A Spatial Hedonic Model with Time-Varying Parameters: A New Method Using Flexible Least Squares

Todd H. Kuethe[1], Kenneth A. Foster[1], and Raymond J.G.M.Florax[1,2]

[1] Department of Agricultural Economics, West Lafayette, Purdue University

[2] Department of Spatial Economics, VU University, Amsterdam, The Netherlands

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Abstract

The following paper outlines a new econometric model designed to capture both the temporal and spatial dynamics of housing prices. The paper combines existing spatial econometric techniques with a model that allows parameters to evolve over time. In addition, we provide an empirical application to the price effects of confined animal feeding operations to a data set of residential real estate in Tippecanoe County, Indiana from 1993 through 2006.

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1 Introduction

Hedonic price analysis is a popular tool in applied economic research. The technique has been applied to various goods to capture the marginal contribution of a number of attributes to its total sales price (Lancaster, 1966; Rose, 1974). Hedonic price models are attractive because the results are simple to interpret, are almost always consistent with intuition, and appeal to Lancaster's theory of choice and revealed preference (Kawamura and Mahajan, 2005). The most popular application is the analysis of housing prices in order to estimate the value of "non-priced" environmental attributes (Kim et al., 2003). These implicit values are often hard to estimate by other methods and hedonic price analysis provides a data intensive alternative. The hedonic price function can be expressed in the basic theoretical form.

$$P = f(S, E, L) \tag{1}$$

where P is a vector of observed prices of a composite good that possesses a vector of structural characteristics such as square footage and lot size denoted by S, E a vector of socioeconomic and environmental variables like neighborhood demographics or the presence of environmental disamenities, and L a vector of locational attributes such as the distance to urban centers.

Estimation of hedonic price models has become increasingly sophisticated in recent years. One of the leading developments is the use of spatial econometrics to more accurately model the effects of location as a determinant of housing prices. Spatial econometric estimation is becoming increasingly popular because of consistent evidence that property values exhibit a systematic pattern in their spatial distribution and, as a result, are said to be spatially autocorrelated. There are a number of reasons to suspect housing values may be spatially autocorrelated. For example, neighborhoods often develop at the same time leading to similar structural characteristics, and these neighborhoods, by definition, share a number of locational amenities (Basu and Thibodeau, 1998). Bowen and Prestegaard (2001) argue that sales prices are often influenced by real estate professionals, so local housing market conditions likely play a role in each observed transaction. Additionally, Gelfand et al. (1998) assert that homogeneous neighborhoods will serve as a proxy for other variables including similar income levels and occupational status of homeowners. In terms of estimation, spatial autocorrelation can arise from three distinct sources: (i) the price is affected by the price of neighboring houses, (ii) relevant spatially correlated variables have been omitted, or (iii) the functional form is misspecified or suffers from measurement error (Wilhelmsson, 2002).

Spatial hedonic models have been employed to examine the marginal contribution of a number of environmental amenities and disamenities including visibility of different types of land cover (Paterson and Boyle, 2001), air quality (Kim et al., 2003), the nearest environmental hazard (Brasington and Hite, 2005), traffic volume (Kawamura and Mahajan, 2005), oil and natural gas facilities (Boxall et al., 2005), commuter rail access (Armstrong and Rodriguez, 2006), school quality (Brasington and Haurin, 2006), airport noise (Cohen and Coughlin, 2006), transportation accessibility (Shin et al., 2007), proximity to a lakefront (Espey et al., 2007), and a bundle of other environmental attributes including distance to parks, greenways, and brownfields (Munroe, 2007).

Generally, hedonic price models are used to examine cross-sectional data. When it is necessary to use a longer time series of observations however, it is commonly accepted to use indicator variables for each designated period (e.g., years, months, or weeks) (see Pace et al., 1998; Thibodeau, 2003). This technique is a simple method to remove some of the heterogeneity that results from pooling over time. However, this may lead to an undesirable number of dummy variables as the time series grows longer. In an effort to overcome this shortcoming, this paper presents a methodology that directly models the temporal movements of the implicit attribute values using a time-varying parameter model. This innovation captures the effects of the time of sale, not only on the total sales price, but on each attribute value. The model attempts to account for the inherent spatial autocorrelation by including a number of spatial crossregressive variables.

The remainder of the paper is organized as follows. Section 2 outlines the proposed econometric method. Section 3 presents an empirical application using a geocoded time series of housing transactions from 1993 through 2006. The application explores the price effects of the presence of confined animal feeding operations (CAFOs) on residential real estate values in Tippecanoe County, Indiana. Section 4 concludes with discussion and suggestions for future research.

