

## ABSTRACT

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Using a data set of Wake County, North Carolina, property sales for the period 1992-2000, this study provides evidence as to the acceptability of spatial aggregation in hedonic property value models. Both statistical tests and tests based upon prediction errors are performed in order to identify the circumstances under which aggregation is statistically acceptable or acceptable from a practical standpoint. This study makes extensive use of spatial econometric techniques in order to control for the spatial correlation problems which exist in models where location matters, and discusses the importance of specification and functional form as determinants of both the acceptability of aggregation and predictive power. Since multiple specifications and types of models are estimated, this study also provides guidance as to the type of model or specification providing the best performance when used to estimate hedonic property value models.

The primary finding of this study is that while statistical tests typically reject aggregation, the effects of aggregation upon prediction errors is negligible. We would typically expect less than a 2000 dollar increase in mean absolute prediction error from aggregating the entire county, while in several cases the out-of-sample predictions would be improved. Further, in many cases aggregation yields more plausible coefficient values, especially for less important determinants of property values. These results may indicate that aggregation is preferable to extensive disaggregation when conducting hedonic property values studies, especially if one is concerned with the coefficient estimates. I also find that a spatial error model is typically preferred over OLS and Box-Cox alternatives, even when those alternatives include additional variables describing the locational characteristics of the properties and the spatial error model does not.

# **Spatial Aggregation and Prediction in the Hedonic Model**

by

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**Department of Economics**

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To Naoko and Sean.

## Biography

Charles Michael Fulcher was born on May 26, 1972, to Michael and Betty Fulcher in Martinsville, Virginia. As a child he was often accused of being too smart for his own good (a claim which has since been proven to be completely without merit) and proved to be a source of constant consternation for his teachers. Nonetheless, in 1990 he graduated from Fieldale-Collinsville High School as the valedictorian of his class, his last bit of academic glory. After a thoroughly unimpressive four years at the University of Virginia, he graduated in 1994 with a double major in Economics and Foreign Affairs. Seeking to make use of both of these subjects, he then entered the International Economics Masters Program at Radford University. While there, his interest in Economics was rekindled and, more importantly, he met his future wife. In 1996, he entered the Economics Ph.D. program at North Carolina State University, despite not having completed the requirements for his Master's degree. He corrected this oversight in 2001 and thus received his Master of Science in International Economics. This cleared the way for the completion of his Ph.D. and the end of a long academic journey.

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First and foremost, I must thank my wife, Naoko, for her support and encouragement as this dissertation took much longer than I had promised or she had expected. I can only hope that I will be able to make it up to her someday. I must also thank Ray Palmquist for coaching me through the intricacies of hedonic property value models. His invaluable assistance made this research possible. Steve Margolis, Wally Thurman, and Mike Walden also provided valuable guidance which helped shape this research. I am also grateful to the Wake County Revenue Department for providing both financial support and the data used in this study.

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# Chapter 1

## Introduction

Determining the extent of a market has long been an issue for practitioners wishing to employ hedonic regression techniques. While it has been argued that the delineation of homogeneous submarkets is necessary in order to accurately estimate coefficient values, there is considerable disagreement about how this delineation should be accomplished. While many studies have considered entire urban areas as a single market, other researchers have suggested that much smaller areas should be used. At the same time, it has not proven evident that extensive disaggregation is preferable, as many studies have found non-plausible coefficients when performing regressions on small areas. Further, there is some evidence that disaggregation does not lead to greatly improved results if the goal of the study is forecasting prices. The goal of any hedonic study is to accurately represent the price schedule existing within a market, so the essential question is how large an area can be used for estimation while still achieving this goal.

This study hopes to shed some light upon the issue of aggregation by identifying the circumstances under which aggregation over space is statistically acceptable or acceptable from a practical standpoint. I investigate the necessity of the spatial disaggregation typically seen in hedonic studies and suggest methods that can deal with spatial correlation problems as part of the estimation procedure. In addition, I discuss the importance of specification and functional form as determinants of both the acceptability of aggregation and predictive power. Since multiple specifications and types of models are estimated in this study, it also provides guidance as to the type of model or specification providing the best performance

when used to estimate hedonic property value models.

This paper is organized as follows. Chapter 2 provides an introduction to the economic theory underlying this study, specifically the household's decision of where to live. As part of this discussion, two of the major theories of housing location choice are presented. These models provide a natural starting point for this study, as they emphasize the role that location and housing characteristics play in the decision process. The hedonic method, one technique often used in environmental and resource economics to assess the value of particular housing characteristics, is also discussed and is the estimation technique used throughout this study. The concept of market segmentation and its impact on estimated coefficient values is introduced and the relevant literature on market segmentation and aggregation in the housing market is discussed.

Chapters 3 and 4 deal with modifications to the estimation procedures which may be employed in order to account for spatial relationships occurring within the data, and to introduce more flexibility into the functional form of the estimating equation. Chapter 3 introduces spatial econometric techniques while Chapter 4 discusses the issue of functional form and its potential contribution to the aggregation issue. The tests of aggregation and predictive ability employed in this study are described in Chapter 5. The data and estimation procedures employed in this study are described in Chapter 6. The results are discussed in Chapter 7, which Chapter 8 offers the conclusions that may be drawn and suggestions of modifications for future work.

## Chapter 2

# The Housing Decision

The decision of where to live is possibly the most important decision that a household makes. Accordingly, considerable thought is given to the decision as the household weighs the pros and cons of particular locations. As each individual has a different set of preferences, so do the households to which they belong. Therefore, within an area we would expect all households to arrange themselves in an orderly fashion based upon their preferences for the different attributes of housing. This chapter describes the theory behind this decision of where to live and the econometric technique used to extract information about household preferences for various housing and location characteristics given these housing choices. In addition, the theory and literature concerning market segmentation is discussed. This provides insight into the specifications and techniques that have been used in previous studies as well as the results that were found.

### 2.1 Models of Location Choice

In an early model of housing choice, Alonso (1964) describes the household's location decision as a tradeoff between rents and commute times. In his model it is assumed that each household has a single worker and all employment is located at the center of the urban area, where rents are higher than at the periphery. Workers commute to their jobs in the central business district from their residences in the surrounding area. It is assumed that

all households have identical income and utility, which is an obviously unrealistic but simplifying assumption. Household utility is dependent on housing, all other goods consumed by the household, and the distance from the residence to the work site. The households maximize this utility subject to a budget constraint that includes the price of housing, the price of all other goods, and the price of the work commute. In maximizing their utility, households choose their commute times and the price they pay for land and housing. This implies that households will move down the rent gradient until the disutility of a longer trip to work outweighs the additional savings in the price of land consumed.

An alternative formulation of the housing decision is offered by Muth (1969). As in Alonso's model, it is assumed that households maximize their utility subject to a budget constraint and that land is more expensive as one moves towards the center of the area. However, in Muth's model it is assumed that the distance to work does not directly enter the utility function, though it does enter the budget constraint both through its direct cost as well as through its effect on the price of housing. Also, Muth's model explicitly incorporates the supply side of the housing market, modeling the production of housing as a competitive industry producing a homogeneous commodity. Firms alter their use of land and nonland inputs in response to factor prices, and housing prices are assumed to be exogenous. Thus, as Goodman and Thibodeau (1998) summarize, with capital and labor mobile within an urban area and buyers also mobile, the only factor that should systematically impact the housing prices within an area will be the differential price of land. If house prices differ within the metropolitan area by more than the difference in the price of land, these differentials will then be eliminated by both supplier and demander responses. The demand for "overpriced" houses will decrease while the supply of houses in areas with cheaper land will increase, restoring equilibrium in the long run.

While these models are clearly simplified representations of the housing decision process, they provide a useful theoretical starting point to a more detailed analysis. Indeed, a considerable amount of research in urban economics has dealt with generalizing the somewhat restrictive assumptions of these models. However, a survey of this literature is beyond the scope of this study. Nonetheless, both of these theories stress the importance of the location of the property, both through its effect on commuting times and the price paid. However, location is certainly not the only factor influencing a household's housing decision. In addition to commute times, households consider a variety of other housing and neighborhood characteristics when making their decision of where to locate. Housing

characteristics include such factors as the square footage, the number of bathrooms, the presence of a garage, or any number of other structural attributes. Neighborhood characteristics may include proximity to parks and shopping centers, the presence of children, or the like. That is, households choose a set of housing characteristics that maximizes their utility subject to their constraints. Households' preferences for these characteristics, as well as the availability of houses with the desired characteristics, may then have an impact on the prices paid for housing. One method of attempting to ascertain the contribution of particular characteristics to the total value of a house is the hedonic technique popularized by Griliches (1971). This method is described in the next section. The importance of location in the models suggests that if location could be explicitly accounted for within the estimation procedure, we would expect improvements over models that address the location issue in other ways. This explicit accounting of location is the intention of spatial econometrics, which is discussed in the next chapter.

## 2.2 The Hedonic Method

The hedonic model assumes that consumers derive utility not from the consumption of a good directly, but rather from the consumption of the characteristics contained within a good. As this is a hedonic study of the housing market and following the notation of Rosen (1974), let  $\mathbf{z} = (z_1, z_2, \dots, z_n)$  represent the  $n$  characteristics of houses. These characteristics are objectively measured in the sense that all consumers perceive the amount of characteristics in the houses identically, though they may value these attributes differently. There are assumed to be a large number of differentiated houses available in the market, so that for all practical purposes consumers face a choice among the various combinations of  $\mathbf{z}$  that is continuous. While this assumption may not strictly be true in the case of housing, it provides an adequate approximation as the type of houses constructed tends to closely conform to the continuum of preferences of prospective buyers.

The equilibrium price of a house is given by  $p(\mathbf{z}) = p(z_1, z_2, \dots, z_n)$ , which reflects the fact that the price of a house is a function of the level of the various characteristics it contains. This function is the hedonic price function, the estimated equilibrium price of any given package of characteristics. Individual consumers choose the levels of characteristics they wish to consume and thus the prices that they pay, but they are unable to affect the



equilibrium price schedule as the housing market is competitive.

Consumers choose the house with the characteristics that maximize their utility subject to their budget constraint. The utility function of consumer  $j$  is given by

$$u^j = U^j(\mathbf{z}, x, \alpha^j) \quad (2.1)$$

where  $\alpha^j$  is a vector of parameters that characterize the preferences of the household and  $x$  is the non-housing numeraire good. Note again that housing does not enter the utility function directly, but rather it is the characteristics embodied in the house that generate utility. Consumer  $j$ 's budget constraint is given by

$$m^j = p(\mathbf{z}) + x \quad (2.2)$$

where  $m^j$  is the consumer's income and all prices have been normalized by dividing by the price of the numeraire good. The first-order conditions of this maximization problem are:

$$U_{z_i}^j = \lambda^j \cdot p_i \quad i = 1, \dots, n \quad (2.3)$$

$$U_x^j = \lambda^j \quad (2.4)$$

$$m^j = p(\mathbf{z}) + x \quad (2.5)$$

where the subscripts on the functions denote partial derivatives,  $p_i$  is the marginal price of attribute  $i$ , and  $\lambda^j$  is the Lagrange multiplier. From the first-order conditions it can therefore be seen that the marginal rate of substitution between a characteristic and the numeraire good is equal to the marginal price of that characteristic:

$$\frac{\partial p}{\partial z_i} = p_i = \frac{U_{z_i}}{U_x} \quad i = 1, \dots, n \quad (2.6)$$

It is also possible to derive the amount a consumer would be willing to pay for a house with a particular set of characteristics given the income of the consumer, his preferences, and the level of utility attained. This bid function  $\theta^j(\mathbf{z}; m^j, \alpha^j, u^j)$  is implicitly defined by

$$U^j(\mathbf{z}, m^j - \theta^j, \alpha^j) = u^j. \quad (2.7)$$

Since the bid function defines the amount the consumer is willing to pay for  $\mathbf{z}$  at a fixed level of income and utility, and  $p(\mathbf{z})$  is the minimum price they must pay in the market, utility is maximized at the point where  $\theta(\mathbf{z}^*; m, \alpha, u^*) = p(\mathbf{z}^*)$  and  $\theta_{z_i}(\mathbf{z}^*; m, \alpha, u^*) = p_i(\mathbf{z}^*)$  for each attribute and consumer, where  $\mathbf{z}^*$  and  $u^*$  are optimum quantities. Since each consumer's

utility function depends on their vector of socio-economic variables  $\alpha^j$  and consumers have varying income levels, these bid functions will differ between individuals. As a result, the choice of housing characteristics, housing prices, and marginal characteristic prices will differ between consumers.

To complete the model, it is necessary to discuss the behavior of the housing producers. Letting  $M^k(\mathbf{z})$  denote the number of houses produced by producer  $k$  that have the set of attributes  $\mathbf{z}$ , these producers face a total cost function  $C^k(M, \mathbf{z}; \beta)$ , which is derived from minimizing factor costs subject to a production function constraint and where  $\beta$  is a shift parameter reflecting differences between the individual firms. Each producer will maximize profits  $\pi^k = M^k \cdot p(\mathbf{z}) - C^k(M, \mathbf{z}; \beta)$  by choosing the optimal levels of  $M$  and  $\mathbf{z}$  where the unit revenue for a house with a set of characteristics  $\mathbf{z}$  is given by the implicit price function for characteristics,  $p(\mathbf{z})$ .

Producers are competitors and thus all firms observe the same prices and cannot affect them through their production decisions. That is,  $p(\mathbf{z})$  is independent of  $M$ , though the marginal costs of attributes  $p_{z_i}(\mathbf{z})$  are not necessarily constant. The optimal choice of  $M$  and  $\mathbf{z}$  requires:

$$p_i(\mathbf{z}) = C_{z_i}(M, \mathbf{z})/M \quad i = 1, \dots, n \quad (2.8)$$

$$p(\mathbf{z}) = C_M(M, \mathbf{z}) \quad (2.9)$$

This means that at the optimal set of characteristics, the marginal revenue from additional characteristics equals their marginal cost of production per unit sold. Also, houses are produced up to the point where the unit revenue  $p(\mathbf{z})$  equals the marginal production cost, evaluated at the optimal set of characteristics.

Symmetrically to the demand case, one can derive the amount that a producer would be willing to accept for a house with a set of characteristics  $\mathbf{z}$  given a constant level of profits and when the quantities produced of each type of house are optimally chosen. This offer function  $\phi(\mathbf{z}; \pi, \beta)$  is found by eliminating  $M$  from

$$\pi = M \cdot \phi - C(M, \mathbf{z}) \quad (2.10)$$

$$C_M(M, \mathbf{z}) = \phi \quad (2.11)$$

and solving for  $\phi$  in terms of  $\mathbf{z}$ ,  $\pi$ , and  $\beta$ . Since the offer function defines the amount the seller is willing to accept for a design  $\mathbf{z}$  at a fixed level of profits, and  $p(\mathbf{z})$  is the

maximum price that can be attained in the market, profit is maximized at the point where  $\phi(\mathbf{z}^*; \pi^*, \beta) = p(\mathbf{z}^*)$  and  $\phi_{z_i}(\mathbf{z}^*; \pi^*, \beta) = p_i(\mathbf{z}^*)$  for each attribute. Equilibrium in this market then requires a hedonic price function  $p(\mathbf{z})$  that equates the supply and demand for each house with characteristics  $\mathbf{z}$ .

This model is implemented by regressing the price of a house on its relevant characteristics. The identification of the relevant characteristics is a contentious issue beyond the scope of this study, as the opinions of what attributes are important to the housing decision varies between researchers. Nonetheless, this study does employ multiple specifications in order to provide insight as to the effect of specification on aggregation tests and prediction errors. In addition to the specification, the functional form of the regression is an important consideration that has a large impact on the results and their interpretation. Specifically, in a linear regression the estimated coefficient for a characteristic may be viewed as the estimated dollar value of that characteristic per unit. However, with the other functional forms that are often employed, this interpretation is not correct. The importance of functional form will be discussed in Chapter 4.

## 2.3 Market Segmentation

Since the hedonic function is the envelope of the household bid functions and seller offer functions, and as it represents the market tradeoffs among the various characteristics in a competitive equilibrium, a necessary assumption is that there is a single market in which the households and suppliers of housing interact. In most hedonic studies of the housing market, it has been assumed that the market consists of a single metropolitan area. However, other researchers have suggested that areas smaller than metropolitan areas constitute isolated markets (Goodman 1978, Goodman 1981, Straszheim 1973, Straszheim 1974, Palm 1978, Schnare and Struyk 1976, Dale-Johnson 1982, are examples). Still other studies have gone so far as to assume that there is a single market for housing in the entire United States (Linneman 1980, Smith and Deyak 1975). Thus there appears to be little consensus as to the extent of aggregation that is acceptable when applying hedonic property value models.

As we are discussing a market, it is natural to discuss market segmentation in terms of the supply of housing and the demand for housing. Critics of pooling have argued that

there may be systematic differences in the influences on demand and supply in different areas that may lead to market segmentation. If isolated markets do exist, then the hedonic prices of the housing characteristics will be constant within the submarkets but will vary between submarkets, reflecting the marginal valuations of characteristics for the group choosing to live within that submarket. In such a case, if one is concerned with the accurate estimation of coefficients for each area then pooling will be inappropriate.

Among the supply side influences that have appeared in the literature, Straszheim (1974) argues that there is a “huge” variation in the type of housing available across urban areas and suggests that spatial variation in prices over time will alter the course and density of new construction but is unlikely to make it worthwhile to tear down the existing housing stock. As a result, the types of houses available within any given area will display some degree of persistence. Schnare and Struyk (1976) also note that the supply of certain types of housing may be fixed for relatively long periods of time, due both to the durability of the housing stock and the length of the construction process. Goodman (1981) adds that there may be a lack of vacant land except at the periphery of heavily developed areas, which may further diminish the availability of new housing in already developed areas. However, it is necessary to distinguish between long-run and short-run equilibrium in these cases. While in the short-run there may be differences in supply leading to different price structures within urban areas, we would expect such differences to disappear in the long-run as both producers and consumers respond to these price differences. In the long-run, we would expect producers to increase the supply of houses in areas of high demand, while consumers substitute towards lower-priced housing.<sup>1</sup> Of course, this assumes that such substitution by consumers is possible, a matter determined by the demand side market influences.

Among the demand side influences that have been discussed, Goodman (1981), Straszheim (1975) and Michaels and Smith (1990) note that prospective owners may look for housing in a limited area. This is a far more compelling potential source of bias than the supply influences discussed above, since the hedonic technique assumes that consumers consider all feasible transactions before making their housing decision. If an individual does not evaluate all feasible choices, it is possible that their decision may be non-optimal. However, it would be equally non-optimal for a consumer to attempt to evaluate all of the potential housing choices within an area, due to the search costs such evaluation would entail.

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<sup>1</sup>Of course there are limits to the quantity of housing that can be squeezed into already developed areas, but within Raleigh a substantial amount of infill has been built and continues to be developed.

Goodman cites search costs, racial discrimination, and proximity to friends or employment centers as potential reasons for consumers making their housing decision before considering all of their options. Straszheim stresses the role of racial discrimination in the housing market, an influence that one hopes has lessened in the years since his study. Michaels and Smith focus on the search costs and informational asymmetries involved in making a housing decision, postulating that individuals do not have the information necessary to evaluate all of the feasible exchanges and do not have the resources available to obtain this information. Within large areas consumers may therefore employ realtors to help them develop this information, and thus the realtors' evaluations become an important determinant of the location and type of housing that is ultimately purchased. Schnare and Struyk (1976) as well as Straszheim (1974) note that individuals may have inelastic demands for certain neighborhood characteristics or types of housing. They may prefer certain neighborhood amenities, and these amenities may not be easily duplicated. As a result, individuals may not view different areas as substitutes. Likewise, if there are spatial differences in structural characteristics, and individuals have inelastic preferences for these characteristics, then the individual may limit the areas in which they seek housing. If consumers have strong preferences for certain types of neighborhoods, then it may be possible to capture the impact of these preferences by the inclusion of dummy variables describing the characteristics of interest. However, Straszheim argues that the inclusion of neighborhood characteristics in pooled regressions is likely to alter the coefficients of the quality indices as well as the intercept. For this reason, he feels that there is no substitute for stratification or allowing the coefficients to vary across submarkets.

While these potential demand and supply influences may affect the prices paid within the housing market, each of the concerns offered above overlooks the fact that the existence of a well-functioning market does not require every consumer to consider every property when making their housing decision. Rather, the existence of a submarket requires a particular group of consumers to only consider housing within a certain area, while all other groups will never consider housing within that area. This is a far more stringent condition that implies rather severe lack of substitution by the consumers of housing. As long as there are a sufficient number of consumers shopping for and purchasing housing throughout the area, there is reason to suspect that there is a single housing market within the area. The mere existence of clusters of particular types of housing need not necessarily lead to a market breakdown. Rather, it is likely that this natural evolution of the housing

market will be reflected in the decisions of consumers and in the prices that they face. Of course, this is a simplistic representation of a complicated issue, as the criteria outlined above could lead one to consider the entire nation as a single market. While that is a possibility, it is not an assertion of this study. Rather, I consider all of Wake County to be a single housing market, implicitly assuming that the household has already made the decision to locate within the county. Different people may look for housing in different areas of the county, but this does not necessarily indicate the presence of submarkets as long as there is sufficient overlap in the areas searched by different groups.

Since housing submarkets are typically defined in empirical work as areas for which the hedonic prices of the characteristics are constant (Goodman and Thibodeau 1998), it would be simplest to recognize any variation in hedonic prices across areas as evidence of market segmentation.<sup>2</sup> However, the issue is more complicated than this definition would allow. Housing market segmentation is a situation arising when a group or groups of people will only consider housing within a particular area or of a particular type, leading to a different price structure for the characteristics of houses within that area or of that type. That the coefficients vary across areas or housing types is a necessary but not sufficient condition for the existence of housing market segmentation. It is entirely possible that the coefficients vary across areas or housing types because of misspecification of the hedonic regression.<sup>3</sup> If a particular characteristic is important to most consumers and this characteristic is not included in the regression, then the estimates of the other coefficients are likely to be biased (Kennedy 1996). This points out that an accurate specification is needed to capture as completely as possible the differences between houses that are located in different neighborhoods. It is necessary to accurately describe both the characteristics of the house as well as the characteristics of the location. This is a problem directly related to the ideas behind location theory, and has been addressed in several different ways. Census data on the socioeconomic characteristics of residents has often been used as a measure of neighborhood quality, and school quality or accessibility to magnet schools has also been included in property value studies (Walden 1990). Focusing on environmental concerns, Smith and Deyak (1975) assume that if pollution levels vary within a housing market and consumers prefer higher air quality, the price of low pollution level sites will be bid up relative to the

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<sup>2</sup>An alternative definition of submarkets is offered by Grigsby *et al.* (1987). They define a submarket as a set of dwellings that are substitutes for each other but poor substitutes for the dwellings in other areas.

<sup>3</sup>Schnare and Struyk (1976) make this point as well, noting that “for any observed variation, there are two competing explanation: (1) market segmentation and (2) misspecification of the estimating equation”.

high pollution level sites. However, they assume that the housing market consists of a set of cities rather than neighborhoods within a city, an assumption that is tenuous at best as it assumes that the consumers are perfectly mobile across large distances and are able to evaluate the houses at these different locations. Nonetheless, this research as well as that in Deyak and Smith (1974) indicate that pollution levels are one characteristic that should be addressed if pollution levels can be assumed to vary within the area the researcher is treating as a single market. Another housing characteristic that is more likely to be relevant when dealing with smaller areas is the issue of accessibility, which as Jackson (1979) points out is determined by the spatial distribution of work places, shopping centers, schools and other trip destinations as well as the existing transportation network. As a result of the complexity of the accessibility problem, an empirical specification is difficult to formulate. Likewise it is impossible to directly represent the concepts of search costs, proximity to friends, and racial discrimination within this framework. In addition, it would be impossible to completely describe every characteristic that factors into the housing decision, due both to data problems and the problems associated with estimating regressions with large numbers of parameters. Thus it is necessary to assume that while these are all factors in the housing decision, they are not the major determinants of this decision. This is not an unreasonable assumption, since the goal of any property value study is to present a parsimonious model that nonetheless captures the key factors influencing the housing decision.

Even if the conditions necessary for pooling are not explicitly met, aggregation may provide a useful approximation to the true market conditions. This is an important consideration, as economic models do not purport to convey the absolute truth but rather offer adequate approximations to the economic behavior of agents. It is on this issue that the results concerning aggregation are mixed. Straszheim (1974), admittedly the most vocal critic of aggregation, argues that the urban housing market is a set of unique submarkets with demand and supply influences within each resulting in differing price structures. In his study of the San Francisco Bay area housing market, he defines zones based on racial composition, municipal boundaries and housing characteristics. He finds that there is substantial spatial variation in the prices of most attributes, and he finds a significant reduction in the sum of squared errors when dividing the area into these submarkets. Palm (1978) divides the San Francisco market into an alternative set of submarkets based on the districts within which realtors exchange information on house listings and also finds that an F-test supported disaggregation at the .01 significance level. Goodman (1978) obtains sim-

ilar results in his study of the New Haven area. Michaels and Smith (1990) used realtor evaluations of what constituted a submarket in suburban Boston and divided the area into four submarkets based upon these assessments. Using the Brown-Durbin-Evans cusum of squares test, they found that a single hedonic price function was not appropriate for the market. They also used the Tiao and Goldberger (1962) test to compare individual coefficients across the submarkets. They found that 15 of the 21 coefficients were significantly different across the submarkets. However, it is worth noting that the role of bathrooms, pools, parking, year built, and accessibility to work centers were not significantly different across the areas.

Schnare and Struyk (1976) and Ball and Kirwan (1977) offer rebuttals to these findings that disaggregation is preferable. When testing for market segmentation in thirteen suburban Boston municipalities, Schnare and Struyk found that while the prices of the individual housing attributes did vary over space, this variation is small relative to the overall variation in housing prices. This is an important distinction, because while the standard F-test identifies significant differences in attribute prices, it is incapable of assessing the importance of these differences. Indeed, they are not the first to recognize this limitation of the F-test. In a study of automobile prices, Ohta and Griliches (1975) noted that with large samples and using standard tests, we are likely to reject most simplifying hypotheses such as coefficient stability on purely statistical grounds. Schnare and Struyk also found that when using standard census data, there were smaller errors with the unstratified model than with the one allowing for market segmentation because the data were not as complete when using the segmented model.<sup>4</sup> Ball and Kirwan use cluster analysis of housing characteristics to identify potential submarkets in Bristol, England. They find variations in coefficients between the clusters, but note that many clusters have different sets of significant variables. This is due to the fact that there is little variation in the characteristics of houses within the clusters, which makes it impossible to accurately estimate the contribution of those characteristics to the house prices. Further, they find that an F-test did not reject the equality of coefficients across the areas.

Thus the evidence regarding market segmentation is mixed. While most researchers have found that simple F-tests usually reject aggregation, these tests may be

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<sup>4</sup>Many census variables are only available at the census tract level in order to protect the privacy of individuals. When running regressions using block group level data, such variables must necessarily be omitted from the specification.



overly restrictive, especially if the goal is the prediction of property values. If the object of interest is instead the coefficient values themselves, then there is evidence that disaggregation leads to implausible estimates due to a lack of heterogeneity in the proposed submarkets. Also, the source of the rejection of aggregation may be the misspecification of the hedonic regression equation. These are all issues that must be weighed when making the decision of whether aggregation is acceptable for a particular study.

## Chapter 3

# Spatial Econometrics

In any model where location matters, it is likely that the observations will exhibit some degree of spatial dependence. Loosely speaking, the existence of spatial dependence means that the observations at one location have some nonzero relationship with the observations at other locations. More formally, Anselin (1988) defines spatial dependence to be “the existence of a functional relationship between what happens at one point in space and what happens elsewhere”. This definition is based upon Tobler’s (1970) first law of geography, which states that “everything is related to everything else, but near things are more related than distant things”.

In the case of housing, it is clearly evident that the location of a house has a large impact on its selling price. This dependence of house prices on their location then suggests that spatial dependence may be seen in the hedonic price model. As a result, we would suspect that spatial econometrics would have something to offer for the analysis of property values. Since most spatial econometric techniques have close counterparts in time series econometrics, we might expect the application of these techniques to be a straightforward affair. However, while spatial dependence is similar to dependence in time, there is an important difference between time series and spatial econometrics. While dependence in time is one-directional with past observations affecting the present but not vice-versa, spatial dependence may be multidirectional. As a result, most of the standard econometric results from time series analysis do not directly apply in the case of spatial dependence and must be modified for use in spatial analysis.

Anselin and Bera (1998) formally define spatial autocorrelation as the condition

$$Cov(y_i, y_j) = E(y_i y_j) - E(y_i) \cdot E(y_j) \neq 0, i \neq j \quad (3.1)$$

where  $y_i$  and  $y_j$  are observations on a random variable at locations  $i$  and  $j$ , and where the pairs of  $i, j$  locations have some discernible spatial structure or arrangement. However, such a definition does not completely address the issues with which spatial econometrics is concerned. While the definition establishes the coincidence of values as an important part of spatial dependence, it does not address the cause of the nonzero covariance. It may be possible that there are clusters of very similar homes that are accordingly similarly priced. We would expect there to be strong correlations between these houses due to their proximity and similarity. In such a situation, if our hedonic regression is well specified it will accurately value the house characteristics, and we will still be able to accurately predict house values. That is, the correlations in house prices have no real bearing on the estimation procedure or the accuracy of any predictions that may be made based on this estimation. Thus, what we are actually interested in is any correlations between observations that are not expected. Such correlations provide clues as to the influences on house values that are not captured in our hedonic regression. More formally, we are interested in situations where  $cov(y_i|x_i, y_j|x_j) \neq 0$ . This expression describes a situation where, after controlling for house characteristics, non-zero covariance between observations still exists.

An additional problem with the definition of spatial autocorrelation offered by Anselin and Bera (1998) is that it subsumes two distinct concepts under one term. To clarify, spatial dependence may take the form of spatial error dependence (spatial autocorrelation), spatial lag dependence (spatial autoregression), or some combination of spatial error and lag dependence. While spatial autocorrelation and spatial autoregression are terms that are often used interchangeably in the spatial econometrics literature, they actually are distinct concepts and arise for different reasons. Thus, I will treat these types of dependence separately, demonstrating the impact that each has on the standard econometric results and how each may be dealt with through the use of spatial econometric techniques. Specifically, I will discuss maximum likelihood techniques for dealing with spatial dependence, though it should be noted than other econometric methods have been applied to the problem.<sup>1</sup>

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<sup>1</sup>In addition to maximum likelihood techniques, Anselin (1999) and Anselin and Bera (1998) discuss instrumental variable, spatial two stage least squares, and method of moments estimators. LeSage (1999) reviews Bayesian techniques for the estimation of spatial models.

### 3.1 Spatial Error Models

Because the price of a house is dependent upon the attributes of its location in addition to its physical characteristics, we should expect the prices of houses in the vicinity to be dependent upon the same locational attributes. Correlation in the error terms may result in this case. This form of spatial dependence is called spatial error dependence or spatial autocorrelation and is typically seen in cases where there are omitted variables in the hedonic equation that are spatially correlated. In the case of housing, these omitted variables are likely to be the attributes of the surrounding neighborhood that affect the value of the houses within the neighborhood but do not explicitly appear in the regressions. Assuming that these omitted spatially correlated variables are not correlated with the independent variables in the regression equation, the consequence of this omission is that OLS estimates will be unbiased but inefficient.

A separate and more problematic possibility is that variables appearing in the regressions are subject to measurement error. This may be because the attributes are not directly observable or because proxies that are used in place of the variables do not fully capture the effect of the omitted variables. Concentrating on the spatial characteristics of the observations rather than their physical characteristics, if we are trying to describe the attributes of a neighborhood and those attributes are not directly observable, we would like to use proxies that apply to the same geographic area. However, the geographic boundaries of the available proxies may differ from those of the actual neighborhoods. For example, the socioeconomic characteristics of residents are often used as measures of neighborhood quality. However, this data is typically available only at the census tract or census block group level, and there is no reason to suspect that these divisions accurately define neighborhoods. As a result, it is probable that the neighborhood attributes will be measured with some error, leading to spatially autocorrelated error terms. However, this error-in-variables problem leads to biased parameter estimates due to the addition of an error term that is correlated with a regressor.<sup>2</sup> This bias necessitates the use of alternative approaches to estimation such as weighted regressions or instrumental variables, which is beyond the scope of this study. Further, it is possible that simply allowing for spatially correlated errors may be preferable to using potentially mismeasured spatial variables. Thus, I will concentrate

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<sup>2</sup>For a more thorough discussion of the error-in-variables problem, one may refer to Kennedy (1996, p.137).

on the omission of relevant variables that are spatially correlated and the correlation in error terms such omission implies.

For  $N$  observations, it is impossible to estimate the  $N \times N$  covariance terms from the data. Thus structure must be imposed upon the problem so that a finite number of parameters describing the autocorrelation may be estimated. This is accomplished by the use of two methods: weight matrices and direct specification of the covariance structure. Since this study makes use of weight matrices exclusively, the following discussion focuses on this method. However, a discussion of the direct specification of covariance structure appears in the appendix and provides an interesting contrast.

The weight matrix approach has been the method most commonly used in the real estate literature. In this approach, the process generating the error terms is modelled as

$$y = X\beta + u \quad (3.2)$$

$$u = \lambda Wu + \varepsilon \quad (3.3)$$

where  $y$  is an  $(N \times 1)$  vector of house prices,  $X$  is an  $(N \times K)$  matrix of house characteristics,  $u$  is an  $(N \times 1)$  vector of correlated error terms, and  $\beta$  is a  $(K \times 1)$  vector of regression coefficients. The process generating the correlations is shown in Eq.(3.3), where  $\varepsilon$  is an  $(N \times 1)$  vector of  $iid \sim N(0, \sigma^2)$  error terms which are uncorrelated with  $X$  and  $\lambda$  is an unknown scalar autocorrelation parameter.  $W$  is the weight matrix that represents the spatial structure of the data. In this weight matrix, the  $i, j^{th}$  element  $w_{ij}$  represents the potential spatial dependence between the  $i^{th}$  and  $j^{th}$  observation, with  $w_{ij} = 0$  for  $i = j$  so that an observation is not spatially dependent on itself. The weight matrix represents the potential spatial dependence rather than the actual dependence since it is multiplied by the autocorrelation parameter  $\lambda$  in Eq.(3.3).

Typically the weight matrix is specified by the researcher. Therefore, all results are conditional upon this choice of  $W$ . While this has been a topic of considerable criticism and debate, there is unfortunately no consensus as to the correct specification of the weight matrix. Among the specifications that have been suggested in the literature are first and second-order contiguity matrices based upon Delaunay triangulations or common borders, or nearest neighbor weight matrices where  $w_{ij} = 1$  if  $j$  is one of the  $m$  nearest neighbors to  $i$  (where  $m$  is the number of nearest neighbors included, again specified by the researcher) and  $w_{ij} = 0$  otherwise. A variation of the nearest neighbor weight matrix has  $w_{ij} = 1$  for all  $j$  such that  $i$  and  $j$  are separated by a distance less than some specified limit. One

may also choose to set the weights based on the distances between the observations, with  $w_{ij} = 1/D_{ij}^p$  where  $D$  is the  $(N \times N)$  matrix of the distances between observations and  $P$  is some constant. It is worth noting that this specification is not practical for large data sets, as the calculation of the full distance matrix is a computationally intensive process.

If we solve Eq.(3.3) for  $u$ , we find that

$$u = (I - \lambda W)^{-1} \varepsilon \quad (3.4)$$

so that Eq.(3.2) may be rewritten as

$$y = X\beta + (I - \lambda W)^{-1} \varepsilon \quad (3.5)$$

and the variance-covariance matrix is therefore found to be

$$E[uu'] = \sigma^2 (I - \lambda W)^{-1} (I - \lambda W')^{-1}. \quad (3.6)$$

Dubin (1998b) notes that this variance matrix typically will not have a constant on the diagonal, so in this type of model  $u$  is heteroskedastic even though  $\varepsilon$  is not.<sup>3</sup> As a result of this nonspherical error, OLS estimates will not be biased but will be inefficient. More efficient estimators will be obtained through the use of methods that take advantage of the error covariance structure implied by the spatial process. Specifically, the spatial error model may be considered as a special case of general parameterized nonspherical errors terms, with  $E[uu'] = \sigma^2 \Omega(\theta)$ , where  $\theta$  is a vector of parameters (Anselin and Bera 1998). For the spatial error process described in Eq.(3.3), this may be written as

$$\Omega(\lambda) = [(I - \lambda W)'(I - \lambda W)]^{-1}. \quad (3.7)$$

Anselin (1988) and Anselin and Bera (1998) demonstrate that under the assumption of normality, the log likelihood function takes the form

$$L = -\frac{1}{2} \ln |\Omega(\lambda)| - \frac{1}{2} \ln(2\pi) - \frac{1}{2} \ln(\sigma^2) - \frac{(y - X\beta)' \Omega(\lambda)^{-1} (y - X\beta)}{2\sigma^2} \quad (3.8)$$

where  $\Omega(\lambda)$  is as defined in Eq.(3.7). Maximizing Eq.(3.8) w.r.t.  $\sigma^2$  and  $\beta$  yields the familiar generalized least square results

$$\hat{\sigma}^2 = \frac{u'u}{n} \quad (3.9)$$

$$\hat{\beta} = [X' \Omega(\lambda)^{-1} X]^{-1} X' \Omega(\lambda)^{-1} y \quad (3.10)$$

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<sup>3</sup>Dubin (1998b) also notes that this variance matrix is difficult to visualize since it involves the product of two inverted matrices. She therefore employs correlograms to demonstrate the correlation structure for various choices of weighting matrices and values of the spatial autocorrelation parameter  $\lambda$ .

where  $u = (y - X\beta)(I - \lambda W)$ . However, unlike the case of autocorrelation in a time series model, a consistent estimate of  $\lambda$  cannot be obtained from the OLS residuals and therefore the two-step feasible GLS approach is not possible. Rather, the estimate of  $\lambda$  must be obtained from the maximization of the concentrated likelihood function (Anselin 1988, Anselin and Bera 1998). Substituting the GLS expressions for  $\beta$  and  $\sigma^2$  into the likelihood function in Eq.(3.8) yields

$$L_C = -\frac{1}{2} \ln |\Omega(\lambda)| - \frac{1}{2} \ln(2\pi) - \frac{1}{2} \ln \left( \frac{u'u}{n} \right) - \frac{n}{2} \quad (3.11)$$

where  $u'u$  is a function of the spatially filtered  $y$  and  $X$  variables and may be written as

$$u'u = y'\Omega(\lambda)^{-1}y - y'\Omega(\lambda)^{-1}X(X'\Omega(\lambda)^{-1}X)^{-1}X'\Omega(\lambda)^{-1}y.$$

This may be further simplified by noting that  $\ln |\Omega(\lambda)| = 2 \ln |I - \lambda W|$  and by applying a simplification suggested by Ord (1975). Ord showed that the spatial Jacobian term in the likelihood function may be expressed as a function of the eigenvalues  $\omega_i$  of the spatial weights matrix as

$$|I - \lambda W| = \prod_{i=1}^N (1 - \lambda \omega_i). \quad (3.12)$$

Substituting this into the concentrated log likelihood function yields the equation to be maximized with respect to  $\lambda$ ,

$$L_C = \sum_{i=1}^N \ln(1 - \lambda \omega_i) - \frac{1}{2} \ln(2\pi) - \frac{1}{2} \ln \left( \frac{u'u}{n} \right) - \frac{n}{2}. \quad (3.13)$$

An estimate of  $\lambda$  is usually obtained by a grid search over this concentrated log likelihood function, though it is also possible to use iterative techniques to solve for  $\lambda$  and the  $\beta$  vector implicit in the  $u$  term simultaneously.

### 3.2 Spatial Lag Models

When the value of surrounding observations can be assumed to directly affect the value of an observation, the process is said to be a spatially autoregressive one. More commonly, this is referred to as a spatial lag model. For example, it is possible that the construction of a mansion in a middle-class neighborhood may have a positive impact on the prices of the houses in that neighborhood by adding to their prestige. It is also possible

that the house may seem out of place in relation to its neighbors, thus decreasing its own value. As a result, the direction of this effect may not always be evident. However, the latter case is typically considered unlikely, and most applications of spatial lag models constrain the effect to be positive. All of the spatial lag models estimated in this study follow this convention and assume that any effect will be a positive one.

More formally, Anselin and Bera (1998) define the mixed regressive, spatially autoregressive process as

$$y = \rho W y + X\beta + \varepsilon \quad (3.14)$$

where all variables are as previously defined but  $\varepsilon$  is defined more generally as  $\varepsilon \sim N(0, \sigma^2 I)$ . The presence of the spatially lagged term  $W y$  is similar to the inclusion of a serially autoregressive term for the dependent variable in a time-series model. This term causes a nonzero correlation with the error term that is similar to the inclusion of an endogenous variable. It is important to note that there are differences between the spatially and serially autoregressive processes. As Anselin and Bera (1998) note, in the time-series case  $y_{t-1}$  and  $\varepsilon_t$  are uncorrelated unless there is also autocorrelation in the error terms.<sup>4</sup> However, in the spatial model  $(W y)_i$  is always correlated with  $\varepsilon_i$  as well as the error terms at all other locations. As a result, the OLS estimator will no longer be consistent. To see this, focus on the simple spatially autoregressive process

$$\begin{aligned} y &= \rho W y + \varepsilon \\ &= (I - \rho W)^{-1} \varepsilon \end{aligned} \quad (3.15)$$

Since dependence in the spatial model is not unidirectional,  $(I - \rho W)^{-1}$  is a full matrix. This matrix can be written as the power series

$$\sum_{k=0}^{\infty} (\rho W)^k = (I + \rho W + \rho^2 W^2 + \dots) \quad (3.16)$$

if  $|\rho W_{ij}| < 1$ . Substituting this back into Eq.(3.15) then yields

$$\begin{aligned} y &= (I + \rho W + \rho^2 W^2 + \dots) \varepsilon \\ &= \varepsilon + \rho W \varepsilon + \rho^2 W^2 \varepsilon + \dots \end{aligned} \quad (3.17)$$

Thus  $W y$  may be written as

$$W y = W \varepsilon + \rho W^2 \varepsilon + \rho^2 W^3 \varepsilon + \dots \quad (3.18)$$

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<sup>4</sup>See Kennedy (1996, p.142) for a more thorough explanation.



To determine if  $Wy$  is correlated with  $\varepsilon$  in Eq.(3.15), note that

$$\text{plim}_{n \rightarrow \infty} \frac{(Wy)'\varepsilon}{n} = \frac{(W\varepsilon + \rho W^2\varepsilon + \rho^2 W^3\varepsilon + \dots)\varepsilon}{n} \neq 0 \quad (3.19)$$

meaning that the terms are correlated so that the OLS estimator will not be consistent.

In the case of Eq.(3.14), the variance-covariance matrix is found to be

$$E(\varepsilon\varepsilon') = \sigma^2(I - \rho W)^{-1}(I - \rho W')^{-1} \quad (3.20)$$

Note that with the exception of the spatial correlation parameter, this is identical to Eq.(3.6), the error structure for the spatial error model. This variance matrix is full, so each location is correlated with all other locations, but in a manner that decays with the order of contiguity (Anselin and Bera 1998). As a result, this simultaneity must be accounted for within the estimation procedure to avoid biased and inconsistent results.

Applying the Ord simplification of the spatial Jacobian that was previously discussed, the log likelihood function for the spatial lag model is found to be

$$L = \sum_{i=1}^N \ln(1 - \rho\omega_i) - \frac{N}{2} \ln(2\pi) - \frac{N}{2} \ln(\sigma^2) - \frac{(y - \rho Wy - X\beta)'(y - \rho Wy - X\beta)}{2\sigma^2}. \quad (3.21)$$

The estimates of  $\beta$  and  $\sigma^2$  are obtained from the first-order conditions in the usual manner and are found to be:

$$\hat{\beta}_{ML} = (X'X)^{-1}X'(I - \rho W)y \quad (3.22)$$

$$\hat{\sigma}_{ML}^2 = \frac{(y - \rho Wy - X\hat{\beta})'(y - \rho Wy - X\hat{\beta})}{N} \quad (3.23)$$

Anselin (1988, 1999) and Anselin and Bera (1998) demonstrate that conditional on  $\rho$  these estimates are simply OLS applied to the spatially filtered dependent and independent variables. Specifically, if we define  $\hat{\beta}_0 = (X'X)^{-1}X'y$  as the OLS estimate without the lagged dependent variable, then the associated residual is  $e_0 = y - X\hat{\beta}_0$ . Similarly, the OLS estimate regressing  $Wy$  on  $X$  is  $\hat{\beta}_L = (X'X)^{-1}X'Wy$  and the associated residual is  $e_L = y - X\hat{\beta}_L$ . Thus  $\hat{\beta}_{ML}$  and  $\hat{\sigma}_{ML}$  may be rewritten as

$$\hat{\beta}_{ML} = \hat{\beta}_0 - \rho\hat{\beta}_L \quad (3.24)$$

$$\hat{\sigma}_{ML} = (e_0 - \rho e_L)'(e_0 - \rho e_L)/N \quad (3.25)$$

These may be substituted back into Eq.(3.21), yielding the concentrated log likelihood function in terms of the autocorrelation parameter  $\rho$ .

$$L_C = \sum_{i=1}^N \ln(1 - \rho\omega_i) - \frac{N}{2} \ln \left[ \frac{(e_0 - \rho e_L)'(e_0 - \rho e_L)}{N} \right] \quad (3.26)$$

where  $e_0$  are the OLS residuals from a regression of  $y$  on  $X$  and  $e_L$  are the OLS residuals from a regression of  $Wy$  on  $X$ . A maximum likelihood estimate of  $\rho$  is obtained through a numerical optimization of this concentrated log likelihood function (Anselin and Bera 1998).

Eq.(3.14) is called a mixed regressive, spatially autoregressive model because in this model the dependent variable is spatially lagged but the independent variables are unlagged. If we suspect that the value of a house is also affected by the characteristics of its neighbors, then the spatial Durbin model shown below in Eq.(3.27) may be more appropriate.

$$y = \rho Wy + X\beta_1 + \rho WX\beta_2 + \varepsilon \quad (3.27)$$

This type of model adds a spatial lag of the dependent variable as well as a spatial lag of the independent variables to the classical regression model. This type of model is discussed in Anselin and Bera (1998) as well as other reviews but is not further considered in this study.

### 3.3 General Spatial Models

The spatial lag model may also be modified to incorporate spatial dependence in errors, yielding the most general form of the spatially dependent model. This is shown in Eq.(3.28-3.29) below.

$$y = \rho W_1 y + X\beta + u \quad (3.28)$$

$$u = \lambda W_2 u + \varepsilon \quad (3.29)$$

This type of model allows the prices of surrounding properties to influence a property's sale price while also allowing for correlation in the error terms. As it is specified above, this type of model also allows a different weight matrix for the spatial lag and the spatial error process and accordingly a different spatial autocorrelation parameter  $\rho$  and  $\lambda$ , respectively. This specification may be appropriate if we feel that a different set of neighbors exert influence through the spatial lag than through the spatial error. To clarify, in

this study the set of potential neighbors for the spatial lag weight matrix is limited to those observations that sold prior to the observation in question while the spatial error weight matrix does not have this constraint. This constraint is applied since the spatial lag parameter is multiplied by the sale prices of the neighbors in the spatial lag model. Thus it seems logical that we should require the houses used as neighbors to have already been sold if we expect these sale prices to have an impact on the sale price of the observation in question.

## Chapter 4

# Functional Form

Considerable discussion in the literature has involved the correct specification and functional form of the hedonic price function. Cropper, Deck and McConnell (1988) note that since economic theory does not specify the form of the hedonic price function, empirical research has focused on a goodness of fit criterion for choosing the functional form. Indeed, the semi-log functional form employed for my analysis was chosen based on goodness of fit. When compared to linear and log-linear formulations, the semi-log functional form fit the data better. However, Cropper *et al.* argue that if the goal of a study is the valuation of characteristics, then a functional form that accurately estimates attribute prices should be employed. It is also likely that increased flexibility will influence the findings of tests of aggregation and enhance the predictive power of the hedonic regressions. It is one goal of this study to determine the impact that a more flexible functional form has on these issues.

Box and Cox (1964) introduced the transformation that has typically been used to introduce flexibility in hedonic price functions. For a hedonic property value model, the quadratic Box-Cox functional form suggested by Halvorsen and Pollakowski (1981) takes the form

$$y^{(\theta)} = \alpha_0 + \sum_{i=1}^m \beta_i X_i^{(\lambda)} + \frac{1}{2} \sum_{i=1}^m \sum_{j=1}^m \gamma_{ij} X_i^{(\lambda)} X_j^{(\lambda)}, \quad (4.1)$$

where  $y$  is the house price, the  $X_i$  are the house characteristics,  $\gamma_{ij} = \gamma_{ji}$ , and  $y^{(\theta)}$  and  $X_i^{(\lambda)}$  are the Box-Cox transformations of the dependent and independent variable respectively,

$$y^{(\theta)} = \begin{cases} \frac{y^\theta - 1}{\theta} & \text{when } \theta \neq 0 \\ \log y & \text{when } \theta = 0 \end{cases} \quad (4.2)$$

$$X_i^{(\lambda)} = \begin{cases} \frac{X_i^\lambda - 1}{\lambda} & \text{when } \lambda \neq 0 \\ \log X_i & \text{when } \lambda = 0 \end{cases} \quad (4.3)$$

This form of the equation nests most of the other common functional forms used in hedonic studies, and thus may be used to test the appropriateness of these forms. In a study of San Francisco, Halvorsen and Pollakowski strongly reject all of the functional forms typically used in applications of the hedonic method. However, several authors have also noted problems with the Box-Cox functional form. Typically, the same Box-Cox transformation is applied to all of the independent variables. Cassel and Mendelsohn (1985) point out that this may create difficulties if one is interested in a minor environmental characteristic such as air quality. In this case, the transformation parameter will be determined primarily from the major characteristics but applied to all characteristics. This incorrect transformation of the environmental variable could lead to incorrect environmental welfare measures (Palmquist 2000). For this reason, Cassel and Mendelsohn advocate the use of simpler functional forms. In addition to this concern, Cropper *et al.* find that while the linear and quadratic Box-Cox forms provide the best estimates of marginal attribute prices when all of the characteristics are observed, when there are omitted or misspecified variables in the estimating equation the quadratic Box-Cox form performs poorly. In such cases, the linear Box-Cox and simpler forms such as linear, semi-log and double log perform better.

Thus while the quadratic Box-Cox functional form has received attention as a tool for testing functional forms, the linear Box-Cox form appears to be the best choice for estimating hedonic price functions. In the study by Cropper *et al.*, this was the form that was found to perform the best in the presence of misspecification, which is always a concern in hedonic models. This functional form may be written generally as

$$y^{(\theta)} = \alpha_0 + \sum_{i=1}^m \beta_i X_i^{(\lambda)} + \sum_{j=1}^l \gamma_j Z_j, \quad (4.4)$$

where  $y^{(\theta)}$  and  $X_i^{(\lambda)}$  are as previously defined and  $Z_j$  denotes characteristics that are not subject to transformation. These untransformed characteristics will typically be dummy variables that appear in the specification.

In this study, four different Box-Cox transformations are used. The first transforms only the dependent variable, while the others add transformations to different sets of the independent variables. One transforms the heated areas of the house, one transforms heated area and the lot size, and one transforms the heated area, lot size, and age. By transforming these variables, flexibility is introduced into the estimating equation and the results are potentially improved. At the same time, by limiting the number of variables transformed I avoid the problem of applying an incorrect transformation to one of the less important variables. Together, these results may also provide evidence as to the type of transformation that provides the best estimates, should the Box-Cox model be chosen as the best one for estimating hedonic property values models.

