Determinants of Iowa Cropland Cash Rental Rates: Testing Ricardian Rent Theory

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Abstract

Based on the Ricardian rent theory, this study employs the variable profit function to analyze the determinants of Iowa cropland cash rental rates using county-level panel data from 1987 to 2005. Accounting for spatial and temporal autocorrelations, responses of local cash rental rates to changes in output prices and other exogenous variables are estimated. We find that Iowa cash rental rates are largely determined by output/input prices, soil quality, relative location, and other county-specific factors. Cash rents go up by $79 for a $1 increase in corn price in the short run. The marginal value of cropland quality, as represented by row-crop corn suitability rating index, is about $1.05. Ethanol plants are not found to have a significant local effect on cash rental rates, impacting local rental markets mainly through the national futures price. Scale of the local livestock industry and adoption of genetically engineered crops have significant impacts on local cash rental rates. In addition, changes in crop output prices are found to have long-run effects on cash rental rates. The long-run change in cash rents is approximately $109-$114 for a $1 change in corn price and is reached in about four years. Our research may be viewed as a test of the Ricardian rent theory. We find limited support for the theory.

Iowa is one of the major corn growing states in the United States, producing 19% of U.S. corn and 16% of U.S. soybeans in 2006. As a result of rapid expansion in the ethanol industry, the amount of corn used for ethanol production increased from 600 million bushels in 2001 to nearly 1.8 billion bushels in 2006. The U.S. Department of Agriculture estimates that 3.4 billion bushels of corn will be used in ethanol production in the 2007/08 crop year. In spring 2007, farmers responded by planting an estimated 92.9 million acres to corn, the most since World War II, and a 19% increase over 2006. Biofuel-derived demand for corn pushed up the price of corn nearly 70% between September 2006 and March 2007. How do the cash rental rates respond to high corn prices? Do they increase immediately to the new equilibrium level or adjust dynamically? These are the sorts of questions we seek to answer in this study.

Farmland is the main financial asset of crop farmers. In 2006, the total value of Iowa's 32.6 million acres of farmland was about $105 billion and the average value per acre was at an all-time high of $3,204 (Iowa State University Extension 2006a). A better understanding of the determinants of local cash rental rates is important because, for Iowa, an increasing fraction of farmland is being farmed by tenant operators. Excluding land in government programs, the amount of land that is rented increased from 43% to 59% between 1982 and 2002. By 2002 more than two-thirds of the leased farmland was under a cash rent arrangement (Iowa State University Extension 2004).

In the Ricardian rent theory, rent is defined as "that portion of the produce of the earth, which is paid to the landlord for the use of the original and indestructible powers of the soil" (Ricardo 1821, p. 67). Ricardo argued that rent is what remains from gross farm revenue after all the production costs have been paid. In Ricardo's view, rent is the value of the difference in productivity, which is crucial in determining the existence and magnitude of land rent. Ricardo explained this by pointing out that in the first settling of a country, only the very best lands go under cultivation. These lands are the most fertile, the closest to the market, and with

the lowest cost for producing grain. When the last piece of land is cultivated, production cost equals the sum of wage cost and the normal rate of profit, assuming that rent on this last piece of land is zero and the farmers are indifferent between farming and not farming. But on the more productive land, higher productivity produces a surplus that is expropriated by the landlord in the form of rent.

Economic theory suggests that higher crop production profits resulting from good grain prices will ultimately accrue to the farmland owners because farmland, not labor, is the most limiting resource in agriculture. It is reasonable to assume that tenant farmers are identical and in plentiful supply since much of farm labor involves only lower levels of technical skills. Demand for farm labor has been rapidly reduced because of mechanization and other labor-saving technologies. Farm jobs fell from 12.4% of non-metro low-skill jobs in 1976 to 6.2% by 2004 (Gibbs, Kusmin, and Cromartie 2005). From 1960 to 2004, total labor (hired, self-employed and unpaid family) use in Iowa agriculture declined by about 90% (Huffman 2007). Much of this labor has been available to re-enter agriculture if only because many farmers have reluctantly turned to part-time off-farm employment. Hence, farmland becomes the residual claimant of profits. Farmers bid aggressively to expand their land base. With the assumption of free entry and exit from farming in a perfectly competitive market, competitive bidding on land use ensures that rent payments equal the difference between revenues and other costs.

The objective of this study is to empirically investigate the determinants of Iowa cropland cash rental rates, to analyze the dynamic adjustment process of cash rental rates to changes in output prices, and to provide evidence on the validity of the Ricardian rent theory. The literature on formal analysis of farmland cash rental rates is limited. Kurkalova, Burkart, and Secchi (2004) estimated the cropland cash rental rates in the Upper Mississippi River Basin in 1997. Assuming the cropland cash rental rate to be a monotonic function of corn yield potential, they express the per acre cash rental rate as a function of the corn yield estimate. Dhuyvetter

and Kastens (2002) used a costs-based approach to determine equitable crop share and then determined the cash equivalent amount of that crop share arrangement. The cash rental rates are obtained after that value has been risk-adjusted. In the literature on seeking to measure the incidence of agricultural subsidies on land rents, several papers have discussed different ways of modeling farmland rental rates. Lence and Mishra (2003) modeled land rents as a function of acreage-weighted corn and soybean revenues and government payments. Goodwin, Mishra, and Ortalo-Magné (2004) developed regressions of cash rents against expected market earnings, expected government payments, and indicators of urban pressure.

The land rent literature is distinct from, but strongly related to, the land price literature. In that literature, land rent is the most widely accepted factor affecting farmland price. Early studies found evidence to support a causal relationship between land rents and farmland prices. They tended to conclude that residual returns, or rents, unidirectionally cause farmland prices (Phipps 1984; Awokuse and Duke 2006). But because of the apparent divergence between comparatively stable farm income levels and continuously increasing land prices, people have sought other theoretical and empirical frameworks to help explain the farmland price movement.

Most studies of farmland pricing have assumed that the value of an income-producing asset is the capitalized value of the current and future stream of earnings from owning the asset, known as the constant discount rate present value model (CDR-PVM). Traditional time series analysis also provided support for the validity of this linkage, in which changes in expected returns to farming should explain changes in farmland prices. However, studies found that the CDR-PVM may not be appropriate for pricing farmland. Falk (1991) found that although farmland price and rent movements are highly correlated, price movements are not consistent with the implications of CDR-PVM. Tegene and Kuchler (1993) also rejected the present value model of land price. Lence and Miller (1999) didn't reject the CDR-PVM in the presence of typical transaction costs, and thus showed that the CDR-PVM is consistent with typical

transaction costs assuming a one-period holding horizon.

The focus of this study is on the farmland rental market instead of the asset market. Compared with land prices in the asset market, land rents more likely reflect optimal pricing behavior, as they are less vulnerable to asset bubbles and present less severe transaction costs issues. Although some progress has been made toward finding the relationship between land rents and land prices, the literature has not fully investigated the nature and determinants of land rents. A better grasp of the fundamentals of farmland cash rents might help us better understand land pricing issues. Thus, there is a need to examine what factors influence the level of land rents and how land rents respond to changes in exogenous variables. In this study, a unique data set of local cash rental rates is exploited. It consists of county-level cash rental rates for the state of Iowa from 1987 to 2005. The data were collected from an annual survey conducted by Iowa State University Extension. It appears to be unique because, to our knowledge, no other consistently collected county-level data covers any state in the United States.[1]

Our contributions are three-fold. First, we find the short-run determination of cash rental rates in Iowa. In particular we estimate how they are affected by output/input prices, soil quality, relative location, and other county-specific factors. We also find that cash rents go up by \$79 for a \$1 change of corn price in the short run. The marginal value of cropland quality is about \$1.05, as represented by the row-crop corn suitability rating index. And ethanol plants are not found to have a statistically significant local effect on cash rental rates, as their effects are largely channeled through national futures prices. Scale of local livestock industry and adoption rate of genetically engineered crops have significant impacts on local cash rental rates. Our second contribution is to contrast short- and long-run responses to corn prices. The possible changes of land rents is approximately \$109-\$114 for a \$1 change in corn price, which

[1]Most of the other rental rates collections have either county-level data for shorter periods of time or long time series data but only across fewer statistics regions. For example, University of Minnesota Extension has collected county-level data from 2002 to 2007; University of Nebraska Extension has data for 1981-2007, but only by agricultural statistics districts.

could be reached in three to four years. The first-year increase in land rents will be around $80 on average, which is consistent with our estimation result in the short-run analysis. Adjustment paths to the long-run equilibrium vary considerably across the state.

Our third contribution is to provide evidence on the validity of the Ricardian rent theory (RRT) in Ricardo's original and classical application, namely, in the farmland rental market. We believe we are the first to do so. Different from farmland in the arid West, where water rights are important, deep-soiled, well-watered farmland in rural Iowa is close to a "commodity" in crop production. Hence, our cash rental rates data are close to ideal for the purpose of testing the theory. In the short-run analysis, the RRT has been straightforwardly applied to farmland rental markets. It seems to handle the observed hedonic characteristics fairly well, giving plausible explanations for the determinants of local cash rental rates. But in the analysis of rent responses to a $1 increase in corn price, it seems to have failed. By contrast with the average value of $135 predicted by the theory, the rent response in the short run is estimated to be $80 from the variable profit function. The low estimation result may be due to inertia in leasing contract re-negotiations. Inertia can be explained by relationship-specific investments, community ties, and other related issues.

Hence, in addition to contemporaneous and static estimation, we also apply long-term, dynamic analysis. We obtain the long-run price effect of $109-$114, which still doesn't fully cover the theoretical value. We speculate that part of the reason for the discrepancy may be that intellectual property rights owned by seed suppliers provide them with bargaining power, so that they benefit in the process of cash rents allocation. In other words, the bargaining assumptions underlying the RRT may not be valid. And some of the disparity may also be explained by price and income supports provided by government programs, which may eliminate cash rents responses to output price movements when prices are low.

The paper proceeds as follows. First, a model of farmland cash rental rates is developed

using the variable profit function framework. A more detailed description of data follows. Then we present the estimation method for a random effects model that takes into account spatial and temporal autocorrelations. We also explain and analyze the estimation results. The dynamic effects of corn prices on cash rental rates are examined. Finally, concluding remarks are presented.

Methods

Consider a tenant farmer facing a multiple output production technology that has M variable outputs and inputs denoted by $y_i, i = 1, 2, ..., M$. Here, outputs are positive, $y_i > 0$, and inputs are negative, $y_i < 0$. There are also N fixed inputs denoted by $z_h, h = 1, 2, ..., N$. At the beginning of a production period, he/she rents land, which is in fixed supply in a certain region. The tenancy involves a formal contractual agreement, and the duration of a contract is for a year, which is renewable and renegotiable annually. In the production period, the tenant farmer makes all the input and production decisions. He/she also pays a fixed cash rental rate to the landowner. Following the RRT, land rent is the highest bid a tenant can afford to pay for the use of the land. It is the rental value, which will make the tenant farmer indifferent between farming and not farming.

Let R be the fixed cash rental rate, $p_i, i = 1, 2, ..., M$ be the output/input prices, and let $x_l, l = 1, 2, ..., L$ denote a number of region-specific factors. The time variable t is included to proxy technological change. For Q, the set of technically feasible output and input choices, the cash rental rate for one unit of land is determined by

$$R(\mathbf{p}; \mathbf{z}, \mathbf{x}, t) = \pi(\mathbf{p}; \mathbf{z}, \mathbf{x}, t) = \max \left\{ \sum_{i=1}^{M} p_i y_i; (\mathbf{y}; \mathbf{z}, \mathbf{x}, t) \in Q \right\}.$$

Here, $\mathbf{y}$, $\mathbf{p}$, $\mathbf{z}$, and $\mathbf{x}$ are the vectors of the outputs/inputs, output/input prices, fixed inputs,

and region-specific factors, respectively. Thus, rent is the profit, or residual farm return (farm return less variable costs), obtained from the use of rented land given the production possibilities set Q.

The cash rental rate $R(\mathbf{p}; \mathbf{z}, \mathbf{x}, t)$ has the following properties (Chambers 1988, p. 120), which ensure that a one-to-one relationship exists between the production technology and its dual transformation: (1) homogeneous of degree one in $\mathbf{p}$; and (2) non-decreasing (non-increasing) and convex in p_i if i is an output (input). The convexity of the cash rental rate function in prices $p_i, i = 1, 2, ..., M$ requires that the Hessian matrix with element $\partial^2\pi/\partial p_i \partial p_j, i, j = 1, 2, ..., M$ be positive semi-definite.

