Environ Resource Econ (2009) 42:509–534
DOI 10.1007/s10640-008-9221-0

A Spatial Hedonic Approach to Assess the Impact of Swine Production on Residential Property Values

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Accepted: 16 June 2008 / Published online: 16 July 2008

Abstract A spatial hedonic model is developed to assess monetary harm of confined animal feeding operations (CAFOs) on property values, taking explicitly into account spatial dependence in property values. Spatial autocorrelation was found in the form of spatial lag dependence, not spatial error dependence. When spatial lag dependence is explicitly taken into account, on average the impact coefficient estimate of a CAFO is reduced by 18%. For example, the impact on the value of the median house ($63,520) 1 mile from a swine facility with 10,000 head fell from −$6,800 to −$5,200, or 23.5%. The magnitude of the spatial autoregressive parameter was about 0.2 for the 1-mile distance band, meaning one-fifth of the house value could be explained by the values of the neighboring houses.

Keywords Spatial hedonics · Spatial autocorrelation · Housing values · Hog farms · Pigs · Odor · Confined animal feeding operations · CAFO

1 Introduction

The U.S. swine industry is undergoing radical change in both size and structure. The traditional hog farm structure integrated with crop production has been transformed into larger, more integrated systems. For example, the share of the hog farms with at least 1,000 head

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increased to 19% in 2002, from 2% in 1992.[1] These larger farms now represent 87% of the nation's hog inventory, compared with 47 percent in 1992 (NASS). The geography of the swine industry is also changing. While the Midwest is still the largest hog-producing area, North Carolina leads a shift of investment to new locales. Hog inventories in North Carolina more than tripled in the last decade from 2.8 million in 1990 to 9.5 million in 2006. Hog production in the United States only increased 8 million head, or 13% over the same period. Many of the new animals originated in four states, North Carolina, Iowa, Minnesota, and Oklahoma, while significant losses were seen in the traditional hog producing states of Illinois, Indiana and Nebraska. Oklahoma, North Carolina, and Utah led the nation in terms of growth rate increasing their herds over 70%.

Community concern about the negative impact of swine facilities on their health, environment, and the overall quality of life has increased as the industry has expanded, intensified production, and changed its geography (Schiffman et al. 1995; Thu et al. 1997; Okun 1999; Wing and Wolf 2000; University of Iowa and Iowa State University 2002). Negative externalities produced by confined animal feeding operations (CAFOs) on the environment and community cause conflicting property right issues with rural residents. Residents argue that nuisances caused by the CAFOs, such as poor air quality, increased truck traffic, and animal waste disposal are impacting their water supplies, enjoyment of clean air and pastoral viewscapes, and sense of control of their land, homes, and families (Periera and Goldsmith 2005).

Producers, on the other hand, defend their rights to earn a living from their land and local economic development authorities value the jobs and economic activity associated with livestock farming. These conflicting property right issues related to the environment and community are the dominant issue facing CAFOs and their ability to operate and compete in the global agri-food system.

While it is argued that negative impacts exist, there is little research empirically measuring the impact. Measuring the effects of CAFO's allows stakeholders to specify harms and seek compensation or relief. Policymakers are challenged to get the prices right as to the quantity and quality of livestock production in their community if there is not good evidence as to harm or benefits. Our research addresses the empirical measurement problem and has at its first objective to provide policymakers, industry, and stakeholders a methodology and actual parcel-level estimates of affects posed by swine CAFOs.

The means for estimating those point estimates of impacts is very difficult. Discussed below in the literature review are two lines of research that focus on methodology. The first uses survey techniques to directly ask neighbors to state the harms they perceive. This approach unfortunately is fraught with biases that are hard to correct.

The second methodological approach, the subject of this research, utilizes hedonics to indirectly measure impacts and avoid the bias problem. Three peer-reviewed studies estimate the effects of CAFOs on their neighbors using hedonic regression (Palmquist et al. 1997; Ready and Abdalla 2005; Herriges et al. 2005). The researchers have improved the methodological rigor of impact estimation but do correct for spatial autocorrelation that is theorized to impact estimation efficiency. Advancing the methodological estimation of CAFO impacts by introducing spatial error correction techniques is the second objective of our research. Improving the estimation provides more robust estimators and allows policymakers, industry, and stakeholders to be more confident when they employ the findings.

[1] The new EPA rules on CAFOs, effective on April 14, 2003, classify CAFOs into three categories: small, medium, and large. A swine operation with at least 2,500 head (each 55 lbs or more) or 10,000 head (each under 55 lbs) is now a large CAFO. A medium CAFO will have at least 750–2,499 (each 55 lbs or more) or 3,000–9,000 head (each under 55 lbs).

The following literature review sets our study within three important domains of previous research: the first is the methodological literature of spatial hedonic theory; second is empirical analysis where housing values are used to monetize negative externalities, and third is livestock impact measurement. Sections on the study area and data, model specification, estimation and analysis, and the conclusion follow the literature review.

2 Literature Review

Hedonic models in housing and real estate have traditionally used housing physical attributes and locational characteristics variables to estimate the contribution of housing attributes on housing price. The theory underlying these models is attributed to Rosen (1974),[2] in which the interactions of the consumers and the producers determine the equilibrium hedonic or implicit prices of the attributes associated with a differentiated product. Examples of physical attribute variables for a house include floor area, the number of rooms, the number of bathrooms, or house age. For locational characteristics, two kinds of measures are commonly employed: an accessibility measure such as distance to the Central Business District (CBD) and a neighborhood indicator measure such as median household income. Housing values, for example, would be negatively associated with distance to CBD due to increased transportation cost. Similarly, median household income can be an indicator for neighborhood quality. Locational variables are also used to measure the negative externality of a noxious facility such as a landfill, hazardous waste site, or oil and natural gas facilities (Kohlhase 1991; Hite et al. 2001; Boxall et al. 2005). The hypothesis being that the impact on a property's price is a function of the distance from the facility.

[2] In a competitive market the interactions of the consumers and the producers for a differentiated product determine the equilibrium hedonic or implicit prices (Rosen 1974). Rosen defines a value or bid function as $\theta(z_i, \ldots, z_n; u, y)$, indicating an expenditure a consumer is willing to pay for alternative housing values $(z_i, \ldots, z_n)$ at a given utility, u, and income, y. The first partial derivative of the housing bid function with respect to housing attribute, $\partial\theta/\partial z_i$, reveals the consumer's implicit bid for the home's underlying attributes, z_i's. Symmetrically, Rosen defines an offer function, $\phi(z_i, \ldots, z_n; \pi, \beta)$, indicating unit prices the seller is willing to accept for the housing it produces with a given output, π, and factor prices and production function parameters, β. The tangency of the offer and bid functions for housing bundles achieves a market equilibrium. A joint envelope of a family of bid functions and another family of offer functions represents a market clearing implicit price function $p(z)$.

Let $\boldsymbol{Z}$ be a vector of housing characteristics $(z_i, \ldots, z_i, \ldots, z_n)$ of housing $\boldsymbol{H}$. The hedonic price function for $\boldsymbol{H}$ expresses the price of $\boldsymbol{H}$ as a function of its characteristics (Freeman 1993). Specifically,

$$P_H = P_H\,(z_i, \ldots, z_i, \ldots, z_n) \tag{1}$$

Also, let $\boldsymbol{X}$ be the composite good expressed as the numeraire that includes all other goods except housing. Assuming a consumer buys only one house, his/her utility function is:

$$U = U\,(X, Z) \tag{2}$$

In order to maximize a utility function subject to the budget constraint $M = P_H + X$, the individual must choose levels of each characteristic to satisfy

$$\frac{\partial U/\partial z_i}{\partial U/\partial X} = \partial P_H/\partial z_i \tag{3}$$

Equation 3 conveys that the marginal willingness to pay for z_i must equal the marginal cost of purchasing more of z_i, other things being equal. The partial derivative of the hedonic price equation with respect to a characteristic, z_i, is the implicit marginal price of that characteristic.

Much of the current research, including Rosen (1974), structures the regressors as independent drivers of a house's value. There is little theory on which to draw for direction with respect to interaction among variables.[3] Herriges et al. (2005) take an ad hoc approach employing interaction terms for wind direction, farm size, and farm distance in various combinations, with little success. While we model wind as a distinct effect, farm distance and hog number are combined into an interaction term.

The theorized effects of distance and hog numbers, both separately and together on odor level, for example, are not well understood. A small farm that is close to a house may affect a house's value more than a larger farm further away. We conclude that the two effects are inseparable, and modeled the effect as such. Distance decay measuring locational effects is well documented in gravity models in spatial interaction theory (Isard 1961). Ambient air concentration, for example, is negatively associated with the distance from a source, and falls off at a slower rate as distance increases (Petts and Eduljee 1994). In this way the hedonic model assumes that the effects of locational and environmental variables decline with distance, and our use of distance bands (discussed below) allows for a non linear decay in a farm's impact on neighboring house values.