As was the case with the spatial models, maximum likelihood techniques are applied to estimate the Box-Cox equation,

$$y^{(\theta)} = X^{(\lambda)}\beta_1 + Z\beta_2 + \epsilon, \quad (4.5)$$

where  $y^{(\theta)}$  is an  $(N \times 1)$  vector of transformed house prices,  $X^{(\lambda)}$  is an  $(N \times K)$  matrix of transformed house characteristics,  $Z$  is an  $(N \times L)$  matrix of untransformed house characteristics,  $u$  is an  $(N \times 1)$  vector of error terms that are  $NID(0, \sigma^2)$ , and  $\beta_1$  and  $\beta_2$  are  $(K \times 1)$  and  $(L \times 1)$  vectors of regression coefficients, respectively. Since it is assumed that the residuals are normally and independently distributed, we can derive the log-likelihood function in the same manner as was used for the spatial models. The log-likelihood in this case is found to be

$$L = (\theta - 1) \sum_{i=1}^n \ln y - \frac{n}{2} \ln(2\pi) - \frac{n}{2} \ln(\sigma^2) - \frac{1}{2\sigma^2} (y^{(\theta)} - X^{(\lambda)}\beta_1 + Z\beta_2)' (y^{(\theta)} - X^{(\lambda)}\beta_1 + Z\beta_2). \quad (4.6)$$

Maximization of this likelihood function then yields estimates of the transformation parameters  $\theta$  and  $\lambda$  as well as the  $\beta_1$  and  $\beta_2$  coefficients. Tests of aggregation may also be based upon the results of this estimation, as in the case of the spatial error and spatial lag models. Further, predicted values may be easily generated using the parameter estimates, so that a comparison of the prediction errors between the models can be performed.

## Chapter 5

# Aggregation Tests

This study attempts to determine whether aggregation is acceptable from a statistical or practical standpoint for several subareas of Wake County as well as for the entire county. Three types of tests are performed in order to determine the acceptability of aggregation: statistical structural stability tests, comparison of regression standard errors, and comparison of prediction errors. Together, these tests should demonstrate the actual impact of aggregation on the estimates generated by the hedonic regressions. This chapter describes each of these types of tests, as well as modifications that must be made to the tests when applying the spatial econometric techniques that were discussed earlier.

### 5.1 Structural Stability Tests

Traditionally, testing for the existence of spatial segmentation of a housing market has consisted of first defining the submarkets that one suspects to exist, and then running regressions on these assumed submarkets individually and the market as a whole. Typically, the error sums of squares between the aggregate and individual markets are then compared using an  $n$ -way F-test.<sup>1</sup> The null hypothesis of this test is that all of the  $n$  groups belong to the same process, and the test statistic is

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<sup>1</sup>A derivation of this test statistic based upon the work of Chow (1960) may be found in Dhrymes (1971).

$$\frac{ESS_R - \sum_j ESS_j}{\sum_j ESS_j} \cdot \frac{T - nk}{p(n - 1)} \sim F_{p(n-1), T-nk} \quad (5.1)$$

where  $j = 1, \dots, n$  identifies each group,  $k$  is the number of parameters estimated in the separate regressions,  $p$  is the number of restriction imposed in the combined regression, and  $T$  is the total number of observations. In this test,  $ESS_R$  denotes the error sum of squares from a regression including all of the observations while  $ESS_j, j = 1, \dots, n$  denotes the error sum of squares from the  $n$  separate regressions. The pooled regression naturally constrains the parameters to be the same for both groups, unless particular variables that are believed to differ between the groups are explicitly accounted for through the use of dummy variables.<sup>2</sup> Through the use of such dummy variables, subsets of parameters can be tested. This is especially useful in property value studies, since we have reason to suspect that land values will differ between areas. If our specification is unable to capture such differences, it would be inappropriate to constrain these coefficients to be the same. Thus we may allow these parameters to vary between groups, and test equality of the other parameters. We reject the null hypothesis that aggregation is acceptable if the calculated F-statistic is larger than the critical value for the chosen level of significance.

The  $n$ -way F-test must be modified for use with spatial models. Anselin (1990) demonstrates that when the error variance is nonspherical, the exact Chow test is no longer applicable and must be generalized. For  $\Phi = \sigma^2\Omega$ , the generalized Chow test is written as

$$C_G = (e'_R\Omega^{-1}e_R - e'_U\Omega^{-1}e_U)/\sigma^2 \sim \chi_K^2 \quad (5.2)$$

where  $e_R$  and  $e_U$  are the residuals from the restricted and unrestricted regressions, respectively,  $K$  is the number of independent variables in the regressions, and  $\sigma^2$  is the variance. Substituting the residuals  $e$  and the estimates of  $\Omega^{-1}$  and  $\sigma^2$  from the spatial models then generates what Anselin calls a spatial Chow test.

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<sup>2</sup>While this study concentrates upon the equivalence of all coefficients across regressions as well as the predictive ability of pooled regressions, in practice one may only be interested in the equivalence of a single coefficient across the separate groups. Testing for equality of this type may be accomplished in several ways. If one expects the value of a particular characteristic to vary between areas, one can create a new variable interacting that characteristic and a dummy variable for each area. Then it is possible to allow the value to vary between the proposed submarkets through the inclusion of these newly created variables in the pooled regression. This necessitates an adjustment in the degrees of freedom of the calculated F-statistic, but is nonetheless easily implemented. However, Tiao and Goldberger (1962) developed a test specifically for the task of comparing individual coefficients across regressions that does not require the creation of new variables. This test is described in the appendix but is not applied in this study.



For the case of spatial error autocorrelation in Eq.(3.2-3.3), the variance-covariance matrix was shown in Eq.(3.6) to be defined as  $E[uu'] = \sigma^2(I - \lambda W)^{-1}(I - \lambda W')^{-1}$  so that  $\Omega^{-1} = (I - \lambda W')(I - \lambda W)$ . Therefore the spatial Chow test statistic for the spatial error model is found to be

$$C_{SE} = (e'_R(I - \lambda W')(I - \lambda W)e_R - e'_U(I - \lambda W')(I - \lambda W)e_U)/\sigma^2 \sim \chi_K^2. \quad (5.3)$$

In the spatial lag model, the variance-covariance matrix is  $E(\varepsilon\varepsilon') = \sigma^2(I - \rho W)^{-1}(I - \rho W')^{-1}$  as was shown in Eq.(3.20). In this case  $\Omega^{-1} = (I - \rho W')(I - \rho W)$  so the spatial Chow test statistic is then

$$C_{SL} = (e'_R(I - \rho W')(I - \rho W)e_R - e'_U(I - \rho W')(I - \rho W)e_U)/\sigma^2 \sim \chi_K^2. \quad (5.4)$$

In addition to the differences between the spatial parameters and weight matrices in the spatial lag and spatial error models, the residuals also differ between these models. The residuals in the spatial lag model are defined as  $e = (I - \hat{\rho}W)y - X\hat{\beta}$ , while the residuals in the spatial error model are  $e = (I - \hat{\lambda}W)y - (I - \lambda W)X\hat{\beta}$ . Similarly, for the more general model in Eqs.(3.28-3.29) incorporating both spatial lag and spatial error dependence, the residuals are found to be  $e = (I - \hat{\lambda}W_2)(I - \hat{\rho}W_1)y - (I - \hat{\lambda}2W_2)X\hat{\beta}$ . Since in the general case the effects of both the spatial lag and spatial error are present, the variance-covariance matrix is defined by  $E[uu'] = \sigma^2(I - \rho W_1)^{-1}(I - \lambda W_2)^{-1}(I - \lambda W_2')^{-1}(I - \rho W_1')^{-1}$ , where care is now taken to differentiate the spatial error weight matrix  $W_2$  from the spatial lag weight matrix  $W_1$ . Therefore  $\Omega^{-1} = (I - \rho W_1')(I - \lambda W_2')(I - \lambda W_2)(I - \rho W_1)$  and the spatial Chow test statistic for the general spatial model is

$$\begin{aligned} C_{GS} = & (e'_R(I - \rho W_1')(I - \lambda W_2')(I - \lambda W_2)(I - \rho W_1)e_R \\ & - e'_U(I - \rho W_1')(I - \lambda W_2')(I - \lambda W_2)(I - \rho W_1)e_U)/\sigma^2 \sim \chi_K^2. \end{aligned} \quad (5.5)$$

These statistics may be easily calculated using the estimates from the maximum likelihood procedure.

Anselin (1988) states that this test statistic may be formulated as a Wald test, a Lagrange multiplier Test, or a likelihood ratio test, with the distinguishing feature between these formulations lying in the specification of  $\sigma^2$ . The Wald test uses the estimate of  $\sigma^2$  from the unrestricted model, while the Lagrange multiplier test uses the estimate of  $\sigma^2$  from the restricted model and the likelihood ratio test uses the estimate of  $\sigma^2$  from both. However,

his claim that the test may be formulated as a Wald or Lagrange Multiplier test is not true since the test statistic uses the residuals from both the unconstrained and constrained regressions. A true Wald test statistic only requires computation of the unrestricted model, while a true Lagrange Multiplier test uses only information from the restricted model. It should also be noted that this test has only asymptotic validity and that the interpretation of the different forms of the test may lead to conflicts in finite samples since the tests themselves are only asymptotically equivalent (Anselin 1988). Thus while Anselin develops a spatial analogy to the Chow test, it seems more appropriate to simply identify the test in Eq.(5.2) as a likelihood ratio test, specifically one that constrains the variance to be the same in the subgroups being aggregated. The homoskedasticity assumption is added since in most applications of his test Anselin estimates a single equation for the unrestricted model, allowing the parameter estimates but not the variance to differ between the two groups. However, this assumption may be easily dropped and the test statistic adjusted accordingly should one suspect heteroskedasticity between the samples. An explicit likelihood ratio test could also allow the variances to differ in the disaggregated markets.

Since the maximum likelihood techniques used in the estimation of the spatial models facilitate the use of likelihood ratio tests, all of the aggregation test results are reported as likelihood ratio tests. That is, even in the cases where the models were estimated using OLS, the value of the maximized likelihood function is calculated using the parameter estimates and these maximized likelihood values were used to perform likelihood ratio tests as though the model had been estimated using maximum likelihood techniques. This has no impact on the results of the tests, but does allow for easier comparison across models as well as allowing for likelihood ratio tests across the models should one wish to conduct them.

## 5.2 Comparison of Regression Standard Errors

While the  $n$ -way F-test has been the standard test used in aggregation studies, there are reasons to believe that it is too restrictive to be of practical importance. McCloskey (1985) notes that significant differences are not necessarily large since small differences may be significant in large samples. This point is reiterated in McCloskey and Ziliak (1996) where it is noted that “ordinary usage in economics takes statistical significance to be the

same as economic significance” (p.98). Thus we must be careful to not dismiss aggregation simply on statistical grounds.

Ohta and Griliches (1975) argue that the F-test is too stringent and rejects aggregation too often. As was noted previously, they argue that with large samples and using standard tests we are likely to reject coefficient stability on purely statistical grounds. Thus such rejections do not necessarily mean that aggregation is without merit. To determine the appropriateness of aggregation, they propose a more practical criterion. Specifically, they propose comparing the standard errors of the regressions and accepting aggregation if the difference in those standard errors does not exceed 10%. This seemingly arbitrary cutoff was chosen based on their study of automobile prices. In that study, they used a semi-log functional form so the standard errors of the regressions could be viewed as measuring the unexplained variation in prices in roughly percentage units. Thus the difference in the standard errors of the constrained and unconstrained regressions may be viewed as a measure of the price-explanatory power of a model. In their regressions, the standard errors were approximately 0.1. A 10% difference in standard errors between the constrained and unconstrained models then equates to 0.01 and implies that while the lack of fit of the constrained regression is increased by 10% relative to the unconstrained model, the fit to the actual price data is only 1% smaller in the constrained regression. This difference is deemed to be “just noticeable” in terms of economic significance (p.339). Indeed, if the goal of a study is the accurate prediction of prices, then this seems to be a more applicable test of aggregation than the F-test.

### 5.3 Comparison of Prediction Errors

It is also possible to explicitly test a model’s ability to make accurate predictions of sale prices. One may be particularly concerned with the ability of a model to predict sale prices for out-of-sample observations. To test the predictive power of the regressions in this study, the observations for any particular zone were divided into two groups: 10% of the observations were randomly selected for an out-of-sample test group, while the remaining 90% were used in a hedonic regression to calculate coefficient values. The estimated price of each property was then calculated for both the in-sample and out-of-sample groups using the regression coefficients and compared to the actual prices for the observations.

Several measures of predictive ability are available, leaving it up to the researcher to determine the measure that best achieves the goal of the study. If one is concerned with minimizing the absolute size of the prediction error for a group of observations, the mean absolute error is the appropriate measure to use. The median is the appropriate predictor of house prices in this case. To see this, note that the loss function for the absolute prediction error is written as

$$L(y, \hat{y}) = |y - \hat{y}|, \quad (5.6)$$

where  $y$  is a continuous dependent variable and  $\hat{y}$  is the prediction of that variable. Therefore the expected loss is

$$EL = \int_{-\infty}^{\infty} |y - \hat{y}| f(y) dy = \int_{-\infty}^{\hat{y}} (\hat{y} - y) f(y) dy + \int_{\hat{y}}^{\infty} (y - \hat{y}) f(y) dy, \quad (5.7)$$

where  $f(y)$  is the density function for  $y$ . Minimizing this expected loss with respect to  $\hat{y}$  yields

$$\frac{\partial EL}{\partial \hat{y}} = \int_{-\infty}^{\hat{y}} f(y) dy + \int_{\hat{y}}^{\infty} -f(y) dy = 0. \quad (5.8)$$

Since by the definition of a density function  $\int_{-\infty}^{\infty} f(y) dy = 1$ ,

$$\int_{-\infty}^{\hat{y}} f(y) dy = \int_{\hat{y}}^{\infty} f(y) dy. \quad (5.9)$$

This requirement is satisfied at the median, so the median is the measure which minimizes the absolute prediction error.

If one adopts the philosophy that it is best to be close in percentage terms to the actual sale prices of all of the houses, the absolute percentage error is the measure of interest. However, when dealing with percentage errors neither the median nor the mean is the optimal predictor. To see this, note that the absolute percent prediction error loss function is written as

$$L(y, \hat{y}) = \frac{|y - \hat{y}|}{\hat{y}}, \quad (5.10)$$

where  $y$  and  $\hat{y}$  are as defined before. The expected loss is then

$$EL = \int_{-\infty}^{\infty} \frac{|y - \hat{y}|}{\hat{y}} f(y) dy = \int_{-\infty}^{\hat{y}} \frac{\hat{y} - y}{\hat{y}} f(y) dy + \int_{\hat{y}}^{\infty} \frac{y - \hat{y}}{\hat{y}} f(y) dy, \quad (5.11)$$

where  $f(y)$  is again the density function for  $y$ . Minimizing this expected loss with respect to  $\hat{y}$  yields

$$\frac{\partial EL}{\partial \hat{y}} = \int_{-\infty}^{\hat{y}} \frac{\hat{y} - (\hat{y} - y)}{\hat{y}^2} dF(y) + \int_{\hat{y}}^{\infty} \frac{-\hat{y} - (y - \hat{y})}{\hat{y}^2} dF(y) \quad (5.12)$$

$$= \frac{1}{\hat{y}^2} \left[ \int_0^{\hat{y}} y dF(y) - \int_{\hat{y}}^{\infty} y dF(y) \right] = 0, \quad (5.13)$$

where  $dF(y)$  is substituted for  $f(y)dy$  since the density function  $f(y)$  is the derivative of the distribution function  $F(y)$ . This expression can be simplified by noting that the conditional expectation of  $y$  given  $y < \hat{y}$  may be written as

$$E(y|y < \hat{y}) = \frac{\int_0^{\hat{y}} y dF(y)}{P(y < \hat{y})}, \quad (5.14)$$

which may be rewritten as

$$\int_0^{\hat{y}} y dF(y) = P(y < \hat{y}) E(y|y < \hat{y}). \quad (5.15)$$

Similarly,

$$\int_{\hat{y}}^{\infty} y dF(y) = P(y > \hat{y}) E(y|y > \hat{y}). \quad (5.16)$$

Substituting Eq.(5.15) and Eq.(5.16) into Eq.(5.13) yields

$$P(y < \hat{y}) E(y|y < \hat{y}) = P(y > \hat{y}) E(y|y > \hat{y}). \quad (5.17)$$

Since we know that  $E(y|y < \hat{y}) < E(y|y > \hat{y})$  by simple logic,  $P(y < \hat{y}) > P(y > \hat{y})$  in order for Eq.(5.17) to be true. Since  $P(y < \hat{y}) = P(y > \hat{y})$  at the median, the optimal predictor for absolute percent error is larger than the median. Since the mean is larger than the median, the mean is a better predictor in this case, though not optimal.

One may also be interested in ensuring that there are a limited number of predictions with large errors. If this is the case, one may be more interested in the predictor with the smallest root mean squared error, which penalizes large forecast errors more heavily than small errors. While this measure is not used in this study, the optimal estimator

could be found by minimizing the root mean squared error loss function with respect to the predicted value. The optimal predictor in this case would be the mean.

As the semi-log functional form is used in this study, the log of price is what is actually predicted by the regressions. However, in practice we are more likely to be interested in the ability to predict the actual price. This necessitates an easily achieved conversion from log prices to prices. To see this, recall that the semi-log model may be written as

$$\ln P = X\beta + \varepsilon, \quad (5.18)$$

where  $P$  is the sale price,  $X$  are independent variables,  $\beta$  is the vector of regression coefficients, and  $\varepsilon$  is a vector of error terms distributed  $N(0, \sigma^2)$ . Converting from the log of price to actual prices yields

$$P = e^{X\beta} \cdot \varepsilon^* \quad (5.19)$$

where  $\varepsilon^* = e^\varepsilon$  which is lognormally distributed. The expected value of  $P$  is then

$$E(P) = e^{X\beta} E(\varepsilon^*) = e^{X\beta} e^{\sigma^2/2} \quad (5.20)$$

and an estimate of the mean is therefore

$$\hat{E}(P) = e^{X\beta} e^{\hat{\sigma}^2/2}. \quad (5.21)$$

Similarly, the median is found to be

$$MD(P) = e^{X\beta} MD(\varepsilon^*) = e^{X\beta}, \quad (5.22)$$

since an estimate of the median of a lognormal distribution is 1.

To assess the predictive ability of the regressions in this study, the absolute difference between the price and expected price using the median as the predictor is calculated for each observation, and the mean absolute difference for all observations is also computed for both groups. To avoid biasing the results, this was repeated for five different randomly selected samples, and the mean absolute errors were then averaged over these five samples. This produces a simple measure of predictive ability that allows one to observe how close the predicted prices of the various models come to the actual sale prices of homes.

It is also possible to calculate the prediction errors for the spatial models. As described by Goldberger (1962), in the presence of nonspherical errors the pattern of the sample residuals contain additional information which can be used to reduce the prediction

variance. That is, if we observe clusters of residuals of the same sign, we should correct for this tendency to mispredict. This idea is the basis for the best linear unbiased predictor (BLUP), a process known as kriging in the geostatistics literature. This procedure minimizes the expected value of the squared difference between the actual and predicted value of the dependent variable, with the ultimate goal of deriving some linear combination of the residuals that may be used to improve out-of-sample predictions. This weighted average of the estimation errors is an approximation of the locational effects, and is used to estimate the error term for houses not in the data but for which we would like to predict a value.

For the standard model  $y = X\beta + \varepsilon$  with  $\varepsilon \sim (0, \Omega)$ , the best linear unbiased prediction is found to be

$$\hat{p} = X'_* \hat{\beta} + w' \Omega^{-1} e \quad (5.23)$$

where  $X_*$  is a vector of characteristics for the house whose value is to be predicted,  $w$  is the  $(N \times 1)$  vector of correlations between the point to be predicted and the  $N$  observations in the data set, and all other variables are as they were previously defined. A derivation of this estimator appears in the appendix. While they are not shown here, similar estimators for the spatial lag model and the more general model incorporating spatial lag and error dependence may also be derived.

This technique has generally been applied in the geostatistics literature, where there is a heavy emphasis on the direct specification of the covariance structure as is discussed in the appendix. While this method is preferable when the covariance structure is specified, this prediction method is not applicable for the weight matrix approach.<sup>3</sup> Nonetheless, it is possible to use the spatial correlations present within the data to improve the predictions of the spatial models. Pace and Barry (1999) suggest the use of a “smoothing” predictor defined for the spatial error, spatial lag, and general spatial models, respectively, as

$$\text{Spatial Error: } \hat{p} = X\hat{\beta} + \lambda W_2 e \quad (5.24)$$

$$\text{Spatial Lag: } \hat{p} = X\hat{\beta} + \rho W_1 y \quad (5.25)$$

$$\text{General Spatial: } \hat{p} = X\hat{\beta} + \rho W_1 y + \lambda W_2 e \quad (5.26)$$

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<sup>3</sup>In the case of the spatial error model, it is possible to form the  $\Omega^{-1}$  matrix using the weight matrix  $W$  and the estimate of  $\rho$ , and BLUP may be applied as though the covariance matrix was directly estimated (Pace and Barry 1999). In cases where there is both serial correlation and measurement error, Pace and Barry note that while this estimate will no longer be BLUP, it does use the correlation structure to improve prediction and thus may be viewed as having a smoothing effect. As such, it should provide better predictions than techniques which do not allow for spatial influences.

These are the spatial predictors applied in this study.

The tests described in this chapter and the theory in the preceding chapters form the basis for this study of Wake County property values. The tests provide easily applied methods of assessing the appropriateness of aggregation over space, while the theory provides clues as to the characteristics which matter to consumers and the importance of location in the housing decision. Spatial econometrics provides a methodology that explicitly accounts for the role of space as part of the estimation process, while the Box-Cox functional form provides an easy way to introduce flexibility into the estimating equation. With all of these tools in hand, it is possible to ascertain not only the appropriateness of aggregation, but also to provide some guidance as to the best type of model for estimating hedonic property value models.



## Chapter 6

# Data and Estimation Procedures

Having discussed in previous chapters the economic theory, econometric techniques, and aggregation tests that are used in this study, it is now possible to discuss the estimation procedures employed. This chapter first describes the data used in this study as well as the programs and techniques used in the creation of this dataset. Then the steps undertaken in order to estimate the models and perform the aggregation tests are described.

### 6.1 Data

The data used in this study of Wake County, North Carolina, consists of 104,998 sales of single family houses occurring within the county during the period 1992-2000. The data on parcel characteristics and sales were provided by the Wake County Revenue Department in the form of an Oracle database. Two versions of the database were used for this study, one covering the period 1992-1999 and one covering the period 1992-2000. While these databases contain the same information on the properties within the county, there are important differences between the two versions. At the time the first version of the database was received, the Revenue Department was in the final stages of their revaluation process. As a result, the database contained both the 1992 assessed values that were then being used for tax purposes and the updated 2000 assessed values. These values provided a

convenient way of screening the data to eliminate sales that were not arm's length or that were listed as parcel sales when in fact they were land sales. However, this version of the database was received prior to the end of the year, and therefore did not have all of the sales for 1999. After developing a strategy for the elimination of suspect sales, it was decided that an updated version of the database should be obtained, since this would also allow the addition of the sales for 2000. An unfortunate development with this later version of the database was the removal of the 1992 assessed values since the Revenue Department had completed the revaluation process by that time. This necessitated a reformulation of the screening strategy, the details of which are discussed below.

The database proved to be an exceptionally rich source of information about the characteristics of the properties. The format of the data permitted the calculation of the square footage of different areas within the house such as garages, decks, basements, and attics. Thus it is possible for these areas to be directly included in the hedonic regressions rather than being included through the use of dummy variables. However, as only the current characteristics of a parcel are stored in the database, a necessary assumption was that these characteristics were the same for all previous sales of the parcel.

In addition to the characteristics of the house, information about the house's sales as well as its location was contained in the database. This location was in the form of "easting" and "northing" coordinates from the North Carolina State Plane Coordinate System. These coordinates provide an easy method of calculating the distance between parcels and also of assigning the parcels to their appropriate zones. While the bulk of the database preparation was accomplished in SAS, the assignment to zones was carried out in the ArcView GIS system. In addition, the preliminary zones used for specification testing and screening were created within ArcView. A map showing the boundaries of these zones appear in Figure 6.1. The goal when creating these zones was to maintain sufficient heterogeneity within each area to permit the estimation of a hedonic regression producing meaningful coefficients, while also ensuring that the houses contained within each group were homogeneous enough to consider as a single market. These zones were primarily created along the boundaries of the 20 Wake County townships. To ensure that there were enough observations within each zone, these townships were combined on the basis of their access to major roads. In addition, prior beliefs about the similarities and differences of the neighborhoods contained within each of the areas were incorporated into the process.

An important concern when estimating any type of regression is the specification.

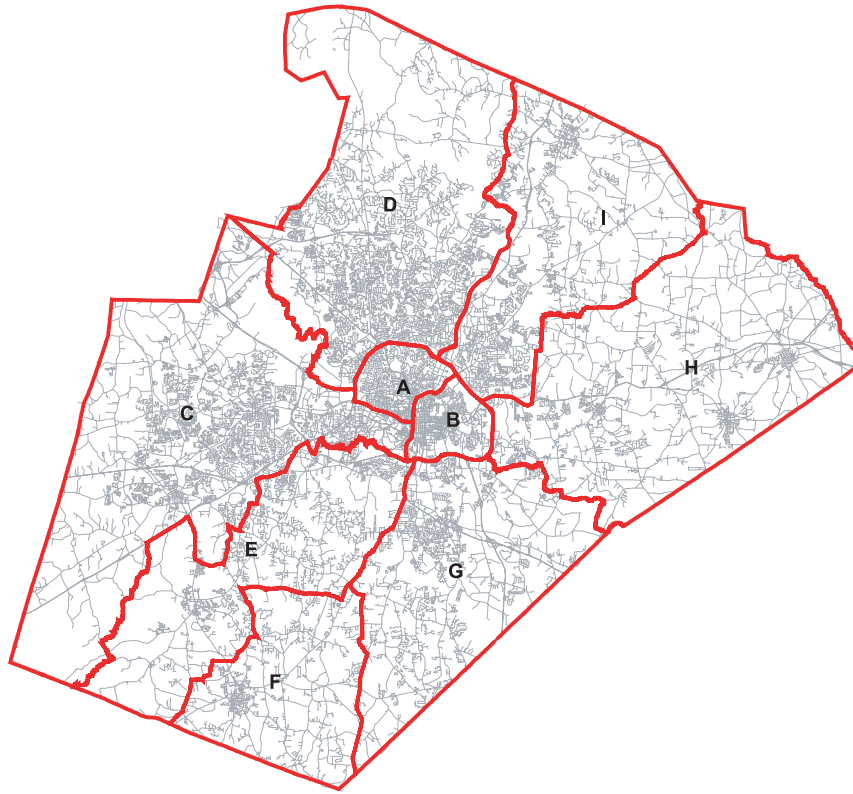


Figure 6.1: Wake County Screening and Specification Zones.

Identification of the correct specification is particularly difficult in property value studies, since there are a myriad of factors that affect the decision of where to live as well as the desirability and hence value of the residence. It is necessary to balance the desire to create the perfect specification against the need for parsimony. It is well known that the addition of any variable, regardless of its statistical significance in the estimation, will increase the fit of a regression equation or at the very least will not have a negative impact on the fit. Thus it is necessary to avoid the temptation to include all of the potential variables. A conscious effort must be made to include only those variables that are important to the question at hand.

Thus while far more characteristics were available in the database, the base specification ultimately used for estimation was arrived at through the use of stepwise regressions in the nine Wake County zones. Variables that were significant and of the correct sign in a

majority of the zones were included in the final specification. This is not to say, however, that the specification was entirely dictated by the results of these regressions. Several key variables typically appearing in hedonic property value models were required to appear in the stepwise regressions and thus appear in the final specification. In addition, variables that were felt to be important determinants of house values were included in the final specification regardless of their performance in the stepwise regressions. For example, dummy variables indicating that house is of poor condition or has no heating are included in the final specification although these variables are not significant in a majority of the zones. While there are relatively few houses in the data that meet these criteria, these are certainly characteristics that can be expected to have a negative impact on a property's selling price. The number of independent variables included in this base specification was 35. Of these 35 variables, 15 are the area in square feet of the various components of the house, 8 are dummy variables indicating the presence or absence of certain characteristics, and 4 are variables indicating the quality and condition of the property as determined by the Wake County assessors. The remaining variables describe other physical characteristics of the property, specifically the number of bathrooms, age, lot size in acres, the number of stories, and the number of fireplaces. Squared terms of the main heated area, age, and acreage are also included to allow for nonlinearity in those terms. A complete list of the variables in the base specification is provided in Table 6.1.

In addition to the house characteristics present in the database, a number of neighborhood and house characteristics were derived from additional sources. Using data from the 1990 and 2000 censuses, it was possible to create a number of variables that describe the neighborhoods in each area. When selecting the variables for inclusion in the regressions, a conscious effort was made to choose characteristics that could be observed from the curbside. This was done in order to simulate the characteristics that might be seen by a potential homeowner as he drives through neighborhoods looking at available houses. For example, when driving through a neighborhood, it is possible to get a sense for the number of children in that neighborhood by the presence of toys in lawns. However, it is impossible to form an opinion as to the average education level of the residents of that neighborhood. Using this admittedly subjective criterion combined with the performance of the variables in the hedonic regressions, the census variables included relate to the demographic makeup of the neighborhood, the value of the houses, and percent owner occupied. A complete list of census variables along with the other spatial variables included appears in Table 6.2.

Table 6.1: List of Variables in Base Specification

lprice	log(sale price of property).
baths	Number of bathrooms.
regheatarea	Main heated living area in square feet.
sqregheat	regheatarea <sup>2</sup> .
age	Age of structure, calculated as sale year-year built.
sqage	age <sup>2</sup> .
acreage	Lot size in acres.
sqacre	acreage <sup>2</sup> .
bsmtheat	Basement heated area in square feet.
bsmtunheat	Unheated basement heated area in square feet.
atticheat	Attic heated area in square feet.
atticunheat	Attic unheated area in square feet.
otherunheatarea	Other unheated areas within house (e.g., unfinished rooms) in square feet.
carport	Carport area in square feet.
encporch	Enclosed porch area in square feet.
scrporch	Screened porch area in square feet.
opnporch	Open porch area in square feet.
garage	Garage area in square feet.
storage	Storage area in square feet.
patio	Patio area in square feet.
deck	Deck area in square feet.
stoop	Stoop area in square feet.
fireplaces	Number of fireplaces.
story	Number of stories.
detgarage	Dummy variable indicating presence of detached garage.
walldum1	Dummy variable indicating presence of brick walls.
bsmtdum1	Dummy variable indicating presence of full basement.
bsmtdum2	Dummy variable indicating presence of partial basement.
heatdum6	Dummy variable indicating house has limited/partial heating.
heatdum7	Dummy variable indicating house has no heating.
acum1	Dummy variable indicating house has air conditioning.
poolres	Dummy variable indicating presence of swimming pool.
grade	Numeric grade assessed by Revenue Department.
condadum	Dummy variable indicating house is of condition A.
condcdum	Dummy variable indicating house is of condition C.
condddum	Dummy variable indicating house is of condition D.

Table 6.2: List of Additional Spatial Variables

perc_nonwhite_1990	Percent non-white for 1990 census block group.
medianvalue	Median house values for census block group.
medttw	Median time to work for census block group.
perc_under18	Percent of population under age of 18 for census block group.
perc_owner_occ	Percent owner occupied housing for census block group.
nearestpark	Distance to nearest park.
nearestsc	Distance to nearest shopping center.
bigparkdistance	Distance to nearest large park (larger than 70 acres).
taxrate	Property tax rate for area.

The census variables are block group level data. In addition, the median value, median time-to-work, percent under 18, and percent owner occupied variables make use of data from both the 1990 and 2000 censuses. Specifically, the interpolated values for these values were calculated for each observation based on the observation's sale year. To create these interpolated values, there was assumed to be a simple linear trend between the 1990

and 2000 values. While this is a simplification that is unlikely to yield the true values for the variables at the actual time of the sale, these values should nonetheless be closer to the true values than either the 1992 or 2000 values alone. One caveat about this approach deals with the boundaries of the census block groups between the 1990 and 2000 censuses. Changes were made to these boundaries between the censuses, but as these changes were not large it was assumed that they did not lead to large changes in the values of the variables used in this study. It should also be noted that it was impossible to create an interpolated value for the percent non-white variable due to changes in the way the 2000 census defines race. Thus the performance of both variables in the regressions was tested, and as the 1990 value tended to perform better it was included in the final specification.

The other spatial variables consist of three variables measuring the distance to recreation and shopping areas, and a tax rate variable that accounts for differences in property taxes between the localities of Wake County. The distance variables were derived from GIS sources. These variables measure the distance to the nearest park, the nearest large park (larger than 70 acres), and the nearest of four major shopping centers in the area. These distances are not the simple straight line distance found in most studies, however. Rather, an effort was made to account for how far a household would actually have to drive to visit these parks and shopping centers. This was accomplished through the use of ArcView. Using a shapefile containing only the major roads in Wake County, all of the 471 intersections of these major roads were identified. Then, the actual driving distance from each of these major intersections to each of the parks and shopping centers was calculated by finding the shortest network distance over a shapefile containing all of the roads in Wake County. To calculate the total distance from each property to the shopping centers and parks, the following steps were then taken. First, the Euclidean distance from each property to the closest major intersection was determined. This distance was then added to the distance from that intersection to each of the parks and shopping centers to find the total distance. While this method is not as exact as directly determining the driving distance from each property to each shopping center and park, the method employed has some advantages worth noting. Since there are a relatively large number of major road intersections, the driving distance from each property to the nearest major intersection is unlikely to be greatly different from the Euclidean distance between the points. As it takes considerably longer to calculate network distances than Euclidean distances, only calculating the network distances from the major intersections yields large time savings. Further, since this method

yields the distance to the nearest major intersection, it is possible to calculate some measure of major road accessibility as a natural by-product of this method. While such a measure is not employed in this study, accessibility is a concern in many property value studies and the existence of such a variable could be of use in other applications.

The creation of the Wake County data set proceeded as follows. An initial raw data set consisting of all sales for the period 1992-1999 was created using the earlier version of the database that included the 1992 and 2000 assessed values for the complete parcel as well as its land. In order to eliminate land sales and parcel sales that were not arm's length, this data set was screened on the basis of the 1992 and 2000 values for the assessed total value and the assessed land value. This screening was accomplished in the following manner. A linear trend was calculated between the 1992 and 2000 assessed values. If the price of the sale was less than 150 percent of the trend assessed land value then the sale was deemed to be a land sale and was eliminated. If the price of the sale was less than 80 percent of the trend total assessed value then the sale was deemed to be not arm's length and was eliminated. This produced 92,639 sales during the period 1992-1999; 27,282 sales were screened out due either to inaccuracies within the database or failure to meet these sale price criteria.

After screening the 1992-1999 data set, hedonic regressions were run for each of the nine areas of Wake County. Price indexes were then created for each zone using the year dummy variable coefficients from the regressions. It was then assumed that prices increased an additional 10% in 2000 for zones A and B and 5% in the other zones, as these were the trends during the 1992-1999 period. The complete 1992-2000 price index series was then merged into the 1992-2000 Wake County data set that was created from the later version of the Oracle database. These indexes were then used to inflate the prices of all parcels to their 2000 levels. These 2000 prices were then compared to the 2000 assessed values using the same criteria discussed previously to determine if an observation is a valid house sale. The addition of the 2000 sales resulted in the 104,998 sales mentioned before. The additional variables from other sources were then merged into this dataset.

While it is a hypothesis of this study that the entire county may be treated as a single housing market, it was not my intention to bias my results through the creation of inappropriate zones. Thus, while the nine zones appearing in Figure 1 are used for the purposes of specification testing and screening, less subjective zones were used for the actual estimations and aggregation tests. Specifically, the Triangle Multiple Listing Service (MLS)

zones for Wake County are used. This was a logical choice, since most house sales occur through realtors and these zones are used by realtors for the purpose of identifying potential homes for clients. Since a person seeking a home tells their realtor the areas in which they are interested, these MLS zones are natural candidates for consideration as submarkets. These zones are shown in Figure 6.2. It should be noted that due to the limited number of observations occurring in several of these areas, it proved necessary to merge some of the zones in order to have a similar number of observations within all zones. Specifically, zones were merged in order to obtain at least 200 observations within a zone for each year. The decision of how to merge the zones was a subjective one, based on my opinions as to the similarities between zones. Zones 12 and 13 were merged into Zone 11, and Zones 15 and 17 were merged into Zone 10. After merging these zones, 15 MLS Zones remained.

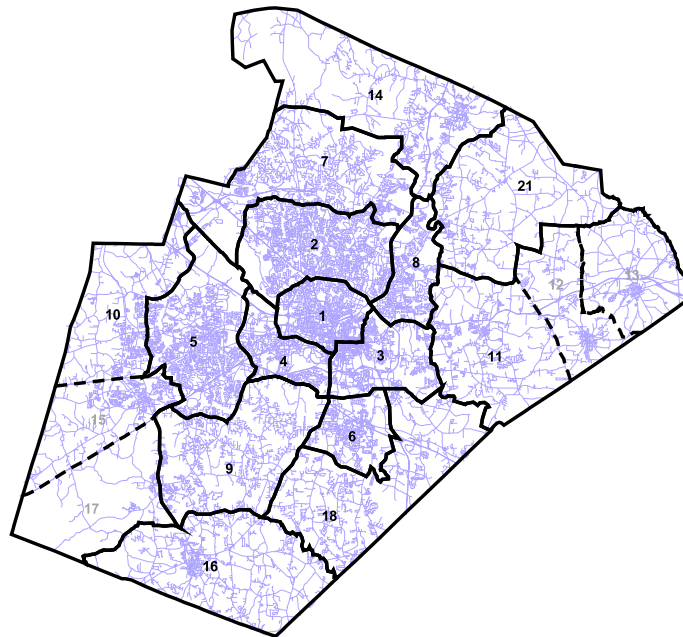


Figure 6.2: Wake County MLS Zones.

For the purposes of aggregation and prediction testing, these zones were grouped into three MLS groups. These three groups consisted of the North Raleigh Area, the Cary-Morrisville-Apex and surrounding areas, and Eastern Wake County. Zones 1 and 4 were not included in any of these groups, because they are considered both by the Wake County Revenue Department as well as the Triangle MLS to be dissimilar to the surrounding areas.



As a result, they are only included in the tests for aggregation of the entire county. These three MLS groups are shown in Figure 6.3.

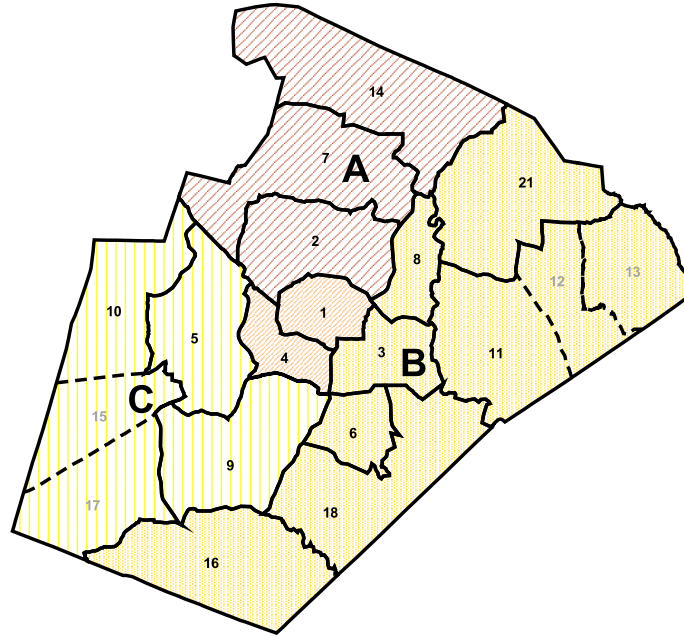


Figure 6.3: Wake County MLS Zone Groups.

## 6.2 Estimation Procedures

All of the estimation and aggregation testing for this study was performed using MATLAB. The estimation of the OLS models and creation of the aggregation test statistics as well as the mean average prediction errors were straightforward affairs and require little discussion, as the description of the tests themselves in the preceding chapter provides a guide as to the steps taken to construct the measures. It is the attempt to account for spatial differences among the areas that bears discussion.

It may be possible that the explicit accounting of space within the hedonic model may lead to a statistical acceptance of aggregation, while also leading to improved predictive power. Two methods were used to attempt to account for spatial variations within the data. First, the specification was varied to allow for differences in land values between zones and additional spatial variables were added to the base specification. Second, spatial

econometric models were estimated, using both the base specification and the expanded specification. To estimate the spatial econometric models, I employed the spatial econometric routines from the Econometric Toolbox created by LeSage (1999). Among many other routines, this toolbox consists of a number of programs that may be used to estimate spatial error, spatial lag, and general spatial models. Further, these programs calculate the asymptotic T-statistics for testing the significance of the coefficient estimates, which allows for easy comparison with the output from other statistical packages. These spatial routines make use of the sparse matrix techniques advocated by Pace and Barry (1999) and therefore permit the estimation of spatial models with large numbers of observations. However, the programs provided by LeSage only create weight matrices on the basis of contiguity. While this may be appropriate for many applications, in the case of housing it is likely that differences in size and the timing of sales should also be incorporated in the creation of the weight matrix. This is in line with the comparable sales approach employed as a part of most appraisal processes. In this approach, appraisers will look at the sale prices of several properties with characteristics similar to the house they are appraising. Further, the appraisers prefer comparable sales in the vicinity, and that occurred within some time frame. Thus, I employ similar methods when constructing my weight matrices.

Two types of weight matrices were created for my study for both the spatial error and spatial lag cases. Both types of weight matrices identify the ten nearest neighbors of the observations. While an alternative number of neighbors could be used, there is no consensus on the correct number of neighbors, so this choice is simply a maintained assumption. The spatial error and spatial lag weight matrices differ in that the spatial lag weight matrix uses a time constraint to ensure that all of the neighbors occur earlier in time than the observation in question. As was discussed earlier, this requires the houses used as neighbors to have already been sold since we expect these sale prices to have an impact on the sale price of the observation in question. Further, the use of a different weight matrix for the spatial error and spatial lag cases removes the potential for identification issues when estimating the general spatial model, which uses both of these weight matrices. Since the models are estimated for individual years, this type of weight matrix does have one drawback. Ten of the observations for each year will not have a full set of ten neighbors, since there will not be ten sales prior to the sale date of those observations. However, the theoretical and practical advantages of this approach would appear to outweigh this drawback.

The first type of spatial weight matrix employed a size constraint in order to limit

the potential neighbors to houses that were similar in size to the observation in question. All observations with a main heated area more than 300 square feet larger or smaller than the house in question were eliminated from consideration as potential neighbors. This was intended to approximate the comparable sales technique by using similar houses as neighbors. If a house is similar in size to another house, it seems likely that its other characteristics will also be similar. Having eliminated the houses not meeting this size constraint, the distance from the property to the remaining observations was calculated. This distance is not simply a physical distance, but also incorporates distance in time. To accomplish this, it was assumed that a distance in time of one year was equivalent to a distance of space of one mile. The total distance in miles was then calculated as the sum of the distance in space and the temporal distance, where the distance in time is converted to miles. To determine the nearest neighbors, the distances for these potential neighbors were ordered from smallest to largest, and the observations having the ten smallest distances were designated as the nearest neighbors of a particular observation. It should be noted, however, that the use of this size constraint may again prevent some observations from having a full set of neighbors. If there are not ten houses meeting the size constraint, then there will not be ten neighbors for that particular observation. The other type of weight matrix removes the size constraint, and thus ensures that each observation will have a full set of neighbors. However, since these neighbors are based solely on distance without taking into account size differences, these neighbors may not necessarily be similar in characteristics to the observation.

One important consideration when using this size constraint on the weight matrix concerns the spatial lag model. While imposing the size constraint ensures that the houses considered as neighbors are similar to the house in question, using this set of neighbors for the spatial lag of the dependent variable precludes the possibility of a mansion having a positive impact on the value of any smaller houses that be in the vicinity. If we want to allow such effects, then the size constraint may be inappropriate and we may define the spatial lag weight matrix as the nearest neighbors in terms of distance occurring before the sale date of the observation in question.

The weight matrices constructed using this method were then used in the estimation of the spatial error, spatial lag, and general spatial models as discussed in Chapter 3. Using the results from these spatial regressions, it is possible to employ the techniques discussed in Chapter to test for structural stability and predictive power. The results of

these tests are discussed in Chapter 7 and the conclusions that may be drawn from this study are discussed in the Chapter 8.

## Chapter 7

# Results

The results of this study may be broadly grouped into two categories. The first category comprises the various tests of the acceptability of aggregation while the second attempts to determine to best type of model for estimating hedonic property value models. The tests of the acceptability of aggregation include the standard tests of aggregation discussed earlier, the comparison of regression standard errors suggested by Ohta and Griliches (1975), and the comparison of prediction errors. The question that these tests attempt to answer is whether aggregation is acceptable from a statistical or practical standpoint. As these tests are conducted I also investigate whether the addition of variables proxying for neighborhood characteristics, the use of flexible functional forms, or the application of spatial econometric techniques leads to a greater acceptance of aggregation. As a part of discussion, I simulate two situations that may arise in empirical work – small samples and limited specifications – and demonstrate that in such cases aggregation may lead to more reliable coefficient estimates even when statistical tests reject such aggregation.

It is also possible to make two types of comparisons when analyzing the results. The first investigates whether altering the specification within a particular type of model alters the results. This comparison is possible since all of the tests are conducted using three specifications. The first specification includes the variables listed in Table 6.1. The second specification allows for differing land values between MLS zones. Specifically, the land coefficients were allowed to vary between the MLS zones being aggregated. Location theory as discussed in Chapter 2 indicates that we should expect land values to decrease as we

move away from the central business district. Since I have not attempted to identify a single central business district for Wake County, and indeed have made no assumptions about the distribution of employment throughout the county, I do not have any preconceptions about how the value of land should vary within or between the zones. In actuality, the value of land should be allowed to vary continuously with the distance from the central business district rather than be constrained to be a single value for the entire zone, but my goal in allowing land values to vary was to determine if any correction would appreciably change the results of the aggregation tests. The third specification attempts to account for any further spatial differences that may exist between the areas by including the variables listed in Table 6.2. As was discussed earlier, these variables were derived from census and GIS sources, and sought to describe the characteristics of the neighborhoods as well as the houses' proximity to recreation and shopping areas. These variables are included since there may be differences other than land values existing between the MLS zones. Specifically, the types of neighborhoods present within the zones may be different. By including variables that are proxies for the characteristics of these neighborhood, it is hoped to control for these differences. When comparing the prediction errors of the different models a fourth specification is estimated. This "sparse" specification includes only baths, regheatarea, sqregheat, acreage, sqacre, age, sqage, and grade and is used to discern the impact of aggregation on prediction errors and coefficient estimates when a limited number of variables are included in the specification.

The other type of comparison that is possible is between the various types of models that are estimated. Eight different types of models are estimated: OLS; Box-Cox transforming price only; Box-Cox transforming price, regheatarea, acreage, and age; Box-Cox transforming price, regheatarea, and acreage; Box-Cox transforming price and regheatarea; spatial error; spatial lag; and the general spatial model. In the Box-Cox regressions, it should be noted that a separate transformation parameter is estimated for the dependent and independent variables where applicable. While OLS provides the baseline case against which the other models may be compared, the Box-Cox model attempts to improve on the OLS predictions by introducing more flexibility into the estimating equation, while the spatial models attempt to use the spatial correlation within the data to improve the estimates. While we might expect the spatial models to provide the best results based on the simple assumption that location matters in real estate, the dominance of the spatial models is not assured beforehand. Thus this comparison by itself is an important one, as

it provides some guidance as to whether flexible functional forms or spatial models are a more important consideration when estimating hedonic models. As part of this comparison, the predictive ability of the spatial models is compared to the OLS and Box-Cox models to determine if explicitly accounting for the spatial correlations present within the data improves predictive ability. Further, the predictive performance of the spatial models when not including the additional neighborhood variables is compared to the OLS and Box-Cox results when these neighborhood variables are included. This comparison evaluates the necessity of the collection of additional neighborhood variables such as census data, distances to recreation areas, and the like. These variables have traditionally been used in hedonic studies as proxies for the differences that occur between neighborhoods. Since spatial econometric techniques explicitly account for these spatial differences as part of the estimation procedure, these methods should yield comparable results.

## 7.1 Aggregation Tests

The results of all of the traditional aggregation tests were, as might be expected, dismal. The statistical tests are simply too stringent for aggregation to ever be found acceptable without compromising the quality of the results. In an unreported experiment, aggregation was found to be acceptable for six very small sub-areas of MLS Zone 7. However, this acceptance would appear to be the result of an exceptionally poor regression fit for all of the areas, caused both by the limited number of observations as well as the homogeneity of the houses in the sample. In cases where a good regression fit and meaningful coefficient values were achieved, aggregation was rejected even in that experiment.

The aggregation tests were performed for each year in the 1992-2000 period for Groups A, B, and C as well as the whole county. Together, these comprise 864 individual tests of aggregation. And in each of these cases, the coefficients were found to be statistically significantly different in the MLS zones being aggregated. The results were invariant even when allowing the values of the land coefficients (acreage and sqacre) to differ between the zones and when adding the additional neighborhood characteristics. Further, even the use of spatial econometric techniques and flexible functional forms did not alter the results. While the use of these models as well as the different specifications led to reductions in the  $\chi^2$  test statistic in all of the cases, the reductions were minor and did not lead to an

acceptance of aggregation. Tables containing all of the aggregation test results appear in Appendix B, while Table 7.1 below summarizes these results.

Table 7.1: Aggregation Test Results Summary

Specification Used	Number of Tests	Number of Rejections	Percent Rejection
Base Specification	288	288	100%
Varying Land Coefficients	288	288	100%
Additional Spatial Variables	288	288	100%

It is worth noting that while allowing the land coefficients to vary between zones in the aggregated regressions reduced the aggregation test statistics, the addition of the spatial variables did not often lead to a further reduction in the test statistic. Rather, in most cases aggregation was more strongly rejected. One possible source of this anomalous result is the data itself. The census data is included at the block group level, and there are numerous block groups within each MLS zone. As a result, the inclusion of these variables allows for considerable variation within the MLS zone. Therefore in many cases the maximized value of the likelihood function increases more in the individual zones than in the aggregated zone. This leads to a stronger rejection of aggregation. But as aggregation was already strongly rejected in all cases, this somewhat counterintuitive finding does not change the overall results. In all cases aggregation is rejected with a P-Value of  $< .0001$ .

## 7.2 Comparison of Standard Errors

While the statistical test for aggregation rejected the null hypothesis that the coefficients were the same between the areas being aggregated in each of the 864 cases, the comparison of regression standard errors between the disaggregated and aggregated regressions yields somewhat different results. As was the case in the Ohta and Griliches (1975) study, the regression standard errors were in the neighborhood of 0.1. Thus a 10% difference in standard errors between the aggregated and disaggregate implies that while aggregation increases the lack of fit of the regression by 10% relative to the disaggregated regressions, the fit to the actual price data is only 1% smaller in the aggregated regression. Using this 10% cutoff suggested by Ohta and Griliches to be “just noticeable” in terms of economic significance, aggregation was accepted in 259 of the 432 cases tested. The total number of cases tested differs from the number of aggregation tests due to the fact



that it was impossible to include a comparison of the Box-Cox regression standard errors. This was the case because a weighted average of the SERs from the disaggregated Box-Cox regressions often is larger than the SER from the aggregated regression. This is a counterintuitive and misleading result, and is simply an artifact of the method used to obtain a SER for the disaggregated regression. Rather than estimating a single constrained and unconstrained equation, the unconstrained SER is calculated as a weighted average of the SERs from the individual regressions of the groups being aggregated. While this method creates no problems in the OLS and spatial models, in the Box-Cox cases the SERs are highly variable leading to weighted averages that are larger than the SER of the aggregated regression. While in theory this shortcoming could be overcome by respecifying the estimating equation and estimating a single unconstrained model, it is unlikely that convergence could be obtained for an equation with multiple lambdas.

If the cutoff is relaxed to 15%, the results are even more striking, with aggregation accepted in 393 of the 432 cases. Further county-wide aggregation is typically accepted. Thus, comparing the fit of the regressions to the price data indicates that even though statistical tests reject aggregation, the actual impact of the aggregation on the predictions of the model is minor. The results of the SER comparisons for Groups A, B, and C as well as Wake County appear in Appendix C, while Table 7.2 summarizes these results.

Table 7.2: SER Comparison Results Summary

Specification Used	10% Cutoff			15% Cutoff		
	Number of Tests	Number of Rejections	Percent Rejection	Number of Tests	Number of Rejections	Percent Rejection
Base Specification	144	66	45%	144	20	14%
Varying Land Coefficients	144	48	33%	144	3	2%
Additional Spatial Variables	144	59	41%	144	6	4%

While these summary might appear to indicate that the best results are obtained when allowing the land values to vary but without adding the additional neighborhood characteristics to the specification, this is not necessarily the case. As was mentioned before, it is possible to obtain statistical acceptance of aggregation in some cases at the cost of accurate estimates. Thus the issue of which specification provides the best fit to the data must also be considered. And an analysis of the SERs show that the addition of the spatial variables does improve the regression fit as expected. However, this improvement is greater for the individual zones than the aggregated zones leading to a reduced acceptance of aggregation on the basis of SER comparison when using the full specification. Nonetheless,

this does not alter the finding that the results of aggregation are minor when based upon this criterion.