To examine the determinants of local cash rental rates and obtain a set of output supply, variable input demand and fixed input shadow price equations, we need to adopt a flexible functional form for the profit function, which is a second-order Taylor's approximation to any arbitrary functional form. The transcendental logarithmic function form (Chambers 1988, p. 180; Weaver 1983; McKay, Lawrence, and Vlastuin 1983) is employed for the cash rental rates function and is written as

$$\begin{aligned} \ln(R) &= \alpha_0 + \sum_{i=1}^{M} \alpha_i \ln(p_i) + \frac{1}{2} \sum_{i=1}^{M} \sum_{j=1}^{M} \gamma_{ij} \ln(p_i) \ln(p_j) + \sum_{h=1}^{N} \beta_h z_h + \frac{1}{2} \sum_{h=1}^{N} \sum_{k=1}^{N} \phi_{hk} z_h z_k \\ &\quad + \sum_{i=1}^{M} \sum_{h=1}^{N} \delta_{ih} \ln(p_i) z_h + \sum_{i=1}^{M} \phi_{it} \ln(p_i) t + \sum_{h=1}^{N} \varphi_{ht} z_h t + \sum_{l=1}^{L} \eta_l x_l + \phi_t t + \frac{1}{2} \phi_{tt} t^2 \end{aligned} \tag{1}$$

The symmetry conditions need to be imposed to ensure the profit function is fully identifiable. Linear homogeneity of cash rental rates function in prices $p_i, i = 1, 2, ..., M$, requires further restrictions. The restrictions are

$$\text{Symmetry:} \quad \gamma_{ij} = \gamma_{ji}, \quad \phi_{hk} = \phi_{kh}. \tag{2}$$

$$\text{(3)} \qquad \text{Homogeneity:} \quad \sum_{i=1}^{M} \alpha_i = 1, \quad \sum_{i=1}^{M} \gamma_{ij} = 0, \quad \sum_{i=1}^{M} \phi_{it} = 0, \quad \sum_{i=1}^{M} \delta_{ih} = 0.$$

We impose the linear homogeneity condition in $\mathbf{p}$ by normalizing all input/output prices and price-related variables by one of the output prices, say, p_M. Thus, equation (1) can be rewritten as the following, where $\mathbf{p}^* = (p_1/p_M, p_2/p_M, ..., p_{M-1}/p_M)$ and $R^* = R/p_M$.

$$\begin{aligned} \ln(R^*) &= \alpha_0 + \sum_{i=1}^{M-1} \alpha_i \ln(p_i^*) + \frac{1}{2} \sum_{i=1}^{M-1} \sum_{j=1}^{M-1} \gamma_{ij} \ln(p_i^*) \ln(p_j^*) + \sum_{h=1}^{N} \beta_h z_h + \frac{1}{2} \sum_{h=1}^{N} \sum_{k=1}^{N} \phi_{hk} z_h z_k \\ &+ \sum_{i=1}^{M-1} \sum_{h=1}^{N} \delta_{ih} \ln(p_i^*) z_h + \sum_{i=1}^{M-1} \phi_{it} \ln(p_i^*) t + \sum_{h=1}^{N} \varphi_{ht} z_h t + \sum_{l=1}^{L} \eta_l x_l + \phi_t t + \frac{1}{2} \phi_{tt} t^2 \end{aligned} \tag{4}$$

Equation (4) is estimated based on the data described in the next section.

Data

In this study, we used annual survey data of typical cash rental rates per acre of cropland for the state of Iowa over the period 1987-2005 as reported in Iowa State University Extension (2007). Copies of this survey were mailed to potential respondents in March. Potential respondents were persons employed in one of the following occupations: (1) agricultural leaders, (2) real estate brokers, (3) professional farm managers, (4) farmers, and (5) landowners. In the survey, the respondents provide information based on their best judgments about typical cash rental rates for cropland at the county level. The survey is to be mailed back by early May. For each county, there are about 15-20 responses by individuals doing business in that county or a neighboring county. This data set provides a reasonably accurate measure of typical cash rents of corn and soybean farmland for Iowa counties.

While initiated in 1980, the actual survey data didn't cover all 99 counties of Iowa until 1997. In order to ensure temporal variation in our panel data set, we choose the cash rental

rates data covering 83 counties in Iowa.[2] Among the total 99 counties, we include most of the counties in northern and western Iowa. The 16 counties in the southeast corner of the state are left out because of data limitations. Most of the missing counties started to collect cash rental rates data after 1995. The cash rental rates for the 83 counties in 2005 are shown in figure 1.

We choose y =(corn, soybean, fertilizer) as the outputs and variable input; x =(soil quality, distance indices to terminal market) as fixed inputs, where the distance indices are in both south-north and east-west directions for each county. County-level scale of livestock industry, local ethanol production effect, normalized distance to nearby metropolitan areas, and adoption rate of genetically engineered crops are chosen as county-specific factors influencing local cash rental rates. Each of these chosen variables and its relationship to local cash rental rates is now discussed in greater detail.

Output and Input Prices

In Iowa, most corn is planted between April 20 and May 10. The optimum time to plant varies from year to year; however, having planting done by mid-May is a goal most producers strive to achieve (Iowa State University Extension 2001). Similarly, the planting time for soybeans is from May 15 to June 1. Crops are harvested from October to November of the same year. In each spring, the tenant farmer must make decisions on planting and input choices as well as formulate marketing plans for the new crop year. They can observe and use price information from the futures contracts expiring right after harvest time to formulate harvest price expectations. On the Chicago Board of Trade (CBOT), the December contract for corn and the November contract for soybeans are the first available futures contracts after harvest time. Hence we use spring average prices of corn and soybean futures contracts as expected output prices in our study. They are calculated as the average daily settlement prices for

[2]See the Appendix for detailed information about missing data, omitted counties, and data treatment.

the December (November) maturity futures contract during April for corn (soybeans).[3] The producer price index for nitrogen fertilizer is used as the input price, which can be found in the ERS/USDA data set "U.S. Fertilizer Use and Price."

Soil Quality

Soil quality is the capacity of the soil to function. Its critical functions for agricultural production include sustaining productivity and biological activity, regulating and partitioning water flow, filtering and buffering, and storing and cycling nutrients (Karlen et al. 1997). Besides the corn suitability rating (CSR) index used in this study, traditional measures of soil quality include (1) land capability classes (LCC) and the prime farmland designation to measure land capability and suitability, which have been collected in the National Resources Inventory (NRI); (2) crop yield per acre to measure soil productivity; and (3) highly erodible land (HEL) to measure soil erodibility (U.S. Department of Agriculture 1997).

The CSR is an index procedure developed in Iowa to rate each type of soil for its potential row-crop productivity (Iowa State University Extension 2006b). The CSR considers average weather conditions as well as frequency of use of the soil for row-crop production. Ratings range from 100 for soils that have no physical limitations, occur on minimal slopes, and can be continuously row-cropped, to as low as 5 for soils with severe limitations for row crops. Land with a CSR rating below 65 is generally considered to be unsuitable for row crop production. The CSR can be used to rate the potential yield of one soil against that of another over a relatively long period of time. In our case, we assume the CSR remains unchanged over our sampling period. Each soil type in Iowa has a CSR. By identifying the soil types and acres of each soil type in a tract of land, a weighted average CSR can be computed for the tract.

We use the average row-crop CSR index to measure soil quality in this study, as reported

[3]The reason we use the average April price is explained in the next section.

in Iowa State University Extension (2007). By assuming that best-quality farmland is put into crop production, the county-level index is obtained by (1) sorting the acreage of each soil type in a county by the CSR in descending order; (2) using the county's actual crop planting acreage to locate the cut-off point in the CSR series; and (3) multiplying the CSR at a given level above the cut-off point by the corresponding acres, then dividing the result by the county's planting acreage. The average row-crop CSR index map of Iowa is shown in figure 2.

Since the CSR measures the general soil productivity, good corn farmland is also considered to be good soybean land. Figure 2 illustrates that a large proportion of land in Iowa is high-grade farmland and can be planted to crops. Most counties have an average row-crop CSR index above 70. Farmland in North Central Iowa has higher quality than land elsewhere. Southern Iowa has the worst quality farmland compared with the rest of the state, mainly because it tends to have higher erodibility.

Distance to Terminal Market

We use the relative location of each county in both south-north and east-west directions to reflect a county's distance to terminal market and relative transportation cost. Counties located closer to the Mississippi River have a transportation advantage since these locations provide better access to international and domestic terminal markets. For farmers in these counties, it has been beneficial to transport their harvest by waterway, the cheapest mode of transportation. Taking advantage of the rectangle shapes and arrangement of most counties in Iowa, we identify relative location using two distance indices in the south-north and east-west directions. The relative distance indices for the southeast corner of the state (Lee County) are assumed to be 1 and 2.5, respectively. The numbers in parentheses in figure 3 are the distance indices we used in this study.

Scale of Livestock Industry

Iowa ranked seventh in cattle production in 2006. Cattle are raised all around the state. Iowa also leads the nation in pork production, raising 25% of U.S. hogs in 2006. The livestock industry has been the Iowa corn grower's most important customer. Prior to the expansion of the ethanol market, two-thirds of Iowa's corn crop had gone to feed livestock. The presence of livestock in a county should increase local demand for corn and thus increase cropland rental prices. Also, the Iowa livestock industry generates large quantities of manure and other organic residues. The vast majority of operations apply the waste directly to land owned or rented by the operation or sell the manure to nearby areas. Availability of livestock manure is expected to affect local cash rents.

We use total grain-consuming animal units in each county to represent a county's scale of livestock industry. An animal unit is a standard unit for comparing actual animal numbers for the main types of livestock raised in Iowa, including cattle, hogs, and sheep/lambs. An animal unit is based on the dry-weight quantity of feed consumed by the average milk cow during the base period. We adopted a set of animal unit conversion factors, developed by the U.S. Department of Agriculture (1974), to relate feed consumption for each type of livestock to the feed consumed by the average milk cow.

Data were obtained from various sources. The county-level annual cattle (1987-90, 2001-07), hogs (1987-89), and sheep/lambs (1987-90) quantity data were downloaded from the website of the National Agricultural Statistics Service (NASS 2007). The three years (1992, 1997 and 2002) of Census of Agriculture data from NASS are used to linearly interpolate the missing data. Figure 4 shows total grain-consuming animal units for the sample counties in 2005.

Ethanol Plant Effect

The effect ethanol plants have on corn price and basis has been an issue investigated in several papers. McNew and Griffith (2005) examined the impact of ethanol plants on local grain market prices by estimating the effects of 12 ethanol plants in the Midwest that opened in 2001 and 2002. They found that these new ethanol plants increased local grain prices, but markets downstream from a new plant have a smaller price impact. Gallagher, Wisner, and Brubacker (2006) conducted a cross-sectional price-location analysis for 270 cities and towns in Iowa in spring 2003 to determine the impact of ethanol plants on the corn price surface. The results showed that for four conventional non-farmer-owned firms, price increases as one gets closer to the processing plants; while five of six farmer cooperatives failed to show any statistically significant effect on nearby prices. Olson, Klein, and Taylor (2007) found the impact of ethanol production on corn basis varies by district in South Dakota from \$0.04 to \$0.27 per bushel, with a state average impact of \$0.24 in 2005.

Iowa had an early start in corn-based ethanol production. By the end of 2006, there were 23 ethanol plants operating in 22 counties with total production capacity of 1.2 billion gallons, as shown in table 1. In this study, a county's index of ethanol plant effect is constructed by summing its weights in corn supply areas over nearby ethanol plants using

$$E_{it} = \sum_{n=1}^{N_t} w_{in}(t).$$

Here $w_{in}(t)$ is the proportion that county i has in the corn supply area of ethanol plant n at year t. Each corn supply area is assumed to be a circle centered at the ethanol production facility and to be proportional to the production capacity of that plant. N_t is total number of ethanol plants in production at time t. All counties inside each corn supply area share the total supply, i.e., the proportion ranges from 0 to 1 and the sum over all counties is 1. Following opening

dates of ethanol plants, we construct the panel data of the effect of ethanol production on all sample counties for the period 1987-2005. Figure 5 shows the ethanol plants in operation by the end of 2005 and the corresponding corn supply areas, which are based on the map constructed in Wisner (2006).

But the cash rents data may not be disaggregated enough, spatially and temporally, to fully capture the local effect of ethanol plants. This may be especially true when an ethanol plant is not located at the geographic center of a county. It is difficult to identify the true hinterland of an ethanol plant, as it depends on fine local geography. Table 1 also shows that the vast majority of ethanol production capacity came online since January 2004. This new capacity has been spatially dispersed, but mainly in the North Central and Northwest of the state. We also notice that ethanol demand for corn has affected the corn prices pattern across Iowa since January 2006 (Hart 2007). Typically, by contrast with the strongest basis in East Iowa, North Central and West Iowa tend to have the weakest basis, which is mainly determined by transportation costs. This basis pattern is consistent with what we attempt to capture by the distance to terminal market variable in this study. But many ethanol plants opened between fall 2005 and fall 2006 and this is likely the reason for the basis shift in North Central and Northwest Iowa. In short, we are not very confident about the variable's ability to identify the existence of this effect.

Urbanization Effect

Land price in the farmland market is greatly influenced by development pressure of accessible urban areas (Shi, Phipps, and Colyer 1997). Livanis et al. (2006) showed that urban sprawl has three important effects on farmland values: (1) it changes non-farm opportunities, (2) it creates a speculative component, and (3) it can alter net agricultural returns. While Iowa is not a rapidly developing state, urban expansion, together with other non-farming motives for

purchases, are among the long-term factors influencing Iowa's farmland market (Duffy 2004). Closer proximity to big metropolitan areas generates stronger development pressures and could possibly lead to higher cash rental rates.

The influence of urban development on local farmland rental markets should increase with the size of urban population and decrease with the distance between two locations. Hence, the urbanization influence of a metropolitan area on each county is measured by the distance between them, normalized by the population in that area. The urbanization effect index for county i is represented by the minimum value of all urbanization influences as

$$\mathrm{UE}_i = \min\left(\frac{d_{ij}}{n_j}\right), \quad \forall j$$

where d_{ij} is the distance between county i and metropolitan area j, $j = 1, 2, ..., 10$ in our case, and n_j is the population size of that metropolitan area.

By the ranking for population of metropolitan statistical areas the in U.S. (U.S. Census Bureau 2000), the top 10 biggest metropolitan areas in Iowa are chosen. The included areas are Omaha/Council Bluffs, Des Moines, Davenport/Moline/Rock Island, Cedar Rapids, Sioux Falls, Waterloo/Cedar Falls, Sioux City, Iowa City, Dubuque, and Ames. Figure 6 shows locations of chosen areas with population data from the U.S. Census 2000 in parentheses. Google Maps data are used to measure the distances between the geographic center of each county and nearby metropolitan areas.

Adoption of Genetically Engineered Crops

Iowa farmers have adopted genetically engineered (GE) crops widely since their introduction in 1996. One of the most important benefits of GE crops has been to confer tolerance to herbicides that are used for weed control (Byrne et al. 2004). Another important benefit of GE crops is

to confer protection against insect pests. This class of crop trait could substantially improve yields where pest damage is rampant and/or reduce use of chemical pesticides (Wu and Butz 2004).

Many field tests and farm surveys have examined the yield and cost effects of using GE crops. The majority of the results show that GE crops produce slightly higher yields than conventional crops. Based on 1996-1998 Agricultural Resources Management Survey data, the U.S. Department of Agriculture (USDA) has observed that adopters of Bt corn have obtained higher yields than non-adopters. Fernandez-Cornejo and Caswell (2006) point out that currently available GE crops do not increase the yield potential of a hybrid variety. However, GE crops can prevent yield losses as compared with non-GE hybrids, particularly when pest infestation is high. Pesticide use rates on corn and soybeans have declined since the introduction of GE corn and soybeans in 1996.