The spatial econometric model research also addresses some of the effects of variable interaction and non linearity. Day et al. (2007), as well as our work (see below), recognize the potential for interdependence among covariates and clustering due to omitted spatial variables. Spatial covariance, in this study, is expressed as a smooth decay function of distance between observations.

2.1 Spatial Autocorrelation

Hedonic models using locational variables, however, do not fully account for spatial autocorrelation in housing prices. Positive spatial autocorrelation refers to the cluster of similar values in space while negative autocorrelation refers to the inverse in which locations are surrounded by dissimilar neighbors (Anselin and Bera 1998). Housing prices may be positively spatially autocorrelated because neighborhood residential properties can share location amenities that are not explicitly captured by means of an explanatory variable (Dubin 1998; Basu and Thibodeau 1998). The boundaries of neighborhoods are not always clear-cut and the objective measures of neighborhood quality are often difficult to obtain. The residuals from hedonic models are likely to be spatially autocorrelated. Therefore each house price may hold some explanatory power for each other house, within a reasonable distance. Thus spatial autocorrelation parallels temporal autocorrelation in that neighborhood values in space hold explanatory power. OLS estimates will be unbiased but inefficient under the presence of spatial autocorrelation (Dubin et al. 1999). The inclusion of a spatially lagged variable in the hedonic model addresses this loss of information (Anselin and Bera 1998).

In addition it is important to note that spatial autocorrelation can arise from a mismatch in spatial scale of the data (Anselin and Bera 1998). For example using an indicator variable for neighborhood quality, such as median income, induces a spatial mismatch as the data is only available on the census tract or block-group level. The spatial scale of the census tract or block-group level is larger than that of an individual house, resulting in spatial autocorrelation.[4]

[3] Thanks to an anonymous reviewer for this suggestion.

[4] Spatial autocorrelation between spatial objects can be formally defined by the moment condition as follows (Anselin and Bera 1998, p. 241):

$$cov[y_i, y_j] = E[y_i y_j] - E[y_i] \cdot E[y_j] \neq 0, \quad \text{for } i \neq j$$

Two alternative approaches, direct and indirect representation, model the covariance structure (Anselin 2001a; Cressie 1993). Direct representation, adopted from a geostatistical approach, assumes a continuous surface and expresses spatial interaction as a continuous function of distance.[5] In contrast, an indirect representation, or lattice approach presumes that the spatial effect is a function of the interaction among discrete spatial objects, not simply spatial distance.

The direct approach's advantage is that the correlation among the residuals is modeled as structured matrix of effects that is directly a function of distance between any two observations. The direct approach closely follows time series analysis where weights are applied to years and the relationship between pairs of years is consistent over time (Dubin 1998; Basu and Thibodeau 1998). For example a distance decay function that reflects the distance pairs between objects is often applied to reflect the degree of correlation. Subsequently the direct approach may be best applied in settings with smooth and constant distance relationships among observations, such as found in urban or planned suburban areas.

In contrast, an indirect representation, or lattice approach, presumes that the spatial effect is a function of the interaction among discrete spatial objects, such as two neighboring houses in a rural setting, thus the effect may not simply be a function of distance. Although direct representation has been applied to real estate markets, an indirect approach is more suited to economic studies dealing with discrete objects in a defined space, such as a county or region (Anselin and Bera 1998). Moreover, specifications used in direct representation have estimation and identification problems. For example, the nuisance parameter is not identified under the null hypothesis, resulting in a singular information matrix (Anselin 2001b).

In indirect representation, the specification of a spatial process indirectly determines a covariance structure which requires constructing a relevant spatial weights matrix. In indirect representation, two types of spatial dependence, spatial lag dependence and error dependence, are conventionally distinguished (Anselin 1988). Spatial lag dependence, used in this study, arises from spatial interaction between economic agents such as counties or states, or mismatch in spatial scale. Spatial lag dependence is modeled by incorporating a spatially lagged dependent variable in hedonic models, analogous to the inclusion of a serially autoregressive term for the dependent variable (y_{t-1}) in a time-series context. The inclusion of a spatial lagged dependent variable has two implications (Anselin and Bera 1998). First, OLS estimates will be biased and inconsistent because a spatially lagged dependent variable

Footnote 4 continued.
where i, j refer to individual locations and y_i and y_j denote the value of a random variable at that location. The covariance structure becomes spatial when non-zero i, j pairs are interpreted "in terms of spatial structure, spatial interaction or the spatial arrangement of the observations" (Anselin 2001a, p. 312).

[5] Direct representation improves spatially autocorrelated residuals by directly estimating the covariance structure (Dubin 1998; Basu and Thibodeau 1998). Spatial covariance is expressed as a smooth decay function of the distance between observations. For example, Dubin (1998) specified the covariance structure as:

$$K_{ij} = b_1 \exp(-d_{ij}/b_2)$$

where d_{ij} is the distance between the i and jth observations and b_1 and b_2 are parameters to be estimated. Basu and Thibodeau (1998) used a semivariogram to estimate the covariance structure as:

$$\gamma(s_i - s_j) = 0.5\text{Var}\{\xi(s_i) - \xi(s_j)\} = C(0) - C(s_i - s_j)$$

where s_i denotes location of an observation i and $\xi(s_i)$ denotes the hedonic residual for an observation at s_i.

is endogenous and always correlated with the error term. Second, the simultaneity must be explicitly accounted for, either in a maximum likelihood estimation framework or by using a proper set of instrumental variables.

On the other hand, spatial error dependence arises from noise in the model and can be specified as a spatial process for the disturbance term. The effect of a spatial residual autocorrelation on the OLS estimator is analogous to time-series results. The OLS estimates will be unbiased, but inefficient. More efficient estimators are obtained by specifying the error covariance implied by the spatial process.

2.2 Spatial Weights Matrix

The specification of a covariance structure in indirect representation requires constructing a relevant spatial weights matrix. Whereas the spatial weights of the direct representation are geostatistically based, the lattice approach is more flexible allowing for alternative means to specify the representation of the relationship among neighbors (Anselin and Bera 1998). There is very little theoretical guidance in the choice of spatial weights (Anselin 2002).

A spatial weights matrix, usually denoted by W, specifies neighborhood sets for each observation as nonzero elements. In each row i, a nonzero element, w_{ij}, defines j as being a neighbor of i. So $w_{ij} = 1$ when i and j are neighbors, and $w_{ij} = 0$ otherwise. Establishing the neighborhood set in this fashion reflects the range of spatial interaction. In the case of the housing market, for example, nonzero pairs in a spatial weights matrix would indicate the extent of the externality effect on neighboring houses. By convention, an observation is not a neighbor to itself, so that the diagonal elements are zero ($w_{ii} = 0$). In most cases, the spatial weights matrix is row standardized so that weights across rows sum to one. This amounts to averaging of the neighboring values and allows for spatial smoothing. Standardizing weights also makes the spatial parameters comparable between models.

There are different ways to define neighborhoods and a weights matrix.[6] Conventionally, neighbors refer to locations adjacent to each other sharing common boundaries or vertexes, so, for example, a county in a regular grid will have four neighbors (rook or bishop criterion) or eight neighbors (queen criterion) (Anselin 2002). For example, in Fig. 1, the five observations in a regular grid have one or four neighbors that share borders (rook criterion). Figure 2 is a corresponding 5×5 spatial weights matrix where the left panel denotes the number of neighbors and the right-hand panel shows the standardized weights matrix that is used in the estimation.[7] For example, using the rook criterion, observation #3 has four neighbors and each is weighted at 25% in order that the weights sum to one.

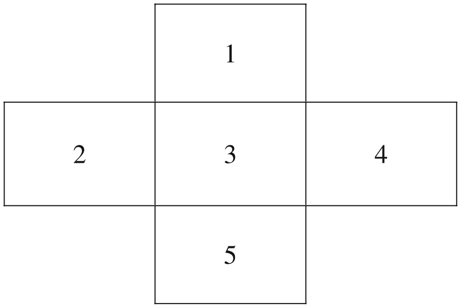
For an irregular grid, the number of neighbors will depend on the shape of the grid. This notion of neighbors based on contiguity cannot be applied to rural housing markets because houses are not contiguous and can be separated by great distances. Constructing a weights matrix in rural areas based on contiguity, as would occur using a direct representation, will yield many “islands,” or observations with no connections, and makes the analysis of spatial autocorrelation irrelevant.

In a direct approach neighbors are defined as the locations within a given distance. For the type of distance, a physical distance-band is commonly used (Can 1990; Can and Megbolugbe 1997; Pace and Gilley 1997; Kim et al. 2003). The number of neighbors, however, will vary if the sizes of spatial units differ. A distance-band weights matrix is not feasible for rural

[6] The weights also can be based on economic distance or a general metric such as a social network structure. See Anselin and Bera (1998) and Anselin (2002) for details.