### 7.3 Prediction Errors

The effect of aggregation on the predictive ability of a model may also be a guide as to whether aggregation is acceptable from a practical standpoint. While this comparison is related to the comparison of regression standard errors discussed above, this provides a more concrete measure of the error that may be expected when aggregating and also allows for the calculation of in-sample and out-of-sample prediction errors. As was discussed in Chapter 5, the median is the minimum loss predictor when minimizing the absolute prediction error. For this reason, the results in this section focus on the mean absolute error (MAE) when using the median as the predictor of house prices.

To assess the impact of aggregation, a comparison is made between the prediction errors from the aggregated regressions and a weighted average of the prediction errors from each of the individual MLS zones being aggregated. The weights used in the average are the number of observations in each zone relative to the total number of observations in the group being aggregated. The results of these comparisons appear in Tables 1-4 in Appendix D. Before discussing these results, it should be noted that the spatial weight matrices used for these regressions do not apply the size constraint to the neighbors. Since in general the prediction errors for the spatial models are lower when using this unconstrained weight matrix, these are the results that appear in Appendix D.

However, it may also be of interest whether the prediction results are particular to the specification or the type of weight matrix used. Thus while they do not all appear in the appendix, the prediction errors were calculated for three different cases. First, the prediction errors are calculated using the full specification and using a weight matrix without a size constraint for the spatial models. This type of weight matrix allows any house to be a neighbor, without requiring it to be of a similar size to a particular observation. Secondly, the full specification is again used, but the weight matrix is altered to require a particular observation's neighbors to have a heated area within 300 square feet of the observation in question. This type of weight matrix approximates the comparable sales approach used by appraisers by requiring houses to be similar to one another to be considered neighbors.

Then, a sparse specification is used while using the weight matrix without a size constraint.

The comparisons between the weighted average and aggregate regression prediction errors are summarized in Table 7.3. In these comparisons, the in-sample results are exactly as expected. In nearly every case, regardless of the specification used, the model being estimated, the weight matrix being used, or the zones being aggregated, the weighted average of the individual zone prediction errors outperformed the prediction error from the aggregated regression. The only exceptions when using the full specification involved the estimation of the Box-Cox model for MLS Group A in 1997 and the estimation of the general spatial model for MLS Group B in 1999. When estimating the sparse specification and using the weight matrix without the size constraint, the prediction errors were lower in the aggregated regressions in 2 cases.

However, while the weighted average of the individual zones typically provided a lower mean absolute prediction error, there was not a large difference between the weighted average MAE and the MAE from the aggregated regression. In fact, of the 288 cases when using the unconstrained weight matrix, only 66 have a difference of greater than 10 percent and only 1 has a difference of greater than 20 percent. Indeed, the average difference was 801 dollars. When using the weight matrix with a size constraint, there are 80 cases where this difference is greater than 10 percent. Only 3 have differences exceeding 20 percent, and the average difference is only 867. When estimating the sparse specification, 58 cases exceed the 10 percent criterion. 36 exceed the 20 percent criterion, but the average difference is only 739. Thus in all of these models, the effects of aggregation on the prediction errors is minor.

The out-of-sample results are considerably different and provide even stronger evidence that aggregation is not the evil some researchers have suggested. Specifically, the weighted average of individual zone prediction errors is not always preferred, and in many cases the aggregated results produce considerably lower prediction errors. Overall, the prediction errors from the aggregated regressions outperform the weighted average from the individual zones, as they are preferred in over half of the cases. As was the case for the in-sample results, the actual differences between the predictions are small, but these differences are larger than in the in-sample cases. Nonetheless, the average differences are less than 2000 dollars.

In addition to providing information about the effects of aggregation, the prediction errors that were generated provide valuable information as to the best type of model

Table 7.3: Prediction Error Comparison Results Summary

	Lowest MAE		Avg. Diff.	MAE Diff.	
	Wt. Avg.	Agg.		> 10%	> 20%
<b>In-Sample</b>					
Weight Matrix without Size Constraint	287	1	801	66	1
Weight Matrix with Size Constraint	286	2	867	80	3
Sparse Specification	250	2	739	58	36
<b>Out-of-Sample</b>					
Weight Matrix without Size Constraint	118	170	1539	154	62
Weight Matrix with Size Constraint	115	173	1552	148	63
Sparse Specification	84	204	1796	165	88

to use for property value models when the goal is the accurate prediction of prices. One measure of which model provides the best estimates is simply how often that each model produces the lowest MAE. There are 15 individual MLS zones, 3 aggregation groups, and the entire county, which results in 171 cases for both the in-sample and out-of-sample observations. Table 7.4 summarizes the best in-sample and out-of-sample predictors for both types of weight matrices as well as when the sparse specification is used.

Table 7.4: Model with Lowest Mean Absolute Error

Model	Weight Matrix without Constraints			Weight Matrix with Size Constraint			Sparse Specification		
	In-Sample	Out-of-Sample	Total	In-Sample	Out-of-Sample	Total	In-Sample	Out-of-Sample	Total
OLS*	0	6	6	3	8	11	1	9	10
Box-Cox*	43	24	67	54	29	83	-	-	-
Spatial Error	16	57	73	7	52	59	23	70	93
Spatial Error*	98	42	140	98	46	144	124	49	173
Spatial Lag	0	7	7	1	7	8	0	14	14
Spatial Lag*	10	13	23	3	8	11	11	10	21
General Spatial	1	9	10	1	12	13	0	9	9
General Spatial*	3	13	16	4	9	13	12	10	22

\* Includes Census and Distance Variables

As can be seen from these results, the spatial error models consistently outperform the other types of models. Thus if one wishes to estimate a single type of model, one of the spatial error models would appear to be the best choice. Based upon these results, it would appear that the primary decision faced is whether or not to include additional spatial variables in the specification estimated. Further, the results above do not convey the dominance of the spatial error models when multiple zones are aggregated. In these models, one of the spatial error models is chosen for 67 of the 72 cases when using the weight matrices without the size constraint, 67 of the 72 cases when using the weight matrices with the size constraint, and 70 of the 72 cases when estimating using a sparse specification. Thus

if we have already chosen to aggregate the zones, one of the spatial error models would be the logical choice for estimation.

Another measure of the best model for estimation may be derived based on the performance of each model relative to the other models. While the results of such a measure should be similar to the simple measure previously reported, assessing the relative performance of the models would penalize models that only occasionally provide the best results. To construct this measure, the models were ranked from best to worst in terms of prediction errors for each year in each zone and aggregation group. The models were assigned a numerical value based on their performance relative to the other models. For the cases where a full specification was estimated, the best performing model received a 1, while the worst performing model received an 8. In the case where a sparse specification was used, these values ranged from 1 to 7 since the Box-Cox models were not estimated. These values were then summed over years, zones and aggregation groups. The model are then ranked based on these sums. The results of these tests when using the mean absolute error criterion appear in Table 7.5 below.

Table 7.5: Model Rankings Based on Mean Absolute Error

Model	Weight Matrix without Constraints			Weight Matrix with Size Constraint			Sparse Specification		
	In-Sample	Out-of-Sample	Overall	In-Sample	Out-of-Sample	Overall	In-Sample	Out-of-Sample	Overall
OLS*	6	7	7	5	6	6	5	6	6
Box-Cox*	4	6	5	2	4	4	-	-	-
Spatial Error	3	1	2	4	2	2	3	1	2
Spatial Error*	1	2	1	1	1	1	1	2	1
Spatial Lag	8	8	8	8	8	8	7	7	7
Spatial Lag*	5	4	4	6	5	5	4	4	4
General Spatial	7	5	6	7	7	7	6	5	5
General Spatial*	2	3	3	3	3	3	2	3	3

\* Includes Census and Distance Variables

As was the case in the previous test, the spatial error models tend to be the best predictors. However, it is interesting to note that when using the unconstrained weight matrix the third place model is no longer the Box-Cox model, but rather is the general spatial model including the additional spatial variables. This indicates that in many cases while the general spatial model produced larger prediction errors than the spatial error model, it still provided lower prediction errors than the Box-Cox model. Thus, this measure provides a more accurate ranking of the models than could be obtained by simply counting the number of times a particular model is chosen.

It was mentioned earlier that different measures of predictive accuracy exist should one be concerned with limiting outliers or if one is interesting is errors in percentage terms rather than absolute errors. It was also shown in Chapter 5 that the median is not the minimum loss predictor for absolute percentage error. Nonetheless, it may be of interest whether the model rankings change when comparing mean absolute prediction error while using the median as the house price predictor.<sup>1</sup> These results are summarized in Table 7.6 below. These results indicate that even when using this alternative measures of predictive accuracy the spatial error models dominate, especially when including the additional location variables.

Table 7.6: Model Rankings Based on Mean Absolute Percentage Error

Model	Weight Matrix without Constraints			Weight Matrix with Size Constraint			Sparse Specification		
	In-Sample	Out-of-Sample	Overall	In-Sample	Out-of-Sample	Overall	In-Sample	Out-of-Sample	Overall
OLS*	6	7	6	6	6	6	5	6	5
Box-Cox*	5	6	5	2	4	4	-	-	-
Spatial Error	3	2	2	4	2	2	3	2	2
Spatial Error*	1	1	1	1	1	1	1	1	1
Spatial Lag	8	8	8	8	8	8	7	7	7
Spatial Lag*	4	4	4	5	5	5	4	4	4
General Spatial	7	5	7	7	7	7	6	5	6
General Spatial*	2	3	3	3	3	3	2	3	3

\* Includes Census and Distance Variables

As was mentioned in earlier, one may also be interested in the performance of the spatial models without the additional neighborhood variables relative to the OLS and Box-Cox models when these variables are included. Such a comparison will provide guidance as to whether the sometimes costly and difficult collection of these variables is necessary. Table 7.7 summarizes the results from simply counting the number of times each model provides the best prediction, while Table 7.8 summarizes the results when applying the ranking criterion discussed above. These results demonstrate that if one is faced with a choice between acquiring additional variables to describe neighborhoods or simply estimating a spatial model, they should opt for the spatial model. Further, they should choose a spatial error model. Thus the usefulness of spatial econometric techniques for property value models is clearly determined, regardless of their inability to lead to a statistical acceptance of

<sup>1</sup>To assess the impact of using the median as the predictor when calculating MAPE instead of a more optimal predictor, the model rankings for the entire county were compared using both the median and mean as the house price predictor. While the mean should be a more optimal predictor, there was only a single difference between the rankings when using the different predictors. In all cases, the top 5 models remain unchanged.

aggregation.

Table 7.7: Spatial Models vs. Extra Variables Lowest MAE

Model	Weight Matrix without Constraints			Weight Matrix with Size Constraint			Sparse Specification		
	In-Sample	Out-of-Sample	Total	In-Sample	Out-of-Sample	Total	In-Sample	Out-of-Sample	Total
OLS*	9	16	25	12	24	36	39	25	64
Box-Cox*	63	32	95	84	36	120	-	-	-
Spatial Error	95	96	191	73	88	161	127	115	242
Spatial Lag	0	12	12	1	9	10	2	19	21
General Spatial	4	15	19	1	14	15	3	12	15

\* Includes Census and Distance Variables

Table 7.8: Spatial Models vs. Extra Variables Rankings Based on MAE

Model	Weight Matrix without Constraints			Weight Matrix with Size Constraint			Sparse Specification		
	In-Sample	Out-of-Sample	Overall	In-Sample	Out-of-Sample	Overall	In-Sample	Out-of-Sample	Overall
OLS*	3	4	3	3	3	3	2	3	2
Box-Cox*	2	3	2	1	2	2	-	-	-
Spatial Error	1	1	1	2	1	1	1	1	1
Spatial Lag	5	5	5	5	5	5	4	4	4
General Spatial	4	2	4	4	4	4	3	2	3

\* Includes Census and Distance Variables

## 7.4 Coefficient Estimates

Finally, it may be informative to test the impact of aggregation on the coefficient estimates produced by the models. Appendix E contains sample regression results for 1992 for the OLS and spatial error models using the unconstrained weight matrices. These models are estimated both using the full set of observations and randomly selecting 50 observations from each group. These small samples simulate estimating hedonic property value models using very small areas, while combining these areas demonstrates the potential benefits of aggregation on these estimates. Further, the models are estimated using the three different specifications discussed earlier: the base specification, the full specification that includes the additional spatial variables, and the sparse specification.

The most readily apparent result of aggregation in these results is that more coefficients are significant and of the expected sign in the aggregated regressions than in the individual regressions. This is the case regardless of the specification used or the size of the samples. This most likely arises simply because aggregation introduces more heterogeneity

into the observations used for estimation, making it easier to discern the impact of the different variables. Nonetheless, it is comforting to find that the addition of a bathroom has a positive and significant impact of a property's selling price in the aggregated regressions, since this is not always the case in the individual regressions.

A similar effect can be expected when estimating using small samples. With a small number of observations, it becomes more difficult to distinguish the influence of some of the less important factors in a property's value. For example, while we may expect a condition rating of less than average to have a negative impact on the value of a house, in none of the individual zone OLS regressions using the base specification and small samples is the condition "D" dummy variable significant, and the condition "C" dummy variable is only significant in 2 of the zones. Aggregating even these small samples yields coefficients that are of the expected sign and that are significant. This is an important reason why aggregation may be preferable based upon coefficient estimates regardless of the results of aggregation tests. Often researchers may be interested in some environmental factor that may affect a limited number of properties. Only when a sufficient number of properties exhibiting that factor exist in the data can an accurate estimate of that factor's impact be derived.

While there are numerous examples in the sample results of the positive impacts of aggregation, aggregation should not be considered a cure-all for the problems that arise when estimating with small samples. While more variables are significant and of the expected sign when aggregating, by no means are all of the variables significant. Nonetheless, this improvement of the ability to estimate the impact of less important factors provides further evidence that aggregation is not without merit. Further, as analysis of the results for the spatial error models demonstrates, the improvements from aggregation are not limited to the OLS case.



## Chapter 8

# Conclusions

This study makes use of what I believe to be one of the best datasets ever available for use in hedonic estimation. Using this data, I attempt to determine whether aggregation is acceptable from a statistical or practical standpoint by conducting several types of tests of aggregation. The results of this study indicate that while there may be statistically significant differences in coefficient values between areas, aggregation has a limited impact on the ability of the hedonic regressions to predict house prices both in-sample and out-of-sample.

Likelihood ratio tests of aggregation were performed for each year in the 1992-2000 period for MLS Groups A, B, and C as well as the whole county. Together, these comprise 864 individual tests of aggregation, and in each of these cases the coefficients were found to be statistically significantly different in the MLS zones being aggregated. The results were invariant even when allowing the values of the land coefficients (acreage and sqacre) to differ between the zones and when adding additional neighborhood characteristics to control for locational differences between observations. Further, even the use of spatial econometric techniques and flexible functional forms did not alter the results.

While the statistical test for aggregation rejected the null hypothesis that the coefficients were the same between the areas being aggregated in each of the 864 cases, the comparison of regression standard errors between the disaggregated and aggregated regressions typically accepts aggregation. Using the 10% cutoff suggested by Ohta and Griliches to be “just noticeable” in terms of economic significance, aggregation was accepted

in 259 of the 432 cases tested. If the cutoff is relaxed to 15%, the results were even more striking, with aggregation accepted in 393 of the 432 cases.

A comparison of mean absolute prediction errors between aggregated and disaggregate regressions indicates that we would typically expect less than a 2000 dollar increase in mean absolute prediction error from aggregating over all zones, while in several cases the out-of-sample predictions would be improved. Thus the limited negative impact of aggregation on predictive power, coupled with the more plausible coefficient values produced by the pooled regressions as well as the potential problems with sample size that arise when running separate regressions, may indicate that aggregation is preferable to extensive disaggregation when conducting hedonic property values studies.

This study also provides evidence as to the best type of model for estimating hedonic property value models. I find that a spatial error model is typically preferred over OLS and Box-Cox alternatives, even when those alternatives include additional spatial variables and the spatial error model does not. This finding provides further evidence of the potential benefits of the use of spatial econometric techniques. While future research may focus on refinements to these models, such as attempting to determine an optimal weight matrix, the results of this study indicate that the impact of aggregation need not be a concern.

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## Appendix A

# Supplemental Information

### Tiao-Goldberger Test for Individual Coefficient Stability

In situations where the one is considered with the equality of individual parameters across subgroups, Tiao and Goldberger (1962) offer a test which is based on comparing the parameter estimates to a weighted sum of the estimates across all of the models.

$$F^{TG} = \frac{\sum_{j=1}^L (\hat{b}_{ji} - \bar{b}_i)^2 / P_{ji}}{\sum_{j=1}^L SSR_j} \frac{\sum_{j=1}^L (T_j - K_j)}{(L - 1)} \quad (\text{A.1})$$

where

$$\bar{b} = \frac{\sum_{j=1}^L (\hat{b}_{ji} / P_{ji})}{\sum_{j=1}^L (1 / P_{ji})} \quad (\text{A.2})$$

$L$  is the number of models,  $\hat{b}_{ji}$  is the OLS estimate of the  $i$ th parameter in the  $j$ th independent model,  $P_{ji}$  is the diagonal element for the  $i$ th parameter of the  $(X^T X)_j^{-1}$  matrix,  $SSR_j$  is the sum of squared residuals for the  $j$ th model,  $T_j$  is the number of observations in the  $j$ th group, and  $K_j$  is the number of parameters estimated in the  $j$ th model. In small samples, this statistic is approximately distributed as an  $F$  distribution with  $L - 1$  numerator degrees of freedom and  $\sum_{j=1}^L (T_j - K_j)$  denominator degrees of freedom. In large samples, this statistic is approximately distributed as a  $\chi^2$  distribution with  $L - 1$  degrees of freedom.

It should be noted that the  $n$ -way F-test discussed in the main text may also be formulated as a test of the equality of a subset of the parameters. The above test was developed to conserve on computing power, an issue which may be of less importance today.

## Direct Specification of Covariance Structure

The alternative approach to dealing with spatial autocorrelation does not begin with an assumed error process and derive the covariance matrix, but rather assumes a functional form for the covariance structure itself. The parameters of this function are then estimated along with the regression coefficients using maximum likelihood techniques. This approach starts with the assumption that house prices and the residuals are tied to a particular location. If we assume that the residuals are second-order stationary, the correlation between the observations is a function of the distance between the houses (Dubin, Pace and Thibodeau 1999). As was noted earlier, it is impossible to estimate the  $N^2$  elements of the correlation matrix with  $N$  observations so we must impose structure upon the problem. In this case we do so by assuming the existence of a correlation function which can be used to model the spatial relationships. The types of functions which have been used to model the correlations are covariograms, correlograms, and semivariograms. Dubin *et al.* (1999) note that for second-order stationary processes, the covariogram and correlogram are statistically equivalent to the variogram. Therefore, I will only discuss the correlogram and semivariogram. I will also assume that the dependence between observations depends only on the distance between the observations and not the direction. This is the case of isotropy, while a process which depends on both direction and distance is said to be anisotropic. Incorporating this assumption, the correlogram models the correlations between observations as a function of the distance separating them, while the semivariogram models the variance of the difference between house values as a function of the distance separating the houses.

When constructing correlograms, functions which allow the correlations to drop as the observations become farther apart are typically chosen. While many functions have been suggested, the three most commonly used are the negative exponential, the Gaussian, and the spherical.<sup>1</sup> In these functions which appear below,  $K_{ij}$  represents the elements of the correlation matrix,  $b_1$  and  $b_2$  are the unknown parameters which are to be estimated, and  $d_{ij}$  is the distance between observations  $i$  and  $j$ .

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<sup>1</sup>Cressie(1993) discusses additional forms for the semivariogram.



Negative Exponential:

$$K_{ij} = \begin{cases} b_1 \exp\left(-\frac{d_{ij}}{b_2}\right) & \text{if } i \neq j \\ 1 & \text{if } i = j \end{cases} \quad (\text{A.3})$$

Gaussian:

$$K_{ij} = \begin{cases} b_1 \exp\left(-\frac{d_{ij}^2}{b_2}\right) & \text{if } i \neq j \\ 1 & \text{if } i = j \end{cases} \quad (\text{A.4})$$

Spherical:

$$K_{ij} = \begin{cases} b_1 \left(1 - \frac{3d_{ij}}{2b_2} + \frac{d_{ij}^3}{2b_2^3}\right) & \text{if } i \neq j \text{ and } 0 \leq d_{ij} < b_2 \\ 1 & \text{if } i = j \\ 0 & \text{if } d_{ij} > b_2 \end{cases} \quad (\text{A.5})$$

As was previously mentioned, these are all decreasing functions of the distance between observations. In the negative exponential correlogram,  $b_1$  is the intercept and  $b_2$  determines the rate at which the correlations decrease as distance increases. When the distance is zero, the correlation must be one since it is the correlation of a house with itself. However, Dubin *et al.* (1999) note that it is possible that the correlation will be discontinuous at the origin, since for small separation distances the correlation will be considerably less than one. To allow for this discontinuity known as the nugget effect in the geostatistics literature, the intercept is therefore calculated. The Gaussian correlogram is similar to the negative exponential, with the exception that in the Gaussian case the exponent is squared. This causes the correlations to decrease more quickly as the distance between observations increases. The spherical case is different, however, since it sets a distance boundary on the correlations. In the negative exponential and Gaussian cases, the correlations asymptotically approach zero. However, the spherical correlogram allows nonzero correlations only within a specified range. For all distances greater than  $b_2$ , the correlation equals zero.

Since  $E[uu'] = \sigma^2 K = \Omega$ , the estimation of the spatial model using correlograms is quite similar to the case using weight matrices. This is to be expected, as we are merely specifying a particular functional form for the correlations rather than assuming a form of the weight matrix. Accordingly, this decision of functional form is as important to the results as was the specification of the weight matrix. When using correlograms, the log

likelihood function to be maximized is

$$L = -\frac{1}{2} \ln |K| - \frac{1}{2} \ln(2\pi) - \frac{1}{2} \ln(\sigma^2) - \frac{(y - X\beta)' K^{-1} (y - X\beta)}{2\sigma^2} \quad (\text{A.6})$$

which is maximized with respect to  $\beta$ ,  $\sigma^2$ , and the parameters of  $K$  ( $b_1$  and  $b_2$ ).

The semivariogram approach is not quite as straightforward. Letting  $s_i = (x_i, y_i)$  denote the location of  $i$  and where  $\varepsilon(s_i)$  is the residual from the hedonic regression for observation  $i$ , the semivariogram is defined as

$$\gamma_{ij} = \frac{1}{2} E[\varepsilon(s_i) - \varepsilon(s_j)]^2 \quad (\text{A.7})$$

The common forms of the semivariogram are the same as for the correlogram: negative exponential, Gaussian, and spherical. These forms are shown below.

Negative Exponential:

$$\gamma(d_{ij}, \theta) = \begin{cases} \theta_0 + \theta_1 \left[ 1 - \exp\left(-\frac{d_{ij}}{\theta_2}\right) \right] & \text{if } i \neq j \\ 0 & \text{if } i = j \end{cases} \quad (\text{A.8})$$

Gaussian:

$$\gamma(d_{ij}, \theta) = \begin{cases} \theta_0 + \theta_1 \left[ 1 - \exp\left(-\frac{d_{ij}^2}{\theta_2^2}\right) \right] & \text{if } i \neq j \\ 0 & \text{if } i = j \end{cases} \quad (\text{A.9})$$

Spherical:

$$\gamma(d_{ij}, \theta) = \begin{cases} \theta_0 + \theta_1 \left( \frac{3d_{ij}}{2\theta_2} - \frac{d_{ij}^3}{2\theta_2^3} \right) & \text{if } i \neq j \text{ and } 0 \leq d_{ij} < b_2 \\ 0 & \text{if } i = j \\ \theta_0 + \theta_1 & \text{if } d_{ij} > b_2 \end{cases} \quad (\text{A.10})$$

The common estimation procedure when applying the semivariogram method is as follows. First,  $\beta$  is estimated using OLS. These residuals are then used in the method of moments estimator for the semivariogram suggested by Matheron (1963)

$$g(d_{ij}) \equiv \sum_{N(d_{ij})} [\varepsilon(s_i) - \varepsilon(s_j)]^2 / 2|N(d_{ij})| \quad (\text{A.11})$$

where the average is taken over  $N(d_{ij}) \equiv \{(s_i, s_j) : s_i - s_j \in T(d_{ij}); i, j = 1, \dots, n\}$  and where  $T(d_{ij})$  denotes a tolerance region around  $d_{ij}$ . This essentially divides the separation

distances into ranges so that there are  $N(d_{ij})$  ranges. The parameters of the semivariogram can then be fit to the  $g(d_{ij})$  function by minimizing the function

$$S(\theta) = \sum_{k=1}^K [g(d_{ij}(k)) - \gamma(d_{ij}(k), \theta)]^2 \quad (\text{A.12})$$

with respect to  $\theta$  through the use of some iterative technique. In this equation,  $d_{ij}(k)$  for  $k = 1, \dots, K$  denotes the distance ranges for which the method of moments estimator in Eq.(A.11) is calculated.

After the parameters in  $\theta$  are calculated, they are used to estimate the elements of the variance-covariance matrix  $\Omega$  using the chosen functional form.  $\beta$  is then reestimated using the GLS estimator  $B_1 = (X'\Omega^{-1}X)^{-1}X'\Omega^{-1}y$ , and this revised estimator for  $\beta$  is used to recompute the predicted values and the associated residuals. These residuals are then used to recompute the parameters of the semivariogram, and these parameters are used to recompute  $\Omega$ . This process continues to iterate until the  $\beta$  values converge.

## Derivation of the Best Linear Unbiased Predictor

The classical linear regression model is given by

$$y = X\beta + \varepsilon \quad (\text{A.13})$$

where  $\varepsilon \sim (0, \Omega)$  and where  $y$  is the vector of dependent variables,  $X$  is the matrix of independent variables  $\beta$  is the vector of regression coefficients,  $\varepsilon$  is the vector of disturbances, and  $\Omega$  is the variance-covariance matrix.

If we wish to predict the value of an out-of-sample observation, the actual value will be

$$y_* = X_*\beta + \varepsilon_* \quad (\text{A.14})$$

where  $\varepsilon_* \sim (0, \sigma_*^2)$  and where  $y_*$  is the dependent variable,  $X_*$  is the vector of independent variables and  $\beta$  is as previously defined. Further, assumes that the covariance of the prediction disturbance with the sample disturbance is given by  $E\varepsilon_*\varepsilon = w$ .

Since we are seeking the best linear unbiased predictor of  $y_*$ , we are looking for the linear predictor

$$p = c'y, \quad (\text{A.15})$$

where  $c$  is a vector of constants, such that  $\sigma_p^2 = E(p - y_*)(p - y_*)'$  is a minimum subject to  $E(p - y_*) = 0$ . Combining Eqs.(A.13), (A.14), and (A.15) yields

$$p = c'X\beta + c'\varepsilon \quad (\text{A.16})$$

$$p - y_* = (c'X - X'_*)\beta + c'\varepsilon - \varepsilon_*. \quad (\text{A.17})$$

The unbiasedness condition  $E(p - y_*) = 0$  then requires that  $(c'X - X'_*) = 0$  so that for an unbiased prediction the prediction error is

$$p - y_* = c'\varepsilon - \varepsilon_*. \quad (\text{A.18})$$

Thus the prediction variance is found to be

$$\begin{aligned} \sigma_p^2 &= E(p - y_*)(p - y_*)' \\ &= E(c'\varepsilon - \varepsilon_*)(c'\varepsilon - \varepsilon_*)' \\ &= E[c'\varepsilon\varepsilon'c - \varepsilon_*^2 - 2c'\varepsilon_*\varepsilon] \\ &= c'\Omega c - \sigma_*^2 - 2c'w \end{aligned} \quad (\text{A.19})$$

To minimize this variance subject to the unbiasedness condition, we minimize the Lagrangian

$$L = c'\Omega c - \sigma_*^2 - 2c'w - 2\lambda'(X'c - X_*). \quad (\text{A.20})$$

The first-order conditions are given by

$$\frac{\partial L}{\partial c} = 2\Omega c - 2w - 2X\lambda \quad (\text{A.21})$$

$$\frac{\partial L}{\partial \lambda} = 2X'c - 2X_*. \quad (\text{A.22})$$

These are set equal to zero and can then be written in matrix form as

$$\begin{bmatrix} \Omega & X \\ X' & 0 \end{bmatrix} \begin{bmatrix} c \\ -\lambda \end{bmatrix} = \begin{bmatrix} w \\ X_* \end{bmatrix} \quad (\text{A.23})$$

so that the solution for  $c$  and  $\lambda$  may be found as

$$\begin{bmatrix} c \\ -\lambda \end{bmatrix} = \begin{bmatrix} \Omega & X \\ X' & 0 \end{bmatrix}^{-1} \begin{bmatrix} w \\ X_* \end{bmatrix} \quad (\text{A.24})$$

Applying the rule for the inversion of a partitioned matrix, the inverse which appears in the equation above is found to be

$$\begin{bmatrix} \Omega & X \\ X' & 0 \end{bmatrix}^{-1} = \begin{bmatrix} \Omega^{-1} - \Omega^{-1}X(X'\Omega^{-1}X)^{-1}X'\Omega^{-1} & -\Omega^{-1}X(X'\Omega^{-1}X)^{-1} \\ (X'\Omega^{-1}X)^{-1}X'\Omega^{-1} & (X'\Omega^{-1}X)^{-1} \end{bmatrix} \quad (\text{A.25})$$

so that

$$\begin{bmatrix} c \\ \lambda \end{bmatrix} = \begin{bmatrix} \Omega^{-1} - \Omega^{-1}X(X'\Omega^{-1}X)^{-1}X'\Omega^{-1} & \Omega^{-1}X(X'\Omega^{-1}X)^{-1} \\ (X'\Omega^{-1}X)^{-1}X'\Omega^{-1} & -(X'\Omega^{-1}X)^{-1} \end{bmatrix} \begin{bmatrix} w \\ X_* \end{bmatrix} \quad (\text{A.26})$$

Thus the estimate of  $c$  is

$$\hat{c} = [\Omega^{-1} - \Omega^{-1}X(X'\Omega^{-1}X)^{-1}X'\Omega^{-1}]w + \Omega^{-1}X(X'\Omega^{-1}X)^{-1}X_* \quad (\text{A.27})$$

and the best linear unbiased predictor is then

$$\hat{p} = \hat{c}'y = X_*'(X'\Omega^{-1}X)^{-1}X'\Omega^{-1}y + w'\Omega^{-1}y - w'\Omega^{-1}X(X'\Omega^{-1}X)^{-1}X'\Omega^{-1}y. \quad (\text{A.28})$$

This equation may be simplified by recognizing the term  $(X'\Omega^{-1}X)^{-1}X'\Omega^{-1}y$  as the GLS estimator of  $\beta$ . Making this substitution and rearranging terms yields

$$\begin{aligned} \hat{p} = \hat{c}'y &= X_*'\hat{\beta} + w\Omega^{-1}y - w'\Omega^{-1}X\hat{\beta} \\ &= X_*'\hat{\beta} + w\Omega^{-1}(y - X\hat{\beta}) \\ &= X_*'\hat{\beta} + w\Omega^{-1}e \end{aligned} \quad (\text{A.29})$$

where  $e$  is the vector of sample residuals. Eq.(A.29) is the form of the best linear unbiased predictor which appears in the main text.

## Appendix B

# Aggregation Test Results

Table B.1: Aggregation Test Results for MLS Group 1 - OLS and Spatial Models

Year	OLS					Spatial Error					Spatial Lag					General Spatial				
	Sum	Agg.	$\chi^2$	R	Prob.	Sum	Agg.	$\chi^2$	R	Prob.	Sum	Agg.	$\chi^2$	R	Prob.	Sum	Agg.	$\chi^2$	R	Prob.
<b>Base Specification</b>																				
1992	2618	2400	437	67	<.0000	3847	3696	301	69	<.0000	3805	3605	399	69	<.0000	3879	3727	304	71	<.0000
1993	2969	2756	425	67	<.0000	4443	4259	368	69	<.0000	4305	4068	475	69	<.0000	4470	4282	377	71	<.0000
1994	2643	2462	364	67	<.0000	3990	3853	274	69	<.0000	3930	3764	331	69	<.0000	4031	3886	290	71	<.0000
1995	2956	2710	492	67	<.0000	4133	3969	328	69	<.0000	4065	3819	493	69	<.0000	4153	3979	347	71	<.0000
1996	3176	2955	441	65	<.0000	4508	4341	333	67	<.0000	4431	4213	437	67	<.0000	4533	4359	348	69	<.0000
1997	3702	3470	464	68	<.0000	5181	5014	335	70	<.0000	5132	4908	448	70	<.0000	5208	5037	343	72	<.0000
1998	4417	3924	985	70	<.0000	6099	5702	794	71	<.0000	5993	5476	1032	71	<.0000	6142	5717	851	73	<.0000
1999	3394	3062	664	71	<.0000	4717	4497	439	73	<.0000	4647	4336	621	73	<.0000	4745	4507	475	75	<.0000
2000	1954	1740	427	69	<.0000	2891	2720	343	71	<.0000	2881	2657	448	71	<.0000	2915	2731	369	73	<.0000
<b>Varying Land Coefficients</b>																				
1992	2618	2433	370	63	<.0000	3847	3700	293	65	<.0000	3805	3648	314	65	<.0000	3879	3738	283	67	<.0000
1993	2969	2814	309	63	<.0000	4443	4278	329	65	<.0000	4305	4145	322	65	<.0000	4470	4312	316	67	<.0000
1994	2643	2529	228	63	<.0000	3990	3894	191	65	<.0000	3930	3832	195	65	<.0000	4031	3933	196	67	<.0000
1995	2956	2809	293	63	<.0000	4133	4020	225	65	<.0000	4065	3920	291	65	<.0000	4153	4041	225	67	<.0000
1996	3176	3026	300	61	<.0000	4508	4370	275	63	<.0000	4431	4272	318	63	<.0000	4533	4392	282	65	<.0000
1997	3702	3564	277	64	<.0000	5181	5076	211	66	<.0000	5132	5009	245	66	<.0000	5208	5103	210	68	<.0000
1998	4417	4142	549	66	<.0000	6099	5877	444	67	<.0000	5993	5737	510	67	<.0000	6142	5910	466	69	<.0000
1999	3394	3193	403	67	<.0000	4717	4561	312	69	<.0000	4647	4469	355	69	<.0000	4745	4581	329	71	<.0000
2000	1954	1815	277	65	<.0000	2891	2747	288	67	<.0000	2881	2736	291	67	<.0000	2915	2773	286	69	<.0000
<b>Additional Spatial Variables</b>																				
1992	2755	2524	463	81	<.0000	3903	3719	368	83	<.0000	3859	3681	356	83	<.0000	3919	3754	330	85	<.0000
1993	3121	2914	413	81	<.0000	4495	4311	368	83	<.0000	4372	4185	374	83	<.0000	4513	4334	359	85	<.0000
1994	2760	2612	298	81	<.0000	4044	3929	231	83	<.0000	3991	3866	250	83	<.0000	4066	3954	224	85	<.0000
1995	3101	2917	368	81	<.0000	4211	4060	301	83	<.0000	4161	3994	333	83	<.0000	4219	4076	286	85	<.0000
1996	3283	3107	351	79	<.0000	4550	4403	292	81	<.0000	4514	4342	343	81	<.0000	4573	4424	298	83	<.0000
1997	3838	3662	351	82	<.0000	5265	5130	270	84	<.0000	5233	5073	320	84	<.0000	5278	5146	265	86	<.0000
1998	4548	4280	535	84	<.0000	6155	5927	456	85	<.0000	6065	5831	467	85	<.0000	6184	5959	449	87	<.0000
1999	3517	3310	413	85	<.0000	4778	4608	340	87	<.0000	4723	4544	358	87	<.0000	4789	4625	327	89	<.0000
2000	2068	1898	341	83	<.0000	2949	2791	317	85	<.0000	2951	2787	328	85	<.0000	2966	2809	315	87	<.0000

Sum = sum of likelihoods from individual zone regressions

Agg. = likelihood from aggregated regression

R = number of restrictions

Prob. = P-value

Table B.2: Aggregation Test Results for MLS Group 1 - Box-Cox Transformations

Year	Box-Cox <sup>1</sup>					Box-Cox <sup>2</sup>					Box-Cox <sup>3</sup>					Box-Cox <sup>4</sup>				
	Sum	Agg.	$\chi^2$	R	Prob.	Sum	Agg.	$\chi^2$	R	Prob.	Sum	Agg.	$\chi^2$	R	Prob.	Sum	Agg.	$\chi^2$	R	Prob.
<b>Base Specification</b>																				
1992	-31747	-31958	422	101	<.0000	-27634	-27842	417	101	<.0000	-31714	-31940	451	101	<.0000	-31740	-31954	428	101	<.0000
1993	-36922	-37107	370	101	<.0000	-32169	-32347	355	101	<.0000	-36913	-37092	358	101	<.0000	-36923	-37101	356	101	<.0000
1994	-37420	-37631	423	101	<.0000	-32685	-32898	427	101	<.0000	-37403	-37620	434	101	<.0000	-37424	-37633	418	101	<.0000
1995	-32460	-32689	457	101	<.0000	-28317	-28551	468	101	<.0000	-32452	-32684	463	101	<.0000	-32468	-32698	460	101	<.0000
1996	-37460	-37720	520	98	<.0000	-32703	-32968	529	98	<.0000	-37447	-37721	547	98	<.0000	-37469	-37729	519	98	<.0000
1997	-42653	-42925	544	103	<.0000	-37260	-37517	512	103	<.0000	-42632	-42920	575	103	<.0000	-42673	-42932	519	103	<.0000
1998	-45127	-45573	891	106	<.0000	-39374	-39799	849	106	<.0000	-45125	-45578	908	106	<.0000	-45154	-45584	860	106	<.0000
1999	-37687	-38017	660	107	<.0000	-32922	-33257	669	107	<.0000	-37670	-38015	690	107	<.0000	-37700	-38031	663	107	<.0000
2000	-27888	-28106	437	105	<.0000	-24448	-24661	425	105	<.0000	-27887	-28107	439	105	<.0000	-27910	-28118	415	105	<.0000
<b>Varying Land Coefficients</b>																				
1992	-31747	-31923	352	95	<.0000	-27634	-27809	352	95	<.0000	-31714	-31877	326	95	<.0000	-31740	-31922	364	95	<.0000
1993	-36922	-37054	263	95	<.0000	-32169	-32294	249	95	<.0000	-36913	-37036	247	95	<.0000	-36923	-37050	254	95	<.0000
1994	-37420	-37560	280	95	<.0000	-32685	-32830	291	95	<.0000	-37403	-37537	266	95	<.0000	-37424	-37567	287	95	<.0000
1995	-32460	-32577	234	95	<.0000	-28317	-28445	257	95	<.0000	-32452	-32565	227	95	<.0000	-32468	-32595	254	95	<.0000
1996	-37460	-37642	365	92	<.0000	-32703	-32898	389	92	<.0000	-37447	-37634	373	92	<.0000	-37469	-37661	383	92	<.0000
1997	-42653	-42830	354	97	<.0000	-37260	-37426	331	97	<.0000	-42632	-42809	355	97	<.0000	-42673	-42844	342	97	<.0000
1998	-45127	-45291	327	100	<.0000	-39374	-39558	368	100	<.0000	-45125	-45282	315	100	<.0000	-45154	-45341	375	100	<.0000
1999	-37687	-37849	324	101	<.0000	-32922	-33093	342	101	<.0000	-37670	-37831	320	101	<.0000	-37700	-37870	340	101	<.0000
2000	-27888	-27998	222	99	<.0000	-24448	-24587	277	99	<.0000	-27887	-27997	219	99	<.0000	-27910	-28046	271	99	<.0000
<b>Additional Spatial Variables</b>																				
1992	-31611	-31835	447	122	<.0000	-27497	-27719	444	122	<.0000	-31585	-31808	446	122	<.0000	-31605	-31829	449	122	<.0000
1993	-36771	-36953	364	122	<.0000	-32023	-32193	339	122	<.0000	-36772	-36947	349	122	<.0000	-36779	-36947	337	122	<.0000
1994	-37289	-37487	395	122	<.0000	-32557	-32748	381	122	<.0000	-37274	-37479	409	122	<.0000	-37295	-37486	383	122	<.0000
1995	-32324	-32473	298	122	<.0000	-28181	-28336	310	122	<.0000	-32329	-32465	273	122	<.0000	-32330	-32482	304	122	<.0000
1996	-37362	-37574	424	119	<.0000	-32599	-32818	438	119	<.0000	-37347	-37569	444	119	<.0000	-37365	-37582	434	119	<.0000
1997	-42525	-42745	441	124	<.0000	-37123	-37329	411	124	<.0000	-42501	-42736	470	124	<.0000	-42532	-42749	434	124	<.0000
1998	-45015	-45221	410	127	<.0000	-39257	-39454	394	127	<.0000	-45010	-45214	410	127	<.0000	-45031	-45240	418	127	<.0000
1999	-37592	-37773	361	128	<.0000	-32817	-32996	358	128	<.0000	-37577	-37763	372	128	<.0000	-37589	-37773	367	128	<.0000
2000	-27785	-27955	340	126	<.0000	-24331	-24507	352	126	<.0000	-27785	-27956	342	126	<.0000	-27795	-27969	348	126	<.0000

Sum = sum of likelihoods from individual zone regressions

Agg. = likelihood from aggregated regression

R = number of restrictions

Prob. = P-value

<sup>1</sup> Transforming Dependent Variable, Acreage, Heated Area and Age.<sup>2</sup> Transforming Dependent Variable Only.<sup>3</sup> Transforming Dependent Variable, Acreage and Heated Area.<sup>4</sup> Transforming Dependent Variable and Heated Area.



Table B.3: Aggregation Test Results for MLS Group 2 - OLS and Spatial Models

Year	OLS					Spatial Error					Spatial Lag					General Spatial				
	Sum	Agg.	$\chi^2$	R	Prob.	Sum	Agg.	$\chi^2$	R	Prob.	Sum	Agg.	$\chi^2$	R	Prob.	Sum	Agg.	$\chi^2$	R	Prob.
<b>Base Specification</b>																				
1992	2656	2204	905	203	<.0000	3684	3281	807	209	<.0000	3651	3251	800	209	<.0000	3710	3307	806	215	<.0000
1993	3314	2711	1205	209	<.0000	4570	4127	886	214	<.0000	4505	3991	1029	214	<.0000	4586	4140	890	220	<.0000
1994	3771	3160	1223	205	<.0000	5307	4847	920	210	<.0000	5202	4666	1072	210	<.0000	5334	4870	927	216	<.0000
1995	3656	3104	1103	206	<.0000	5042	4652	780	211	<.0000	4959	4498	922	211	<.0000	5069	4678	782	217	<.0000
1996	3711	3202	1018	210	<.0000	5154	4726	855	216	<.0000	5149	4696	905	216	<.0000	5178	4764	829	222	<.0000
1997	4200	3482	1436	209	<.0000	5733	5019	1428	215	<.0000	5641	4949	1385	215	<.0000	5742	5028	1427	221	<.0000
1998	4993	4149	1688	208	<.0000	6804	6249	1109	214	<.0000	6726	6095	1261	214	<.0000	6814	6253	1123	220	<.0000
1999	3584	2851	1465	211	<.0000	4982	4472	1019	216	<.0000	4939	4442	993	216	<.0000	5000	4510	980	222	<.0000
2000	2042	1465	1154	207	<.0000	2858	2317	1082	211	<.0000	2865	2315	1100	211	<.0000	2880	2329	1102	217	<.0000
<b>Varying Land Coefficients</b>																				
1992	2656	2248	816	191	<.0000	3684	3305	759	197	<.0000	3651	3288	726	197	<.0000	3710	3335	750	203	<.0000
1993	3314	2841	945	197	<.0000	4570	4163	813	202	<.0000	4505	4073	863	202	<.0000	4586	4180	811	208	<.0000
1994	3771	3290	963	193	<.0000	5307	4896	821	198	<.0000	5202	4754	897	198	<.0000	5334	4918	831	204	<.0000
1995	3656	3207	898	194	<.0000	5042	4674	736	199	<.0000	4959	4568	781	199	<.0000	5069	4701	734	205	<.0000
1996	3711	3323	775	198	<.0000	5154	4808	691	204	<.0000	5149	4799	699	204	<.0000	5178	4842	673	210	<.0000
1997	4200	3598	1204	197	<.0000	5733	5084	1298	203	<.0000	5641	5040	1202	203	<.0000	5742	5092	1299	209	<.0000
1998	4993	4324	1339	196	<.0000	6804	6312	982	202	<.0000	6726	6210	1032	202	<.0000	6814	6316	995	208	<.0000
1999	3584	3115	939	199	<.0000	4982	4561	843	204	<.0000	4939	4548	781	204	<.0000	5000	4596	809	210	<.0000
2000	2042	1550	984	195	<.0000	2858	2450	815	199	<.0000	2865	2457	816	199	<.0000	2880	2462	836	205	<.0000
<b>Additional Spatial Variables</b>																				
1992	2805	2343	925	244	<.0000	3782	3358	848	250	<.0000	3760	3319	881	250	<.0000	3790	3368	844	256	<.0000
1993	3492	2971	1042	250	<.0000	4668	4213	910	255	<.0000	4631	4121	1019	255	<.0000	4677	4218	917	261	<.0000
1994	3966	3422	1087	246	<.0000	5417	4947	940	251	<.0000	5346	4821	1050	251	<.0000	5433	4960	945	257	<.0000
1995	3837	3342	991	247	<.0000	5128	4731	793	252	<.0000	5084	4608	951	252	<.0000	5142	4741	802	258	<.0000
1996	3882	3444	876	251	<.0000	5265	4866	799	257	<.0000	5270	4836	867	257	<.0000	5279	4878	802	263	<.0000
1997	4372	3655	1434	249	<.0000	5829	5122	1415	255	<.0000	5796	5076	1439	255	<.0000	5835	5122	1426	261	<.0000
1998	5162	4380	1563	249	<.0000	6885	6345	1080	255	<.0000	6851	6238	1227	255	<.0000	6897	6345	1104	261	<.0000
1999	3693	3212	963	252	<.0000	5056	4598	916	257	<.0000	5033	4580	906	257	<.0000	5068	4619	898	263	<.0000
2000	2128	1622	1012	247	<.0000	2929	2490	879	251	<.0000	2936	2491	890	251	<.0000	2952	2493	917	257	<.0000

Sum = sum of likelihoods from individual zone regressions

Agg. = likelihood from aggregated regression

R = number of restrictions

Prob. = P-value

Table B.4: Aggregation Test Results for MLS Group 2 - Box-Cox Transformations

Year	Box-Cox <sup>1</sup>					Box-Cox <sup>2</sup>					Box-Cox <sup>3</sup>					Box-Cox <sup>4</sup>				
	Sum	Agg.	$\chi^2$	R	Prob.	Sum	Agg.	$\chi^2$	R	Prob.	Sum	Agg.	$\chi^2$	R	Prob.	Sum	Agg.	$\chi^2$	R	Prob.
<b>Base Specification</b>																				
1992	-27927	-28390	925	238	<.0000	-24148	-24591	887	238	<.0000	-27930	-28392	924	238	<.0000	-27948	-28396	896	238	<.0000
1993	-33371	-33981	1220	245	<.0000	-28838	-29435	1195	245	<.0000	-33369	-33981	1224	245	<.0000	-33373	-33979	1211	245	<.0000
1994	-40554	-41117	1125	241	<.0000	-35105	-35658	1106	241	<.0000	-40554	-41114	1120	241	<.0000	-40558	-41116	1117	241	<.0000
1995	-36066	-36620	1107	242	<.0000	-31213	-31754	1083	242	<.0000	-36055	-36612	1114	242	<.0000	-36076	-36621	1090	242	<.0000
1996	-40376	-41280	1809	246	<.0000	-34989	-35867	1757	246	<.0000	-40333	-41280	1893	246	<.0000	-40389	-41278	1779	246	<.0000
1997	-43212	-44191	1959	245	<.0000	-37441	-38411	1941	245	<.0000	-43182	-44188	2012	245	<.0000	-43198	-44186	1976	245	<.0000
1998	-47587	-48587	2000	244	<.0000	-41225	-42218	1985	244	<.0000	-47591	-48590	1997	244	<.0000	-47594	-48590	1990	244	<.0000
1999	-38983	-39726	1487	247	<.0000	-33839	-34654	1631	247	<.0000	-38974	-39715	1482	247	<.0000	-38982	-39810	1654	247	<.0000
2000	-24623	-25246	1246	243	<.0000	-21427	-22021	1189	243	<.0000	-24631	-25244	1227	243	<.0000	-24650	-25255	1211	243	<.0000
<b>Varying Land Coefficients</b>																				
1992	-27927	-28351	848	224	<.0000	-24148	-24546	796	224	<.0000	-27930	-28332	804	224	<.0000	-27948	-28349	803	224	<.0000
1993	-33371	-33816	890	231	<.0000	-28838	-29293	911	231	<.0000	-33369	-33769	801	231	<.0000	-33373	-33838	929	231	<.0000
1994	-40554	-40968	828	227	<.0000	-35105	-35516	822	227	<.0000	-40554	-40956	803	227	<.0000	-40558	-40973	829	227	<.0000
1995	-36066	-36502	872	228	<.0000	-31213	-31652	878	228	<.0000	-36055	-36490	871	228	<.0000	-36076	-36518	885	228	<.0000
1996	-40376	-41143	1534	232	<.0000	-34989	-35746	1515	232	<.0000	-40333	-41125	1584	232	<.0000	-40389	-41158	1539	232	<.0000
1997	-43212	-44073	1723	231	<.0000	-37441	-38296	1710	231	<.0000	-43182	-44066	1768	231	<.0000	-43198	-44073	1750	231	<.0000
1998	-47587	-48415	1655	230	<.0000	-41225	-42043	1636	230	<.0000	-47591	-48416	1650	230	<.0000	-47594	-48418	1647	230	<.0000
1999	-38983	-39497	1029	233	<.0000	-33839	-34350	1023	233	<.0000	-38974	-39499	1050	233	<.0000	-38982	-39506	1048	233	<.0000
2000	-24623	-25129	1012	229	<.0000	-21427	-21928	1002	229	<.0000	-24631	-25124	987	229	<.0000	-24650	-25163	1026	229	<.0000
<b>Additional Spatial Variables</b>																				
1992	-27786	-28248	923	286	<.0000	-23990	-24449	918	286	<.0000	-27780	-28239	918	286	<.0000	-27792	-28253	922	286	<.0000
1993	-33186	-33717	1061	293	<.0000	-28657	-29174	1034	293	<.0000	-33190	-33697	1015	293	<.0000	-33191	-33719	1056	293	<.0000
1994	-40354	-40859	1010	289	<.0000	-34904	-35404	1001	289	<.0000	-40357	-40859	1004	289	<.0000	-40358	-40862	1008	289	<.0000
1995	-35885	-36398	1027	290	<.0000	-31025	-31534	1017	290	<.0000	-35875	-36400	1050	290	<.0000	-35889	-36400	1023	290	<.0000
1996	-40187	-41034	1694	294	<.0000	-34792	-35621	1657	294	<.0000	-40157	-41032	1752	294	<.0000	-40196	-41033	1673	294	<.0000
1997	-43019	-44024	2009	292	<.0000	-37250	-38239	1978	292	<.0000	-43018	-44023	2011	292	<.0000	-43007	-44017	2020	292	<.0000
1998	-47404	-48366	1925	292	<.0000	-41046	-41988	1885	292	<.0000	-47406	-48369	1925	292	<.0000	-47416	-48363	1894	292	<.0000
1999	-38867	-39400	1066	295	<.0000	-33721	-34251	1060	295	<.0000	-38858	-39404	1092	295	<.0000	-38864	-39407	1087	295	<.0000
2000	-24540	-25055	1030	290	<.0000	-21345	-21860	1031	290	<.0000	-24550	-25050	1001	290	<.0000	-24567	-25095	1056	290	<.0000

Sum = sum of likelihoods from individual zone regressions

Agg. = likelihood from aggregated regression

R = number of restrictions

Prob. = P-value

<sup>1</sup> Transforming Dependent Variable, Acreage, Heated Area and Age.<sup>2</sup> Transforming Dependent Variable Only.<sup>3</sup> Transforming Dependent Variable, Acreage and Heated Area.<sup>4</sup> Transforming Dependent Variable and Heated Area.