The labor savings obtained from less weeding and pesticide spraying leads to a drop in labor demand for a given level of output. With a fixed amount of labor, machinery input, and time available in a planting season, a higher adoption rate of GE crops is expected to result in excess production capacity in the short run. In turn, this should motivate tenant farmers to compete for more farmland through bidding up cash rental rates. Hence, we expect that adoption of GE crops should have a significant positive effect on cash rental rates. State-level adoption rates, as given by total planting acreage data, are drawn from the ERS/USDA data set "Adoption of Genetically Engineered Crops in the U.S."

Estimation

Since cash rental rates are not accounting profits, we do not have a breakdown of profit sources. Therefore it is inappropriate to use the commonly applied seemingly unrelated regressions

(SUR) estimation procedure to jointly estimate the parameters in output supply and input demand share equations. Using soybean price as the numéraire price, we consider the estimation of equation (4) based on the panel data of 83 counties over 1987 to 2005.

In dealing with this panel data set, we explicitly take into account (1) spatial autocorrelation due to neighboring counties; (2) temporal autocorrelation due to time-lagged behavior of farmland rental agreements; and (3) individual heterogeneity across counties. The county-level data are organized by spatial units of observations. The existence of spatial dependence follows from the existence of a variety of spatial interaction phenomena. The estimations errors of these contiguous counties are correlated. The test result for spatial autocorrelation based on Moran's I statistic (Anselin 1988, p. 101) is $Z_I = 80.530$ and statistically significant. Farmland rental agreements are also liable to exhibit lagged behavior over time. Temporal autocorrelation in the error term is expected. Applying the Wooldridge test for autocorrelation in panel data (Wooldridge 2002, p. 282), we get the value of the F-statistic as 296.715, which is statistically significant and confirms our expectation.

Next, we account for heterogeneity across counties by using the random effects estimator. To justify the random effects model, a one-sided Breusch and Pagan's Lagrange Multiplier test (Greene 2003, p. 224) for the null hypothesis of no random effects, $\sigma_\mu^2 = 0$, yields a χ_1^2 test statistic of 277.82, which is statistically significant. However, we are still concerned about possible correlation between the regressors and the random effects. To address this concern, we compute a Hausman test statistic for misspecification (Greene 2003, p. 301), based on the difference between the fixed effects and random effects estimators. This yields a χ_{20}^2 test statistic of 1.28 with $P > \chi_{20}^2 = 0.99$, which is not statistically significant. Therefore, we fail to reject the null hypothesis of exogeneity, and the random effects estimator is found to be consistent and asymptotically efficient.

With these complications, there is no ready-to-use procedure to estimate equation (4). Fol-

lowing the likelihood function derivation in Baltagi et al. (2004), we extend the estimation procedure proposed by Elhorst (2003) to a panel data random effects model accounting for both spatial and temporal autocorrelations.[4] Our panel data regression model is specified as

$$y_{ti} = X'_{ti}\beta + u_{ti} \tag{5}$$

where $i = 1, ..., N$ denotes the cross-section dimension and $t = 1, ..., T$ denotes the time series dimension. The cash rental rate on the ith county for the tth time period is y_{ti}. The K dimensional vector of explanatory variables defined in equation (4) is X_{ti}.

By assumption, the disturbance term u_{ti} has random county effects, spatially autocorrelated residual disturbances, and first-order serially correlated residual disturbances. Employing a random effects model, we have the disturbance term for time t:

$$u_t = \mu + \epsilon_t \tag{6}$$

where $u_t = (u_{t1}, ..., u_{tN})'$. And $\mu = (\mu_1, \mu_2, ..., \mu_N)'$ denotes the unobserved individual random effects for the counties. We assume $\mu \overset{iid}{\sim} N(0, \sigma^2_\mu)$ to be independent of ϵ. Vector $\epsilon_t = (\epsilon_{t1}, ..., \epsilon_{tN})'$ represents the residual disturbance and can be expressed as

$$\epsilon_t = \delta W \epsilon_t + \nu_t, \quad \text{and} \quad \nu_t = \rho \nu_{t-1} + e_t \tag{7}$$

where $\nu_t = (\nu_{t1}, ..., \nu_{tN})'$ and $e_t = (e_{t1}, ..., e_{tN})'$. The spatial autocorrelation coefficient satisfying $|\delta| < 1$ is δ, while ρ is the temporal autocorrelation coefficient in the range of $(-1, 1)$.

W is the spatial contiguity matrix and is constructed based on the notion of binary contiguity between spatial units, i.e., two counties having a common border of non-zero length are

[4]The codes are modified from the Matlab code provided by Dr. Elhorst, which is for the random effects model with spatial autocorrelation and can be found at http://www.regroningen.nl/irios.html.

considered to be contiguous. A value of 1 is assigned for the corresponding matrix element; otherwise the element is 0. The diagonal elements of W are all 0 since one spatial unit can't be its own neighbor. And the rows of the W matrix are standardized so that they sum to one.

With the normality assumption of $e_{ti} \sim N(0, \sigma_e^2)$, we have $\nu_{it} \sim N\left(0, \sigma_e^2/(1-\rho^2)\right)$ by equation (7). Let $B = I_N - \delta W$, $\theta^2 = \frac{\sigma_\mu^2}{\sigma_e^2}$, $\alpha = \sqrt{\frac{1+\rho}{1-\rho}}$, $d^2 = (\iota_T^\alpha)'\iota_T^\alpha$ with $\iota_T^\alpha = (\alpha, \iota_{T-1}')$, and assign ι_T as a vector of ones of dimension T. The log-likelihood function for the panel data regression model can be written as[5]

$$
\begin{aligned}
l(\beta, \sigma_e^2, \delta, \rho, \theta^2) &= -\frac{NT}{2}\ln(2\pi\sigma_e^2) + \frac{1}{2}N\ln(1-\rho^2) - \frac{1}{2}\sum_{i=1}^{N}\ln\left(1 + d^2(1-\rho)^2\theta^2(1-\delta w_i)^2\right) \\
&\quad + T\sum_{i=1}^{N}\ln(1-\delta w_i) - \frac{1}{2\sigma_e^2}\sum_{t=1}^{T} e_t^{**\prime} e_t^{**} \qquad (8)
\end{aligned}
$$

where $e_t^{**} = y_t^{**} - X_t^{**}\beta$, and

$$
\begin{aligned}
y_t^{**} &= P\overline{y}_\alpha^* + B(y_t^* - \overline{y}_\alpha^*) = (I_N - \delta W)y_t^* + (P\overline{y}_\alpha^* - (I_N - \delta W)\overline{y}_\alpha^*) \\
X_t^{**} &= (I_N - \delta W)X_t^* + \left(P\overline{X}_\alpha^* - (I_N - \delta W)\overline{X}_\alpha^*\right) \qquad (9)
\end{aligned}
$$

Here, w_i is the ith characteristic root of W, $\overline{y}_\alpha^*$ is the "α" average of y_t, i.e., $\overline{y}_\alpha^* = y_t' \times \iota_T^\alpha/(\alpha + T - 1)$, and $\overline{X}_\alpha^*$ is similarly defined. P is such that $P'P = \left(d^2(1-\rho)^2\theta^2 I_N + (B'B)^{-1}\right)^{-1}$. Here $P = \Lambda^{-\frac{1}{2}}R$, where R is an $N \times N$ matrix in which the ith column is the characteristic vector r_i of $\left(d^2(1-\rho)^2\theta^2 I_N + (B'B)^{-1}\right)^{-1}$. Note that r_i is the same as the characteristic vector of the spatial weight matrix W. And Λ is an $N \times N$ diagonal matrix with the ith diagonal element being $c_i = d^2(1-\rho)^2\theta^2 + 1/(1-\delta w_i)^2$.

[5]See Baltagi et al. (2004) and Elhorst (2003) for details on a very similar derivation.

Estimates of β and σ_e^2 are then solved as follows:

$$\hat{\beta} = \left(X^{**\prime}X^{**}\right)^{-1}\left(X^{**\prime}y^{**}\right) \quad \text{and} \quad \hat{\sigma_e^2} = \sum_{i=1}^{N} e_t^{**\prime}e_t^{**}/NT \tag{10}$$

Substituting $\hat{\beta}$ and $\hat{\sigma_e^2}$ into the log-likelihood function (8), the concentrated log-likelihood function of δ, ρ and θ^2 is obtained:

$$\begin{aligned} l(\delta,\rho,\theta^2) &= \text{Constant} - \frac{NT}{2}\ln\left(\sum_{t=1}^{T} e_t^{**\prime}e_t^{**}\right) - \frac{1}{2}\sum_{i=1}^{N}\ln\left(1+d^2(1-\rho)^2\theta^2(1-\delta w_i)^2\right) \\ &\quad + \frac{1}{2}N\ln(1-\rho^2) + T\sum_{i=1}^{N}\ln(1-\delta w_i) \end{aligned} \tag{11}$$

In summary, the estimation procedure is as follows:

1. Choose the initial values of δ, ρ and θ^2 in the specified ranges.

2. Given δ, ρ and θ^2, solve for $\hat{\beta}$ from equation (10), which is the generalized least square (GLS) estimator of β.

3. Substitute the $\hat{\beta}$ obtained in step (2) into equation (11), then use optimization techniques to obtain maximum likelihood estimates (MLE) of δ, ρ and θ^2.

4. Iterate between step (2) and step (3) until results satisfy a predetermined convergence criterion.

Price Data Selection

Before we get into discussion of the estimation results, one point that needs to be made clear concerns why we use average April futures price as expected output price in our estimation. The actual cash rental rates data collection happens in spring (April) while most rental contracts are entered into in late summer (August) of the previous year. In the annual cash rental rates

survey, experts are asked to provide information about "current, typical" cash rental rates in their counties. Rental contracts are sometimes renegotiated after major price movements. What happens is that the landowner and tenant farmer sometimes agree to wait until after January to set the rent in the event that prices rise significantly after September 1st. It is not clear whether the experts answer the question with reference to prior August rental agreements or to the market environment pertaining at the time of the survey response.

In order to further determine the information content of cash rental rates data, we follow the idea of a comprehensive specification test (Greene 2003, p. 154). In our case, Model 1 is the model using average year t April price for the year t harvest futures contract price, while Model 0 uses average year $t-1$ August price for the year t harvest contract price. Other model specifications are the same as the variable profit function structure in equation (4).

In the unrestricted model, we assume that the actual price in forming the expected output price takes the form of a weighted average of April and August prices, as

$$\kappa \ln(p_{Apr}) + (1-\kappa)\ln(p_{Aug}).$$

Here, p_{Apr} and p_{Aug} are the average April price in year t and August price in year $t-1$, respectively, and κ is a weight between 0 and 1. Model 0 assumes $\kappa = 0$ and Model 1 assumes $\kappa = 1$. We use the concentrated log-likelihood function (11) to find the maximum likelihood estimate of κ using grid search. This is a simplified estimation method since κ cannot be separately estimated with other parameters in equation (11). The result in table 2 shows that the maximum likelihood estimate of κ is 1, which means that model 1 is the appropriate model for the estimation. Variable descriptions and estimates of the parameters in equation (4) are given in tables 3 and 4. The parameter estimates for the numéraire output, soybeans, are derived using the symmetry and homogeneity constraints in equations (2)-(3).

Analysis of Estimation Results

From the estimation results, the coefficients of spatial autocorrelation (δ), temporal autocorrelation (ρ), and the fraction of variance due to unobservable effects (θ^2) are all statistically significant at the 1% level, which confirms our model specification tests. Furthermore, the point estimate of spatial autocorrelation is 0.789 and highly significant. This indicates the existence of important spatial dependencies in the data. The point estimate of the temporal autocorrelation is 0.371 and is also highly significant. This confirms the existence of time-lagged behavior in farmland rental agreements.

All the coefficients of region-specific factors have intuitively correct signs. Scale of livestock industry, normalized distance to metropolitan areas, and adoption rate of GE crops all significantly affect the local cash rental rates. As expected, total animal units and adoption of GE crops considerably increase what tenant farmers pay to landowners. The urbanization effect is estimated as -0.023 and is marginally significant. This indicates that farmland rents are somewhat higher for counties closer to big metropolitan areas, as expected. That the effect is only marginally significant should not be surprising, as Iowa is a rural state, and county-level reporting units are likely insufficiently disaggregated to catch any small-city effects. The estimated coefficient of ethanol production effect is 0.011 and is not significant, which means that production of ethanol plants in Iowa have not been found to have a local effect on cash rental rates. We have already included national futures prices as expected output prices, accounting for the global effect of ethanol production. So ethanol production impacts local farmland rental markets mainly through the national futures price.

If the RRT applies, then Hotelling's Lemma allows profit share equations to be obtained as

$$S_i = \frac{\partial \ln(R)}{\partial \ln(p_i)} = \frac{p_i y_i}{R}, \quad i = 1, 2, ..., M. \tag{12}$$

where S_i is the share of net output i in variable profit. Here, $S_i > 0$ if p_i is an output price and $S_i < 0$ if p_i is an input price.

