{4}$$
$$u = \lambda W_2 u + \varepsilon$$
$$\varepsilon \sim N(0,\sigma^2 I_n).$$

Here, W_2 is a weights matrix applied to the spatial lag in the error term, but it may be identical to W_1.

Alternatively, if both the dependent variable and independent variable show autocorrelation the model is called spatial Durbin model (SDM):

$$y = \rho W_1 y + X\beta + W_2 X\beta_2 + \varepsilon \tag{5}$$

$$\varepsilon \sim N(0, \sigma^2 I_n).$$

A sixth specification suggested by Angerz, McCombie, and Roberts (2007) contains autocorrelation in the independent variables and the errors and is referred to as a spatial hybrid model (SHM):

$$y = X\beta + W_1 X\beta_2 + u \tag{6}$$

$$u = \lambda W_2 u + \varepsilon$$

$$\varepsilon \sim N(0, \sigma^2 I_n).$$

Finally, a possibility exists where the dependent and independent variables and errors show autocorrelation:

$$y = \rho W_1 y + X\beta + W_2 X\beta_2 + u \tag{7}$$

$$u = \lambda W_3 u + \varepsilon,$$

where W_3 is a distinct spatial weights matrix for the lagged error, which may be the same as W_1 and or W_2.

2.3 Selection of Spatial Models

To look for the discrepancies between spatial and non-spatial model specifications, Kuhn (2006) re-analyzed results from an OLS regression conducted on plant distribution data in Germany using several spatial autoregressive models. The author found only the spatial error model (SEM) reduced autocorrelation in residuals to an insignificant level, and it had a much better fit than the OLS specification. The Akaike's Information Criterion (AIC) for OLS was -4930.7 and its R-squared value was 0.35, while the spatial error model had values of -5931.9 and 0.66, respectively. More importantly, several of the signs on the regression coefficients were flipped between the OLS and spatial error model indicating that ignoring spatial autocorrelation can dramatically affect results.

Angerz, McCombie, and Roberts (2005) write that a key advantage of the spatial cross-regressive model (SCM) is the ability to identify and estimate impacts of different independent variables on cross-regional spillovers separately. When combined with an SAR model, it examines both the spatial component of the dependent and independent variables in a SDM model. Yet he acknowledges that this specification is prone to multicollinearity effects between the lagged dependent and lagged independent terms. Angerz, McCombie, and Roberts (2005) report that the spatially lagged autoregressive (SAR) model with a lagged dependent variable and the spatial error model (SEM) are the most commonly applied methods, and that determining the best candidate between the two generally depends on a comparison of two Lagrange Multiplier tests.

Brasington (2005) used spatial econometrics to address spillovers and omitted variable bias in a study of spatial education production functions. Specifically, he specified Bayesian spatial error, spatial autoregressive, and spatial Durbin models to accommodate for heteroskedasticity, outliers, and omitted variables. Brasington reported higher adjusted R-squared values for the spatial equations suggesting that spatial methods added explanatory power to the model. He also provided a thorough explanation of the Bayesian specifications' ability to use prior information and a large number of random draws to converge to a true joint posterior distribution. In his work, he applied LeSage's (1999b) recommended default values for priors to obtain his results.

In another paper, Brasington and Hite (2005) used spatial hedonic analysis of housing prices to explore demand curves for environmental quality, finding significant spatial effects in all six hedonic house price estimations they performed. Their work used a spatial Durbin model to capture a spatial lag of the dependent variable as well as the explanatory variable. They acknowledge the generality of this model compared to spatial autoregressive and spatial error versions, but praise its ability to capture spatial dependence from a greater range of sources as well as improving the ability to capture the influence of omitted variables. This is accomplished through the spatial lag term picking up unobserved influences from nearby observations in space that are affecting house values; i.e., the unmeasured variables that affect the neighboring houses also affect the price of the house in question. Brasington and Hite list several examples of the unobserved influences like air pollution, shopping centers, interstate highways, lakes, and hospitals that vary across space. They also compared their results to two-stage least squares models (2SLS) and limited information maximum likelihood models (LIML) finding that 2SLS did a poor job of explaining the variation in the dependent variable and LIML was better but sometimes provided estimates less consistent with the researchers' expectations.

In a paper exploring different empirical growth specifications, Fingleton and Lopez-Bazo (2005) suggest that the correct spatial specification, whether it is substantive (model variables) or nuisance (errors), results in different interpretations. They conclude that models representing the spatial spillover effects as substantive and that include exogenous or endogenous spatial lags are much preferred over those that simply treat the external effects as nuisance variables in an SEM specification. Their position is expressed clearly in "the selection of the spatial error model on the basis of diagnostic indicators reflects the existence of omitted effects that should, if possible, be included as important and explicit variables in our modeling." (p. 15).

Mur and Angulo (2005) present results from a Small Monte Carlo study to aid in using and interpreting the spatial Durbin equation and discriminating between spatial model specifications (SAR, SEM, and SDM) with a focus on the Common Factors Test as a guide in the decision making process. They find that the Common Factors Test can be relied upon to help decide between two alternatives and that Lagrange Multiplier tests can and should be used complementarily to address different dimensions of the problem.

The summary of these studies indicates that testing for and modeling spatial autocorrelation in the relationships between dependent and independent variables is crucial in obtaining unbiased and efficient estimates, but that the selection of which spatial specification to use is also critical. There appears to be no decisive criteria explicitly outlining the steps to follow in specifying a spatial model but rather guidelines that can be used to justify selecting one model over another. McMillen (2003) warns that autocorrelation that leads to using a more complex spatial model may be "produced spuriously by model misspecification" (p. 215). However, he recommends that simple models be subject to diagnostic tests and rejected in favor of more complex models rather than vice versa. Several authors (McMillen, 2003; Fingleton and Lopez-Bazo, 2005) caution against the broad application of spatial error models (SEM), in effect calling its use a "catch all" for poor model specification regarding right-hand side variables.

2.4 Studies of Spatial Distribution of Agriculture and Related Industries

Various studies have examined aspects of geographical distribution in the livestock industry as a whole or in parts of the United States during the past two decades. Many of these studies placed particular emphasis on measuring the impact of environmental regulations (Herath, Weersink, and Carpentier, 2004 and 2005; Herath and Weersink, 2004; Isik, 2004; Roe, Irwin, and Sharp, 2002; Osei and Lakshminarayan, 1996) while others have focused on land values (Adelaja, Miller and Taslim, 1998), policy factors (Rahelizatovo and Gillespie, 1999), and promotional recruiting efforts (Eberle, et al., 2004) in addition to many of the traditional economic and natural resource factors incumbent in the livestock operation location decision. Additionally, there have been several studies that have incorporated variables to test for the presence of spatial agglomeration in specific sectors of the industry (Peterson, 2002; Roe, Irwin, and Sharp, 2002; Herath, Weersink, and Carpentier, 2004; Isik, 2004). Significant evidence of agglomeration economies has been found to be present in the dairy industry (Peterson, 2002; Herath, Weersink, and Carpentier, 2004; Isik 2004). A more detailed review of their findings is included in the next two sections.

2.4.1 Studies Using Spatial Econometric Methods

Roe, Irwin, and Sharp (2001) conducted spatial econometric analysis on the natural logarithm of a county's total hog inventory for fifteen leading hog producing states examining firm specific, locality specific and spatial agglomeration factors. They used a mix of variables to capture input availability and market access, regulatory stringency and local business climate, firm characteristics, urban encroachment and population factors, and the impact of other nearby livestock industry. Their results show that hog production is influenced by agglomeration effects from intra-industry activity and through inter-industry effects though the size of the effect is smaller. Their findings for urban encroachment and population were less clear and mixed across regions, while they found market access variables significant for all regions. For the most part, environmental stringency had a quelling effect on county and per farm hog inventories.

The input availability results showed that feed inputs are still important but commercially mixed feed had varying impacts in different regions. The spatial econometric technique used included a weight matrix of inverse distances and limited the influence radius to 200 miles from the county center. They applied LaGrange multiplier tests to check for spatially correlated errors.

Peterson (2002) applied a similar model to the dairy industry nationwide using the natural logarithm of changes in milk marketed through the FMMO system between 1997 and 2002 during May as the dependent variable and variables reflecting input availability, market prices and access, the influence of urban encroachment, and climatic conditions. Assuming a constant influence of space across the nation, the inverse distance weight matrix was again chosen and a geometric decay in the spatial lag structure was utilized. Her results were consistent with Osei and Lakshminarayan (1996), but state level wage rates for agricultural livestock workers had a positive coefficient attributed to the influence of other state level variables with positive influences on milk production. This suggested that those other state level variables outweighed the influence of wage rates. Her results also suggested climate and FMMO output prices have a large impact in determining the spatial distribution of the dairy industry. More importantly, she found that areas with increasing dairy production were attracting additional dairies and encouraging local expansion.

Measuring the number of new large farms for hogs, beef cattle, and dairy at the state level, Herath and Weersink (2004) examined the effects of environmental regulations; climate; business environment; market access; relative prices for feed, outputs, land, labor, and property tax; and agglomeration economies proxied by the percentage of State Gross Product derived from agriculture and percentage of rural population on the growth of large confined animal feeding operations. For the dairy industry, they examined 29 states looking for increases in dairy farms with more than 200 cows between 1993 and 2000. Their study is unique in its development and application of an annual regulatory stringency index series that captures temporal changes in regulatory standards for the lower 48 states which was used in this study and a later study (Herath, Weersink, and Carpentier 2004) considering the U.S. on a regional level. They found a positive yet not statistically significant coefficient for environmental stringency in the dairy sector implying that tougher environmental laws were being passed following an increase in large dairy operations. Relative prices were generally not significant with the exception of farm labor wage rate which had a positive effect. This was credited to the need for qualified managers on large dairy farms rather than just labor. Dairy industry processing capacity as measured by whole milk equivalent for manufactured dairy products had a highly significant effect. Rural population percentage was positive and significant. Their subsequent study reported similar results; dairy inventories respond most to farm-labor wage rate, rural population percentage, processing capacity, farmland availability, and mean temperature.

Isik (2004) conducted a behavioral model of dairy location and production to analyze the impact of traditional production factors and environmental regulations on the geographic concentration and spatial structure of the dairy industry. The model considered the natural logarithm of the county dairy inventory, the natural logarithm of the average number of cows per farm, the natural logarithm of the change in county inventory, and the natural logarithm of the change in share of inventory as the dependent variables of the model. Isik used a spatial weights matrix of inverse distances between counties and established an upper radius of influence of 200 miles to test for spatial autocorrelation among the dependent variables. His results show that production levels were positively correlated across counties over the period of study (1992-1997) and that agglomeration economies were important in determining the changes in production levels over time. Additionally, he found that variation in state environmental regulation may influence the relocation decisions of dairy producers from areas of high to lower regulation.

Cohen and Morrison-Paul (2004) analyzed the food manufacturing industry to evaluate the cost effects of spatial agglomeration spillovers across states on the location decision of food processors between 1986 and 1996. Their study considered own industry, input supply, and output demand sectors in identifying potential thick and thin market factors that would affect the average and marginal costs associated with location. For the food processing industry, they identified agglomeration factors such as proximity to equipment suppliers, product distribution networks, specialized banking services, access to information from government or university extension, as well as the compromise between locating close to rural sources of agricultural products compared to access to demand from the urban market place. Weighting adjacent states equally and setting all others to zero, they found that “the spatial dimension is a key component of cost performance” and important average cost economies exist with own industry concentration, neighboring-state, supply-side agglomeration effects and own- state, demand-side urbanization effects. They found that the determinants of location include a mix of internal and external marginal cost economies with concentration patterns matching low marginal cost patterns for a region.

2.4.2 Other Studies on Dairy Location

Eveland et al. (2005) examined the number of building permits issued for agricultural facilities during the period 1996 to 2001 in the dominant agricultural area of southwest Ontario by surveying municipalities in that region. They reported that large farms located according to existing industry trends rather than choosing to concentrate in areas of less environmental regulation, however their results suggest that agglomeration effects exist in areas of production intensity that justify a network of support services for the industry.

In a related study, Weersink and Eveland (2006) regressed building permits and building permit densities on environmental stringency, relative prices, business climate, and infrastructure variables to quantify the results of the aforementioned survey. Their conclusions suggest that new facilities are erected where the livestock industry is already concentrated, indicating agglomeration economies may play a role, and that economic factors related to infrastructure are more important than environmental standards in determining the site of new or expanded operations.

Yavuz et al. (1996) conducted a spatial equilibrium analysis to measure the relative significance of supply, demand, and policy factors on the regional distribution of milk production across eleven regions in the U.S. for 1970, 1980, and 1991. Their results indicated that supply factors caused the largest impact on regional distribution of milk in all regions except the Southeast, where real milk support prices had a greater impact. The decrease in real support price and per capita consumption of various milk products were the second and third most important factors in other regions while minimal changes in regional distribution were attributable to population changes and per capita income.

Osei and Lakshminarayan (1996) explored the determinants of dairy farm location with emphasis on the role of environmental regulations using a standard logit model. They identified environmental regulation stringency as determined by four environmental indicators: air quality, groundwater quality, soil conservation and an aggregate policy stringency index. Additionally, they included milk price distribution, population density, production costs, and natural endowments including temperature and precipitation as variables in their model. For the period between 1982 and 1992, they found that higher average temperatures and milk prices increased the probability that a dairy farm would locate in a county, while precipitation, population density, and production cost variables such as feed cost per animal and per acre land values were inversely related to the likelihood of dairy location. Regarding environmental stringency, they found counties in states with increased regulation were associated with lower probabilities of dairy farm location although the presence of the population density variable affected the marginal elasticity of the environmental variables. This suggests that dairies choose to locate away from dense populations and that the presence of stringent environmental policies may contribute to the migration of dairies to areas of less regulation. This study examined the factors affecting the probability of dairy farm locating in a county but did not consider the actual number of farms locating there nor production intensity.

Rahelizatovo and Gillespie (1999) examined the structure of the Louisiana dairy industry addressing the impact of agricultural policies, technology, and macroeconomic variables on producers in the state. Using a micro-data non-stationary Markov chain analysis to estimate results, they determined that government buyout programs like the Dairy Termination Program, low milk and higher input prices, high interest rates, and increased environmental pressures were likely to reduce production in the state while technological improvements increasing productivity and competitiveness of a firm were instrumental in mitigating exit from the industry.

Chavas and Magand (1988) found that the impact of dairy profitability on dairy farm numbers (entry and exit) varied by region with more traditional dairy areas such as the Northeast and Lake States less influenced by profitability. Their study incorporated a time-varying Markov chain process testing the probabilities of a firm's transition between size categories in two successive time periods. Adelaja, Miller, and Taslim (1998) confirmed the influence of increasing land prices in New York, New Jersey, and Pennsylvania on the reduction of herd size in those states. Their model included cross-terms between causal variables and dummy variables for location to measure the impact of milk, feed, and land prices across states.

Using a mail survey instrument to gather responses from 404 dairy producers in three size categories from eight states, Eberle et al. (2004) compared the impacts of promotional efforts versus economic factors on influencing producers' decisions regarding the establishment, expansion, or relocation of a dairy. They concluded that the most important factor driving expansion/establishment decisions for dairies of all sizes was market availability for milk and co-products while public promotion efforts and support rated the lowest. The item ranked second in importance varied by dairy size. For owners of large dairies with 1,000 or more cows, regulatory environment was ranked number two while, for small dairy owners, family and community ties received second place. Extension services, access to university research, assistance in obtaining licenses and permits, and guaranteed loans all had average ratings indicating a positive impact, as well as labor training programs for large dairies. Tax breaks and dairy recruitment activities, on the other hand, received neutral or negative ratings from the group as a whole.

Mosheim and Lovell (2006) used shadow cost functions to analyze economic efficiency and scale economies in the dairy industry considering data from the 2000 Agricultural Resource Management Survey. They found that technical efficiency improves but allocative efficiency deteriorates as purchased feed proportion rises and that small farms maintain an edge in efficiency relative to larger farms but the scale economies of larger farms outweighs those efficiency advantages. They also report that variable costs are 5 percent lower in traditional areas over non-traditional ones owing in part to less feed and energy consumption. Additionally, milk produced per cow varied widely across states. There is a strong correlation between the number of head per farm and the quantity of milk produced per cow with this correlation increasing from 1985 to

2005 indicating scale economies are becoming more important drivers in determining the optimum size of herd which may, in turn, affect the decision on the best place to locate.

In summary, dairy location is driven by natural endowments, input costs, market availability, business environment in relation to urban areas, and the existence of agglomeration economies. The influence of environmental regulations is not consistent through the studies consulted, but it is regularly identified as a significant variable. There appears to be some indication that location may also be affected by the area's ability to accommodate larger herd sizes and realize scale economies as the optimal herd size grows larger.

CHAPTER 3 - DAIRY LOCATION DECISION AND DATA

The decision of whether to establish a new dairy or expand an existing one in a particular county is assumed to be largely determined by the venture's profitability in that county. One could consider the profit function, $\Pi_i(.)$ of an example farmer in county i as,

$$\Pi_i = p_i f_i(Y_i, X_i, Z_i) - w_i X_i - c_i$$

where p_i is a vector of output prices, f_i is the production function, Y_i is a vector of outputs, X_i is a vector of inputs, Z_i is a vector of supply shifters, w_i is a vector of input prices, and c_i is a vector of fixed costs of production and operation.

For new and expanding dairies in the current era of specialization, the sale of the primary output, milk, accounts for the greatest share of farm income (Miller and Blayney, 2006), and is the sole output considered in this thesis. Other studies have used dairy inventories (Isik, 2004) or numbers of dairy farms (Osei and Lakshminarayan, 1996; Herath and Weersink, 2004) to measure the intensity of dairy activity in a geographic area. In this thesis, milk output is measured as pounds of milk marketed in May through the FMMO in 1997 and 2002. It was chosen as the dependent variable because it best represents the intensity of production due to variations in productivity of dairy animals across the country.

Based on the location literature reviewed in the previous chapter, a general model of regional milk production measured by county-level FMMO marketings includes explanatory variables in several categories: agglomeration effects measured by other agricultural industries, input availability, market accessibility and output price, natural endowments, and business climate including urban encroachment.