[7] For the further exposition of a spatial weights matrix, see Anselin (1988, 2002).

Fig. 1 Observations in regular grid



Observations

	1	2	3	4	5	Standardized Matrix				
1	0	0	1	0	0	0	0	1	0	0
2	0	0	1	0	0	0	0	1	0	0
3	1	1	0	1	1	0.25	0.25	0	0.25	0.25
4	0	0	1	0	0	0	0	1	0	0
5	0	0	1	0	0	0	0	1	0	0

Fig. 2 Spatial weights matrix

studies since lot sizes vary greatly in rural areas. Building a weights matrix on a distance band produces an uneven number of neighbors from rural clusters (hamlets) or a small number of neighbors for larger lots (farms).

Alternatively with the lattice (indirect) representation used in this study, the k-nearest neighbors for each house are employed to represent unconnected houses in a contiguity base or an uneven number of neighbors in a distance-band case (Pace et al. 1988; Can and Megbolugbe 1997). Choosing k-nearest neighbors ensures a constant number of neighbors for each house. The idea of k-nearest neighbors corresponds to the practice of the "comparable-sales" approach employed in residential real estate appraisal (Can and Megbolugbe 1997).

2.3 Empirical Studies

The issue of spatial autocorrelation has received little attention in hedonic studies in rural settings. One recent exception identified a significant and negative impact on housing values due to the proximity of oil and gas facilities (Boxall et al. 2005). Day et al. (2007) effectively address spatial autocorrelation to improve their hedonic model of noise pollution in Birmingham, England. They utilized a thick dataset comprising 10,848 residential property transactions and 1,940 socio-economic enumeration districts. Their study is unique for a number of reasons, most importantly they estimate demand equations for noise and the associated welfare impact of noise reduction. One nice feature of their data, as compared with studies of CAFO impacts on property values, is that there is a robust noise measure for each housing observation. There is none such measure for livestock's impacts. Livestock researchers more crudely test whether there is an effect, while Day et al. are able to estimate the demand for an economic good (peace and quiet).

The purpose of our article is to advance the methodology of rural hedonic studies to explicitly address spatial autocorrelation in housing prices when rural property values are impacted by confined animal feeding operations (CAFOs). To date, none of the existing studies on the impact of swine operations on property values has addressed the issue of spatial autocorrelation in housing prices. Several hedonic studies in real estate and housing markets have applied an indirect representation of the covariance structure among spatial objects when addressing spatial autocorrelation. Yet, no study examines the issue of spatial autocorrelation in housing prices in rural settings, much less where CAFOs are concerned.

There are three published studies of impact of swine facilities on housing values, Palmquist et al. (1997); Ready and Abdalla (2005), and Herriges et al. (2005). Palmquist et al. (1997) find that hog operations in North Carolina cause a reduction in house price up to 9% depending on the number of hogs and their distance from the house. They estimate that the effect of a new hog operation located within one-half mile of a house would decrease the house value by 4.75% if a house is exposed to an intermediate level of manure.

They used 237 arm's length sales transactions over an 18 month period from a nine county area as the dependent variable in their hedonic regression model. Though the study area was spatially diverse they did not analyze the observations for sample selection bias. They were able to purge the data of non-rural and non-residential observations. They unfortunately did not have the precise location of the hog farms in the region. As a result they were forced to aggregate farms into three distance rings, 0–1/2 mile, 1/2 to 1 mile, and 1–2 mile from each of the 237 housing observations. Assumptions a priori were no impacts beyond two miles and a uniform distribution of animals within a distance ring. The precise characteristics of the farm, its distance, and hence its fundamental relationship with a house were not incorporated into the model. The lack of spatial precision prohibited an analysis of wind affects, and spatial autocorrelation could not be corrected.

A second article, by Ready and Abdalla (2005) involved 8,090 house sales over a five year period and 71 livestock operations. The author employed a log-linear functional form, a two-stage least squares estimation procedure, and did not address spatial autocorrelation. They found a 4% reduction in housing value 0.5 miles for a swine facility, but no impact beyond one mile or due to wind. Interestingly they found that large farms did not have greater impact. In fact they conclude that the smaller farms between 200 and 300 animal equivalent units did decrease housing values.

Herriges et al. (2005) like our study, used precise GIS farm locations and were able to address wind direction, but did not address spatial autocorrelation. They found that a moderate-size livestock operation (250,000 live weight pounds) can cause −26% reduction in property value in Iowa if the property is downwind and 1/4 mile away from the facility. Unfortunately these results are not robust because so few the livestock-related coefficients were significant. Only two of nine estimated effects were significantly different from zero, and oddly these were for the small farm category. Similar to our results they show a distance decay effect whereby at 1.5 miles the impact of smaller farms on housing values is only 25% of the negative impact at 1/4 mile. Their data comprised 550 livestock facilities in five counties area and 1,145 "arms-length" house sales. They did not discuss why the larger farm categories had no significant effect on housing values. There may be scale economies in abatement, which we found, but there may simply have been spatial data bias. On average there are 2.5 livestock facilities within 3 miles of a house, but almost half of the housing observations originate from one county that has only 5% of the farms. One motivation for testing for spatial autocorrelation is to address unspecified errors associated with the spatial distribution.

The effects of directional heterogeneity on housing values due to wind need to be evaluated where localized environmental disamenities are involved (Cameron 2006). Airborne movement of swine and manure odor and particulates from farms to neighbors is of concern where CAFOs are present. Palmquist et al. (1997) did not address the affects of wind and therefore assumes homogeneous effects of a swine facility on housing values no matter the directional relationship between the farm and the home. Herriges et al. (2005) included directional dummies for wind. Only two coefficients were statistically significant among the nine direction models estimated. Interestingly the two significant coefficients were associated with the smallest size class of livestock production and not the larger farms as might be hypothesized.

Incorporating a spatially lagged dependent variable and spatial parametric drift in a study of housing prices in Columbus, Ohio, offered a better explanation of the variations than traditional hedonic price models (Can 1990). Similarly, incorporating a spatially lagged dependent variable to consider the house price index in Miami, Florida not only increased the explanatory power of the model, reflected in a higher R^2, but also addressed the problem of omitted housing structure variables (Can and Megbolugbe 1997).

In contrast to these studies specifying a spatially lagged dependent variable, a spatially autocorrelated error term was specified through a weighted average of the errors on nearby properties for housing data in Boston (Pace and Gilley 1997). The weight was given to each census tract and set as the distance between two tracts relative to all other tracts. The estimation results showed that modeling spatial dependence of the errors was significantly beneficial, resulting in a 44% reduction of the errors relative to the OLS.

A lattice perspective has also been used in the environmental economics literature. The OLS model overestimated the effect of air quality on housing prices in Seoul, Korea in the presence of spatial lag dependence (Kim et al. 2003). On the other hand, a spatial autoregressive (SAR) error model did little to change the benefit estimation of improving air quality in the South Coast Air Basin counties (Beron et al. 2004). The authors noted the arbitrariness of selecting 1.5 mile designation of a neighbor. More reasonable may be to analyze smaller distance bands in this densely populated region of Southern California in combination with spatial weights that decline with distance.

3 Study Area and Data

Craven County located in southeastern North Carolina is chosen as a study area for three reasons: first, geographically coded real estate ($N = 25,684$ housing values) and swine industry data ($N = 26$ farms and 85,000 pigs) are available; second, the farms are located in one of the nations most significant swine regions, and third, land use is heterogeneous where neither agriculture nor non-agriculture rural residents dominate.

Three categories of data collection are involved in this study: (1) assessed property values and sale prices, including location and description information; (2) general neighborhood indicators, and (3) hog operation and location (Table 1).

Table 1 Descriptive statistics for houses within 3 mile distance ($n = 2,155$)

Variables	Definition	Mean	Std. Dev.	Min.	Max.
Dependent variable					
VALUE	Assessed property values ($)	81,862	60,892	6,260	628,710
Independent variable					
BASEAREA	Base area (sq. ft)	1,461	449	480	3,876
ROOM	Number of rooms	5.8	1.1	2	13
BATHROOM	Number of bathrooms	1.6	0.6	1	6
LOTSIZE	Lot size (acres)	1.4	1.6	0.05	10
AGE	Age of house (years)	32	25	1	173
INCOME	Median household income by census block-group ($1,000)	36.2	11.3	22.1	61.4
DCDB	Distance to the central business district (miles)	14.1	6.3	2.9	26.7
DSCHOOL	Distance to the nearest school (miles)	3.8	2.1	0.1	9.2
DOPEN	Distance to the nearest open space (miles)	0.2	0.2	0.001	1.3
HOG_D	Number of hogs divided by distance to the nearest farm	3,158	3,779	264	32,555
SIZE	1 if a farm is large (>2,500 head)	0.5	0.5	0	1

Both assessed vales and sale prices were initially collected for use as the dependent variable. Rural housing datasets are plagued by low degrees of freedom due to a limited number of transactions, which in turn creates significant estimation problems (Cole et al. 1986; Benson et al. 1998; Kiel and Zabel 2001). The sales data in Craven County were problematic because of the rural context of the study where housing density was low and sales turnover was slow. Like many rural settings, there existed a high percentage of out-of-market values, which reduced the size of the available data. For example, 25.5% of the 5,352 rural houses in the county had zero recorded as the sales price. Another 27.8% had no information on their sales price. Arms length transactions are central to efficient sales models (Pace et al. 1988; Can and Megbolugbe 1997).