For the fixed input, we have the similar derivation as

$$s_h = \frac{\partial \ln(R)}{\partial z_h} = \frac{w_{z_h}}{R}, \quad h = 1, 2, ..., N. \tag{13}$$

where w_{z_h} is the shadow price of fixed input z_h. And the fixed input share equations can be defined as

$$\frac{z_h w_{z_h}}{R} = z_h \frac{\partial \ln(R)}{\partial z_h} = z_h s_h, \quad h = 1, 2, ..., N.$$

Applying (12) and (13) to equation (1) yields

$$\begin{aligned} S_i &= \alpha_i + \sum_{j=1}^{M} \gamma_{ij} \ln(p_j) + \sum_{h=1}^{N} \delta_{ih} z_h + \phi_{it} t, \quad i = 1, 2, ..., M. \\ s_h &= \beta_h + \sum_{k=1}^{N} \phi_{hk} z_k + \sum_{i=1}^{M} \delta_{ih} \ln(p_i) + \varphi_{ht} t, \quad h = 1, 2, ..., N. \\ w_{z_h} &= R \left(\beta_h + \sum_{k=1}^{N} \phi_{hk} z_k + \sum_{i=1}^{M} \delta_{ih} \ln(p_i) + \varphi_{ht} t \right), \quad h = 1, 2, ..., N. \end{aligned} \tag{14}$$

In our case, the estimated shares for outputs and fixed inputs are positive at sample means of explanatory variables. And the variable input, fertilizer, has negative estimated share. So the corresponding translog profit function satisfies the monotonicity requirement. The average shadow price of soil quality is about \$1.05, and the average shadow prices for relative location in the North (B_N) and West (B_W) are \$0.22 and \$1.11, respectively. These computations are performed at the sample means for all related variables.

For the translog functional form, the curvature constraint at the approximation point implies

that the following matrix is positive semi-definite:

$$H_1 = \begin{bmatrix} \gamma_{11} + \alpha_1^2 - \alpha_1 & \gamma_{12} + \alpha_1\alpha_2 & \cdots & \gamma_{1M} + \alpha_1\alpha_M \\ \gamma_{12} + \alpha_1\alpha_2 & \gamma_{22} + \alpha_2^2 - \alpha_2 & \cdots & \gamma_{2M} + \alpha_2\alpha_M \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{M1} + \alpha_M\alpha_1 & \gamma_{M2} + \alpha_M\alpha_2 & \cdots & \gamma_{MM} + \alpha_M^2 - \alpha_M \end{bmatrix}$$

It is not uncommon for this curvature property to be violated in empirical applications (Diewert and Wales 1987). In our case, the estimated translog profit function doesn't satisfy this curvature condition at the approximation point.

The price elasticities of variable input/output i with respect to price p_j are defined as

$$\begin{aligned} \epsilon_{ii} &= \frac{\gamma_{ii}}{S_i} + S_i - 1 \quad i = 1, 2, ..., M. \\ \epsilon_{ij} &= \frac{\gamma_{ij}}{S_i} + S_j \qquad i, j = 1, 2, ..., M, i \neq j. \end{aligned} \tag{15}$$

Here, ϵ_{ii} is the elasticity of supply (demand) if i is an output (variable input).

The elasticities of fixed input z_h's shadow price w_{z_h} with respect to input/output price p_i are

$$\varsigma_{ih} = S_i + \delta_{ih}, \qquad i = 1, 2, ..., M, h = 1, 2, ..., N. \tag{16}$$

The price responses of fixed input z_h with respect to quantity of the fixed input z_k are[6]

$$\begin{aligned} \zeta_{hh} &= R\left(s_h^2 + \phi_{hh}\right) \quad h = 1, 2, ..., N. \\ \zeta_{hk} &= R\left(s_h s_k + \phi_{hk}\right) \quad h, k = 1, 2, ..., N, h \neq k. \end{aligned} \tag{17}$$

[6]We calculate responses of prices instead of price elasticities because of the ordinal nature of the fixed input variables, the CSR index and the two relative location indices. It makes more sense to measure the responses to unit changes, rather than percentage changes, of these discrete variables.

Here, ζ_{hh} is the response of the shadow price of fixed input z_h to a unit change in its quantity.

The responses of variable quantity y_i to the quantity of fixed input z_h are

$$\xi_{ih} = \frac{R}{p_i}(S_i s_h + \delta_{ih}), \qquad i = 1, 2, ..., M, h = 1, 2, ..., N. \tag{18}$$

The elasticity of supply and demand are obtained by evaluating equation (17), using parameter estimates in table 2 and appropriate sample means of output shares and exogenous variables.

Table 5 reports these elasticities estimation results evaluated at sample average over the 1997-2005 period. This period is chosen because the 1996 so-called Freedom to Farm Act freed acres up to follow market signals, and we expect this might make a difference in farmers' responses. Estimated own-price elasticities of supply and demand have signs consistent with the implication of profit maximization, with ϵ_{ii} being positive for both outputs and negative for the variable input. The estimated own price elasticities of corn and soybeans are 1.06 and 2.72, respectively. They indicate considerable short-run flexibility in the outputs. While the partial elasticity of soybeans with respect to the price of corn is -0.38, that of corn with respect to the soybeans price is 0.35. The correlation between corn and soybean futures prices is 0.75 over the sample period. This comparatively high correlation may be responsible for the unexpected soybean price elasticities.

The results also suggest that corn output is very responsive to fertilizer price, with the elasticity being -1.41, while the own price elasticity of fertilizer is -1.49. The responses of corn, soybean supply, and fertilizer demand to a one-unit change in the CSR are 0.52, 0.24 and 0.07, respectively. In terms of shadow price response to endowment of fixed input, a one-unit increase in the CSR decreases its shadow price by \$0.07. And one more county in the east-west direction leads to a \$0.72 drop in the corresponding shadow price, while that amount for the south-north direction is \$2.46. Although the absolute values of these elasticities are large, none are entirely

unreasonable. As the estimates are predicated on the RRT, they provide some evidence on its validity.

The estimated yields of corn and soybeans derived from the profit share equation (12) are 79 bushels and 29 bushels per acre, respectively.[7] By the RRT, in which the response of cash rents to a marginal increase in corn price is equal to the estimated yield in quantity, the current period cash rent increase corresponding to a $1 increase in corn price is also about $79. Some reflection on the economic foundations of this response is warranted. Perhaps a change in output price should have both short- and long-term effects on cash rental rates. In other words, past changes in corn prices should affect present cash rental rates, but the incidence of the effects may be distributed across several future time periods. While higher corn prices drive up the local cash rental rates, contract re-negotiation in local markets may exhibit inertia due to community ties, relationship-specific investments (RSIs), and market power issues.

Because the process of contract enforcement is typically difficult and costly, enduring personal relationships and community ties are sometimes important for landlords when selecting tenants. It is also well recognized in the literature that RSIs are positively related with contract duration, especially for fixed cash rent contracts (e.g., Joskow 1987; Bandiera 2005; Jacoby and Mansuri 2006). Among the four types of RSIs recognized in Williamson (1983), non-salvageable physical specific assets and human specific assets are most relevant to farmland rental markets. Tenant farmers may make investments in equipment and machinery that are specific to the rented land and may lose values in alternative uses. Some human capital investments, such as learning about capabilities of given land, are tied to specific land and cannot be easily transferred to another landlord-tenant relationship. There are similar RSIs on the landlord side as well. Thus, landlord and tenant farmer more likely prefer a longer-term contract and may be reluctant to repeatedly negotiate leasing contracts over time. So the adjustment of cash rental

[7] These yields are much lower than typical Iowa yields. We will discuss implications of the disparity at a later juncture.

rates to long-run equilibrium is expected be a long-term process, which is the topic we turn to in the next section.

Long-Run Price Effect Analysis

In this section, the parameter of interest is the average long-run effect of expected corn price on cash rental rates. An error correction model (ECM) is used to estimate this long-run effect. The ECM is a class of models with a general form equivalent to the traditional autoregressive distributed lag (ARDL) models (Greene 2003, p. 579). We are going to look at two dimensions of the relationship between cash rental rates and expected corn prices: the long-run effect; and the potentially heterogeneous, dynamic adjustment path for each county. To be consistent with what we have done above, we consider the long-run effect by analyzing the relationship between cash rental rates and corn futures prices where both are normalized by the corresponding soybean futures prices over the period of 1987-2005.

In the literature, there are two commonly used estimation procedures for applying panel data to obtain long-run effects. The first one is the mean group (MG) estimator, which was proposed by Pesaran and Smith (1995). The MG procedure is to obtain a distinct regression estimate for each group or county in our case, and then average the coefficients over all groups to obtain the average effect. Pesaran and Smith (1995) showed that the MG estimation produces consistent estimates of the average of the parameters. The second procedure is referred to as pooled mean group (PMG) estimation, and was introduced in Pesaran, Shin, and Smith (1999). It allows the intercepts, short-run coefficients, and error variances to differ across groups but constrains the long-run multipliers to be the same. It has been shown to generate consistent estimates of short-run and long-run coefficients.

Unit Root Tests

Before applying the estimation procedures to our long-run price effect analysis, we turn to using various stationarity or unit root tests on the data series in order to better understand their time series properties.

Individual Time Series Unit Root Tests

In the following sub-section, we randomly choose Floyd County as an example to illustrate unit root tests for the individual county's data series. The purpose of the unit root tests is to examine whether the time series is a stationary process with a high degree of autocorrelation, or a random walk with drift. We applied the augmented Dickey-Fuller (ADF) test (Greene 2003, p. 643) and KPSS test (Kwiatkowski et al. 1992) on both the soybean normalized corn prices and the soybean normalized cash rents series.

The null hypothesis of the ADF test is that the series contains a unit root, and the alternative is that the series is level stationary. The test result is conditional on the model specification, including whether or not to impose a constant and a lagged difference. The lags of the first difference of the variable are included to account for possible serial autocorrelation. The ADF test has low statistical power to reject a unit root. And the statistical power is further reduced with the addition of the lagged difference. The KPSS test, in contrast to the ADF test, takes stationarity as the null hypothesis. It also suffers from the low power problem. We include both a constant and lag one first difference term for the tests. The results are summarized in table 6.

From the results, we fail to reject the null hypotheses for both series at the 5% significance level in ADF tests. In KPSS tests, we fail to reject the null hypothesis for both series at the 1% significance level. The test results indicate that different unit root tests lead to ambiguous and inconclusive outcomes on the existence of unit root in the series. In applying stationarity

or unit root tests to a small sample, the non-rejection of a null hypothesis doesn't necessarily lead to acceptance. With 19 observations in each data series that we are examining, failing to reject the null hypothesis is a relatively weak outcome. In other words, the test results are not strong enough for us to draw a conclusion on the properties of the data. In order to get more reliable results, we employ panel data unit root tests to further investigate this issue on cash rental rates.

The issue of whether agricultural commodity futures prices are stationary or not is still controversial. While some of the empirical evidence finds unit root behavior in these prices, others have concluded that prices are stationary. Dorfman (1993) inferred that most of the commodity futures price series, which are traded on the Chicago Mercantile Exchange (CME), are stationary. Liu (2005) tested stationarity in daily corn, soybean meal, and lean hog futures prices traded on the CBOT. He found that all three futures price series do not reject the existence of a unit root. Wang and Tomek (2007) point out that ADF test outcomes are influenced by the model specification underlying the hypothesis test. This is one of the reasons why different studies may get conflicting results. We are not going to explore this topic further since it is not a necessary assumption to make in carrying out our analysis. We prefer to assume the stationarity of normalized corn futures price in our study because there is no compelling theoretical reason for the unit root behavior in the normalized corn futures price.

Panel Unit Root Tests for Cash Rental Rates

Panel data unit root tests have been proposed as alternative more powerful tests than those based on individual time series. The Levin-Lin-Chu test (Levin, Lin, and Chu 2002), hereafter denoted by LLC, the Im-Pesaran-Shin test (Im, Pesaran, and Shin 2003), hereafter denoted by IPS, and the cross-sectionally augmented Dickey-Fuller test (Pesaran 2007), hereafter denoted by CADF, are applied on the panel data of cash rental rates. Both the LLC and IPS tests

assume that the individual processes are cross-sectionally independent. In the CADF test, the standard ADF regressions are augmented with the cross-sectional averages of lagged levels and first-differences of the individual series to account for the cross-sectional dependence.

Under the null hypothesis, the LLC test assumes that all series in the panel are non-stationary against the alternative that all series are stationary. It can be applied for homogeneous panels, i.e., the autoregressive coefficients for unit roots are assumed to be the same across sections. Under the null hypothesis of the IPS test, all series in the panel are assumed to be non-stationary. The alternative hypothesis allows for a fraction of the series in the panel to be stationary. The IPS test allows for heterogeneous panels. The CADF test can be applied to heterogenous panels with cross-sectional dependence. The null hypothesis assumes that all series are non-stationary. Baltagi, Bresson, and Pirotte (2007) studied the performance of panel unit root tests when spatial effects are present that account for cross-sectional correlation. Their findings show that tests like the CADF test, which explicitly allow for cross-sectional dependence, have better performance than other classical panel unit root tests that assume cross-sectional independence.

The test results in table 7 show that the null hypotheses of non-stationarity for all three tests are rejected. Compared with unit root tests of individual time series, panel unit root tests provide stronger evidence that the cash rental rates are stationary over the sample period. There is no gain from applying panel unit root tests on the normalized corn price series since it does not have cross-sectional variation.

Panel Analysis of Long-Run Price Effect

In this section, we apply MG and PMG estimation procedures to the ECM to analyze the average long-run price effect. In particular, this approach allows us to simultaneously investigate both long-run relationships and short-run dynamic adjustment toward equilibrium after a

change in expected corn price.

In the ECM, the error correction rate, the short-run effect, and their standard errors are estimated directly. The long-term multiplier can also be easily calculated. More importantly, we expect the long-run equilibrium relationships between cash rental rates and expected corn price to be the same across all counties, because of similar climatological conditions, contiguous locations, and technology spillovers affecting them in analogous ways. The individual adjustment path of each county to the long-run equilibrium may differ considerably because of county-specific factors. For example, counties with better-quality farmland and those closer to a big metropolitan area may tend to adjust quicker and more completely to price changes. While imposing the same long-run multipliers, PMG estimation allows for variability among short-run coefficients. This structure in turn allows the dynamic specification, including the individual lag structure, to differ across counties. The MG estimation doesn't impose any parameter constraint, allowing all parameters to vary freely.