Milk output will increase in counties where dairying is more profitable due to higher output prices (milk price), lower production costs (including input acquisition costs, environmental compliance costs, and taxes), or shift factors such as technology or agglomeration economies. The increase may occur through expansion of existing production or relocation from other regions if the expected profits compensate for the cost associated with relocation. Due to raw milk's perishability as a constant-flow commodity and the FMMO pricing structure dependent on utilization percentages, the individual producer has little impact on determining the price received for his product aside from quality components or volume premiums. The best means for increasing profitability is through lowering production cost while maintaining a particular quality on a consistent basis (Wolf, 2003). Therefore, it is expected that a region's production costs factor more heavily in the location decision than its marketing opportunities.

Data for this thesis were compiled for 2,907 counties in 45 states for the Agricultural Census years of 1997 and 2002, while observations for some variables were collected for a greater period when available—generally 1994 through 2005. Alaska and Hawaii were excluded because, although milk is produced in those states, the economic and production factors influencing the location decisions are likely quite different from those for the contiguous 48 states. The states of Montana, Nevada, and Wyoming, which consistently have ranked in the bottom third of milk producing states over the sample period, were excluded for reasons further developed in the State and County Exclusions section of this chapter.

The data collected and used in the model estimations for this thesis were of primarily five types. Demographic data reflected county-level population estimates, unemployment rates, per capita income, and state-level wage rates for agricultural workers. Geographic data consisted of latitude and longitude coordinates for each county and address information for processing plants. Agricultural data were taken primarily from National Agricultural Statistics Service for production quantities and livestock inventories, while the milk price data used were Mailbox Milk Prices calculated by the Agricultural Market Service. Weather data included temperature, precipitation, and humidity levels. Dollar values were deflated to 1982-84 values using the non-seasonally adjusted Producer Price Index for agricultural products from the Department of Labor Statistics.

Tables with the summary statistics for each of the years used in the models are included in Appendix A. Each year's data represents the mean, standard deviation, minimum and maximum for the counties included in the model for that year ranging from 2,154 counties in the model for the change in milk marketings between 1997 and 2002 to

2,380 counties in 1997. Detailed descriptions and sources for the variables listed in the leftmost column of Tables A-1 and A-2 are described below. The first three or four characters of the variable are used in the text with the two digit representing the years omitted for simplicity. For example, *CRN* refers to the bushels of corn produced in a county for 1997, 2002, and 2004 respectively.

3.1 FMMO Milk Marketing Data

A list of counties and their respective marketing order, if applicable, was provided by Robert Schoening from the Central Federal Milk Marketing Order 32 for both 1997 and 2002 and was used both to determine the marketing order associated with a county and as the primary source for assigning a county to one of the reporting areas for mailbox price. The effect of belonging to a Federal Milk Marketing Order (or the California Order) was measured using a dummy variable of 1 if the county belonged to an order and 0 if it did not in 1997 and 2002, respectively. The expected sign for the MMO coefficient is positive corresponding to the likelihood that high producing regions are regulated under the FMMO system.

The quantities of milk marketed through the FMMO system in the months of May and December for each year from 1995 through 2005 were also obtained from Robert Schoening. Data availability from the marketing order was limited to only those two months. Since spring is naturally the period of greatest production by dairy cows, it was decided to use the May marketings for each year (*MMM*) as the dependent variable for the estimations assuming that milk production during the rest of the year remained proportional to the May levels. Counties reporting zero marketings may have produced milk that was marketed outside the FMMO system, but as previously mentioned, this is less than 20 percent of production. In counties with few producers, the reporting of milk marketings were suppressed and denoted as N/A. Because N/A values were unusable in the estimation, those counties were dropped from consideration. Counties that reported zeros were retained so the distortion caused by dropping the N/A counties is expected to be minimal. In 1997, there were 2,380 counties that disclosed May marketings as positive values (1,475 counties) or zero (864 counties); in 2002 the number was 2,339

(1,644 positive values, 736 zeros). The number of counties reporting in both years was 2,154.

3.2 Demographic Data

Demographic data were collected from the U.S. Census Bureau, the U.S. Department of Labor, and the Bureau of Economic Analysis. July 1 population estimates at the county level were taken from Population Division of the U.S. Census Bureau website. Observations from 2000 through 2005 were found in the Annual Estimates of Population for counties, and the 1993 through 1999 estimates were obtained from the Annual Time Series of Population Estimates and Demographic Components of Change: April 1, 1990 to July1, 1999 in the archive section of the same website. Population (*POP*) is predicted to have a negative impact on the amount of milk marketed in the county, as dairies are likely to locate away from areas of higher populations due to increased likelihood of urban-rural conflict through complaints about odor or higher environmental compliance costs. Land prices are also likely to be higher in areas with higher population density as urban expansion acquires farmland for development. On a scale beyond the county level, a positive sign on population might be associated with higher market access in a region, but at the county-level scale it is expected that population is inversely related to milk production.

Unemployment rates reflect the availability of local labor and were taken from the U.S. Department of Labor's Labor Force Data by County for the years 1995 through 1997 and 2000 through 2004. A county with a higher unemployment rate (*UEM*) may signal an abundant supply of laborers or receptiveness to an opportunity to generate jobs and economic activity and is expected to be associated with larger milk marketings.

The availability of wage data for field and livestock workers was limited to the state level and reflects the cost of labor inputs beyond the family or owners' contribution. Herath, Weersink, and Carpentier (2004) found higher farm-labor wages to deter dairy location, while Peterson (2002) found a positive relationship, a result she attributed to the effect of other state-level factors positively related to milk marketings. Assuming that new or expanding dairies need additional labor beyond the owner's share, it is expected that states with higher average wage rates are less attractive to dairy producers and the coefficient on wage rate (*WAG*) will be negative.

Per capita personal income (*PCI*) at the county level was found on the Bureau of Economic Analysis website and was included to capture social acceptance and concern for environmental quality. Higher incomes should engender greater concern for environmental quality, assuming it's a normal good, and may reflect less tolerance for nuisance behaviors associated with livestock production (odor or traffic). Areas of higher income may also indicate a reliance on other economic growth activities with fewer perceived negative externalities. The coefficient for *PCI* is predicted to be negative with the expectation that an inverse relationship exists between personal income and quantity of milk marketed.

3.3 Geographic Data

In order to evaluate the spatial relationship between observations, the location of one observation relative to another must be determined. The latitude and longitude coordinates for county centroids (the geographic center of the county) were obtained from Peterson (2002).

Most of the plants represented are fluid milk processors in one of two categories. Distributing plants are primarily engaged in processing raw milk into consumer ready packages for beverage consumption, while supply plants supply raw milk to distributing plants and process manufactured dairy products as well. Most of the street addresses for the supply and distribution plant lists collected from the Agricultural Market Service website for 2001 through 2004 also came from Peterson, although additions and corrections were made using McCrae's Blue Book, Google Search engine, U.S. Postal Service online zip code finder, and phone calls to individual plants. Due to limitations on data availability, the 2002 AMS listing of FMMO regulated plants was combined with the 2001 handler list from the California Department of Agriculture to create a best approximation of plant locations used for both 1997 and 2002. The geocoding feature of the ArcGIS 9.2 software package was used to convert the physical address of each plant on the list into latitude and longitude coordinates.

Special consideration was taken to eliminate repeat occurrences of the same physical plant that may have switched orders or transferred ownership under a new name thus being listed twice in the AMS or California Dept. of Agriculture spreadsheets. Also, if two plants shared a zip code and no street information was available for one, the same address was used for both to simplify the lookup procedure. Coordinates were matched to addresses in the ArcGIS software automatically for addresses with a 65 percent spelling and overall match score of above 65 percent. Remaining addresses were then interactively matched to coordinates using the suggested addresses from the program and manually matching street numbers as closely as possible resulting in a 97 percent match rate. Unmatched addresses as well as those plants where no street address could be located were given the latitude and longitude of the city in which they were located as listed by the U.S. Census Gazetteer.

It should be noted that the listing used included only the plants regulated by the FMMO system representing plants handling volumes large enough to require participation in the FMMO system and excluding many smaller plants that are unregulated. Since our dependant variable is FMMO marketed milk, however, it is a reasonable limitation to consider only regulated plants.

Using these coordinates and the coordinates for the county centers, the Haversine formula for great circle distance provided the number of plants within 600 miles of the center of each county that were included as a variable (*PLA600*) in the model. In cases where the street address was unavailable, most notably all California plants, the latitude and longitude of the associated zip code as provided by the Gazetteer webpage of the U.S. Census was used. Anecdotal evidence collected from conversations with FMO economist Robert Schoening and Kelly Downs, a Dairy Farmers of America market specialist, confirm that 600 miles is a reasonable upper bound distance for fluid milk to travel for processing due to Department of Transportation regulations on driving time for a tanker truck operator (Schoening, 2007; Downs, 2007). Although milk is bought and sold over greater distances, it may be remixed at an intermediate location before reaching its destination. It is expected that the quantity of milk marketed through the FMO system exhibits a positive correlation with the accessibility of processing plants as suggested by Herath, Weersink, and Carpentier (2004) and Peterson (2002).

3.4 Agricultural Data

Agricultural data obtained from the 1997 and 2002 Censuses of Agriculture (COA) included county acreages, livestock populations, livestock farm inventories by size, crop production quantities, asset valuation, property tax estimates, and feed expenses.

COA reports are sometimes suppressed mostly to protect producer anonymity. Spatial continuity is required in the independent variable matrix of the spatial lag model and necessitates imputing values for these missing variables. Several methods were used depending on the number of missing observations for each variable and the availability of suitable data for approximating the values of those variables. Missing values of Land in Farms (*FLA*), Value of Feed Purchased (*FD$*), and Value of Land and Buildings (*LV$*) were simply calculated using existing data while the suppressed values for number of cattle, hogs, corn, corn silage, and alfalfa were determined using regressions as described later.

When available, values for the 2002 COA Land in Farms were substituted for suppressed values for the same category in the 1997 COA. In instances where the 2002 data or both 2002 and 1997 values were suppressed, the Proportion of Land in Farms reported in the 2002 COA was multiplied by total number of acres in the county in 2002 to obtain values for the observations. If the 2002 COA reported *Z* (indicating that the value was less than one-half percent) a value of 0.005 was inserted and multiplied by the county acreage. The percentage of farmland in a county was calculated by dividing the Land in Farms acres in 2002 and 1997 by the total acres in 2002 and 1997, respectively or, when necessary, by using the Proportion of Land in Farms reported by the COA. It is expected that milk marketings will be larger in counties with a higher percentage of land utilized for agriculture reflecting a greater availability of feed and acceptance of agrarian pursuits.

The values of feed purchased were imputed using 2002 data for suppressed 1997 values and vice versa for sixty-five counties combined between the two years. When both values were suppressed, the values from reporting counties were summed and subtracted from the reported state total and the remainder was divided equally among the non-reporting counties in the given state. This calculation was applied to twenty-three counties. Because the larger dairies purchase a higher percentage of their feed rather than produce it themselves, it is expected that the coefficient on feed purchased (*FD$*) will be positive.

The same method of using 1997 values for 2002 was utilized to impute missing observations for the Value of Land and Buildings for seven counties and property taxes paid estimates for twelve counties. The value of property taxes paid was divided by the value of land and buildings to determine a property tax rate (*T/VL*) with the intuition that capital intensive dairies would avoid counties with higher tax rates. The predicted effect of value in land and buildings is more difficult to ascertain and may vary due to the different requirements of the two dairy types. Regions with well established dairy production will have land and building values that reflect the capital investment of existing dairies, while producers considering relocation or who did so near the time of the Census would be expected to avoid more expensive areas while balancing the need for feed availability and other pull factors in the region.

Missing values for the number of cattle and hogs in a county as well as the quantities of corn for grain, corn for silage, and alfalfa harvested in a county were imputed using simple ordinary least squares (OLS) regressions on selected agricultural and demographic variables including a bivariate state variable and an interaction variable between the state and each of the other variables. Quantities of corn harvested for grain were estimated first with the results being used in the regressions for hogs, cattle, and silage.

The quantity of corn harvested for grain (*CRN*) was regressed on average annual temperature, annual precipitation, proportion of land in farms, per capita personal income, population density and dummy variables representing the state and variable interactions. Quantities of alfalfa (*ALF*) and corn for silage (*SIL*) were regressed on annual temperature, annual precipitation, proportion of land in farms, per capita personal income, population density, and dummy variables as well as quantities of corn for grain with the expectation that availability of these inputs locally would have an elevating effect on milk production in the county.

Cattle inventories (*CAT*) were estimated using corn quantities, total acres, temperature, precipitation, and per capita personal income, while the equation used for hog inventories substituted the value of land and buildings for the total acres variable. The expected signs for the *CAT* and *HOG* variables are positive indicating that counties with higher activity levels of animal agriculture and inter-industry agglomeration effects increase the amount of milk produced in livestock intensive counties. This thesis also followed the example of Peterson (2002) in counting the number of cattle farms over 500 head (CAT5+) and hog operations with over 1000 animals (HGK+) to capture the agglomeration effect of other large animal operations with the expectation that the coefficients on both would be positive as local acceptance of intensive animal agriculture combined with regional attributes and agglomeration of resources would increase the concentration of large dairies in the county.

The models attempt to capture the influence of environmental stringency on the state level through the use of an Environmental Stringency Index (*ESI*) for the year 2000 developed by Herath, Weersink, and Carpentier (2004). The index is essentially a compilation of various sources measuring state regulation nationwide through the presence (or absence) of policies regulating different environmental attributes in a state and the state's position relative to the mean of other states from similar studies on a smaller scale across time. Thus the index represents the current and past regulatory situation for each state and was selected because this feature partially adjusts for the prospect that changes enacting stricter regulations were made in response to increased livestock industry activity in a state. Because it is a nationwide index, it fails to account for regional circumstances that may make certain policies more appropriate in some states and less so in others. Also, there may be localized regulation affecting certain counties that are not captured in this variable. Finally, because only a year 2000 index was available, it is possible that it misses laws enacted in 2000 or 2001 or applies restrictions to counties in 1997 that did not exist until a later date. It follows to reason that the coefficient on *ESI* would be negative indicating the preference of dairy producers to locate in areas of less restriction and lower compliance costs.

3.5 Milk Price Data

In January 1995, the Agricultural Marketing Service Dairy Programs section began publishing a mailbox milk price that is defined as the "net price received by dairy farmers for milk, including all payments received for milk sold and deducting costs associated with marketing the milk." (USDA AMS, 2007) The definition of payments includes the over-order and volume premiums, payments under pricing tools administered by individual states, payments from superpool organizations or marketing agencies, seasonal production bonuses, and cooperative dividends. The deducted costs include hauling charges, costs associated with cooperative membership, mandated assessments, marketing service deductions specific to each FMMO, and promotional assessments. Because the payment and cost varies greatly even within a particular FMMO due to the influence of multiple cooperatives and producer associations, this price is considered the best representation of the actual payment in dollars per hundredweight received by the producer for his milk, hence the term "mailbox price" (USDA AMS, 2005).

Mailbox price lists were obtained from the AMS Dairy Programs website for the years 1995 through 2005. This is the best representation of the price a dairy farmer received for their milk, as it accounts for all payments received for milk sold and the costs related to marketing the milk that may be withheld by the cooperative it was marketed through (USDA AMS, 2005). The average mailbox price (*MBP*) in each year was calculated using January through December reported prices for the years 1995 through 1997 and 2002, while 2000 through 2001 averages represent only the months of January through October due to availability. The AMS publishes the mailbox prices for geographic regions that best represent areas receiving similar prices but those areas do not necessarily correspond directly to the FMMO divisions. For example, the Upper Midwest Marketing Order includes the states of Wisconsin, Minnesota, and parts of Michigan, but in the 2001 and 2002 AMS system each state has its own mailbox price reported separately. The reported MBP includes the weighted average of the prices reported for all orders that received milk from the indicated region.

The reporting areas varied greatly by year; 1995 through 1997 reflected the many smaller marketing orders that existed prior to consolidation, 2000 was divided strictly according to the divisions of the consolidated orders, and 2001 and 2002 were again expanded to reflect price variations within specific states or regions within the marketing orders. According to Schoening (2006), counties associated with a particular order rarely change associations, so there is little likelihood of County A belonging to one marketing order in 2001 and a different order in 2002. However, this redistribution and the existence of unaffiliated counties posed a challenge in effectively assigning every county under consideration to a reporting area. Excluding the counties and states omitted from the observations for other reasons (see Appendix D), 551 counties were unassociated with a FMO in pre-reform days, while 346 counties were unassociated under the reformed marketing order system.

The first reference in determining which Reporting Area a county was associated with was the Mailbox Milk Price table itself. For example, all counties in Idaho were assigned the reported mailbox price for Idaho in a given year. Similarly, since the footnote for the Southeast States included all of Georgia, all Georgia counties received the Southeast States average. In 2000 especially, the order language for the marketing order was used to help determine which order a county belonged to. All counties in Oklahoma belonged to the Central Order so that price was assigned. In Indiana, several counties belonged to the Appalachian Marketing Order and were assigned that price while other counties in the state were given a different price.

If a county was unassigned and in a state or region that was not clearly defined by the AMS price table, the Sources of Milk for Federal Order Markets by State and County report was used to determine which order/reporting area received the greatest quantity of milk from that county and assigned the county to that area. Occasionally a county was assigned to an order in which mailbox prices for individual states were reported but not the state in which the county was located. For example, the northern portions of Indiana and western Pennsylvania belong to the Mideast Order but only Michigan and Ohio prices were reported. In this case, an Indiana-Western Pennsylvania price was estimated as the average of the Ohio and Michigan price. For other situations, similar state average was estimated from adjacent states or bordering market orders. If a county was unassociated and not listed in the Sources document, its geographic position relative to the nearest reported area was used to determine its association. Finally, if the geographical association was vague or uncertain, a simple average of the different reported prices for milk marketed from the state in surrounding areas was calculated and applied to those counties. This averaging method was applied to 119 counties in

Missouri, Virginia, Kentucky and Texas during the 1995-1997 period and 176 counties of Indiana, Pennsylvania, and West Virginia in 2001 and 2002.