Further data analysis was conducted on non-zero but low sale price transactions. Houses transacted since 1990 with the ratio of sale price/assessed value (S/A) greater than 0.5 were deemed to be "arm's-length" transactions for the purpose of analysis. Selecting only "arm's-length" transactions in this fashion further reduced the sample size to 1,431. The sales dataset was 26.7% the size of the assessed value dataset after employing these three cleaning routines. The data then at any one of the half-mile distance bands was thin. For example, only 18 and 219 sale-price observations were available at .50 and 1.75 miles respectively, from any of the 26 hog farms, about one-sixth of the 1,241 assessed-value observations. Herriges et al. (2005), noted above, was also plagued by this problem of spatial bias.

Finally housing sales and the associated data may not be temporally or spatially continuous, while assessed valuations are. Lack of temporal continuity among rural properties may occur because of the longer average ownership tenure. This lag of price discovery may make assessed values a more current representation of the true value of the house (Cole et al. 1986). Sample imbalances may occur due to rural transactions being spatially clustered, thus spatially correlated, near higher density locations such as rural hamlets or rural-urban fringes. For example, at 1.75 miles about 45% ($n = 98$) of the 219 sale-price observations were centered on the two large farms located at the rural-urban fringe. In contrast, only 19% ($n = 230$) of assessed value observations were near these two farms.

Hedonic regression estimation resulted in poorer performance with the sales-based model compared to an assessed-value model due to the spatial anomalies and poor data quality. Goodness of fit was 5–21% inferior across the 11 distance band models.[8] Both models though were effective and comparable estimating the marginal impact of physical attributes on housing value. The sales model though was ineffective estimating the effect of locational variables. Only one out the five locational variables employed in the model was reliable, including the variable reflecting the proximity and size of a swine facility. The assessed model on the other hand was robust across all the locational variables. The superior performance of the assessed model with respect to location variables may have occurred because of superior spatial properties of assessed data that was noted above. Additionally there has been an extensive research literature favorably comparing assessed (or appraisal) values and sales prices in determining the true underlying value of a property.

In a study exploring the temporal component of valuations, Cole et al. (1986) found sale price and assessed values were quite comparable. They found no impact of temporal lags among sales activity and tax assessment cycles. In a relatively small ($n = 318$) dataset of rural vacation homes, Boyle and Taylor (2001) were concerned about lot and house characteristic measurement errors by assessors. They found no statistical difference between a detailed survey of the lot and housing characteristics and tax assessor records.

Assessments, because of their breadth of data may in fact be a better estimate of the value of location (Schuler 1990). Sample selectivity bias can affect sale price data as repeat-sale homes were found to originate from a different population than longer tenured homes (Clapp and Giaccotto 1992). Rural homes tend to have higher tenure. Rush and Bruggink (2000) found good overall comparability but undervaluation when appraisers valued bathrooms and air conditioning. Appraisals may have undervalued these amenities because the valuations were taken from the state appraisal manual. Alternatively Janssen and Söderberg 1999), who also analyzed the impact of the rules and regulations that guide the appraisal process, found much higher out of sample predictability with an assessed value model. The reason, they surmised, may be that the standards and regulations guiding appraisers and assessors lend greater homogeneity to the data, and as a result make estimates more efficient.

But legitimate questions were also raised (but not tested) that appraisers or assessors might be pressured by parties to a future sale, thus biasing their results (Smolen and Hambleton 1997; Wolverton 2000). There is a concern that appraisers or assessors may not have complete information about the comparable sales they utilized in their analysis (Allen et al. 1986). This has proven difficult to empirically measure. Discounts and premiums due to the contingency

[8] Due to space limitations the tabular results are not presented. Results can be found in a working paper; Kim, J. and P.D. Goldsmith, 2006. "Can Assessed Values Tell Something That Sale Prices Don't? The Case of Rural Hedonic Settings," and can be obtained from the authors.

nature of many transactions are often reflected in a sale prices but are not readily known to assessors.

In sum, we estimated our model using assessed values because the data were significantly more continuous across space and time, and correspondingly the statistical properties of the data were superior. As a result, a detailed comparison revealed that the assessed model provided superior estimators given the context of our study.

Data on assessed property values were obtained from the Craven County GIS Website. Craven County completed a countywide revaluation of 50,000 individual parcels as of January 1, 2002 based on a 8-year total revaluation cycle mandated by North Carolina General Statutes. The County updated new values for all properties in January 2003.

For the analysis purposes, rural houses were identified from the Craven parcels map with the following procedures: first, since the Craven parcels map includes every parcel including residential, commercial, agricultural, and open space, only parcels whose building type and land use were residential were deemed to be residential parcels with houses. Second, only houses with at least one bedroom and bathroom including mobile homes were selected. Third, houses in census-defined urban areas ($n = 12,799$) were excluded for two reasons. First, because of their higher population density, they may swamp the data compared to the sparsely populated rural areas. Secondly, high population density common to urban areas leads to high levels of spatial autocorrelation that is difficult to specify, difficult to disentangle from non spatial determinants of housing value, and significantly differ from the spatial effects common to rural settings. As a result, 1,100 urban house observations (9%) were removed within 2 miles of the nearest farm.[9] Additionally, 91 census-defined rural houses located in the same blocks with urban houses were deemed to be urban and were also excluded from the sample. Houses in the two townships (Township 5 and 6) with no hog farms were also excluded from the sample, as the minimum distance from the two townships to the nearest farm is about 7.25 and 19 miles, respectively. Houses with lot size over 10 acres were considered outliers and excluded to avoid houses with farm or timber tracts, following (Palmquist et al. 1997).[10] These selection procedures reduced the dataset to 5,352 non-urban houses (Fig. 3).

[9] There were 12 and 317 urban houses removed within 1 and 1.5 miles of the nearest farm, respectively.

[10] The issue of outlier observation arises due to a lack of enough observations, in particular, at closer distance to hog farms. This research utilizes assessed values as the dependent variable and takes all house values within each distance band as its sample. Yet insufficient observations was still of concern with the closer distance bands even when assessed values were used. For example, there are 523 houses at 1 mile distance away from the 26 farms, which amounts to only 20 houses on average per farm. Under this circumstance, an outlier may well influence regression results. The outlier problem is more pronounced when houses are divided into two groups, one for medium farms and the other for large farms, in order to examine scale economies in environmental impact abatement. The tests we performed for outliers therefore were critical.

Indeed, one influential outlier, or an observation with high leverage, was detected and removed from the sample. Four measures were used to identify such an observation with high leverage: (1) leverage versus residual squared plot, (2) Cook's distance, (3) added-variable plot, and (4) DFBETA.

Leverage versus residual squared plot checks potentially influential observations and outliers at the same time. The removed house was shown to have a very high leverage for medium farms within 1 mile distance.

Cook's distance assesses how much a particular observation affects regression estimates. The higher the Cook's D is, the more influential an observation. The conventional cut-off point is **4/n** and the lowest value that Cook's D can assume is zero. The outlier house had a Cook's d value of 0.08, highest among the 243 houses surrounded by medium farms within 1 mile distance. The cut-off point was 0.02 (= 4/243).

An added-variable plot, or partial-regression leverage plot shows the relationship between the dependent variable and an independent variable after both dependent variable and independent variable have been adjusted for all other variables. The outlier house had a very strong (positive) effect on the HOG_D coefficient value by pulling up the regression line.