Following Pesaran, Shin, and Smith (1999), we formulate the fixed effects panel data model in the error correction representation as

$$\triangle y_{it} = \alpha_i y_{i,t-1} + \beta_i x_{i,t-1} + \sum_{j=1}^{p-1} \gamma_{ij} \triangle y_{i,t-j} + \sum_{j=0}^{q-1} \lambda_{ij} \triangle x_{i,t-j} + \mu_i + \varepsilon_{it} \tag{19}$$

where $t = 1, 2, ..., T$, and $i = 1, 2, ..., N$; y_{it} and x_{it} are the dependent variable and explanatory variable for county i at time t; $\triangle y_{it} = y_{it} - y_{i,t-1}$, $\triangle x_{it} = x_{it} - x_{i,t-1}$, $\triangle y_{i,t-j}$ and $\triangle x_{i,t-j}$ are j period lagged values of y_{it} and x_{it}; and μ_i represents the fixed effect. The disturbances ε_{it} are assumed to be independently distributed across i and t with mean 0 and variance $\sigma_i^2 > 0$. In our case the dependent variable, y_{it}, is the normalized cash rental rate of county i at time t and x_{it} is the normalized corn futures price over t. There is no cross-sectional variation in futures prices data.

The long-run relationship between y_{it} and x_{it} can be defined by

$$y_{it} = \theta_i x_{it} + \nu_{it}, \quad i = 1, 2, ..., N$$

where $\theta_i = -\frac{\beta_i}{\alpha_i}$ are the long-run coefficients, and ν_{it} is assumed to be a stationary process.

Equation (19) can be rewritten as

$$\triangle y_{it} = \alpha_i \nu_{i,t-1} + \sum_{j=1}^{p-1} \gamma_{ij} \triangle y_{i,t-j} + \sum_{j=0}^{q-1} \lambda_{ij} \triangle x_{i,t-j} + \mu_i + \varepsilon_{it} \tag{20}$$

where $\nu_{i,t-1}$ is the error correction term, hence, α_i is the error correction coefficient measuring the adjustment speed toward the long-run equilibrium.

By imposing the long-run homogeneity constraint, $\theta_i = \theta, i = 1, 2, ..., N$, PMG estimation constrains the long-run coefficients to be the same. The pooled maximum likelihood estimation is applied for parameter estimation. Derivation and computation details are provided in Pesaran, Shin and Smith (1999).[8] Because of the linear nature of (19), we can obtain the PMG estimators by

$$\hat{\alpha}_{PMG} = \frac{1}{N} \sum_{i=1}^{N} \tilde{\alpha}_i, \qquad \hat{\beta}_{PMG} = \frac{1}{N} \sum_{i=1}^{N} \tilde{\beta}_i, \qquad \hat{\gamma}_{jPMG} = \frac{1}{N} \sum_{i=1}^{N} \tilde{\gamma}_{ij}, \quad j = 1, 2, ..., p-1,$$

and

$$\hat{\lambda}_{jPMG} = \frac{1}{N} \sum_{i=1}^{N} \tilde{\lambda}_{ij}, \quad j = 0, 1, ..., q-1, \qquad \hat{\theta}_{PMG} = \tilde{\theta}.$$

The MG estimation allows for heterogeneity among all the parameters in incorporating

[8] The codes are modified from the Gauss code provided in the paper, which can be found at http://www.econ.cam.ac.uk/faculty/pesaran.

county-specific long-run and short-run effects. The estimates of the parameters are as follows:

$$\hat{\alpha}_{MG} = \frac{1}{N}\sum_{i=1}^{N}\hat{\alpha}_i, \qquad \hat{\beta}_{MG} = \frac{1}{N}\sum_{i=1}^{N}\hat{\beta}_i, \qquad \hat{\gamma}_{jMG} = \frac{1}{N}\sum_{i=1}^{N}\hat{\gamma}_{ij}, \quad j = 1, 2, ..., p-1,$$

and

$$\hat{\lambda}_{jMG} = \frac{1}{N}\sum_{i=1}^{N}\hat{\lambda}_{ij}, \quad j = 0, 1, ..., q-1, \qquad \hat{\theta}_{MG} = \frac{1}{N}\sum_{i=1}^{N}\left(-\frac{\hat{\beta}_i}{\hat{\alpha}_i}\right).$$

where $\hat{\alpha}_i$, $\hat{\beta}_i$, $\hat{\gamma}_{ij}$, and $\hat{\lambda}_{ij}$ are the OLS estimates for an individual county using (19).

The lag order was first chosen for each county on the unrestricted model by using the Akaike information criterion (AIC),[9] subject to a maximum lag of 3. Then, the long-run homogeneity constraint was imposed using these AIC-determined lag orders. Table 8 shows the MG and PMG estimation results. The results for individual counties are not reported because of limited space. They are all statistically significant. The two sets of estimates, MG and PMG, of the error correction coefficient and short-run coefficient are all significant with similar results. The long-run multipliers are all significant, while the estimates are different to some extent.

Figure 7 reports long-run effects obtained from the MG estimation procedure over sample counties. It demonstrates that significant long-run price effects are present in most of the counties, and they vary considerably across the state. Also, the distribution of the long-run effects is in line with that of historical cash rental rates. This observation is confirmed by the OLS regression results reported in table 9, which suggests that the county cash rental rate for 2005 is highly significant in explaining the variation of long-run price effects. It may be that long-run effects and historical cash rental rates are related in some way to counties' specific factors. Adjustment speeds, represented by the error correction coefficients obtained from the PMG estimation procedure, are reported in figure 8. They range from 0.3421 to 1. In some counties, the error correction coefficients are 1 since the AIC chooses the static model as the

[9]Using Bayesian Information Criterion (SBC), we get similar results. In some cases, because of SBC's heavier penalty for lost degrees of freedom, it will lead to a simpler model than AIC (Greene 2003, p. 565).

best-fitting model for them. An adjustment speed value of 1 means that cash rental rates will adjust to long-run equilibrium instantaneously. The regression results in table 9 implicate higher soil quality, which is statistically significant at the 1% level, as a factor in explaining heterogeneity in speeds of adjustment. Figures 2 and 8 lend some support to the hypothesis that sluggish responses to price movement are due to thinner cropland rental markets, where good land is comparatively scarce.

The long-run price effect analysis provides us with an answer to the following question: If corn price were to increase \$1 in the year t, how would it affect cash rental rates? In general, changes in the corn price have both short-term and long-term effects on cash rental rates. In the long run, the possible size of the changes in cash rental rates will be approximately \$109-\$114, which could be reached in three to four years. The first-year increase is about \$80 on average, which is consistent with what we get from the variable profit function estimation provided earlier. The adjustment speed and corresponding dynamic adjustment path to the long-run equilibrium vary across the state and depend mainly on the average soil quality of cropland in a specific county. As shown in figure 9, cash rental rates will increase an average of \$20-\$25 in the year following the price shock, \$5-\$7 in year $t+2$, \$1-\$2 in year $t+3$, and so on.

However, we note that the average yield in Iowa over the 1987-2005 period is 135 bushels per acre. The RRT suggests that the long-run equilibrium level corresponding to \$1 increase of corn price should be around \$135. It is about \$20 more than our long-run effect estimation. Besides estimation error, the price and income supports farmers obtained from U.S. agricultural programs through the data range may explain part of this disparity. When the effect of a downward corn price movement is eliminated by government support through a price floor, then cash rents should respond to an increase in corn price only when it is above a certain level.

Also, the questionable bargaining power assumption underlying the RRT may provide us with another explanation for incomplete long-run responses. In addition to landlords and ten-

ant farmers, seed suppliers may have some degree of bargaining power in the division of cash rents. Private seed companies are typically well protected by patents, licenses, and other intellectual property rights (Moschini and Lapan 1997). These protections, and also seed industry concentration, may have enabled seed companies to capture the benefits of their innovation through prices (Jolly and Lence 2000). In other words, continuing adoption of GE corn and soybeans may have conferred seed companies with significant bargaining power, and seed companies may be able to appropriate some farmland cash rents. So lack of consideration for the role that seed suppliers may play is perhaps another reason why the estimated long-run response in rent to a $1 increase in corn price is only about 0.82 of what RRT suggests.

Conclusions

Using unique panel data set and a random effects model, we find that cropland cash rental rates in Iowa are largely determined by output/input prices, soil quality, relative location, and other county-specific factors. This is investigated in the variable profit function framework. Also, cash rents go up by about $79 for a $1 increase in corn price in the short run. The marginal value of cropland quality is about $1.05, as represented by the row-crop CSR index. We find no significant local effects of ethanol plants on cash rents, as their effects appeared to be largely channeled through national futures prices. The dynamic analysis results indicate that the total effect of land rents is approximately $109-$114. The adjustment paths vary considerably across the state and probably depend on farmland soil quality. The validity of Ricardian rent theory is tested. In an analysis of cash rent responses to a $1 increase in corn price, the short-run analysis failed to meet the average value of $135 suggested by the theory. Part of this discrepancy might be explained by inertia in the contract re-negotiation process, which may be induced by community ties and relationship-specific investments in the

rented land and contractual relation. Furthermore, the long-run price effect estimate is still \$20 below the theoretical value. The price and income support that farmers have received from government programs may be one explanation for this shortfall. Some of the disparity may also be captured by seed suppliers, as they certainly have market power when pricing GE corn and soybean seeds.

We have four remarks about future possible extensions to our study. First, the theory of cooperative games is particularly well suited for analyzing the behavior of participants in the division of farmland cash rents. In the game, landlord, tenant farmer, and seed supplier come together to bargain over the surplus cash rents. Cash rents can be assumed to be divided among them according to the Shapley value (Shapley 1953), which defines the payoff to each individual participant based on his marginal contribution to the surplus. As a measure of bargaining power in this allocation game, the Shapley value pins down the magnitude of rent that each player will receive in the bargaining process and would allow us to better understand the equilibrium impact of rapidly changing biotechnology on land rents.

Second, government payments have important effects on farmland cash rents. Whether farmers are the ultimate recipients and to what extent they benefit from government payments are still open questions. Roberts, Kirwan, and Hopkins (2003) used data from the 1992 and 1997 Census of Agriculture and found that \$0.34-\$0.41 of every \$1 of government payment is reflected in the land rents. From Kirwan (2005), we learn that landlords capture \$0.25 of the marginal subsidy per acre. Using Iowa county-level panel data over the 1996-2000 period, Lence and Mishra (2003) concluded that a \$1 additional payment for market assistance and production flexibility contracts pushed up cash rental rates by \$0.86 per acre. Goodwin, Mishra, and Ortalo-Magné (2004) indicate that an additional \$1 in loan deficiency payments raises the cash rents by \$0.57. Exploring our unique panel data set may help us shed clearer light on this issue.

A third possible extension is to break out a real option component to land rents. After negotiating and signing a rental agreement, which typically happens in August in Iowa, the tenant farmer has the option to choose between corn and soybeans for the next crop season. Hence, the corn and soybean futures prices, price volatilities, and correlation between these prices will affect a farmer's planting decision and land rents that he/she is willing to pay. The real option component of land rents could help us better understand the determinants of cropland cash rental rates. Finally, there is the issue of institutional price floors, such as the loan rate program and the target price program that was terminated in 1996. One can test for asymmetric responses of cash rental rates to corn price when the price is above or below a government price floor.

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Table 1. Iowa Ethanol Plants in Operation, 2006

	Company	Location	County	Capacity	Opening Date
1	Sunrise Energy	Blairstown, IA	Benton	6	Nov. 25, 1999
2	Siouxland Energy	Sioux Center, IA	Sioux	25	Jan. 8, 2002
3	Quad County Corn Processor	Galva, IA	Ida	30	Mar. 7, 2002
4	Tall Corn Ethanol	Coon Rapids, IA	Carroll	54	Aug. 9, 2002
5	Little Sioux Corn Processor	Marcus, IA	Cherokee	55	Apr. 3, 2003
6	Northeast Iowa Grain Processors	Earlville, IA	Delaware	15	Sep. 1, 2003
7	Iowa Ethanol	Hanlontown, IA	Worth	45	Feb. 26, 2004
8	Otter Creek Ethanol	Ashton, IA	Osceola	55	Mar. 25, 2004
9	Big River Resources	West Burlington, IA	Des Moines	52	Aug. 29, 2004
10	Hawkeye Renewables	Iowa Falls, IA	Hardin	45	Oct. 28, 2004
11	Golden Grain Energy, LLC	Mason City, IA	Cerro Gordo	55	Dec. 15, 2004
12	Voyager Ethanol	Emmestburg, IA	Palo Alto	54	Feb. 24, 2005
13	Xethanol BioFuels	Blairstown, IA	Benton	5.5	Jul. 1, 2005
14	Amaizing Energy	Denison, IA	Crawford	40	Sep.1, 2005
15	VeraSun Energy Corp.	Ft. Dodge, IA	Webster	110	Sep. 7, 2005
16	Corn, LP	Goldfield, IA	Wright	50	Dec. 1, 2005
17	Global Ethonal	Lakota, IA	Kossuth	145	Dec. 1, 2005
18	Horizon Ethanol	Jewell, IA	Hamilton	60	Mar. 2, 2006
19	Frontier Ethanol	Gowrie, IA	Webster	60	May 31, 2006
20	Pine Lake Corn Processors	Steamboat Rock, IA	Hardin	24	May 16, 2005
21	Lincolnway Energy	Nevada, IA	Story	50	May 22, 2006
22	Hawkeye Renewables	Fairbank, IA	Buchanan	100	Jun. 1, 2006
23	US Bioenergy Corp	Albert City, IA	Buena Vista	100	Nov. 1, 2006

Note: the annual production capacity is in million gallons per year.