Another challenge was imputing a mailbox price for counties associated with a marketing order or reporting area where the price was suppressed due to confidentiality concerns. Upon the advice of John Mycrantz with the Pacific Northwest Marketing Order, mailbox prices in counties regulated under the former Central Arizona and Arizona-Las Vegas Federal Marketing Order were calculated by taking the blend or uniform price reported and subtracting $0.15 for promotion fees retained by the cooperative. This estimate of promotional costs is consistent with Dhuyvetter et al. (2000). Mycrantz said that very little milk from this marketing order receives premiums for components so this estimation should approximate closely the price received by farmers in the relevant counties (Mycrantz, 2007).

Other marketing orders for 1995 through 1997 that held suppressed values included the Michigan Upper Peninsula, Central Illinois, Upper Midwest, Greater Kansas City, and Eastern South Dakota. Robert Schoening of the Central Federal Milk Marketing Order helped to devise an estimation procedure that determined the average difference between the blend/uniform price and mailbox price of two adjacent reporting regions and applied that difference to the blend/uniform price of the undisclosed region for the years 1995 to 1997. The procedure is described in Table 3-1. Due to the reorganization of the Federal Marketing Orders, this problem was minimized in the subsequent period of interest. In the 2000 to 2002 period, 27 counties in the Texarkana (extreme northeast) region of Texas were excluded from the West Texas reporting area. Discussion with Dan Martin of the Southwest FMMO resulted in the subtraction/addition of $0.05 per hundredweight for those counties from the West Texas mailbox price (Martin, 2007).

Table 3-1 Method for Assigning the 1997 FMMO Price When Missing

Area	Method Used to Assign Mailbox Price
Michigan Upper Peninsula	Average difference between uniform price and mailbox price of the Southern Michigan and Upper Midwest Orders.
Central Illinois	Average difference between uniform price and mailbox price of the Chicago Regional and Southern Illinois/Eastern Missouri Orders.
Greater Kansas City	Average difference between uniform price and mailbox price of the Nebraska/Western Iowa and Southwest Plains Orders.
Eastern South Dakota	Average difference between uniform price and mailbox price of the Nebraska/Western Iowa and Upper Midwest Orders.

3.6 Weather Data

Data for monthly precipitation totals, average temperature, and average maximum and minimum temperatures were collected from the National Climatic Data Center (NCDC) records through the Weather Data Library at Kansas State University. Precipitation and average temperature data were included from all applicable NCDC cooperative reporting stations to maximize coverage area while maximum and minimum average temperatures were limited to stations in the Historic Climate Network (HCN). HCN stations have been selected for high quality data with few missing observations and their broad geographic distribution. Data were reported by stations at the weather division level so each county with a reporting station was assigned to the corresponding division. Counties without a reporting station were assigned a weather division based on their location in relation to nearby counties with stations.

The precipitation variables (*PCP*) were determined by summing the monthly precipitation amounts reported in each year and calculating the average of the ten year period prior to 1997 and 2002. Excessive rainfall creates muddy conditions in drylots and contributes to a higher relative humidity which is an important deterring factor in cooling animals during hot periods. Heavy rains during a short time-frame can also flood waste lagoons and contribute to accidental runoff of contaminated water. However, adequate rainfall reduces irrigation costs for feed production. Therefore, the expected sign on the rainfall variable is ambiguous.

The ten-year annual average was used to calculate an average temperature variable that was used in the regressions to impute missing NASS values for corn, silage, alfalfa, hogs and cows. In the spatial regression models, however, a ten-year average for the maximum of the average monthly minimum temperatures was used to indicate areas where the lowest temperatures (the one month average of the daily minimums) remained above a comfortable level for an extended period. Heat adversely affects feed intake and milk production in dairy animals at temperatures above 80 degrees or lower with elevated relative humidity levels (Keown, Kononoff, and Grant, 2005). Shade and misting systems can mitigate some of the effects of high temperatures, especially in areas of lower humidity but they add to construction and operation costs and can contribute to muddy lots (Jones and Stallings, 1999). Cooler nighttime temperatures allow relief from high daytime temperatures, but in areas with extremely warm, humid nights, cows can easily become stressed. The highest minimum temperature variable (*XMIN*) captures the one month period when the average minimum temperature was at its maximum suggesting warm nighttime temperatures and even hotter readings during the day. It is expected that the coefficient on this variable will be negative corresponding to less milk produced in areas with higher minimum temperatures.

In addition, the ten-year average for the minimum of the average monthly maximum temperatures was used to identify counties with at least one month when the average daily high was below 32°F. The effects of extended cool temperature periods on milk production and animal well-being are not as pronounced as those for heat, but freezing temperatures and other winter weather conditions are likely to complicate day-to-day dairy operations and require additional facility investments to protect animals from the elements, thereby discouraging milk production in those counties. It is expected that the sign on the dummy variable for average maximum temperatures below 32°F (*DMY*) is negative.

Humidity compounds the negative effects of high temperatures by making it more difficult to keep animals cool. In more arid climates, evaporative cooling and misters are effective in mitigating high temperatures, but areas of higher humidity are at a disadvantage for these methods. High humidity also prevents the evenings from cooling off to temperatures that allow a reprieve from daytime heat as earlier indicated. The humidity data (*HUM97*) used is 1997 average values from Peterson (2002) and is predicted to have a negative correlation with milk production.

3.7 State and County Exclusions

In several instances it was deemed prudent to omit an entire state or individual counties from the data set because of missing or unavailable data and the difficulty of establishing reasonable estimations for those missing values. Because the dependent variable is quantity of milk marketed through the FMMO system, states that are entirely unregulated by the FMMO system and geographically remote from the next closest FMMO pose an obstacle to obtaining reliable results from the model. With the exception of California, where production and price data are readily available for the state marketing order, and states like Vermont and Maine that are almost unilaterally associated with the Northeast Marketing Order, states without FMMO association or that were not accounted for in the AMS mailbox price listing were excluded as explained below.

Montana was excluded because the relatively small quantity of milk produced in the state is marketed through the state order that does not keep records on per county production nor does the state report a mailbox price received by farmers. Monte Nick of the Montana Milk Control Bureau affirmed the suggestion of dropping the state entirely from this analysis (Nick, 2007).

None of the counties in Wyoming were associated with an AMS mailbox price reporting area, and only two counties in the state specified values for FMMO marketings in any of the years observed. Wyoming's ranking of 47 or 48 among the 48 states further justifies its exclusion from this thesis (USDA Federal Milk Market Administrator, various issues.)

Mark French of the Nevada State Dairy Commission suggested omitting Nevada as it is not regulated by the FMMO system, nor does it have a milk pooling system due to limited supply and few dairy farms (French, 2007). Many prices and quantities for the state were suppressed to protect confidentiality, and he expressed concerns that estimation attempts would lead to greater inaccuracies than simply leaving out the state.

In addition to the counties of Montana, Nevada, and Wyoming, 70 other counties across the nation were eliminated due to missing values for NASS COA values combined with zero values for milk marketed through the FMMO system and few or no dairies reported in the Dairy Farms by Inventory table from the NASS data for either 1997 or 2002. A table listing those counties is included as Appendix D. Generally, these counties were in heavily urbanized areas with few agricultural statistics reported, though some counties in Oklahoma, Idaho, Colorado, and New Mexico are markedly rural. The metropolitan centers of Virginia that operate as independent counties were also excluded.

To summarize, the following decision tree was used to determine if a county should be excluded from the analysis.

1. Is the county regulated under a FMO or associated with a Reporting Area?
    If yes, use the assigned price.
    2. If no, is county listed in the "Sources of Milk for Federal Order Markets by State and County"?
        If yes, use the price assigned to the FMO where the majority of the counties milk was marketed.
        3. If no, does the county have any FMO marketings or N/A?
            If yes, assign geographically or using average of prices for counties in the state if its location does not provide sufficient indicators.
            4. If no, the county is excluded from consideration.

CHAPTER 4 - ESTIMATION PROCEDURE

Research on economic geography and the use of spatial econometric methods in economic studies has blossomed in the last two decades as modeling procedures and theoretical tools have removed or minimized the computational and technical barriers surrounding it (Fujita, Krugman, and Venables, 2000). The spatial econometric routines used in this thesis were developed primarily by James LeSage and are available online through his *Econometrics Toolbox*. LeSage's accompanying manual *The Theory and Practice of Spatial Econometrics* was also used for guidance in selection and application of the routines and suggested interpretations of the resulting estimations. The dairy location model developed at the beginning of Chapter 3 was estimated using 1997 and 2002 data, as well as the changes in observations between 1997 and 2002. This last specification was implemented with the goal of forecasting the future geographical distribution of dairies.

4.1 Weight Matrices

The construction of the spatial weights matrix used to formalize the spatial relationship between the observations is of as critical importance as the model itself and the procedures to test for spatial autocorrelation are inherently dependent upon it. There are a multitude of methods that can be applied in the process, and rules for structuring the weight matrix are still being contested by researchers (Kastens, 2007).

There are essentially two distinct types of matrices that embody numerous variations within each type. The contiguity matrix assigns values based on shared borders, but may also specify the degree at which a border is considered to be shared either through the length of the shared border or relative position. Often a binary matrix is used where "ones" represent shared boundaries; however the more complex "second order" relationships require additional indicators. The distance matrix calculates weights based on the distance between points and assumes a constant influence of distance across space. Two approaches to distance matrices include geometric decay, where the impact decreases at an increasing rate with distance, or assigning an upper bound distance of influence. Because it is assumed that the influencing factors for dairy location are more closely associated with distance (transportation of inputs or output, climate, population) rather than being dependent upon shared boundaries, an inverse distance matrix was used where a variable's influence is expected to diminish as the observations grow farther apart.

Using the Haversine Formula for great circle distance included in Appendix B, the decimal degree coordinates for latitude and longitude were used to calculate matrices of distances between the county centroids for each of the counties reporting marketings (zero or a positive number) for each year considered. From these distance matrices, the spatial weights matrices were determined following the example of Roe, Irwin, and Sharp (2002), Isik (2004), and Peterson (2002), with weights assigned using an inverse distance function, $w_{ij} = 1/d_{ij}$ where d_{ij} equals the centroid-to-centroid distance in miles between counties i and j. In an inverse distance matrix, the main diagonal indicating the distance of a coordinate from itself equals zeros, but each location has some distance relationship to every other location resulting in a memory intensive matrix that can create computational difficulties. An effective remedy is to determine a distance beyond which the influence of the spatial factors is considered to be zero. Assuming that there should be an upper limit distance beyond which the activities of one region no longer affect production in another, Roe, Irwin, and Sharp (2001) and Isik (2002) report the lowest Akaike's Information Criterion statistics for the models specifying an upper bound of 200 miles. Following their examples for guidance, the distance matrices were constructed where values greater than 200 miles were replaced with zeros to reflect the expectation that spatial effects are negligible past that distance. The primary result of this action was the creation of sparse matrices that greatly aid in the computational speed of the model. The matrices were also standardized so that rows sum to unity and each value represents a percentage of the whole assuring the predictions are unbiased (Kastens, 2007).

4.2 Model Selection

The determination of which model specification to use is largely an empirical question with ongoing debate between economists on the advantages and drawbacks of each. Concurrently, various testing methods for aiding in the selection of the most appropriate model(s) have been proposed and discussed with no definitive procedures relevant for all applications (Kastens, 2007). Therefore, the author followed the general suggestions of LeSage (1999b) for selecting models based upon the testing routines included in his manual and resulting signs and significance of the spatial coefficients.

A set of LaGrange Multiplier tests were first conducted to assess the appropriateness of the spatial lag models for the current application. The LaGrange Multiplier test for spatial autocorrelation in the residuals of a regression model without any spatial lag (LME) was applied to OLS residuals, and a LaGrange Multiplier test for spatial autocorrelation in the residuals of a spatial autoregressive model (LMS) was applied to the SAR residuals. The test statistics follow Chi-squared distributions with one degree of freedom. Table 4-1 presents the results of the LME and LMS test for all three models. Both LME and LMS tests revealed the presence of spatial autocorrelation in the OLS and SAR residuals, suggesting that some spatial effects are indeed present in the current data set. The LMS test results suggest that the inclusion of the lagged dependent variable failed to eliminate spatial dependence in the SAR residuals.

Table 4-1 Lagrange Multiplier (LM) Tests for Spatial Correlation in OLS and SAR Residuals

Test Statistic	2002	1997	1997-2002
LME (OLS Residuals) Marginal Probability Critical Value: chi(1) 17.611	136.78 0	361.35 0	74.75 0
LMS (SAR Residuals) Marginal Probability Critical Value: chi(1) 6.635	141.86 0	551.8 0	185.34 0

The next stage of model selection, as outlined in LeSage (1999b), is based on the signs and statistical significance of the autoregressive lag coefficients. LeSage (1999b) suggests that either negative values or insignificant coefficients for ρ in the SAC model (equation 4) would indicate that SEM model is preferred (equation 2), while the same circumstances for λ suggest the SAR model (equation 1) is better. The rationale for rejecting negative coefficients is their implication that neighboring counties have more dissimilar relationship than distant counties, a counterintuitive conclusion. Some of the recent literature reviewed faults the SEM specification as perhaps more indicative of poor model specification and variable omission than of actual spatial correlation in the errors that cannot be explicitly modeled (McMillen, 2003; Fingleton, Lopez-Bazo, 2004). The SAC specification combines the spatial autocorrelation in the spatially lagged dependent variable with spatially correlated errors, again lumping unspecified spatial correlation together in the error term when perhaps the model is lacking other important variables. The literature is relatively empty with regards to the application of the SHM model (equation 6); Angerz, McCombie, and Roberts (2005) being the exception, and LeSage (1999b) does not address it at all. Similarly, the model estimating spatial correlation in all three terms (equation 7) is only given a cursory mention in the literature, so the SHM and inclusive models were excluded from the scope of this thesis.

The SDM model presents an additional set of spatially lagged explanatory variables that include the influence of the independent variables in the counties nearby allowing identification and estimation of their cross-regional spillover effects (Angerz, McCombie, and Roberts, 2005). In short, not only would county A's silage production affect the production levels of county A, but silage produced in nearby counties B and C would also have a spillover effect that impacts production. This captures the presence of thick market effects that exceed a county's physical boundaries and, in the case of this thesis, includes those counties within 200 miles of county A. The SAR and SDM models were chosen because they are capable of measuring spatial autocorrelation in the lagged dependent and independent variables providing substantive explanations for the correlation rather than attributing it to nuisance effects. Because the literature supports model specifications that attempt to explain the spatial correlation through explanatory rather than nuisance variables, the SDM model with the spatially lagged independent variable matrix was initially preferred over the SEM or SAC suggested by LeSage (1999b). One drawback of the SDM model, however, is the tendency towards collinearity in some applications as mentioned by LeSage (1999b) and Angerz, McCombie, and Roberts (2005).

To test for the sign and significance of the coefficient on the spatial lag, SAR, SDM, SAC, and SEM models were estimated. The complete results from models can be viewed in Appendix G. As shown in Table 4-2, the SAC model resulted in exceedingly large negative ρ coefficients with statistical significance at the 5 percent level, suggesting it is an inappropriate specification. The spatial coefficient was significant for both SAR and SDM in the change model and for the 1997 SAR model. The negative sign on the SDM ρ parameter is concerning but is perhaps attributable to the fact it is biased since the estimation method ignored the censored nature of the dependent variable as discussed below. The SEM results show both λ coefficients for 1997 and 2002 were statistically significant indicating that there is spatial autocorrelation in the error terms, consistent with the LaGrange Multiplier tests above.

Table 4-2 Spatial Lag Parameter Estimates, 2002, 1997, and Change 1997-2002

	2002		1997		Change	
	Adj. R^2	ρ, λ	Adj. R^2	ρ, λ	Adj. R^2	ρ, λ
SAR (ρ)	0.8567	0.037978	0.7867	0.115952*	0.5294	0.155971*
SDM (ρ)	0.8735	-0.039963	0.8238	0.005972	0 .5462	0.409959*
SAC (ρ, λ)	0.8846	-1.206933* 1.121856*	0.8375	-1.402249* 1.129699*	0.5495	-0.200993* 0.708998*
SEM (λ)	0.8627	0.621954*	0.8066	0.781980*	0.8627	0.625983*

* indicates significance at 95% confidence interval.

4.3 Correcting for Censored Observations and Heteroskedasticity

Because the quantity of milk marketed in a county cannot be less than zero, the dependent variable is bounded on the lower end by zero and justifies the use of Tobit specifications for the models used. Moreover, given the cross-sectional nature of the data, heteroskedasticity is a concern and can be accommodated using a Bayesian sampling estimation routine for each model developed by LeSage (1999b). The *Econometrics Toolbox* contains routines for estimating heteroskedastic Tobit versions of the SAR, SDM, and SEM models. Brasington (2005) employed a Bayesian spatial error model to address heteroskedasticity in a study introducing a spatial education production function. LeSage (1999b) has applied the Tobit versions of these spatial models to housing data from Harrison and Rubinfield (1978) to demonstrate the potential for substantial differences in coefficient measurements and significance levels between censored and uncensored samples.

LeSage's routines use Markov Chain Monte Carlo (MCMC) simulations to derive sample distributions of parameter estimates. Following LeSage's recommendations, 1,100 draws were taken and the first 100 were omitted to allow for a steady state to be reached. Comparing the means and variances from the first 300 runs to those from the entire process for similarity provided a check for convergence. The coefficient estimates, β, from the uncensored SAR and SDM models for 1997 and 2002 (Appendix G) were used as starting values.

The estimated coefficients from the Tobit estimations were used to predict the values of milk marketings which were compared to the actual values in calculating the root mean squared errors. The model with the smallest root mean square error was then selected to predict out-of-sample for the year 2004. The tobit specification was not applied to the 2002-1997 change model because the dependent variable was not truncated at zero, but a Bayesian sampling routine for both the SAR and SDM models was applied to ensure reliable confidence intervals for coefficient estimates.