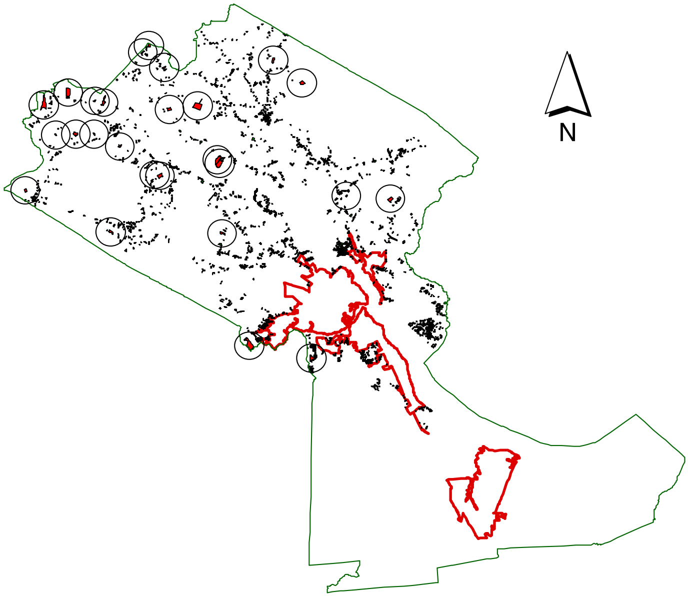


Fig. 3 Craven county rural homes and hog farms under study. *Note*: Circles represent 1-mile radius from hog farms, thick lines within the county represent urban census areas, red blocks represent farms, and black marks represent houses

Information on general neighborhood characteristics originated from the 2000 Census. The Census Bureau reports the median household income and average commuting time to work at the census block-group level. The spatial information on the census block-groups is available in the form of the Census 2000 TIGER (Topologically Integrated Geographic Encoding and Referencing System) Shape files.

Data on the 26 hog operations were acquired from the North Carolina Department of Environment and Natural Resources, Division of Water Resources, and Craven County Appraisal Office (Table 2). North Carolina hog data include: farm number, farm name, design capacity, steady-state live weight, owners name, and mailing address. The steady-state live weight represents the collective weight of all animals at a facility and is a more accurate means of size comparison.[11] The steady-state live weight is divided by an average hog weight (135 lb.) to get an average number of animal "units" for an operation. Alternatively, the actual number of hogs could be used to compare farm sizes. But data on the number of hogs by different types such as sows, nurseries, or piglets are not available. Using steady-state live weight can account for different types of hogs on a farm and is considered more representative of

Footnote 10 continued.

Lastly, DFBETA assesses how the coefficient is changed by deleting the observation. The conventional cut-off point is $2/\sqrt{n}$. In the case of houses within 1 mile distance, the cut-off point in DFBETA value for HOG_D is 0.13 ($= 2/\sqrt{243}$). In contrast, the DFBETA value for the outlier house was 0.90, well above the horizontal line. The value of 0.90 means that by being included in the analysis (as compared to being excluded), the house increases the coefficient for HOG_D by 0.90 standard errors, i.e., 0.90 times the standard error for HOG_D or by ($0.9 * 0.0005$) for the houses within 1 mile distance.

[11] Division of Water Resources website, "Important Facts about Lists of Animal Operations," ftp://h2o.enr.state.nc.us/pub/Non-Discharge/Animal%20Operations%20Info/

Table 2 Hog farms and hog numbers in Craven

No.	Design capacity	Steady state live weight	Head
1	5,200	156,000	1,156
2	5,200	156,000	1,156
3	5,200	156,000	1,156
3-1	2,640	79,200	587
4	3,500	1,515,500	11,226
5	3,672	495,720	3,672
6	3,840	115,200	853
7	3,840	115,200	853
8	2,448	330,480	2,448
9	3,200	96,000	711
10	2,400	324,000	2,400
11	720	311,760	2,309
12	1,400	189,000	1,400
13	2,629	354,915	2,629
14	3,520	475,200	3,520
15	3,144	424,440	3,144
16	–	417,600	3,100
17	1,500	202,500	1,500
18	4,320	583,200	4,320
19	2,400	1,039,200	7,698
20	2,960	88,800	658
21	820	355,060	2,630
22	4,896	660,960	4,896
23	7,680	230,400	1,707
24	5,200	702,000	5,200
25	4,580	1,700,140	12,594
26	1,760	237,600	1,760
Sum	88,669	11,512,075	85,283

The number of head is obtained by dividing steady-state weight by an average hog weights (135 lbs)
The number of heads for the farm #16 is obtained from the Environmental Defense website as the design capacities for those farms are not available from North Carolina data
The two farms, farm #3 and 3-1, are treated as one farm as they are on the same parcel
Names of farm owners (as well as home owners) are omitted for privacy concerns

the quantity than the actual number of hogs.[12] The locations of the farms were verified by comparing owners' names and parcel IDs with Craven County Appraisal Office's records.

4 Model Specification

The estimation of a spatial hedonic model was preceded by diagnostics of spatial autocorrelation in the hedonic OLS model. To that end, the Robust Lagrange Multiplier (LM) test,[13] a two-way test for both spatial lag dependence and spatial error dependence, was used. Spatial lag dependence was found, so a spatially lagged dependent variable (W) was incorporated into the model.

$$Y = \rho W \cdot Y + X\beta + \varepsilon \tag{1}$$

where ρ is the spatial autoregressive parameter, W is the k-nearest neighbor weights matrix, X is a vector of independent variables as above, and ε is an error term.

[12] Environmental Defense website, http://www.scorecard.org/env-releases/def/aw_wastes.html

[13] There are two types of the LM test, the LM test and the Robust LM test. The LM test is a one-way test in the sense that it tests for only one type of spatial dependence. The Robust LM test is a two-way test accounting for the presence of both types of spatial dependence (see Anselin and Bera (1998) for details).

Specific to our context, the spatial lag dependence model is specified as:

$$\begin{aligned}\mathrm{VTF} = {} & \beta_0 + \rho W \cdot \mathrm{VTF} + \beta_1 \mathrm{BASEAREA} + \beta_2 \mathrm{ROOM} + \beta_3 \mathrm{BATHROOM} \\ & + \beta_4 \mathrm{LOTSIZE} + \beta_5 \mathrm{AGE} + \beta_6 \mathrm{INCOME} + \beta_7 \mathrm{DCBD} + \beta_8 \mathrm{DOPEN} \\ & + \beta_9 \mathrm{DSCHOOL} + \beta_{10} \mathrm{HOG\_}D + \beta_{11} \mathrm{SIZE}\end{aligned} \tag{2}$$

where VTF is Box-Cox transformed assessed property values, ρ is the spatial autoregressive parameter, W is the k-nearest neighbor weights matrix, BASEAREA is the base area of a house, ROOM is the number of rooms, BATHROOM is the number of bathrooms, LOTSIZE is lot size, AGE is house age.

Several variables capture the socio-economic context in which the homes are set. There is assumed to be interaction between socio-economic state and a physical attribute, but little guiding theory. The spatial model in part indirectly captures the effects of socio-economic state by means of the house's location when spatial correlation is taken into account. Nonetheless bathrooms, for example, may be valued differently by different population subsets.

A second problem is that housing attributes and socio-economic data are presented in different spatial scale. This makes estimating the interaction effect difficult and the resulting estimator inefficient. Day et al. (2007) faced this problem as they had individual house attribute data but their socioeconomic data were defined at the enumeration district level, an aggregation of 191 homes. In our case, like Day et al. (2007) the home is unique to the parcel level under study, but there is no matching socio-economic data on the owner.

Four variables are utilized to integrate socio-economic factors into the model in order to achieve more robust estimators. INCOME is median household income by census block group, DCBD is the distance to central business district, DOPEN is the distance to nearest open space, and DSCHOOL is the distance to the nearest school.

As noted above, Herriges et al. (2005) created several interaction terms among the wind direction, distance, and farm size variables in an attempt to improve fit. Without theoretical guidance we opted not to employ an interaction term involving wind. This provided no better result than found in Herriges et al.

Finally are environmental variables of particular interest to this study. HOG_D is the number of representative hog units in the nearest farm divided by the distance, and SIZE is a dummy variable for farm size (= 1 if greater than 2,500[14] head). Theoretically size and distance are thought to be interrelated. A pig's impact on a house's value may be quite different depending on its distance from the house. Hog_D reflects this theoretical notion that the two are difficult to disentangle. At the same time Hog_D is a ratio and is not a very practical variable for analysis because it obscures the distance and farm size effects.

The distance problem was addressed by following Palmquist et al. (1997) and utilizing distance bands. Using precise distance measures avoided imprecision due to the aggregation of effects or the assumption of a uniform spatial farm distribution within bands, as was the case with Palmquist et al. (1997). The farm size effect was addressed by the inclusion of a size dummy variable. Tests were negative for multicollinearity between Hog_D and Size.

Eleven quarter-mile band models (Eq. 2) were estimated from a half-mile up to three miles (Table 3). Variables were cumulative with respect to distance so that the three mile band model included all farms and all houses. For example, there were 528 houses within one mile of a farm.

[14] USEPA definition of a CAFO.