2 Methodology

There have been a number of advances in the estimation of spatial panel data models in recent years (see Anselin, 2006; Baltagi et al., 2007). The following section outlines an alternative estimation of spatial panel data models. The proposed technique is especially useful for locational data observed in continuous time, and it is a straightforward method for estimating a spatial econometric model with time-varying parameters.

There are three popular forms of time-varying parameter models (Rao, 2000). First, the parameters are assumed to vary across subsets of observations within the sample but they are non-stochastic. Second, the parameters are stochastic and assumed to be generated by a stationary stochastic process. Third, stochastic parameters may be generated by a process that is nonstationary. Our model falls into this third category using a technique designed to capture parameter movements that evolve slowly over time.

The parameter movements are modeled using Flexible Least Squares (FLS) developed by Kalaba and Tesfatsion (1988). FLS has been used to examine a number of economic problems such as money demand (Tesfatsion and Veitch, 1990), productivity growth (Dorfman and Foster, 1991), income and consumption in West Germany (Lütkepohl and Herwatz, 1996), presidential approval (Wood, 2000), US meat demand (Poray et al., 2001), the sensitivity of South Korean stock markets (He, 2001), factor betas of the US stock market (He, 2005), inflation persistence in new EU member nations (Darvas and Varga, 2007), and statistical arbitrage (Montana et al., 2008).

2.1 Flexible least squares

FLS consists of two speciation equations one that captures the traditional least squares residual and the second that examines the dynamic time path of parameter movements.

The measurement specification:

$$y_t - x_t\beta_t = \eta_t, \qquad t = 1, 2, ..., T \tag{2}$$

The prior dynamic specification:

$$\beta_{t+1} - \beta_t = \varepsilon_t, \qquad t = 1, 2, ..., T \tag{3}$$

where x_t is a $1 \times K$ row vector of known exogenous regressors, and β_t is a $K \times 1$ column vector of unknown coefficients.

The two specification equations are incorporated in a minimization problem with two residual components. The measurement specification leads to the traditional sum of squared errors (i.e. the measurement residual):

$$r_M^2(\beta|t) = \sum_{t=1}^{T}(y_t - x_t\beta_t)^2 \tag{4}$$

The dynamic specification uses a similar structure to minimize the coefficient change (i.e. the dynamic residual):

$$r_D^2(\beta|t) = \sum_{t=1}^{T-1}(\beta_{t+1} - \beta_t)'(\beta_{t+1} - \beta_t) \tag{5}$$

The two minimization criteria are combined in a weighted cost function that penalizes coefficient movements in addition to the traditional measurement residual:

$$C(\beta|\delta, t) = \frac{\delta}{1-\delta} r_D^2 + r_M^2, \quad \text{where} 0 < \delta < 1 \tag{6}$$

The weighting parameter δ forces $\hat{\beta}_t$ toward or away from a constant value. As δ gets close to zero, the FLS coefficients converge to the constant parameter OLS estimates. Therefore, it can be shown that OLS is a special case of FLS in which a restriction fixes the potentially time-varying coefficients to constant values (Kalaba and Tesfatsion, 1988). As δ approaches one, the coefficient estimates change drastically over time and approach the random coefficient model estimator in which the measurement errors are zero (see Swamy, 1970). It is common to express the weighting parameter as $\mu = (\frac{\delta}{1-\delta})$ where $\mu \in [0, \infty)$.

Previous studies have been unable to establish an agreeable method to select the smoothing parameter μ. Poray et al. (2001) suggest selecting by minimizing the scaled distance from the origin to the efficiency frontier space using the following criterion:

$$\min_{\mu} = \sqrt{\frac{SSE_{fls}^2(\mu)}{SSE_{ols}^2} + \frac{SSD_{fls}^2(\mu)}{SSE_{rc}^2}} \tag{7}$$

where SSE_{ols}^2 is the sum of squared errors of the traditional constant parameter model ($\delta = 0$), SSE_{rc}^2 is the sum squared residuals of the random coefficient model ($\delta = 1$), SSE_{fls}^2 is the sum of squared errors of the FLS measurement equation, and SSD_{fls}^2 is the sum of squared errors of the FLS dynamic equation.

After selecting a weighting parameter μ, the FLS algorithm includes recursion of the following cost equation given any time series with at least two periods (Kladroba, 2005):

$$\phi_t = \inf_{\beta_t} [(y_t - x_t\beta_t)'(y_t - x_t\beta_t) + \mu(\beta_{t+1} - \beta_t)'(\beta_{t+1} - \beta_t) + \phi_{t-1}] \tag{8}$$