CHAPTER 5 - RESULTS

As outlined in the preceding chapter, three spatial lag tobit models were estimated using the 1997 and 2002 data. Selected results from the SAR tobit, SDM tobit, and SEM tobit models are summarized in Table 5-1. The complete MATLAB printouts can be viewed in Appendix H with the results for all models. Definitions for the variable names can be found in Chapter 3 or in Appendix A: Descriptive Statistics.

Table 5-1 Tobit Model Results, 2002 and 1997

	2002 Parameters			1997 Parameters		
	RMSE	ρ, λ	Counties[a]	RMSE	ρ, λ	Counties[a]
SARt (ρ)	19.529	0.028024*	1,414	15.134	0.051812*	1,573
SDMt (ρ)	39.438	0.973265*	65	16.553	0.870357	347
SEMt (λ)	14.437	0.018850*	1,379	12.801	0.071950*	1,491

* indicates significance at 95% confidence interval.
[a] Counties with positive milk marketings. Actual values were 1,644 in 1997 and 1,475 in 2002.

Possibly due to the influence of collinearity between the matrix of the independent variables and its lag, the SDM tobit model yielded exceedingly high ρ values (0.973265 for 2002 and 0.870357 for 1997 results). The Belsley, Kuh, and Welch (1980) method addressed in LeSage (1999a) for diagnosing these relationships was applied to the [X WX] matrix and showed that collinear relationships existed between the independent and lagged independent variables for *PLA600* and *MBP*, respectively, and between the lagged independent variables for *T/VL$* and *POP* and *HOGS* and *HGK+*. These collinearity relationships may explain the large ρ values for the SDM tobit models in both years. The SDM tobit model predicted non-negative, non-zero milk marketings in only 65 counties nationwide in 2002 and 347 counties in 1997, obviously another indication of poor model performance. The SAR tobit model, on the other hand, predicted positive milk marketings for 1,414 of the actual 1,475 counties with marketings in 2002 and for 1,573 of the 1,644 counties in 1997. The RMSE for the 2002 and 1997 SAR tobit model results were 15.134 and 19.529, respectively, and were better than the RMSE values for the SDM tobit results, especially in 2002. The RMSE for the SEM tobit model indicates that it is a superior predictor compared to the SAR tobit model and was used in making predictions for 2004. The coefficients of the SAR and SEM tobit models are similar in sign and magnitude, and, because of the limitations of the SEM models mentioned previously, only the SAR results are interpreted in the subsequent discussion.

5.1 Results from Bayesian Spatial Autoregressive Tobit Models

Tables 5.2 and 5.3 on the following pages show the results from the SAR tobit models in 2002 and 1997. The positive and significant coefficients on the spatial lag parameter ρ for both 1997 and 2002 suggest the presence of spatial agglomeration economies at work in the dairy sector. The ρ value for 1997 is 0.051812 and for 2002 is 0.02804 indicating that the influence of the spatially lagged dependent variable is rather restricted. The decrease in the ρ value from 1997 to 2002 suggests that the agglomeration effect of milk marketing levels in nearby counties decreased over time.

The influence of feed input quantities produced in a county is mixed by type. Silage (*SIL*) had a significant positive impact at the 5 percent level, and corn for grain (*CRN*) had a significant negative impact. Alfalfa production (*ALF*) and dollars spend on feed (*FDS*) yielded insignificant coefficients in both years. The influence of silage production is the most dramatic with a production increase of 1,000 tons increasing milk marketings by 69,653 lbs, holding all else constant, and elasticity at the sample mean of 0.467 in 1997. The same change in production brings about a marketing increase of 71,020 lbs in 2002 with an elasticity of 0.456. The negative coefficient on corn was unexpected, but not unrealistic, as ease of transportation makes local production less crucial. The elasticity for corn is -0.088 in 1997 and -0.061 in 2002, which converts to a decrease of milk marketings in a county by 120,000 pounds when corn production increases by one million bushels for 2002. The sign on alfalfa was positive in 1997 and negative in 2002 suggesting that sourcing alfalfa from non-local counties might have become a more predominant practice, consistent with the increase in western-style dairy operations and the expectation that areas with large cow populations would produce more alfalfa. The coefficient, however, was not statistically significant in either year.

Table 5-2 Results from SAR Tobit Model, 2002

Variable	Coefficient [a]	Std. Dev.	p-value	Elasticity [b]
Constant	1.92910	1.9423	0.1480	~
ρ	0.02800 ***	0.0077	0.0000	~
SIL02	701020 ***	0.3699	0.0000	0.45630
CRN02	-0.12050 ***	0.0145	0.0000	-0.06060
ALF02	-0.01500	0.2272	0.4650	-0.00060
FD$02	0.00210	0.0048	0.3200	0.00390
CAT02	1.21290 ***	0.4469	0.0030	0.06470
CAT5+02	-0.08190 ***	0.0119	0.0000	-0.12100
HOG02	-0.24110	0.2138	0.1310	-0.00800
HGK+02	0.00760	0.0109	0.2480	0.00530
DMO02	0.53120 ***	0.1803	0.0010	~
MBP02	-0.17820 *	0.1168	0.0620	-0.37150
LV$02	0.28490 ***	0.0337	0.0000	0.19890
T/VL02	0.51240 **	0.2699	0.0270	0.04210
HUM97	0.00170	0.0136	0.4620	0.01990
PCP02	0.05110 ***	0.0089	0.0000	0.33870
XMIN02	-0.07280 ***	0.0149	0.0000	-0.81410
DMY02	0.32920 **	0.1649	0.0250	~
ACR02	-0.01580 *	0.011	0.0780	-0.01550
PTF02	-0.00260	0.0031	0.1980	-0.02260
POP02	-0.39150 **	0.1843	0.0140	-0.00620
WAG02	0.15000 *	0.1051	0.0850	0.20610
UEM02	-0.05740 **	0.0332	0.0430	-0.05630
PCI02	-2.53250 **	1.2171	0.0150	-0.10390
ESI00	0.05580 *	0.0369	0.0580	0.02810
PLA600	0.00540 ***	0.0008	0.0000	0.04680
No. of Observations	2339			

[a] *significant at 10%, ** at 5%, *** at 1%

[b] Evaluated at the mean of the independent variable

Table 5-3 Results from the SAR Tobit Model, 1997

Variable	Coefficient [a]	Std. Dev.	p-value	Elasticity [b]
Constant	3.754300 ***	1.4731	0.0060	~
ρ	0.051800 ***	0.0087	0.0000	~
SIL97	6.965300 ***	0.2726	0.0000	0.46730
CRN97	-0.149800 ***	0.0133	0.0000	0.08790
ALF97	0.110000	0.1610	0.2330	0.00490
FD$97	0.002400	0.0032	0.2250	0.00490
CAT97	0.047100	0.3293	0.4380	0.00300
CAT5+97	-0.034200 ***	0.0088	0.0000	-0.05370
HOG97	-0.328100 *	0.2437	0.0750	-0.01240
HGK+97	0.005200	0.0107	0.3230	0.00440
DMO97	0.510500 ***	0.1197	0.0000	~
MBP97	-0.429100 ***	0.0944	0.0000	-0.94890
LV$97	0.385000 ***	0.0367	0.0000	0.20390
T/VL97	0.863500 ***	0.2336	0.0000	0.08180
HUM97	0.011100	0.0104	0.1430	0.14940
PCP97	0.042200 ***	0.0065	0.0000	0.31670
XMIN97	-0.035100 ***	0.0118	0.0020	-0.44170
DMY97	0.158900	0.1393	0.1260	~
ACR97	-0.013600 **	0.0099	0.0910	-0.01500
PTF97	-0.000400	0.0025	0.4260	-0.00380
POP97	-0.139900	0.1480	0.1630	-0.00230
WAG97	-0.001100	0.1007	0.4880	-0.00120
UEM97	-0.106900 ***	0.0187	0.0000	-0.11390
PCI97	-6.600600 ***	1.4829	0.0000	-0.22770
ESI00	0.115600 ***	0.0264	0.0000	0.06630
PLA600	0.005900 ***	0.0007	0.0000	0.05670
No. of observations	2380			

[a] *significant at 10%, ** at 5%, *** at 1%

[b] Evaluated at the mean of the independent variable

Other variables related to production costs included the value of land and buildings, tax rate, state level wages for agricultural workers, and unemployment rates. The value of land and buildings (*LV$*) and tax rate (*T/VL$*) were positive and statistically significant at the 5 percent level in both years. Because this value was reported for the same year that the marketings took place and construction occurs prior to the increased production, this likely reflects the value that a dairy operation and associated improvements bring to the land. The effect of the tax rates may simply be overshadowed by the influence of other more important considerations in location selection. The reported state-level wage for agricultural and livestock workers (*WAG*) had a negative, although insignificant, sign in 1997 as hypothesized, but the sign switched to positive in 2002 and was significant at the 10 percent level. This is likely attributable to other state-level positive factors as mentioned by Peterson (2002). County unemployment rates (*UEM*) had a negative impact on dairy production in both years, but the elasticities fell from -0.114 in 1997 to -0.056 in 2002. Possible interpretations are that dairies are not greatly concerned about labor availability, although this is inconsistent with the reality of the industries labor demands, or that areas of higher unemployment may not be actively or effectively pursing dairy operations as an economic booster.

The per capita income, population, county acreage total, and percent of land in farms represent important business climate variables indicating a county's acceptance of agriculture within its borders. The sign on per capita income (*PCI*) indicates a negative relationship between milk marketings and affluence, with elasticities of -0.228 and -0.104 in 1997 and 2002, respectively. This supports the assertion that counties with higher incomes are less likely to support animal agriculture as a means of economic growth, possibly due to its association with a negative environmental externality. County population (*POP*) had the expected negative coefficient in both years, but was significant in 2002 only with an elasticity of -0.006. This indicates that for every one million person increase in population, the county's milk marketings would fall by 391,000 pounds. The percentage of a county's land in farms (*PTF*) was negative but insignificant in both years, while the total county acres (*ACR*) was significant at the 10 percent level and negative with elasticities of -0.015 in both 1997 and 2002. Apparently, simply having more land available for agriculture has not been a driving factor in the dairy location industry. It is also plausible that this variable fails to capture a meaningful relationship between land availability and dairy production nationwide because the western-style dairy requires less land for operation than traditional dairies.

The number of cattle in a county (*CAT*) was not statistically significant in 1997 but significant and positively correlated with milk marketings in 2002, while the number cattle operations over 500 head was negative and significant in both years. A possible interpretation for this inconsistency is that generally, counties suitable for livestock production are favorable to dairy production, but those counties where multiple large cattle feeding operations exist may compete with dairies for available resources within the county. The elasticity for total cattle numbers was 0.065 in 2002. The magnitude of the negative effect for the *CAT5+* variable increased between 1997 and 2002 so that one additional operation would reduce milk marketings by 82,000 pounds in 2002, while it was only 34,000 pounds in 1997. The elasticities for 1997 and 2002 were -0.003 and -0.121 suggesting that dairies have become more competitive with large cattle operations over time.

The number of hogs in a county (*HOG*) had a slightly negative impact on milk marketings, which was significant at the 10 percent level in 1997 and became insignificant in 2002. This suggests that the resources and infrastructure demands of the dairy and hog industries have become increasingly independent of each other, perhaps resulting from the consolidation and geographic relocation that the industries have undergone.

The climatic variables exhibited mixed results as well. Relative humidity (*HUM97*) was not significant in either year, possibly due to the use of a yearly average that poorly reflected historic trends or because it failed to account for seasonal extremes that might affect milk production. The ten-year average precipitation levels (*PCP*) were positively correlated with milk marketings and statistically significant at the 5 percent level. A one inch increase in the ten-year average results in increased milk marketings between 40,000 and 50,000 pounds for the two years and the corresponding elasticities were 0.316 and 0.339 in 1997 and 2002.

The dummy variable for the ten-year average for the coldest monthly average high below freezing (*DMY*) was positive in both years although not significant in 1997. This indicates a county with at least one month where the average high temperature is below freezing will market almost 33,000 more pounds of milk than a county with no months with an average high below 32°F in 2002. The sign was contrary to expectations but reveals that colder temperatures have not deterred milk production. It may simply be capturing higher levels of milk marketings in the traditional producing regions in the upper Midwest and Northeast.

The signs for the ten-year average lowest monthly maximum temperature average were, on the other hand, negative as predicted although the magnitudes were relatively small. As the average minimum monthly temperature increased by one degree, the quantity of milk marketed was reduced by 70,000 pounds in 2002 but only by 30,000 pounds in 1997. This result suggests that, contrary to the results of previous studies, warmer temperatures are not always correlated with greater dairy activity. This suggests the need for further work to examine the influence of persistent high temperatures. Although obtaining comprehensive, division-level data for the temperature-humidity index (THI) poses a considerable obstacle, the impact of the THI on dairy distribution and regional productivity would be interesting to measure.

The mailbox price received by farmers (*MBP*) was significant at the 5 percent level in 1997 but only at the 10 percent level in 2002. It is negative in both years, although its magnitude shrinks to one half its 1997 size in 2002 suggesting that the restructuring of the FMMO system had substantial impacts on the pricing system. Correspondingly, elasticity on the mailbox prices changed dramatically in the time period considered; it fell from -0.949 in 1997 to -0.372 in 2002. The negative coefficient reinforces the concept that production costs outweigh the influence of milk prices in the location decision though producers are likely less conscious of price in 2002.

Counties regulated under the FMMO or California order system (*DMO*) had May marketings on average of 500,000 pounds greater than counties not associated with either the FMMO or California system in both years. Finally, the number of plants within 600 miles of the county center was statistically significant at the 5 percent level in 1997 and 2002, but the size of the influence was very small. An additional plant within 600 miles would increase May production by approximately 5,000 pounds in either year. This finding reflects the need for more region specific analysis as the distance milk routinely travels from farm to processor varies widely across the country.

The variable measuring environmental stringency across states (*ESI*) was positive and significant at the 5 percent level in 1997 and at the 10 percent level in 2002. The unexpected sign may, as Herath, Weersink, and Carpentier (2004) suggest, be attributable to the effect of growth in a region's dairy industry prompting the passage of more restrictive legislation to regulate it. This is very likely in the 1997 results because the environmental index measure includes the years 1998, 1999, and 2000 when additional legislation may have been enacted.

As stated earlier, the SEM tobit model outperformed the SAR tobit model on the basis of RMSE and was used for out-of-sample prediction using the 2004 data available for the mailbox prices, maximum and minimum average temperatures, precipitation, population, state level agricultural wages, unemployment percentage, per capita income, and milk marketings. The predicted quantities of milk marketed for counties in May 2004 were compared with actual milk marketings for that same month and year. Overall, the SEM tobit model resulted in an RMSE of 15.152, 4.4 million pounds lower than the RMSE for the SAR tobit and, although it failed to predict positive marketings in 141 counties that did market milk, its overall predicted quantity of milk nationwide was much closer to the actual value than the SAR tobit model as shown in Table 5-4. The actual average for 2004 milk marketings was 4.92 million pounds compared to 4.67 million pounds predicted by the SEM model. The greatest errors were underestimations of the marketings in the largest 20 counties where the model was off in some cases by almost one half of the actual production quantity. Nonetheless, the model predicted the greatest quantities of milk produced in the highest producing counties. For the 505 counties marketing between 3 million and 60 million pounds, the model performed slightly better with an average error of about 6.4 million pounds. For all the counties with positive marketings, the model's average error was 5.23 million pounds. Compared to the actual average marketings of 7.88 million pounds for all positive counties, the model is a disappointing predictor for milk marketings.

Table 5-4 Out of Sample Predictions Using the SAR and SEM Tobit Models, 2004

	RMSE	No. of Counties with Positive Predictions	Total Quantity of Milk Predicted in million lbs
SAR Tobit 2004	19.573	1,241	5,782.13
SEM Tobit 2004	15.152	1,184	10,671.17
Actual 2004 Value	~	1,325	11,239.00

5.2 Results of Bayesian SAR and SDM Change Models

The change model used the difference between 2002 May milk marketings and the 1997 May milk marketings as the dependent variable with the independent variable matrix consisting of 1997 values to determine whether the economic and agricultural state of one year can explain future marketings. The SAR and SDM models had almost exactly the same RMSE of 7.81 million pounds, but with the average change of only 1.41 million pounds, neither model was a reliable predictor for values. The SAR model more closely resembled the actual changes taking place, although it predicted decreases in milk marketings in 1,424 counties when the actual number of counties was 880. The SDM model predicted that 1,480 counties would have decreases. Neither model had more than eight variables significant at the 10 percent level. Results for the Bayesian SAR model are shown in Table 5-4 and are interpreted below.

Table 5-5 Results from the Bayesian SAR Change Model

Dependent variable is the Change in Marketings from 1997-2002.

Variable	Coefficient [a]	Std. Dev.	p-value	Elasticity [b]
Constant	0.812580 **	0.4747	0.0500	~
ρ (spatial coefficient)	0.008820	0.0082	0.1422	~
SIL97	0.604850 ***	0.0905	0.0000	0.16125
CRN97	0.008430 *	0.0053	0.0544	0.01852
ALF97	-0.014600	0.0672	0.4077	-0.00248
FD$97	-0.000800	0.0012	0.2488	-0.00610
CAT97	-0.626500 ***	0.1300	0.0000	-0.14717
CAT5+97	0.008540 **	0.0032	0.0022	0.04988
HOG97	0.068600	0.0815	0.2022	0.00995
HGK+97	-0.001900	0.0040	0.3277	-0.00602
DMO97	-0.110800 ***	0.0440	0.0033	~
MBP97	-0.004900	0.0327	0.4233	-0.04000
LV$97	-0.014500	0.0119	0.1100	-0.02866
T/VL97	0.077660	0.0832	0.1811	0.00075
HUM97	-0.001400	0.0037	0.3655	-0.00050
PCP97	-0.001600	0.0024	0.2455	-0.07934
XMIN97	0.001410	0.0043	0.3611	0.03905
DMY97	0.009890	0.0564	0.4355	~
ACR97	0.000008	0.0030	0.5200	0.00022
PTF97	-0.000600	0.0008	0.2277	-0.00249
POP97	-0.210800 **	0.0805	0.0122	-7.93193
WAG97	-0.074100 **	0.0406	0.0411	-0.00444
UEM97	0.002900	0.0061	0.3211	0.01189
PCI97	-0.636900	0.5345	0.1288	-2.52335
ESI00	-0.005700	0.0111	0.3100	-0.00073
PLA600	-0.000600 ***	0.0003	0.0055	-0.00132
No. of observations	2154			

[a] *significant at 10%, ** at 5%, *** at 1%

[b] Evaluated at the mean of the independent variable

The ρ spatial lag coefficient was positive but insignificant at the 10 percent level suggesting that the change in milk marketings between 2002 and 1997 in one county was not influenced by the changes in the milk marketings of nearby counties. This is contrary to expectations and to Peterson's (2002) finding of a ρ value of 0.2281. However, she used changes in the independent variables across years rather than observations from a single year in her estimation.