Table 3 Distance band statistics

Distance band to nearest farm (mile)	Number of houses	Mean distance to farm (mile)	Hog summary statistics				Hog/D summary statistics			
			Mean (head)	Standard deviation (head)	Min (head)	Max (head)	Mean	Standard deviation	Min	Max
0.50	109	0.35	3,138	2,200	658	12,594	10,288	8,545	1,442	32,556
0.75	262	0.53	3,787	2,952	658	12,594	8,133	7,028	1,040	32,556
1.00	523	0.70	3,824	2,919	658	12,594	6,316	5,792	683	32,556
1.25	730	0.82	3,568	2,805	658	12,594	5,260	5,298	533	32,556
1.50	1,004	0.97	3,416	2,705	658	12,594	4,423	4,803	465	32,556
1.75	1,241	1.09	3,416	2,813	658	12,594	3,981	4,500	377	32,556
2.00	1,474	1.22	3,733	3,179	658	12,594	3,809	4,247	358	32,556
2.25	1,688	1.33	3,911	3,408	658	12,594	3,636	4,068	294	32,556
2.50	1,862	1.43	3,997	3,546	658	12,594	3,486	3,945	264	32,556
2.75	2,023	1.52	3,943	3,515	658	12,594	3,309	3,847	264	32,556
3.00	2,155	1.61	3,850	3,475	658	12,594	3,158	3,779	264	32,556

4.1 Wind

The role of prevalent wind direction is examined by including three dummy variables (SW, SE, and NW) for wind directions in the hedonic model. The hypothesis is that houses downwind will be more adversely affected by hog farms than houses elsewhere. To that end, dummy variables are added for SW, SE, and NW.

SW $= 1$ if a house is located in southwest, 0 otherwise. SE $= 1$ if a house is located in southeast, 0 otherwise. NW $= 1$ for a house in northwest, 0 otherwise. The expected sign is negative for SW and SE and positive for NW, as prevalent wind direction is north or north-north east for nine months, January to September, and southwest for the rest of year.

5 Estimation Results

The spatial lag model was estimated by grouping all houses in quarter mile increments from 0.5 to 3 miles from the nearest farm (Tables 4–6). Shown are three distance bands between 0.75, 1, and 1.25 mile.[15]

There was a strong presence of spatial lag dependence arising from some shared local amenities that affects housing values in a common way. The Robust LM test was highly significant for spatial lag dependence ($p < 0.00$), whereas it was not for spatial error dependence ($p = 0.85$, 0.76 and 0.18 for 0.75, 1, and 1.25 miles, respectively). The presence of strong lag dependence was consistent across the 3- to 9-nearest neighbor weights matrix. All k $\{3, 5, 7, 9\}$ weight matrix models were not significantly different from each other. Therefore only the diagnostic results and the estimation of spatial lag model from the 3-nearest neighbor weights matrix were reported.[16]

Two sets of spatial lag models, i.e., the maximum likelihood (ML) and the spatial two-stage least squares (2SLS) estimation, were estimated for the three distance bands. The ML estimation assumes normality. In contrast, the 2SLS estimation, using spatially lagged explanatory variables as instruments, is robust to nonnormality and consistent, but not necessarily efficient. Given the nonnormality found in the OLS estimates with a significant Jarque–Bera test for normality ($p < 0.05$), the 2SLS estimates seem more appropriate than the ML estimation. In addition, the 2SLS-robust estimation can be an alternative to the ML estimation, when heteroskedasticity is present. In fact, strong evidence of heteroskedasticity was present as indicated by significant White test ($p < 0.05$).

All housing physical variables (BASEAREA, ROOM, BATHROOM, LOTSIZE, and AGE) were significant at a 1% significance level and showed the expected signs. The locational variables (INCOME, DCBD, DOPEN, and DSCHOOL) were significant at the 5%

[15] Results for closer and further distance bands (0.5 miles and beyond 1.75 miles up to 3 miles) are not shown, as the variable of interest HOG_D was not significant. These results can be supplied directly by the authors upon request.

For two distance bands (1.5 and 1.75 mile), the results of the Robust LM test indicated that both spatial lag and error dependence were present, preventing the estimation of the spatial lag or spatial error dependence model. The implication is that the estimation of spatial lag dependence model would have spatial error dependence remaining and visa- versa. The joint estimation of both spatial lag and spatial error dependence therefore is not feasible. Appropriately identifying two spatial weight matrices, one pertaining to spatial lags and the other to spatial errors, appears not to be possible.

[16] The number of nearest neighbors selected as a weights matrix in real estate studies ranges from 3 (Can and Megbolugbe 1997) up to 15 nearest neighbors (Pace et al. 1998). The use of 3-nearest neighbor weights matrix for this article conforms to the practice of using three sales comparables in real estate appraisal (Lusht 2000).

Table 4 Estimated spatial hedonic model for 0.75 mile distance band

Variable	Models			
	Box-Cox (OLS)	Spatial lag (ML)	Spatial lag (2SLS)	Spatial lag (2SLS-Robust)
P		0.213(0.046)***	0.227(0.058)***	0.221(0.058)***
CONSTANT	32.536(4.930)***	21.831(5.140)***	21.138(5.559)***	19.788(5.455)***
BASEAREA	0.012(0.001)***	0.012(0.001)***	0.012(0.001)***	0.011(0.001)***
ROOM	1.123(0.507)**	1.253(0.474)***	1.262(0.486)***	1.305(0.459)***
BATHROOM	4.486(1.129)***	3.937(1.056)***	3.901(1.091)***	4.549(1.222)***
LOTSIZE	1.701(0.292)***	1.514(0.275)***	1.502(0.284)***	1.496(0.358)***
AGE	−0.148(0.024)***	−0.150(0.022)***	−0.150(0.023)***	−0.141(0.032)***
INCOME	0.341(0.067)***	0.239(0.066)***	0.232(0.070)***	0.247(0.065)***
DCBD	−0.334(0.126)***	−0.264(0.119)**	−0.260(0.122)**	−0.247(0.107)**
DOPEN	8.589(1.939)***	7.349(1.840)***	7.269(1.887)***	7.348(1.665)***
DSCHOOL	0.869(0.304)***	0.693(0.286)**	0.682(0.294)**	0.693(0.273)**
HOG_D	−0.00017(0.000089)*	−0.00015(0.000083)*	−0.00014(0.000086)*	−0.00012(0.000080)
SIZE	2.925(1.254)**	2.123(1.182)*	2.071(1.220)*	1.532(1.158)
Jarque–Bera[a]	8.51**			
White/BP[b]	100.51**	46.11***		
LM-error	8.92***	0.06	0.09	
Robust LM-error	10.39			
LM-lag	11.07***			
Robust LM-lag	10.71***			

$N = 262$

* Significant at 10%, ** significant at 5%, *** significant at 1%; Standard errors in parentheses

[a] Jarque–Bera test on normality of errors

[b] White or Breusch–Pagan test on heteroskedasticity

Note: LM tests and ML estimation are carried out with 3-nearest neighbor weight matrix

Table 5 Estimated spatial hedonic model for 1 mile distance band

Variable	Models			
	Box-Cox (OLS)	Spatial lag (ML)	Spatial lag (2SLS)	Spatial lag (2SLS-Robust)
ρ		0.187(0.034)***	0.194(0.045)***	0.188(0.048)***
CONSTANT	41.114(4.695)***	28.475(5.054)***	27.953(5.474)***	27.313(5.657)***
BASEAREA	0.016(0.001)***	0.015(0.001)***	0.015(0.001)***	0.014(0.001)***
ROOM	2.072(0.482)***	2.063(0.461)***	2.063(0.467)***	2.293(0.483)***
BATHROOM	6.807(1.130)***	6.196(1.086)***	6.171(1.105)***	6.392(1.260)***
LOTSIZE	2.203(0.312)***	1.993(0.300)***	1.984(0.306)***	2.056(0.366)***
AGE	−0.248(0.023)***	−0.248(0.022)***	−0.248(0.022)***	−0.237(0.030)***
INCOME	0.495(0.067)***	0.385(0.067)***	0.380(0.070)***	0.393(0.068)***
DCBD	−0.386(0.140)***	−0.267(0.136)**	−0.263(0.139)*	−0.273(0.132)**
DOPEN	8.533(1.905)***	7.147(1.845)***	7.089(1.877)***	6.826(1.735)***
DSCHOOL	0.789(0.283)***	0.707(0.272)***	0.703(0.275)**	0.664(0.276)**
HOG_D	−0.00033(0.0001)***	−0.00024(0.0001)**	−0.00024(0.0001)**	−0.00021(0.0001)**
SIZE	4.999(1.223)***	3.208(1.219)***	3.134(1.262)**	2.703(2.703)**
Jarque–Bera[a]	15.22***			
White/BP[b]	138.00***	82.34***		
LM-error	15.14***	0.10	0.006	
Robust LM-error	0.09			
LM-lag	30.84***			
Robust LM-lag	15.80***			

$N = 523$

* Significant at 10%, ** significant at 5%; *** significant at 1%; Standard errors in parentheses