Table B.5: Aggregation Test Results for MLS Group 3 - OLS and Spatial Models

Year	OLS					Spatial Error					Spatial Lag					General Spatial				
	Sum	Agg.	$\chi^2$	R	Prob.	Sum	Agg.	$\chi^2$	R	Prob.	Sum	Agg.	$\chi^2$	R	Prob.	Sum	Agg.	$\chi^2$	R	Prob.
<b>Base Specification</b>																				
1992	3020	2873	294	66	<.0000	4316	4172	287	68	<.0000	4180	4019	323	68	<.0000	4326	4179	294	70	<.0000
1993	3474	3331	287	67	<.0000	5139	5020	238	69	<.0000	4905	4758	294	69	<.0000	5160	5038	245	71	<.0000
1994	3871	3681	378	67	<.0000	5628	5441	374	69	<.0000	5485	5309	352	69	<.0000	5683	5501	363	71	<.0000
1995	3945	3691	510	68	<.0000	5532	5293	477	70	<.0000	5394	5117	554	70	<.0000	5549	5301	496	72	<.0000
1996	4224	3945	557	67	<.0000	5855	5616	477	69	<.0000	5763	5504	519	69	<.0000	5872	5639	466	71	<.0000
1997	4539	4327	424	67	<.0000	6260	6113	294	69	<.0000	6200	6017	366	69	<.0000	6288	6142	291	71	<.0000
1998	5411	4969	884	68	<.0000	7444	7050	788	70	<.0000	7384	6937	894	70	<.0000	7500	7093	814	72	<.0000
1999	4416	4028	776	68	<.0000	6115	5826	577	69	<.0000	5982	5623	718	69	<.0000	6134	5833	603	71	<.0000
2000	2452	2126	653	69	<.0000	3563	3287	553	71	<.0000	3534	3212	645	71	<.0000	3586	3295	580	73	<.0000
<b>Varying Land Coefficients</b>																				
1992	3020	2887	265	62	<.0000	4316	4185	261	64	<.0000	4180	4038	284	64	<.0000	4326	4194	263	66	<.0000
1993	3474	3357	235	63	<.0000	5139	5040	199	65	<.0000	4905	4792	225	65	<.0000	5160	5061	199	67	<.0000
1994	3871	3729	283	63	<.0000	5628	5464	329	65	<.0000	5485	5355	261	65	<.0000	5683	5532	301	67	<.0000
1995	3945	3723	445	64	<.0000	5532	5329	405	66	<.0000	5394	5146	497	66	<.0000	5549	5336	425	68	<.0000
1996	4224	4007	434	63	<.0000	5855	5673	363	65	<.0000	5763	5567	394	65	<.0000	5872	5696	352	67	<.0000
1997	4539	4374	330	63	<.0000	6260	6132	257	65	<.0000	6200	6052	296	65	<.0000	6288	6163	249	67	<.0000
1998	5411	5042	739	64	<.0000	7444	7104	681	66	<.0000	7384	7008	751	66	<.0000	7500	7153	694	68	<.0000
1999	4416	4144	545	64	<.0000	6115	5880	468	65	<.0000	5982	5707	550	65	<.0000	6134	5891	487	67	<.0000
2000	2452	2227	451	65	<.0000	3563	3350	425	67	<.0000	3534	3315	438	67	<.0000	3586	3367	438	69	<.0000
<b>Additional Spatial Variables</b>																				
1992	3166	2985	360	80	<.0000	4379	4221	316	82	<.0000	4289	4118	342	82	<.0000	4383	4228	311	84	<.0000
1993	3663	3470	386	81	<.0000	5206	5084	245	83	<.0000	5015	4853	323	83	<.0000	5217	5096	242	85	<.0000
1994	4050	3859	382	81	<.0000	5704	5519	370	83	<.0000	5565	5398	335	83	<.0000	5736	5559	353	85	<.0000
1995	4124	3826	596	82	<.0000	5624	5373	503	84	<.0000	5524	5222	605	84	<.0000	5629	5376	508	86	<.0000
1996	4365	4115	500	81	<.0000	5934	5725	419	83	<.0000	5849	5612	473	83	<.0000	5937	5729	414	85	<.0000
1997	4657	4471	372	81	<.0000	6329	6183	292	83	<.0000	6273	6104	338	83	<.0000	6336	6194	284	85	<.0000
1998	5539	5155	768	82	<.0000	7524	7183	682	84	<.0000	7443	7059	769	84	<.0000	7549	7201	696	86	<.0000
1999	4581	4281	601	82	<.0000	6211	5943	537	83	<.0000	6097	5799	595	83	<.0000	6222	5947	550	85	<.0000
2000	2557	2288	538	83	<.0000	3625	3386	477	85	<.0000	3589	3347	485	85	<.0000	3629	3391	476	87	<.0000

Sum = sum of likelihoods from individual zone regressions

Agg. = likelihood from aggregated regression

R = number of restrictions

Prob. = P-value

Table B.6: Aggregation Test Results for MLS Group 3 - Box-Cox Transformations

Year	Box-Cox <sup>1</sup>					Box-Cox <sup>2</sup>					Box-Cox <sup>3</sup>					Box-Cox <sup>4</sup>				
	Sum	Agg.	$\chi^2$	R	Prob.	Sum	Agg.	$\chi^2$	R	Prob.	Sum	Agg.	$\chi^2$	R	Prob.	Sum	Agg.	$\chi^2$	R	Prob.
<b>Base Specification</b>																				
1992	-33720	-33906	371	99	<.0000	-29327	-29510	365	99	<.0000	-33719	-33906	373	99	<.0000	-33718	-33907	376	99	<.0000
1993	-40668	-40834	332	101	<.0000	-35420	-35586	333	101	<.0000	-40666	-40834	335	101	<.0000	-40669	-40833	328	101	<.0000
1994	-45569	-45811	485	101	<.0000	-39746	-39977	462	101	<.0000	-45569	-45812	486	101	<.0000	-45564	-45813	497	101	<.0000
1995	-43711	-43972	522	102	<.0000	-38134	-38396	524	102	<.0000	-43716	-43978	524	102	<.0000	-43713	-43976	525	102	<.0000
1996	-46249	-46605	713	101	<.0000	-40338	-40682	686	101	<.0000	-46259	-46605	691	101	<.0000	-46258	-46605	695	101	<.0000
1997	-51235	-51589	708	102	<.0000	-44708	-45068	719	102	<.0000	-51237	-51599	724	102	<.0000	-51238	-51600	725	102	<.0000
1998	-58920	-59501	1163	103	<.0000	-51409	-51988	1160	103	<.0000	-58919	-59497	1157	103	<.0000	-58880	-59487	1214	103	<.0000
1999	-47324	-47762	876	104	<.0000	-41296	-41734	875	104	<.0000	-47320	-47761	881	104	<.0000	-47316	-47755	877	104	<.0000
2000	-32468	-32858	779	104	<.0000	-28404	-28792	774	104	<.0000	-32465	-32858	785	104	<.0000	-32464	-32857	786	104	<.0000
<b>Varying Land Coefficients</b>																				
1992	-33720	-33892	342	93	<.0000	-29327	-29496	337	93	<.0000	-33719	-33891	343	93	<.0000	-33718	-33893	348	93	<.0000
1993	-40668	-40808	280	95	<.0000	-35420	-35561	281	95	<.0000	-40666	-40807	282	95	<.0000	-40669	-40808	277	95	<.0000
1994	-45569	-45762	387	95	<.0000	-39746	-39926	360	95	<.0000	-45569	-45762	386	95	<.0000	-45564	-45762	395	95	<.0000
1995	-43711	-43937	452	96	<.0000	-38134	-38364	459	96	<.0000	-43716	-43941	451	96	<.0000	-43713	-43942	459	96	<.0000
1996	-46249	-46542	587	95	<.0000	-40338	-40620	563	95	<.0000	-46259	-46544	569	95	<.0000	-46258	-46544	572	95	<.0000
1997	-51235	-51541	613	96	<.0000	-44708	-45020	623	96	<.0000	-51237	-51549	625	96	<.0000	-51238	-51551	626	96	<.0000
1998	-58920	-59425	1010	97	<.0000	-51409	-51915	1013	97	<.0000	-58919	-59418	998	97	<.0000	-58880	-59417	1074	97	<.0000
1999	-47324	-47642	636	98	<.0000	-41296	-41611	630	98	<.0000	-47320	-47642	643	98	<.0000	-47316	-47633	633	98	<.0000
2000	-32468	-32754	573	98	<.0000	-28404	-28691	573	98	<.0000	-32465	-32754	578	98	<.0000	-32464	-32757	584	98	<.0000
<b>Additional Spatial Variables</b>																				
1992	-33578	-33792	428	120	<.0000	-29182	-29396	429	120	<.0000	-33577	-33790	426	120	<.0000	-33571	-33793	445	120	<.0000
1993	-40481	-40697	431	122	<.0000	-35233	-35447	428	122	<.0000	-40473	-40685	424	122	<.0000	-40482	-40693	421	122	<.0000
1994	-45387	-45632	491	122	<.0000	-39557	-39797	479	122	<.0000	-45383	-45630	494	122	<.0000	-45380	-45633	505	122	<.0000
1995	-43531	-43832	602	123	<.0000	-37949	-38263	627	123	<.0000	-43533	-43830	595	123	<.0000	-43529	-43840	622	123	<.0000
1996	-46107	-46433	652	122	<.0000	-40199	-40511	624	122	<.0000	-46120	-46434	628	122	<.0000	-46119	-46434	629	122	<.0000
1997	-51099	-51427	655	123	<.0000	-44569	-44905	674	123	<.0000	-51095	-51430	670	123	<.0000	-51093	-51435	684	123	<.0000
1998	-58778	-59301	1046	124	<.0000	-51271	-51797	1051	124	<.0000	-58771	-59292	1043	124	<.0000	-58741	-59293	1105	124	<.0000
1999	-47161	-47520	720	125	<.0000	-41132	-41490	717	125	<.0000	-47159	-47520	723	125	<.0000	-47146	-47512	733	125	<.0000
2000	-32366	-32695	659	125	<.0000	-28302	-28630	654	125	<.0000	-32361	-32695	668	125	<.0000	-32363	-32695	665	125	<.0000

Sum = sum of likelihoods from individual zone regressions

Agg. = likelihood from aggregated regression

R = number of restrictions

Prob. = P-value

<sup>1</sup> Transforming Dependent Variable, Acreage, Heated Area and Age.<sup>2</sup> Transforming Dependent Variable Only.<sup>3</sup> Transforming Dependent Variable, Acreage and Heated Area.<sup>4</sup> Transforming Dependent Variable and Heated Area.

Table B.7: Aggregation Test Results for Wake County - OLS and Spatial Models

Year	OLS					Spatial Error					Spatial Lag					General Spatial				
	Sum	Agg.	$\chi^2$	R	Prob.	Sum	Agg.	$\chi^2$	R	Prob.	Sum	Agg.	$\chi^2$	R	Prob.	Sum	Agg.	$\chi^2$	R	Prob.
<b>Base Specification</b>																				
1992	8712	6830	3764	475	<.0000	12578	11220	2716	489	<.0000	12353	10902	2903	489	<.0000	12650	11320	2660	503	<.0000
1993	10241	7795	4891	485	<.0000	15014	13245	3537	499	<.0000	14571	12582	3978	499	<.0000	15089	13351	3476	513	<.0000
1994	10659	7985	5348	481	<.0000	15672	13890	3565	495	<.0000	15372	13447	3850	495	<.0000	15815	14086	3459	509	<.0000
1995	11004	8242	5523	480	<.0000	15511	13680	3662	494	<.0000	15200	12873	4655	494	<.0000	15593	13728	3730	508	<.0000
1996	11522	8867	5309	485	<.0000	16301	14516	3568	499	<.0000	16092	14015	4155	499	<.0000	16374	14663	3423	513	<.0000
1997	12948	10032	5832	487	<.0000	18095	16098	3994	501	<.0000	17868	15597	4541	501	<.0000	18163	16236	3854	515	<.0000
1998	15345	11165	8362	488	<.0000	21287	18186	6203	502	<.0000	21037	17431	7212	502	<.0000	21406	18298	6216	516	<.0000
1999	11916	8259	7315	491	<.0000	16868	14552	4631	505	<.0000	16544	13604	5879	505	<.0000	16936	14607	4658	519	<.0000
2000	6641	3788	5707	486	<.0000	9894	7964	3859	500	<.0000	9823	7535	4577	500	<.0000	9962	7991	3942	514	<.0000
<b>Varying Land Coefficients</b>																				
1992	8712	7282	2861	447	<.0000	12578	11330	2497	461	<.0000	12353	11129	2450	461	<.0000	12650	11455	2390	475	<.0000
1993	10241	8482	3517	457	<.0000	15014	13403	3220	471	<.0000	14571	13014	3114	471	<.0000	15089	13545	3087	485	<.0000
1994	10659	8894	3530	453	<.0000	15672	14085	3174	467	<.0000	15372	13899	2946	467	<.0000	15815	14333	2965	481	<.0000
1995	11004	8988	4031	452	<.0000	15511	13839	3345	466	<.0000	15200	13332	3736	466	<.0000	15593	13905	3376	480	<.0000
1996	11522	9647	3748	457	<.0000	16301	14705	3190	471	<.0000	16092	14447	3292	471	<.0000	16374	14873	3003	485	<.0000
1997	12948	10966	3963	459	<.0000	18095	16284	3622	473	<.0000	17868	16140	3455	473	<.0000	18163	16480	3365	487	<.0000
1998	15345	12514	5663	460	<.0000	21287	18629	5317	474	<.0000	21037	18371	5331	474	<.0000	21406	18835	5143	488	<.0000
1999	11916	9743	4346	463	<.0000	16868	15089	3559	477	<.0000	16544	14648	3793	477	<.0000	16936	15193	3485	491	<.0000
2000	6641	4703	3877	458	<.0000	9894	8259	3269	472	<.0000	9823	8128	3391	472	<.0000	9962	8336	3253	486	<.0000
<b>Additional Spatial Variables</b>																				
1992	9234	7545	3378	572	<.0000	12851	11492	2718	586	<.0000	12689	11240	2898	586	<.0000	12882	11559	2646	600	<.0000
1993	10871	8863	4016	582	<.0000	15278	13603	3351	596	<.0000	14917	13145	3543	596	<.0000	15320	13673	3294	610	<.0000
1994	11268	9321	3895	577	<.0000	15975	14357	3236	591	<.0000	15706	14067	3279	591	<.0000	16048	14487	3121	605	<.0000
1995	11616	9511	4210	576	<.0000	15821	14065	3513	590	<.0000	15622	13622	3998	590	<.0000	15855	14106	3497	604	<.0000
1996	12092	10133	3918	581	<.0000	16599	14980	3239	595	<.0000	16469	14647	3645	595	<.0000	16643	15043	3201	609	<.0000
1997	13521	11399	4243	582	<.0000	18405	16583	3644	596	<.0000	18276	16320	3914	596	<.0000	18434	16650	3568	610	<.0000
1998	15908	13003	5810	584	<.0000	21580	18946	5268	598	<.0000	21369	18586	5566	598	<.0000	21648	19039	5218	612	<.0000
1999	12513	10345	4336	587	<.0000	17164	15360	3608	601	<.0000	16941	14958	3966	601	<.0000	17198	15432	3533	615	<.0000
2000	7094	5240	3709	581	<.0000	10135	8483	3304	595	<.0000	10099	8354	3488	595	<.0000	10180	8530	3300	609	<.0000

Sum = sum of likelihoods from individual zone regressions

Agg. = likelihood from aggregated regression

R = number of restrictions

Prob. = P-value

Table B.8: Aggregation Test Results for Wake County - Box-Cox Transformations

Year	Box-Cox <sup>1</sup>					Box-Cox <sup>2</sup>					Box-Cox <sup>3</sup>					Box-Cox <sup>4</sup>				
	Sum	Agg.	$\chi^2$	R	Prob.	Sum	Agg.	$\chi^2$	R	Prob.	Sum	Agg.	$\chi^2$	R	Prob.	Sum	Agg.	$\chi^2$	R	Prob.
<b>Base Specification</b>																				
1992	-102056	-103856	3601	511	<.0000	-88667	-90433	3532	511	<.0000	-102021	-103857	3671	511	<.0000	-102065	-103854	3579	511	<.0000
1993	-120467	-122771	4608	521	<.0000	-104730	-107005	4550	521	<.0000	-120456	-122772	4633	521	<.0000	-120476	-122767	4582	521	<.0000
1994	-133342	-135953	5221	517	<.0000	-116109	-118683	5148	517	<.0000	-133328	-135953	5251	517	<.0000	-133346	-135953	5214	517	<.0000
1995	-121702	-124317	5230	516	<.0000	-105946	-108516	5141	516	<.0000	-121686	-124329	5285	516	<.0000	-121723	-124292	5139	516	<.0000
1996	-132795	-135906	6222	521	<.0000	-115650	-118701	6101	521	<.0000	-132749	-135906	6314	521	<.0000	-132822	-135903	6162	521	<.0000
1997	-147399	-150729	6659	523	<.0000	-128425	-131729	6607	523	<.0000	-147351	-150748	6795	523	<.0000	-147409	-150748	6678	523	<.0000
1998	-162991	-167451	8921	524	<.0000	-141963	-146389	8852	524	<.0000	-162991	-167472	8962	524	<.0000	-162988	-167464	8952	524	<.0000
1999	-136008	-139502	6987	527	<.0000	-118600	-122144	7088	527	<.0000	-135983	-139493	7019	527	<.0000	-136013	-139587	7147	527	<.0000
2000	-94561	-97555	5988	522	<.0000	-82727	-85655	5856	522	<.0000	-94565	-97553	5977	522	<.0000	-94609	-97559	5898	522	<.0000
<b>Varying Land Coefficients</b>																				
1992	-102056	-103440	2769	481	<.0000	-88667	-90033	2731	481	<.0000	-102021	-103382	2721	481	<.0000	-102065	-103453	2776	481	<.0000
1993	-120467	-122093	3251	491	<.0000	-104730	-106388	3316	491	<.0000	-120456	-122015	3118	491	<.0000	-120476	-122151	3350	491	<.0000
1994	-133342	-135060	3436	487	<.0000	-116109	-117856	3495	487	<.0000	-133328	-135027	3398	487	<.0000	-133346	-135127	3561	487	<.0000
1995	-121702	-123443	3483	486	<.0000	-105946	-107850	3808	486	<.0000	-121686	-123414	3456	486	<.0000	-121723	-123624	3802	486	<.0000
1996	-132795	-135031	4471	491	<.0000	-115650	-117972	4644	491	<.0000	-132749	-135016	4534	491	<.0000	-132822	-135174	4703	491	<.0000
1997	-147399	-149684	4570	493	<.0000	-128425	-130852	4855	493	<.0000	-147351	-149663	4625	493	<.0000	-147409	-149870	4924	493	<.0000
1998	-162991	-165897	5812	494	<.0000	-141963	-145080	6234	494	<.0000	-162991	-165870	5759	494	<.0000	-162988	-166158	6341	494	<.0000
1999	-136008	-137879	3741	497	<.0000	-118600	-120577	3954	497	<.0000	-135983	-137883	3800	497	<.0000	-136013	-138021	4015	497	<.0000
2000	-94561	-96240	3358	492	<.0000	-82727	-84702	3951	492	<.0000	-94565	-96239	3348	492	<.0000	-94609	-96610	4000	492	<.0000
<b>Additional Spatial Variables</b>																				
1992	-101553	-103216	3326	615	<.0000	-88143	-89798	3312	615	<.0000	-101516	-103166	3298	615	<.0000	-101543	-103220	3355	615	<.0000
1993	-119843	-121806	3926	625	<.0000	-104113	-106062	3900	625	<.0000	-119841	-121736	3790	625	<.0000	-119858	-121825	3936	625	<.0000
1994	-132727	-134727	4001	620	<.0000	-115486	-117480	3987	620	<.0000	-132709	-134709	4000	620	<.0000	-132727	-134750	4047	620	<.0000
1995	-121099	-123147	4096	619	<.0000	-105331	-107427	4192	619	<.0000	-121098	-123121	4048	619	<.0000	-121109	-123208	4197	619	<.0000
1996	-132240	-134698	4918	624	<.0000	-115085	-117534	4898	624	<.0000	-132206	-134700	4988	624	<.0000	-132263	-134737	4948	624	<.0000
1997	-146812	-149396	5168	625	<.0000	-127826	-130455	5259	625	<.0000	-146770	-149377	5215	625	<.0000	-146788	-149479	5380	625	<.0000
1998	-162436	-165619	6366	627	<.0000	-141410	-144652	6484	627	<.0000	-162422	-165589	6335	627	<.0000	-162429	-165730	6602	627	<.0000
1999	-135469	-137485	4033	630	<.0000	-118052	-120093	4081	630	<.0000	-135448	-137500	4105	630	<.0000	-135452	-137537	4169	630	<.0000
2000	-94139	-95979	3680	624	<.0000	-82294	-84208	3827	624	<.0000	-94148	-95971	3645	624	<.0000	-94181	-96117	3873	624	<.0000

Sum = sum of likelihoods from individual zone regressions

Agg. = likelihood from aggregated regression

R = number of restrictions

Prob. = P-value

<sup>1</sup> Transforming Dependent Variable, Acreage, Heated Area and Age.<sup>2</sup> Transforming Dependent Variable Only.<sup>3</sup> Transforming Dependent Variable, Acreage and Heated Area.<sup>4</sup> Transforming Dependent Variable and Heated Area.

## Appendix C

# Comparison of Regression Standard Error Results

Table C.1: Comparison of SERs for MLS Group 1

Year	OLS			Spatial Error			Spatial Lag			General Spatial		
	Wt.Avg.	Agg.	% Diff	Wt.Avg.	Agg.	% Diff	Wt.Avg.	Agg.	% Diff	Wt.Avg.	Agg.	% Diff
<b>Base Specification</b>												
1992	0.100	0.106	6.05	0.088	0.093	4.65	0.092	0.099	6.63	0.089	0.093	4.57
1993	0.102	0.107	4.80	0.089	0.094	4.94	0.095	0.102	6.56	0.089	0.093	4.79
1994	0.112	0.117	4.25	0.102	0.106	3.68	0.106	0.111	4.82	0.101	0.105	4.04
1995	0.090	0.097	6.89	0.082	0.086	4.69	0.086	0.093	7.94	0.082	0.087	4.77
1996	0.096	0.101	5.31	0.088	0.092	4.24	0.092	0.098	6.24	0.088	0.092	4.46
1997	0.093	0.098	5.01	0.087	0.090	3.49	0.089	0.095	5.65	0.087	0.090	3.80
1998	0.084	0.093	10.05 †	0.076	0.082	8.10	0.079	0.089	11.17 †	0.076	0.082	8.38
1999	0.090	0.098	8.20	0.083	0.088	5.59	0.086	0.094	8.54	0.083	0.088	5.74
2000	0.111	0.120	6.94	0.104	0.110	6.09	0.105	0.115	8.59	0.103	0.110	6.40
<b>Varying Land Coefficients</b>												
1992	0.100	0.105	5.01	0.088	0.093	4.61	0.092	0.097	5.26	0.089	0.093	4.57
1993	0.102	0.105	3.21	0.089	0.093	4.60	0.095	0.099	4.41	0.089	0.093	4.36
1994	0.112	0.114	2.35	0.102	0.105	2.83	0.106	0.109	2.86	0.101	0.104	2.96
1995	0.090	0.094	3.75	0.082	0.085	3.40	0.086	0.090	4.73	0.082	0.085	3.33
1996	0.096	0.099	3.36	0.088	0.092	3.75	0.092	0.096	4.58	0.088	0.091	3.84
1997	0.093	0.096	2.71	0.087	0.089	2.49	0.089	0.092	3.11	0.087	0.089	2.54
1998	0.084	0.088	5.16	0.076	0.079	4.25	0.079	0.084	5.30	0.076	0.079	4.52
1999	0.090	0.094	4.63	0.083	0.086	4.01	0.086	0.091	4.85	0.083	0.086	4.24
2000	0.111	0.116	4.11	0.104	0.110	5.58	0.105	0.112	5.60	0.103	0.109	5.44
<b>Additional Spatial Variables</b>												
1992	0.096	0.102	6.17	0.087	0.093	5.70	0.090	0.096	5.93	0.088	0.093	5.54
1993	0.098	0.102	4.47	0.088	0.093	4.90	0.093	0.098	5.26	0.088	0.093	4.87
1994	0.108	0.112	3.08	0.101	0.104	3.18	0.104	0.108	3.67	0.100	0.104	3.27
1995	0.086	0.090	4.62	0.081	0.085	4.46	0.083	0.088	5.43	0.081	0.085	4.39
1996	0.093	0.097	3.81	0.088	0.091	3.94	0.089	0.094	4.90	0.087	0.091	4.05
1997	0.090	0.093	3.38	0.086	0.088	3.12	0.087	0.091	4.05	0.086	0.088	3.12
1998	0.081	0.085	4.67	0.075	0.079	4.50	0.078	0.082	4.83	0.075	0.079	4.56
1999	0.087	0.091	4.50	0.082	0.086	4.33	0.084	0.089	4.94	0.082	0.086	4.38
2000	0.107	0.112	4.93	0.102	0.108	5.94	0.102	0.109	6.30	0.102	0.108	5.98

† Exceeds 10% difference

‡ Exceeds 15% difference



Table C.2: Comparison of SERs for MLS Group 2

Year	OLS			Spatial Error			Spatial Lag			General Spatial		
	Wt.Avg.	Agg.	% Diff	Wt.Avg.	Agg.	% Diff	Wt.Avg.	Agg.	% Diff	Wt.Avg.	Agg.	% Diff
<b>Base Specification</b>												
1992	0.095	0.107	11.35 †	0.086	0.099	12.63 †	0.089	0.102	13.11 †	0.086	0.099	13.16 †
1993	0.091	0.104	13.25 †	0.082	0.092	11.35 †	0.085	0.098	13.99 †	0.082	0.092	11.50 †
1994	0.095	0.107	11.19 †	0.085	0.095	9.63	0.090	0.102	11.86 †	0.085	0.095	9.83
1995	0.088	0.098	10.89 †	0.078	0.086	8.53	0.081	0.092	11.61 †	0.078	0.086	8.92
1996	0.095	0.105	9.17	0.089	0.097	8.84	0.090	0.100	10.24 †	0.089	0.097	8.94
1997	0.092	0.104	10.84 †	0.086	0.099	12.54 †	0.089	0.102	12.58 †	0.086	0.099	12.67 †
1998	0.085	0.097	11.95 †	0.077	0.084	8.61	0.079	0.088	10.75 †	0.076	0.084	8.78
1999	0.095	0.111	14.26 †	0.087	0.098	11.17 †	0.089	0.100	11.15 †	0.087	0.098	11.07 †
2000	0.108	0.128	15.98 ‡	0.100	0.123	18.72 ‡	0.100	0.124	19.36 ‡	0.098	0.122	19.58 ‡
<b>Varying Land Coefficients</b>												
1992	0.095	0.106	10.07 †	0.086	0.098	11.86 †	0.089	0.100	11.91 †	0.086	0.098	12.36 †
1993	0.091	0.100	9.83	0.082	0.091	10.60 †	0.085	0.096	11.74 †	0.082	0.092	10.73 †
1994	0.095	0.104	8.29	0.085	0.094	8.74	0.090	0.099	9.83	0.085	0.094	8.91
1995	0.088	0.096	8.35	0.078	0.085	8.29	0.081	0.090	9.78	0.078	0.086	8.56
1996	0.095	0.102	6.37	0.089	0.096	7.39	0.090	0.097	7.79	0.089	0.096	7.33
1997	0.092	0.101	8.40	0.086	0.098	11.49 †	0.089	0.099	10.61 †	0.086	0.098	11.53 †
1998	0.085	0.093	8.58	0.077	0.083	7.72	0.079	0.086	8.45	0.076	0.083	7.87
1999	0.095	0.103	7.97	0.087	0.096	9.51	0.089	0.098	8.50	0.087	0.096	9.18
2000	0.108	0.124	13.02 †	0.100	0.116	14.20 †	0.100	0.116	14.17 †	0.098	0.116	14.92 †
<b>Additional Spatial Variables</b>												
1992	0.091	0.102	10.74 †	0.084	0.097	13.58 †	0.085	0.099	14.33 †	0.084	0.097	13.62 †
1993	0.086	0.097	10.67 †	0.080	0.091	12.03 †	0.081	0.094	14.01 †	0.080	0.091	12.20 †
1994	0.091	0.100	9.17	0.083	0.093	10.24 †	0.086	0.098	11.76 †	0.083	0.093	10.26 †
1995	0.084	0.092	8.92	0.077	0.085	9.02	0.079	0.089	11.85 †	0.077	0.085	9.19
1996	0.092	0.099	6.88	0.087	0.095	8.53	0.087	0.096	9.76	0.086	0.095	8.67
1997	0.089	0.099	10.05 †	0.085	0.097	12.45 †	0.086	0.099	12.98 †	0.085	0.097	12.61 †
1998	0.083	0.092	9.93	0.076	0.082	8.26	0.077	0.085	10.21 †	0.075	0.082	8.51
1999	0.093	0.101	7.44	0.086	0.096	10.34 †	0.087	0.097	9.95	0.086	0.095	10.07 †
2000	0.105	0.120	12.34 †	0.097	0.114	15.35 ‡	0.097	0.114	15.49 ‡	0.095	0.114	16.59 ‡

† Exceeds 10% difference

‡ Exceeds 15% difference

Table C.3: Comparison of SERs for MLS Group 3

Year	OLS			Spatial Error			Spatial Lag			General Spatial		
	Wt.Avg.	Agg.	% Diff	Wt.Avg.	Agg.	% Diff	Wt.Avg.	Agg.	% Diff	Wt.Avg.	Agg.	% Diff
<b>Base Specification</b>												
1992	0.094	0.096	2.80	0.083	0.087	4.03	0.089	0.093	4.51	0.083	0.087	4.39
1993	0.096	0.099	2.84	0.083	0.085	2.97	0.091	0.094	3.84	0.083	0.085	3.01
1994	0.096	0.099	3.42	0.084	0.088	4.54	0.090	0.094	4.05	0.085	0.088	4.11
1995	0.091	0.095	4.98	0.083	0.088	5.13	0.087	0.093	6.30	0.083	0.088	5.19
1996	0.089	0.094	5.68	0.083	0.088	5.21	0.086	0.091	6.03	0.083	0.088	5.19
1997	0.092	0.095	3.59	0.087	0.090	2.59	0.089	0.093	3.66	0.087	0.089	2.63
1998	0.088	0.095	7.11	0.083	0.089	6.42	0.085	0.092	7.68	0.083	0.089	6.69
1999	0.087	0.094	7.47	0.080	0.085	5.54	0.084	0.091	7.47	0.080	0.085	5.71
2000	0.105	0.116	9.48	0.098	0.107	8.50	0.100	0.111	10.31 †	0.097	0.107	8.92
<b>Varying Land Coefficients</b>												
1992	0.094	0.096	2.41	0.083	0.086	3.76	0.089	0.093	3.91	0.083	0.087	4.07
1993	0.096	0.098	2.21	0.083	0.085	2.57	0.091	0.094	2.95	0.083	0.085	2.56
1994	0.096	0.098	2.34	0.084	0.088	4.24	0.090	0.093	2.97	0.085	0.088	3.59
1995	0.091	0.095	4.25	0.083	0.087	4.20	0.087	0.093	5.62	0.083	0.087	4.29
1996	0.089	0.093	4.33	0.083	0.087	4.08	0.086	0.090	4.60	0.083	0.086	4.00
1997	0.092	0.094	2.64	0.087	0.089	2.36	0.089	0.092	2.93	0.087	0.089	2.31
1998	0.088	0.094	5.86	0.083	0.088	5.68	0.085	0.091	6.43	0.083	0.088	5.79
1999	0.087	0.092	4.96	0.080	0.084	4.60	0.084	0.089	5.62	0.080	0.084	4.74
2000	0.105	0.112	6.28	0.098	0.105	7.00	0.100	0.107	7.02	0.097	0.105	7.14
<b>Additional Spatial Variables</b>												
1992	0.089	0.093	3.97	0.082	0.086	4.24	0.086	0.090	5.09	0.082	0.086	4.32
1993	0.092	0.095	3.97	0.082	0.084	2.97	0.088	0.092	4.23	0.082	0.084	2.99
1994	0.092	0.095	3.36	0.084	0.088	4.36	0.088	0.092	3.91	0.084	0.087	4.10
1995	0.087	0.092	5.85	0.082	0.086	5.17	0.085	0.091	6.88	0.082	0.086	5.27
1996	0.086	0.091	4.85	0.082	0.086	4.64	0.084	0.089	5.49	0.082	0.086	4.63
1997	0.090	0.092	2.85	0.086	0.089	2.67	0.088	0.091	3.32	0.086	0.089	2.64
1998	0.086	0.092	5.92	0.082	0.087	5.64	0.084	0.090	6.56	0.082	0.087	5.76
1999	0.084	0.089	5.28	0.079	0.083	5.22	0.082	0.087	6.04	0.079	0.083	5.41
2000	0.102	0.110	7.34	0.096	0.104	7.58	0.098	0.106	7.72	0.096	0.104	7.65

† Exceeds 10% difference

‡ Exceeds 15% difference

Table C.4: Comparison of SERs for Wake County

Year	OLS			Spatial Error			Spatial Lag			General Spatial		
	Wt.Avg.	Agg.	% Diff	Wt.Avg.	Agg.	% Diff	Wt.Avg.	Agg.	% Diff	Wt.Avg.	Agg.	% Diff
<b>Base Specification</b>												
1992	0.101	0.118	14.48 †	0.090	0.101	10.90 †	0.094	0.108	13.07 †	0.090	0.102	11.61 †
1993	0.100	0.120	16.53 ‡	0.087	0.100	12.44 †	0.093	0.110	15.44 ‡	0.088	0.101	12.81 †
1994	0.105	0.126	16.32 ‡	0.094	0.105	10.63 †	0.098	0.113	13.32 †	0.094	0.106	11.26 †
1995	0.095	0.116	18.26 ‡	0.086	0.096	11.36 †	0.089	0.108	17.25 ‡	0.085	0.097	11.90 †
1996	0.097	0.117	16.54 ‡	0.089	0.100	10.74 †	0.092	0.108	14.68 †	0.089	0.100	11.37 †
1997	0.096	0.115	16.07 ‡	0.089	0.100	10.16 †	0.092	0.107	13.93 †	0.089	0.100	10.75 †
1998	0.090	0.114	21.05 ‡	0.082	0.097	15.15 ‡	0.085	0.106	19.83 ‡	0.082	0.098	15.92 ‡
1999	0.096	0.124	22.23 ‡	0.086	0.100	13.92 †	0.091	0.113	19.86 ‡	0.086	0.101	14.56 †
2000	0.117	0.154	24.21 ‡	0.106	0.127	16.48 ‡	0.109	0.139	21.98 ‡	0.106	0.128	17.50 ‡
<b>Varying Land Coefficients</b>												
1992	0.101	0.112	10.44 †	0.090	0.100	10.41 †	0.094	0.106	10.96 †	0.090	0.101	10.78 †
1993	0.100	0.113	11.32 †	0.087	0.099	11.81 †	0.093	0.106	12.09 †	0.088	0.099	11.88 †
1994	0.105	0.117	9.94	0.094	0.104	10.12 †	0.098	0.109	10.04 †	0.094	0.104	10.02 †
1995	0.095	0.108	12.72 †	0.086	0.096	10.70 †	0.089	0.104	13.78 †	0.085	0.096	11.26 †
1996	0.097	0.109	11.09 †	0.089	0.099	10.34 †	0.092	0.104	11.59 †	0.089	0.099	10.39 †
1997	0.096	0.107	10.11 †	0.089	0.100	10.16 †	0.092	0.103	10.38 †	0.089	0.099	9.95
1998	0.090	0.105	13.63 †	0.082	0.095	13.45 †	0.085	0.099	14.59 †	0.082	0.095	13.82 †
1999	0.096	0.110	12.35 †	0.086	0.097	10.77 †	0.091	0.104	12.76 †	0.086	0.098	11.58 †
2000	0.117	0.139	15.62 ‡	0.106	0.123	14.12 †	0.109	0.130	16.27 ‡	0.106	0.125	15.62 ‡
<b>Additional Spatial Variables</b>												
1992	0.096	0.109	12.45 †	0.088	0.099	11.55 †	0.091	0.104	13.16 †	0.088	0.099	11.62 †
1993	0.095	0.109	13.11 †	0.086	0.098	12.45 †	0.090	0.105	13.84 †	0.086	0.098	12.54 †
1994	0.100	0.113	11.20 †	0.092	0.103	10.64 †	0.095	0.108	11.38 †	0.092	0.103	10.57 †
1995	0.090	0.103	13.18 †	0.084	0.095	11.91 †	0.086	0.101	14.79 †	0.084	0.095	12.06 †
1996	0.093	0.105	11.79 †	0.087	0.098	10.90 †	0.089	0.102	13.14 †	0.087	0.098	11.05 †
1997	0.092	0.104	10.95 †	0.088	0.098	10.43 †	0.089	0.101	11.97 †	0.088	0.098	10.41 †
1998	0.087	0.101	13.99 †	0.081	0.094	13.89 †	0.083	0.098	15.40 ‡	0.081	0.094	14.02 †
1999	0.092	0.105	12.52 †	0.085	0.096	11.68 †	0.088	0.101	13.67 †	0.085	0.096	11.80 †
2000	0.111	0.130	14.86 †	0.104	0.123	15.39 ‡	0.105	0.126	17.08 ‡	0.103	0.123	15.89 ‡

† Exceeds 10% difference

‡ Exceeds 15% difference

## Appendix D

# Comparison of Mean Absolute Errors

Table D.1: Comparison of MAEs for MLS Group A (Aggregated vs. Weighted Average)

In Sample																
Year	OLS*		Box-Cox*		Spat. Err.		Spat. Err.*		Spat. Lag.		Spat. Lag.*		Gen. Spat.		Gen. Spat.*	
	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.
1992	12378	<b>11682</b>	12079	<b>11722</b>	11113	<b>10827</b>	11088	<b>10744</b>	12055	<b>11377</b>	11725	<b>11235</b>	11855	<b>11249</b>	11521	<b>11113</b>
1993	12658	<b>11928</b>	12179	<b>11674</b>	11546	<b>11039</b>	11442	<b>10925</b>	12870	<b>12005</b>	12266	<b>11660</b>	12617	<b>11970</b>	12028	<b>11602</b>
1994	13714	<b>12875</b>	13949	<b>13526</b>	12832	<b>12370</b>	12615	<b>12162</b>	13850	<b>12938</b>	13346	<b>12654</b>	13512	<b>12730</b>	13061	<b>12558</b>
1995	13840	<b>13016</b>	13052	<b>12533</b>	13283	<b>12639</b>	13028	<b>12412</b>	14531	<b>13328</b>	13622	<b>12848</b>	14342	<b>13174</b>	13427	<b>12727</b>
1996	12987	<b>12447</b>	12431	<b>12169</b>	12169	<b>11634</b>	12091	<b>11536</b>	13466	<b>12554</b>	12766	<b>12185</b>	13194	<b>12351</b>	12542	<b>12022</b>
1997	13488	<b>12905</b>	<b>13342</b>	13488	12776	<b>12302</b>	12682	<b>12290</b>	13819	<b>12896</b>	13192	<b>12651</b>	13506	<b>12644</b>	13061	<b>12548</b>
1998	13668	<b>12861</b>	12268	<b>11911</b>	12432	<b>11990</b>	12443	<b>11929</b>	13872	<b>12836</b>	13076	<b>12489</b>	13657	<b>12552</b>	12852	<b>12317</b>
1999	15758	<b>14891</b>	14438	<b>14151</b>	14923	<b>14433</b>	14682	<b>14207</b>	16265	<b>14955</b>	15270	<b>14570</b>	16017	<b>14781</b>	15021	<b>14421</b>
2000	19152	<b>17704</b>	18815	<b>17926</b>	18707	<b>17395</b>	18456	<b>17152</b>	19814	<b>17908</b>	18636	<b>17385</b>	19719	<b>17802</b>	18519	<b>17303</b>

Out of Sample																
Year	OLS*		Box-Cox*		Spat. Err.		Spat. Err.*		Spat. Lag.		Spat. Lag.*		Gen. Spat.		Gen. Spat.*	
	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.
1992	<b>10814</b>	12534	<b>10480</b>	12532	<b>9963</b>	11578	<b>10223</b>	11471	<b>10773</b>	12189	<b>10269</b>	11972	<b>10394</b>	12027	<b>10276</b>	11876
1993	14577	<b>13677</b>	13503	<b>13294</b>	13240	<b>12728</b>	12829	<b>12621</b>	15059	<b>13823</b>	14284	<b>13562</b>	14191	<b>13828</b>	<b>13503</b>	13592
1994	15125	<b>14316</b>	15439	<b>14912</b>	<b>13627</b>	13970	<b>13506</b>	13782	14901	<b>14274</b>	14425	<b>13964</b>	<b>14073</b>	14228	<b>13676</b>	14075
1995	<b>12151</b>	14357	<b>11705</b>	13862	<b>10728</b>	14043	<b>11157</b>	13753	<b>11807</b>	14748	<b>11771</b>	14186	<b>11401</b>	14591	<b>11330</b>	14066
1996	16930	<b>14250</b>	16435	<b>13944</b>	16113	<b>13422</b>	15955	<b>13299</b>	17181	<b>14247</b>	16513	<b>13882</b>	16649	<b>14087</b>	15984	<b>13725</b>
1997	<b>12002</b>	14190	<b>11812</b>	14767	<b>11290</b>	13464	<b>11537</b>	13522	<b>11510</b>	14071	<b>11425</b>	13893	<b>11578</b>	13803	<b>11632</b>	13833
1998	15517	<b>15021</b>	14248	<b>13925</b>	<b>13811</b>	14110	14062	<b>14022</b>	15895	<b>15042</b>	15231	<b>14661</b>	14898	<b>14719</b>	14560	<b>14469</b>
1999	17769	<b>17202</b>	<b>16176</b>	16450	<b>15948</b>	16706	<b>16184</b>	16480	17872	<b>17257</b>	17400	<b>16833</b>	<b>16689</b>	17048	16805	<b>16681</b>
2000	22184	<b>20305</b>	22228	<b>20544</b>	21394	<b>19584</b>	21704	<b>19753</b>	21404	<b>20039</b>	21328	<b>19958</b>	21508	<b>19946</b>	21217	<b>19897</b>

\* Includes Census and Distance Variables

Table D.2: Comparison of MAEs for MLS Group B (Aggregated vs. Weighted Average)

In Sample																
Year	OLS*		Box-Cox*		Spat. Err.		Spat. Err.*		Spat. Lag.		Spat. Lag.*		Gen. Spat.		Gen. Spat.*	
	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.
1992	7090	<b>6053</b>	6977	<b>6029</b>	6724	<b>6060</b>	6616	<b>5833</b>	7102	<b>6309</b>	6944	<b>6010</b>	7060	<b>6345</b>	6877	<b>6114</b>
1993	7153	<b>6054</b>	7009	<b>5977</b>	6708	<b>5988</b>	6673	<b>5833</b>	7379	<b>6255</b>	7039	<b>5970</b>	7230	<b>6258</b>	6947	<b>6014</b>
1994	7643	<b>6973</b>	7523	<b>6861</b>	7068	<b>6722</b>	7043	<b>6563</b>	7859	<b>7179</b>	7506	<b>6889</b>	7639	<b>7066</b>	7334	<b>6819</b>
1995	7416	<b>6526</b>	7255	<b>6422</b>	6844	<b>6339</b>	6765	<b>6222</b>	7590	<b>6724</b>	7301	<b>6464</b>	7383	<b>6661</b>	7132	<b>6445</b>
1996	7879	<b>7152</b>	7948	<b>7314</b>	7700	<b>7275</b>	7598	<b>7095</b>	8043	<b>7340</b>	7782	<b>7087</b>	7905	<b>7318</b>	7681	<b>7112</b>
1997	7475	<b>6822</b>	7469	<b>6854</b>	7253	<b>6723</b>	7198	<b>6674</b>	7625	<b>7001</b>	7429	<b>6803</b>	7456	<b>6985</b>	7299	<b>6823</b>
1998	7172	<b>6512</b>	7030	<b>6369</b>	6924	<b>6471</b>	6775	<b>6359</b>	7442	<b>6704</b>	7104	<b>6472</b>	7403	<b>6664</b>	7042	<b>6448</b>
1999	8450	<b>7992</b>	8403	<b>7983</b>	8306	<b>7854</b>	8205	<b>7776</b>	8719	<b>8104</b>	8410	<b>7947</b>	8635	<b>8321</b>	8344	<b>8298</b>
2000	9890	<b>8831</b>	9845	<b>8491</b>	10292	<b>9005</b>	9814	<b>8826</b>	10506	<b>8993</b>	9860	<b>8797</b>	10424	<b>8998</b>	9822	<b>8797</b>
Out of Sample																
Year	OLS*		Box-Cox*		Spat. Err.		Spat. Err.*		Spat. Lag.		Spat. Lag.*		Gen. Spat.		Gen. Spat.*	
	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.
1992	<b>6347</b>	7169	<b>6286</b>	7283	<b>6396</b>	7126	<b>6216</b>	6948	<b>6466</b>	7463	<b>6222</b>	7126	<b>6516</b>	7446	<b>6255</b>	7233
1993	7942	<b>7455</b>	7797	<b>7353</b>	<b>6977</b>	7410	<b>7146</b>	7223	7970	<b>7733</b>	7806	<b>7371</b>	<b>7473</b>	7755	7433	<b>7413</b>
1994	8518	<b>7959</b>	8119	<b>7915</b>	<b>6721</b>	7506	7853	<b>7499</b>	<b>7568</b>	8163	8438	<b>7854</b>	<b>7241</b>	7910	8143	<b>7766</b>
1995	7747	<b>7409</b>	7867	<b>7275</b>	7614	<b>7270</b>	7644	<b>7195</b>	8415	<b>7602</b>	7851	<b>7341</b>	7860	<b>7544</b>	7826	<b>7414</b>
1996	<b>7854</b>	8369	<b>7910</b>	8663	<b>7504</b>	8593	<b>7544</b>	8313	<b>7892</b>	8637	<b>7790</b>	8294	<b>7707</b>	8641	<b>7603</b>	8366
1997	<b>7075</b>	7643	<b>7062</b>	7684	<b>6743</b>	7556	<b>6696</b>	7517	<b>7066</b>	7877	<b>6995</b>	7621	<b>6855</b>	7926	<b>6755</b>	7681
1998	9335	<b>7315</b>	9065	<b>7086</b>	8979	<b>7233</b>	8959	<b>7148</b>	9452	<b>7463</b>	9286	<b>7288</b>	9369	<b>7460</b>	9171	<b>7271</b>
1999	<b>7723</b>	8956	<b>7726</b>	8912	<b>7425</b>	8902	<b>7392</b>	8743	<b>7689</b>	9119	<b>7524</b>	8911	<b>7476</b>	9349	<b>7390</b>	9253
2000	<b>10081</b>	10877	<b>10130</b>	10360	<b>10443</b>	10703	<b>9990</b>	10872	<b>10132</b>	10720	<b>9855</b>	10843	<b>10159</b>	10719	<b>9831</b>	11021

\* Includes Census and Distance Variables

Table D.3: Comparison of MAEs for MLS Group C (Aggregated vs. Weighted Average)

In Sample																
Year	OLS*		Box-Cox*		Spat. Err.		Spat. Err.*		Spat. Lag.		Spat. Lag.*		Gen. Spat.		Gen. Spat.*	
	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.
1992	10753	<b>10243</b>	10690	<b>10246</b>	9916	<b>9671</b>	9909	<b>9576</b>	10720	<b>10462</b>	10510	<b>10054</b>	10739	<b>10686</b>	10446	<b>9994</b>
1993	12103	<b>11491</b>	12031	<b>11478</b>	10525	<b>10317</b>	10477	<b>10185</b>	12031	<b>11698</b>	11795	<b>11311</b>	11869	<b>11610</b>	11490	<b>11110</b>
1994	12765	<b>12406</b>	12579	<b>12329</b>	11597	<b>11478</b>	11544	<b>11383</b>	12700	<b>12396</b>	12495	<b>12167</b>	12353	<b>12222</b>	12126	<b>11967</b>
1995	12885	<b>12276</b>	12598	<b>12049</b>	12080	<b>11828</b>	11990	<b>11716</b>	13112	<b>12646</b>	12816	<b>12237</b>	12813	<b>12377</b>	12567	<b>12054</b>
1996	12107	<b>11600</b>	12138	<b>11658</b>	11506	<b>11343</b>	11422	<b>11192</b>	12278	<b>11833</b>	12047	<b>11561</b>	11955	<b>11619</b>	11802	<b>11411</b>
1997	12231	<b>11744</b>	12710	<b>12268</b>	11739	<b>11500</b>	11650	<b>11353</b>	12302	<b>11885</b>	12090	<b>11671</b>	12027	<b>11659</b>	11862	<b>11484</b>
1998	13186	<b>12543</b>	13421	<b>12578</b>	12318	<b>12026</b>	12209	<b>11886</b>	13033	<b>12527</b>	12903	<b>12367</b>	12808	<b>12318</b>	12679	<b>12176</b>
1999	14112	<b>13545</b>	13696	<b>13500</b>	13180	<b>12999</b>	13201	<b>12925</b>	14173	<b>13706</b>	13910	<b>13436</b>	14024	<b>13460</b>	13691	<b>13270</b>
2000	17363	<b>16717</b>	17390	<b>17160</b>	16946	<b>16472</b>	16763	<b>16287</b>	17758	<b>16929</b>	17250	<b>16677</b>	17544	<b>16734</b>	17065	<b>16506</b>
Out of Sample																
Year	OLS*		Box-Cox*		Spat. Err.		Spat. Err.*		Spat. Lag.		Spat. Lag.*		Gen. Spat.		Gen. Spat.*	
	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.
1992	<b>10718</b>	11364	<b>10640</b>	11285	<b>9484</b>	10853	<b>9564</b>	10691	<b>10566</b>	11664	<b>10474</b>	11173	<b>10309</b>	12018	<b>10102</b>	11134
1993	<b>12896</b>	13000	<b>12813</b>	12978	<b>11425</b>	11789	<b>11427</b>	11639	<b>13072</b>	13314	<b>12635</b>	12840	<b>12447</b>	13151	<b>12008</b>	12589
1994	<b>12762</b>	14449	<b>12677</b>	14160	<b>11366</b>	13429	<b>11555</b>	13301	<b>12321</b>	14417	<b>12380</b>	14157	<b>11866</b>	14164	<b>11895</b>	13898
1995	<b>12017</b>	14919	<b>11973</b>	14629	<b>10908</b>	14294	<b>10888</b>	14177	<b>12253</b>	15320	<b>11955</b>	14880	<b>11586</b>	14902	<b>11393</b>	14603
1996	<b>11365</b>	14439	<b>11369</b>	14617	<b>10838</b>	14213	<b>10655</b>	13996	<b>11712</b>	14627	<b>11270</b>	14360	<b>11321</b>	14410	<b>10891</b>	14201
1997	<b>11089</b>	15037	<b>11392</b>	15654	<b>10419</b>	14730	<b>10188</b>	14583	<b>11156</b>	15221	<b>10830</b>	14958	<b>10559</b>	14895	<b>10294</b>	14709
1998	<b>10918</b>	16550	<b>11037</b>	16756	<b>10189</b>	15790	<b>10144</b>	15621	<b>10663</b>	16493	<b>10573</b>	16324	<b>10382</b>	16095	<b>10352</b>	15936
1999	<b>13854</b>	17758	<b>13443</b>	17646	<b>13237</b>	17096	<b>12936</b>	16854	<b>14517</b>	18173	<b>13780</b>	17718	<b>13876</b>	17722	<b>13221</b>	17317
2000	<b>20287</b>	20411	<b>20215</b>	20950	<b>19410</b>	19980	<b>19707</b>	19973	21107	<b>20650</b>	20470	<b>20380</b>	<b>20343</b>	20363	<b>20084</b>	20217

\* Includes Census and Distance Variables

Table D.4: Comparison of MAEs for Wake County (Aggregated vs. Weighted Average)