Silage (*SIL*) was significant at the 5 percent level and had an elasticity at the means of 0.161. For every one percent increase in a county's 1997 silage production, the amount of milk marketed in May of that year increased by .161 percent. Unlike the earlier models, corn production (*CRN*) was positive and significant at the 10 percent level. The elasticity of 0.019 means that a one percent increase in 1997 corn production increases milk marketings by 0.019 percent. These coefficients indicate that counties with greater feed production were likely to experience small increases in milk marketings. Alfalfa production and dollars spent on feed were both insignificant variables.

The cattle variables were oppositely signed in this estimation, as compared to the tobit models for 1997 and 2002, and both were significant at the 5 percent level. The number of cattle in the county in 1997 had a negative influence on the change in milk marketings with the coefficient of -0.626 indicating that for every additional 100,000 head of cattle milk marketings between 1997 and 2002 would decrease by 626,000 pounds. The elasticity on (*CAT*) was -0.147. The number of cattle operations greater than 500 head had a positive coefficient and an elasticity of 0.050. For every additional operation in 1997, milk marketings would be expected to increase by just over 8,000 pounds between 1997 and 2002. The variables on hog production (*HOG* and *HGK+)* were both insignificant.

Association with either the FMMO system or California system (*DMO*) was significant at the 5 percent level and negatively influenced the change in marketings. A county regulated under the 1997 system was predicted to reduce marketings by 110,794 pounds in 2002. Peterson (2002) found a similar sign on FMMO membership and commented that this suggests the milk production growth has happened outside federal and California regulation. The reorganization of the milk marketing orders in 2000 may have also affected the influence of FMMO membership.

Population and state-level agricultural wages were both negative and significant at 5 percent. The coefficient on population (*POP*) had an elasticity of -7.93 so a one percent increase in the 1997 county population would cause almost an 8 percent decease in milk marketings. This result is that small increases in population have a considerably larger effect on milk marketings and that dairies are choosing to expand or relocate away from more populated areas. State-level wages (*WAG*) had an elasticity of -0.004 and indicates that states with higher 1997 wages would cause county level milk marketings to fall across the five year period. The number of processing plants in a 600 mile radius (*PLA600*) was the only other significant variable and was negative, although extremely small in magnitude. An additional plant as listed on the 2001 registry, cause a reduction in milk marketings between 1997 and 2002 of only 624 pounds, a very inconsequential quantity.

As mentioned earlier in this section, the models for the change in marketings between 1997 and 2002 did an exceptionally poor job of predicting the actual changes in marketings between those years. This suggests that the variables from a single year are not that revealing about the production decisions of dairy farmers five years into the future.

CHAPTER 6 - CONCLUSIONS

6.1 Summary of Findings

By applying spatial econometric methods in the form of a Spatial Autoregressive tobit model (SAR tobit) to county-level observations and the quantities of milk marketed through the FMMO system in May of the corresponding year, the presence of spatial agglomeration economies was confirmed in the dairy industry in both 1997 and 2002, although in much smaller magnitudes than previous studies have suggested (Peterson, 2002; Isik, 2004). This could be in part due to the use of different variables and spatial econometric methods as well as the different time period considered. Moreover, the coefficient on the spatially lagged dependent variable diminished in size between the two time periods from 0.052 in 1997 to 0.028 in 2002 but remained significant at the 1 percent level in both years. Alternative specifications for the spatial model, namely spatial Durbin models with both spatially lagged dependent and independent variables and combined models including both spatially lagged dependent and error terms, were rejected because they resulted in spatial parameters either greater than 1 or that were negative. These results indicate that those models may have been inappropriate in this application or, in the case of the SDM tobit model where collinearity between the independent and lagged independent variables was problematic, were in some way mis-specified.

A fourth model specification, the spatial error tobit model, captured spatial autocorrelation among the error terms and performed better than the SAR tobit in predicting the actual values of milk marketings in 2002 and an out-of-sample year 2004. The impacts of the different variables were fairly robust across both models maintaining consistent signs and comparable magnitudes, but the SAR tobit was preferred for interpretation due its substantive nature of addressing spatial autocorrelation rather than attributing it to nuisance effects in the error terms.

Determinants that positively impact the quantities of milk marketed from an individual county in both years included the local production of corn silage for feed, regulation under either the FMMO or California Marketing Order systems, precipitation, and the number of processing plants within a 600 mile radius. Similarly, Peterson (2002) found that association with FMMOs had a positive influence on milk marketings. Deterrents to milk marketings included factors such as corn production, higher per capita incomes, higher unemployment percentages, and the presence of large (500 head or more) cattle operations in the county. The last variable is notable because in 2002 the total number of cattle in a county actually had a significant, positive effect on milk marketings.

Other noteworthy changes across years included the rise in significance of county population in 2002 as deterrent to dairy production and the fall from significance at the 10 percent level of hog production from 1997 to 2002. The positive effect of state level agricultural wages also became significant at the 10 percent level in 2002 whereas it had previously been insignificant and negative. This is in accord with Peterson (2002) who also found a positive relationship between state wage rates and dairy production. An interesting finding contrary to other studies (Isik, 2004; Peterson, 2002; Osei and Lakshminarayan, 1996) is that higher temperatures do not unequivocally attract dairies as shown by the negative and highly significant coefficient on the variable (*XMIN*) measuring the hottest monthly minimum temperatures over ten years.

The findings of this study varied from those of Peterson (2002) in several areas. This is likely due to the decision to use the actual values from 1997 and 2002 for the variables rather than the change between the two years, different estimation procedures to arrive at values for missing variables, and to the inclusion or exclusion of particular states and counties from the study.

The out-of-sample predictions for 2004 applying the parameters from the 2002 SAR tobit model was unsuccessful suggesting that using the agricultural census data from 2002 for 2004 was inappropriate and that there were problems with the choice of data used as a proxy for certain variables in the 2002 SAR tobit model. Additionally, the increase of western style dairying and other effects the chosen variables may have failed to capture might also have contributed to greater inaccuracy in the prediction.

6.2 Suggestions for Further Research

There are without doubt many modifications and alternative model specifications that would expand on the work from this thesis and provide further insight into the determinants of the geographic distribution of the U.S. dairy industry. Described below are a few of the areas the author believes would be most fruitful in terms of future work in this area.

Additional refinement of the independent variables included in the SDM model to eliminate collinearity between those variables and their lags is a starting point. Perhaps the incorporation of spatial autocorrelation in the error terms with lagged independent variables as suggested in Angerz, McCombie, and Roberts (2007) SHM model would help to capture some of the nuisance autocorrelation that may exist due to the use of observations from the county-level. It is reasonable to believe that there may be considerable spatial autocorrelation among independent variables such as feed production and intensity of other livestock industries that would influence the quantities of milk marketed within a county.

The specification and construction of the weight matrix is vital to the application of spatial econometrics and has extensive ramifications for the model results (Kastens, 2007; Isik, 2004). Altering the spatial weights matrix by varying the maximum distance of influence or squaring the distance terms and conducting additional sensitivity analysis might result in quite different parameter estimates for the spatial lags that are more effective in building predictive models.

Regarding specific independent variables, data limitations present in this study may be overcome by using a smaller subset of data for regional analysis. Other variables that may have bearing on the dairy location decision are water availability, ownership and capacity of processing plants, and a more recent and locally focused measure of the business environment provided by a county.

Water availability is an important issue for dairies in some locations. An examination of groundwater sources and differences in state regulations regarding water rights may provide useful insights in understanding the dairy operator's decision regarding expansion or relocation.

Processing plant ownership, capacity, and effective area of coverage vary greatly across the country with older, lower capacity plants operating in the traditional regions while modern plants in the West are often much larger. Due in part to these variations in capacity, the "geographic footprint" of a plant changes relative to the region of the country. The 600 mile radius for plant interaction was a course approximation for the area of influence of processing plants that varies widely by geographic location within the U.S. Further research should incorporate regional level considerations such as topography, the number of stops required to fill a tanker, and variations in travel time associated with transportation infrastructure and the degree of urban development surrounding the plant. Additionally, the ownership of a plant as a private enterprise or as a cooperative might influence the intensity of production and marketing in county.

A more precise method of measuring overall business environment in a county or regions should be devised to integrate the effects of both state and local environmental standards, zoning laws, and the influence of recruitment activities on dairy production and milk marketings. On the producer side, future studies may also include membership in cooperatives or other marketing associations in regions in and out of FMMO regulation to determine the effect of those organizations on dairy location.

More general data limitations are that agricultural census data are only available at five year intervals and that counties are divided as administrative political boundaries rather than divisions representative of the influence of different variables on the dairy industry. A possible approach to overcome these limitations may be to use survey-collected data. Such surveys of individual farms could identify the presence of common, farm-level factors that influence dairy location decisions, addressing above-mentioned shortcomings related to the specifications of explanatory variables.

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Appendix A - Descriptive Statistics

Table A-1 Summary Statistics for 2002 Observations

VAR	Variable Description	Units	Average	Std. Dev.	Max	Min
LON00	County Centroid Longitude	Decimal Degrees	-91.3465	11.3621	-68.5951	-124.0635
LAT00	County Centroid Latitude	Decimal Degrees	38.3788	4.8512	48.8230	25.4905
SIL02	Corn Silage Harvested	100,000 Tons	0.3787	1.1171	30.2880	0
CRN02	Corn for Grain Harvested	Million Bushels	2.9642	6.1064	48.3325	0
ALF02	Alfalfa Harvested 2002	100,000 Tons	0.2324	0.5696	8.9863	0
FD$02	Feed Purchased 2002	Million Dollars	10.8606	24.0610	441.8879	0
CAT02	Cattle and calves Inventory 2002	100,000 Head	0.3144	0.4512	9.0012	0
CAT5+02	Cattle Operations Over 500 Head 2002	number	8.7118	15.9427	293.0000	0
HOG02	Hogs and pigs Inventory	100,000 Head	0.1966	0.5884	8.8794	0
HGK+02	Hog Operations Over 1000 Head 2002	number	4.1038	13.4663	269.0000	0
2MMO	Post-Reform Federal Milk Marketing Order	~	33.6023	42.4760	135.0000	0
MBP02	Mailbox Price 2002	Dollars	12.2899	0.7381	15.3737	10.7879
LV$02	Est. Market Value of Land and Buildings 2002	100,000 Dollars	3.9286	4.3974	70.1017	0
PT$02	Property Taxes Paid 2002	100,000 Dollars	0.01893	0.0260	0.4658	0
T/VL02	Property Tax Rate 2002	%	0.4848	0.2599	3.5573	0
HUM97	Relative Humidity	%	69.7669	6.5245	85.4025	29.0900
PCP02	10 Year Average Precipitation 1992-2002	Inches	39.1049	13.1820	99.2109	4.7282
XMIN02	10 Year Avg Highest Monthly Avg Temp Min	Degrees Fahrenheit	65.9566	6.0096	86.3000	42.0000
NMAX02	10 Year Avg Lowest Monthly Avg Temp Max	Degrees Fahrenheit	39.5125	12.5079	75.4000	7.7000
ACR02	Land Acres 2002	100,000 Acres	5.79488	7.4920	128.3360	0.2988
PTF02	Percent of Land in Farms	%	52.2049	30.4509	181.6000	0.0000
POP02	Population 2002	Million People	0.0928	0.3006	9.7638	0.0001
WAG02	State Average Field & Livestock Wage Rate	Dollars	8.0952	0.6850	9.3939	6.9596
UEM02	Unemployment Rate 2002	%	5.7838	1.9027	19.7000	1.6000
PCI02	Per Capita Income	100,000 Dollars	0.2419	0.0570	0.6633	0.0529
ESI00	Environmental Stringency Index	number	2.9653	1.6159	6.9900	0
PLA600	Number of Processing Plants in 600 miles	number	50.2347	35.1050	147.0000	1.0000
MMM02	Milk Marketed FMO May 2002	Million Pounds	5.8947	25.8155	790.8051	0
	No. of Observations = 2339					

Table A-2 Summary Statistics for 1997 Observations

VAR	Variable Description	Units	Average	Std. Dev.	Max	Min
LON00	County Centroid Longitude	Decimal Degrees	-91.2668	11.2646	-68.3396	-124.1582
LAT00	County Centroid Latitude	Decimal Degrees	38.3981	4.7691	48.8230	25.4905
SIL97	Corn Silage Harvested 1997	100,000 Tons	0.3506	0.9049	17.3367	0
CRN97	Corn Grain Harvested 1997	Million Bushels	3.0677	5.7949	47.4351	0
ALF97	Alfalfa Harvested 1997	100,000 Tons	0.2336	0.5554	10.2181	0
FD$97	Feed Purchased 1997	Million Dollars	10.5432	23.6008	304.8592	0
CAT97	Cattle and calves Inv. 1997	100,000 Head	0.3331	0.4407	6.4413	0
CAT5+97	Cattle Operations Over 500 Head 1997	number	8.2101	15.7580	281.0000	0.0000
HOG97	Hogs and pigs Inventory 1997	100,000 Head	0.1978	0.5127	7.5869	0.0000
HGK+97	Hog Operations Over 1000 Head 1997	number	4.3849	12.5108	219.0000	0
1MMO	Pre-Reform Federal Milk Marketing Order	~	42.6084	46.5161	139.0000	0
MBP97	Mailbox Price 1997	Dollars	11.5567	0.6254	14.0744	10.1085
LV$97	Market Value of Land and Buildings 1997	100,000 Dollars	2.7678	3.1068	57.5995	0
PT$97	Property Taxes Paid 1997	100,000 Dollars	0.0132	0.0179	0.346	0
T/VL97	Property Tax Rate 1997	%	0.4953	0.2892	2.1690	0
HUM97	Relative Humidity	%	69.7579	6.4702	85.4025	29.0900
PCP97	10 Year Average Precipitation 1987-97	Inches	39.2516	13.6823	96.1755	4.9991
XMIN97	10 Year Avg Highest Monthly Avg Temp Min	Degrees Fahrenheit	65.8509	5.6781	86.6000	41.2000
NMAX97	10 Year Avg Lowest Monthly Avg Temp Max	Degrees Fahrenheit	39.0532	11.9036	75.3000	9.6000
ACR97	Land Acres 1997	100,000 Acres	5.7738	7.4174	128.3983	0.2988
PTF97	Percent of Land in Farms 1997	%	53.1106	30.3372	141.2483	0
POP97	Population 1997	Million People	0.0873	0.2913	9.1261	0.0001
WAG97	State Average Field & Livestock Wage Rate 97	Dollars	5.7811	0.5456	7.1568	5.0399
UEM97	Unemployment Rate 1997	%	5.5683	3.0520	33.2000	1.2000
PCI97	Per Capita Income	100,000 Dollars	0.1803	0.0395	0.4554	0.0435
ESI00	Environmental Stringency Index	number	2.9965	1.6254	6.9900	0
PLA600	Number of Processing Plants in 600 miles	number	50.4874	35.1184	147.0000	1.0000
MMM97	Milk Marketed FMO May 1997	Million Pounds	5.2259	19.7466	498.8217	0
	No. of Observations = 2380					

Appendix B - Great Circle Distance Formula

The following haversine formula for great circle distance was used to calculate the centroid-to-centroid distance (d_{ij}) between counties *i* and *j* using the decimal degree latitude and longitude coordinates taken from Peterson (2002). Coordinates in decimal degrees were converted to radians by multiplying each value by pi/180. Using MATLAB 7.0.4, the radian coordinates were used to calculate the change in radians, "c", that was then multiplied by the radius of the earth, r = 3956.55 miles, to determine the distance in miles between the two points. The haversine formula is accurate to within 0.5 percent when the points are not antipodal, or on opposite sides of the earth, and assumes that the earth is perfectly spherical. This last assumption does not greatly affect the resulting distances but explains the use of the geometric mean of the earth's radius rather than either the longest or shortest value (Moveable Type Scripts, 2007).

Haversine formula for great circle distance:

$$C = 2\arcsin\{\sin^2[(lat_1 - lat_2)/2] + \cos(lat_1)*\cos(lat_2)*\sin^2[(long_1 - long_2)/2]\}^{1/2}.$$

Appendix C - Temperature Data

The average temperature minimum and maximum data were obtained by utilizing the most complete records for each reporting weather division. When multiple stations reported in a division, the stations with the fewest missing years were retained. Ten year averages included ten years whenever possible, but some averages reflected a shorter period due to missing years. Also, no years with fewer than six months reported were included in the 10-year averages to avoid including only winter or summer seasons that would distort the average. Weather divisions that did not have a reporting station were assigned the average temperatures of the division number immediately preceding and following the missing division (only the preceding division was applied in the case of the highest number division missing a value). For the maximum minimum temperatures, the station reporting the highest value was used for the respective division, conversely the lowest minimum maximum was used as well.

Appendix D - Supply and Distribution Plant Address Determination

Plant data for California were only available from the 2001 and 2007 registered plant list obtained from the California Department of Agriculture. For FMMO regulated plants, special consideration was taken to eliminate repeat occurrences of the same physical plant that may have switched orders or transferred ownership under a new name thus being listed twice in the AMS spreadsheets. Also, if two plants shared a zip code and no street information was available for one, the same address was used for both to simplify the lookup procedure. The addresses for each year were then imported into ArcView 9.2 ArcMap Streetmap software in order to geocode the street address with a specific latitude and longitude. Matches were made automatically for addresses with a 65 percent spelling and overall match score of above 65 percent. Remaining addresses were then interactively matched using suggested addresses from the program matching street numbers as closely as possible resulting in a 97 percent match rate. Unmatched addresses as well as those plants where no street address could be located were given the latitude and longitude of the city in which they were located as listed by the U.S. Census Gazetteer.