[a] Jarque–Bera test on normality of errors

[b] White or Breusch–Pagan test on heteroskedasticity

Note: LM tests and ML estimation are carried out with 3-nearest neighbor weight matrix

Table 6 Estimated spatial hedonic model for 1.25 mile distance band

Variable	Models			
	Box-Cox (OLS)	Spatial lag (ML)	Spatial lag (2SLS)	Spatial lag (2SLS-Robust)
P		0.167(0.029)***	0.151(0.037)***	0.144(0.039)***
CONSTANT	38.524(3.150)***	28.177(3.539)***	29.365(3.851)***	29.336(4.010)***
BASEAREA	0.012(0.001)***	0.012(0.001)***	0.012(0.001)***	0.012(0.001)***
ROOM	1.488(0.327)***	1.502(0.316)***	1.504(0.319)***	1.595(0.339)***
BATHROOM	5.085(0.750)***	4.747(0.726)***	4.796(0.735)***	4.911(0.794)***
LOTSIZE	1.979(0.218)***	1.794(0.212)***	1.784(0.216)***	1.812(0.263)***
AGE	−0.192(0.015)***	−0.187(0.014)***	−0.188(0.015)***	−0.185(0.019)***
INCOME	0.397(0.046)***	0.315(0.046)***	0.318(0.049)***	0.323(0.048)***
DCBD	−0.298(0.095)***	−0.230(0.093)**	−0.243(0.095)**	−0.247(0.091)***
DOPEN	6.418(1.275)***	5.542(1.243)***	5.654(1.259)***	5.813(1.165)***
DSCHOOL	0.424(0.187)**	0.432(0.181)**	0.432(0.182)**	0.401(0.180)**
HOG_D	−0.00021(0.0001)***	−0.00016(0.0001)**	−0.00017(0.0001)**	−0.00014(0.0001)**
SIZE	3.821(0.780)***	2.790(0.774)***	2.968(0.795)***	2.877(0.804)***
Jarque–Bera[a]	8.87**			
White/BP[b]	139.94***	79.43***		
LM-error	24.06***	1.36	0.95	
Robust LM-error	1.82			
LM-lag	36.09***			
Robust LM-lag	13.85***			

$N = 730$

* Significant at 10%, ** significant at 5%, *** significant at 1%; Standard errors in parentheses

[a] Jarque–Bera test on normality of errors

[b] White or Breusch–Pagan test on heteroskedasticity

Note: LM tests and ML estimation are carried out with 3-nearest neighbor weight matrix

Table 7 Estimated marginal prices for prevalent wind direction effects

	0.5	0.75	1	1.25	1.5	1.75
BASEAREA	32***	63***	41***	41***	38***	35***
ROOM	1,829	6,071**	5,381***	4,882***	3,723***	3,434***
BATHROOM	15,428***	23,457***	17,944***	16,910***	13,430***	13,042***
LOTSIZE	2,319*	8,027***	5,356***	6,367***	6,451***	5,074***
AGE	−434***	−767***	−639***	−633***	−552***	−483***
INCOME	992**	1,759***	1,297***	1,379***	1,219***	1,092***
DCBD	−888	−1,793**	−987***	−851***	−735***	−605***
DOPEN	26,129**	43,083***	22,170***	20,490***	14,146***	11,521***
DSCHOOL	4,166***	5,338***	2,436***	1,720***	737	521
HOG_D	0.144	−0.753[a]	−0.804***	−0.650***	−0.406**	−0.343*
SIZE	−9,804	13,623**	12,292***	11,819***	9,822***	7,928***
SW	−9,349	4,528	2,151	−1,168	696	185
SE	−10,277	−10,275	−5,303	−5,577*	268	1,387
NW	−7,547	−2,875	−2,005	762	3,581	6,058***
λ	0	0.279	0.314	0.288	0.274	0.2
Adjusted R^2	0.677	0.779	0.821	0.810	0.781	0.769

[a] p-value = 0.10
* significant at 10%, ** significant at 5%, *** significant at 1%
Note: Marginal prices are derived using median house value of $63,520 at 3-mile distance band

level. INCOME was positive, meaning that property values are positively associated with household income. The negative sign on DCBD meant that property values declined moving away from the CBD and may be due to decreasing access to urban amenities. Consistent with the negative sign on DCBD was a positive sign on DOPEN. So the further from open space the higher the value of the home, ceteris paribus. The positive DOPEN is inconsistent with the findings of Ready and Abdalla (2005) who found that proximity to open space increased housing values. The reason for the different findings may be due to the fact that their research centered on more densely populated regions in Eastern Pennsylvania where open space is scarce. Somewhat counterintuitive was the positive sign on DSCHOOL suggesting that close proximity to schools was not a positive amenity for non-urban houses in our study area.

The estimated marginal prices for wind effects were generally insignificant and those that were statistically significant were inconsistent with the underlying hypothesis (Table 7). These results are similar to Herriges (2005) where significant impact on housing values due to wind was limited. In our model SW is not significant for all distance bands. SE is negative and significant at 10% for only 1.25 and 2.75 mile distance bands out of the 11 distance bands considered. NW is positive and significant at 10% between 1.75 and 2.25 mile distance bands. As a result we can not say that wind direction has an impact on housing values. HOG_D remains negative and significant up to 1.75 mile, consistent with earlier results when no wind direction variables were included.

The two variables related to hog farm impact (HOG_D and SIZE) were significant at the 10% level with a negative sign for HOG_D and a positive sign for SIZE. The negative HOG_D suggested that hog farms negatively affect property values. The positive sign on SIZE may be indicative of scale economies in abatement as larger farms on a per pig basis may more effectively manage their neighborhood affects. Superior availability of resources, or as suggested by Ready and Abdalla (2005), newer technologies to manage odor and manure may be more common with larger farms.

Consistent with the results of the robust LM test, the spatial autoregressive parameter (ρ) in the ML estimation was positive and highly significant for all three distance bands

($p < 0.00$). Compared with the linear Box-Cox model estimates, all variables retained their signs and significance, but the magnitude of the coefficients decreased in the ML estimates when incorporating the spatial lag effect into the model. This suggests that the linear Box-Cox model estimates will be biased if spatial lag dependence is not taken into account. The magnitude of the spatial autoregressive parameter captured the extent to which a house value at one location was related to its neighbors. For example, ρ was about 0.2 for the 1-mile distance band, meaning one-fifth of the house value could be explained by the values of the neighboring houses. After the spatial lag effect was introduced, there was no remaining spatial error dependence, as the LM test was no longer significant for error dependence.

As with the linear Box-Cox model however, heteroskedasticity was still present in the ML estimation. Subsequently, the 2SLS and 2SLS-robust estimations were carried out to address nonnormality and heteroskedasticity. Compared with the ML estimates, the change in the coefficients was more pronounced in the 2SLS-robust estimation than in the 2SLS estimation, given that the 2SLS-robust estimation took heteroskedasticity into account. All variables though retained their signs and significance in the 2SLS and 2SLS-robust estimations.[17]

Accounting for spatial autocorrelation in housing prices changed the magnitude of the impact of hog farms on property values. Property values declined per hog by −\$0.51 at 0.75 mile, −\$0.68 at 1 mile, and −\$0.53 at 1.25 mile in the linear Box-Cox model estimates. Compared to the linear Box-Cox model spatial lag property value loss estimates decreased \$.04 (8%) to −\$0.47 at 0.75 mile, \$.16 (24%) to −\$0.52 at 1 mile, and \$.11 (21%) to −\$0.42 at 1.25 mile. The impact on the value of the median house (\$63,520) 1 mile from a swine facility with 10,000 head fell from −\$6,800 to −\$5,200, or 23.5%. Thus not accounting for spatial autocorrelation in the form of spatial lag dependence over stated the negative impact of hog farms on neighboring housing values by 18% on average.

Our estimate of a \$−0.52 per hog, or \$−5, 200 (−8.2%) per house, impact on the value of a house located 1-mile from a swine facility is consistent with the results of previous research. There clearly appears to be a negative effect, but at the same time increased employment caused by the "siting" or expansion of a livestock facility can increase housing demand and correspondingly push up housing prices. There has been only one study, and none that have been peer-reviewed, that shows a positive affect.

Additionally our results and associated approach demonstrate that methodology matters. We successfully make very precise and robust estimates of the effect on housing values. To date no other study has successfully been able to achieve that. Our use of spatial methods combined with spatial error correction lends confidence to those that might want to introduce the point estimates into policy instruments. In the end that is our contribution, a robust estimator that policymakers, industry, and stakeholders can employ when attempting to "get the prices right" by determining the level of harm at the parcel level, and then compensate the harmed parties for their losses.