In Sample																
	OLS*		Box-Cox*		Spat. Err.		Spat. Err.*		Spat. Lag.		Spat. Lag.*		Gen. Spat.		Gen. Spat.*	
Year	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.
1992	11439	<b>9923</b>	11073	<b>9911</b>	10231	<b>9494</b>	10207	<b>9339</b>	11167	<b>10096</b>	10861	<b>9707</b>	11074	<b>10148</b>	10744	<b>9683</b>
1993	11870	<b>10303</b>	11519	<b>10195</b>	10386	<b>9578</b>	10354	<b>9454</b>	11859	<b>10473</b>	11370	<b>10113</b>	11704	<b>10430</b>	11128	<b>10042</b>
1994	12673	<b>11192</b>	12218	<b>11273</b>	11160	<b>10606</b>	11210	<b>10473</b>	12609	<b>11271</b>	12056	<b>11002</b>	12200	<b>11110</b>	11747	<b>10890</b>
1995	12736	<b>11002</b>	12141	<b>10778</b>	11449	<b>10734</b>	11461	<b>10544</b>	12908	<b>11353</b>	12338	<b>10911</b>	13183	<b>11203</b>	12126	<b>10815</b>
1996	12331	<b>10778</b>	11929	<b>10728</b>	11251	<b>10433</b>	11231	<b>10314</b>	12585	<b>10977</b>	11983	<b>10661</b>	12160	<b>10997</b>	11737	<b>10560</b>
1997	12464	<b>10974</b>	12094	<b>11290</b>	11469	<b>10653</b>	11545	<b>10582</b>	12820	<b>11156</b>	12073	<b>10869</b>	12443	<b>11109</b>	11868	<b>10768</b>
1998	12746	<b>11126</b>	12059	<b>10767</b>	11369	<b>10686</b>	11488	<b>10563</b>	13084	<b>11237</b>	12221	<b>10941</b>	13123	<b>11068</b>	11999	<b>10812</b>
1999	14781	<b>12959</b>	13455	<b>12620</b>	13099	<b>12497</b>	13223	<b>12393</b>	15288	<b>13214</b>	14192	<b>12793</b>	15768	<b>13296</b>	13891	<b>12800</b>
2000	18458	<b>15871</b>	17779	<b>15946</b>	17371	<b>15762</b>	17304	<b>15467</b>	19511	<b>16589</b>	17788	<b>15755</b>	20972	<b>16653</b>	17610	<b>15652</b>
Out of Sample																
	OLS*		Box-Cox*		Spat. Err.		Spat. Err.*		Spat. Lag.		Spat. Lag.*		Gen. Spat.		Gen. Spat.*	
Year	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.	Agg.	Avg.
1992	10679	<b>10087</b>	10216	<b>10075</b>	<b>9280</b>	9672	<b>9407</b>	9507	10424	<b>10283</b>	10081	<b>9871</b>	<b>10026</b>	10342	<b>9813</b>	9848
1993	12942	<b>10461</b>	12353	<b>10357</b>	11223	<b>9707</b>	11256	<b>9613</b>	13025	<b>10612</b>	12364	<b>10272</b>	12450	<b>10571</b>	11842	<b>10205</b>
1994	12806	<b>11375</b>	12297	<b>11448</b>	<b>10710</b>	10770	11308	<b>10633</b>	12018	<b>11471</b>	12063	<b>11190</b>	11380	<b>11290</b>	11511	<b>11062</b>
1995	11621	<b>11218</b>	11275	<b>10984</b>	<b>10251</b>	10884	<b>10506</b>	10735	11767	<b>11561</b>	11258	<b>11128</b>	11581	<b>11410</b>	<b>10936</b>	11015
1996	13083	<b>10875</b>	12735	<b>10847</b>	11847	<b>10543</b>	11935	<b>10412</b>	12875	<b>11119</b>	12540	<b>10769</b>	12524	<b>11118</b>	12150	<b>10669</b>
1997	11540	<b>11163</b>	<b>11032</b>	11482	<b>10544</b>	10824	<b>10568</b>	10772	11936	<b>11344</b>	11133	<b>11059</b>	<b>11204</b>	11287	<b>10701</b>	10958
1998	13399	<b>11327</b>	12550	<b>10958</b>	11381	<b>10861</b>	11849	<b>10764</b>	13223	<b>11415</b>	12812	<b>11142</b>	12753	<b>11242</b>	12254	<b>11016</b>
1999	14189	<b>13195</b>	13027	<b>12876</b>	12795	<b>12737</b>	12722	<b>12624</b>	15498	<b>13486</b>	13842	<b>13029</b>	15147	<b>13541</b>	13249	<b>13029</b>
2000	20872	<b>16181</b>	20517	<b>16426</b>	18931	<b>16064</b>	19954	<b>15778</b>	20743	<b>16901</b>	20224	<b>16064</b>	21659	<b>16974</b>	19997	<b>16014</b>

\* Includes Census and Distance Variables



Table D.5: Comparison of MAEs for MLS Zone 1

In Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	19313	<b>18996</b>	19551	19077	21288	19222	21387	19291
1993	18500	18426	<b>17599</b>	17702	18655	18075	18589	18068
1994	22175	21481	<b>21218</b>	21373	22147	21804	21904	21696
1995	21515	21807	22530	21515	22645	<b>21262</b>	22375	21382
1996	22379	21474	<b>20842</b>	21167	23086	22223	26780	21937
1997	22388	21600	<b>21460</b>	21609	23884	22357	26099	22069
1998	21669	<b>20188</b>	21441	21074	22880	21482	22857	21279
1999	27892	<b>26007</b>	26250	26245	30402	27473	32982	27500
2000	33087	33000	33459	<b>31774</b>	40483	33087	42486	32717
Out of Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	19147	18393	18087	<b>17710</b>	20403	19099	19273	17967
1993	27184	<b>26358</b>	26656	26491	27764	27233	27198	26616
1994	17853	17347	18190	16702	18793	17178	18684	<b>16563</b>
1995	21551	21891	<b>19680</b>	21551	20266	21201	20114	21420
1996	22706	21318	<b>20487</b>	20837	27050	23372	27278	21593
1997	23932	24118	25275	<b>22527</b>	26729	23891	30636	22678
1998	23947	<b>20744</b>	21279	21865	27820	24186	25081	22240
1999	23025	22773	<b>18342</b>	19120	25794	22742	23551	19529
2000	53363	<b>52459</b>	52537	52690	53796	53363	54216	52627

\* Includes Census and Distance Variables

Table D.6: Comparison of MAEs for MLS Zone 2

In Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	10515	10551	9882	<b>9816</b>	10357	10256	10140	10079
1993	10470	10245	9863	<b>9784</b>	10659	10354	10470	10212
1994	11617	12280	11030	<b>10892</b>	11720	11503	11371	11189
1995	12005	<b>11609</b>	11785	11654	12459	11958	12233	11836
1996	11769	11658	11190	<b>11149</b>	12147	11661	11772	11441
1997	12827	12855	<b>12118</b>	12155	12990	12609	12594	12384
1998	13136	12514	12308	<b>12205</b>	13198	12759	12901	12615
1999	14390	13844	13727	<b>13697</b>	14635	14150	14380	13977
2000	15848	15964	15784	15564	16183	15602	15988	<b>15528</b>
Out of Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	8256	8278	<b>7941</b>	8038	8925	8480	8420	8290
1993	10975	11227	10246	<b>10024</b>	11079	10873	10776	10388
1994	13980	15699	13038	<b>12681</b>	14665	13693	13760	13045
1995	9816	9843	<b>9000</b>	9373	9470	9490	9129	9319
1996	12979	12802	12663	<b>12461</b>	13527	12790	12937	12564
1997	11739	11958	11482	<b>11456</b>	11592	11591	11498	11523
1998	18225	17071	<b>16438</b>	16527	18515	18076	17108	17097
1999	17270	<b>15814</b>	15972	16060	17259	16942	16447	16403
2000	25848	25866	24459	25212	25094	25509	<b>24418</b>	25107

\* Includes Census and Distance Variables

Table D.7: Comparison of MAEs for MLS Zone 3

In Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	5134	5308	5606	5134	5382	<b>5097</b>	5387	5115
1993	5629	<b>5557</b>	5892	5629	6238	5614	6294	5736
1994	6303	<b>5895</b>	6426	6129	6880	6306	6818	6226
1995	5945	6107	6131	5914	6084	<b>5874</b>	6084	5925
1996	6701	<b>6635</b>	6893	6668	7181	6707	7052	6682
1997	5750	<b>5598</b>	5733	5732	5749	5707	5773	5712
1998	5194	5327	5281	<b>5109</b>	5490	5194	5516	5207
1999	6573	6828	6544	6562	6560	6573	6627	<b>6515</b>
2000	9699	<b>7816</b>	9809	9699	9793	9691	9786	9661

Out of Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	7193	7383	<b>6089</b>	7193	6448	7432	6502	7592
1993	6391	6308	<b>6156</b>	6391	6386	6303	6798	6361
1994	<b>14861</b>	46734	15445	15055	17152	16703	16952	16605
1995	6704	6661	<b>6596</b>	6606	7701	7075	7699	7354
1996	7409	7505	8028	7392	<b>6980</b>	7241	7474	7315
1997	4456	4331	4436	4351	4319	4332	4308	<b>4261</b>
1998	5983	6197	6071	6116	6141	<b>5983</b>	6368	6861
1999	7894	7826	7700	7930	<b>7524</b>	7894	7870	7938
2000	10902	11192	11312	10902	11347	<b>10899</b>	12050	11762

\* Includes Census and Distance Variables

Table D.8: Comparison of MAEs for MLS Zone 4

In Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	6368	6347	6533	<b>6296</b>	6712	6368	6785	6341
1993	5578	5529	5696	<b>5389</b>	6089	5534	6074	5534
1994	7071	6986	6750	<b>6659</b>	7112	6874	7254	7314
1995	5939	5960	5799	<b>5656</b>	6749	5849	7444	5904
1996	6390	<b>6119</b>	6169	6322	6416	6187	6450	6211
1997	6111	<b>6007</b>	6573	6111	6657	6111	6751	6115
1998	8870	<b>8734</b>	9129	8870	9416	8871	9244	8969
1999	7570	7291	<b>7175</b>	7388	7621	7474	7585	7465
2000	9768	<b>8029</b>	9410	9768	10311	9770	11007	10035

Out of Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	<b>6503</b>	6510	7063	6638	7413	6503	7683	6558
1993	7060	7244	<b>5751</b>	7118	6225	7085	6273	7284
1994	8300	7923	7426	<b>7290</b>	9062	8546	8130	7826
1995	8344	7960	<b>5825</b>	7378	8016	8409	8006	7729
1996	<b>4369</b>	5373	4956	4411	6395	4872	5462	4925
1997	9469	9589	<b>8551</b>	9469	9381	9469	8862	9472
1998	8819	8414	7707	8819	7797	8819	<b>7647</b>	8969
1999	8820	9551	8958	8648	10168	8819	9160	<b>8559</b>
2000	12486	19308	<b>12169</b>	12486	12569	12428	12888	14551

\* Includes Census and Distance Variables

Table D.9: Comparison of MAEs for MLS Zone 5

In Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	10205	10313	9425	<b>9360</b>	10059	9951	9929	9861
1993	12138	12197	10616	<b>10500</b>	12129	11910	11862	11572
1994	13168	13188	11949	<b>11851</b>	13149	13003	12827	12668
1995	13701	13571	13069	<b>12973</b>	14070	13650	13744	13420
1996	12842	12937	12377	<b>12230</b>	13065	12785	12777	12563
1997	13670	14514	13305	<b>13192</b>	13770	13600	13510	13373
1998	14343	14135	13916	<b>13704</b>	14499	14290	14343	14145
1999	17470	17890	<b>16546</b>	16583	17671	17375	17281	17125
2000	19329	20158	18564	<b>18506</b>	19551	19320	19176	18991

Out of Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	9775	9872	<b>8529</b>	8593	9405	9504	9098	9181
1993	13398	13446	<b>11700</b>	11791	13142	12885	12489	12581
1994	13533	13578	12001	<b>11907</b>	13212	13245	12650	12538
1995	12121	12133	11569	<b>11212</b>	12874	12109	12288	11574
1996	13665	13653	13031	<b>12750</b>	14420	13629	13684	13109
1997	11876	12467	11036	11105	11589	11744	<b>10940</b>	11102
1998	11628	11573	11088	<b>10849</b>	11580	11535	11234	11156
1999	15262	15654	14381	<b>14307</b>	16143	15292	14861	14583
2000	24064	25027	23052	<b>22833</b>	24788	24269	23806	23346

\* Includes Census and Distance Variables

Table D.10: Comparison of MAEs for MLS Zone 6

In Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	5402	5374	5508	<b>5336</b>	5586	5390	5542	5354
1993	5515	<b>5476</b>	5656	5512	5659	5515	5661	5514
1994	6023	5891	6006	<b>5838</b>	6153	5967	6092	5926
1995	7181	7192	7083	<b>7025</b>	7302	7198	7204	7115
1996	6303	6304	6545	6290	6488	<b>6192</b>	6452	6202
1997	5829	5814	5825	<b>5715</b>	6101	5812	6068	5953
1998	6343	<b>6162</b>	6468	6343	6560	6343	6511	6333
1999	7243	<b>6841</b>	7323	7220	7412	7246	7371	7239
2000	7973	<b>7870</b>	8062	7973	8064	7973	8046	7956

Out of Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	6287	6687	<b>6137</b>	6314	6144	6242	6189	6304
1993	5262	<b>5105</b>	5458	5220	5469	5262	5461	5172
1994	6857	7288	6716	6728	6556	<b>6387</b>	6574	6527
1995	7674	<b>7666</b>	7979	8218	8113	8065	8099	8245
1996	8294	8312	8325	8231	8323	<b>8148</b>	8253	8202
1997	8024	8662	7680	7675	7681	7876	7631	<b>7597</b>
1998	6034	6188	5425	6020	5702	6034	<b>5417</b>	6023
1999	9450	8836	<b>8183</b>	9406	8556	9426	8363	9406
2000	9620	<b>9512</b>	9738	9620	9770	9620	9743	9841

\* Includes Census and Distance Variables

Table D.11: Comparison of MAEs for MLS Zone 7

In Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	13908	14083	12704	<b>12659</b>	13513	13297	13522	13230
1993	14189	13931	12651	<b>12543</b>	13948	13755	14072	13770
1994	14985	15910	14596	<b>14250</b>	14848	14563	14550	14331
1995	15251	14548	14467	<b>14187</b>	15371	14905	15259	14752
1996	14083	13608	12855	<b>12708</b>	13918	13679	13849	13540
1997	13642	15206	13026	<b>12985</b>	13437	13358	13266	13316
1998	13617	<b>12211</b>	12472	12457	13412	13181	13110	12922
1999	16437	16077	16060	<b>15620</b>	16434	16076	16272	15894
2000	21101	21881	20030	<b>19957</b>	20930	20561	20911	20466

Out of Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	13867	14388	12374	12705	<b>12102</b>	12320	12309	12562
1993	17292	16619	14351	<b>13999</b>	16112	16080	15492	15131
1994	16529	17260	15593	<b>15400</b>	16446	16519	15763	15785
1995	14628	14205	<b>12651</b>	13595	13386	14226	13307	13868
1996	21513	21238	20441	<b>20216</b>	22435	21578	21536	20979
1997	14388	16444	<b>13367</b>	13643	13725	13694	13513	13765
1998	14445	13166	<b>12449</b>	12748	14214	14118	13369	13421
1999	17217	16741	<b>15604</b>	15949	17105	17093	16405	16390
2000	21016	21193	21405	21132	20242	<b>20058</b>	20800	20924

\* Includes Census and Distance Variables

Table D.12: Comparison of MAEs for MLS Zone 8

In Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	6008	6062	5880	<b>5549</b>	6165	5833	6149	5851
1993	6162	6115	5685	<b>5564</b>	6004	5834	6090	5973
1994	6561	6594	6324	<b>6102</b>	6821	6396	6643	6365
1995	6211	6145	6241	<b>6098</b>	6509	6209	6406	6171
1996	8078	8677	8087	8028	8102	<b>8010</b>	8047	8015
1997	5988	5981	5695	<b>5651</b>	6105	5963	5942	5803
1998	5750	5708	5601	<b>5559</b>	5878	5701	5796	5644
1999	7164	7176	7018	<b>6989</b>	7329	7189	7251	7105
2000	6495	<b>6363</b>	6755	6495	6746	6487	6752	6431

Out of Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	5729	5909	6165	5855	5647	<b>5460</b>	5926	5783
1993	5906	5869	5595	<b>5537</b>	6360	5708	6069	5825
1994	6614	6784	6291	<b>6211</b>	6409	6542	6334	6281
1995	9505	8526	9181	8605	<b>8375</b>	9306	8581	8561
1996	8165	8166	7682	7987	7515	7894	<b>7478</b>	7907
1997	6532	6749	6224	<b>6147</b>	6301	6278	6274	6178
1998	5552	5342	5513	<b>5289</b>	5941	5416	5717	5360
1999	5983	6021	<b>5689</b>	5693	6420	5937	6007	5690
2000	8561	8524	<b>8460</b>	8561	8609	8548	8478	8809

\* Includes Census and Distance Variables

Table D.13: Comparison of MAEs for MLS Zone 9

In Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	11542	<b>11203</b>	11465	11282	12785	11477	13875	11476
1993	11278	11177	10853	<b>10589</b>	12155	11175	12707	11340
1994	13586	13264	<b>12928</b>	12946	13442	13025	13714	13136
1995	13035	<b>12550</b>	13063	12917	13387	13019	13378	13019
1996	10729	<b>10215</b>	10739	10433	11264	10706	11039	10631
1997	10577	<b>9813</b>	10200	10075	10705	10433	10511	10246
1998	9994	<b>9325</b>	9613	9507	10008	9743	9887	9699
1999	10980	<b>10233</b>	11002	10919	10931	10697	10919	10696
2000	14364	14451	14454	14346	14404	14213	14398	<b>14206</b>

Out of Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	12261	12808	12744	<b>11968</b>	14522	12317	15553	12024
1993	10593	10579	10611	10923	10987	<b>10395</b>	11581	10682
1994	13750	13685	14188	13932	13277	<b>13177</b>	14693	13549
1995	11232	<b>10483</b>	12148	11883	11426	11111	11977	11611
1996	10186	9563	<b>9010</b>	9645	9971	10203	9396	9961
1997	10357	9823	10192	9730	10523	9972	10151	<b>9636</b>
1998	9300	8722	8559	8372	8176	8620	<b>8075</b>	8096
1999	<b>11026</b>	11700	11622	11065	11727	11057	11726	11099
2000	<b>11305</b>	12687	11819	11370	12595	11811	12451	11829

\* Includes Census and Distance Variables

Table D.14: Comparison of MAEs for MLS Zone 10

In Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	8089	8090	7845	<b>7731</b>	8598	8061	9344	8072
1993	8250	7978	7787	<b>7774</b>	8564	8206	8429	8170
1994	9107	8966	8791	<b>8600</b>	9242	8940	9105	8858
1995	8986	8726	8610	<b>8487</b>	9369	8958	9055	8753
1996	10151	10480	10068	<b>9999</b>	10225	10131	10134	10052
1997	9881	10718	9873	<b>9670</b>	10085	9844	9885	9712
1998	11999	12670	11315	<b>11233</b>	11787	11734	11472	11417
1999	10298	10143	9845	<b>9639</b>	10553	10294	10331	10120
2000	13556	<b>13535</b>	14048	13554	13887	13546	13889	13548

Out of Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	9683	<b>8975</b>	10208	9636	10387	9666	11502	9847
1993	12404	12330	12098	<b>11956</b>	13287	12572	12669	12164
1994	9901	<b>8873</b>	9455	9295	9797	9648	9412	9361
1995	9517	9287	8878	<b>8861</b>	9625	9513	9089	9178
1996	8921	9297	9021	8814	8782	8797	8774	<b>8766</b>
1997	9452	9718	9268	9269	9572	9434	9285	<b>9253</b>
1998	10431	10876	9800	<b>9722</b>	10323	10300	9832	9785
1999	12464	12264	12122	<b>11622</b>	13215	12667	12608	11973
2000	13949	14313	<b>13247</b>	13918	14054	13982	13704	14016

\* Includes Census and Distance Variables

Table D.15: Comparison of MAEs for MLS Zone 11

In Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	6801	6781	6746	<b>6671</b>	6867	6801	6890	6780
1993	5695	5528	5620	<b>5436</b>	5784	5648	5756	5662
1994	6367	6265	5732	<b>5697</b>	6395	6315	6354	6269
1995	6377	6095	5745	<b>5649</b>	6471	6272	6489	6316
1996	6093	5966	6050	<b>5951</b>	6236	5975	6209	5986
1997	7211	7245	<b>7062</b>	7109	7290	7211	7230	7193
1998	6804	<b>6512</b>	6728	6625	6852	6675	6817	6661
1999	7361	7282	7250	<b>7228</b>	7456	7336	7360	7298
2000	8144	8196	8262	8144	8268	<b>8133</b>	8249	8212

Out of Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	7412	7479	<b>7305</b>	7530	7329	7412	7476	7656
1993	7990	8219	<b>7247</b>	7673	7514	7876	7346	7855
1994	6346	6606	6320	<b>6053</b>	6396	6170	6741	6430
1995	7211	7246	<b>6439</b>	6802	6918	7023	6883	7395
1996	5872	5775	5989	5744	5904	<b>5530</b>	5976	5577
1997	6586	6803	6541	6615	<b>6418</b>	6586	6656	6643
1998	18368	<b>18004</b>	18269	18280	18317	18348	18288	18321
1999	5994	6122	6024	5855	6212	5965	5926	<b>5840</b>
2000	8702	8658	9075	8702	8862	<b>8658</b>	8852	8880

\* Includes Census and Distance Variables

Table D.16: Comparison of MAEs for MLS Zone 14

In Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	10715	10242	9745	<b>9385</b>	9760	9633	9694	9661
1993	11215	10814	11316	10978	11924	<b>10742</b>	12141	10882
1994	11148	10770	10604	<b>10574</b>	11741	11152	12504	12548
1995	9210	<b>9155</b>	9635	9210	9625	9186	9621	9185
1996	9522	9262	9210	<b>9052</b>	9494	9140	9514	9118
1997	10814	<b>10173</b>	10614	10529	10841	10534	10822	10660
1998	10122	<b>9461</b>	9849	9782	10323	9933	10124	9909
1999	12613	<b>10434</b>	12536	12275	12336	12162	12352	12157
2000	15859	<b>14947</b>	16680	15859	16570	15860	16599	15775

Out of Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	10337	9811	9106	<b>8816</b>	9844	8930	9425	9262
1993	18425	<b>17060</b>	17788	17858	19150	20039	19565	20951
1994	13085	12583	14537	14712	12131	<b>11895</b>	13606	13769
1995	11636	<b>11528</b>	12180	11633	12316	11605	12288	11616
1996	14825	14585	14691	14486	<b>13911</b>	13949	14267	13998
1997	9842	9793	8904	9441	9000	9516	<b>8880</b>	9839
1998	13589	<b>12676</b>	13342	13171	13881	13662	13641	13540
1999	14204	14128	13965	13965	14145	13907	13935	<b>13895</b>
2000	20637	20770	17368	20637	<b>16917</b>	20418	17007	20592

\* Includes Census and Distance Variables

Table D.17: Comparison of MAEs for MLS Zone 16

In Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	6761	6268	6303	<b>6128</b>	7207	6745	7321	7723
1993	6821	6780	7000	6810	6980	<b>6767</b>	6962	6772
1994	7733	7601	7314	<b>7231</b>	7724	7642	7574	7481
1995	6743	6597	<b>6353</b>	6357	6628	6597	6529	6506
1996	7613	<b>7164</b>	7663	7547	7706	7619	7713	7592
1997	7267	<b>7137</b>	7417	7267	7540	7264	7558	7267
1998	6869	<b>6562</b>	6725	6669	7101	6862	6965	6793
1999	11646	11808	10827	<b>10763</b>	11480	11400	13273	14258
2000	11381	11370	11630	<b>11342</b>	11722	11375	11723	11398

Out of Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	5832	<b>5284</b>	7384	7703	6272	5753	7028	7619
1993	8192	9002	10632	<b>8122</b>	23627	8414	19423	8395
1994	8607	8569	<b>7475</b>	7879	8411	8517	7742	8095
1995	6161	<b>5909</b>	5959	6070	6525	6210	6215	6263
1996	7733	7650	<b>7595</b>	7813	7721	7801	7638	7806
1997	9848	<b>8858</b>	10138	9834	10193	9739	10310	9713
1998	7918	8312	8037	7933	8041	7928	7924	<b>7872</b>
1999	<b>10696</b>	11740	12985	13103	11198	11092	15095	16398
2000	13806	11864	<b>11511</b>	12416	13291	13621	11529	12439

\* Includes Census and Distance Variables

Table D.18: Comparison of MAEs for MLS Zone 18

In Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	6193	6149	6409	<b>6137</b>	6743	6196	6612	6164
1993	7251	7052	7023	<b>6936</b>	7795	7251	7601	7205
1994	9553	9439	9207	<b>9108</b>	9751	9515	9530	9314
1995	6804	<b>6629</b>	6890	6699	7441	6727	7422	6760
1996	7056	<b>6985</b>	7292	7029	7454	6999	7504	7001
1997	10204	11206	10141	10204	10078	10167	<b>10065</b>	10676
1998	8502	<b>8403</b>	8512	8407	8780	8494	8777	8583
1999	9135	9052	9366	9071	9379	<b>9012</b>	9472	9039
2000	10389	<b>9902</b>	10712	10389	10408	10092	10432	10033

Out of Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	7208	7119	7191	<b>7095</b>	7630	7211	7315	7122
1993	7895	7771	<b>7524</b>	7951	7692	7895	7718	7959
1994	8653	8721	8141	8385	8646	8162	<b>8096</b>	8293
1995	10780	<b>10122</b>	10809	10257	12711	11223	11825	10840
1996	11138	<b>10555</b>	10971	10997	11536	11207	11191	11115
1997	9737	9907	9603	9737	9488	9721	<b>9468</b>	10191
1998	12498	12638	12060	<b>11952</b>	12981	12535	12345	12102
1999	8836	<b>8512</b>	8513	8622	9127	8770	8922	8583
2000	12310	12282	<b>11362</b>	12310	11875	12705	11851	12742

\* Includes Census and Distance Variables

Table D.19: Comparison of MAEs for MLS Zone 21

In Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	5871	5944	5870	<b>5728</b>	6224	5869	6551	5941
1993	5756	5800	5763	<b>5666</b>	6165	5756	6211	5783
1994	7570	7542	7603	<b>7358</b>	7931	7413	7823	7421
1995	6911	6694	6543	<b>6419</b>	7257	6847	7083	6772
1996	8130	9184	8539	8130	8323	<b>8058</b>	8395	8263
1997	6730	<b>6439</b>	6654	6440	7492	6719	7791	6687
1998	7273	7033	7291	<b>7014</b>	7578	7250	7646	7179
1999	7589	7536	7586	<b>7402</b>	7952	7589	<b>7892</b>	7525
2000	9539	<b>9477</b>	9606	9539	9675	9539	9764	9576

Out of Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	8204	9220	<b>7834</b>	8200	8483	8209	8094	8228
1993	10524	<b>10334</b>	10678	10441	11104	10524	11244	10509
1994	8719	9320	<b>6933</b>	8276	8694	8537	7460	8367
1995	8014	<b>7744</b>	8452	8836	7972	7964	8015	8796
1996	9541	10571	10327	9541	10167	<b>9455</b>	10368	9828
1997	7161	7245	7268	7355	7634	<b>7136</b>	8209	7489
1998	7576	<b>6762</b>	7192	7449	7167	7697	7504	7767
1999	9026	<b>8702</b>	9808	9048	9498	9026	9622	8941
2000	20461	18689	<b>16976</b>	20461	17261	20461	17207	22244

\* Includes Census and Distance Variables

Table D.20: Comparison of MAEs for MLS Group A

In Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	12378	12079	11113	<b>11088</b>	12055	11725	11855	11521
1993	12658	12179	11546	<b>11442</b>	12870	12266	12617	12028
1994	13714	13949	12832	<b>12615</b>	13850	13346	13512	13061
1995	13840	13052	13283	<b>13028</b>	14531	13622	14342	13427
1996	12987	12431	12169	<b>12091</b>	13466	12766	13194	12542
1997	13488	13342	12776	<b>12682</b>	13819	13192	13506	13061
1998	13668	<b>12268</b>	12432	12443	13872	13076	13657	12852
1999	15758	<b>14438</b>	14923	14682	16265	15270	16017	15021
2000	19152	18815	18707	<b>18456</b>	19814	18636	19719	18519

Out of Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	10814	10480	<b>9963</b>	10223	10773	10269	10394	10276
1993	14577	13503	13240	<b>12829</b>	15059	14284	14191	13503
1994	15125	15439	13627	<b>13506</b>	14901	14425	14073	13676
1995	12151	11705	<b>10728</b>	11157	11807	11771	11401	11330
1996	16930	16435	16113	<b>15955</b>	17181	16513	16649	15984
1997	12002	11812	<b>11290</b>	11537	11510	11425	11578	11632
1998	15517	14248	<b>13811</b>	14062	15895	15231	14898	14560
1999	17769	16176	<b>15948</b>	16184	17872	17400	16689	16805
2000	22184	22228	21394	21704	21404	21328	21508	<b>21217</b>

\* Includes Census and Distance Variables



Table D.21: Comparison of MAEs for MLS Group B

In Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	7090	6977	6724	<b>6616</b>	7102	6944	7060	6877
1993	7153	7009	6708	<b>6673</b>	7379	7039	7230	6947
1994	7643	7523	7068	<b>7043</b>	7859	7506	7639	7334
1995	7416	7255	6844	<b>6765</b>	7590	7301	7383	7132
1996	7879	7948	7700	<b>7598</b>	8043	7782	7905	7681
1997	7475	7469	7253	<b>7198</b>	7625	7429	7456	7299
1998	7172	7030	6924	<b>6775</b>	7442	7104	7403	7042
1999	8450	8403	8306	<b>8205</b>	8719	8410	8635	8344
2000	9890	9845	10292	<b>9814</b>	10506	9860	10424	9822

Out of Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	6347	6286	6396	<b>6216</b>	6466	6222	6516	6255
1993	7942	7797	<b>6977</b>	7146	7970	7806	7473	7433
1994	8518	8119	<b>6721</b>	7853	7568	8438	7241	8143
1995	7747	7867	<b>7614</b>	7644	8415	7851	7860	7826
1996	7854	7910	<b>7504</b>	7544	7892	7790	7707	7603
1997	7075	7062	6743	<b>6696</b>	7066	6995	6855	6755
1998	9335	9065	8979	<b>8959</b>	9452	9286	9369	9171
1999	7723	7726	7425	7392	7689	7524	7476	<b>7390</b>
2000	10081	10130	10443	9990	10132	9855	10159	<b>9831</b>

\* Includes Census and Distance Variables

Table D.22: Comparison of MAEs for MLS Group C

In Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	10753	10690	9916	<b>9909</b>	10720	10510	10739	10446
1993	12103	12031	10525	<b>10477</b>	12031	11795	11869	11490
1994	12765	12579	11597	<b>11544</b>	12700	12495	12353	12126
1995	12885	12598	12080	<b>11990</b>	13112	12816	12813	12567
1996	12107	12138	11506	<b>11422</b>	12278	12047	11955	11802
1997	12231	12710	11739	<b>11650</b>	12302	12090	12027	11862
1998	13186	13421	12318	<b>12209</b>	13033	12903	12808	12679
1999	14112	13696	<b>13180</b>	13201	14173	13910	14024	13691
2000	17363	17390	16946	<b>16763</b>	17758	17250	17544	17065

Out of Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	10718	10640	<b>9484</b>	9564	10566	10474	10309	10102
1993	12896	12813	<b>11425</b>	11427	13072	12635	12447	12008
1994	12762	12677	<b>11366</b>	11555	12321	12380	11866	11895
1995	12017	11973	10908	<b>10888</b>	12253	11955	11586	11393
1996	11365	11369	10838	<b>10655</b>	11712	11270	11321	10891
1997	11089	11392	10419	<b>10188</b>	11156	10830	10559	10294
1998	10918	11037	10189	<b>10144</b>	10663	10573	10382	10352
1999	13854	13443	13237	<b>12936</b>	14517	13780	13876	13221
2000	20287	20215	<b>19410</b>	19707	21107	20470	20343	20084

\* Includes Census and Distance Variables

Table D.23: Comparison of MAEs for Wake County

In Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	11439	11073	10231	<b>10207</b>	11167	10861	11074	10744
1993	11870	11519	10386	<b>10354</b>	11859	11370	11704	11128
1994	12673	12218	<b>11160</b>	11210	12609	12056	12200	11747
1995	12736	12141	<b>11449</b>	11461	12908	12338	13183	12126
1996	12331	11929	11251	<b>11231</b>	12585	11983	12160	11737
1997	12464	12094	<b>11469</b>	11545	12820	12073	12443	11868
1998	12746	12059	<b>11369</b>	11488	13084	12221	13123	11999
1999	14781	13455	<b>13099</b>	13223	15288	14192	15768	13891
2000	18458	17779	17371	<b>17304</b>	19511	17788	20972	17610
Out of Sample								
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Err.*	Spat. Lag.	Spat. Lag.*	Gen. Spat.	Gen. Spat.*
1992	10679	10216	<b>9280</b>	9407	10424	10081	10026	9813
1993	12942	12353	<b>11223</b>	11256	13025	12364	12450	11842
1994	12806	12297	<b>10710</b>	11308	12018	12063	11380	11511
1995	11621	11275	<b>10251</b>	10506	11767	11258	11581	10936
1996	13083	12735	<b>11847</b>	11935	12875	12540	12524	12150
1997	11540	11032	<b>10544</b>	10568	11936	11133	11204	10701
1998	13399	12550	<b>11381</b>	11849	13223	12812	12753	12254
1999	14189	13027	12795	<b>12722</b>	15498	13842	15147	13249
2000	20872	20517	<b>18931</b>	19954	20743	20224	21659	19997

\* Includes Census and Distance Variables

Table D.24: Comparison of MAEs for MLS Zone 1 (Spatial vs. Extra Variables)

In Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag	Gen. Spat.
1992	19313	<b>18996</b>	19551	21288	21387
1993	18500	18426	<b>17599</b>	18655	18589
1994	22175	21481	<b>21218</b>	22147	21904
1995	<b>21515</b>	21807	22530	22645	22375
1996	22379	21474	<b>20842</b>	23086	26780
1997	22388	21600	<b>21460</b>	23884	26099
1998	21669	<b>20188</b>	21441	22880	22857
1999	27892	<b>26007</b>	26250	30402	32982
2000	33087	<b>33000</b>	33459	40483	42486

Out of Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag.	Gen. Spat.
1992	19147	18393	<b>18087</b>	20403	19273
1993	27184	<b>26358</b>	26656	27764	27198
1994	17853	<b>17347</b>	18190	18793	18684
1995	21551	21891	<b>19680</b>	20266	20114
1996	22706	21318	<b>20487</b>	27050	27278
1997	<b>23932</b>	24118	25275	26729	30636
1998	23947	<b>20744</b>	21279	27820	25081
1999	23025	22773	<b>18342</b>	25794	23551
2000	53363	<b>52459</b>	52537	53796	54216

\* Includes Census and Distance Variables

Table D.25: Comparison of MAEs for MLS Zone 2 (Spatial vs. Extra Variables)

In Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag	Gen. Spat.
1992	10515	10551	<b>9882</b>	10357	10140
1993	10470	10245	<b>9863</b>	10659	10470
1994	11617	12280	<b>11030</b>	11720	11371
1995	12005	<b>11609</b>	11785	12459	12233
1996	11769	11658	<b>11190</b>	12147	11772
1997	12827	12855	<b>12118</b>	12990	12594
1998	13136	12514	<b>12308</b>	13198	12901
1999	14390	13844	<b>13727</b>	14635	14380
2000	15848	15964	<b>15784</b>	16183	15988

Out of Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag.	Gen. Spat.
1992	8256	8278	<b>7941</b>	8925	8420
1993	10975	11227	<b>10246</b>	11079	10776
1994	13980	15699	<b>13038</b>	14665	13760
1995	9816	9843	<b>9000</b>	9470	9129
1996	12979	12802	<b>12663</b>	13527	12937
1997	11739	11958	<b>11482</b>	11592	11498
1998	18225	17071	<b>16438</b>	18515	17108
1999	17270	<b>15814</b>	15972	17259	16447
2000	25848	25866	24459	25094	<b>24418</b>

\* Includes Census and Distance Variables

Table D.26: Comparison of MAEs for MLS Zone 3 (Spatial vs. Extra Variables)

In Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag	Gen. Spat.
1992	<b>5134</b>	5308	5606	5382	5387
1993	5629	<b>5557</b>	5892	6238	6294
1994	6303	<b>5895</b>	6426	6880	6818
1995	<b>5945</b>	6107	6131	6084	6084
1996	6701	<b>6635</b>	6893	7181	7052
1997	5750	<b>5598</b>	5733	5749	5773
1998	<b>5194</b>	5327	5281	5490	5516
1999	6573	6828	<b>6544</b>	6560	6627
2000	9699	<b>7816</b>	9809	9793	9786

Out of Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag.	Gen. Spat.
1992	7193	7383	<b>6089</b>	6448	6502
1993	6391	6308	<b>6156</b>	6386	6798
1994	<b>14861</b>	46734	15445	17152	16952
1995	6704	6661	<b>6596</b>	7701	7699
1996	7409	7505	8028	<b>6980</b>	7474
1997	4456	4331	4436	4319	<b>4308</b>
1998	<b>5983</b>	6197	6071	6141	6368
1999	7894	7826	7700	<b>7524</b>	7870
2000	<b>10902</b>	11192	11312	11347	12050

\* Includes Census and Distance Variables

Table D.27: Comparison of MAEs for MLS Zone 4 (Spatial vs. Extra Variables)

In Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag	Gen. Spat.
1992	6368	<b>6347</b>	6533	6712	6785
1993	5578	<b>5529</b>	5696	6089	6074
1994	7071	6986	<b>6750</b>	7112	7254
1995	5939	5960	<b>5799</b>	6749	7444
1996	6390	<b>6119</b>	6169	6416	6450
1997	6111	<b>6007</b>	6573	6657	6751
1998	8870	<b>8734</b>	9129	9416	9244
1999	7570	7291	<b>7175</b>	7621	7585
2000	9768	<b>8029</b>	9410	10311	11007

Out of Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag.	Gen. Spat.
1992	<b>6503</b>	6510	7063	7413	7683
1993	7060	7244	<b>5751</b>	6225	6273
1994	8300	7923	<b>7426</b>	9062	8130
1995	8344	7960	<b>5825</b>	8016	8006
1996	<b>4369</b>	5373	4956	6395	5462
1997	9469	9589	<b>8551</b>	9381	8862
1998	8819	8414	7707	7797	<b>7647</b>
1999	<b>8820</b>	9551	8958	10168	9160
2000	12486	19308	<b>12169</b>	12569	12888

\* Includes Census and Distance Variables

Table D.28: Comparison of MAEs for MLS Zone 5 (Spatial vs. Extra Variables)

In Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag	Gen. Spat.
1992	10205	10313	<b>9425</b>	10059	9929
1993	12138	12197	<b>10616</b>	12129	11862
1994	13168	13188	<b>11949</b>	13149	12827
1995	13701	13571	<b>13069</b>	14070	13744
1996	12842	12937	<b>12377</b>	13065	12777
1997	13670	14514	<b>13305</b>	13770	13510
1998	14343	14135	<b>13916</b>	14499	14343
1999	17470	17890	<b>16546</b>	17671	17281
2000	19329	20158	<b>18564</b>	19551	19176

Out of Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag.	Gen. Spat.
1992	9775	9872	<b>8529</b>	9405	9098
1993	13398	13446	<b>11700</b>	13142	12489
1994	13533	13578	<b>12001</b>	13212	12650
1995	12121	12133	<b>11569</b>	12874	12288
1996	13665	13653	<b>13031</b>	14420	13684
1997	11876	12467	11036	11589	<b>10940</b>
1998	11628	11573	<b>11088</b>	11580	11234
1999	15262	15654	<b>14381</b>	16143	14861
2000	24064	25027	<b>23052</b>	24788	23806

\* Includes Census and Distance Variables

Table D.29: Comparison of MAEs for MLS Zone 6 (Spatial vs. Extra Variables)

In Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag	Gen. Spat.
1992	5402	<b>5374</b>	5508	5586	5542
1993	5515	<b>5476</b>	5656	5659	5661
1994	6023	<b>5891</b>	6006	6153	6092
1995	7181	7192	<b>7083</b>	7302	7204
1996	<b>6303</b>	6304	6545	6488	6452
1997	5829	<b>5814</b>	5825	6101	6068
1998	6343	<b>6162</b>	6468	6560	6511
1999	7243	<b>6841</b>	7323	7412	7371
2000	7973	<b>7870</b>	8062	8064	8046

Out of Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag.	Gen. Spat.
1992	6287	6687	<b>6137</b>	6144	6189
1993	5262	<b>5105</b>	5458	5469	5461
1994	6857	7288	6716	<b>6556</b>	6574
1995	7674	<b>7666</b>	7979	8113	8099
1996	8294	8312	8325	8323	<b>8253</b>
1997	8024	8662	7680	7681	<b>7631</b>
1998	6034	6188	5425	5702	<b>5417</b>
1999	9450	8836	<b>8183</b>	8556	8363
2000	9620	<b>9512</b>	9738	9770	9743

\* Includes Census and Distance Variables

Table D.30: Comparison of MAEs for MLS Zone 7 (Spatial vs. Extra Variables)

In Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag	Gen. Spat.
1992	13908	14083	<b>12704</b>	13513	13522
1993	14189	13931	<b>12651</b>	13948	14072
1994	14985	15910	14596	14848	<b>14550</b>
1995	15251	14548	<b>14467</b>	15371	15259
1996	14083	13608	<b>12855</b>	13918	13849
1997	13642	15206	<b>13026</b>	13437	13266
1998	13617	<b>12211</b>	12472	13412	13110
1999	16437	16077	<b>16060</b>	16434	16272
2000	21101	21881	<b>20030</b>	20930	20911

Out of Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag.	Gen. Spat.
1992	13867	14388	12374	<b>12102</b>	12309
1993	17292	16619	<b>14351</b>	16112	15492
1994	16529	17260	<b>15593</b>	16446	15763
1995	14628	14205	<b>12651</b>	13386	13307
1996	21513	21238	<b>20441</b>	22435	21536
1997	14388	16444	<b>13367</b>	13725	13513
1998	14445	13166	<b>12449</b>	14214	13369
1999	17217	16741	<b>15604</b>	17105	16405
2000	21016	21193	21405	<b>20242</b>	20800

\* Includes Census and Distance Variables

Table D.31: Comparison of MAEs for MLS Zone 8 (Spatial vs. Extra Variables)

In Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag	Gen. Spat.
1992	6008	6062	<b>5880</b>	6165	6149
1993	6162	6115	<b>5685</b>	6004	6090
1994	6561	6594	<b>6324</b>	6821	6643
1995	6211	<b>6145</b>	6241	6509	6406
1996	8078	8677	8087	8102	<b>8047</b>
1997	5988	5981	<b>5695</b>	6105	5942
1998	5750	5708	<b>5601</b>	5878	5796
1999	7164	7176	<b>7018</b>	7329	7251
2000	6495	<b>6363</b>	6755	6746	6752

Out of Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag.	Gen. Spat.
1992	5729	5909	6165	<b>5647</b>	5926
1993	5906	5869	<b>5595</b>	6360	6069
1994	6614	6784	<b>6291</b>	6409	6334
1995	9505	8526	9181	<b>8375</b>	8581
1996	8165	8166	7682	7515	<b>7478</b>
1997	6532	6749	<b>6224</b>	6301	6274
1998	5552	<b>5342</b>	5513	5941	5717
1999	5983	6021	<b>5689</b>	6420	6007
2000	8561	8524	<b>8460</b>	8609	8478

\* Includes Census and Distance Variables

Table D.32: Comparison of MAEs for MLS Zone 9 (Spatial vs. Extra Variables)

In Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag	Gen. Spat.
1992	11542	<b>11203</b>	11465	12785	13875
1993	11278	11177	<b>10853</b>	12155	12707
1994	13586	13264	<b>12928</b>	13442	13714
1995	13035	<b>12550</b>	13063	13387	13378
1996	10729	<b>10215</b>	10739	11264	11039
1997	10577	<b>9813</b>	10200	10705	10511
1998	9994	<b>9325</b>	9613	10008	9887
1999	10980	<b>10233</b>	11002	10931	10919
2000	<b>14364</b>	14451	14454	14404	14398

Out of Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag.	Gen. Spat.
1992	<b>12261</b>	12808	12744	14522	15553
1993	10593	<b>10579</b>	10611	10987	11581
1994	13750	13685	14188	<b>13277</b>	14693
1995	11232	<b>10483</b>	12148	11426	11977
1996	10186	9563	<b>9010</b>	9971	9396
1997	10357	<b>9823</b>	10192	10523	10151
1998	9300	8722	8559	8176	<b>8075</b>
1999	<b>11026</b>	11700	11622	11727	11726
2000	<b>11305</b>	12687	11819	12595	12451

\* Includes Census and Distance Variables

Table D.33: Comparison of MAEs for MLS Zone 10 (Spatial vs. Extra Variables)

In Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag	Gen. Spat.
1992	8089	8090	<b>7845</b>	8598	9344
1993	8250	7978	<b>7787</b>	8564	8429
1994	9107	8966	<b>8791</b>	9242	9105
1995	8986	8726	<b>8610</b>	9369	9055
1996	10151	10480	<b>10068</b>	10225	10134
1997	9881	10718	<b>9873</b>	10085	9885
1998	11999	12670	<b>11315</b>	11787	11472
1999	10298	10143	<b>9845</b>	10553	10331
2000	13556	<b>13535</b>	14048	13887	13889

Out of Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag.	Gen. Spat.
1992	9683	<b>8975</b>	10208	10387	11502
1993	12404	12330	<b>12098</b>	13287	12669
1994	9901	<b>8873</b>	9455	9797	9412
1995	9517	9287	<b>8878</b>	9625	9089
1996	8921	9297	9021	8782	<b>8774</b>
1997	9452	9718	<b>9268</b>	9572	9285
1998	10431	10876	<b>9800</b>	10323	9832
1999	12464	12264	<b>12122</b>	13215	12608
2000	13949	14313	<b>13247</b>	14054	13704

\* Includes Census and Distance Variables

Table D.34: Comparison of MAEs for MLS Zone 11 (Spatial vs. Extra Variables)

In Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag	Gen. Spat.
1992	6801	6781	<b>6746</b>	6867	6890
1993	5695	<b>5528</b>	5620	5784	5756
1994	6367	6265	<b>5732</b>	6395	6354
1995	6377	6095	<b>5745</b>	6471	6489
1996	6093	<b>5966</b>	6050	6236	6209
1997	7211	7245	<b>7062</b>	7290	7230
1998	6804	<b>6512</b>	6728	6852	6817
1999	7361	7282	<b>7250</b>	7456	7360
2000	<b>8144</b>	8196	8262	8268	8249

Out of Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag.	Gen. Spat.
1992	7412	7479	<b>7305</b>	7329	7476
1993	7990	8219	<b>7247</b>	7514	7346
1994	6346	6606	<b>6320</b>	6396	6741
1995	7211	7246	<b>6439</b>	6918	6883
1996	5872	<b>5775</b>	5989	5904	5976
1997	6586	6803	6541	<b>6418</b>	6656
1998	18368	<b>18004</b>	18269	18317	18288
1999	5994	6122	6024	6212	<b>5926</b>
2000	8702	<b>8658</b>	9075	8862	8852

\* Includes Census and Distance Variables

Table D.35: Comparison of MAEs for MLS Zone 14 (Spatial vs. Extra Variables)

In Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag	Gen. Spat.
1992	10715	10242	9745	9760	<b>9694</b>
1993	11215	<b>10814</b>	11316	11924	12141
1994	11148	10770	<b>10604</b>	11741	12504
1995	9210	<b>9155</b>	9635	9625	9621
1996	9522	9262	<b>9210</b>	9494	9514
1997	10814	<b>10173</b>	10614	10841	10822
1998	10122	<b>9461</b>	9849	10323	10124
1999	12613	<b>10434</b>	12536	12336	12352
2000	15859	<b>14947</b>	16680	16570	16599

Out of Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag.	Gen. Spat.
1992	10337	9811	<b>9106</b>	9844	9425
1993	18425	<b>17060</b>	17788	19150	19565
1994	13085	12583	14537	<b>12131</b>	13606
1995	11636	<b>11528</b>	12180	12316	12288
1996	14825	14585	14691	<b>13911</b>	14267
1997	9842	9793	8904	9000	<b>8880</b>
1998	13589	<b>12676</b>	13342	13881	13641
1999	14204	14128	13965	14145	<b>13935</b>
2000	20637	20770	17368	<b>16917</b>	17007

\* Includes Census and Distance Variables



Table D.36: Comparison of MAEs for MLS Zone 16 (Spatial vs. Extra Variables)

In Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag	Gen. Spat.
1992	6761	<b>6268</b>	6303	7207	7321
1993	6821	<b>6780</b>	7000	6980	6962
1994	7733	7601	<b>7314</b>	7724	7574
1995	6743	6597	<b>6353</b>	6628	6529
1996	7613	<b>7164</b>	7663	7706	7713
1997	7267	<b>7137</b>	7417	7540	7558
1998	6869	<b>6562</b>	6725	7101	6965
1999	11646	11808	<b>10827</b>	11480	13273
2000	11381	<b>11370</b>	11630	11722	11723

Out of Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag.	Gen. Spat.
1992	5832	<b>5284</b>	7384	6272	7028
1993	<b>8192</b>	9002	10632	23627	19423
1994	8607	8569	<b>7475</b>	8411	7742
1995	6161	<b>5909</b>	5959	6525	6215
1996	7733	7650	<b>7595</b>	7721	7638
1997	9848	<b>8858</b>	10138	10193	10310
1998	<b>7918</b>	8312	8037	8041	7924
1999	<b>10696</b>	11740	12985	11198	15095
2000	13806	11864	<b>11511</b>	13291	11529

\* Includes Census and Distance Variables

Table D.37: Comparison of MAEs for MLS Zone 18 (Spatial vs. Extra Variables)

In Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag	Gen. Spat.
1992	6193	<b>6149</b>	6409	6743	6612
1993	7251	7052	<b>7023</b>	7795	7601
1994	9553	9439	<b>9207</b>	9751	9530
1995	6804	<b>6629</b>	6890	7441	7422
1996	7056	<b>6985</b>	7292	7454	7504
1997	10204	11206	10141	10078	<b>10065</b>
1998	8502	<b>8403</b>	8512	8780	8777
1999	9135	<b>9052</b>	9366	9379	9472
2000	10389	<b>9902</b>	10712	10408	10432

Out of Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag.	Gen. Spat.
1992	7208	<b>7119</b>	7191	7630	7315
1993	7895	7771	<b>7524</b>	7692	7718
1994	8653	8721	8141	8646	<b>8096</b>
1995	10780	<b>10122</b>	10809	12711	11825
1996	11138	<b>10555</b>	10971	11536	11191
1997	9737	9907	9603	9488	<b>9468</b>
1998	12498	12638	<b>12060</b>	12981	12345
1999	8836	<b>8512</b>	8513	9127	8922
2000	12310	12282	<b>11362</b>	11875	11851

\* Includes Census and Distance Variables

Table D.38: Comparison of MAEs for MLS Zone 21 (Spatial vs. Extra Variables)

In Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag	Gen. Spat.
1992	5871	5944	<b>5870</b>	6224	6551
1993	<b>5756</b>	5800	5763	6165	6211
1994	7570	<b>7542</b>	7603	7931	7823
1995	6911	6694	<b>6543</b>	7257	7083
1996	<b>8130</b>	9184	8539	8323	8395
1997	6730	<b>6439</b>	6654	7492	7791
1998	7273	<b>7033</b>	7291	7578	7646
1999	7589	<b>7536</b>	7586	7952	7892
2000	9539	<b>9477</b>	9606	9675	9764

Out of Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag.	Gen. Spat.
1992	8204	9220	<b>7834</b>	8483	8094
1993	10524	<b>10334</b>	10678	11104	11244
1994	8719	9320	<b>6933</b>	8694	7460
1995	8014	<b>7744</b>	8452	7972	8015
1996	<b>9541</b>	10571	10327	10167	10368
1997	<b>7161</b>	7245	7268	7634	8209
1998	7576	<b>6762</b>	7192	7167	7504
1999	9026	<b>8702</b>	9808	9498	9622
2000	20461	18689	<b>16976</b>	17261	17207