Table 2. Grid Search Result for Price Selection

κ	Log-likelihood	κ	Log-likelihood
0	1074.44	0.5	1095.65
0.8	1158.49	0.9	1176.61
0.95	1183.84	1	1189.76

Table 3. Variables Description

Variable	Description
pc	Normalized corn futures prices
pf	Normalized fertilizer prices
CSR	Soil quality
B_W	County relative location in the east-west direction
B_N	County relative location in the south-north direction
t	Time ($t = 1$ at 1987)
Scale of Livestock Industry	Grain-consuming animal units
Ethanol Production Effect	Effect of local ethanol production
Urbanization Effect	Minimum normalized distance to metropolitan areas
Adoption of GM Crops	Adoption ratio of GE crops
θ^2	Fraction of variance due to unobservable effects
δ	Spatial autocorrelation
ρ	Temporal autocorrelation

Table 4. Estimates of the Random Effects Model

	Explanatory Variables	Parameter	Asymp. t-stat.	Z-Value
1	Constant	0.387	0.173	0.863
2	ln(pc)	1.683	1.528	0.126
3	ln(pf)	-2.906	–5.095	0.000
4	$\frac{1}{2}\ln(\mathrm{pc})^2$	0.559	0.562	0.574
5	$\ln(\mathrm{pc}) \times \ln(\mathrm{pf})$	-3.934	-9.518	0.000
6	$\frac{1}{2}\ln(\mathrm{pf})^2$	-1.145	-2.098	0.036
7	CSR	0.061	1.216	0.224
8	$\mathrm{B_W}$	-0.030	-0.467	0.641
9	$\mathrm{B_N}$	0.186	2.683	0.007
10	$\frac{1}{2}(\mathrm{CSR})^2$	-0.001	-0.976	0.329
11	$\frac{1}{2}(\mathrm{B_W})^2$	0.006	3.106	0.002
12	$\frac{1}{2}(\mathrm{B_N})^2$	-0.020	-6.389	0.000
13	$\mathrm{CSR} \times \mathrm{B_W}$	-0.0002	-0.269	0.788
14	$\mathrm{CSR} \times \mathrm{B_N}$	-0.0009	-1.193	0.233
15	$\mathrm{B_W} \times \mathrm{B_N}$	0.001	0.793	0.428
16	$\ln(\mathrm{pc}) \times \mathrm{CSR}$	-0.00009	0.019	0.984
17	$\ln(\mathrm{pc}) \times \mathrm{B_W}$	0.003	0.276	0.783
18	$\ln(\mathrm{pc}) \times \mathrm{B_N}$	-0.012	-0.888	0.375
19	$\ln(\mathrm{pf}) \times \mathrm{CSR}$	0.002	0.691	0.490
20	$\ln(\mathrm{pf}) \times \mathrm{B_W}$	0.005	0.809	0.419
21	$\ln(\mathrm{pf}) \times \mathrm{B_N}$	-0.001	-0.187	0.852
22	$\ln(\mathrm{pc}) \times t$	0.247	9.731	0.000
23	$\ln(\mathrm{pf}) \times t$	0.082	4.146	0.000
24	$\mathrm{CSR} \times t$	-0.0004	-2.728	0.006
25	$\mathrm{B_W} \times t$	-0.0003	-0.754	0.451
26	$\mathrm{B_N} \times t$	-0.0008	-2.072	0.038
27	t	0.264	8.382	0.000
28	t^2	-0.009	-10.232	0.000
29	Scale of Livestock Industry	0.018	2.260	0.024
30	Ethanol Plant Effect	0.012	0.781	0.435
31	Urbanization Effect	-0.023	-1.781	0.075
32	Adoption of GM Crops	0.820	7.992	0.000
33	θ^2	0.643	8.556	0.000
34	δ	0.789	43.211	0.000
35	ρ	0.371	13.488	0.000
	R^2	0.9866		
	adjusted R^2	0.9863		
	Number of cross-sections	83		
	Number of years	19		
	Total number of observations	1577		

Table 5. Estimated Elasticities/Responses at Sample Mean, 1997-2005

	Corn Price	Soybean Price	Fertilizer Price Index	Quantity of CSR	Quantity of B_W	Quantity of B_N
Quantity of corn	1.06	0.35	-1.41	0.52	0.29	0.31
Quantity of soybean	-0.38	2.72	-2.34	0.24	0.23	-0.07
Quantity of fertilizer	1.88	0.39	-1.49	0.07	0.06	0.07
Shadow price of CSR	1.74	-1.59	0.85	-0.07	-0.02	-0.11
Shadow price of B_W	1.75	-1.60	0.86	-0.02	-0.72	0.13
Shadow price of B_N	1.73	-1.58	0.85	-0.11	0.13	-2.46

Note: Columns 2-4 in the table are partial elasticities, while the last 3 columns are responses to unit changes of corresponding fixed inputs.

Table 6. Individual Time Series Unit Root Tests

	ADF	KPSS
Cash rental rates	-1.661	.712
Corn futures prices	-2.584	.497

Notes: The 1% and 5% critical values are -3.750 and -3.000 for ADF test, respectively; for KPSS test, the corresponding values are 0.739 and 0.463, respectively. Both tests are carried out in STATA 9 (STATA Corporation 2005).

Table 7. Panel Unit Root Tests for Cash Rental Rates

	Test Statistics	1% Critical Value	p-value
LLC	-16.614	-4.709	0.000
IPS	-1.991	-1.730	0.000
C-ADF	-2.531	-2.180	0.000

Note: All tests are carried out in STATA 9 (STATA Corporation 2005).

Table 8. Estimates of the Error Correction Model

	MG	Std. Err.	PMG	Std. Err.
Long-run multiplier	113.701	2.685	108.717	2.142
Error correction coefficient	-0.736	0.026	-0.730	0.026
Short-run coefficient	79.413	2.871	81.755	2.920

Table 9. Regression Analysis of Long-run Effect (MG) and Adjustment Speed (PMG) Estimates

	Long Run Effect			Adjustment Speed		
Explanatory Variables	Parameter	t-stat.	Z-Value	Parameter	t-stat.	Z-Value
Constant	10.91	0.31	0.76	-0.16	-0.40	0.69
CSR	-0.64	-1.60	0.11	0.01**	2.34	0.02
Rent 2005	1.09***	5.88	0.00	0.001	0.65	0.52
B_N	0.88	0.88	0.38	-0.002	-0.21	0.83
B_W	-0.21	-0.30	0.77	-0.01	-1.37	0.17
Urbanization effect	0.64	0.03	0.98	-0.057	-0.23	0.82
R^2	0.3158			0.1145		
adjusted R^2	0.2714			0.0570		

Notes: See Table 3 for definitions of the explanatory variables.

Single (*), double (**), and triple (***) asterisks denote significance at 0.10, 0.05, and 0.01 levels, respectively.

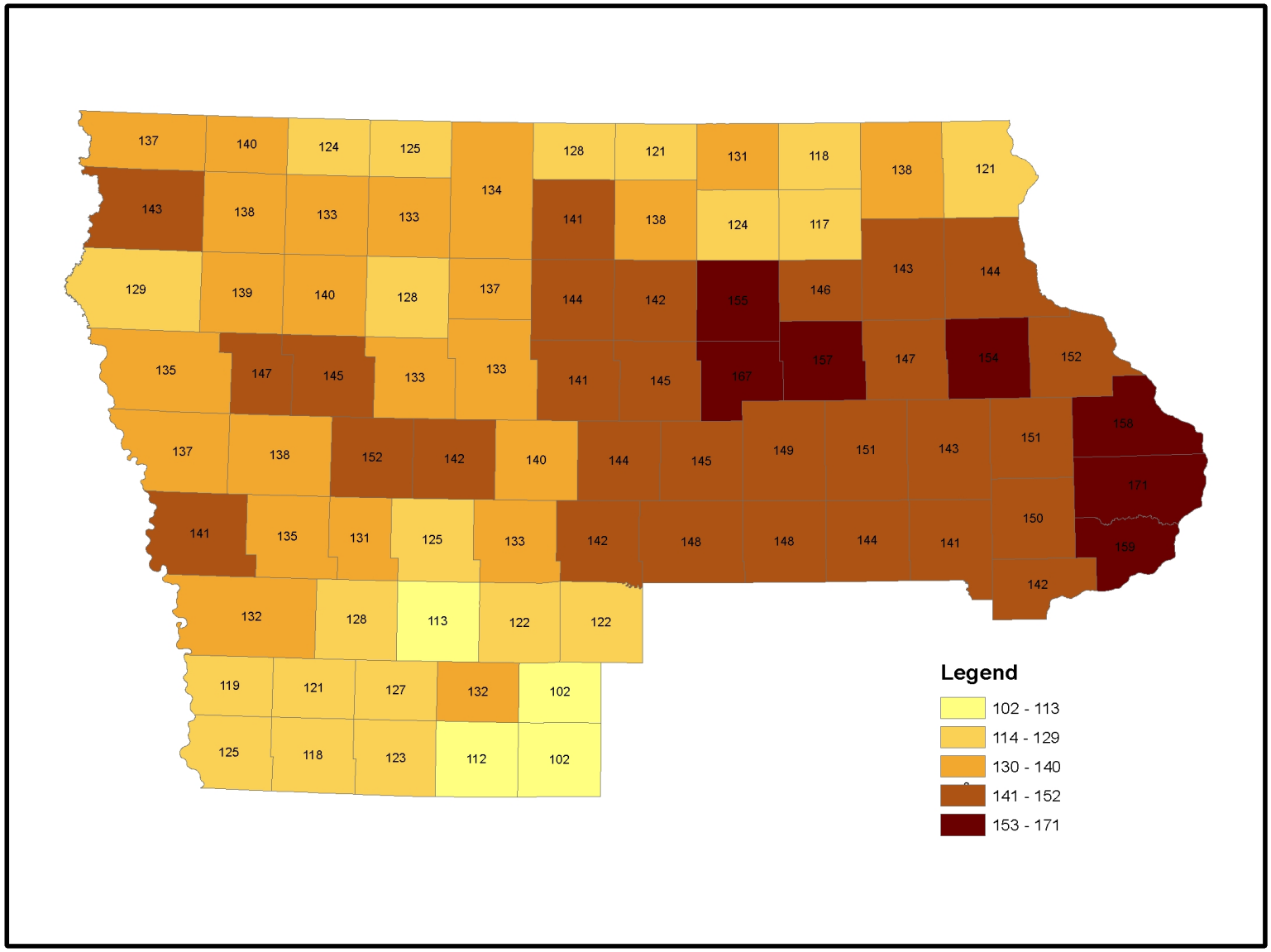

Figure 1. Cash Rental Rates, 2005 ($/acre/year)