The descriptive power of FLS can be obtained in at least three ways. First, for any given value of μ, there exists a single coefficient sequence which simultaneously minimizes both types of error. This set forms the lower envelope of the set of all attainable coefficient sequences. The slope of this envelope, called the cost-efficient frontier, provides additional explanatory power (Kalaba and Tesfatsion, 1990a). FLS is said to provide a better description when the cost-efficient frontier is steep (Kalaba and Tesfatsion, 1989). This would indicate a large reduction in the measurement error given only a small increase in the dynamic error. This trade-off is similar to the trade-off between the parameter variance and length used to argue in favor of shrinkage and Stein-rule estimators such as Ridge regression. The primary difference is that shrinkage estimates typically argue that they introduce bias in order to gain greater precision whereas proponents of FLS argue that the constant parameter assumption is incorrect and thus introduce a reduction in parameter precision in order to reduce bias. Second, graphing the parameter adjustment paths provides additional useful information on the time variation of the parameters. The graphs provide a visualization of the parameter movements which may indicate gradual or drastic parameter change. Third, the moments of the coefficient estimates can provide insightful comparisons with traditional constant parameter estimates. For instance, the standard deviation of the FLS estimates provides a measure of the extent of time variation (Wood, 2000).

2.2 Relationship to the Kalman Filter

It has been previously shown that the FLS algorithm is a generalized form of a number of well-known filters such as those developed by Kalman, Larson-Peschon, and Swerling (Kalaba and Tesfatsion, 1990b). The comparison that is most prevalent in the literature is the relationship between FLS and the Kalman Filter (KF) (Kalman, 1960).

The KF describes parameter transformation over time through a measurement equation and a transition equation in a fashion similar to the measurement and dynamic equations in FLS.

$$Y_t = X_t\beta_t + \eta_t \tag{9}$$

$$\beta_{t+1} = A\beta_t + \varepsilon_{t+1} \tag{10}$$

where A is a matrix defining the transformation process of the parameters from time t to time $t+1$. However, the major difference lies in the necessary assumptions with respect to the error distribution for both the measurement and transition equations in the KF (η_t and ε_t, respectively).

$$\mathrm{E}(\varepsilon\varepsilon') = \Sigma \tag{11}$$

$$\mathrm{E}(\eta\eta') = \Omega \tag{12}$$

where both Σ and Ω are presumed to be constant across all observations. In addition, estimation requires initial values for the parameters β_0 and its variance Σ_0. Both of these assumptions are not required for FLS estimation (Kladroba, 2005).

However, the similarities between FLS and KF may lead to a greater understanding of each of the two techniques. Tucci (1990) provides an early discussion of the relationship captured in the FLS smoothing parameter μ where $\mu^{-1} = \Sigma$.

Bond et al. (2003) found the FLS and KF produced "remarkably similar results"(p. 100). In fact, the authors used FLS estimates for the initial values of the KF coefficients that is $\beta_0 = \hat{\beta}_{t,\mathrm{FLS}}$ which may provide an additional value of the FLS method.

However, it is important to note that FLS also suffers from a number of limitations. Previous studies argue that the dynamic weight parameter μ should be allowed to change across the time series as opposed to assigning a single value throughout (Rao, 2000). Perhaps the greatest drawback is that FLS is designed as a purely descriptive tool. The model is unable to accommodate traditional statistical tests which require assumptions with respect to the distribution of the errors (Lütkepohl, 1993). Without such assumptions it is difficult to argue that a model represents an adequate or a poor description of the data generation process. To a large extent the Poray et al. method for choosing μ addresses this concern. Given μ conditional testing can ensue. However, the Poray et al. approach yields a Bayesian interpretation. The outcome is consistent with the posterior derived from a classical prior of zero measurement error and constant parameters together with the observed likelihood.

2.3 The spatial crossregressive model

The spatial crossregressive model has been widely overlooked in the spatial hedonic literature, yet the model appears to be well suited for a number of spatial studies (Florax and Folmer, 1992). The spatial crossregressive model is desirable for two distinct reasons. First, the specification directly accounts for one of the theoretical motivations for spatial autocorrelation in housing prices that is, similarity of characteristics within a community (Basu and Thibodeau, 1998). Second, the spatial crossregressive model is attractive because the spatial component is not correlated with the errors, and as a result, can be estimated using ordinary least squares (OLS) (Anselin, 2002). The model is presented below.

$$Y = X\beta + WZ\gamma + \varepsilon \tag{13}$$

where Y is a vector of housing prices, X a set of explanatory variables, and W is a row-normalized spatial weights matrix which defines the "neighborhood" for all observations. The variable Z represents the set of characteristics that may or may not be a subset of X. In the former case Z can contain the linearly independent columns of X. When premultiplied by W, the variable reflects the weighted average of Z characteristics of neighboring homes. If the model is free of spatial spillover effects, the coefficient γ will not be significantly different than zero, and the model reduces to the traditional aspatial specification. More common functional forms in the spatial hedonic literature include the spatial lag model, the spatial error model, and the spatial Durbin model. The spatial lag model contains an endogenous variable (WY) and the error model has a non-spherical error process. As a result, estimation is restricted to maximum likelihood, general moments, or instrumental variables [1]. The ability to estimate a spatial crossregressive model with OLS allows for a simple extension to FLS estimation.