The data only lists plants that handle enough quantity to be regulated under the FMMO system. Additionally, plants can drop in and out of regulated status monthly by restricting their sales (distribution plants) or restricting their sales and shipments (supply plants). For this reason, FMO regulation of a plant during in any month in the year was considered enough to include it on the list as the plant continued operation though it was simply unregulated during the rest of the year.

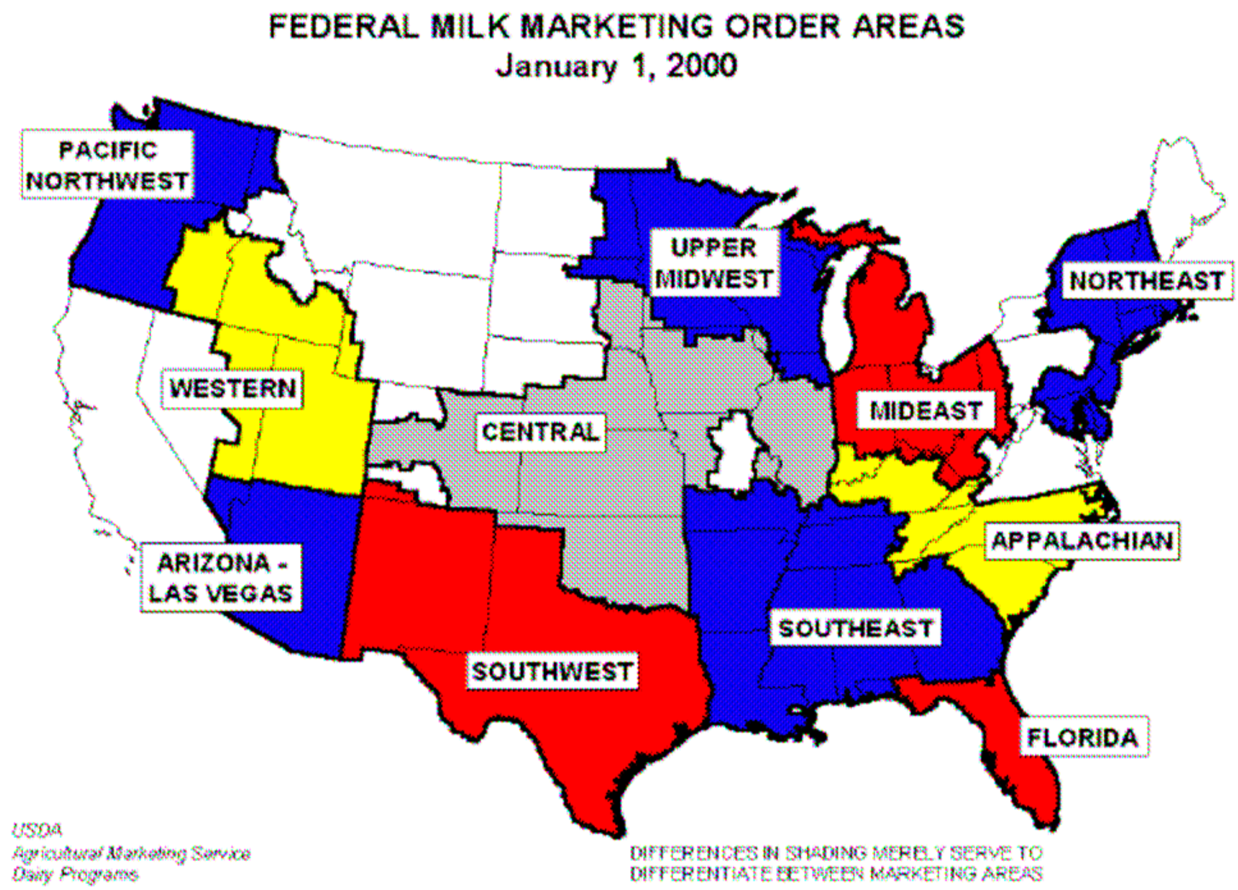
Appendix E - Counties Excluded for Reasons of Missing Data

Counties Excluded from Consideration

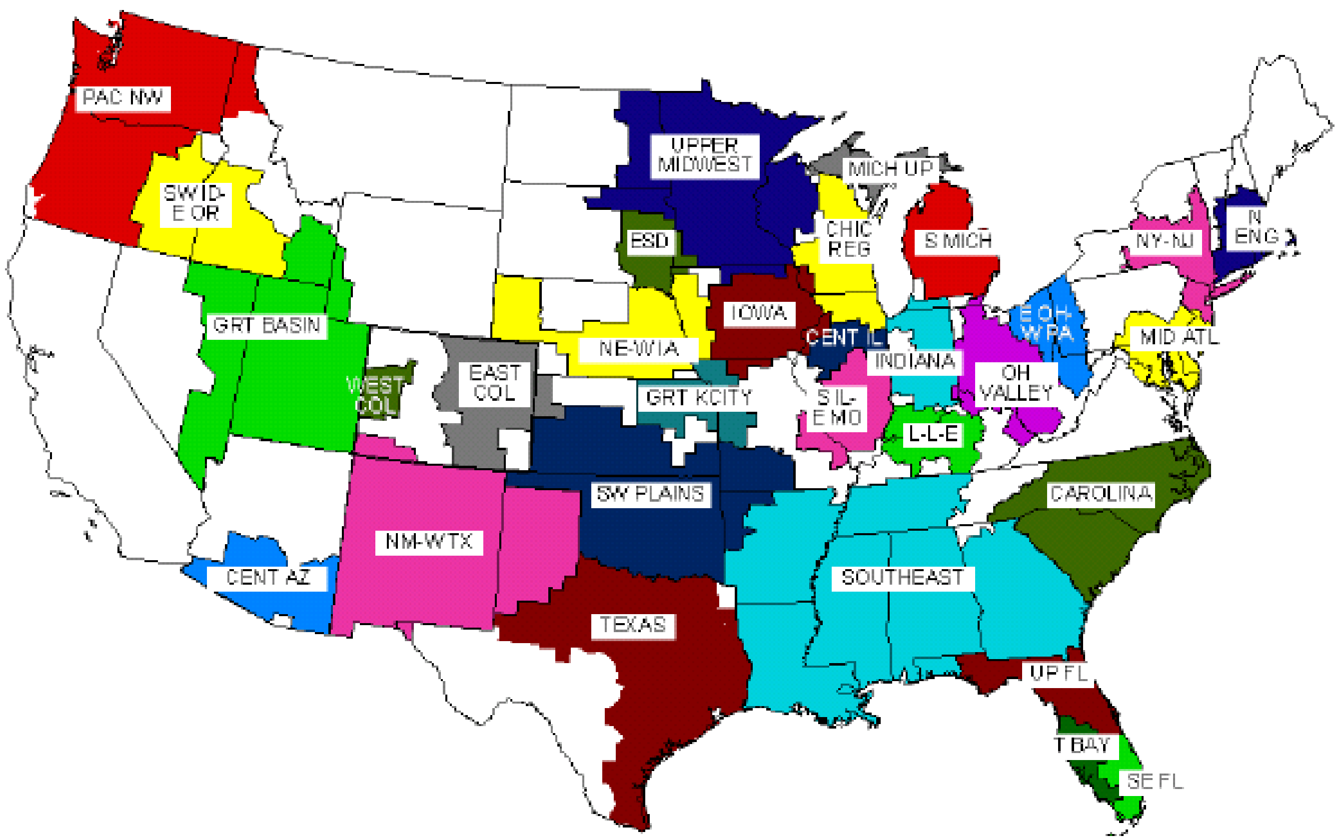
State	*County Omitted*
California	San Francisco
	Alpine
Colorado	Broomfield
	Denver
	Dolores
	Hinsdale
	Mineral
	Ouray
	San Juan
Florida	Dade
Idaho	Clark
	Clearwater
	Custer
New Jersey	Hudson
New Mexico	Harding
	Los Alamos
New York	Bronx
	New York
	Kings
	Queens
Oklahoma	Atoka
	Carter
	Choctaw
	Cotton
	Greer
	Jackson
	Jefferson
	Kiowa
	Latimer
	Love
	Pittsburg
	Pushmataha
	Woods
	Woodward
Virginia	Accomack
	Amherst
	Arlington
	Bath
	Buchanan
	Charles City
	Chesapeake City

	Chesterfield
	Essex
	Fairfax
	Gloucester
	Greensville
	Henrico
	James City
	King George
	Lancaster
	Lunenberg
	Mathews
	Middlesex
	New Kent
	Nelson
	Northhampton
	Northumberland
	Rappahannock
	Southhampton
	Stafford
	Suffolk City
	Sussex
	Virginia Beach
	York
West Virginia	Braxton
	Clay
	Hampshire
	Pendleton
	Pocahontas
	Webster

Appendix F - Federal Milk Marketing Order, 2000



Appendix G - Federal Milk Marketing Order Map - Prior to Restructuring, 1998



Appendix H - MATLAB Results

Spatial Autoregressive Model Estimates (SAR) 2002

Dependent Variable = MMM02
R-squared = 0.8582
Rbar-squared = 0.8567
sigma^2 = 94.2198
Nobs, Nvars = 2339, 25
log-likelihood = -7824.4035
# of iterations = 11
min and max rho = -1.0000, 1.0000
total time in secs = 125.6400
time for lndet = 50.0320
time for t-stats = 63.9680
Pace and Barry, 1999 MC lndet approximation used
order for MC appr = 50
iter for MC appr = 30

Variable	Coefficient	Asymptotic t-stat	z-probability
ONE	-40.582827	-10.871683	0.000000
SIL02	16.608392	50.087054	0.000000
CRN02	-0.256477	-4.814919	0.000001
ALF02	0.425225	0.808272	0.418934
FD$02	0.238761	15.112914	0.000000
CAT02	-15.914001	-13.468124	0.000000
CAT5+02	0.441429	14.875805	0.000000
HOG02	-1.516760	-1.958393	0.050184
HGK+02	-0.112206	-3.163455	0.001559
DMO02	0.974979	1.380305	0.167493
MBP02	-0.581105	-3.931438	0.000084
LV$02	0.292803	3.974788	0.000070
T/VL02	-1.598211	-1.704080	0.088366
HUM97	-0.164454	-3.355583	0.000792
PCP02	0.155270	5.047892	0.000000
XMIN02	0.442973	8.007793	0.000000
DMY02	2.137752	3.214704	0.001306
ACR02	0.268619	7.448452	0.000000
PTF02	-0.015661	-1.427719	0.153373
POP02	3.132331	4.032486	0.000055
WAG02	2.177200	5.450272	0.000000
UEM02	0.446885	3.608388	0.000308
PCI02	-5.725147	-1.375472	0.168985
ESI00	-0.273363	-1.886734	0.059196
PLA600	0.014061	4.336217	0.000014
rho	0.037978	1.535908	0.124561

Spatial Durbin Model (SDM) 2002

Dependent Variable = FIPS
R-squared = 0.8761
Rbar-squared = 0.8735
sigma^2 = 82.6359
log-likelihood = -7670.9847
Nobs, Nvars = 2339, 25
iterations = 14
min and max rho = -1.0000, 1.0000
total time in secs = 288.1570
time for lndet = 51.3280
time for t-stats = 221.8130
Pace and Barry, 1999 MC lndet approximation used
order for MC appr = 50
iter for MC appr = 30

Variable	Coefficient	Asymptotic t-stat	z-probability
ONE	11.784553	0.768678	0.442084
SIL02	16.775921	47.805951	0.000000
CRN02	-0.291545	-4.366656	0.000013
ALF02	0.539441	1.024252	0.305716
FD$02	0.238537	14.954220	0.000000
CAT02	-17.674250	-14.207949	0.000000
CAT5+02	0.553767	18.110920	0.000000
HOG02	-0.695982	-0.925779	0.354561
HGK+02	-0.167441	-4.827951	0.000001
DMO02	-0.546692	-0.526343	0.598650
MBP02	-1.911141	-2.217695	0.026576
LV$02	0.074911	0.972654	0.330725
T/VL02	-0.743980	-0.615940	0.537934
HUM97	-0.441233	-11.505222	0.000000
PCP02	0.097470	2.040740	0.041277
XMIN02	0.156296	1.731053	0.083442
DMY02	3.945216	4.163041	0.000031
ACR02	0.283262	6.461830	0.000000
PTF02	-0.036087	-2.546995	0.010865
POP02	0.715066	0.926131	0.354378
WAG02	1.102010	1.414974	0.157076
UEM02	0.117895	0.780779	0.434932
PCI02	-8.162742	-1.674499	0.094033
ESI00	-0.000288	-0.001256	0.998998
PLA600	-0.000511	-0.024460	0.980486
W-SIL02	-0.813110	-0.644620	0.519173
W-CRN02	-0.160820	-0.704377	0.481198
W-ALF02	2.736641	1.377436	0.168378
W-FD$02	-0.282862	-3.890676	0.000100
W-CAT02	27.815907	6.623396	0.000000

W-CAT5+02	-1.145805	-10.323601	0.000000
W-HOG02	-0.025849	-0.005097	0.995933
W-HGK+02	0.279341	1.109788	0.267090
W-DMO02	0.929627	0.469448	0.638749
W-MBP02	1.591477	1.319584	0.186974
W-LV$02	2.038001	6.938312	0.000000
W-T/VL02	3.221247	1.126117	0.260116
W-HUM97	0.132149	1.009160	0.312898
W-PCP02	-0.032077	-0.343707	0.731067
W-XMIN02	0.061774	0.493248	0.621837
W-DMY02	-4.342253	-2.271748	0.023102
W-ACR02	-0.398069	-3.152645	0.001618
W-PTF02	0.004249	0.119579	0.904816
W-POP02	18.066433	6.113062	0.000000
W-WAG02	1.218512	0.872164	0.383119
W-UEM02	-0.356788	-0.737107	0.461057
W-PCI02	-89.222086	-4.906272	0.000001
W-ESI00	-0.438072	-0.974056	0.330029
W-PLA600	-0.013360	-0.580892	0.561313
rho	-0.039963	-1.740672	0.081741

General Spatial Model Estimates (SAC) 2002

Dependent Variable = FIPS
R-squared = 0.8858
Rbar-squared = 0.8846
sigma^2 = 76.1284
log-likelihood = -6299.0873
Nobs, Nvars = 2339, 25
iterations = 57
total time in secs = 1150.7650
time for optimiz = 176.4530
time for lndet = 135.2510
time for t-stat = 815.3590

Variable	Coefficient	Asymptot t-stat	z-probability
ONE	21.675103	1.391761	0.163995
SIL02	16.949175	50.721303	0.000000
CRN02	-0.308386	-4.986378	0.000001
ALF02	0.523192	1.039665	0.298496
FD$02	0.218856	14.228822	0.000000
CAT02	-16.824087	-14.098731	0.000000
CAT5+02	0.517448	17.536859	0.000000
HOG02	-0.663079	-0.920412	0.357357
HGK+02	-0.159226	-4.814308	0.000001
DMO02	-0.542193	-0.556843	0.577635
MBP02	-1.761859	-2.111029	0.034770
LV$02	0.039539	0.541970	0.587839
T/VL02	0.485801	0.426945	0.669419
HUM97	-0.482852	-6.646493	0.000000
PCP02	0.041960	0.933002	0.350819
XMIN02	0.383306	3.971419	0.000071
DMY02	4.202368	4.729527	0.000002
ACR02	0.313353	7.602974	0.000000
PTF02	-0.020539	-1.534750	0.124845
POP02	-0.822022	-1.116359	0.264268
WAG02	0.826717	1.138315	0.254989
UEM02	0.190245	1.311826	0.189579
PCI02	-4.427214	-0.943547	0.345401
ESI00	0.110498	0.518096	0.604391
PLA600	0.030102	1.765136	0.077541
rho	-1.206933	-21.152117	0.000000
lambda	1.121856	76.240204	0.000000

Spatial Error Model Estimates (SEM) 2002

Dependent Variable = MMM02
R-squared = 0.8641
Rbar-squared = 0.8627
sigma^2 = 90.5781
log-likelihood = -7788.832
Nobs, Nvars = 2339, 25
iterations = 16
min and max rho = -0.9900, 0.9900
total time in secs = 175.1720
time for optimiz = 39.0000
time for lndet = 59.3440
time for t-stats = 74.5160
Pace and Barry, 1999 MC lndet approximation used
order for MC appr = 50
iter for MC appr = 30

Variable	Coefficient	Asymptot t-stat	z-probability
ONE	-24.155159	-6.011679	0.000000
SIL02	16.537644	47.222255	0.000000
CRN02	-0.267908	-4.382353	0.000012
ALF02	0.360341	0.664626	0.506290
FD$02	0.255170	15.777501	0.000000
CAT02	-18.025272	-14.465087	0.000000
CAT5+02	0.545526	17.679696	0.000000
HOG02	-1.063489	-1.367643	0.171424
HGK+02	-0.151548	-4.260352	0.000020
DMO02	-0.212479	-0.239644	0.810606
MBP02	-0.735451	-2.097474	0.035952
LV$02	0.155114	2.039286	0.041421
T/VL02	-1.270318	-1.142336	0.253314
HUM97	-0.232344	-3.645757	0.000267
PCP02	0.177714	4.499134	0.000007
XMIN02	0.348404	4.522097	0.000006
DMY02	2.870358	3.485767	0.000491
ACR02	0.237228	5.819196	0.000000
PTF02	-0.022034	-1.730239	0.083588
POP02	1.732907	2.199708	0.027828
WAG02	1.785165	3.269808	0.001076
UEM02	0.264433	1.922080	0.054596
PCI02	-3.810989	-0.798839	0.424384
ESI00	-0.073616	-0.390907	0.695866
PLA600	0.016357	2.498088	0.012487
lambda	0.621954	19.950440	0.000000