\* Includes Census and Distance Variables

Table D.39: Comparison of MAEs for MLS Group A (Spatial vs. Extra Variables)

In Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag	Gen. Spat.
1992	12378	12079	<b>11113</b>	12055	11855
1993	12658	12179	<b>11546</b>	12870	12617
1994	13714	13949	<b>12832</b>	13850	13512
1995	13840	<b>13052</b>	13283	14531	14342
1996	12987	12431	<b>12169</b>	13466	13194
1997	13488	13342	<b>12776</b>	13819	13506
1998	13668	<b>12268</b>	12432	13872	13657
1999	15758	<b>14438</b>	14923	16265	16017
2000	19152	18815	<b>18707</b>	19814	19719

Out of Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag.	Gen. Spat.
1992	10814	10480	<b>9963</b>	10773	10394
1993	14577	13503	<b>13240</b>	15059	14191
1994	15125	15439	<b>13627</b>	14901	14073
1995	12151	11705	<b>10728</b>	11807	11401
1996	16930	16435	<b>16113</b>	17181	16649
1997	12002	11812	<b>11290</b>	11510	11578
1998	15517	14248	<b>13811</b>	15895	14898
1999	17769	16176	<b>15948</b>	17872	16689
2000	22184	22228	<b>21394</b>	21404	21508

\* Includes Census and Distance Variables

Table D.40: Comparison of MAEs for MLS Group B (Spatial vs. Extra Variables)

In Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag	Gen. Spat.
1992	7090	6977	<b>6724</b>	7102	7060
1993	7153	7009	<b>6708</b>	7379	7230
1994	7643	7523	<b>7068</b>	7859	7639
1995	7416	7255	<b>6844</b>	7590	7383
1996	7879	7948	<b>7700</b>	8043	7905
1997	7475	7469	<b>7253</b>	7625	7456
1998	7172	7030	<b>6924</b>	7442	7403
1999	8450	8403	<b>8306</b>	8719	8635
2000	9890	<b>9845</b>	10292	10506	10424

Out of Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag.	Gen. Spat.
1992	6347	<b>6286</b>	6396	6466	6516
1993	7942	7797	<b>6977</b>	7970	7473
1994	8518	8119	<b>6721</b>	7568	7241
1995	7747	7867	<b>7614</b>	8415	7860
1996	7854	7910	<b>7504</b>	7892	7707
1997	7075	7062	<b>6743</b>	7066	6855
1998	9335	9065	<b>8979</b>	9452	9369
1999	7723	7726	<b>7425</b>	7689	7476
2000	<b>10081</b>	10130	10443	10132	10159

\* Includes Census and Distance Variables

Table D.41: Comparison of MAEs for MLS Group C (Spatial vs. Extra Variables)

In Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag	Gen. Spat.
1992	10753	10690	<b>9916</b>	10720	10739
1993	12103	12031	<b>10525</b>	12031	11869
1994	12765	12579	<b>11597</b>	12700	12353
1995	12885	12598	<b>12080</b>	13112	12813
1996	12107	12138	<b>11506</b>	12278	11955
1997	12231	12710	<b>11739</b>	12302	12027
1998	13186	13421	<b>12318</b>	13033	12808
1999	14112	13696	<b>13180</b>	14173	14024
2000	17363	17390	<b>16946</b>	17758	17544

Out of Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag.	Gen. Spat.
1992	10718	10640	<b>9484</b>	10566	10309
1993	12896	12813	<b>11425</b>	13072	12447
1994	12762	12677	<b>11366</b>	12321	11866
1995	12017	11973	<b>10908</b>	12253	11586
1996	11365	11369	<b>10838</b>	11712	11321
1997	11089	11392	<b>10419</b>	11156	10559
1998	10918	11037	<b>10189</b>	10663	10382
1999	13854	13443	<b>13237</b>	14517	13876
2000	20287	20215	<b>19410</b>	21107	20343

\* Includes Census and Distance Variables

Table D.42: Comparison of MAEs for Wake County (Spatial vs. Extra Variables)

In Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag	Gen. Spat.
1992	11439	11073	<b>10231</b>	11167	11074
1993	11870	11519	<b>10386</b>	11859	11704
1994	12673	12218	<b>11160</b>	12609	12200
1995	12736	12141	<b>11449</b>	12908	13183
1996	12331	11929	<b>11251</b>	12585	12160
1997	12464	12094	<b>11469</b>	12820	12443
1998	12746	12059	<b>11369</b>	13084	13123
1999	14781	13455	<b>13099</b>	15288	15768
2000	18458	17779	<b>17371</b>	19511	20972
Out of Sample					
Year	OLS*	Box-Cox*	Spat. Err.	Spat. Lag.	Gen. Spat.
1992	10679	10216	<b>9280</b>	10424	10026
1993	12942	12353	<b>11223</b>	13025	12450
1994	12806	12297	<b>10710</b>	12018	11380
1995	11621	11275	<b>10251</b>	11767	11581
1996	13083	12735	<b>11847</b>	12875	12524
1997	11540	11032	<b>10544</b>	11936	11204
1998	13399	12550	<b>11381</b>	13223	12753
1999	14189	13027	<b>12795</b>	15498	15147
2000	20872	20517	<b>18931</b>	20743	21659

\* Includes Census and Distance Variables

## Appendix E

# Sample Regression Results

Table E.1: 1992 OLS Estimates (Base Spec., All Observations)

Variable	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Zone 7	Zone 8	Zone 9	Zone 10
intercept	10.385**	10.024**	9.7076**	10.385**	10.203**	9.5928**	10.549**	9.5051**	9.8969**	9.7124**
baths	0.0272**	0.0325**	0.0119	0.0272**	0.0177**	0.0467**	0.0339**	0.019**	0.0398**	0.0208*
regheatarea	0.4622**	0.428**	0.5522**	0.4622**	0.4313**	0.371**	0.5317**	0.5161**	0.5171**	0.5035**
sqregheat	-0.04**	-0.039**	-0.088**	-0.04**	-0.038**	-0.032	-0.055**	-0.059**	-0.052**	-0.055**
acrage1	0.183**	.	.	.	.	.	.	.	.	.
sqacre1	-0.007**	.	.	.	.	.	.	.	.	.
acrage2	.	0.145**	.	.	.	.	.	.	.	.
sqacre2	.	-0.042**	.	.	.	.	.	.	.	.
acrage3	.	.	0.2009**	.	.	.	.	.	.	.
sqacre3	.	.	-0.017	.	.	.	.	.	.	.
acrage4	.	.	.	0.183**	.	.	.	.	.	.
sqacre4	.	.	.	-0.007**	.	.	.	.	.	.
acrage5	.	.	.	.	0.1025**	.	.	.	.	.
sqacre5	.	.	.	.	-0.007	.	.	.	.	.
acrage6	.	.	.	.	.	0.1431**	.	.	.	.
sqacre6	.	.	.	.	.	-0.008**	.	.	.	.
acrage7	.	.	.	.	.	.	0.1096**	.	.	.
sqacre7	.	.	.	.	.	.	-0.013**	.	.	.
acrage8	.	.	.	.	.	.	.	-0.076**	.	.
sqacre8	.	.	.	.	.	.	.	0.0165**	.	.
acrage9	.	.	.	.	.	.	.	.	0.0192*	.
sqacre9	.	.	.	.	.	.	.	.	0.0016	.
acrage10	.	.	.	.	.	.	.	.	.	0.0607**
sqacre10	.	.	.	.	.	.	.	.	.	-0.001
acrage11	.	.	.	.	.	.	.	.	.	.
sqacre11	.	.	.	.	.	.	.	.	.	.
acrage14	.	.	.	.	.	.	.	.	.	.
sqacre14	.	.	.	.	.	.	.	.	.	.
acrage16	.	.	.	.	.	.	.	.	.	.
sqacre16	.	.	.	.	.	.	.	.	.	.
acrage18	.	.	.	.	.	.	.	.	.	.
sqacre18	.	.	.	.	.	.	.	.	.	.
acrage21	.	.	.	.	.	.	.	.	.	.
sqacre21	.	.	.	.	.	.	.	.	.	.
age	0.0418**	-0.009**	-0.009**	0.0418**	-0.009**	-0.007**	-0.005**	-0.004**	-0.005**	-0.011**
sqage	0.0018**	0.0001**	304E-7	0.0018**	0.0001**	138E-7	59E-6**	-46E-6	531E-7	0.0001**
bsmtheat	0.1075**	0.0001**	0.0001**	0.1075**	0.0001**	0.0001**	0.0001**	674E-8	563E-7	0.0001**
bsmtunheat	-0.003**	-59E-7	0.0003**	-0.003**	515E-7**	0.0001	334E-7	0.0001	0.0001**	405E-7
atticheat	-0.006**	0.0001**	0.0002*	-0.006**	0.0001**	0.0002**	0.0001**	0.0001**	0.0002**	0.0002**
atticunheat	0.0001**	0.0001**	354E-8	0.0001**	347E-7**	0.0001	594E-8	0.0001**	282E-7	413E-7
otherunheatarea	0.0001**	0.0001	-0.005	0.0001**	0.0001**	-12E-6	0.0001**	0.0002*	-8E-6	0.0001
walldum1	327E-7	0.0069	-0.017	327E-7	0.0183**	0.0012	0.0389**	0.065**	0.0202	0.0414
bsmtdum1	0.0002**	0.0825**	0.0064	0.0002**	0.0702**	0.09**	0.0491**	0.1211**	0.0839**	0.0641
bsmtdum2	0.0001**	0.0722**	0.0297	0.0001**	0.0714**	0.0471*	0.0525**	0.118**	0.0722**	0.035
heatdum6	0.0002**	.	-0.021	0.0002**	-0.001	0.0877	.	.	0.3022**	0.1144
heatdum7	0.0139	.	0.3685**	0.0139	.	-0.179	-0.466**	.	.	0.3831**
acdum1	0.0719**	0.0917**	0.096**	0.0719**	0.0264	0.0796**	-0.357**	0.1092*	0.2216**	0.2767**
story	0.0753**	-0.001	0.0009	0.0753**	-0.035**	-0.034**	-0.065**	-0.012	-0.031**	0.029
detgarage	-0.157**	0.0408**	-0.016	-0.157**	0.0823**	0.0495**	0.0138	0.0162	0.013	0.0085
condadum	-0.282**	-0.031**	0.0262	-0.282**	0.0119	.	-0.001	.	.	.
condcdum	0.1426**	-0.047**	-0.079**	0.1426**	-0.046	-0.013	-0.092**	-0.042**	-0.071**	-0.012
condddum	-0.062**	.	-0.21**	-0.062**	.	-0.138**	.	0.0439	.	-0.03
carport	0.0978**	0.0001**	0.0002**	0.0978**	0.0001**	0.0001**	-42E-6	0.0001	-45E-7	0.0001
encporch	-0.032	0.0003**	-67E-6	-0.032	0.0002**	-11E-5	-12E-5	0.0005**	0.0003**	0.0006**
scrporch	-0.095*	0.0001**	0.0005**	-0.095*	0.0002**	0.0001	0.0003**	0.0002**	0.0002**	-72E-6
opnporch	-46E-6	0.0001**	-34E-6	-46E-6	0.0002**	201E-7	0.0001**	0.0002**	0.0001**	31E-6
garage	0.0005**	0.0002**	0.0003**	0.0005**	0.0002**	0.0002**	0.0001**	0.0002**	0.0002**	0.0001**
storage	0.0001**	0.0002**	0.0005**	0.0001**	0.0002**	-63E-6	142E-7	-29E-5	-1E-4	147E-7
patio	0.0001**	2E-5	0.0001	0.0001**	0.0001**	-69E-6	155E-8	-67E-6	0.0002**	15E-6
deck	0.0002**	0.0001**	0.0002**	0.0002**	0.0001**	141E-7	0.0001**	0.0002**	0.0001**	0.0001
stoop	0.0001	0.0003**	0.0001	0.0001	0.0007**	0.0001	0.0007**	0.0005	0.0001	0.0004
fireplaces	407E-7*	0.0558**	0.0564**	407E-7*	0.0357**	0.0212	-0.007	0.0168	0.0665**	0.0454**
poolres	0.0001**	0.0207	0.1964	0.0001**	0.059**	-0.018	0.0197	0.0106	0.0033	-0.012
grade	0.0004**	0.0063**	0.0076**	0.0004**	0.0059**	0.0108**	0.0056**	0.0107**	0.0052**	0.0068**
nobs	2866	1679	289	2866	2095	392	983	555	648	356
rsqr	0.9219	0.9265	0.9047	0.9219	0.9493	0.8982	0.9282	0.8998	0.9124	0.9206

\* Significant at .10 level

\*\* Significant at .05 level

Table E.1(continued)

Variable	Zone 11	Zone 14	Zone 16	Zone 18	Zone 21	Group 1	Group 2	Group 3	Wake Co.
intercept	9.956**	9.9011**	9.3117**	9.3279**	9.2548**	10.006**	9.5378**	10.041**	9.9936**
baths	0.0556**	0.0468**	0.0264	0.0427**	0.0548**	0.0295**	0.0463**	0.0239**	0.029**
regheatarea	0.6158**	0.4627**	0.7055**	0.6576**	0.6523**	0.4807**	0.6179**	0.4583**	0.5093**
sqregheat	-0.087**	-0.037**	-0.125**	-0.111**	-0.089**	-0.048**	-0.092**	-0.043**	-0.055**
acreage1	.	.	.	.	.	.	.	.	0.3966**
sqacre1	.	.	.	.	.	.	.	.	-0.146**
acreage2	.	.	.	.	.	0.2083**	.	.	0.22**
sqacre2	.	.	.	.	.	-0.068**	.	.	-0.08**
acreage3	.	.	.	.	.	.	-0.011	.	-0.149**
sqacre3	.	.	.	.	.	.	0.0195**	.	0.0529**
acreage4	.	.	.	.	.	.	.	.	0.0379
sqacre4	.	.	.	.	.	.	.	.	0.0374**
acreage5	.	.	.	.	.	.	.	0.0685**	0.2289**
sqacre5	.	.	.	.	.	.	.	0.0176	-0.069**
acreage6	.	.	.	.	.	.	0.052**	.	-0.013
sqacre6	.	.	.	.	.	.	0.001	.	0.0073**
acreage7	.	.	.	.	.	0.1043**	.	.	0.0893**
sqacre7	.	.	.	.	.	-0.011**	.	.	-0.007**
acreage8	.	.	.	.	.	.	0.0591**	.	0.0213
sqacre8	.	.	.	.	.	.	-0.002	.	0.0057*
acreage9	.	.	.	.	.	.	.	0.0306**	0.0703**
sqacre9	.	.	.	.	.	.	.	0.0009	-0.00064
acreage10	.	.	.	.	.	.	.	0.0359**	0.0737**
sqacre10	.	.	.	.	.	.	.	0.0002	-0.002**
acreage11	0.0216	.	.	.	.	.	-0.012	.	-0.038**
sqacre11	-0.001	.	.	.	.	.	0.0047**	.	0.0092**
acreage14	.	0.1103**	.	.	.	0.0713**	.	.	0.0748**
sqacre14	.	-0.016**	.	.	.	-0.007**	.	.	-0.007**
acreage16	.	.	0.1439**	.	.	.	-0.048**	.	-0.066**
sqacre16	.	.	-0.046**	.	.	.	0.0304**	.	0.034**
acreage18	.	.	.	0.036	.	.	-0.02*	.	-0.042**
sqacre18	.	.	.	0.0018	.	.	0.0155**	.	0.0193**
acreage21	.	.	.	.	0.0135	.	0.0176*	.	0.012
sqacre21	.	.	.	.	0.0022	.	0.0028**	.	0.0035**
age	-0.007**	-0.005**	-0.004*	-0.008**	-0.007**	-0.007**	-0.006**	-0.008**	-0.007**
sqage	499E-8	412E-7	408E-9	0.0001*	0.0001**	562E-7**	354E-8	596E-7**	0.0000453**
bsmtheat	0.0001**	0.0002**	987E-8	0.0002**	111E-7	0.0001**	0.0001**	0.0001**	0.0001**
bsmtunheat	0.0001*	0.0002	0.0002	0.0004**	-28E-5	129E-8	0.0001**	0.0001**	0.0000198*
atticunheat	0.0003**	0.0002**	0.0003**	0.0002**	0.0002**	0.0001**	0.0002**	0.0002**	0.0002**
otherunheatarea	0.0001	-96E-6	0.0002**	-81E-6	-81E-6*	395E-7**	0.0001**	302E-7**	0.0000449**
walldum1	0.0463**	0.0784**	0.0315	0.0214	0.0429	0.0156**	0.0217**	0.0214**	0.0133**
bsmtum1	0.1225**	0.007	0.1558*	0.1489**	0.0738	0.076**	0.1028**	0.0692**	0.0904**
bsmtum2	0.0767**	-0.005	0.1029*	0.0471	0.0977	0.0682**	0.0693**	0.0715**	0.0806**
heatdum6	.	.	-0.216*	0.5893**	.	.	-0.049	0.0813*	-0.052**
heatdum7	0.3048**	-0.376**	-0.198	.	-0.3**	-0.251**	0.0455	0.25**	-0.101**
acdum1	0.1073**	0.0031	0.1034	0.0369	0.2305**	0.0691**	0.0948**	0.1237**	0.0793**
story	-0.002	-0.024	-0.044*	0.0155	-0.036**	-0.019**	-0.011	-0.025**	-0.016**
detgarage	0.0478**	-0.025	0.0672**	0.0654**	0.0654**	0.0431**	0.0525**	0.0463**	0.0494**
condadum	.	0.027	.	.	.	-0.02**	-0.017	0.0082	0.0374**
condcdum	-0.041*	-0.134**	-0.122**	0.0287	-0.015	-0.073**	-0.037**	-0.048**	-0.079**
condddum	-0.164**	-0.41**	1.0175**	-0.39**	0.0774	-0.421**	-0.108**	-0.107*	-0.26**
carport	224E-7	0.0002	0.0002**	292E-7	-99E-6	0.0001**	0.0001**	54E-6*	0.0001**
encporch	144E-7	0.001**	0.0004	0.0002	0.0002	0.0002**	0.0002**	0.0003**	0.0002**
scrporch	0.0003**	0.0004**	0.0001	0.0002	-23E-7	0.0002**	0.0002**	0.0001**	0.0002**
opnporch	0.0003**	0.0003**	0.0002**	41E-6	541E-7	0.0001**	0.0001**	0.0001**	0.0001**
garage	0.0002**	0.0001**	0.0002**	0.0002**	0.0001**	0.0002**	0.0002**	0.0002**	0.0002**
storage	-16E-5	0.0004	402E-7	0.0002	0.0001	0.0001	0.0001	0.0002**	0.0001**
patio	251E-7	0.0002**	-54E-6	0.0001	-44E-6	165E-7	958E-8	0.0001**	0.0000582**
deck	0.0001**	0.0002**	-37E-6	0.0002**	341E-7	0.0001**	0.0002**	0.0001**	0.0001**
stoop	0.0007**	0.0009	0.0001	303E-7	0.0002	0.0004**	0.0003**	0.0005**	0.0003**
fireplaces	0.0803**	0.1382**	0.071**	0.0455**	0.0014	0.0487**	0.0549**	0.0422**	0.0628**
poolres	-0.038	0.0984	0.0803	0.1638**	0.0475	0.02	0.0216	0.0242*	0.019**
grade	0.0035**	0.0057**	0.0098**	0.0102**	0.0102**	0.0061**	0.0084**	0.0059**	0.0056**
nobs	495	239	281	307	364	2901	2683	3099	9461
rsqr	0.9012	0.9407	0.9029	0.9285	0.9235	0.9317	0.8979	0.9365	0.9326

\* Significant at .10 level

\*\* Significant at .05 level

Table E.2: 1992 OLS Estimates (Full Spec., All Observations)

Variable	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Zone 7	Zone 8	Zone 9	Zone 10
intercept	10.511**	9.7778**	9.3178**	10.511**	9.9734**	10.137**	7.6881**	6.8868**	10.179**	10.089**
baths	0.0262**	0.0354**	0.0081	0.0262**	0.0209**	0.0443**	0.0323**	0.0237**	0.0298**	0.0106
regheatarea	0.4302**	0.3738**	0.4615**	0.4302**	0.4208**	0.371**	0.5035**	0.4953**	0.4336**	0.3758**
sregheat	-0.037**	-0.03**	-0.069*	-0.037**	-0.037**	-0.033	-0.051**	-0.058**	-0.037**	-0.031*
acreage1	0.1479**	.	.	.	.	.	.	.	.	.
sqacre1	-0.003	.	.	.	.	.	.	.	.	.
acreage2	.	0.1192**	.	.	.	.	.	.	.	.
sqacre2	.	-0.033**	.	.	.	.	.	.	.	.
acreage3	.	.	0.1611**	.	.	.	.	.	.	.
sqacre3	.	.	-0.008	.	.	.	.	.	.	.
acreage4	.	.	.	0.1479**	.	.	.	.	.	.
sqacre4	.	.	.	-0.003	.	.	.	.	.	.
acreage5	.	.	.	.	0.1265**	.	.	.	.	.
sqacre5	.	.	.	.	-0.016	.	.	.	.	.
acreage6	.	.	.	.	.	0.1233**	.	.	.	.
sqacre6	.	.	.	.	.	-0.006*	.	.	.	.
acreage7	.	.	.	.	.	.	0.0827**	.	.	.
sqacre7	.	.	.	.	.	.	-0.008**	.	.	.
acreage8	.	.	.	.	.	.	.	-0.053**	.	.
sqacre8	.	.	.	.	.	.	.	0.0144**	.	.
acreage9	.	.	.	.	.	.	.	.	0.0718**	.
sqacre9	.	.	.	.	.	.	.	.	-0.002**	.
acreage10	.	.	.	.	.	.	.	.	.	0.0645**
sqacre10	.	.	.	.	.	.	.	.	.	-92E-5
acreage11	.	.	.	.	.	.	.	.	.	.
sqacre11	.	.	.	.	.	.	.	.	.	.
acreage14	.	.	.	.	.	.	.	.	.	.
sqacre14	.	.	.	.	.	.	.	.	.	.
acreage16	.	.	.	.	.	.	.	.	.	.
sqacre16	.	.	.	.	.	.	.	.	.	.
acreage18	.	.	.	.	.	.	.	.	.	.
sqacre18	.	.	.	.	.	.	.	.	.	.
acreage21	.	.	.	.	.	.	.	.	.	.
sqacre21	.	.	.	.	.	.	.	.	.	.
age	0.0679**	-0.008**	-0.006**	0.0679**	-0.01**	-0.007**	-0.006**	-0.001	-0.006**	-0.013**
sqage	0.0007*	0.0001**	235E-7	0.0007*	0.0001**	262E-7	0.0001**	-13E-5**	0.0001	0.0001**
bsmtheat	0.1148**	0.0001**	0.0001**	0.1148**	0.0001**	0.0001**	0.0001**	368E-7	609E-7	0.0001
bsmtunheat	-0.003**	202E-8	0.0004**	-0.003**	57E-6**	0.0001	328E-7	0.0002*	0.0001**	-19E-6
atticheat	-0.007**	0.0001**	0.0002**	-0.007**	0.0001**	0.0002**	0.0001**	0.0001**	0.0002**	0.0001**
atticunheat	0.0001**	0.0001**	332E-7	0.0001**	309E-7**	0.0001	115E-7	0.0001**	0.0001**	432E-7
otherunheatarea	0.0001**	504E-7	-0.005	0.0001**	0.0001**	-1E-5	0.0001*	0.0002**	445E-7	0.0002
walldum1	419E-7*	0.0099	-0.008	419E-7*	0.0197**	0.0084	0.0394**	0.0592**	0.0352**	0.0502*
bsmtum1	0.0002**	0.0812**	0.0192	0.0002**	0.0652**	0.0997**	0.0342*	0.0876**	0.0881**	0.1**
bsmtum2	0.0001**	0.0688**	0.0484	0.0001**	0.0675**	0.0604**	0.0482**	0.0823**	0.0654**	0.0137
heatdum6	0.0002**	.	-0.023	0.0002**	-0.009	0.0768	.	.	0.2254**	0.0477
heatdum7	0.0188**	.	0.3261**	0.0188**	.	-0.168	-0.423**	.	.	0.2579**
acdum1	0.0689**	0.0793**	0.102**	0.0689**	0.0159	0.0629**	-0.292**	0.1155**	0.2191**	0.2319**
story	0.0718**	-0.005	-0.006	0.0718**	-0.036**	-0.031*	-0.062**	-0.018	-0.028**	0.0143
detgarage	-0.162**	0.0378**	0.0009	-0.162**	0.0882**	0.0467**	0.0181	0.0176	0.0143	0.0567*
condadum	-0.316**	-0.013	0.0449	-0.316**	0.0264	.	0.039**	.	.	.
condcdum	0.1414**	-0.04**	-0.029	0.1414**	-0.032	-0.028	-0.08**	-0.041*	-0.094**	-0.056*
condddum	-0.057**	.	-0.123**	-0.057**	.	-0.114*	.	0.0598	.	-0.065
carport	0.0872**	596E-7*	0.0002**	0.0872**	0.0001**	0.0001**	269E-7	0.0001*	-92E-7	0.0001
encporch	-0.035*	0.0003**	-22E-5	-0.035*	0.0002**	-12E-5	-16E-5	0.0004**	0.0002	0.0007**
scrporch	-0.094*	0.0001**	0.0005**	-0.094*	0.0002**	0.0001	0.0003**	0.0002**	0.0001*	266E-7
opnporch	-32E-6	0.0001**	451E-7	-32E-6	0.0002**	278E-7	0.0001*	0.0002**	0.0002**	0.0001
garage	0.0004**	0.0002**	0.0002**	0.0004**	0.0002**	0.0002**	0.0001**	0.0002**	0.0002**	0.0002**
storage	0.0001**	0.0002**	0.0004**	0.0001**	0.0002**	-19E-6	136E-7	-38E-5**	-13E-6	-48E-6
patio	0.0002**	2E-5	431E-7	0.0002**	0.0001**	-78E-6	267E-7	-46E-6	0.0001	0.0001
deck	0.0002**	0.0001**	0.0002**	0.0002**	0.0001**	3E-5	0.0001**	0.0002**	0.0001**	0.0001
stoop	0.0001	0.0003**	0.0001	0.0001	0.0007**	0.0002	0.0005**	0.0006*	-81E-6	0.0005*
fireplaces	412E-7*	0.0501**	0.0441**	412E-7*	0.0304**	0.0162	-0.011	0.0196	0.0707**	0.043**
poolres	0.0001**	0.0086	0.1906	0.0001**	0.0598**	-0.01	0.0155	0.0064	0.0159	0.0033
grade	0.0004**	0.0058**	0.0081**	0.0004**	0.0055**	0.0103**	0.0049**	0.0088**	0.0047**	0.0052**
perc.nonwhite.1990	0.0265**	-88E-5	0.0004	0.0265**	-7E-5	0.0004	0.0113**	0.0112**	0.0012	-38E-6
medianvalue	0.0462**	116E-8**	257E-8**	0.0462**	165E-9*	39E-8	-58E-8	564E-9	28E-10	176E-8
medttw	0.0055**	0.0013	-24E-5	0.0055**	-92E-5	0.0057	0.0066**	-0.01	-0.005**	0.0009
perc_under18	-37E-5	-0.001	0.0048*	-37E-5	-97E-6	0.0014	0.0494**	0.0202**	-0.003	0.0004
perc_owner_occ	458E-9**	0.0004	0.0005	458E-9**	0.0008**	-28E-5	0.0079**	0.0025**	0.0022**	0.0003
nearestpark	-55E-5	0.0039	-0.009	-55E-5	0.0003	0.0203**	0.0042	-0.01	0.0071	-0.004
nearestsc	-0.001*	-0.012**	0.0386	-0.001*	-0.002	0.0617**	-0.022**	-0.125**	-0.006	-0.02**
bigparkdistance	0.0001	0.0037**	-0.002	0.0001	0.004**	-0.014**	0.0097**	0.0347**	-0.002	-54E-5
taxrate	0.0024	-0.003	0.0777*	0.0024	0.0343**	0.0159	0.1061**	0.0211	0.2211**	-0.019
nobs	2866	1679	289	2866	2095	392	983	555	648	356
rsqr	0.9249	0.932	0.9121	0.9249	0.9511	0.8992	0.9359	0.9133	0.9292	0.9305

\* Significant at .10 level

\*\* Significant at .05 level



Table E.2(continued)

Variable	Zone 11	Zone 14	Zone 16	Zone 18	Zone 21	Group 1	Group 2	Group 3	Wake Co.
intercept	10.445**	8.8528**	8.9667**	9.4486**	8.6575**	9.6315**	9.4478**	10.054**	10.046**
baths	0.0467**	0.0384*	0.036	0.0358**	0.062**	0.0299**	0.0394**	0.0234**	0.0285**
regheatarea	0.5016**	0.4619**	0.6469**	0.5982**	0.579**	0.4643**	0.5533**	0.4458**	0.4742**
sregheat	-0.061**	-0.036**	-0.114**	-0.095**	-0.077**	-0.045**	-0.077**	-0.041**	-0.048**
acrage1	.	.	.	.	.	.	.	.	0.2577**
sqacre1	.	.	.	.	.	.	.	.	-0.057
acrage2	.	.	.	.	.	0.173**	.	.	0.1739**
sqacre2	.	.	.	.	.	-0.048**	.	.	-0.059**
acrage3	.	.	.	.	.	.	0.0088	.	-0.102**
sqacre3	.	.	.	.	.	.	0.0151*	.	0.0447**
acrage4	.	.	.	.	.	.	.	.	0.0678**
sqacre4	.	.	.	.	.	.	.	.	0.03*
acrage5	.	.	.	.	.	.	.	0.0085	0.0923**
sqacre5	.	.	.	.	.	.	.	0.0617**	0.0097
acrage6	.	.	.	.	.	.	0.063**	.	0.0023
sqacre6	.	.	.	.	.	.	-17E-5	.	0.0057**
acrage7	.	.	.	.	.	0.081**	.	.	0.0424**
sqacre7	.	.	.	.	.	-0.007**	.	.	0.0018
acrage8	.	.	.	.	.	.	0.0179	.	0.0389**
sqacre8	.	.	.	.	.	.	0.0055*	.	0.0039
acrage9	.	.	.	.	.	.	.	0.0669**	0.0755**
sqacre9	.	.	.	.	.	.	.	-0.001*	-0.001**
acrage10	.	.	.	.	.	.	.	0.048**	0.0713**
sqacre10	.	.	.	.	.	.	.	-34E-5	-0.002**
acrage11	0.053**	.	.	.	.	.	0.0183	.	0.043**
sqacre11	-0.004*	.	.	.	.	.	0.0014	.	-0.0006
acrage14	.	0.0611	.	.	.	0.1216**	.	.	0.1332**
sqacre14	.	-0.009	.	.	.	-0.014**	.	.	-0.017**
acrage16	.	.	0.2385**	.	.	.	0.0219	.	-0.00066
sqacre16	.	.	-0.073**	.	.	.	0.0146**	.	0.0201**
acrage18	.	.	.	0.0077	.	.	-0.021	.	-0.002
sqacre18	.	.	.	0.009	.	.	0.0149**	.	0.0102**
acrage21	.	.	.	.	0.0507**	.	0.0211**	.	0.0541**
sqacre21	.	.	.	.	-9E-4	.	0.003**	.	-0.00066
age	-0.007**	-0.004*	-0.004	-0.007**	-0.012**	-0.007**	-0.007**	-0.008**	-0.007**
sqage	151E-7	245E-7	-99E-7	0.0001	0.0002**	0.0001**	157E-7*	0.0001**	0.0000538**
bsmtheat	0.0001**	0.0002**	-18E-6	0.0002*	-29E-6	0.0001**	0.0001**	0.0001**	0.0001**
bsmtunheat	0.0001	0.0001	0.0002	0.0003**	-51E-5	284E-8	0.0001**	595E-7**	0.0000208**
atticheat	0.0003**	0.0003**	0.0002**	0.0002*	0.0001**	0.0001**	0.0002**	0.0001**	0.0002**
atticunheat	0.0001*	-1E-4	0.0002**	-83E-6	-73E-6	378E-7**	0.0001**	302E-7**	0.0000396**
otherunheatarea	0.0003	0.0001	.	-68E-6	.	0.0001**	0.0001	0.0001**	0.0001**
walldum1	0.0559**	0.068**	0.0328	0.0186	0.0473	0.017**	0.0297**	0.0239**	0.016**
bsmtum1	0.1174**	0.0113	0.1842**	0.1546**	0.0878**	0.0741**	0.1021**	0.0674**	0.0883**
bsmtum2	0.0672**	0.0114	0.1001*	0.0185	0.1162**	0.0678**	0.0729**	0.0663**	0.0794**
heatdum6	.	.	-0.165	0.6086**	.	.	-0.07**	0.0498	-0.065**
heatdum7	0.2852**	-0.467**	-0.217*	.	-0.387**	-0.23**	0.0532	0.2178**	-0.092**
acdum1	0.1051**	0.0236	0.1088*	-0.008	0.2483**	0.066**	0.0907**	0.1057**	0.0728**
story	0.0034	-0.021	-0.038*	0.0099	-0.033*	-0.021**	-0.014**	-0.028**	-0.017**
detgarage	0.0566**	-0.024	0.0729**	0.0591**	0.0643**	0.0451**	0.0476**	0.0529**	0.0469**
condadum	.	0.0033	.	.	.	0.0006	-0.006	0.024	0.0396**
condcdum	-0.036	-0.137**	-0.119**	0.0665**	-0.003	-0.076**	-0.032**	-0.048**	-0.073**
condddum	-0.168**	-0.386**	1.4041**	-0.52**	0.0488	-0.414**	-0.101**	-0.103*	-0.236**
carport	282E-7	0.0003	0.0002**	565E-8	-95E-6	0.0001*	0.0001**	564E-7**	0.0001**
encporch	0.0001	0.0009**	0.0003	0.0004	0.0003**	0.0002**	0.0002**	0.0003**	0.0002**
scrporch	0.0003**	0.0004**	596E-7	0.0001	122E-7	0.0002**	0.0002**	0.0001**	0.0002**
opnporch	0.0003**	0.0004**	0.0002**	247E-7	0.0001	0.0001**	0.0001**	0.0001**	0.0001**
garage	0.0002**	0.0002**	0.0002**	0.0002**	0.0002**	0.0002**	0.0002**	0.0002**	0.0002**
storage	-78E-6	0.0004	218E-7	0.0001	0.0001	0.0001	0.0001*	0.0002**	0.0001**
patio	548E-7	0.0002**	-57E-6	0.0001	-57E-6	191E-7	147E-7	0.0001**	0.0000482**
deck	0.0002**	0.0002**	-33E-6	0.0002**	0.0001**	0.0001**	0.0002**	0.0001**	0.0001**
stoop	0.0007**	0.001	-36E-6	0.0001	0.0002	0.0003**	0.0003**	0.0004**	0.0003**
fireplaces	0.0828**	0.1303**	0.0711**	0.04*	-0.001	0.0492**	0.0473**	0.0383**	0.0568**
poolres	-0.026	0.1282	0.0729	0.1392**	0.072*	0.0141	0.0268*	0.026*	0.0177**
grade	0.0034**	0.0059**	0.0095**	0.01**	0.0093**	0.0056**	0.0075**	0.0057**	0.0051**
perc_nonwhite_1990	0.001	0.0016	0.0005	0.0049**	-0.022	0.0002	-33E-5*	-76E-6	-0.0005**
medianvalue	118E-8	399E-8	144E-8	17E-7**	159E-7	789E-9**	169E-8**	287E-9**	5.89E-7**
medttw	561E-7	0.0103	0.0017	0.0096*	0.031	0.0039**	0.0025**	-0.003**	-0.00015
perc_under18	-0.002	0.0282	0.001	-0.007	0.1148	-0.002**	0.0002	0.0015**	0.0000114
perc_owner_occ	-25E-5	-0.001	0.0005	-0.003*	-0.06	0.0004**	0.0002	0.0009**	0.0006**
nearestpark	0.0222**	0.0146	-0.071**	-0.023**	-0.003	0.0018	-76E-5	0.0038**	-0.001*
nearestsc	-0.007	0.014	0.1149**	0.024*	-0.019	-0.019**	-0.008**	-0.003**	-0.003**
bigparkdistance	-0.005	-0.006	-0.011**	-0.002	0.0058	0.0052**	0.0014**	-56E-5	-0.00034*
taxrate	0.0161	0.0267	0.134**	.	0.0831	0.0264**	-0.01	0.0682**	0.0247**
nobs	495	239	281	307	364	2901	2683	3099	9461
rsqr	0.9055	0.9415	0.9084	0.9347	0.9341	0.9356	0.9045	0.9402	0.9361

\* Significant at .10 level

\*\* Significant at .05 level

Table E.3: 1992 OLS Estimates (Sparse Spec., All Observations)

Variable	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Zone 7	Zone 8	Zone 9	Zone 10
intercept	10.361**	10.007**	9.2589**	10.361**	10.043**	9.4123**	10.159**	9.3143**	9.8327**	9.7706**
baths	0.0635**	0.08**	0.059**	0.0635**	0.0492**	0.1046**	0.0469**	0.0547**	0.0645**	0.0477**
regheatarea	0.5502**	0.4881**	0.7204**	0.5502**	0.5345**	0.2932**	0.5515**	0.6149**	0.7504**	0.6194**
sqregheat	-0.054**	-0.048**	-0.115**	-0.054**	-0.052**	-0.016	-0.052**	-0.07**	-0.091**	-0.078**
acreage1	0.2257**	.	.	.	.	.	.	.	.	.
sqacre1	-0.01**	.	.	.	.	.	.	.	.	.
acreage2	.	0.2385**	.	.	.	.	.	.	.	.
sqacre2	.	-0.058**	.	.	.	.	.	.	.	.
acreage3	.	.	0.392**	.	.	.	.	.	.	.
sqacre3	.	.	-0.066**	.	.	.	.	.	.	.
acreage4	.	.	.	0.2257**	.	.	.	.	.	.
sqacre4	.	.	.	-0.01**	.	.	.	.	.	.
acreage5	.	.	.	.	0.1951**	.	.	.	.	.
sqacre5	.	.	.	.	-0.029	.	.	.	.	.
acreage6	.	.	.	.	.	0.1807**	.	.	.	.
sqacre6	.	.	.	.	.	-0.013**	.	.	.	.
acreage7	.	.	.	.	.	.	0.1636**	.	.	.
sqacre7	.	.	.	.	.	.	-0.022**	.	.	.
acreage8	.	.	.	.	.	.	.	-0.015	.	.
sqacre8	.	.	.	.	.	.	.	0.0084**	.	.
acreage9	.	.	.	.	.	.	.	.	0.0416**	.
sqacre9	.	.	.	.	.	.	.	.	0.0023**	.
acreage10	.	.	.	.	.	.	.	.	.	0.0831**
sqacre10	.	.	.	.	.	.	.	.	.	-0.002**
acreage11	.	.	.	.	.	.	.	.	.	.
sqacre11	.	.	.	.	.	.	.	.	.	.
acreage14	.	.	.	.	.	.	.	.	.	.
sqacre14	.	.	.	.	.	.	.	.	.	.
acreage16	.	.	.	.	.	.	.	.	.	.
sqacre16	.	.	.	.	.	.	.	.	.	.
acreage18	.	.	.	.	.	.	.	.	.	.
sqacre18	.	.	.	.	.	.	.	.	.	.
acreage21	.	.	.	.	.	.	.	.	.	.
sqacre21	.	.	.	.	.	.	.	.	.	.
age	0.0779**	-0.006**	-0.01**	0.0779**	-0.004**	-0.004**	-0.002	-0.003*	-0.003	-0.01**
sqage	0.0003	557E-7**	362E-7	0.0003	-14E-6	-36E-6	-5E-6	-43E-6	-65E-6	0.0001**
story	0.1316**	-0.038**	-0.039	0.1316**	-0.061**	-0.053**	-0.096**	-0.042**	-0.078**	-0.011
grade	-0.005**	0.0069**	0.0113**	-0.005**	0.0071**	0.0134**	0.0061**	0.0127**	0.0069**	0.0084**
nobs	2866	1679	289	2866	2095	392	983	555	648	356
rsqr	0.8874	0.8918	0.8639	0.8874	0.9168	0.8503	0.9052	0.8545	0.8734	0.8986

\* Significant at .10 level

\*\* Significant at .05 level

Table E.3(continued)

Variable	Zone 11	Zone 14	Zone 16	Zone 18	Zone 21	Group 1	Group 2	Group 3	Wake Co.
intercept	9.5898**	9.5235**	8.855**	9.1002**	9.079**	9.967**	9.2524**	9.9744**	9.876**
baths	0.1125**	0.1029**	0.1502**	0.0724**	0.108**	0.0595**	0.0927**	0.0531**	0.064**
regheatarea	0.8479**	0.5995**	0.6986**	0.7527**	0.7992**	0.5653**	0.754**	0.5937**	0.6402**
sregheat	-0.133**	-0.06**	-0.117**	-0.119**	-0.119**	-0.059**	-0.115**	-0.064**	-0.075**
acreage1	.	.	.	.	.	.	.	.	0.5159**
sqacre1	.	.	.	.	.	.	.	.	-0.189**
acreage2	.	.	.	.	.	0.2922**	.	.	0.3069**
sqacre2	.	.	.	.	.	-0.08**	.	.	-0.086**
acreage3	.	.	.	.	.	.	0.0113	.	-0.166**
sqacre3	.	.	.	.	.	.	0.013	.	0.0562**
acreage4	.	.	.	.	.	.	.	.	0.1157**
sqacre4	.	.	.	.	.	.	.	.	0.0057
acreage5	.	.	.	.	.	.	.	0.1149**	0.3274**
sqacre5	.	.	.	.	.	.	.	0.0177	-0.101**
acreage6	.	.	.	.	.	.	0.1148**	.	0.0299*
sqacre6	.	.	.	.	.	.	-0.007**	.	0.0008
acreage7	.	.	.	.	.	0.1658**	.	.	0.1583**
sqacre7	.	.	.	.	.	-0.022**	.	.	-0.019**
acreage8	.	.	.	.	.	.	0.118**	.	0.0842**
sqacre8	.	.	.	.	.	.	-0.01**	.	-0.002
acreage9	.	.	.	.	.	.	.	0.0655**	0.1164**
sqacre9	.	.	.	.	.	.	.	-48E-5	-0.003**
acreage10	.	.	.	.	.	.	.	0.0625**	0.1022**
sqacre10	.	.	.	.	.	.	.	-0.001*	-0.004**
acreage11	0.0294*	.	.	.	.	.	0.0105	.	-0.021*
sqacre11	0.0027	.	.	.	.	.	0.0049**	.	0.0085**
acreage14	.	0.1162**	.	.	.	0.1178**	.	.	0.1189**
sqacre14	.	-0.012*	.	.	.	-0.013**	.	.	-0.013**
acreage16	.	.	0.0525	.	.	.	-0.004	.	-0.015
sqacre16	.	.	0.0164	.	.	.	0.0298**	.	0.026**
acreage18	.	.	.	0.0359	.	.	0.0069	.	-0.022*
sqacre18	.	.	.	0.0069	.	.	0.0131**	.	0.0194**
acreage21	.	.	.	.	0.0008	.	0.0427**	.	0.0374**
sqacre21	.	.	.	.	0.0027	.	0.0002	.	0.0007
age	-0.004**	-0.005**	-0.001	-0.006**	-0.006**	-0.004**	-0.005**	-0.005**	-0.005**
sqage	-31E-6	336E-7	-24E-6	452E-7	0.0001**	152E-7	-23E-6**	257E-7**	0.0000208**
story	-0.031	-0.07**	-0.112**	-0.021	-0.08**	-0.058**	-0.046**	-0.063**	-0.05**
grade	0.0063**	0.0093**	0.0146**	0.0126**	0.0126**	0.0068**	0.0111**	0.0072**	0.0068**
nobs	495	239	281	307	364	2901	2683	3099	9461
rsqr	0.8349	0.8864	0.8389	0.8803	0.8991	0.9042	0.8576	0.9035	0.9017

\* Significant at .10 level

\*\* Significant at .05 level

Table E.4: 1992 OLS Estimates (Base Spec., Small Samples)

Variable	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Zone 7	Zone 8	Zone 9	Zone 10
intercept	10.012**	8.4834**	7.9751**	9.0562**	10.405**	10.686**	9.2225**	9.6889**	9.8528**	9.4096**
baths	0.038	0.0507	-0.022	0.0649	-0.039	0.0857	0.0057	-0.02	0.0839**	0.017
regheatarea	0.676	0.7351**	1.0179**	1.3575**	0.5134**	0.2637	0.8262**	0.4192	0.684**	0.35
sqregheat	-0.103	-0.117	-0.188**	-0.308**	-0.04	0.0086	-0.118*	-0.022	-0.059**	-0.013
acrage1	0.3385	.	.	.	.	.	.	.	.	.
sqacre1	0.2849	.	.	.	.	.	.	.	.	.
acrage2	.	0.0487	.	.	.	.	.	.	.	.
sqacre2	.	0.0511	.	.	.	.	.	.	.	.
acrage3	.	.	0.4367	.	.	.	.	.	.	.
sqacre3	.	.	-0.316	.	.	.	.	.	.	.
acrage4	.	.	.	0.0011	.	.	.	.	.	.
sqacre4	.	.	.	0.0471	.	.	.	.	.	.
acrage5	.	.	.	.	0.9637**	.	.	.	.	.
sqacre5	.	.	.	.	-0.805*	.	.	.	.	.
acrage6	.	.	.	.	.	-0.268	.	.	.	.
sqacre6	.	.	.	.	.	0.3627	.	.	.	.
acrage7	.	.	.	.	.	.	0.2095	.	.	.
sqacre7	.	.	.	.	.	.	0.0339	.	.	.
acrage8	.	.	.	.	.	.	.	-0.894*	.	.
sqacre8	.	.	.	.	.	.	.	1.2908	.	.
acrage9	.	.	.	.	.	.	.	.	0.003	.
sqacre9	.	.	.	.	.	.	.	.	-0.009	.
acrage10	.	.	.	.	.	.	.	.	.	-0.041
sqacre10	.	.	.	.	.	.	.	.	.	0.0069**
acrage11	.	.	.	.	.	.	.	.	.	.
sqacre11	.	.	.	.	.	.	.	.	.	.
acrage14	.	.	.	.	.	.	.	.	.	.
sqacre14	.	.	.	.	.	.	.	.	.	.
acrage16	.	.	.	.	.	.	.	.	.	.
sqacre16	.	.	.	.	.	.	.	.	.	.
acrage18	.	.	.	.	.	.	.	.	.	.
sqacre18	.	.	.	.	.	.	.	.	.	.
acrage21	.	.	.	.	.	.	.	.	.	.
sqacre21	.	.	.	.	.	.	.	.	.	.
age	-0.017*	-0.014	-0.001	-0.008	-0.013	-0.012	0.0034	-0.007	0.0071	-0.011*
sqage	0.0003*	0.0003	-62E-6	0.0001	-65E-6	0.0002	-0.001*	59E-6	-12E-5	0.0001
bsmtheat	0.0002	-1E-4	-49E-6	0.0001	0.0001	0.0007*	-4E-5	.	0.0005*	0.0001
bsmtunheat	-22E-6	-12E-6	0.0121	0.0002	-44E-6	0.0007*	0.001	.	323E-7	0.0002
atticheat	0.0005	0.0002	-47E-7	0.0002	0.0001	0.0003	301E-7	-34E-6	0.0002**	551E-7
atticunheat	0.0004	0.0004	0.0002	.	0.0002	.	-1E-4	0.0001	-62E-6	0.0019
otherunheatarea	.	-13E-5	0.0034	.	.	0.0002	.	-83E-5*	.	.
walldum1	-0.104	0.0672	-0.129	0.0173	0.0599	0.0578	0.2497**	0.4499	-0.014	.
bsmtum1	0.1022	0.3349*	-0.2	0.0468	0.0741	-0.474	-0.709**	.	0.0385	.
bsmtum2	0.0956	0.2356*	0.2403	0.1675*	0.0425	-0.214	0.032	.	-0.184	.
heatdum6	.	.	-0.108	.	-0.089	-0.344*	.	.	.	.
heatdum7	.	.	0.7204**	.	.	.	.	.	.	.
acdum1	-0.011	.	0.0628	-0.09	.	-0.13	.	.	0.1295	0.8074**
story	0.0136	0.0108	-0.118*	-0.145*	-0.129*	0.0323	-0.041	-0.017	-0.048	-0.099
detgarage	0.1093	2.1822*	-0.224	.	0.0162	0.1783	-0.454**	0.068	-0.331	0.278
condadum	0.2168*	-0.013	-0.261**	0.0528	.	.	-0.465**	.	.	.
condcdum	0.0457	.	0.2206	-0.119	.	0.3909	.	.	0.0804	0.0008
condddum	.	.	0.1378	.	.	.	.	.	.	.
carport	0.0006	0.0006	-25E-5	-26E-5	472E-7	0.0003	.	-89E-5	-41E-5**	0.0007*
encporch	-23E-5	-0.011*	0.0008	0.0011	.	0.0002	-1E-4	-0.002	.	0.0058**
scrporch	-72E-5	-15E-5	-27E-5	0.0008	0.0001	-54E-5	-23E-5	.	0.0005**	-77E-6
opnporch	-71E-5	0.0001	0.0004	0.0003	0.0003	588E-7	-86E-5**	0.0005**	0.0004**	0.0003
garage	0.0009	0.0003	0.0002	0.0004**	0.0002	0.0002	-4E-5	0.0002	192E-7	0.0002
storage	0.0019	0.0012	0.0005	0.0003	214E-7	0.0007	-0.002	-28E-5	0.0001	-0.002
patio	0.0001	-86E-5**	-24E-6	0.0003	0.0001	-15E-5	428E-7	34E-6	716E-8	0.0004
deck	-25E-5	0.0001	0.0002	0.0002	0.0003	-12E-6	0.0004**	217E-7	0.0003	-22E-5
stoop	-0.001	0.0002	0.0009	0.0027*	0.0006	0.0001	-0.002**	-79E-5	0.0008	0.0014
fireplaces	0.0628	1.522**	-0.023	-0.007	-0.114	0.028	0.2882**	0.0317	0.311	0.3371**
poolres	0.1976	-0.146	0.1925	.	.	-0.042	0.1028	.	0.0761	0.0594
grade	0.0045**	0.0047	0.0226**	0.0103**	0.0056**	0.002	0.0095**	0.0126**	0.001	0.006**
nobs	50	50	50	50	50	50	50	50	50	50
rsqr	0.8861	0.9314	0.9619	0.8734	0.952	0.9019	0.9591	0.8884	0.9688	0.9733

\* Significant at .10 level

\*\* Significant at .05 level

Table E.4(continued)