2.4 Spatial crossregressive flexible least squares

The following equations represent the spatial crossregressive flexible least squares (SXR-FLS) model. The model includes a measurement specification equation which includes a set of spatial crossregressive variables and a dynamic specification equation that models parameter movements for both the traditional and spatial coefficients.

$$\begin{aligned} y_t - x_t\beta_t - W_t z_t \gamma_t &\approx \emptyset, \quad t = 1, ..., T && (14) \\ \theta_{t+1} - \theta_t &\approx \emptyset, \quad t = 1, ..., T-1 && (15) \\ \theta_t &= \begin{bmatrix} \beta_t \\ \gamma_t \end{bmatrix} \end{aligned}$$

Thus, the SXR-FLS cost function can be expressed in the following form.

$$C(\theta; \mu, t) = \mu \sum_{t=1}^{T-1} (\theta_{t+1} - \theta_t)'(\theta_{t+1} - \theta_t) + \sum_{t=1}^{T} (y_t - x_t\beta_t - W_t Z_t \gamma_t)'(y_t - x_t\beta_t - W_t Z_t \gamma_t) \qquad (16)$$

The next section presents an empirical application of the SXR-FLS model.

3 Application

The following application explores the effects of confined animal feeding operations (CAFOs) on residential property values in Tippecanoe County, Indiana. Tippecanoe County has approximately 150,000 residents who are mostly located in the neighboring cities of Lafayette and West Lafayette, home of Purdue University. The majority of the county's 500 square miles of land is devoted to agricultural production. The price effects

[1] It is important to note that the inclusion of spatial crossregressive variables is much different from the traditional spatial correlation problem modeled through adding spatial lags of the dependent variable, WY, or or a spatially lagged error, $W\varepsilon$. Incorporating spatial crossregressive variables, WZ, is more of an omitted variable correction. The potential inclusion of a spatially lagged dependent variable or error is left for future research

attributed to CAFOs have been a popular topic in hedonic price analysis (see Milla et al., 2005). It is important to note that this exploration is for illustrative purposes only, and the estimates are not intended for policy analysis.

3.1 Data

The data analyzed in this paper include 21,115 real estate transactions in Tippecanoe County, Indiana between January 1994 and December 2006 obtained from the local Multiple Listing Service (MLS). The observations are limited to single-family residences which do not include mobile or modular homes. The date of sale was defined as the date on which the home was listed as "off the market."

3.2 Estimation

The model presented in (14) and (15) is estimated with the dependent variable and the regressors expressed in natural logarithms. The log-linear specification is widely used in the literature and endorsed by a number of researchers because of its desirable properties (Malpezzi, 2002). The coefficients for continuous variables can be interpreted as elasticities representing a percentage change in price given a one percent increase in the independent variable and negative predicted prices are precluded. Discrete and dummy variables can also be converted to elasticities using a simple modification (Halvorsen and Palmquist, 1980; Thornton and Innes, 1989).

The selected regressors include two locational dummies for the two largest cities in the county and the remaining rural communities (West Lafayette, Lafayette, and the rest of the county), the age of the home measured in years, and a squared term for age to examine a potential nonlinear relationship with housing prices. There are a number of additional structural variables: a dummy variable for fireplace, finished square footage, number of bedrooms, and lot size measured in square feet. The spatial crossregressive variables include age, age squared, finished square footage, lot size, and number of bedrooms.

The environmental variable of interest for the model is the distance to the nearest confined animal feeding operation. The presence of a CAFO is expected to reduce the sales price, so increasing distance is expected to raise the selling price of a home. The geocoded CAFO facilities were obtained from Indiana Department of Environmental Management, Office of Land Quality. The observations are a cross-section of all registered swine, chicken, turkey, beef or dairy CAFOs that have a large enough number of animals to require IDEM regulation for environmental concerns as of July 27, 2006. To limit the impact of border effects, several CAFOs located in neighboring counties were also included.

Two additional assumptions need to be defined. The spatial weights matrix W is a row-standardized distance matrix calculated for each month of observations. The rows of a row-standardized weighting matrix are scaled to sum to one. Thus, the variables WZ represent a weighted average of neighboring values of Z. Therefore the "neighborhood" is defined as a distance weighted average of all transactions occurring in the same calendar month. The dynamic weighting parameter μ was selected using the J-test suggested by Poray et al. (2001). The test statistic suggested an optimal weighting parameter of $\mu = 4$.