Bayesian Spatial Autoregressive Tobit Model (SART) 2002

Dependent Variable = FIPS
mean of sige draws = 3.1808
r-value = 4
Nobs, Nvars = 2339, 25
censored values = 864
ndraws,nomit =1100, 100
time in secs = 6001.3590
min and max rho = -1.0000, 1.0000

Posterior Estimates

Variable	Coefficient	Std Deviation	p-level
ONE	1.929063	1.942333	0.148000
SIL02	7.102045	0.359875	0.000000
CRN02	-0.120528	0.014482	0.000000
ALF02	-0.015015	0.227227	0.465000
FD$02	0.002157	0.004817	0.320000
CAT02	1.212922	0.446984	0.003000
CAT5+02	-0.081890	0.011970	0.000000
HOG02	-0.241078	0.213802	0.131000
HGK+02	0.007614	0.010994	0.248000
DMO02	0.531226	0.180323	0.001000
MBP02	-0.178194	0.116816	0.062000
LV$02	0.284920	0.033772	0.000000
T/VL02	0.512370	0.269942	0.027000
HUM97	0.001683	0.013679	0.462000
PCP02	0.051063	0.008939	0.000000
XMIN02	-0.072759	0.014888	0.000000
DMY02	0.329223	0.164966	0.025000
ACR02	-0.015752	0.011045	0.078000
PTF02	-0.002553	0.003067	0.198000
POP02	-0.391491	0.184285	0.014000
WAG02	0.150068	0.105119	0.085000
UEM02	-0.057376	0.033178	0.043000
PCI02	-2.532503	1.217139	0.015000
ESI00	0.055786	0.036965	0.058000
PLA600	0.005489	0.000808	0.000000
rho	0.028024	0.007773	0.000000

Bayesian Spatial Durbin Tobit Model (SDMT) 2002

Dependent Variable = FIPS
sige = 4.5146
r-value = 4
Nobs, Nvars = 2339, 50
censored values = 864
ndraws,nomit = 1100, 100
total time in secs = 6066.8750
time for eigs = 27.0780
time for sampling = 6032.4220
Pace and Barry, 1999 MC lndet approximation used
order for MC appr = 50
iter for MC appr = 30
min and max rho = -1.0000, 1.0000

Variable	Coefficient	Std Deviation	p-level
ONE	4.627627	5.985455	0.211000
SIL02	8.533226	0.337614	0.000000
CRN02	-0.085895	0.022391	0.000000
ALF02	0.567852	0.342262	0.053000
FD$02	-0.005160	0.005595	0.179000
CAT02	0.352260	0.573749	0.269000
CAT5+02	-0.058685	0.014808	0.000000
HOG02	-0.050727	0.219863	0.422000
HGK+02	-0.001127	0.011496	0.443000
DMO02	0.244677	0.316060	0.223000
MBP02	-0.012826	0.267774	0.489000
LV$02	0.147551	0.052086	0.001000
T/VL02	0.655696	0.409531	0.045000
HUM97	-0.039268	0.032986	0.114000
PCP02	-0.006799	0.019003	0.353000
XMIN02	-0.054818	0.041064	0.092000
DMY02	-0.282934	0.286842	0.157000
ACR02	0.003224	0.023565	0.451000
PTF02	0.016656	0.005074	0.000000
POP02	-0.107821	0.427082	0.403000
WAG02	0.072130	0.226055	0.382000
UEM02	-0.163586	0.050545	0.002000
PCI02	-4.903901	1.736512	0.003000
ESI00	0.051634	0.066216	0.225000
PLA600	0.022553	0.006722	0.000000
W-SIL02	-8.124624	0.780415	0.000000
W-CRN02	-0.050704	0.072742	0.242000
W-ALF02	0.071164	0.923973	0.474000
W-FD$02	0.089083	0.025779	0.001000
W-CAT02	-2.152972	1.616593	0.093000
W-CAT5+02	0.062196	0.045557	0.093000

W-HOG02	-0.190397	1.534171	0.446000
W-HGK+02	-0.026077	0.076229	0.370000
W-DMO02	-1.623234	0.645669	0.007000
W-MBP02	-0.412451	0.428689	0.155000
W-LV$02	0.026291	0.163964	0.438000
W-T/VL02	-2.202889	1.002861	0.018000
W-HUM97	0.110470	0.053803	0.016000
W-PCP02	0.043570	0.034756	0.112000
W-XMIN02	0.105655	0.068183	0.054000
W-DMY02	1.802334	0.586725	0.001000
W-ACR02	0.006143	0.058441	0.462000
W-PTF02	-0.018802	0.011225	0.050000
W-POP02	-0.508232	2.746517	0.413000
W-WAG02	-0.863305	0.449598	0.032000
W-UEM02	-0.310536	0.163258	0.027000
W-PCI02	-3.734124	8.606724	0.339000
W-ESI00	0.388984	0.138225	0.002000
W-PLA600	-0.017663	0.007674	0.015000
rho	0.973265	0.016570	0.000000

Bayesian Spatial Error Tobit model (SEMT) 2002

Dependent Variable = FIPS
R-squared = 0.6873
sigma^2 = 3.5010
r-value = 4
Nobs, Nvars = 2339, 25
censored values = 864
ndraws,nomit = 1100, 100
time in secs = 524.2190
min and max lambda = -3.4392, 1.0000

Posterior Estimates

Variable	Coefficient	Std Deviation	p-level
ONE	-1.772011	2.359026	0.228000
SIL02	14.088829	0.196895	0.000000
CRN02	-0.135481	0.015223	0.000000
ALF02	-0.396911	0.193050	0.015000
FD$02	0.004704	0.005021	0.182000
CAT02	2.954827	0.539319	0.000000
CAT5+02	-0.124180	0.015976	0.000000
HOG02	0.151152	0.193801	0.201000
HGK+02	-0.030103	0.010402	0.005000
DMO02	0.742452	0.194569	0.000000
MBP02	-0.192891	0.133194	0.079000
LV$02	0.361579	0.038295	0.000000
T/VL02	0.602685	0.270753	0.010000
HUM97	0.027263	0.015922	0.035000
PCP02	0.049280	0.009708	0.000000
XMIN02	-0.045968	0.017277	0.001000
DMY02	0.392943	0.173323	0.011000
ACR02	-0.106987	0.025590	0.000000
PTF02	-0.015688	0.003346	0.000000
POP02	-0.831704	0.406833	0.020000
WAG02	0.183122	0.114813	0.051000
UEM02	0.066517	0.035143	0.031000
PCI02	-2.886450	1.407088	0.022000
ESI00	0.072380	0.042066	0.044000
PLA600	0.002002	0.000890	0.010000
lambda	0.018850	0.012058	0.000000

Spatial Autoregressive Model Estimates (SAR) 1997

Dependent Variable = MMM97
R-squared = 0.7888
Rbar-squared = 0.7867
sigma^2 = 81.0506
Nobs, Nvars = 2380, 25
log-likelihood = -7782.6351
# of iterations = 12
min and max rho = -1.0000, 1.0000
total time in secs = 130.8280
time for lndet = 53.4060
time for t-stats = 66.9220
Pace and Barry, 1999 MC lndet approximation used
order for MC appr = 50
iter for MC appr = 30

Variable	Coefficient	Asymptotic t-stat	z-probability
ONE	-26.837927	-2.353195	0.018613
SIL97	13.244057	40.801927	0.000000
CRN97	-0.292518	-6.200200	0.000000
ALF97	1.031654	2.067255	0.038710
FD$97	0.130457	10.863059	0.000000
CAT97	-13.057591	-13.655755	0.000000
CAT5+97	0.553971	22.192477	0.000000
HOG97	-1.499985	-1.532498	0.125400
HGK+97	-0.023081	-0.564096	0.572689
DMO97	1.889504	3.620101	0.000294
MBP97	-0.573376	-1.028983	0.303488
LV$97	0.373598	3.700946	0.000215
T/VL97	2.142070	2.278565	0.022693
HUM97	-0.106859	-2.833820	0.004600
PCP97	0.137601	4.907440	0.000001
XMIN97	0.348361	6.800255	0.000000
DMY97	1.789378	2.828639	0.004675
ACR97	0.221164	7.974510	0.000000
PTF97	-0.008157	-1.111089	0.266530
POP97	2.483279	3.359623	0.000780
WAG97	0.749247	3.986066	0.000067
UEM97	-0.004642	-0.081936	0.934697
PCI97	-7.448380	-1.978030	0.047925
ESI00	0.059544	0.435432	0.663249
PLA600	0.021816	7.224481	0.000000
rho	0.115952	2.221869	0.026292

Spatial Durbin Model (SDM) 1997

Dependent Variable = MMM97
R-squared = 0.8274
Rbar-squared = 0.8238
sigma^2 = 67.2942
log-likelihood = -7561.0266
Nobs, Nvars = 2380, 25
iterations = 15
min and max rho = -1.0000, 1.0000
total time in secs = 310.1250
time for lndet = 55.1870
time for t-stats = 244.0790
Pace and Barry, 1999 MC lndet approximation used
order for MC appr = 50
iter for MC appr = 30

Variable	Coefficient	Asymptotic t-stat	z-probability
ONE	29.942686	8.986797	0.000000
SIL97	13.347711	39.122103	0.000000
CRN97	-0.316461	-5.022573	0.000001
ALF97	0.109334	0.215960	0.829019
FD$97	0.124236	10.536561	0.000000
CAT97	-14.769893	-14.558961	0.000000
CAT5+97	0.691729	27.280510	0.000000
HOG97	-0.744711	-0.798578	0.424535
HGK+97	-0.079691	-2.029429	0.042415
DMO97	0.722014	1.113619	0.265443
MBP97	0.469068	0.665996	0.505414
LV$97	0.172943	1.718309	0.085740
T/VL97	3.700816	3.208991	0.001332
HUM97	-0.335003	-4.994873	0.000001
PCP97	0.081558	1.824814	0.068029
XMIN97	0.140673	1.590720	0.111673
DMY97	1.623194	1.884132	0.059547
ACR97	0.212855	5.316311	0.000000
PTF97	-0.021061	-1.674999	0.093934
POP97	0.319987	0.457039	0.647643
WAG97	-0.547813	-0.752227	0.451915
UEM97	-0.131095	-1.714484	0.086440
PCI97	-10.740411	-1.700036	0.089124
ESI00	0.106910	0.510367	0.609794
PLA600	-0.024776	-1.403544	0.160455
W-SIL97	-2.358012	-1.831866	0.066971
W-CRN97	0.065387	0.357160	0.720972
W-ALF97	8.445649	5.310010	0.000000
W-FD$97	-0.216221	-3.558090	0.000374

W-CAT97	28.117131	7.769204	0.000000
W-CAT5+97	-1.313527	-15.625021	0.000000
W-HOG97	0.189049	0.036040	0.971250
W-HGK+97	0.139415	0.617915	0.536631
W-DMO97	1.039196	0.728413	0.466361
W-MBP97	-0.821755	-0.805686	0.420424
W-LV$97	3.247355	10.553082	0.000000
W-T/VL97	2.751721	1.050215	0.293619
W-HUM97	0.120720	1.017237	0.309041
W-PCP97	-0.068010	-0.875246	0.381440
W-XMIN97	-0.072008	-0.618569	0.536200
W-DMY97	-5.399645	-2.821507	0.004780
W-ACR97	-0.461715	-4.072183	0.000047
W-PTF97	-0.023190	-0.760133	0.447175
W-POP97	12.286830	4.138265	0.000035
W-WAG97	-0.123917	-0.092413	0.926370
W-UEM97	-0.102772	-0.383766	0.701152
W-PCI97	-91.080318	-4.474414	0.000008
W-ESI00	0.135695	0.335059	0.737581
W-PLA600	0.012499	0.643409	0.519959
rho	0.005972	0.400127	0.689063

General Spatial Model Estimates SAC 1997

Dependent Variable = FIPS
R-squared = 0.8391
Rbar-squared =0.8375
sigma^2 = 62.7351
log-likelihood = -6175.3064
Nobs, Nvars = 2380, 25
iterations = 53
total time in secs = 1124.2970
time for optimiz = 189.4840
time for lndet = 120.9380
time for t-stat = 796.3130

Variable	Coefficient	Asymptot t-stat	z-probability
ONE	14.009428	1.232305	0.217835
SIL97	13.881869	42.329444	0.000000
CRN97	-0.292360	-4.926348	0.000001
ALF97	-0.079312	-0.162799	0.870676
FD$97	0.109803	9.630489	0.000000
CAT97	-13.784250	-14.001606	0.000000
CAT5+97	0.639094	25.450455	0.000000
HOG97	-0.661046	-0.734955	0.462367
HGK+97	-0.083985	-2.221904	0.026290
DMO97	0.949174	1.544089	0.122567
MBP97	0.163209	0.239944	0.810373
LV$97	0.131929	1.365293	0.172161
T/VL97	5.482393	5.027321	0.000000
HUM97	-0.391495	-5.902098	0.000000
PCP97	0.024398	0.584927	0.558596
XMIN97	0.292093	3.334831	0.000854
DMY97	1.467147	1.798765	0.072056
ACR97	0.220275	5.786911	0.000000
PTF97	-0.003412	-0.286209	0.774718
POP97	-0.679170	-1.014522	0.310334
WAG97	-1.001396	-1.478821	0.139188
UEM97	-0.088320	-1.197223	0.231220
PCI97	-5.327842	-0.883039	0.377215
ESI00	0.284738	1.441799	0.149359
PLA600	0.002896	0.189406	0.849775
rho	-1.402249	-20.834784	0.000000
lambda	1.129699	76.689286	0.000000

Spatial Error Model Estimates (SEM) 1997

Dependent Variable = MMM97
R-squared = 0.8085
Rbar-squared = 0.8066
sigma^2 = 74.6617
log-likelihood = -7704.3519
Nobs, Nvars = 2380, 25
iterations = 14
min and max rho = -0.9900, 0.9900
total time in secs = 281.3280
time for optimiz = 39.3130
time for lndet = 150.6410
time for t-stats = 88.3280
Pace and Barry, 1999 MC lndet approximation used
order for MC appr = 50
iter for MC appr = 30

Variable	Coefficient	Asymptot t-stat	z-probability
ONE	-15.241435	-1.112622	0.265871
SIL97	13.254688	38.207924	0.000000
CRN97	-0.277555	-4.511180	0.000006
ALF97	-0.293780	-0.554921	0.578949
FD$97	0.137323	11.297769	0.000000
CAT97	-15.618317	-14.810618	0.000000
CAT5+97	0.715905	25.332583	0.000000
HOG97	-0.940984	-0.967102	0.333493
HGK+97	-0.075707	-1.852993	0.063883
DMO97	1.132090	1.795242	0.072615
MBP97	0.279120	0.373333	0.708900
LV$97	0.225004	2.152998	0.031319
T/VL97	4.035814	3.674147	0.000239
HUM97	-0.193050	-3.050466	0.002285
PCP97	0.137923	3.525136	0.000423
XMIN97	0.181853	2.253426	0.024232
DMY97	1.177653	1.437406	0.150603
ACR97	0.164843	4.102640	0.000041
PTF97	-0.008778	-0.718861	0.472226
POP97	1.144157	1.569176	0.116607
WAG97	0.092479	0.125130	0.900421
UEM97	-0.126765	-1.535369	0.124693
PCI97	-4.515406	-0.691443	0.489287
ESI00	0.130040	0.687913	0.491508
PLA600	0.022607	2.615912	0.008899
lambda	0.781980	13.892232	0.000000

Bayesian Spatial Autoregressive Tobit Model (SART) 1997

Dependent Variable = FIPS
mean of sige draws = 2.1366
r-value = 4
Nobs, Nvars = 2380, 25
censored values = 736
ndraws,nomit =1100, 100
time in secs = 6305.6560
min and max rho = -1.0000, 1.0000

Posterior Estimates

Variable	Coefficient	Std Deviation	p-level
ONE	3.754281	1.473110	0.006000
SIL97	6.965348	0.272558	0.000000
CRN97	-0.149781	0.013345	0.000000
ALF97	0.110040	0.161003	0.233000
FD$97	0.002417	0.003150	0.225000
CAT97	0.047171	0.329338	0.438000
CAT5+97	-0.034212	0.008820	0.000000
HOG97	-0.328058	0.243698	0.075000
HGK+97	0.005238	0.010654	0.323000
DMO97	0.510543	0.119652	0.000000
MBP97	-0.429133	0.094359	0.000000
LV$97	0.385073	0.036725	0.000000
T/VL97	0.863503	0.233568	0.000000
HUM97	0.011189	0.010425	0.143000
PCP97	0.042160	0.006474	0.000000
XMIN97	-0.035051	0.011804	0.002000
DMY97	0.158899	0.139251	0.126000
ACR97	-0.013587	0.009901	0.091000
PTF97	-0.000376	0.002455	0.426000
POP97	-0.139880	0.148005	0.163000
WAG97	-0.001126	0.100713	0.488000
UEM97	-0.106919	0.018688	0.000000
PCI97	-6.600554	1.482932	0.000000
ESI00	0.115599	0.029420	0.000000
PLA600	0.005866	0.000663	0.000000
rho	0.051812	0.008713	0.000000

Bayesian Spatial Durbin Tobit Model (SDMT) 1997

Dependent Variable = FIPS
sige = 3.2932
r-value = 4
Nobs, Nvars = 2380, 50
censored values = 736
ndraws,nomit = 1100, 100
total time in secs = 6374.8280
time for eigs = 27.9530
time for sampling = 6338.6560
Pace and Barry, 1999 MC lndet approximation used
order for MC appr = 50
iter for MC appr = 30
min and max rho = -1.0000, 1.0000