Variable	Zone 11	Zone 14	Zone 16	Zone 18	Zone 21	Group 1	Group 2	Group 3	Wake Co.
intercept	9.0413**	9.5431**	9.8335**	9.0641**	4.6503	9.7097**	9.2547**	9.637**	9.8178**
baths	0.1032**	0.0234	0.0986	0.0324	0.0425	0.0179	0.0506**	0.0429**	0.0358**
regheatarea	0.9988**	1.2201**	0.575*	0.5606**	0.3953	0.6497**	0.7889**	0.4914**	0.6163**
sqregheat	-0.193**	-0.18**	-0.071	-0.088	-0.049	-0.082**	-0.142**	-0.043**	-0.076**
acreage1	.	.	.	.	.	.	.	.	-0.094
sqacre1	.	.	.	.	.	.	.	.	0.2189*
acreage2	.	.	.	.	.	0.3655**	.	.	0.2081**
sqacre2	.	.	.	.	.	-0.134	.	.	-0.141*
acreage3	.	.	.	.	.	.	-0.193	.	-0.365**
sqacre3	.	.	.	.	.	.	0.222	.	0.4101*
acreage4	.	.	.	.	.	.	.	.	-0.052
sqacre4	.	.	.	.	.	.	.	.	0.1339**
acreage5	.	.	.	.	.	.	.	-0.044	0.2242**
sqacre5	.	.	.	.	.	.	.	0.0506	-0.082
acreage6	.	.	.	.	.	.	0.0108	.	-0.09
sqacre6	.	.	.	.	.	.	0.0398	.	0.1797
acreage7	.	.	.	.	.	0.213**	.	.	0.1046*
sqacre7	.	.	.	.	.	-0.035	.	.	-0.011
acreage8	.	.	.	.	.	.	0.1869	.	0.2196
sqacre8	.	.	.	.	.	.	-0.235	.	-0.384
acreage9	.	.	.	.	.	.	.	-0.072**	0.0159
sqacre9	.	.	.	.	.	.	.	0.015**	0.0091
acreage10	.	.	.	.	.	.	.	-0.018	0.0639**
sqacre10	.	.	.	.	.	.	.	0.0036**	-0.002
acreage11	-0.159**	.	.	.	.	.	-0.046	.	-0.026
sqacre11	0.038**	.	.	.	.	.	0.0161	.	0.0096
acreage14	.	0.2359*	.	.	.	0.1823**	.	.	0.1236**
sqacre14	.	-0.094	.	.	.	-0.056	.	.	-0.029
acreage16	.	.	0.3362**	.	.	.	-0.044	.	-0.036
sqacre16	.	.	-0.112**	.	.	.	0.001	.	0.0025
acreage18	.	.	.	0.1859	.	.	-0.033	.	-0.043
sqacre18	.	.	.	-0.052	.	.	0.0154*	.	0.0209**
acreage21	.	.	.	.	0.0107	.	-0.018	.	0.0049
sqacre21	.	.	.	.	-0.02	.	0.0114**	.	0.007**
age	0.0026	-0.021*	-0.001	-0.008	-0.014	-0.016**	-0.004**	-0.004	-0.007**
sqage	-78E-6	0.0004	-1E-4	0.0003	0.0011	0.0003**	-24E-6	135E-8	0.00006**
bsmtheat	.	0.0006**	.	-16E-5	.	33E-6	256E-7	437E-7	0.000024
bsmtunheat	.	-36E-5	.	0.0004	.	0.0001	0.0002	-36E-7	0.0000453
atticheat	0.001**	0.0004**	0.0002	0.0001*	0.0004**	0.0002**	0.0002**	445E-7	0.0002**
atticunheat	-26E-6	-72E-6	0.0006	0.0002	0.0001	-35E-6	0.0002**	-18E-6	0.0000235
otherunheatarea	.	-4E-6	.	.	.	0.0001	-25E-5	.	0.0000234
walldum1	-0.035	0.0564	-0.107	0.065	2.2184	0.0157	-0.006	0.0644**	-0.005
bsmtdum1	0.4429**	0.0322	.	.	0.0464	0.0069	0.1636**	0.1928**	0.1423**
bsmtdum2	.	-0.334	.	0.1223	.	0.1157**	0.1496**	0.0571	0.1602**
heatdum6	.	.	.	0.0769	.	.	0.0439	0.5051**	0.1186*
heatdum7	.	.	.	.	.	.	0.4532**	.	0.3916**
acdum1	-0.096	.	-0.134	.	4.7057	.	0.0739**	0.4509**	0.1173**
story	-0.099**	-0.109	-0.163**	-0.007	-0.011	-0.042	-0.053**	-0.067**	-0.057**
detgarage	-0.059	0.0472	0.2159**	0.0747	0.1338*	0.0024	0.1089**	0.075	0.0731**
condadum	.	0.1662	.	.	.	-0.097**	-0.06	.	0.0826**
condcdum	0.0644	-0.085	-0.288**	0.2427**	.	-0.175**	-0.071**	0.0235	-0.138**
condddum	0.0247	.	.	.	.	.	0.0937	-0.056	-0.177**
carport	-44E-6	0.0006	0.0002	-57E-5*	-0.02	0.0007**	0.0002**	-25E-6	0.0002**
encporch	0.0004	.	0.0001	.	-0.048	0.0003	0.0004**	0.0046**	0.0005**
scrporch	0.0003*	509E-7	-1E-4	-26E-5	-21E-5	577E-7	608E-7	0.0001	0.0001
opnporch	316E-7	0.0004**	0.0003	0.0002	-17E-5	292E-7	0.0002**	0.0004**	0.0000482
garage	0.0002**	-78E-7	0.0002**	0.0001*	133E-7	0.0001	0.0002**	0.0002**	0.0003**
storage	-29E-5	0.0005	0.0002	0.0011	-48E-5	-49E-5	0.0001	0.0003	0.0003
patio	-35E-5**	0.0001	-78E-6	0.0012**	-24E-5	-23E-7	142E-8	-39E-6	-3.9E-6
deck	556E-7	0.0001	-66E-6	0.0002	-72E-6	0.0002**	444E-7	0.0001	0.0001**
stoop	-9E-5	0.0035	-0.002*	0.0012	0.0005	-42E-6	-28E-5	0.0008*	7.12E-6
fireplaces	-0.012	0.0912	0.004	.	0.115	0.1228**	0.0517**	0.1098**	0.0798**
poolres	0.0616	0.0597	0.1943	.	-2.341	0.0526	0.0399	0.02	0.0203
grade	0.0127**	0.0041	0.0075**	0.0139**	0.0137**	0.0076**	0.0106**	0.0057**	0.006**
nobs	50	50	50	50	50	150	350	150	750
rsqr	0.9753	0.9554	0.9526	0.9695	0.9582	0.9411	0.9178	0.9633	0.9339

\* Significant at .10 level

\*\* Significant at .05 level

Table E.5: 1992 OLS Estimates (Full Spec., Small Samples)

Variable	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Zone 7	Zone 8	Zone 9	Zone 10
intercept	10.673**	6.2164**	3.5095*	6.4834**	11.339**	8.9768*	-4.357	17.691**	8.664**	9.3039**
baths	0.0353	0.0949	0.0452	0.1295	-0.049	0.0829	0.0062	-0.01	0.0374	0.0227
regheatarea	0.6144*	0.4812	0.9196**	1.6075**	0.5153**	0.1651	0.6486**	0.2738	0.8704**	0.4942
sqregheat	-0.053	-0.091	-0.139**	-0.38*	-0.043	0.0456	-0.112*	-0.002	-0.081**	-0.059
acreage1	0.2064	.	.	.	.	.	.	.	.	.
sqacre1	1.3624	.	.	.	.	.	.	.	.	.
acreage2	.	0.2487	.	.	.	.	.	.	.	.
sqacre2	.	0.003	.	.	.	.	.	.	.	.
acreage3	.	.	1.6464*	.	.	.	.	.	.	.
sqacre3	.	.	-2.105**	.	.	.	.	.	.	.
acreage4	.	.	.	-0.119	.	.	.	.	.	.
sqacre4	.	.	.	0.188	.	.	.	.	.	.
acreage5	.	.	.	.	0.6289	.	.	.	.	.
sqacre5	.	.	.	.	-0.592	.	.	.	.	.
acreage6	.	.	.	.	.	-0.525	.	.	.	.
sqacre6	.	.	.	.	.	0.6097	.	.	.	.
acreage7	.	.	.	.	.	.	0.216	.	.	.
sqacre7	.	.	.	.	.	.	0.082	.	.	.
acreage8	.	.	.	.	.	.	.	-0.416	.	.
sqacre8	.	.	.	.	.	.	.	0.4695	.	.
acreage9	.	.	.	.	.	.	.	.	0.1572	.
sqacre9	.	.	.	.	.	.	.	.	-0.047	.
acreage10	.	.	.	.	.	.	.	.	.	-0.355**
sqacre10	.	.	.	.	.	.	.	.	.	0.0267**
acreage11	.	.	.	.	.	.	.	.	.	.
sqacre11	.	.	.	.	.	.	.	.	.	.
acreage14	.	.	.	.	.	.	.	.	.	.
sqacre14	.	.	.	.	.	.	.	.	.	.
acreage16	.	.	.	.	.	.	.	.	.	.
sqacre16	.	.	.	.	.	.	.	.	.	.
acreage18	.	.	.	.	.	.	.	.	.	.
sqacre18	.	.	.	.	.	.	.	.	.	.
acreage21	.	.	.	.	.	.	.	.	.	.
sqacre21	.	.	.	.	.	.	.	.	.	.
age	-0.023**	0.0103	0.0109	0.0083	-0.014	-0.01	-0.01	-0.028**	0.0054	-0.02**
sqage	0.0003**	-58E-5	-36E-5*	-24E-5	428E-7	0.0001	-55E-5	0.0005	-77E-6	0.0003**
bsmtheat	-24E-5	-19E-5	-0.001	-76E-6	-46E-6	0.0003	0.0001	.	0.0006	0.0004
bsmtunheat	-35E-6	0.0002	0.007	0.0002	-25E-5	0.0006	0.0016**	.	0.0001	0.0004
atticheat	0.0006*	0.0004*	0.0001	0.0005	0.0001	0.0003	0.0002	472E-7	0.0002**	533E-7
atticunheat	0.0005	0.0006*	106E-7	.	0.0002	.	108E-7	0.0003	354E-7	0.0041
otherunheatarea	.	-35E-5	-0.015	.	.	0.0007	.	-97E-5	.	.
walldum1	-0.101	0.0544	0.0243	-0.05	0.1805	0.05	0.2461*	0.8148	-0.002	.
bsmtdum1	0.2671*	0.2458	-0.337	0.1792	0.2825	-0.051	-1.006**	.	-0.027	.
bsmtdum2	0.096	0.2366	0.4953	0.23	0.1122	-0.074	-0.048	.	-0.171	.
heatdum6	.	.	0.1807	.	0.0321	-0.351	.	.	.	.
heatdum7	.	.	-0.261	.	.	.	.	.	.	.
acdum1	0.063	.	0.2235**	-0.034	.	-0.132	.	.	-0.195	1.2439**
story	0.0476	0.095	-0.187**	-0.137	-0.092	-0.018	0.0208	-0.054	-0.06	-0.226**
detgarage	0.1042	1.8457	0.8531	.	0.0059	0.1793	-0.523**	0.1722*	-0.223	-0.054
condadum	0.1093	-0.05	-0.51**	0.1185	.	.	-0.366**	.	.	.
condcdum	0.3023	.	1.2005**	-0.047	.	0.2924	.	.	0.2269	-0.288
condddum	.	.	2.0215*	.	.	.	.	.	.	.
carport	0.0007	0.0007	-0.001**	-28E-5	-21E-6	0.0004	.	-0.002	-58E-5**	0.0013**
encporch	-0.001	-0.01	0.0009	-8E-4	.	0.0005	-4E-4	-0.003	.	0.0057**
scrporch	-0.001	-27E-5	-42E-5	0.0003	0.0001	0.0003	-18E-6	.	583E-7	-1E-4
opnporch	-0.001**	0.0005	-78E-6	0.0009	0.0007	0.0001	-0.001**	0.0006*	0.0003	168E-7
garage	0.0009	0.0004*	0.0003**	0.0003	0.0003	0.0003	-59E-7	0.0002	29E-6	0.0002
storage	0.0012	0.0007	0.0011*	0.0002	0.0011	-12E-5	0.0009	-35E-5	-85E-5	-0.002
patio	0.0004*	-67E-5	0.0001	0.0002	0.0002	-73E-6	-1E-4	-88E-6	-27E-5	-72E-5
deck	-13E-5	599E-8	0.0005**	519E-7	0.0005	0.0001	0.0003*	-51E-6	0.0001	0.0004*
stoop	-0.004**	0.0001	0.003	0.0019	454E-7	804E-8	-0.002*	0.0021	0.0001	0.0009
fireplaces	-0.131	1.4511*	-0.064	0.0883	0.057	0.0562	0.1982	0.0867	0.8855	0.3023**
poolres	-1.406	-0.182	-0.034	.	.	0.0527	0.1311	.	0.1632	0.1511
grade	137E-7	0.0049	0.0334**	0.0097	0.0043	0.0012	0.0151**	0.0162	0.0007	0.0018
perc_nonwhite_1990	-0.006	-0.006	-0.004**	-0.007	-0.002	-11E-5	0.0603*	-0.049*	0.0025	-0.018
medianvalue	342E-8**	893E-9	-91E-7*	229E-8	707E-9	88E-9	-89E-7	212E-8	-78E-8	-12E-7
medttw	0.0282	0.0266*	-0.035	-0.004	-0.014	-0.002	-0.008	0.0417	-0.001	-0.004
perc_under18	-0.021	-0.022	0.0619*	0.0083	-0.008	-0.005	0.3085	-0.145*	0.0112	-0.024
perc_owner_occ	0.0021	0.0008	0.021	0.0007	0.001	-29E-5	0.0336	-0.006	0.0018	0.0066
nearestpark	-0.217*	0.0117	0.1562	-0.055	0.0487	0.1109*	0.0203	-0.058	-0.013	-0.135*
nearestsc	0.0792	-0.131**	-0.269**	-0.103	0.0343	-0.024	-0.047	0.3825	-0.027	0.1053**
bigparkdistance	0.0004	0.0377**	0.0338	0.038	-0.016	0.0224	0.031*	-0.08	0.0095	0.0167
taxrate	.	-0.145	-0.179	-0.038	-0.02	0.1278	0.0994	-0.081	0.4035**	0.0384
nobs	50	50	50	50	50	50	50	50	50	50
rsqr	0.9558	0.9364	0.9939	0.8686	0.9347	0.8918	0.9707	0.8927	0.9717	0.9867

\* Significant at .10 level

\*\* Significant at .05 level

Table E.5(continued)

Variable	Zone 11	Zone 14	Zone 16	Zone 18	Zone 21	Group 1	Group 2	Group 3	Wake Co.
intercept	9.3758**	15.248	8.1815**	4.7148*	-16.94	9.2257**	8.8678**	9.508**	9.7325**
baths	0.0434	-0.047	0.0826	0.0322	-0.079	0.0146	0.0413**	0.0378**	0.0322**
regheatarea	0.8384*	1.6136**	0.7022**	0.5934**	0.0406	0.6786**	0.7071**	0.4792**	0.5847**
sregheat	-0.147	-0.264**	-0.138*	-0.101*	0.0789	-0.092**	-0.124**	-0.041**	-0.072**
acrage1	.	.	.	.	.	.	.	.	-0.293**
sqacre1	.	.	.	.	.	.	.	.	0.3275**
acrage2	.	.	.	.	.	-0.049	.	.	0.0339
sqacre2	.	.	.	.	.	0.1895	.	.	-0.009
acrage3	.	.	.	.	.	.	-0.356**	.	-0.463**
sqacre3	.	.	.	.	.	.	0.3923	.	0.4989*
acrage4	.	.	.	.	.	.	.	.	0.031
sqacre4	.	.	.	.	.	.	.	.	0.1045**
acrage5	.	.	.	.	.	.	.	-0.158	-0.00038
sqacre5	.	.	.	.	.	.	.	0.2099	0.1381
acrage6	.	.	.	.	.	.	-0.033	.	-0.137
sqacre6	.	.	.	.	.	.	0.0979	.	0.2139
acrage7	.	.	.	.	.	0.1998*	.	.	-0.096
sqacre7	.	.	.	.	.	-0.023	.	.	0.0642*
acrage8	.	.	.	.	.	.	-0.005	.	-0.027
sqacre8	.	.	.	.	.	.	0.008	.	-0.06
acrage9	.	.	.	.	.	.	.	-0.069	0.0029
sqacre9	.	.	.	.	.	.	.	0.0165**	0.0125**
acrage10	.	.	.	.	.	.	.	0.004	0.0776**
sqacre10	.	.	.	.	.	.	.	0.0023	-0.003
acrage11	-0.197	.	.	.	.	.	-0.083*	.	0.0064
sqacre11	0.0459	.	.	.	.	.	0.0273**	.	0.0065
acrage14	.	0.5897**	.	.	.	0.2198*	.	.	0.2203**
sqacre14	.	-0.151	.	.	.	-0.066	.	.	-0.065**
acrage16	.	.	0.5137**	.	.	.	0.1849**	.	0.0711
sqacre16	.	.	-0.163**	.	.	.	-0.063**	.	-0.031
acrage18	.	.	.	0.0148	.	.	0.001	.	-0.013
sqacre18	.	.	.	0.0068	.	.	0.0101	.	0.0143*
acrage21	.	.	.	.	0.3828**	.	-0.022	.	0.0225
sqacre21	.	.	.	.	-0.138**	.	0.012**	.	0.0057*
age	-0.004	-0.003	-0.005	-0.004	-0.013	-0.016**	-0.005**	-0.005*	-0.007**
sqage	829E-8	-5E-4	-18E-6	-0.003	0.0035	0.0003**	-16E-6	297E-7	0.0001**
bsmtheat	.	0.001**	.	-0.005	.	297E-7	182E-7	328E-7	0.0000193
bsmtunheat	.	0.001	.	0.0004	.	0.0001	0.0002	111E-7	0.0000422
atticheat	0.0012**	0.0003*	0.0003**	0.0001**	0.0005**	0.0002**	0.0001**	0.0001	0.0002**
atticunheat	564E-7	298E-7	0.0005	0.0002	0.0002	123E-8	0.0002**	-31E-6	0.0000321
otherunheatarea	.	0.0005	.	.	.	505E-7	-2E-4	.	0.0000426
walldum1	-0.049	-2E-5	-0.188**	0.1384**	8.2392**	0.0139	-36E-5	0.0605*	-0.00018
bsmtum1	0.2006	0.0629	.	.	-0.073	0.0141	0.1694**	0.1722**	0.1334**
bsmtum2	.	-0.835	.	0.1274	.	0.0569	0.151**	0.0642	0.1545**
heatdum6	.	.	.	1.9754	.	.	0.0068	0.4545**	0.0891
heatdum7	.	.	.	.	.	.	0.5276**	.	0.4944**
acdum1	-0.174	.	-0.045	.	17.956	.	0.0807**	0.4387**	0.1181**
story	-0.048	-0.122	-0.132**	-0.005	0.0529	-0.033	-0.047**	-0.07**	-0.049**
detgarage	-0.105	-0.276	0.2077*	0.1239*	0.0962	-0.017	0.1105**	0.0932	0.0703**
condadum	.	0.7901	.	.	.	-0.08	-0.054	.	0.0752**
condcdum	0.0281	-0.183	-0.193	-0.356	.	-0.174**	-0.052*	0.0192	-0.113**
condddum	0.0594	.	.	.	.	.	0.102*	-0.041	-0.146**
carport	0.0003	0.0002	0.0005	-84E-5**	-0.074	0.0008**	0.0002**	108E-7	0.0002**
encporch	0.0025*	.	0.0002	.	-0.162	0.0002	0.0004**	0.0041**	0.0005**
scrporch	0.0005**	114E-7	-56E-5	-31E-5	-35E-5	576E-7	0.0001	481E-7	0.0001*
opnporch	0.0003	0.0001	0.0002	0.0001	-22E-5	0.0001	0.0001*	0.0003**	0.0001
garage	0.0002	-29E-5	0.0003**	0.0001*	-24E-5	0.0001	0.0002**	0.0002**	0.0002**
storage	-0.002	0.0013	328E-8	0.001	-0.002	-46E-5	0.0002	0.0003	0.0003
patio	39E-6	0.0012	-21E-5	0.0016**	-29E-5	0.0001	-2E-5	-8E-5	-0.000017
deck	0.0002	-85E-6	-31E-5*	0.0001	-22E-5	0.0002**	539E-7	0.0001	0.0001**
stoop	0.0003	0.0043*	-0.002*	0.0006	0.0006	0.0001	-33E-5	0.0006	0.0000498
fireplaces	-0.031	-0.041	0.0201	.	0.33	0.1054**	0.0349**	0.09**	0.0646**
poolres	-0.107	-0.387	0.3877**	.	-10.65**	0.0236	0.0843**	0.0263	0.0418
grade	0.0167**	0.0089	0.0114**	0.0129**	0.0177**	0.0071**	0.01**	0.0055**	0.0056**
perc_nonwhite_1990	0.0027	0.0649	0.0021	-0.023	-0.053**	-0.002	-24E-8	-0.001	-0.00035
medianvalue	-34E-7	-53E-6	583E-8**	155E-7	-87E-7*	133E-9	104E-8*	228E-9	8.88E-7**
medttw	0.0101	-0.059	0.0059	-0.089	-0.059	-36E-5	0.0032	-0.002	-0.002
perc_under18	-0.002	0.1006	0.0043	0.1391*	0.361**	-0.007	-49E-5	0.0055*	0.0002
perc_owner_occ	-13E-6	-95E-5	251E-8	0.0432*	.	0.0012	0.0013**	-15E-5	0.0014**
nearestpark	-0.015	-0.007	-0.004	0.2201	-0.072	0.0017	-0.004	0.0058	-0.0005
nearestsc	0.016	0.2569	0.0547	-0.261	0.1199	-0.046**	-0.019**	-0.007	-0.009**
bigparkdistance	-0.004	-0.066	-0.008	0.006	-0.002	0.0122**	0.0054**	0.0022	0.0014*
taxrate	0.0318	0.3129	0.1858	.	0.0811	0.0473	0.0336	0.0519	0.0156
nobs	50	50	50	50	50	150	350	150	750
rsqr	0.9789	0.9639	0.9767	0.985	0.9587	0.9455	0.9283	0.9635	0.94

\* Significant at .10 level

\*\* Significant at .05 level

Table E.6: 1992 OLS Estimates (Sparse Spec., Small Samples)

Variable	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Zone 7	Zone 8	Zone 9	Zone 10
intercept	10.032**	10.492**	9.3434**	8.756**	10.26**	9.8421**	9.8729**	9.6631**	10.064**	9.5257**
baths	0.0792	0.0566*	0.0141	0.0521	-0.024	0.1705**	0.0163	-0.008	0.0617**	0.062
regheatarea	0.8065**	0.3726**	1.1902**	1.0518**	0.5671**	0.2728	0.4652**	0.4831*	0.4735**	0.495*
sqregheat	-0.11**	-0.01	-0.232**	-0.2	-0.031	-0.004	-0.037	-0.017	-0.025	-0.076
acreage1	0.312	.	.	.	.	.	.	.	.	.
sqacre1	0.0253	.	.	.	.	.	.	.	.	.
acreage2	.	0.0761	.	.	.	.	.	.	.	.
sqacre2	.	0.03	.	.	.	.	.	.	.	.
acreage3	.	.	0.0376	.	.	.	.	.	.	.
sqacre3	.	.	0.0922	.	.	.	.	.	.	.
acreage4	.	.	.	-0.222	.	.	.	.	.	.
sqacre4	.	.	.	0.2215	.	.	.	.	.	.
acreage5	.	.	.	.	0.9667**	.	.	.	.	.
sqacre5	.	.	.	.	-0.974**	.	.	.	.	.
acreage6	.	.	.	.	.	0.3732	.	.	.	.
sqacre6	.	.	.	.	.	-0.308	.	.	.	.
acreage7	.	.	.	.	.	.	0.32**	.	.	.
sqacre7	.	.	.	.	.	.	-0.096*	.	.	.
acreage8	.	.	.	.	.	.	.	-0.383	.	.
sqacre8	.	.	.	.	.	.	.	0.3693	.	.
acreage9	.	.	.	.	.	.	.	.	0.0072	.
sqacre9	.	.	.	.	.	.	.	.	0.001	.
acreage10	.	.	.	.	.	.	.	.	.	0.0735**
sqacre10	.	.	.	.	.	.	.	.	.	-0.001
acreage11	.	.	.	.	.	.	.	.	.	.
sqacre11	.	.	.	.	.	.	.	.	.	.
acreage14	.	.	.	.	.	.	.	.	.	.
sqacre14	.	.	.	.	.	.	.	.	.	.
acreage16	.	.	.	.	.	.	.	.	.	.
sqacre16	.	.	.	.	.	.	.	.	.	.
acreage18	.	.	.	.	.	.	.	.	.	.
sqacre18	.	.	.	.	.	.	.	.	.	.
acreage21	.	.	.	.	.	.	.	.	.	.
sqacre21	.	.	.	.	.	.	.	.	.	.
age	-0.012	-0.016**	-0.01**	0.0048	-0.014*	0.0006	0.0026	-68E-5	0.0101	-0.018**
sqage	0.0002*	0.0004	521E-7	-19E-5	0.0001	-12E-5	-78E-5	-11E-5	-7E-4**	0.0002**
story	-0.513**	-0.072	-0.06	-0.104	-0.14**	-0.007	-0.05	-0.022	-0.053	0.0044
grade	0.0082**	0.0053**	0.0086**	0.015**	0.0059**	0.0072**	0.0091**	0.0118**	0.0068**	0.0117**
nobs	50	50	50	50	50	50	50	50	50	50
rsqr	0.8615	0.9088	0.8573	0.7868	0.9452	0.8372	0.9094	0.8706	0.9269	0.9111

\* Significant at .10 level

\*\* Significant at .05 level



Table E.6(continued)

Variable	Zone 11	Zone 14	Zone 16	Zone 18	Zone 21	Group 1	Group 2	Group 3	Wake Co.
intercept	8.4521**	8.7462**	9.191**	9.217**	9.4229**	9.5723**	9.0758**	10.074**	9.7219**
baths	0.0828**	0.14**	0.2641**	0.1416**	0.1147	0.0418**	0.0982**	0.0318	0.0674**
regheatarea	1.2276**	1.2063**	0.663**	0.9554**	0.2404	0.6943**	0.9111**	0.5304**	0.738**
sregheat	-0.249**	-0.207**	-0.087	-0.166**	0.0038	-0.079**	-0.162**	-0.039**	-0.091**
acreage1	.	.	.	.	.	.	.	.	0.1135
sqacre1	.	.	.	.	.	.	.	.	0.0828
acreage2	.	.	.	.	.	0.2576	.	.	0.2993**
sqacre2	.	.	.	.	.	-0.113	.	.	-0.123
acreage3	.	.	.	.	.	.	-0.246*	.	-0.416**
sqacre3	.	.	.	.	.	.	0.355	.	0.5528**
acreage4	.	.	.	.	.	.	.	.	0.0677
sqacre4	.	.	.	.	.	.	.	.	0.0455
acreage5	.	.	.	.	.	.	.	0.3837**	0.3573**
sqacre5	.	.	.	.	.	.	.	-0.467**	-0.268
acreage6	.	.	.	.	.	.	0.228*	.	0.1202
sqacre6	.	.	.	.	.	.	-0.21	.	-0.093
acreage7	.	.	.	.	.	0.1767*	.	.	0.1795**
sqacre7	.	.	.	.	.	-0.043	.	.	-0.033
acreage8	.	.	.	.	.	.	0.201	.	0.2752
sqacre8	.	.	.	.	.	.	-0.19	.	-0.363
acreage9	.	.	.	.	.	.	.	0.0722**	0.0816**
sqacre9	.	.	.	.	.	.	.	-0.005	-0.004
acreage10	.	.	.	.	.	.	.	0.0756**	0.094**
sqacre10	.	.	.	.	.	.	.	-0.002	-0.004*
acreage11	-0.105	.	.	.	.	.	-0.024	.	-0.053
sqacre11	0.028	.	.	.	.	.	0.0083	.	0.0156
acreage14	.	-0.023	.	.	.	0.1608*	.	.	0.1713**
sqacre14	.	0.0383	.	.	.	-0.03	.	.	-0.035
acreage16	.	.	0.1959*	.	.	.	-0.007	.	0.001
sqacre16	.	.	-0.052*	.	.	.	0.0031	.	0.0033
acreage18	.	.	.	-0.114	.	.	-0.006	.	-0.017
sqacre18	.	.	.	0.0375**	.	.	0.0178**	.	0.0224**
acreage21	.	.	.	.	-0.048	.	-0.013	.	0.0149
sqacre21	.	.	.	.	0.0058	.	0.0087**	.	0.0031
age	324E-7	0.0019	-0.006	-0.002	-0.009**	-0.005	-0.005**	-0.011**	-0.006**
sqage	-41E-6	751E-8	-4E-5	0.0002	0.0001**	0.0001	217E-7	0.0001**	0.0000432**
story	-0.008	-0.149**	-0.241**	-0.027	-0.038	-0.096**	-0.061**	-0.08**	-0.084**
grade	0.0149**	0.0119**	0.0102**	0.0092**	0.014**	0.0096**	0.0118**	0.0073**	0.0076**
nobs	50	50	50	50	50	150	350	150	750
rsqr	0.9144	0.9117	0.9245	0.9355	0.9125	0.9011	0.8778	0.9189	0.8998

\* Significant at .10 level

\*\* Significant at .05 level

Table E.7: 1992 Spatial Error Estimates (Base Spec., All Observations)

Variable	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Zone 7	Zone 8	Zone 9	Zone 10
intercept	10.417*	10.235*	9.6931*	9.578*	10.223*	9.6006*	10.854*	9.8918*	10.244*	10.194*
baths	-0.001	0.0278*	0.0141	0.0289	0.022*	0.0437*	0.0273*	0.0261*	0.0273*	0.0105
regheatarea	0.448*	0.372*	0.5397*	0.8115*	0.3896*	0.3698*	0.3565*	0.552*	0.4209*	0.3945*
sqregheat	-0.037*	-0.03*	-0.086*	-0.147*	-0.035*	-0.033	-0.03*	-0.073*	-0.038*	-0.039*
acrage1	0.363*	.	.	.	.	.	.	.	.	.
sqacre1	-0.077	.	.	.	.	.	.	.	.	.
acrage2	.	0.0996*	.	.	.	.	.	.	.	.
sqacre2	.	-0.024*	.	.	.	.	.	.	.	.
acrage3	.	.	0.2138*	.	.	.	.	.	.	.
sqacre3	.	.	-0.02	.	.	.	.	.	.	.
acrage4	.	.	.	0.0326	.	.	.	.	.	.
sqacre4	.	.	.	0.0342	.	.	.	.	.	.
acrage5	.	.	.	.	0.1317*	.	.	.	.	.
sqacre5	.	.	.	.	-0.015	.	.	.	.	.
acrage6	.	.	.	.	.	0.1452*	.	.	.	.
sqacre6	.	.	.	.	.	-0.008*	.	.	.	.
acrage7	.	.	.	.	.	.	0.1019*	.	.	.
sqacre7	.	.	.	.	.	.	-0.01*	.	.	.
acrage8	.	.	.	.	.	.	.	-0.007	.	.
sqacre8	.	.	.	.	.	.	.	0.0112*	.	.
acrage9	.	.	.	.	.	.	.	.	0.0601*	.
sqacre9	.	.	.	.	.	.	.	.	-89E-5	.
acrage10	.	.	.	.	.	.	.	.	.	0.0695*
sqacre10	.	.	.	.	.	.	.	.	.	-0.001
acrage11	.	.	.	.	.	.	.	.	.	.
sqacre11	.	.	.	.	.	.	.	.	.	.
acrage14	.	.	.	.	.	.	.	.	.	.
sqacre14	.	.	.	.	.	.	.	.	.	.
acrage16	.	.	.	.	.	.	.	.	.	.
sqacre16	.	.	.	.	.	.	.	.	.	.
acrage18	.	.	.	.	.	.	.	.	.	.
sqacre18	.	.	.	.	.	.	.	.	.	.
acrage21	.	.	.	.	.	.	.	.	.	.
sqacre21	.	.	.	.	.	.	.	.	.	.
age	-0.007*	-0.009*	-0.009*	-0.002	-0.009*	-0.007*	-0.011*	-0.003*	-0.009*	-0.013*
sqage	565E-7*	0.0001*	301E-7	-18E-6	0.0001*	191E-7	0.0001*	-81E-6	0.0001*	0.0001*
bsmtheat	417E-7	0.0001*	0.0001*	0.0001	0.0001*	0.0001*	0.0001*	366E-7	0.0001*	0.0001*
bsmtunheat	-2E-5	461E-8	0.0003*	887E-8	569E-7*	585E-7	395E-7*	0.0002	0.0001*	-42E-6
atticheat	0.0003*	0.0001*	0.0002*	0.0002*	0.0001*	0.0002*	0.0001*	0.0001*	0.0001*	0.0001*
atticunheat	0.0003*	0.0001*	144E-8	0.0003	348E-7*	0.0001	224E-7	0.0001*	397E-7	0.0001
otherunheatarea	0.0007	0.0001	-0.006	.	0.0001*	-28E-6	386E-7	0.0002*	365E-7	0.0002*
walldum1	-0.003	0.0095	-0.017	-0.053*	0.0191*	0.0042	0.0335*	0.0478*	0.0292*	0.0473*
bsmtum1	0.0922*	0.0854*	0.0029	0.1111*	0.0582*	0.0974*	0.0102	0.109*	0.0768*	0.0633*
bsmtum2	0.0749*	0.0741*	0.0267	0.0693*	0.063*	0.0518*	0.0426*	0.074*	0.0568*	0.02
heatdum6	0.0599	.	-0.023	.	-0.028	0.0967	.	.	0.1263	-0.01
heatdum7	-0.795*	.	0.369*	.	.	-0.191*	-0.438*	.	.	0.1948*
acdum1	0.0483*	0.0776*	0.0963*	-0.053	0.0286	0.0762*	-0.223*	0.1336*	0.1861*	0.239*
story	-0.037	-0.008	0.0013	-0.002	-0.027*	-0.028*	-0.032*	-0.029*	-0.023*	0.014
detgarage	0.0278	0.0327*	-0.016	0.0619	0.079*	0.0488*	0.0039	0.0093	0.0277	0.0465*
condadum	0.0804*	-0.006	0.0248	0.0821*	0.0231	.	0.0595*	.	.	.
condcdum	-0.024	-0.045*	-0.078*	-0.04	-0.028	-0.018	-0.082*	-0.035	-0.096*	-0.036
condddum	-0.503*	.	-0.203*	.	.	-0.128*	.	0.0604	.	-0.06
carport	0.0001	0.0001*	0.0002*	0.0001	0.0001*	0.0001*	557E-7	0.0002*	322E-7	0.0001
encporch	0.0002*	0.0003*	-68E-6	-78E-6	0.0002*	-13E-5	-36E-6	0.0004*	0.0002*	0.0008*
scrporch	0.0003*	0.0001*	0.0005*	0.0001	0.0001*	0.0001*	0.0002*	0.0002*	0.0001*	143E-7
opnporch	-35E-6	0.0001*	-38E-6	0.0002*	0.0002*	347E-7	511E-7	0.0002*	0.0002*	0.0001
garage	0.0001*	0.0002*	0.0003*	0.0001*	0.0002*	0.0002*	0.0001*	0.0001*	0.0002*	0.0002*
storage	0.0002	0.0001*	0.0005*	0.0001	0.0003*	-55E-6	231E-7	-53E-5*	-13E-5	-86E-6
patio	0.0001*	257E-7	0.0001	484E-7	0.0001*	-65E-6	393E-7	-37E-6	0.0001	0.0001
deck	0.0001*	513E-7*	0.0002*	0.0001*	0.0001*	176E-7	0.0001*	0.0001*	0.0001*	0.0001*
stoop	-28E-7	0.0003*	0.0001	0.0003	0.0005*	0.0001	0.0004*	0.0004	2E-5	0.0006*
fireplaces	0.0428*	0.0536*	0.0558*	0.0328*	0.0248*	0.0217*	0.0121	0.0314*	0.0718*	0.0651*
poolres	-0.049	0.013	0.1868	0.0987	0.0368*	-0.021	0.0353*	0.0162	0.0197	-0.014
grade	0.0039*	0.0057*	0.0078*	0.008*	0.0063*	0.0107*	0.0042*	0.0067*	0.004*	0.0042*
lambda	0.6927*	0.613*	0.1152	0.5357*	0.6173*	0.2093*	0.7962*	0.7137*	0.7461*	0.7494*
nobs	545	1679	289	233	2095	392	983	555	648	356
rsqr	0.9217	0.9371	0.905	0.8544	0.9574	0.8993	0.9476	0.9191	0.9334	0.9343

\* Significant at .10 level

\*\* Significant at .05 level

Table E.7(continued)

Variable	Zone 11	Zone 14	Zone 16	Zone 18	Zone 21	Group 1	Group 2	Group 3	Wake Co.
intercept	10.009*	10.065*	9.4365*	9.3104*	9.473*	10.326*	9.7309*	10.2*	10.236*
baths	0.0534*	0.0496*	0.0165	0.0401*	0.0576*	0.026*	0.0447*	0.0239*	0.0273*
regheatarea	0.5809*	0.386*	0.6449*	0.591*	0.4795*	0.3723*	0.5342*	0.3972*	0.4163*
sqregheat	-0.08*	-0.027*	-0.117*	-0.098*	-0.058*	-0.031*	-0.075*	-0.036*	-0.04*
acreage1	.	.	.	.	.	.	.	.	0.3241*
sqacre1	.	.	.	.	.	.	.	.	-0.055
acreage2	.	.	.	.	.	0.1139*	.	.	0.1788*
sqacre2	.	.	.	.	.	-0.027*	.	.	-0.052*
acreage3	.	.	.	.	.	.	0.1212*	.	0.0794*
sqacre3	.	.	.	.	.	.	-0.007	.	0.004
acreage4	.	.	.	.	.	.	.	.	0.0176
sqacre4	.	.	.	.	.	.	.	.	0.0527*
acreage5	.	.	.	.	.	.	.	0.1366*	0.2589*
sqacre5	.	.	.	.	.	.	.	-0.009	-0.074*
acreage6	.	.	.	.	.	.	0.1157*	.	0.1043*
sqacre6	.	.	.	.	.	.	-0.006*	.	-0.005*
acreage7	.	.	.	.	.	0.0868*	.	.	0.1077*
sqacre7	.	.	.	.	.	-0.007*	.	.	-0.011*
acreage8	.	.	.	.	.	.	0.0512*	.	0.0096
sqacre8	.	.	.	.	.	.	0.0025	.	0.0096*
acreage9	.	.	.	.	.	.	.	0.0589*	0.0758*
sqacre9	.	.	.	.	.	.	.	-41E-5	-0.001*
acreage10	.	.	.	.	.	.	.	0.051*	0.0699*
sqacre10	.	.	.	.	.	.	.	-38E-5	-0.001*
acreage11	0.037*	.	.	.	.	.	0.035*	.	0.0336*
sqacre11	-0.003	.	.	.	.	.	-12E-5	.	0.0015
acreage14	.	0.0647*	.	.	.	0.0502*	.	.	0.0733*
sqacre14	.	-0.007	.	.	.	-0.002	.	.	-0.005
acreage16	.	.	0.2664*	.	.	.	0.0103	.	0.0168
sqacre16	.	.	-0.077*	.	.	.	0.0163*	.	0.0139*
acreage18	.	.	.	0.0256	.	.	0.0043	.	-0.035*
sqacre18	.	.	.	0.0029	.	.	0.0088*	.	0.017*
acreage21	.	.	.	.	0.0581*	.	0.0485*	.	0.0497*
sqacre21	.	.	.	.	-0.002	.	0.0006	.	0.0009
age	-0.007*	-0.007*	-0.005*	-0.011*	-0.011*	-0.009*	-0.007*	-0.01*	-0.008*
sqage	11E-6	0.0001*	122E-7	0.0001*	0.0001*	0.0001*	19E-6*	0.0001*	0.0001*
bsmtheat	0.0001*	0.0001*	-78E-7	0.0002*	619E-8	0.0001*	0.0001*	0.0001*	0.0001*
bsmtunheat	0.0001*	0.0002	0.0004	0.0004*	-36E-5	157E-7	0.0001*	547E-7*	0.000026*
atticheat	0.0003*	0.0002*	0.0002*	0.0001*	0.0001*	0.0001*	0.0002*	0.0001*	0.0001*
atticunheat	0.0001	-15E-5*	0.0001*	-11E-5*	-65E-6	38E-6*	452E-7*	339E-7*	0.0000438*
otherunheatarea	0.0002	0.0001	.	-11E-5	.	0.0001*	329E-7	0.0001*	0.0001*
walldum1	0.049*	0.0836*	0.0129	0.028*	0.0569*	0.0198*	0.0275*	0.0265*	0.0183*
bsmtum1	0.1283*	0.0212	0.1294*	0.1389*	0.0718*	0.0647*	0.0988*	0.0609*	0.0779*
bsmtum2	0.0772*	0.0379	0.1186*	0.0301	0.0906	0.0652*	0.0644*	0.0636*	0.0718*
heatdum6	.	.	-0.19*	0.5609*	.	.	-0.044	0.0059	-0.058*
heatdum7	0.3145*	-0.285*	-0.2*	.	-0.377*	-0.21*	0.0736*	0.1431*	-0.071*
acdum1	0.102*	0.0916	0.0566	0.011	0.2115*	0.0685*	0.088*	0.1121*	0.0725*
story	-0.003	-0.034	-0.017	0.0094	-0.028*	-0.017*	-0.016*	-0.02*	-0.017*
detgarage	0.0555*	-0.006	0.1174*	0.0688*	0.0572*	0.0308*	0.0607*	0.0544*	0.0493*
condadum	.	-0.018	.	.	.	0.0109	-7E-4	0.0273	0.0385*
condcdum	-0.041*	-0.14*	-0.152*	0.0416*	0.0108	-0.065*	-0.05*	-0.048*	-0.074*
condddum	-0.177*	-0.348*	1.3462*	-0.34*	0.0585	-0.355*	-0.09*	-0.098*	-0.192*
carport	136E-7	0.0002	0.0002*	477E-7	-12E-5	0.0001*	0.0001*	0.0001*	0.0001*
encporch	0.0001	0.0008*	0.0002	0.0002	0.0003*	0.0002*	0.0002*	0.0002*	0.0002*
scrporch	0.0002*	0.0004*	0.0001	0.0002*	328E-8	0.0002*	0.0002*	0.0001*	0.0002*
opnporch	0.0003*	0.0004*	0.0001*	294E-7	0.0001	0.0001*	0.0001*	0.0001*	0.0001*
garage	0.0002*	0.0002*	0.0002*	0.0002*	0.0002*	0.0002*	0.0002*	0.0002*	0.0002*
storage	-14E-5	0.0005	-1E-5	0.0001	389E-7	6E-5	374E-7	0.0002*	0.0001*
patio	431E-7	0.0001	-1E-4	0.0001	-41E-6	277E-7*	187E-8	0.0001*	0.0000529*
deck	0.0001*	0.0002*	-5E-5	0.0002*	434E-7	0.0001*	0.0001*	0.0001*	0.0001*
stoop	0.0006*	0.0009*	-38E-6	0.0001	0.0001	0.0003*	0.0002*	0.0004*	0.0003*
fireplaces	0.0818*	0.1203*	0.0636*	0.0402*	0.0215	0.0498*	0.051*	0.0377*	0.0517*
poolres	-0.033	0.0558	0.039	0.1384*	0.0881*	0.0189*	0.0227	0.0205	0.0217*
grade	0.0034*	0.0049*	0.0091*	0.0116*	0.0097*	0.0052*	0.0075*	0.0055*	0.0049*
lambda	0.3302*	0.7026*	0.6239*	0.5067*	0.6533*	0.7189*	0.5974*	0.6594*	0.7195*
nobs	495	239	281	307	364	2901	2683	3099	9461
rsqr	0.9037	0.9493	0.9161	0.9352	0.9365	0.9463	0.9106	0.9479	0.9462

\* Significant at .10 level

\*\* Significant at .05 level

Table E.8: 1992 Spatial Error Estimates (Full Spec., All Observations)

Variable	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Zone 7	Zone 8	Zone 9	Zone 10
intercept	10.671*	10.002*	9.3178*	9.4616*	9.9436*	10.226*	8.3463*	6.3354*	10.241*	10.424*
baths	0.0019	0.0301*	0.0081	0.0242	0.0222*	0.0424*	0.0277*	0.0253*	0.0276*	0.0086
regheatarea	0.4223*	0.3533*	0.4615*	0.6551*	0.3837*	0.3789*	0.37*	0.535*	0.4109*	0.3629*
sqregheat	-0.032*	-0.027*	-0.069*	-0.111*	-0.034*	-0.036	-0.032*	-0.069*	-0.035*	-0.03*
acreage1	0.2549*	.	.	.	.	.	.	.	.	.
sqacre1	0.0063	.	.	.	.	.	.	.	.	.
acreage2	.	0.0892*	.	.	.	.	.	.	.	.
sqacre2	.	-0.022*	.	.	.	.	.	.	.	.
acreage3	.	.	0.1611*	.	.	.	.	.	.	.
sqacre3	.	.	-0.008	.	.	.	.	.	.	.
acreage4	.	.	.	0.0075	.	.	.	.	.	.
sqacre4	.	.	.	0.0348	.	.	.	.	.	.
acreage5	.	.	.	.	0.1375*	.	.	.	.	.
sqacre5	.	.	.	.	-0.018	.	.	.	.	.
acreage6	.	.	.	.	.	0.1251*	.	.	.	.
sqacre6	.	.	.	.	.	-0.007*	.	.	.	.
acreage7	.	.	.	.	.	.	0.0896*	.	.	.
sqacre7	.	.	.	.	.	.	-0.007*	.	.	.
acreage8	.	.	.	.	.	.	.	-0.003	.	.
sqacre8	.	.	.	.	.	.	.	0.0105*	.	.
acreage9	.	.	.	.	.	.	.	.	0.0715*	.
sqacre9	.	.	.	.	.	.	.	.	-0.002*	.
acreage10	.	.	.	.	.	.	.	.	.	0.0681*
sqacre10	.	.	.	.	.	.	.	.	.	-0.001
acreage11	.	.	.	.	.	.	.	.	.	.
sqacre11	.	.	.	.	.	.	.	.	.	.
acreage14	.	.	.	.	.	.	.	.	.	.
sqacre14	.	.	.	.	.	.	.	.	.	.
acreage16	.	.	.	.	.	.	.	.	.	.
sqacre16	.	.	.	.	.	.	.	.	.	.
acreage18	.	.	.	.	.	.	.	.	.	.
sqacre18	.	.	.	.	.	.	.	.	.	.
acreage21	.	.	.	.	.	.	.	.	.	.
sqacre21	.	.	.	.	.	.	.	.	.	.
age	-0.007*	-0.009*	-0.006*	-0.004*	-0.01*	-0.007*	-0.01*	-0.001	-0.008*	-0.013*
sage	0.0001*	0.0001*	235E-7	555E-7	0.0001*	301E-7	0.0001*	-12E-5*	0.0001*	0.0001*
bsmtheat	535E-7*	0.0001*	0.0001*	503E-7	0.0001*	0.0001*	0.0001*	381E-7	0.0001*	0.0001*
bsmtunheat	-31E-6	663E-8	0.0004*	366E-7	592E-7*	547E-7	39E-6*	0.0002*	0.0001*	-36E-6
atticheat	0.0003*	0.0001*	0.0002*	0.0002*	0.0001*	0.0002*	0.0001*	0.0001*	0.0001*	0.0001*
atticunheat	0.0002*	0.0001*	332E-7	0.0002	35E-6*	0.0001	212E-7	0.0002*	518E-7*	0.0001
otherunheatarea	0.0006	0.0001	-0.005	.	0.0001*	-25E-6	399E-7	0.0003*	321E-7	0.0001
walldum1	-0.002	0.0102	-0.008	-0.056*	0.0203*	0.0117	0.037*	0.0456*	0.0338*	0.058*
bsmtum1	0.093*	0.0809*	0.0192	0.0997*	0.0585*	0.1054*	0.0068	0.0995*	0.0799*	0.0822*
bsmtum2	0.0757*	0.0716*	0.0484	0.0752*	0.0621*	0.0653*	0.0444*	0.0743*	0.058*	0.0043
heatdum6	0.0399	.	-0.023	.	-0.036	0.083	.	.	0.1557	0.0187
heatdum7	-0.594*	.	0.3261*	.	.	-0.196	-0.429*	.	.	0.2163*
acdum1	0.0492*	0.0735*	0.102*	0.0143	0.0246	0.0588*	-0.23*	0.1387*	0.1974*	0.2466*
story	-0.033	-0.008	-0.006	0.0015	-0.027*	-0.027*	-0.033*	-0.031*	-0.025*	0.014
detgarage	0.0244	0.0312*	0.0009	-0.004	0.0777*	0.0458*	0.0033	0.0127	0.0228	0.0567*
condadum	0.0805*	-0.003	0.0449	0.0548*	0.0254	.	0.0677*	.	.	.
condcdum	0.0071	-0.037*	-0.029	0.0144	-0.023	-0.029	-0.083*	-0.04*	-0.093*	-0.039
condddum	-0.309*	.	-0.123*	.	.	-0.099*	.	0.0946	.	-0.049
carport	0.0001	0.0001*	0.0002*	0.0001	0.0001*	0.0001*	0.0001	0.0002*	212E-7	0.0001
encporch	0.0002*	0.0003*	-22E-5	-26E-5	0.0002*	-14E-5	-62E-6	0.0004*	0.0002*	0.0007*
scrporch	0.0002*	0.0001*	0.0005*	0.0001	0.0001*	0.0001*	0.0002*	0.0001*	0.0001*	55E-6
opnporch	-18E-6	0.0001*	451E-7	0.0003*	0.0002*	393E-7	507E-7	0.0002*	0.0002*	0.0001
garage	0.0001*	0.0002*	0.0002*	0.0001*	0.0002*	0.0002*	0.0001*	0.0001*	0.0002*	0.0002*
storage	0.0002	0.0001*	0.0004*	246E-7	0.0003*	11E-6	365E-7	-56E-5*	-74E-6	-13E-5
patio	609E-7*	275E-7	431E-7	0.0001	0.0001*	-77E-6	416E-7	-3E-5	605E-7	0.0001
deck	0.0001*	519E-7*	0.0002*	0.0001*	0.0001*	335E-7	0.0001*	0.0001*	0.0001*	0.0001*
stoop	-41E-6	0.0003*	0.0001	0.0007	0.0006*	0.0002	0.0004*	0.0005*	-61E-6	0.0006*
fireplaces	0.0408*	0.0504*	0.0441*	0.0284*	0.0237*	0.0162	0.0071	0.0298*	0.0709*	0.0571*
poolres	-0.068	0.011	0.1906*	0.1382*	0.0393*	-0.009	0.0318*	0.0046	0.0206	-0.022
grade	0.0037*	0.0055*	0.0081*	0.0093*	0.0059*	0.0099*	0.0041*	0.0064*	0.0042*	0.0044*
perc.nonwhite.1990	-0.003*	-63E-5	0.0004	-0.006*	-12E-5	0.0006	0.0099*	0.0125*	0.002*	-38E-5
medianvalue	691E-9+	131E-8+	257E-8*	465E-9	401E-9+	561E-9	11E-8+	359E-8+	529E-9+	148E-8
medttw	-0.005	-21E-5	-24E-5	0.0133	-0.001	0.0051	0.0111*	-0.012	-0.005*	0.0055
perc_under18	0.0024	-0.002	0.0048*	0.0135*	-46E-5	0.001	0.0263*	0.0273*	-0.005	0.0015
perc_owner_occ	-12E-6	0.0002	0.0005	-0.002	0.0006*	-35E-6	0.0086*	0.0039*	0.0024*	0.0002
nearestpark	0.0255	0.0032	-0.009	-0.073*	0.0027	0.02*	0.0057	-0.015	0.0097	0.0016
nearestsc	0.0043	-0.004	0.0386	0.0698*	0.0023	0.0685*	-0.009	-0.147*	-0.007	-0.017*
bigparkdistance	-0.004	0.0019	-0.002	-0.005	0.0043*	-0.016*	0.008*	0.0388*	-0.001	-0.007
taxrate	-0.018	0.0128	0.0777*	0.1137*	0.0247	0.0231	0.1299*	0.0773*	0.2015*	-0.039
lambda	0.4202*	0.4943*	0	0.3076*	0.5769*	0.2218*	0.7047*	0.6427*	0.4941*	0.4642*
nobs	545	1679	289	233	2095	392	983	555	648	356
rsqr	0.925	0.9381	0.9121	0.8782	0.9577	0.9003	0.9473	0.9241	0.9339	0.9342

+ Significance indeterminate from asymptotic T-test

\* Significant at .10 level

\*\* Significant at .05 level

Table E.8(continued)