3.3 Results

Table 1 shows the estimation results of the initial spatial crossregressive function using OLS. The model also includes a set of time dummies representing each year of the data to control for heterogeneity (excluding 1993, the base year), but the coefficient estimates are not presented. All of the coefficients have the expected sign, and only two variables are insignificant at standard acceptance levels. A number of the coefficients are quite small in magnitude (yet significant), a common result when estimating the log-linear hedonic function for a relatively large dataset. The model has a reasonable goodness of fit with an adjusted R^2 of 0.57.

Individually, only a portion of the spatial crossregressive explanatory variables were statistically significant. However, Table 2 presents two statistics for a joint test on the significance of all γ coefficients. Both tests, the F-test and Wald's χ^2-test were significant at the 0.01 level. Thus, the spatial lag coefficients are determined to be different from zero jointly.

Table 1 also includes the mean and standard deviation for all of the FLS estimates. The mean estimates are quite similar to the constant parameter estimates of OLS. Only the West Lafayette elasticity appears to have a conflicting sign. The FLS time variation paths are presented in Figures 1 – 11. The housing transactions were captured in continuous time, and therefore the square markers represent the first observation for each year 1993 – 2006. The coefficients for all dummy and discrete variables were recalibrated to represent elasticity estimates.

All of the elasticities appear to vary over time at some level. It would appear homeowners are placing an increasing penalty for homes located in West Lafayette (Figure 1), and the premium for homes located in the outlying county is increasing over the observed interval (Figure 2). The spatial crossregressive variables in Figures 9 – 12 appear to increase over the observed time period. This indicates the demand for neighborhood age, home size, and lot size has increased in recent years. In addition, this may indicate a capitalization of property tax differences and rural school improvements over time. West Lafayette has a higher tax rate than the rest of the country and rural schools in the county have improved academically based on performance measures such as SAT scores, and victories in academic competitions such as Quiz Bowl, Academic Super Bowl, and Math Counts. The time paths for the elasticities for neighborhood values of finished square footage (Figure 10), lot size (Figure 11), and the number of bedrooms (Figure 12), all resemble the time path for the related attribute (Figures 5, 6, and 7, respectively). However, the estimated elasticities for the age of a home and the weighted neighborhood average age appear to move in opposing directions (Figures 3 and 9). This may indicate consumers are placing a higher value on newer homes but prefer to be located in older neighborhoods.

The most interesting time variation path is perhaps the environmental factor – the distance to the nearest CAFO (Figure 8). While the other elasticities appear to follow the proposed smooth dynamic movement, the time variation path for this parameter is shown to vary erratically. This curious result may stem from a number of reasons. The estimation may indicate that the demand for environmental attributes found in traditional hedonic models is a noisy and random process. The parameter movements indicate that consumers are either (i) ill informed as to the nature of the environmental risks, (ii) heterogeneous in their preferences for environmental quality, or (iii) unaware of the proximity of the nearest CAFO at the time of purchase. On the other hand, the estimates may call for a closer look at the quality of the environmental measures employed in this (and other) studies. What appear to be chaotic preferences may actually result from poorly measured explanatory variables. The potential error-in-variables problem may lower the magnitude of the coefficient estimates which is, as previously stated, a common problem in hedonic analysis. That is, the important variable is how close the buyer *thinks* the nearest CAFO is located at the time of purchase.

In either respect, the application indicates the potential for hedonic analysis using SXR-FLS. The technique sheds additional light on hedonic analysis and points toward a number of issues for future research.

4 Discussion

We have proposed a new model in full which (i) incorporates spatial autocorrelation in housing prices across neighborhoods and (ii) allows the coefficients to evolve over time. It was our intent to show that this technique fits well into current needs in hedonic price estimation. Spatial econometrics offers a set of tools to address the spatial relationships found in housing prices. These relationships stem from a set of shared locational characteristics, similar structural characteristics, and the influence of local market forces. SXR-FLS incorporates a number of spatially weighted explanatory variables to account for a number of these relationships.

The model can be applied to a time series of housing transactions to examine the potential time variation in attribute demands using the Flexible Least Squares algorithm developed by Kalaba and Tesfatsion (1988). FLS is based on the prior belief that the true parameters evolve slowly over time. The FLS is attractive because it does not require assumptions of the probabilistic probabilities of the residual error for either the measurement equation or the dynamic equation.

The integration of these two methods leads to a spatial econometric model with time-varying parameters. We provide an empirical application to measure the price effects of the presence of a confined animal feeding operation in Tippecanoe County, Indiana. The illustration indicates the potential for this new method and potentially adds new light to the hedonic pricing literature. The time variation paths indicate that consumer preference for environmental quality may vary erratically across observations, and in addition, traditional hedonic pricing models may not capture willingness-to-pay as well as desired. Future research would benefit from a more precise examination of the ability to capture the demand for environmental quality using SXR-FLS. For example, the marginal effects captured by $\hat{\beta}_t$ and $\hat{\gamma}$ warrant a closer look as they are intended to capture both temporal and spatial variations in consumer preferences. FLS has garnered some attention in the forecasting literature, so future research may also address the use of SXR-FLS to forecast housing price changes. Finally, in its current form, the model does not incorporate the more traditional spatial lag or spatial error terms. It may be of interest to explore whether such a model could be identified.