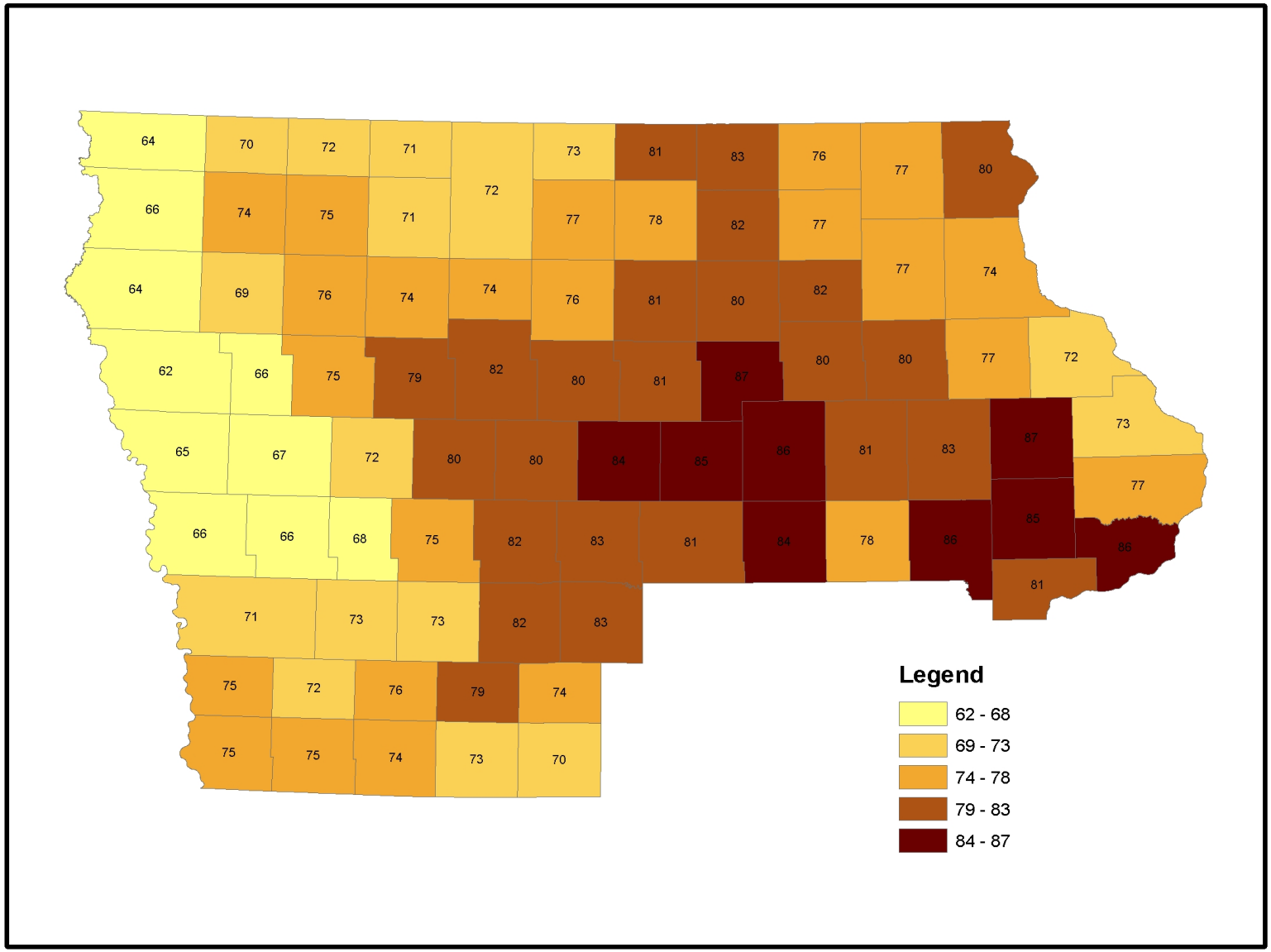

Figure 2. County Average Row Crop CSR Index

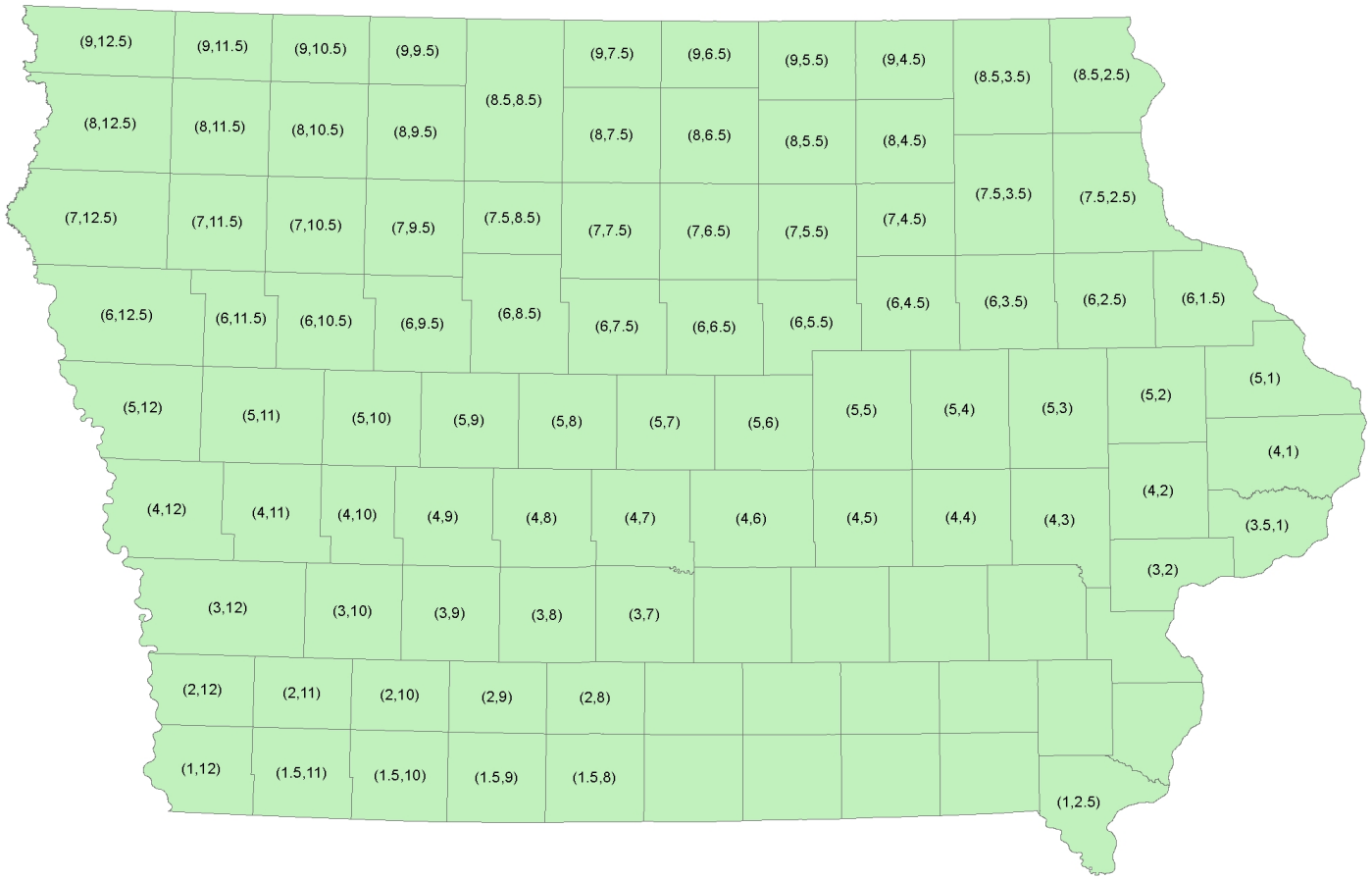

Figure 3. County Relative Location

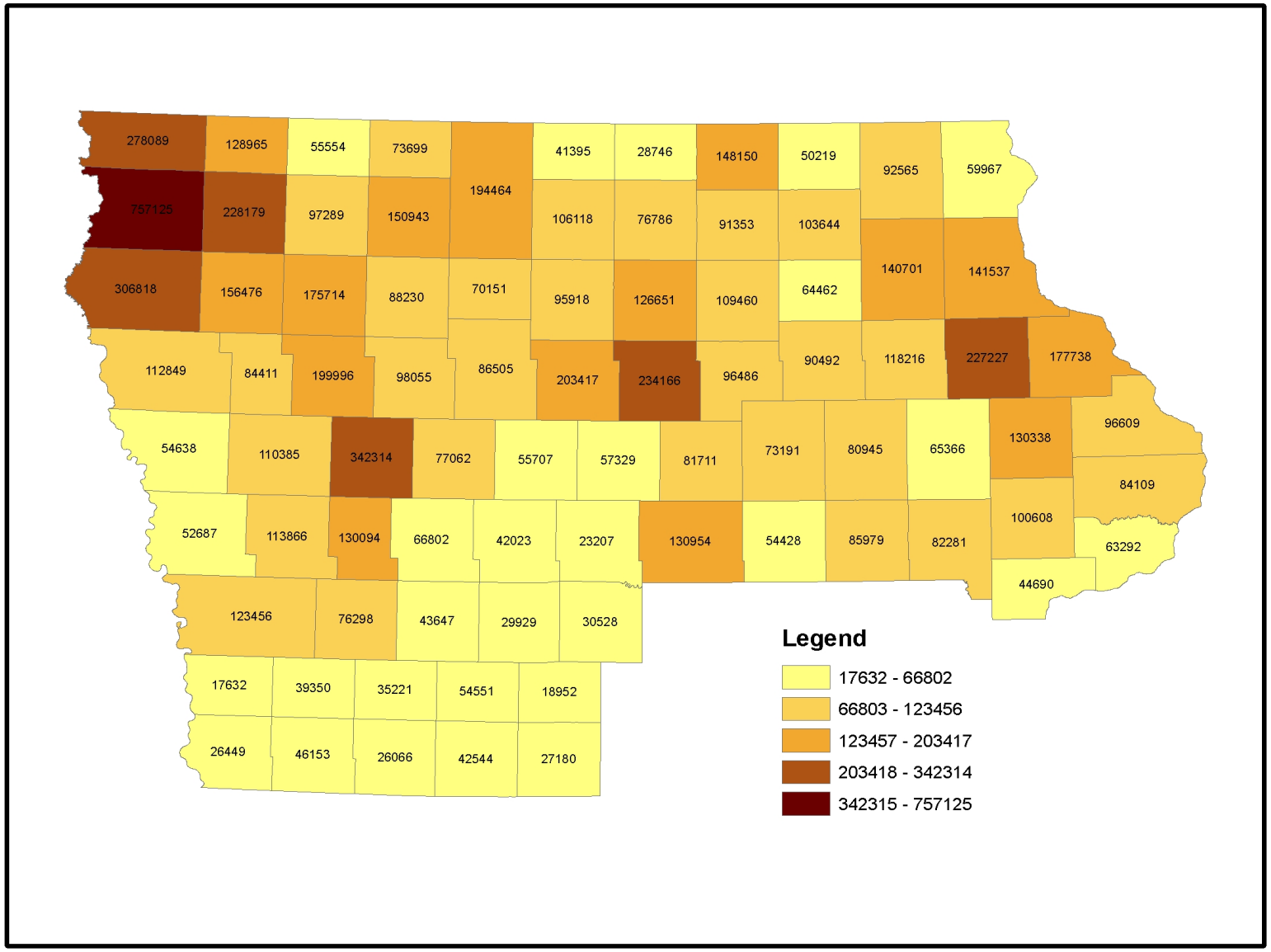

Figure 4. Grain-Consuming Animal Units, 2005

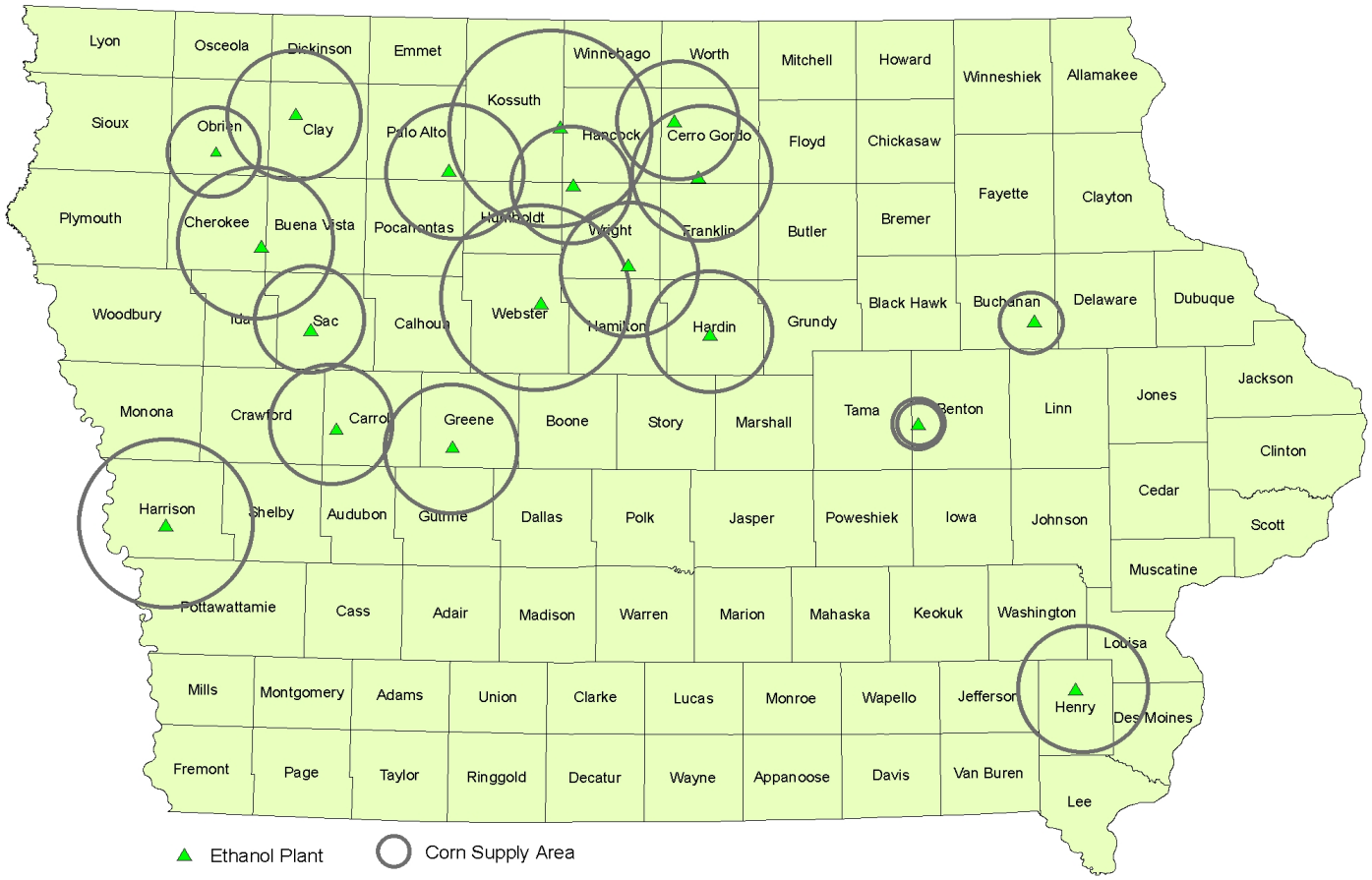

Figure 5. Ethanol Plants in Operation, 2005

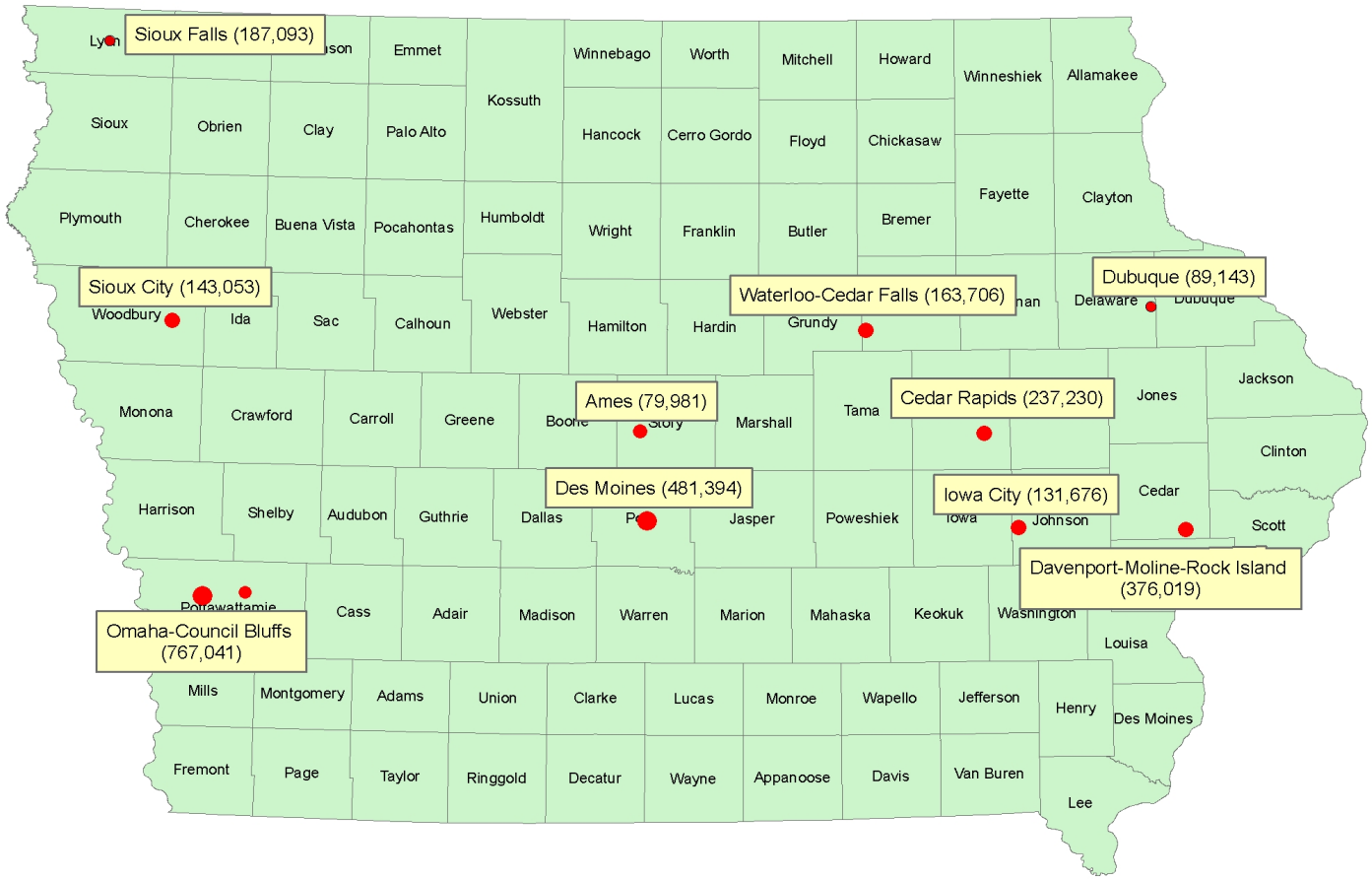

Figure 6. Metropolitan Area Location and Population

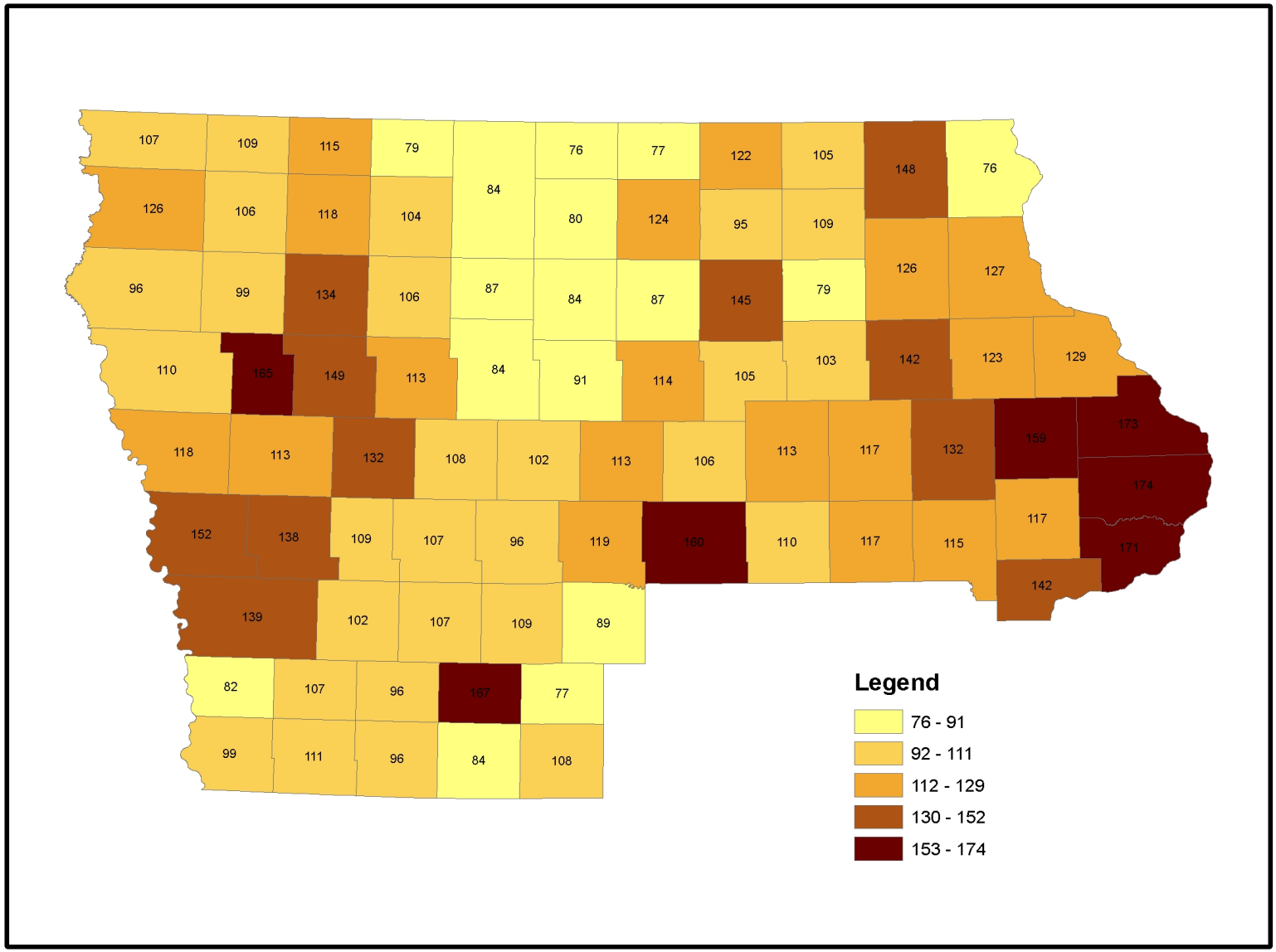

Figure 7. Long-Run Effects (MG)

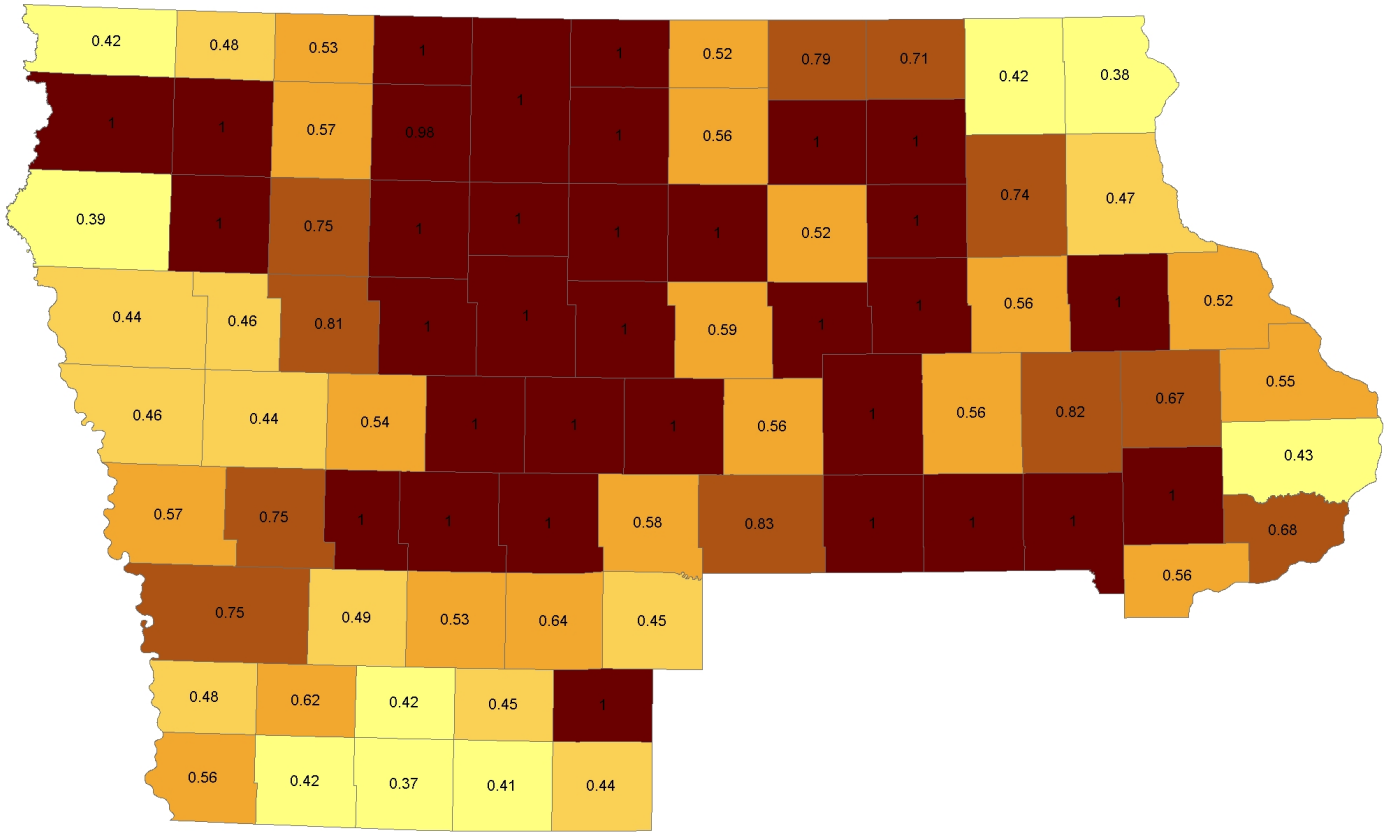

Figure 8. Error Correction Coefficients (PMG)

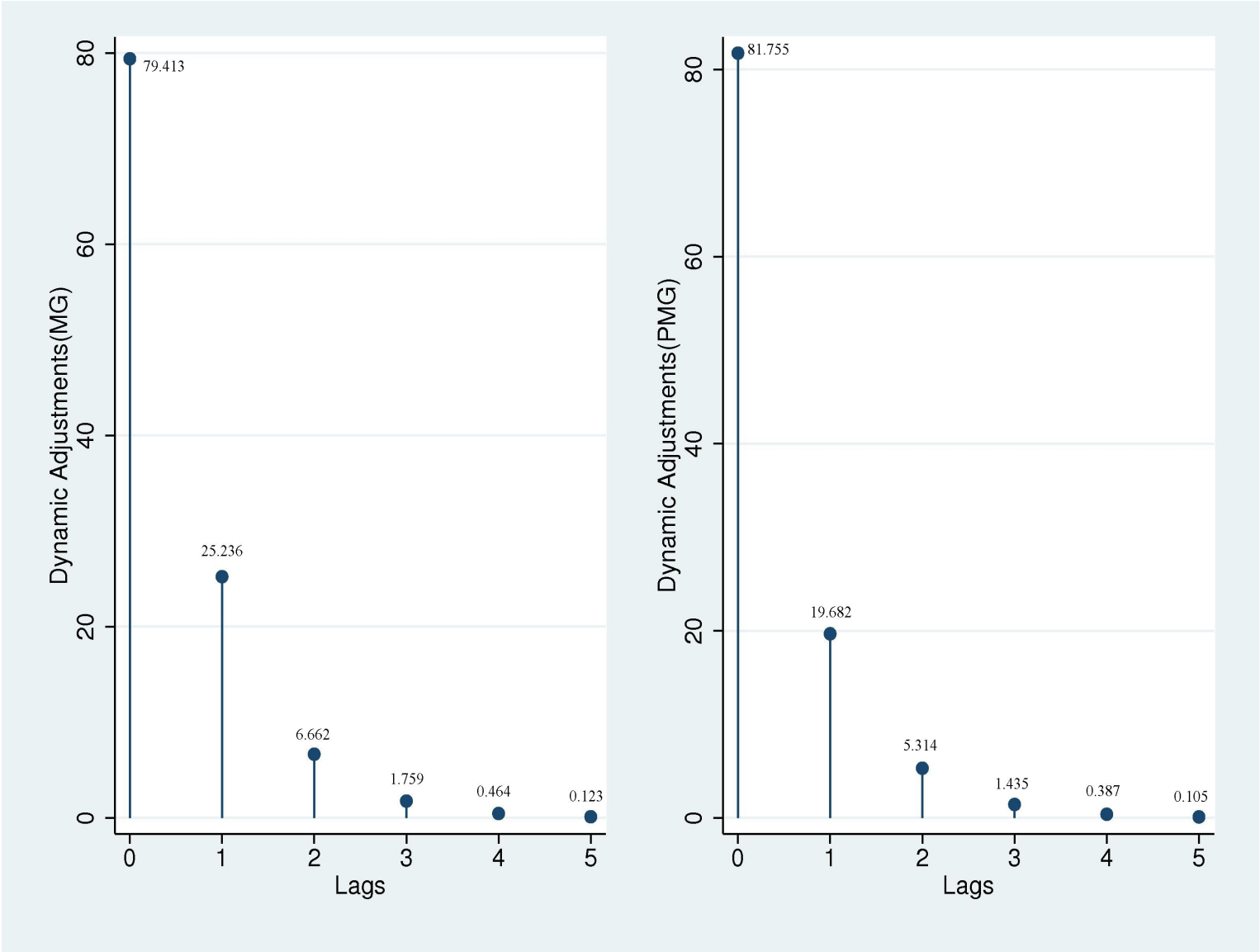

Figure 9. MG/PMG Estimates of Dynamic Adjustments

Appendix

Table 10. Missing Data Information

County	Missing Years	County	Missing Years
Data included in the study (83 counties)			
Adams	1994	Audubon	1988
Calhoun	1993	Cherokee	1994
Clarke	1989,92,94,95,98	Crawford	1998
Decatur	1993	Dubuque	1995
Fremont	1987,88,89	Ida	1993
Iowa	1995	Jones	1995
Mills	1987	Monona	1993,94,95
O'Brien	1994	Palo Alto	1987,88
Plymouth	1994	Poweshiek	1995
Sac	1993	Taylor	1989,94
Union	1995	Woodbury	1993,94,95
Data not included (16 counties)			
Appanoose	1987-96	Davis	1987-92,94,96
Des Moines	1987-92,94-96	Henry	1987-92,94,96
Jefferson	1987-92,94-96	Keokuk	1987-92,94-96
Lee	1987-92,95-96	Louisa	1987-91,94-96
Lucas	1987-92,94-96	Marion	1987-92,94
Mahaska	1987-92,94-95	Monroe	1987-92,94-96
Van Buren	1987-92,94,96	Wapello	1987-92,94-96
Washington	1987-91,94-96	Wayne	1987-92,96

Notes: The missing data for the 83 counties included in this study are linearly interpolated using the corresponding command in Matlab.

We exclude the counties that have missing data for five or more continuous years. The above 16 counties are excluded also because they are spatially contiguous in the southeast corner of Iowa.