Variable	Coefficient	Std Deviation	p-level
ONE	-8.637840	5.012585	0.048000
SIL97	7.836141	0.296184	0.000000
CRN97	-0.110902	0.021826	0.000000
ALF97	0.910735	0.282681	0.000000
FD$97	0.001015	0.003884	0.386000
CAT97	0.011263	0.474097	0.498000
CAT5+97	-0.040057	0.012640	0.000000
HOG97	-0.031413	0.288197	0.459000
HGK+97	-0.001030	0.012213	0.463000
DMO97	0.360679	0.173867	0.025000
MBP97	0.317532	0.197559	0.060000
LV$97	0.219969	0.057444	0.000000
T/VL97	1.358414	0.376198	0.000000
HUM97	-0.006294	0.027507	0.400000
PCP97	0.008309	0.014598	0.281000
XMIN97	-0.060179	0.033376	0.035000
DMY97	-0.437553	0.244466	0.033000
ACR97	-0.003800	0.020457	0.423000
PTF97	0.018219	0.003941	0.000000
POP97	0.066372	0.357053	0.430000
WAG97	-0.088532	0.209873	0.348000
UEM97	-0.104307	0.025170	0.000000
PCI97	-6.931830	2.028597	0.001000
ESI00	0.077726	0.062760	0.115000
PLA600	0.011418	0.005324	0.012000
W-SIL97	-6.422400	0.793189	0.000000
W-CRN97	0.041880	0.057298	0.234000
W-ALF97	-0.934422	0.816657	0.127000
W-FD$97	0.040296	0.019261	0.020000
W-CAT97	-0.325063	1.254211	0.403000
W-CAT5+97	0.108770	0.039480	0.003000

W-HOG97	-1.353389	1.547740	0.182000
W-HGK+97	0.011327	0.064477	0.420000
W-DMO97	-1.842846	0.437843	0.000000
W-MBP97	-0.107430	0.329232	0.374000
W-LV$97	-0.350677	0.176694	0.027000
W-T/VL97	-3.792257	0.967370	0.000000
W-HUM97	-0.016383	0.044535	0.349000
W-PCP97	0.020011	0.022962	0.192000
W-XMIN97	0.110778	0.055227	0.021000
W-DMY97	2.130338	0.641433	0.001000
W-ACR97	-0.090946	0.056333	0.053000
W-PTF97	-0.022106	0.009327	0.007000
W-POP97	2.928191	2.506278	0.130000
W-WAG97	0.536482	0.475154	0.120000
W-UEM97	0.166825	0.098548	0.054000
W-PCI97	5.161657	9.912999	0.296000
W-ESI00	0.230949	0.123012	0.025000
W-PLA600	-0.004203	0.005922	0.227000
rho	0.870357	0.039438	0.000000

Bayesian Spatial Error Tobit Model (SEMT) 1997

Dependent Variable = FIPS
R-squared = 0.5797
sigma^2 = 3.0532
r-value = 4
Nobs, Nvars = 2380, 25
censored values = 736
ndraws,nomit = 1100, 100
time in secs = 526.2960
min and max lambda = -3.6977, 1.0000

Posterior Estimates

Variable	Coefficient	Std Deviation	p-level
ONE	3.643619	2.146506	0.048000
SIL97	12.151593	0.132941	0.000000
CRN97	-0.188355	0.015878	0.000000
ALF97	0.239870	0.322403	0.235000
FD$97	0.005528	0.003192	0.036000
CAT97	1.024147	0.423798	0.009000
CAT5+97	-0.043712	0.010672	0.000000
HOG97	-0.387396	0.311970	0.108000
HGK+97	-0.006920	0.014218	0.315000
DMO97	0.566202	0.138533	0.000000
MBP97	-0.735956	0.121587	0.000000
LV$97	0.534189	0.044808	0.000000
T/VL97	1.062209	0.249179	0.000000
HUM97	0.077031	0.015114	0.000000
PCP97	0.047570	0.007988	0.000000
XMIN97	-0.040361	0.018120	0.013000
DMY97	0.170284	0.167162	0.149000
ACR97	-0.114744	0.023925	0.000000
PTF97	-0.006577	0.002931	0.014000
POP97	0.120870	0.196281	0.271000
WAG97	-0.198771	0.125329	0.062000
UEM97	-0.085318	0.022849	0.000000
PCI97	-8.458059	1.847405	0.000000
ESI00	0.291684	0.037779	0.000000
PLA600	0.004080	0.000863	0.000000
lambda	0.071950	0.019535	0.000000

Spatial Autoregressive Model Estimates (SAR) 2002-1997
Dependent Variable = MMM02-MMM97
R-squared = 0.5346
Rbar-squared = 0.5294
sigma^2 = 29.8919
Nobs, Nvars = 2154, 25
log-likelihood = -5969.5684
# of iterations = 12
min and max rho = -1.0000, 1.0000
total time in secs = 178.1720
time for lndet = 86.3130
time for t-stats = 64.4690
Pace and Barry, 1999 MC lndet approximation used
order for MC appr = 50
iter for MC appr = 30

Variable	Coefficient	Asymptotic t-stat	z-probability
ONE	-1.955372	-0.499005	0.617776
SIL97	4.294903	20.923963	0.000000
CRN97	-0.117647	-3.273737	0.001061
ALF97	0.248844	0.744410	0.456628
FD$97	-0.012363	-1.636977	0.101635
CAT97	-6.024286	-9.404402	0.000000
CAT5+97	0.282597	17.870075	0.000000
HOG97	1.887910	3.027665	0.002465
HGK+97	-0.077849	-2.961784	0.003059
DMO97	0.445397	1.361827	0.173252
MBP97	-0.227577	-0.893120	0.371793
LV$97	0.324071	5.947881	0.000000
T/VL97	-3.282753	-6.186833	0.000000
HUM97	-0.057017	-2.022487	0.043126
PCP97	0.000938	0.053768	0.957120
XMIN97	0.117804	3.596412	0.000323
DMY97	0.635359	1.512223	0.130477
ACR97	-0.115228	-5.275277	0.000000
PTF97	-0.026735	-4.253394	0.000021
POP97	-0.993910	-2.105308	0.035265
WAG97	0.436129	1.516445	0.129407
UEM97	0.090726	1.855826	0.063478
PCI97	-8.624923	-2.159780	0.030790
ESI00	-0.093451	-1.136922	0.255571
PLA600	0.005631	3.065200	0.002175
rho	0.155971	2.201676	0.027688

Spatial Durbin Model (SDM) 2002-1997

Dependent Variable = MMM02-MMM97
R-squared = 0.5563
Rbar-squared = 0.5462
sigma^2 = 28.0170
log-likelihood = -5903.2118
Nobs, Nvars = 2154, 25
iterations = 14
min and max rho = -1.0000, 1.0000
total time in secs = 258.0940
time for lndet = 46.3280
time for t-stats = 194.6560
Pace and Barry, 1999 MC lndet approximation used
order for MC appr = 50
iter for MC appr = 30

Variable	Coefficient	Asymptotic t-stat	z-probability
ONE	12.293867	2.200957	0.027739
SIL97	4.267868	18.761306	0.000000
CRN97	-0.168024	-3.735620	0.000187
ALF97	0.826970	2.325539	0.020043
FD$97	-0.023375	-2.993899	0.002754
CAT97	-6.332673	-8.944541	0.000000
CAT5+97	0.317281	18.421629	0.000000
HOG97	1.729046	2.727662	0.006379
HGK+97	-0.082405	-3.103694	0.001911
DMO97	0.088332	0.200778	0.840872
MBP97	0.110354	0.215146	0.829653
LV$97	0.386313	5.780252	0.000000
T/VL97	-2.686371	-3.441632	0.000578
HUM97	0.048376	1.190012	0.234042
PCP97	-0.016422	-0.533472	0.593707
XMIN97	-0.001623	-0.026020	0.979241
DMY97	0.325064	0.557654	0.577081
ACR97	-0.154375	-5.820310	0.000000
PTF97	-0.047255	-5.569066	0.000000
POP97	-0.731089	-1.459164	0.144520
WAG97	0.511087	1.041215	0.297776
UEM97	0.079705	1.504147	0.132544
PCI97	-1.922511	-0.441804	0.658631
ESI00	-0.069196	-0.484868	0.627770
PLA600	0.005339	0.323498	0.746318
W-SIL97	-3.890925	-3.832382	0.000127
W-CRN97	0.140344	0.965510	0.334290
W-ALF97	-3.602143	-2.925007	0.003444
W-FD$97	0.228213	5.492843	0.000000
W-CAT97	-0.167240	-0.067575	0.946124

W-CAT5+97	-0.230814	-3.628524	0.000285
W-HOG97	-6.549785	-1.842139	0.065455
W-HGK+97	0.225870	1.409300	0.158746
W-DMO97	0.363773	0.362836	0.716728
W-MBP97	-0.094270	-0.141442	0.887521
W-LV$97	0.567666	2.565069	0.010316
W-T/VL97	5.653875	3.169193	0.001529
W-HUM97	-0.179320	-2.572721	0.010090
W-PCP97	-0.026372	-0.504259	0.614079
W-XMIN97	0.063514	0.670796	0.502351
W-DMY97	0.278617	0.230394	0.817785
W-ACR97	0.148057	1.928577	0.053783
W-PTF97	0.032106	1.591410	0.111517
W-POP97	-8.942372	-4.754982	0.000002
W-WAG97	-0.323207	-0.364681	0.715350
W-UEM97	-0.237751	-1.340562	0.180063
W-PCI97	-42.147684	-2.628311	0.008581
W-ESI00	-0.361249	-1.313556	0.188996
W-PLA600	-0.000775	-0.043253	0.965500
rho	0.409959	5.187148	0.000000

General Spatial Model Estimates (SAC) 2002-1997

R-squared = 0.5545
Rbar-squared = 0.5495
sigma^2 = 28.9293
log-likelihood = -4716.0911
Nobs, Nvars = 2154, 25
iterations = 55
total time in secs = 939.6250
time for optimiz = 169.8900
time for lndet = 123.1100
time for t-stat = 629.7970

Variable	Coefficient	Asymptot t-stat	z-probability
ONE	-0.948056	-0.157751	0.874653
SIL97	4.364806	19.851621	0.000000
CRN97	-0.138850	-3.375312	0.000737
ALF97	0.730161	2.080463	0.037483
FD$97	-0.018875	-2.459477	0.013914
CAT97	-6.420218	-9.284466	0.000000
CAT5+97	0.306196	17.949121	0.000000
HOG97	1.882883	2.963581	0.003041
HGK+97	-0.083581	-3.139602	0.001692
DMO97	0.049856	0.123567	0.901658
MBP97	-0.109612	-0.268840	0.788053
LV$97	0.394617	5.975611	0.000000
T/VL97	-3.157222	-4.622954	0.000004
HUM97	-0.020613	-0.536773	0.591424
PCP97	-0.023627	-0.973597	0.330257
XMIN97	0.059258	1.215418	0.224207
DMY97	0.514777	0.995568	0.319460
ACR97	-0.147203	-5.881363	0.000000
PTF97	-0.042595	-5.695122	0.000000
POP97	-0.615729	-1.235481	0.216651
WAG97	0.548326	1.445396	0.148347
UEM97	0.100710	1.924303	0.054317
PCI97	-5.355253	-1.261854	0.207001
ESI97	-0.115252	-0.965629	0.334230
PLA600	0.005312	1.137656	0.255264
rho	-0.200993	-3.747773	0.000178
lambda	0.708998	7.276409	0.000000

Spatial Error Model Estimates (SEM) 2002-1997

Dependent Variable = MMM 97
R-squared = 0.8641
Rbar-squared = 0.8627
sigma^2 = 90.5649
log-likelihood = -7788.7188
Nobs, Nvars = 2339, 25
iterations = 14
min and max rho = -0.9900, 0.9900
total time in secs = 165.2660
time for optimiz = 26.7820
time for lndet = 61.1250
time for t-stats = 76.9840
Pace and Barry, 1999 MC lndet approximation used
order for MC appr = 50
iter for MC appr = 30

Variable	Coefficient	Asymptot t-stat	z-probability
ONE	-23.962769	-6.017855	0.000000
SIL97	16.537188	47.203210	0.000000
CRN97	-0.268042	-4.380330	0.000012
ALF97	0.359760	0.663449	0.507043
FD$97	0.255277	15.782108	0.000000
CAT97	-18.036186	-14.469260	0.000000
CAT5+97	.546133	17.700652	0.000000
HOG97	-1.060806	-1.364140	0.172524
HGK+97	0.151788	-4.267067	0.000020
DMO97	0.219047	-0.246729	0.805118
MBP97	-0.737511	-2.108775	0.034964
LV$97	0.153888	2.022348	0.043140
T/VL97	-1.265974	-1.137084	0.255503
HUM97	-0.232844	-3.646267	0.000266
PCP97	0.177759	4.490884	0.000007
XMIN97	0.346953	4.490517	0.000007
DMY97	0.876757	3.488298	0.000486
ACR97	0.237036	5.810403	0.000000
PTF97	-0.022038	-1.728757	0.083853
POP97	1.725000	2.189502	0.028560
WAG97	0.781359	3.254449	0.001136
UEM97	0.262733	1.910341	0.056089
PCI97	-3.805865	-0.797486	0.425169
ESI00	-0.071907	-0.381086	0.703139
PLA600	0.016357	2.480245	0.013129
lambda	0.625983	19.642662	0.000000

Bayesian Spatial Autoregressive Model 2002-1997
Heteroscedastic model
Dependent Variable = MMM02-MMM97
R-squared = 0.0599
Rbar-squared = 0.0493
mean of sige draws = 0.4176
sige, epe/(n-k) = 61.7659
r-value = 4
Nobs, Nvars = 2154, 25
ndraws,nomit = 1000, 100
total time in secs = 89.0630
time for lndet = 55.2040
time for sampling = 25.6880
Pace and Barry, 1999 MC lndet approximation used
order for MC appr = 50
iter for MC appr = 30
min and max rho = -1.0000, 1.0000
Posterior Estimates

Variable	Coefficient	Std Deviation	p-level
ONE	0.812584	0.474728	0.050000
SIL97	0.604845	0.090489	0.000000
CRN97	0.008429	0.005246	0.054444
ALF97	-0.014624	0.067187	0.407778
FD$97	-0.000807	0.001156	0.248889
CAT97	-0.626489	0.130000	0.000000
CAT5+97	0.008544	0.003155	0.002222
HOG97	0.068598	0.081503	0.202222
HGK+97	-0.001853	0.004039	0.327778
DMO97	-0.110794	0.043990	0.003333
MBP97	-0.004881	0.032704	0.423333
LV$97	-0.014470	0.011931	0.110000
T/VL97	0.077656	0.083189	0.181111
HUM97	-0.001390	0.003726	0.365556
PCP97	-0.001602	0.002358	0.245556
XMIN97	0.001408	0.004249	0.361111
DMY97	0.009886	0.056379	0.435556
ACR97	0.000008	0.003007	0.520000
PTF97	-0.000603	0.000832	0.227778
POP97	-0.210790	0.080540	0.012222
WAG97	-0.074094	0.040641	0.041111
UEM97	0.002897	0.006144	0.321111
PCI97	-0.636895	0.534484	0.128889
ESI00	-0.005744	0.011113	0.310000
PLA600	-0.000624	0.000253	0.005556
rho	0.008817	0.008155	0.142222

Bayesian Spatial Durbin Model 2002-1997

Heteroscedastic model
Dependent Variable = FIPS
R-squared = 0.0596
mean of sige draws = 0.4278
sige, epe/(n-k) = 62.4949
r-value = 4
Nobs, Nvars = 2154, 50
ndraws,nomit = 1000, 100
total time in secs = 121.1090
time for lndet = 54.2180
time for sampling = 59.1560
Pace and Barry, 1999 MC lndet approximation used
order for MC appr = 50
iter for MC appr = 30
min and max rho = -1.0000, 1.0000

Variable	Coefficient	Std Deviation	p-level
ONE	0.721180	1.350424	0.297778
SIL97	0.646861	0.118214	0.000000
CRN97	0.004947	0.006900	0.246667
ALF97	0.032970	0.086932	0.346667
FD$97	-0.000346	0.001259	0.392222
CAT97	-0.585234	0.163473	0.000000
CAT5+97	0.007644	0.003684	0.018889
HOG97	0.076073	0.087134	0.194444
HGK+97	-0.002188	0.004381	0.304444
DMO97	-0.057346	0.060248	0.161111
MBP97	-0.023479	0.067338	0.370000
LV$97	-0.007600	0.015093	0.310000
T/VL97	0.110701	0.109671	0.171111
HUM97	0.000805	0.006739	0.454444
PCP97	-0.001572	0.004452	0.373333
XMIN97	0.005310	0.009592	0.295556
DMY97	0.163074	0.082476	0.016667
ACR97	-0.000970	0.004261	0.402222
PTF97	-0.000408	0.001162	0.338889
POP97	-0.142857	0.105004	0.101111
WAG97	-0.071523	0.072716	0.163333
UEM97	0.003541	0.006812	0.303333
PCI97	-0.762072	0.593270	0.100000
ESI00	0.006505	0.019506	0.360000
PLA600	-0.003405	0.002367	0.083333
W-SIL97	-0.231545	0.173922	0.090000
W-CRN97	0.013365	0.019522	0.247778
W-ALF97	-0.163226	0.203867	0.221111
W-FD$97	-0.002788	0.006026	0.323333

W-CAT97	-0.098368	0.389955	0.394444
W-CAT5+97	0.003539	0.009990	0.348889
W-HOG97	-0.495029	0.454956	0.132222
W-HGK+97	0.022475	0.020711	0.137778
W-DMO97	-0.206652	0.141535	0.070000
W-MBP97	-0.003721	0.099977	0.480000
W-LV$97	-0.026506	0.036559	0.231111
W-T/VL97	0.052414	0.257449	0.416667
W-HUM97	0.008154	0.011561	0.237778
W-PCP97	-0.007217	0.007054	0.152222
W-XMIN97	-0.002943	0.014084	0.420000
W-DMY97	-0.381013	0.183529	0.014444
W-ACR97	0.008063	0.011125	0.222222
W-PTF97	-0.003312	0.002811	0.115556
W-POP97	-0.548337	0.365165	0.054444
W-WAG97	0.017671	0.145064	0.461111
W-UEM97	-0.016544	0.026768	0.257778
W-PCI97	1.505372	2.518609	0.265556
W-ESI00	-0.028868	0.037345	0.201111
W-PLA600	0.003149	0.002552	0.110000
rho	0.050964	0.017283	0.001111