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5 Tables

Table 1. Estimation Results

Variable	OLS Estimates		FLS Mean	(Std. Dev)
Constant	6.650	***	9.068	(0.000)
West Lafayette (d)	0.182	***	– 0.023	(0.001)
Rest of county (d)	– 0.042	***	– 0.004	(0.000)
Age	– 0.012	***	– 0.006	(0.001)
Age squared	0.000	***	0.000	(0.000)
Fireplace (d)	0.300	***	0.098	(0.000)
Finished squre feet	0.033	***	0.005	(0.003)
Bedrooms	0.156	***	0.048	(0.001)
Lot size	0.222	***	0.072	(0.004)
Distance to CAFO	0.000	***	0.000	(0.000)
Spatial Lag Variables				
Age	0.001		0.010	(0.002)
Age squared	0.000	***	0.000	(0.000)
Finished squre feet	0.301	***	0.243	(0.003)
Lot size	0.003		0.017	(0.004)
Bedrooms	– 0.113	***	– 0.082	(0.000)
OLS Adjusted $R^2 = 0.57$				
FLS Total incompatibility cost = 0.000				
FLS $\mu = 4$				

*** Significant at $\alpha = 0.01$, μ was selected using the approach presented in Poray et al. (2001)

Table 2. Joint Tests on Spatial Lag Coefficients

F-test	= 104.44	***
Wald test	= 522.19	***

*** Significant at $\alpha = 0.01$

6 Figures

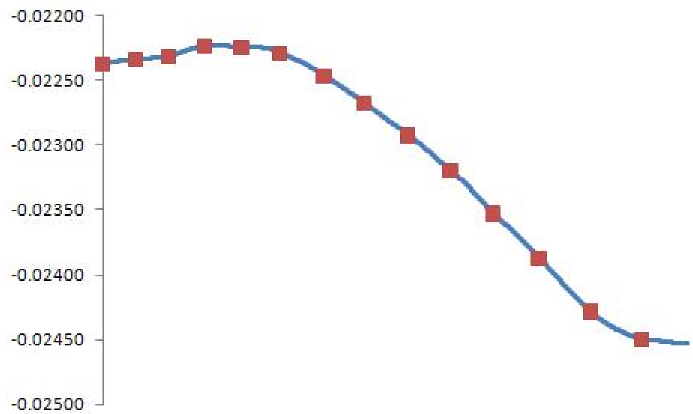

Figure 1: West Lafayette elasticities, 1993 - 2006

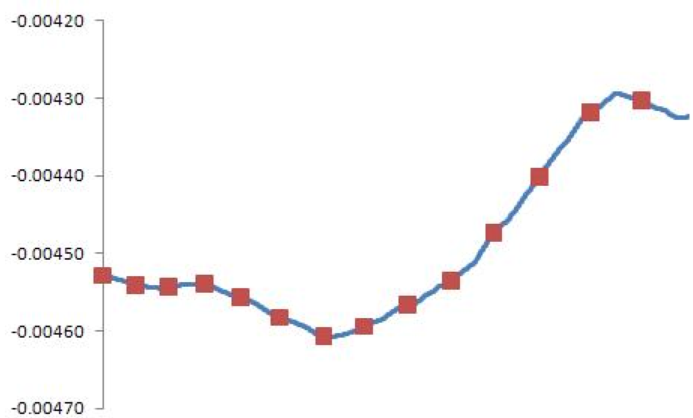

Figure 2: Rest of county elasticities, 1993 - 2006

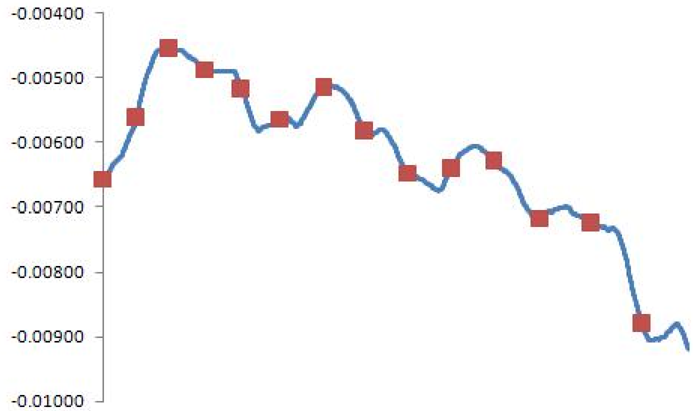

Figure 3: Age elasticities, 1993 - 2006

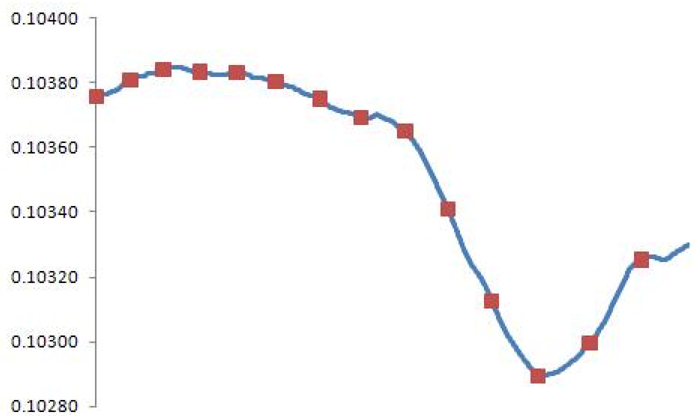

Figure 4: Fireplace elasticities, 1993 - 2006

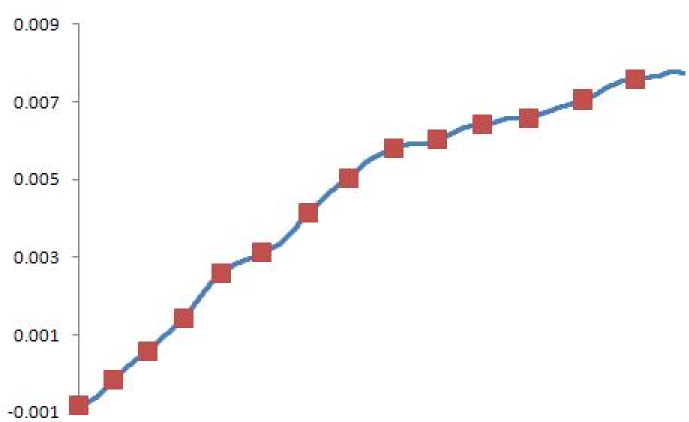

Figure 5: Finished square footage elasticities, 1993 - 2006