Variable	Zone 11	Zone 14	Zone 16	Zone 18	Zone 21	Group 1	Group 2	Group 3	Wake Co.
intercept	10.418*	11.132*	9.0708*	9.4124*	8.9988*	10.092*	9.4375*	10.181*	10.257*
baths	0.0468*	0.0516*	0.0175	0.0361*	0.0571*	0.026*	0.0419*	0.0238*	0.0273*
regheatarea	0.502*	0.3805*	0.6594*	0.5806*	0.5031*	0.3732*	0.5112*	0.3949*	0.4082*
sregheat	-0.061*	-0.027*	-0.12*	-0.093*	-0.063*	-0.032*	-0.069*	-0.036*	-0.039*
acreage1	.	.	.	.	.	.	.	.	0.2235*
sqacre1	.	.	.	.	.	.	.	.	0.0087
acreage2	.	.	.	.	.	0.1211*	.	.	0.1646*
sqacre2	.	.	.	.	.	-0.029*	.	.	-0.048*
acreage3	.	.	.	.	.	.	0.0953*	.	0.0931*
sqacre3	.	.	.	.	.	.	-88E-5	.	0.0025
acreage4	.	.	.	.	.	.	.	.	0.0275
sqacre4	.	.	.	.	.	.	.	.	0.0504*
acreage5	.	.	.	.	.	.	.	0.0949*	0.1245*
sqacre5	.	.	.	.	.	.	.	0.0127	-0.002
acreage6	.	.	.	.	.	.	0.1059*	.	0.1071*
sqacre6	.	.	.	.	.	.	-0.005*	.	-0.006*
acreage7	.	.	.	.	.	0.0681*	.	.	0.0596*
sqacre7	.	.	.	.	.	-0.003	.	.	-0.002
acreage8	.	.	.	.	.	.	0.0263	.	0.0339
sqacre8	.	.	.	.	.	.	0.0058	.	0.0064*
acreage9	.	.	.	.	.	.	.	0.0686*	0.0776*
sqacre9	.	.	.	.	.	.	.	-94E-5	-0.001*
acreage10	.	.	.	.	.	.	.	0.052*	0.0664*
sqacre10	.	.	.	.	.	.	.	-41E-5	-0.001*
acreage11	0.0561*	.	.	.	.	.	0.0425*	.	0.0748*
sqacre11	-0.004*	.	.	.	.	.	-0.001	.	-0.003*
acreage14	.	0.0222	.	.	.	0.0887*	.	.	0.1247*
sqacre14	.	-0.002	.	.	.	-0.008*	.	.	-0.013*
acreage16	.	.	0.3161*	.	.	.	0.0398	.	0.0384*
sqacre16	.	.	-0.092*	.	.	.	0.0101	.	0.0096*
acreage18	.	.	.	0.0078	.	.	-0.007	.	0.0002
sqacre18	.	.	.	0.0083	.	.	0.0113*	.	0.0092*
acreage21	.	.	.	.	0.0657*	.	0.0404*	.	0.0683*
sqacre21	.	.	.	.	-0.002	.	0.0015	.	-0.001
age	-0.007*	-0.007*	-0.004*	-0.008*	-0.013*	-0.009*	-0.007*	-0.01*	-0.008*
sqage	153E-7	0.0001*	-19E-7	0.0001*	0.0001*	0.0001*	248E-7*	0.0001*	0.0001*
bsmtheat	0.0001*	0.0002*	101E-7	0.0002*	43E-7	0.0001*	0.0001*	0.0001*	0.0001*
bsmtunheat	0.0001	0.0002	0.0004	0.0004*	-53E-5	131E-7	0.0001*	553E-7*	0.0000254*
atticheat	0.0003*	0.0002*	0.0002*	0.0002*	0.0001*	0.0001*	0.0002*	0.0001*	0.0001*
atticunheat	0.0001*	-17E-5*	0.0001*	-96E-6*	-62E-6	372E-7*	484E-7*	354E-7*	0.0000433*
otherunheatarea	0.0003	0.0001	.	-86E-6	.	0.0001*	429E-7	0.0001*	0.0001*
walldum1	0.0562*	0.0852*	0.0165	0.0242	0.0417	0.0198*	0.0322*	0.0272*	0.0198*
bsmtdum1	0.1204*	0.0264	0.111	0.1562*	0.0822*	0.0645*	0.0986*	0.0624*	0.0787*
bsmtdum2	0.0697*	0.0613	0.1006*	0.0201	0.0952	0.0651*	0.0657*	0.0627*	0.0724*
heatdum6	.	.	-0.169*	0.6076*	.	.	-0.06*	0.0013	-0.066*
heatdum7	0.2879*	-0.275*	-0.212*	.	-0.396*	-0.195*	0.0697*	0.142*	-0.057*
acdum1	0.1018*	0.1498*	0.043	-0.008	0.2451*	0.0652*	0.0829*	0.1065*	0.0687*
story	0.0027	-0.039*	-0.016	0.0113	-0.024	-0.018*	-0.017*	-0.02*	-0.017*
detgarage	0.0583*	-0.007	0.1351*	0.0645*	0.051*	0.0308*	0.0565*	0.054*	0.0476*
condadum	.	-0.028	.	.	.	0.012	0.0074	0.0242	0.0392*
condcdum	-0.035	-0.139*	-0.16*	0.0658*	-0.003	-0.063*	-0.044*	-0.052*	-0.068*
condddum	-0.171*	-0.374*	1.5459*	-0.495*	0.051	-0.361*	-0.085*	-0.106*	-0.183*
carport	262E-7	0.0002	0.0002*	232E-7	-11E-5	0.0001*	0.0001*	555E-7*	0.0001*
encporch	0.0001	0.0007*	0.0002	0.0004	0.0003*	0.0002*	0.0002*	0.0002*	0.0002*
scrporch	0.0002*	0.0004*	45E-6	0.0002*	307E-7	0.0002*	0.0002*	0.0001*	0.0002*
opnporch	0.0003*	0.0004*	0.0002*	237E-7	61E-6	0.0001*	0.0001*	0.0001*	0.0001*
garage	0.0002*	0.0002*	0.0002*	0.0002*	0.0001*	0.0002*	0.0002*	0.0002*	0.0002*
storage	-79E-6	0.0006*	-38E-6	0.0001	4E-5	573E-7	0.0001	0.0002*	0.0001*
patio	57E-6	0.0001	-11E-5	0.0001	-41E-6	29E-6*	632E-9	0.0001*	0.0000504*
deck	0.0002*	0.0001*	-74E-6	0.0002*	577E-7*	0.0001*	0.0001*	0.0001*	0.0001*
stoop	0.0006*	0.0011*	-56E-7	0.0002	0.0001	0.0003*	0.0002*	0.0004*	0.0003*
fireplaces	0.0829*	0.1172*	0.0609*	0.0394*	0.0116	0.0496*	0.0499*	0.0375*	0.0509*
poolres	-0.025	0.0636	0.0332	0.137*	0.0837*	0.019*	0.0257*	0.0213*	0.0222*
grade	0.0034*	0.0044*	0.0099*	0.0106*	0.0089*	0.0051*	0.0073*	0.0054*	0.0047*
perc_nonwhite_1990	0.0009	0.0013	0.0012	0.0046*	-0.013	-67E-6	-44E-5*	0.0003	-0.001*
medianvalue	118E-8	188E-8	219E-9	171E-8*	102E-7	885E-9+	188E-8+	658E-9+	8.54E-7+
medttw	0.0002	-0.006	-0.003	0.0097*	0.0136	0.0008	0.0021*	-0.003*	-0.002*
perc_under18	-0.002	0.013	0.004	-0.007	0.0797	-0.002	0.0023*	-91E-6	0.0008
perc_owner_occ	-25E-5	0.0003	-0.002	-0.003	-0.036	-86E-6	0.0004	0.0007*	0.0003*
nearestpark	0.0218*	0.0375*	-0.116*	-0.019*	-0.001	0.0047	-25E-5	0.0044*	-0.001
nearestsc	-0.009	0.126*	0.1515*	0.0207	0.0032	-0.008*	-0.009*	-0.001	-0.00049
bigparkdistance	-0.004	-0.033*	-0.01	-0.002	-23E-5	0.0021	0.0014*	-96E-5	-0.00094*
taxrate	0.0176	0.0216	0.1011	.	0.1382	0.0312*	-0.007	0.0236	0.0179*
lambda	0.1094	0.763*	0.689*	0.2737*	0.4503*	0.659*	0.4896*	0.5992*	0.6373*
nobs	495	239	281	307	364	2901	2683	3099	9461
rsqr	0.9057	0.9524	0.9206	0.936	0.9379	0.9462	0.9125	0.9482	0.947

+ Significance indeterminant from asymptotic T-test

\* Significant at .10 level

\*\* Significant at .05 level

Table E.9: 1992 Spatial Error Estimates (Sparse Spec., All Observations)

Variable	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Zone 7	Zone 8	Zone 9	Zone 10
intercept	10.395*	10.264*	9.3362*	9.2694*	10.188*	9.3834*	10.614*	9.8311*	10.309*	9.9537*
baths	0.0243*	0.0724*	0.0666*	0.1034*	0.0503*	0.0992*	0.0402*	0.0643*	0.0479*	0.0404*
regheatarea	0.4798*	0.372*	0.6662*	0.5534*	0.4041*	0.2931*	0.3565*	0.5768*	0.572*	0.5793*
sqregheat	-0.044*	-0.03*	-0.107*	-0.087*	-0.036*	-0.019	-0.026*	-0.071*	-0.064*	-0.073*
acreage1	0.4571*	.	.	.	.	.	.	.	.	.
sqacre1	-0.058	.	.	.	.	.	.	.	.	.
acreage2	.	0.1829*	.	.	.	.	.	.	.	.
sqacre2	.	-0.035*	.	.	.	.	.	.	.	.
acreage3	.	.	0.4346*	.	.	.	.	.	.	.
sqacre3	.	.	-0.074*	.	.	.	.	.	.	.
acreage4	.	.	.	0.1199	.	.	.	.	.	.
sqacre4	.	.	.	-0.014	.	.	.	.	.	.
acreage5	.	.	.	.	0.2526*	.	.	.	.	.
sqacre5	.	.	.	.	-0.051*	.	.	.	.	.
acreage6	.	.	.	.	.	0.1821*	.	.	.	.
sqacre6	.	.	.	.	.	-0.014*	.	.	.	.
acreage7	.	.	.	.	.	.	0.1254*	.	.	.
sqacre7	.	.	.	.	.	.	-0.014*	.	.	.
acreage8	.	.	.	.	.	.	.	0.0499*	.	.
sqacre8	.	.	.	.	.	.	.	0.0025	.	.
acreage9	.	.	.	.	.	.	.	.	0.0774*	.
sqacre9	.	.	.	.	.	.	.	.	-18E-5	.
acreage10	.	.	.	.	.	.	.	.	.	0.0873*
sqacre10	.	.	.	.	.	.	.	.	.	-0.002*
acreage11	.	.	.	.	.	.	.	.	.	.
sqacre11	.	.	.	.	.	.	.	.	.	.
acreage14	.	.	.	.	.	.	.	.	.	.
sqacre14	.	.	.	.	.	.	.	.	.	.
acreage16	.	.	.	.	.	.	.	.	.	.
sqacre16	.	.	.	.	.	.	.	.	.	.
acreage18	.	.	.	.	.	.	.	.	.	.
sqacre18	.	.	.	.	.	.	.	.	.	.
acreage21	.	.	.	.	.	.	.	.	.	.
sqacre21	.	.	.	.	.	.	.	.	.	.
age	-0.005*	-0.005*	-0.009*	0.0019	-0.006*	-0.004*	-0.009*	0.0006	-0.011*	-0.011*
sqage	339E-7*	422E-7*	341E-7	-62E-6	104E-7	-31E-6	547E-7*	-15E-5*	0.0001	0.0001*
story	-0.047*	-0.042*	-0.043	-0.011	-0.051*	-0.045*	-0.063*	-0.059*	-0.072*	-0.017
grade	0.0046*	0.0063*	0.0107*	0.0118*	0.0073*	0.0138*	0.005*	0.0082*	0.0052*	0.0076*
lambda	0.7158*	0.6443*	0.4192*	0.5735*	0.6848*	0.2403*	0.7969*	0.7071*	0.7455*	0.4817*
nobs	545	1679	289	233	2095	392	983	555	648	356
rsqr	0.8944	0.9088	0.8698	0.7926	0.9363	0.8525	0.9314	0.8837	0.9032	0.9046

\* Significant at .10 level

\*\* Significant at .05 level

Table E.9(continued)

Variable	Zone 11	Zone 14	Zone 16	Zone 18	Zone 21	Group 1	Group 2	Group 3	Wake Co.
intercept	9.7333*	9.6764*	8.9308*	9.2176*	9.1804*	10.325*	9.4677*	10.234*	10.207*
baths	0.1015*	0.0901*	0.1356*	0.0591*	0.1053*	0.0557*	0.0852*	0.0492*	0.0583*
regheatarea	0.7411*	0.5104*	0.6389*	0.57*	0.7246*	0.4081*	0.6252*	0.4653*	0.4768*
sqregheat	-0.111*	-0.049*	-0.111*	-0.081*	-0.107*	-0.035*	-0.091*	-0.047*	-0.049*
acreage1	.	.	.	.	.	.	.	.	0.3796*
sqacre1	.	.	.	.	.	.	.	.	-0.032
acreage2	.	.	.	.	.	0.2022*	.	.	0.2839*
sqacre2	.	.	.	.	.	-0.04*	.	.	-0.066*
acreage3	.	.	.	.	.	.	0.1852*	.	0.1442*
sqacre3	.	.	.	.	.	.	-0.024*	.	-0.01
acreage4	.	.	.	.	.	.	.	.	0.0973
sqacre4	.	.	.	.	.	.	.	.	0.0222
acreage5	.	.	.	.	.	.	.	0.2255*	0.3588*
sqacre5	.	.	.	.	.	.	.	-0.031	-0.106*
acreage6	.	.	.	.	.	.	0.1735*	.	0.146*
sqacre6	.	.	.	.	.	.	-0.014*	.	-0.012*
acreage7	.	.	.	.	.	0.129*	.	.	0.1606*
sqacre7	.	.	.	.	.	-0.014*	.	.	-0.019*
acreage8	.	.	.	.	.	.	0.122*	.	0.0934*
sqacre8	.	.	.	.	.	.	-0.008*	.	-0.002
acreage9	.	.	.	.	.	.	.	0.0914*	0.1027*
sqacre9	.	.	.	.	.	.	.	-0.002*	-0.003*
acreage10	.	.	.	.	.	.	.	0.0774*	0.0904*
sqacre10	.	.	.	.	.	.	.	-0.002*	-0.002*
acreage11	0.0729*	.	.	.	.	.	0.0581*	.	0.0671*
sqacre11	-0.002	.	.	.	.	.	0.0005	.	-0.00017
acreage14	.	0.1335*	.	.	.	0.0858*	.	.	0.1083*
sqacre14	.	-0.012*	.	.	.	-0.006	.	.	-0.009*
acreage16	.	.	0.1107*	.	.	.	0.0544*	.	0.0863*
sqacre16	.	.	0.0049	.	.	.	0.0153*	.	0.0034
acreage18	.	.	.	-0.003	.	.	0.0289	.	-0.019
sqacre18	.	.	.	0.0132*	.	.	0.0066	.	0.0171*
acreage21	.	.	.	.	0.0281*	.	0.0705*	.	0.0706*
sqacre21	.	.	.	.	0.0006	.	-0.002	.	-0.00078
age	-0.005*	-0.008*	-0.003	-0.005*	-0.01*	-0.007*	-0.005*	-0.009*	-0.007*
sqage	-82E-7	0.0001*	-19E-7	0.0001	0.0001*	0.0001*	-38E-7	0.0001*	0.0000478*
story	-0.033*	-0.066*	-0.08*	-0.031	-0.079*	-0.054*	-0.047*	-0.056*	-0.05*
grade	0.006*	0.0092*	0.0142*	0.0138*	0.0124*	0.006*	0.0103*	0.0065*	0.0059*
lambda	0.5001*	0.5576*	0.4573*	0.647*	0.5305*	0.7083*	0.6078*	0.6925*	0.7389*
nobs	495	239	281	307	364	2901	2683	3099	9461
rsqr	0.8473	0.8992	0.8505	0.9035	0.9092	0.9239	0.8771	0.9245	0.925

\* Significant at .10 level

\*\* Significant at .05 level

Table E.10: 1992 Spatial Error Estimates (Base Spec., Small Samples)

Variable	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Zone 7	Zone 8	Zone 9	Zone 10
intercept	10.211*	8.4834*	10.384*	10.239*	10.279*	9.5491*	9.2905*	8.5241*	10.764*	8.9664*
baths	-0.048	0.0507	-0.069*	0.0256	-0.034*	0.0301	0.0108	0.0876*	0.076*	0.0323
regheatarea	0.5548*	0.7351*	0.5155	0.3101	0.49*	0.0582	0.6633*	1.1731*	0.5777*	0.9813*
sqregheat	-0.045	-0.117*	-0.082	-0.035	-0.045	0.046	-0.1*	-0.224*	-0.068	-0.139*
acreage1	-0.261	.	.	.	.	.	.	.	.	.
sqacre1	1.0479	.	.	.	.	.	.	.	.	.
acreage2	.	0.0487	.	.	.	.	.	.	.	.
sqacre2	.	0.0511	.	.	.	.	.	.	.	.
acreage3	.	.	0.592*	.	.	.	.	.	.	.
sqacre3	.	.	-0.338	.	.	.	.	.	.	.
acreage4	.	.	.	-1.021*	.	.	.	.	.	.
sqacre4	.	.	.	1.5486*	.	.	.	.	.	.
acreage5	.	.	.	.	-0.002	.	.	.	.	.
sqacre5	.	.	.	.	0.4098	.	.	.	.	.
acreage6	.	.	.	.	.	0.1458	.	.	.	.
sqacre6	.	.	.	.	.	-0.229	.	.	.	.
acreage7	.	.	.	.	.	.	0.1371	.	.	.
sqacre7	.	.	.	.	.	.	0.0574	.	.	.
acreage8	.	.	.	.	.	.	.	-0.452*	.	.
sqacre8	.	.	.	.	.	.	.	0.1209	.	.
acreage9	.	.	.	.	.	.	.	.	-0.001	.
sqacre9	.	.	.	.	.	.	.	.	0.0492	.
acreage10	.	.	.	.	.	.	.	.	.	0.2428*
sqacre10	.	.	.	.	.	.	.	.	.	-0.088*
acreage11	.	.	.	.	.	.	.	.	.	.
sqacre11	.	.	.	.	.	.	.	.	.	.
acreage14	.	.	.	.	.	.	.	.	.	.
sqacre14	.	.	.	.	.	.	.	.	.	.
acreage16	.	.	.	.	.	.	.	.	.	.
sqacre16	.	.	.	.	.	.	.	.	.	.
acreage18	.	.	.	.	.	.	.	.	.	.
sqacre18	.	.	.	.	.	.	.	.	.	.
acreage21	.	.	.	.	.	.	.	.	.	.
sqacre21	.	.	.	.	.	.	.	.	.	.
age	-0.002	-0.014*	-0.013*	-0.01*	-0.014*	-0.007*	0.0037	0.0031	-0.024*	-0.01*
sage	-31E-6	0.0003	0.0001	319E-8	0.0002	-16E-5*	-0.001*	-25E-5	0.0007	399E-7
bsmtheat	-84E-7	-1E-4	0.0002	-13E-6	.	0.0004*	-56E-6	-0.004	0.0001	0.0004*
bsmtunheat	0.0002	-12E-6	-0.038	-24E-5	.	0.0002	0.0012*	.	0.0001	-12E-5
atticheat	0.0005*	0.0002*	0.0002	0.0003	-38E-6	0.0002*	0.0001*	0.0001	0.0001*	0.0009*
atticunheat	-58E-5	0.0004*	.	0.0002	-9E-5	0.0001	-45E-6	-75E-6	-33E-5*	0.0093
otherunheatarea	0.0014*	-13E-5	.	.	.	.	.	.	.	.
walldum1	0.091*	0.0672	0.0075	0.016	0.1029*	0.1418*	0.2063*	-1.998	0.0061	-0.245
bsmtum1	0.0614	0.3349*	10.107	0.198*	.	.	-0.747*	.	-0.075	-0.054
bsmtum2	-0.077	0.2356*	0.1997*	0.0357	.	-0.06	0.0449	2.3265	0.1562	.
heatdum6	.	.	0.5256*	.	.	.	.	.	.	-1.49
heatdum7	-0.554*	.	0.8713*	.	.	.	.	.	.	.
acdum1	-0.011	.	0.5971*	0.1508	.	0.0403	.	.	.	.
story	-0.095	0.0108	0.1194*	-0.059	0.0264	-0.029	0.0185	-0.093*	-0.165*	-0.048
detgarage	0.0753	2.1822*	0.1387*	0.5052*	0.0884	0.0144	-0.392*	0.0364	0.0856	0.143*
condadum	0.1972*	-0.013	0.0126	0.1716*	.	.	-0.365*	.	.	.
condcdum	0.0251	.	-0.37*	0.1339*	.	0.2847*	.	0.0129	.	.
condddum	.	.	-0.438*	.	.	0.2314*	.	.	.	.
carport	-38E-5*	0.0006*	0.0021*	0.0006*	.	0.0002*	.	0.0087	-14E-5	-54E-5*
encporch	0.0002	-0.011*	0.0162	.	0.0003	.	-37E-5	.	.	.
scrporch	-26E-5	-15E-5	-31E-5	0.0006*	-37E-5*	0.0002*	-16E-5	0.0002	0.0006*	-22E-5
opnporch	-32E-5	0.0001	-26E-5	-19E-5	0.0001	0.0004*	-82E-5*	0.0003*	0.0002	0.0004
garage	0.0004*	0.0003*	0.0005*	0.0003*	0.0004*	0.0002*	524E-7	0.0002*	0.0004*	-15E-5*
storage	0.0019*	0.0012	0.001	-6E-4	0.0004	0.0006*	0.0002	0.0007*	0.0004	0.0013
patio	173E-7	-86E-5*	-24E-5	-43E-5	0.0006*	-13E-5	-21E-6	118E-7	-43E-5	0.001
deck	0.0001	0.0001	213E-7	0.0002*	0.0003*	0.0002*	0.0003*	-45E-6	0.0002*	-61E-7
stoop	0.0009	0.0002	-0.002	0.0004	0.0002	0.0002	-0.002*	0.0014	-23E-5	0.0008*
fireplaces	0.1855*	1.522*	0.0941	0.0078	0.0007	0.0907*	0.2439*	0.0043	.	0.1515*
poolres	.	-0.146*	0.0086	.	.	0.0969*	0.1377*	.	0.2391	.
grade	0.0048*	0.0047*	-0.004	0.0069*	0.005*	0.0137*	0.0104*	0.0159*	0.0005	0.0106*
lambda	0	0	0	0	0	0.5323*	0.7687*	0	0	0
nobs	50	50	50	50	50	50	50	50	50	50
rsqr	0.9257	0.9314	0.9283	0.8154	0.9649	0.9414	0.9681	0.952	0.8614	0.9677

\* Significant at .10 level

\*\* Significant at .05 level



Table E.10(continued)

Variable	Zone 11	Zone 14	Zone 16	Zone 18	Zone 21	Group 1	Group 2	Group 3	Wake Co.
intercept	10.383*	9.5418*	9.9647*	8.5527*	9.4918*	9.8261*	9.4621*	10.359*	10.022*
baths	-0.021	0.0231	0.1319*	0.0719*	0.0882	0.019	0.0368*	0.0578*	0.0308*
regheatarea	-0.662*	1.2204*	-0.106	0.5925*	0.6039*	0.6202*	0.5454*	0.509*	0.5411*
sqregheat	0.2456*	-0.18*	0.0725	-0.107*	-0.085*	-0.079*	-0.071*	-0.048*	-0.066*
acrage1	.	.	.	.	.	.	.	.	0.9974*
sqacre1	.	.	.	.	.	.	.	.	-0.709*
acrage2	.	.	.	.	.	0.2547*	.	.	0.296*
sqacre2	.	.	.	.	.	-0.042	.	.	-0.145*
acrage3	.	.	.	.	.	.	0.0093	.	-0.02
sqacre3	.	.	.	.	.	.	0.0019	.	0.0201
acrage4	.	.	.	.	.	.	.	.	0.1424
sqacre4	.	.	.	.	.	.	.	.	-0.019
acrage5	.	.	.	.	.	.	.	0.0096	0.4737*
sqacre5	.	.	.	.	.	.	.	0.3123	-0.301
acrage6	.	.	.	.	.	.	0.0834	.	-0.045
sqacre6	.	.	.	.	.	.	-0.015	.	0.1417
acrage7	.	.	.	.	.	0.1985*	.	.	0.2186*
sqacre7	.	.	.	.	.	-0.027	.	.	-0.047
acrage8	.	.	.	.	.	.	0.3342*	.	0.2756*
sqacre8	.	.	.	.	.	.	-0.207*	.	-0.129
acrage9	.	.	.	.	.	.	.	-0.029	0.1112*
sqacre9	.	.	.	.	.	.	.	0.0616*	0.0044
acrage10	.	.	.	.	.	.	.	-0.009	0.0623
sqacre10	.	.	.	.	.	.	.	0.0158	-0.001
acrage11	0.0742	.	.	.	.	.	0.0493	.	0.0516
sqacre11	-0.1	.	.	.	.	.	-0.019	.	-0.004
acrage14	.	0.2363*	.	.	.	0.1788*	.	.	0.1898*
sqacre14	.	-0.094*	.	.	.	-0.064*	.	.	-0.055*
acrage16	.	.	0.1327*	.	.	.	-0.029	.	-0.003
sqacre16	.	.	-0.045*	.	.	.	-0.016	.	-0.017
acrage18	.	.	.	0.1545*	.	.	-0.039	.	-0.035
sqacre18	.	.	.	-0.044	.	.	0.0205*	.	0.0188*
acrage21	.	.	.	.	-0.071	.	0.0294	.	0.0805*
sqacre21	.	.	.	.	0.0481*	.	0.0031	.	-0.003
age	-0.008*	-0.021*	-0.019*	0.0072	0.0211*	-0.017*	-0.009*	-0.007*	-0.007*
sqage	-25E-6	0.0004	0.0002*	-46E-5	-0.004*	0.0004*	0.0001*	293E-7	0.0000425*
bsmtheat	0.0011*	0.0006*	.	0.0001	0.0012*	519E-7	0.0001*	0.0003*	0.0001*
bsmtunheat	0.0003	-35E-5	.	0.0003*	.	0.0001	0.0001	0.0001*	0.0000599*
atticheat	0.0006*	0.0004*	0.0004*	0.0001	0.0001	0.0002*	0.0002*	0.0001*	0.0002*
atticunheat	0.0005*	-71E-6	0.0002*	-18E-6	-11E-5	-18E-6	0.0001*	-16E-5*	1.46E-6
otherunheatarea	.	-8E-7	.	-13E-5	.	324E-7	0.0002	.	0.0002
walldum1	0.2308*	0.0559	0.0551	-0.014	0.0685	0.0183	0.0299*	0.0114	0.0232*
bsmtum1	-0.521	0.0321	.	0.1297*	.	0.0015	0.1155*	-0.131*	0.0677*
bsmtum2	-0.511	-0.336	0.213*	0.111*	-1.515*	0.098*	0.0637*	0.0481	0.0688*
heatdum6	.	.	-0.66*	.	.	.	-0.153*	-0.066	-0.195*
heatdum7	.	.	.	.	.	.	0.6003*	.	-0.057
acdum1	0.2932*	.	-0.25*	0.2661	.	.	0.1044*	.	0.0549*
story	0.0585	-0.109*	-0.087*	-0.051*	-0.086*	-0.024	-0.02	-0.024	-0.014
detgarage	0.1646*	0.0463	-0.049	0.1977*	0.1026	-0.006	0.0666*	0.0693*	0.0592*
condadum	.	0.172	.	.	.	-0.097*	0.0198	.	0.0259
condcdum	0.2899*	-0.086	0.1717*	0.1928*	-0.092	-0.187*	0.0122	.	-0.08*
condddum	-0.143	.	.	.	.	.	-0.116*	.	-0.109*
carport	0.0001	0.0006*	0.0005*	-6E-4*	.	0.0007*	0.0002*	-61E-6	0.0002*
encporch	0.0021	.	-39E-6	0.0001	0.0005*	0.0003	0.0003	0.0007*	0.0002*
scrporch	-58E-5	478E-7	0.0004	-9E-5	84E-7	604E-7	0.0001	0.0003*	0.0002*
opnporch	0.0003*	0.0004*	385E-7	-38E-5*	0.0003*	0.0001	435E-7	0.0001	0.0000362
garage	0.0004*	-79E-7	0.0001*	0.0002*	0.0003*	0.0001*	0.0002*	0.0003*	0.0002*
storage	-0.001*	0.0005	-29E-5	0.0003*	0.0024*	-67E-5	-96E-7	0.0009	-2.4E-6
patio	0.0001	0.0001	0.0008*	0.0012*	0.0003	362E-7	174E-8	-54E-6	9.4E-6
deck	245E-7	0.0001	0.0002	0.0002	0.0004*	0.0002*	0.0001*	0.0002*	0.0002*
stoop	0.0032*	0.0035*	0.0009	0.0013	0.0015	0.0001	0.0009*	0.0008*	0.0005*
fireplaces	0.1269*	0.0904*	0.0795*	0.3387*	0.005	0.1063*	0.077*	0.0702	0.0812*
poolres	0.3782	0.0569	.	.	0.033	0.0411	0.0844*	0.1211	0.0444
grade	0.0083*	0.0041*	0.0122*	0.013*	0.0095*	0.007*	0.0098*	0.0024*	0.0049*
lambda	0.6165*	0.0137	0	0	0	0.4777*	0.2831*	0	0.3542*
nobs	50	50	50	50	50	150	350	150	750
rsqr	0.9227	0.9554	0.9072	0.9591	0.9551	0.9441	0.9277	0.9155	0.9333

\* Significant at .10 level

\*\* Significant at .05 level

Table E.11: 1992 Spatial Error Estimates (Full Spec., Small Samples)

Variable	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Zone 7	Zone 8	Zone 9	Zone 10
intercept	11.182*	6.2164*	9.0209*	4.758*	10.054*	6.2703*	-4.357	7.6329*	12.169*	2.444*
baths	-0.014	0.0949*	-0.058*	0.0423	-0.022	0.0893*	0.0062	0.0691*	0.009	-0.03
regheatarea	0.4119*	0.4812*	0.0607	-0.484*	0.5764*	0.4399*	0.6486*	0.9199*	0.0096	0.1077
sqregheat	-0.021	-0.091*	0.0356	0.2444*	-0.061*	-0.077*	-0.112*	-0.205*	0.056	0.0009
acrage1	-0.779	.	.	.	.	.	.	.	.	.
sqacre1	1.2078	.	.	.	.	.	.	.	.	.
acrage2	.	0.2487	.	.	.	.	.	.	.	.
sqacre2	.	0.003	.	.	.	.	.	.	.	.
acrage3	.	.	-0.331*	.	.	.	.	.	.	.
sqacre3	.	.	0.2197	.	.	.	.	.	.	.
acrage4	.	.	.	-1.564*	.	.	.	.	.	.
sqacre4	.	.	.	2.9159*	.	.	.	.	.	.
acrage5	.	.	.	.	-0.686*	.	.	.	.	.
sqacre5	.	.	.	.	1.4432*	.	.	.	.	.
acrage6	.	.	.	.	.	0.8035*	.	.	.	.
sqacre6	.	.	.	.	.	-0.553*	.	.	.	.
acrage7	.	.	.	.	.	.	0.216	.	.	.
sqacre7	.	.	.	.	.	.	0.082	.	.	.
acrage8	.	.	.	.	.	.	.	-0.481*	.	.
sqacre8	.	.	.	.	.	.	.	0.1828	.	.
acrage9	.	.	.	.	.	.	.	.	0.0197	.
sqacre9	.	.	.	.	.	.	.	.	0.0372	.
acrage10	.	.	.	.	.	.	.	.	.	1.1438*
sqacre10	.	.	.	.	.	.	.	.	.	-0.403*
acrage11	.	.	.	.	.	.	.	.	.	.
sqacre11	.	.	.	.	.	.	.	.	.	.
acrage14	.	.	.	.	.	.	.	.	.	.
sqacre14	.	.	.	.	.	.	.	.	.	.
acrage16	.	.	.	.	.	.	.	.	.	.
sqacre16	.	.	.	.	.	.	.	.	.	.
acrage18	.	.	.	.	.	.	.	.	.	.
sqacre18	.	.	.	.	.	.	.	.	.	.
acrage21	.	.	.	.	.	.	.	.	.	.
sqacre21	.	.	.	.	.	.	.	.	.	.
age	0.0031	0.0103	-0.004	-0.004	-0.012*	-0.009*	-0.01*	-72E-5	0.0027	-0.035*
sqage	-11E-5	-58E-5*	0.0001*	-35E-5*	0.0002	-11E-5*	-55E-5*	-39E-5	0.0005	0.0002*
bsmtheat	0.0002	-19E-5*	0.0005*	-37E-5*	.	0.0004*	0.0001	-0.003	-27E-5*	0.0002
bsmtunheat	188E-7	0.0002	0.021	-62E-5*	.	0.0009*	0.0016*	.	-71E-6	572E-7
atticheat	0.0009*	0.0004*	0.0003	0.0004*	-15E-5*	-16E-5*	0.0002*	0.0001	0.0002*	0.0002
atticunheat	-31E-5	0.0006*	.	0.0008*	-41E-6	0.0001	108E-7	264E-7	-13E-5	0.0481*
otherunheatarea	0.001	-35E-5*	.	.	.	.	.	.	.	.
walldum1	0.0454	0.0544	-0.09*	0.0606	0.0847*	0.1631*	0.2461*	-1.44	0.2757*	-3.324*
bsmtum1	0.0353	0.2458*	-5.665	0.501*	.	.	-1.006*	.	0.4159*	0.1136*
bsmtum2	-0.07	0.2366*	0.0271	0.1419*	.	-0.316*	-0.048	1.8737	0.1558*	.
heatdum6	.	.	0.075	.	.	.	.	.	.	-6.586*
heatdum7	-0.434*	.	-0.329*	.	.	.	.	.	.	.
acdum1	-0.026	.	0.2866*	0.1237	.	0.0552*	.	.	.	.
story	0.0347	0.095*	0.053*	-0.023	-0.004	-0.128*	0.0208	-0.017	0.0183	0.0379
detgarage	0.0014	1.8457*	0.0438	1.1865*	0.1619*	-0.054*	-0.523*	0.023	0.0207	0.2975*
condadum	0.1289*	-0.05	0.0499	0.0619*	.	.	-0.366*	.	.	.
condcdum	-0.044	.	-0.169	-0.127*	.	0.3682*	.	0.1145	.	.
condddum	.	.	-0.193*	.	.	0.4512*	.	.	.	.
carport	-2E-4	0.0007*	0.0005	0.0011*	.	0.0004*	.	0.0071	0.0002	0.0012
encporch	0.0001	-0.01*	-0.007	.	-19E-5	.	-4E-4*	.	.	.
scrporch	0.0001	-27E-5	0.0002	0.001*	-4E-4*	0.0003*	-18E-6	-7E-5	0.0003*	0.0002
opnporch	13E-6	0.0005	-19E-5	424E-7	-26E-6	0.0005*	-0.001*	0.0004*	0.0004*	-22E-5
garage	0.0002	0.0004*	0.0005*	0.0003*	0.0004*	339E-7	-59E-7	0.0002*	0.0005*	0.0002
storage	0.0012	0.0007	0.0011*	-24E-5	-39E-5	649E-8	0.0009	0.0002	-28E-5	-31E-5
patio	0.0002	-67E-5*	-74E-5*	-16E-5	0.0005*	-5E-4*	-1E-4	0.0001	-65E-5*	0.0207*
deck	0.0003*	599E-8	-24E-6	0.0003*	572E-7	0.0003*	0.0003*	-1E-4	0.0002*	-53E-6
stoop	0.001	0.0001	-0.002*	-62E-5	0.0001	0.0014*	-0.002*	0.0027*	-0.001*	0.001*
fireplaces	0.1261*	1.4511*	0.1383*	-0.043*	-0.038	0.0644*	0.1982*	0.0092	.	2.0929*
poolres	.	-0.182*	0.1566*	.	.	0.1003*	0.1311	.	0.0891	.
grade	0.004*	0.0049*	0.0033	-0.001	0.0059*	0.0201*	0.0151*	0.0202*	-0.002*	0.008*
perc.nonwhite.1990	-0.001	-0.006*	-0.001*	0.0053*	-0.004	0.0051*	0.0603*	-0.02	-0.008*	0.0462*
medianvalue	169E-8*	893E-9	629E-8*	299E-7*	-89E-8*	551E-8*	-89E-7*	-63E-7	-21E-7*	258E-7*
medttw	-0.006	0.0266*	-0.004	0.1212*	-0.004	0.0081	-0.008	0.0341	-0.014*	-0.137*
perc_under18	0.0067	-0.022*	0.0433*	0.0353*	0.0042	0.0072*	0.3085*	-0.065	0.0269*	-0.041*
perc_owner_occ	-0.002	0.0008	0.0038*	-0.003	0.0018*	0.0002	0.0336*	-53E-5	-0.005*	0.028*
nearestpark	-0.024	0.0117	-0.026	-0.156*	0.0064	0.1396*	0.0203*	-0.044*	-0.031*	-0.259*
nearestsc	0.0461	-0.131*	0.0066	-0.168*	-0.014	0.0089	-0.047*	-0.007	0.0432*	0.2593*
bigparkdistance	-0.014	0.0377*	-0.003	0.0383*	0.0042	0.0076	0.031*	0.0331	-0.009*	0.046*
taxrate	.	-0.145*	0.0241	-0.016	0.0283	0.1035*	0.0994	0.0909	0.4091*	-0.009
lambda	0	0	0	0	0	0.9272*	0	0	0	0
nobs	50	50	50	50	50	50	50	50	50	50
rsqr	0.9115	0.9364	0.9758	0.9027	0.9663	0.9719	0.9707	0.9525	0.9145	0.9781

\* Significant at .10 level

\*\* Significant at .05 level

Table E.11(continued)

Variable	Zone 11	Zone 14	Zone 16	Zone 18	Zone 21	Group 1	Group 2	Group 3	Wake Co.
intercept	11.294*	15.248*	9.3121*	11.347*	15.563*	9.279*	9.4063*	10.082*	10.044*
baths	-0.052*	-0.047	0.162*	-83E-5	-0.204*	0.0144	0.038*	0.0516*	0.0284*
regheatarea	-0.888*	1.6136*	0.0347	0.0227	0.7022*	0.6701*	0.4927*	0.475*	0.5312*
sqregheat	0.2622*	-0.264*	0.058	0.0415	-0.109*	-0.09*	-0.057*	-0.042*	-0.063*
acreage1	.	.	.	.	.	.	.	.	0.8892*
sqacre1	.	.	.	.	.	.	.	.	-0.681*
acreage2	.	.	.	.	.	-0.047	.	.	0.2032*
sqacre2	.	.	.	.	.	0.1872	.	.	-0.082
acreage3	.	.	.	.	.	.	-0.019	.	-0.044
sqacre3	.	.	.	.	.	.	0.0067	.	0.026
acreage4	.	.	.	.	.	.	.	.	0.1684
sqacre4	.	.	.	.	.	.	.	.	-0.037
acreage5	.	.	.	.	.	.	.	-0.077	0.1827
sqacre5	.	.	.	.	.	.	.	0.4655	0.0763
acreage6	.	.	.	.	.	.	0.0298	.	-0.087
sqacre6	.	.	.	.	.	.	0.0394	.	0.1927
acreage7	.	.	.	.	.	0.1935*	.	.	0.127*
sqacre7	.	.	.	.	.	-0.02	.	.	-0.012
acreage8	.	.	.	.	.	.	0.2444*	.	0.2429*
sqacre8	.	.	.	.	.	.	-0.139	.	-0.089
acreage9	.	.	.	.	.	.	.	0.0299	0.1107*
sqacre9	.	.	.	.	.	.	.	0.0444*	0.0024
acreage10	.	.	.	.	.	.	.	0.0703	0.0563
sqacre10	.	.	.	.	.	.	.	0.0039	0.0015
acreage11	0.2462	.	.	.	.	.	0.1256	.	0.1941*
sqacre11	-0.195	.	.	.	.	.	-0.059	.	-0.07
acreage14	.	0.5897*	.	.	.	0.2411*	.	.	0.268*
sqacre14	.	-0.151*	.	.	.	-0.076*	.	.	-0.082*
acreage16	.	.	0.142	.	.	.	0.0449	.	0.0738
sqacre16	.	.	-0.054*	.	.	.	-0.04*	.	-0.04*
acreage18	.	.	.	-0.189*	.	.	-0.041	.	0.0043
sqacre18	.	.	.	0.0597*	.	.	0.0192*	.	0.0108
acreage21	.	.	.	.	-76E-5	.	0.0135	.	0.1154*
sqacre21	.	.	.	.	0.0104	.	0.0057	.	-0.007
age	-0.026*	-0.003	-0.009*	-0.011	-0.076*	-0.016*	-0.009*	-0.007*	-0.008*
sqage	0.0001*	-5E-4*	0.0001	0.0011*	0.0032*	0.0003*	0.0001*	347E-7	0.0000463*
bsmtheat	-83E-6	0.001*	.	0.0002*	-29E-5	333E-7	0.0001*	0.0002*	0.0001*
bsmtunheat	-1E-4	0.001*	.	-0.001*	.	0.0001	0.0001*	0.0001	0.0001*
atticheat	0.0004*	0.0003*	0.0005*	0.0002*	0.0002*	0.0002*	0.0002*	0.0002*	0.0002*
atticunheat	0.0009*	298E-7	0.0002*	0.0001	0.0003*	414E-8	0.0001*	-1E-4*	6.33E-6
otherunheatarea	.	0.0005*	.	-0.002*	.	47E-6	0.0001	.	0.0001
walldum1	0.2923*	-2E-5	0.095*	-0.147*	-0.082	0.0144	0.0399*	0.0239	0.0264*
bsmtdum1	1.2123	0.0629	.	0.1876*	.	0.0132	0.1122*	-0.036	0.0639*
bsmtdum2	-0.134	-0.835*	0.0546	0.0045	0.6644	0.0555	0.0585*	0.0568	0.0679*
heatdum6	.	.	-0.579*	.	.	.	-0.168*	-0.186	-0.227*
heatdum7	.	.	.	.	.	.	0.6031*	.	-0.106
acdum1	0.2264*	.	-0.143	0.6359*	.	.	0.1006*	.	0.053*
story	0.0366	-0.122*	-0.03	0.0533*	0.0586	-0.03	-0.021	-0.019	-0.015
detgarage	0.2285*	-0.276*	-0.073	-0.007	0.0941*	-0.021	0.0605*	0.0844*	0.0535*
condadum	.	0.7901*	.	.	.	-0.081*	0.0084	.	0.0279
condcdum	0.6637*	-0.183*	0.0832	1.0577*	-0.007	-0.181*	0.0257	.	-0.078*
condddum	-0.12	.	.	.	.	.	-0.117*	.	-0.124*
carport	0.0015*	0.0002	0.0002	-1E-4	.	0.0008*	0.0002*	0.0002	0.0002*
encporch	0.0073*	.	0.0003	0.0035*	0.0018*	0.0002	0.0003*	0.0006*	0.0002*
scrporch	-0.002*	114E-7	-19E-5	0.0004*	-27E-5	501E-7	0.0001	0.0003*	0.0001*
opnporch	0.0001	0.0001	-67E-7	0.0002	0.0006*	0.0001	0.0001	0.0001	0.0001
garage	0.0008*	-29E-5*	0.0002*	0.0001*	0.0001	0.0001*	0.0002*	0.0003*	0.0002*
storage	-88E-5	0.0013*	0.0004	0.0001	0.0012*	-51E-5	524E-8	0.0007	3.05E-6
patio	0.0002	0.0012*	-15E-6	-0.001*	0.0006*	0.0001	519E-7	-8E-6	0.0000257
deck	195E-7	-85E-6	0.0001	0.0004*	0.0003*	0.0002*	0.0001*	0.0001*	0.0001*
stoop	0.0025*	0.0043*	0.0005	0.0026*	0.0009	0.0001	0.0009*	0.0007*	0.0006*
fireplaces	0.0139	-0.041	0.05*	0.2052*	0.109	0.102*	0.0771*	0.0637	0.0798*
poolres	0.5928*	-0.387*	.	.	0.231*	0.0215	0.0866*	0.0741	0.0421
grade	0.0097*	0.0089*	0.0072*	0.0105*	0.0098*	0.007*	0.0094*	0.0017*	0.0044*
perc.nonwhite_1990	-0.014*	0.0649	0.001	0.0131*	0.0605*	-0.002	-22E-5	-12E-5	-0.00056
medianvalue	883E-8*	-53E-6	231E-8	158E-7*	799E-8*	2E-7	663E-9	-18E-8	3.15E-7+
medttw	0.0482*	-0.059	0.0042	0.0999*	0.0704*	-26E-5	0.0019	-0.006*	-0.00082
perc.owner18	0.0238*	0.1006	0.0029	-0.11*	-0.314*	-0.007*	0.0007	0.0093*	0.0044*
perc.owner_occ	-0.003	-95E-5	0.0012	-0.046*	.	0.0012	0.0007	0.0009	0.0001
nearestpark	0.0385	-0.007	-0.097*	-0.119*	0.1061*	0.0021	-0.004	-0.012	-0.003
nearestsc	0.0994*	0.2569	0.1639*	0.0997*	-0.212*	-0.045*	-0.005	-0.007	-0.005
bigparkdistance	-0.037*	-0.066	-0.014*	-0.003	0.0195	0.0115*	0.0005	0.0045*	-0.00033
taxrate	-0.288*	0.3129*	0.1459*	.	.	0.0545	-0.014	0.1687*	0.0233
lambda	0	0	0	0	0	0.1471	0.083	0	0.3335*
nobs	50	50	50	50	50	150	350	150	750
rsqr	0.9403	0.9639	0.9084	0.9698	0.9727	0.9456	0.9286	0.9249	0.9352

+ Significance indeterminant from asymptotic T-test

\* Significant at .10 level

\*\* Significant at .05 level

Table E.12: 1992 Spatial Error Estimates (Sparse Spec., Small Samples)

Variable	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Zone 7	Zone 8	Zone 9	Zone 10
intercept	10.285*	10.505*	8.7979*	9.7124*	9.6307*	9.2255*	9.8736*	8.7502*	10.441*	9.7789*
baths	0.0384	0.0488*	0.0532	0.1034*	-0.008	0.1409*	0.0163	0.0981*	0.116*	0.0255
regheatarea	0.3378*	0.3956*	1.5629*	-0.604*	0.9245*	0.0235	0.4647*	0.6676*	0.6892*	0.4798*
sqregheat	-0.024	-0.015	-0.416*	0.2702*	-0.134*	0.0718	-0.037	-0.078	-0.092*	-0.041
acreage1	-0.073	.	.	.	.	.	.	.	.	.
sqacre1	0.4495	.	.	.	.	.	.	.	.	.
acreage2	.	0.2021	.	.	.	.	.	.	.	.
sqacre2	.	-0.029	.	.	.	.	.	.	.	.
acreage3	.	.	0.2483*	.	.	.	.	.	.	.
sqacre3	.	.	-0.006	.	.	.	.	.	.	.
acreage4	.	.	.	-0.554	.	.	.	.	.	.
sqacre4	.	.	.	0.712	.	.	.	.	.	.
acreage5	.	.	.	.	-0.495	.	.	.	.	.
sqacre5	.	.	.	.	1.1425*	.	.	.	.	.
acreage6	.	.	.	.	.	0.9298*	.	.	.	.
sqacre6	.	.	.	.	.	-0.791*	.	.	.	.
acreage7	.	.	.	.	.	.	0.3198*	.	.	.
sqacre7	.	.	.	.	.	.	-0.096*	.	.	.
acreage8	.	.	.	.	.	.	.	0.2025	.	.
sqacre8	.	.	.	.	.	.	.	-0.229*	.	.
acreage9	.	.	.	.	.	.	.	.	0.0297	.
sqacre9	.	.	.	.	.	.	.	.	0.0314	.
acreage10	.	.	.	.	.	.	.	.	.	0.0153
sqacre10	.	.	.	.	.	.	.	.	.	0.0148
acreage11	.	.	.	.	.	.	.	.	.	.
sqacre11	.	.	.	.	.	.	.	.	.	.
acreage14	.	.	.	.	.	.	.	.	.	.
sqacre14	.	.	.	.	.	.	.	.	.	.
acreage16	.	.	.	.	.	.	.	.	.	.
sqacre16	.	.	.	.	.	.	.	.	.	.
acreage18	.	.	.	.	.	.	.	.	.	.
sqacre18	.	.	.	.	.	.	.	.	.	.
acreage21	.	.	.	.	.	.	.	.	.	.
sqacre21	.	.	.	.	.	.	.	.	.	.
age	0.0053	-0.019*	-0.014*	0.0019	-0.015*	-0.005	0.0026	0.0055	-0.023*	-0.004
sqage	-14E-5	0.0005*	0.0002*	719E-8	0.0003*	-58E-6	-78E-5	-26E-5	0.0012*	-16E-6
story	0.1013	-0.071	-0.034	-0.054	-0.033	-0.053	-0.05	-0.083*	-0.056	-0.032
grade	0.0052*	0.005*	0.0107*	0.017*	0.0086*	0.0151*	0.0091*	0.0168*	0.0017*	0.01*
lambda	0.6778*	0.4013*	0	0	0	0	0.0031	0	0	0
nobs	50	50	50	50	50	50	50	50	50	50
rsqr	0.8559	0.9131	0.7804	0.742	0.9517	0.8659	0.9094	0.9156	0.8165	0.9352

\* Significant at .10 level

\*\* Significant at .05 level

Table E.12(continued)

Variable	Zone 11	Zone 14	Zone 16	Zone 18	Zone 21	Group 1	Group 2	Group 3	Wake Co.
intercept	9.0126*	8.77*	9.8975*	8.3629*	9.2491*	9.6338*	9.2802*	10.241*	9.9177*
baths	0.1192*	0.1388*	0.21*	0.1071*	0.0404	0.0449*	0.1084*	0.0742*	0.075*
regheatarea	0.8041*	1.2133*	-0.318	1.105*	0.6737*	0.6717*	0.5946*	0.6371*	0.6035*
sqregheat	-0.127*	-0.208*	0.165*	-0.229*	-0.09*	-0.076*	-0.066*	-0.066*	-0.068*
acreage1	.	.	.	.	.	.	.	.	0.7632*
sqacre1	.	.	.	.	.	.	.	.	-0.321
acreage2	.	.	.	.	.	0.2835	.	.	0.4414*
sqacre2	.	.	.	.	.	-0.106	.	.	-0.181*
acreage3	.	.	.	.	.	.	0.0556	.	0.025
sqacre3	.	.	.	.	.	.	-0.006	.	0.0111
acreage4	.	.	.	.	.	.	.	.	0.1295
sqacre4	.	.	.	.	.	.	.	.	0.1308
acreage5	.	.	.	.	.	.	.	-0.433*	0.3452
sqacre5	.	.	.	.	.	.	.	1.1918*	0.0245
acreage6	.	.	.	.	.	.	0.255*	.	0.0537
sqacre6	.	.	.	.	.	.	-0.128	.	0.0951
acreage7	.	.	.	.	.	0.2103*	.	.	0.3182*
sqacre7	.	.	.	.	.	-0.054	.	.	-0.089*
acreage8	.	.	.	.	.	.	0.5464*	.	0.3954*
sqacre8	.	.	.	.	.	.	-0.344*	.	-0.163
acreage9	.	.	.	.	.	.	.	0.0132	0.1767*
sqacre9	.	.	.	.	.	.	.	0.0306	-0.011
acreage10	.	.	.	.	.	.	.	-0.044	0.0857
sqacre10	.	.	.	.	.	.	.	0.0277*	0.0019
acreage11	0.0288	.	.	.	.	.	0.1102	.	0.1084
sqacre11	0.0198	.	.	.	.	.	-0.018	.	-0.006
acreage14	.	-0.006	.	.	.	0.1964*	.	.	0.282*
sqacre14	.	0.0324	.	.	.	-0.047	.	.	-0.082*
acreage16	.	.	0.1492	.	.	.	0.0239	.	0.0291
sqacre16	.	.	-0.046	.	.	.	-0.02	.	-0.018
acreage18	.	.	.	-0.059	.	.	-71E-5	.	-0.014
sqacre18	.	.	.	0.0271*	.	.	0.0185*	.	0.0204*
acreage21	.	.	.	.	0.0718*	.	0.0808*	.	0.132*
sqacre21	.	.	.	.	0.006	.	-0.002	.	-0.006
age	0.0002	0.0014	-0.004	-0.006	0.0045	-0.006*	-0.007*	-0.003	-0.005*
sqage	-41E-6	186E-7	252E-7	-18E-6	-0.002*	0.0001*	587E-7*	-26E-6	3.27E-6
story	-0.062	-0.15*	-0.086	-0.111*	-0.056	-0.087*	-0.08*	-0.017	-0.05*
grade	0.0124*	0.0116*	0.011*	0.0178*	0.0128*	0.0092*	0.0119*	0.0036*	0.0063*
lambda	0.4459*	0.1107	0	0	0	0.3482*	0.1418	0	0.4671*
nobs	50	50	50	50	50	150	350	150	750
rsqr	0.8587	0.9119	0.7899	0.9194	0.9174	0.905	0.8772	0.8845	0.9013

\* Significant at .10 level

\*\* Significant at .05 level