But that being said our estimates are only as robust as the study location. As study boundaries expand the underlying heterogeneity of the hedonic relationships too will expand. For example, preferences related to hog farm proximity may differ from county to county. Extrapolating point estimates in one county may be inappropriate as some counties may have long (short) traditions of hog farming so may be less (more) adversely affected by proximity.

[17] The only exception was HOG _D in the 2SLS-robust estimation for the 0.75-mile distance band. HOG_D was insignificant with p-value of 0.12.

6 Conclusion

This article examined spatial autocorrelation in housing prices to assess the impacts of hog farms on the value of surrounding rural residences. Spatial autocorrelation among housing observations was shown to be present when estimating the affects on a houses value of locational variables such as median household income by census block-group or distance to the facility under study. At the same time spatial autocorrelation in rural settings provides estimation challenges because of spatial discontinuities and poor data quality. As a result our study draws attention to the importance of the spatial features of a dataset when building rural hedonic models. We have shown that the methodological approach that addresses spatial autocorrelation and poor data quality in rural settings will improve coefficient estimates and overall model performance.

There are practical implications of focused attention on methodological issues as well. The hedonic approach is a mechanism for economists to "get prices right." Hedonic estimators can be directly employed in a policy environment as the unit of analysis is the individual property or location observation. Accurate estimation is critical because the very specific and targeted Coasean compensation rules for harmed parties can be developed. So while estimating the impacts on a community is historical as the effects are revealed in the market valuations, there are forward looking policy applications as well. Communities that are seeking to attract or discourage further livestock investment, or individual farm businesses looking to locate in a community need to know ex ante what the impacts might be. The spatial hedonic approach we utilized can be used to estimate the impacts at the parcel level were the siting to take place. Alternative sites could be ranked, and specific identification of harmed parties could take place.

In a separate study we estimated the negative impacts of the hog farms on each affected residential property in the county and balanced those harms with the benefits of economic expansion. The benefit–cost ratio varies significantly depending on a particular location.

Use of hedonics as a policy tool is not without significant shortcomings. More research is needed to make the measurement of costs and benefits more comprehensive, address temporal elements that are not accounted for, capture the additive affects of multiple farms, and include non-monetary effects, both positive (i.e., technology spillovers) and negative (i.e., non-point environmental damage).

Also one certainly can imagine interaction and non linearity among the many variables available to modelers. Spatial econometric theory has helped in some regard but more is needed. To date little theory exists to support what heretofore has been principally an empirical endeavor.

Finally, a key shortcoming is the lack of specificity as to what is the "good," or in our case the "bad" when studying livestock impacts on housing values. A dataset needs to be sufficiently thick to allow for the power of the cross section to proxy for multiple purchases of the same good, as was the case with Day et al. (2007). This problem proves difficult when studying rural settings where data are few and heterogeneity is large.

The more common approach for estimating demand involves repeat purchases of the same good across populations at varying prices and quantities. Such a direct approach for measuring livestock amenities and disamenities is unlikely because the actual good under study is so poorly specified and its valuation is so subjective at this point in time. The results therefore from a study such as ours are really a statement of the relationship between the farms and the neighboring houses, and cannot be strictly applied to the population at large. The hedonic technique could be more directly used to address issues of social welfare if these shortcomings could be overcome.

Appendix

The derivation of the marginal price of the spatial hedonic model follows Kim et al. (2003, pp. 34–35). First, define the spatial lag model with Box-Cox transformed as

$$Y^{(\lambda)} = \rho W Y^{(\lambda)} + \beta X + \varepsilon \tag{1}$$

where $Y^{(\lambda)}$ is a $(n \times 1)$ column vector of transformed assessed values, W is a $(n \times n)$ weights matrix, X is a $(n \times k)$ matrix (where k is the number of explanatory variables), β is a $(k \times 1)$ column vector, and ε is a $(n \times 1)$ column vector.

The reduced form is

$$Y^{(\lambda)} = [I - \rho W]^{-1} \beta X + [I - \rho W]^{-1} \varepsilon \tag{2}$$

Let $\nu = [I - \rho W]^{-1} \varepsilon$ and $A = [I - \rho W]^{-1}$, then

$$Y^{(\lambda)} = A \beta X + \nu \tag{3}$$

Equation 3 can be written as

$$\begin{bmatrix} Y_1^{(\lambda)} \\ Y_2^{(\lambda)} \\ \vdots \\ Y_n^{(\lambda)} \end{bmatrix} = \begin{bmatrix} a_{11}, a_{12}, \ldots, a_{1n} \\ a_{21}, a_{22}, \ldots, a_{2n} \\ \cdots\cdots\cdots\cdots \\ \cdots\cdots\cdots\cdots \\ a_{n1}, \ldots, a_{nn} \end{bmatrix} \cdot \begin{bmatrix} x_{11}, x_{12}, \ldots, x_{1n} \\ x_{21}, x_{22}, \ldots, x_{2n} \\ \cdots\cdots\cdots\cdots \\ \cdots\cdots\cdots\cdots \\ x_{n1}, \ldots, x_{nn} \end{bmatrix} \cdot \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_k \end{bmatrix} + \begin{bmatrix} \nu_1 \\ \nu_2 \\ \vdots \\ \nu_n \end{bmatrix} \tag{4}$$

Define X_k as a column vector $(n \times 1)$ of one housing characteristic. The marginal price can then be derived by taking the derivative of both sides of Eq. 4. First, the derivative of $Y^{(\lambda)}(n \times 1)$ with respect to X_k is defined as follows:

$$\begin{aligned} \frac{\partial Y^{(\lambda)}}{\partial X_k'} &= \begin{bmatrix} \partial Y_1^{(\lambda)}/\partial x_{1k}, \partial Y_1^{(\lambda)}/\partial x_{2k}, \ldots, \partial Y_1^{(\lambda)}/\partial x_{nk} \\ \partial Y_2^{(\lambda)}/\partial x_{1k}, \partial Y_2^{(\lambda)}/\partial x_{2k}, \ldots, \partial Y_2^{(\lambda)}/\partial x_{nk} \\ \cdots\cdots\cdots\cdots\cdots\cdots \\ \cdots\cdots\cdots\cdots\cdots\cdots \\ \partial Y_n^{(\lambda)}/\partial x_{1k}, \partial Y_n^{(\lambda)}/\partial x_{2k}, \ldots, \partial Y_n^{(\lambda)}/\partial x_{nk} \end{bmatrix} \\ &= Y_k^{(\lambda-1)} \begin{bmatrix} \partial Y_1/\partial x_{1k}, \partial Y_1/\partial x_{2k}, \ldots, \partial Y_1/\partial x_{nk} \\ \partial Y_2/\partial x_{1k}, \partial Y_2/\partial x_{2k}, \ldots, \partial Y_2/\partial x_{nk} \\ \cdots\cdots\cdots\cdots\cdots\cdots \\ \cdots\cdots\cdots\cdots\cdots\cdots \\ \partial Y_n/\partial x_{1k}, \partial Y_n/\partial x_{2k}, \ldots, \partial Y_n/\partial x_{nk} \end{bmatrix} = Y_k^{(\lambda-1)} \frac{\partial Y}{\partial X_k'} \end{aligned} \tag{5}$$

On the other hand, the derivative on the right side of Eq. 4 with respect to X_k is

$$\begin{bmatrix} \beta_k a_{11}, \beta_k a_{12}, \ldots, \beta_k a_{1n} \\ \beta_k a_{21}, \beta_k a_{22}, \ldots, \beta_k a_{2n} \\ \cdots\cdots\cdots\cdots\cdots \\ \cdots\cdots\cdots\cdots\cdots \\ \beta_k a_{n1}, \beta_k a_{n2}, \ldots, \beta_k a_{nn} \end{bmatrix} = \beta_k A = \beta_k [I - \rho W]^{-1} \tag{6}$$

It follows that

$$\frac{\partial Y}{\partial X_k'} = [I - \rho W]^{-1} \frac{\beta_k}{Y_k^{(\lambda-1)}} \tag{7}$$

The marginal price of the spatial lag hedonic model consists of two elements. The first element $[I - \rho W]^{-1}$ amounts to a spatial multiplier and can be expanded into an infinite series:

$$\begin{aligned}[I - \rho W]^{-1} &= I + \rho W + \rho^2 W^2 + \cdots \\ &= \left(\frac{1}{1-\rho}\right) \text{ if } W \text{ is row-standardized and } |\rho| < 1 \end{aligned} \tag{8}$$

The presence of a spatial multiplier accounts for spatial spillover effects where a change in the property value at one location affects all other locations, whereas the degree of spillover gradually diminishes over space. In the case of hog farms, the spatial multiplier captures the spillover effects of an environmental impact caused by hog farms over k-nearest neighbors. The second term $\frac{\beta_k}{Y_k^{(\lambda-1)}}$ is due to Box-Cox transformation and reflects nonlinear relationship between property values and housing attributes.

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