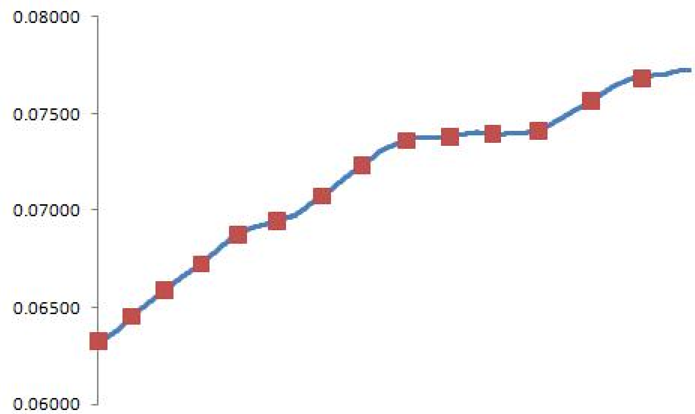

Figure 6: Lot size elasticities, 1993 - 2006

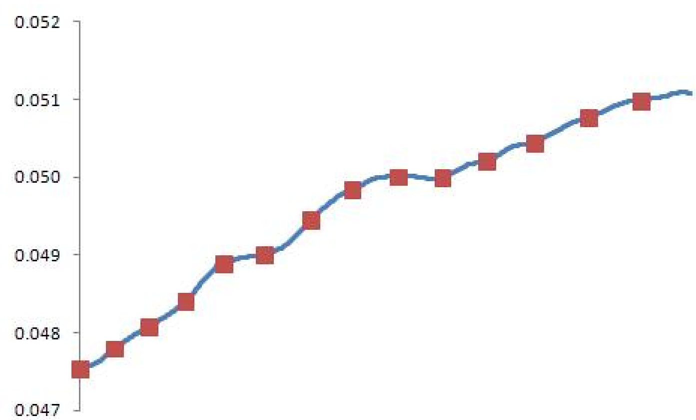

Figure 7: Bedroom elasticities, 1993 - 2006

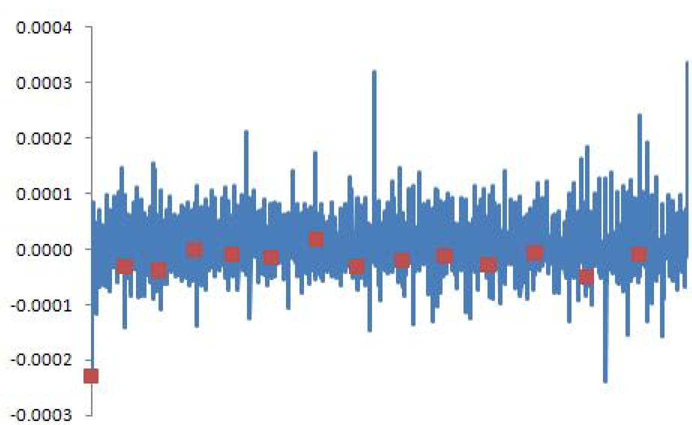

Figure 8: Distance to CAFO elasticities, 1993 - 2006

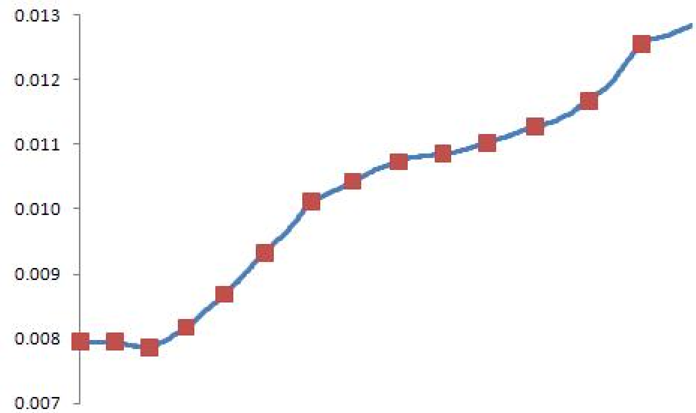

Figure 9: Neighborhood average age coefficients, 1993 - 2006

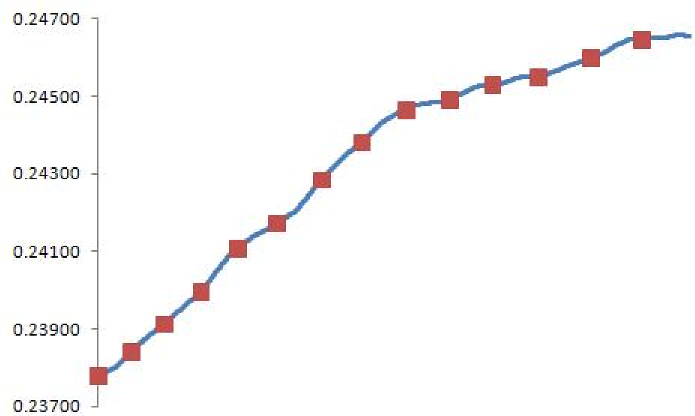

Figure 10: Neighborhood average finished sqare footage coefficients, 1993 - 2006

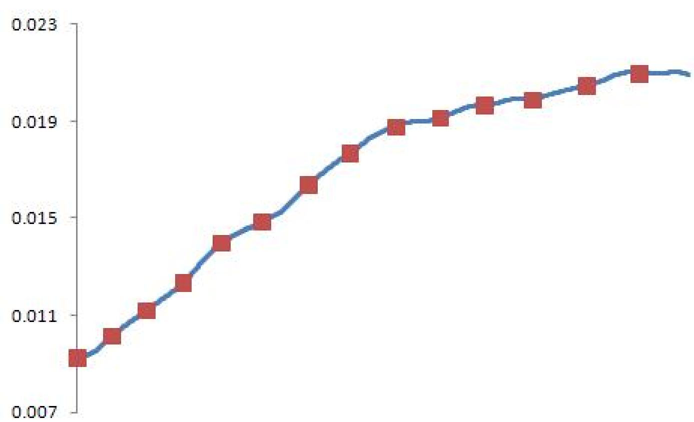

Figure 11: Neighborhood average lot size coefficients, 1993 - 2006

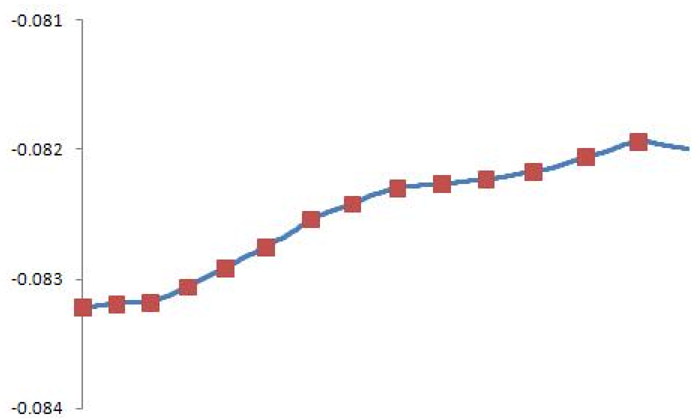

Figure 12: Neighborhood average number of bedrooms coefficients, 1993 - 2006