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Julie Louise Colby

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M.A. degree in Geography

Bruce W. Pigozzi
Major professor

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SOCIAL EQUITY AND THE SPATIAL VARIATION OF THE PROPERTY TAX STRUCTURE OF LANSING, MICHIGAN

By

Julie Louise Colby

A THESIS

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

MASTER OF ARTS

Department of Geography

1999

## ABSTRACT

SOCIAL EQUITY AND THE SPATIAL VARIATION OF THE PROPERTY TAX STRUCTURE OF LANSING, MICHIGAN

By

Julie Louise Colby

Inequities in the property tax structure are tested for and examined using various econometric and GIS methodologies. The inequities under investigation include, vertical, spatial and those based on demographic, social-economic, and housing characteristics. Five years (1994 – 1998) of property sale transaction data from Lansing, Michigan are utilized. First, econometric models are used to test for vertical equity. In all cases, regressive vertical inequity is concluded. Next, the data are partitioned by sale year and subjected to semivariance analysis, *Moran's I* analysis and kriging to create surface maps. Results show that both positive and negative spatial autocorrelation exist at a variety of lag distances. Patterns are revealed that show there are spatial disparities and geographic inequities in the property tax structure. Finally, other biases of the assessment ratio are examined and identified in multiple regression analysis at three geographic scales. The property tax structure of Lansing, Michigan has significant inequity based on sale amount, race, income, housing stock and market dynamics. These inequities may be caused by dynamics in the real estate market and the assessment process itself. The assessment process must change so that inequities are alleviated.

# ACKNOWLEDGMENTS

I would like to acknowledge and thank the following people; without them I could not have produced this document. I wish to thank Jim Myers at the Lansing City Assessor's Office who provided digital access to the parcel sale transaction data used in this thesis and spent time helping me understand the assessor's role in the property tax structure. I am also extremely grateful to the Michigan State University Geography Department and my supportive classmates. Mark Bowersox acted as my GIS consultant and put up with repetitive brain-picking as well as occasional freak-outs, and Colleen Garrity generously allowed me the use of her computer and home office. I owe special thanks to family members and Tim Priest for editing suggestions and general support. Finally, I would like to express appreciation for Bruce Pigozzi, my advisor, who is an excellent role model and provided me the inspiration and unending encouragement I needed to finish my Master's thesis work.

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## LIST OF ABBREVIATIONS

AR .......... Assessment Ratio
AV .......... Assessed Value
BLACK .......... percent of population that is black
HISPANIC .......... percent of population that is Hispanic
INC .......... median household income
LNAV .......... natural log of AV
LNS .......... natural log of S
MV .......... Market Value
PUBLIC .......... percent of households on public assistance
RENTOCC .......... percent of housing units that are renter occupied
S .......... dollar amount of parcel sale transaction
SEASON .......... binary variable: summer = 1,winter = 0
VACANT .......... percent of housing units that are vacant
WHITE .......... percent of population that is white
YEAR .......... median age of housing stock

# INTRODUCTION

The problem under investigation in this thesis is to understand the nature and extent of inequity in the property tax structure of Lansing, Michigan. The objective of this research is to synthesize previous research efforts as well as to incorporate some new GIS technologies in a methodologically comprehensive examination of the social and geographic equity or inequity in property taxation.

This work is not intended to be a case study that exemplifies all property tax structures in the United States. However, in using several years worth of data from one midsize, midwestern capital city, it is hoped that this study will identify any problems and dynamics in the assessment process that are affecting the level of social equity realized by tax payers.

The assessor's offices in Lansing, Michigan and many other cities of similar size and nature are still forced to operate in pre-GIS systems due to lack of appropriated funding and expertise. In fact, in Lansing, the assessor's office does not use geographic methods or evaluate assessments spatially. While the lack of GIS technology would never by the underlying cause of any inequity, this particular technologic and geographic deficiency in local government is especially vexing because the property tax assessment process is inherently geographic and could be greatly aided by the implementation of a geographic information system. Therefore, an additional goal of this thesis is to demonstrate how a precise spatial evaluation of property tax equity could be important for local assessor's offices. However, it should be understood, that although GIS is a powerful tool and could be used to better the assessment process, when used incorrectly, it could just as easily not improve the system. Just because a municipality uses GIS to assess properties, that municipality is not necessarily eliminating inequity from its property tax structure.

The research is empirical by nature and highly data intensive. Many different software packages are used in this thesis. They include *ArcView, ARC/INFO, Access, Excel, GS+, SPSS, SYSTAT* and *Transcad.* In addition, many procedures and methods are applied to the data. For this reason, the organization of this thesis will be atypical. Rather than one traditional "methodology" chapter, this thesis will detail methodologies as they are discussed in the body of the paper. Aside from the first two chapters, which are "Taxation and Assessment" and "Data Preparation" respectively, there are three distinct research avenues in this thesis: Chapter 3, "Vertical Equity Testing", Chapter 4, "Spatial Autocorrelation and Surfaces of Inequity", and Chapter 5, "Explanation of the Assessment Ratio Variation". Each of the three has separate research questions, hypotheses, literature grounding, methodologies, results and conclusions. The final chapter, Chapter 6, will be dedicated to interpreting the meaning and use of this thesis to assessors' offices as well as to recommend future research foci.

# CHAPTER 1

## TAXATION AND ASSESSMENT

This chapter is intended to provide the reader background on the thesis topic, the property assessment process and the legal obligations of taxing bodies to provide taxpayers with a fair and *equitable* property tax. The term equitable, throughout this thesis, will refer to anything "having or exhibiting equity" of which equity is "freedom from bias or favoritism" (Mish 1998, p. 392). These terms should not be confused with *equality* or any others coming from the root *equal.* Things equal are "of the same measure, quantity, amount, or number." That is, to be equal is to be "identical in mathematical value" (Mish 1998, p.391). If property taxes were equal, all property owners would pay the same dollar amount in taxes and *that* would not be equitable.

### The Importance of Equity

There have been two main theories of taxation, the *benefit theory* and the *ability to pay theory,* from which modern day property taxation was born. Central to both the *benefit theory* of taxation and *the ability to pay theory* of taxation are their principles of equity (McCluskey et. al, 1998). Without equity, taxation of any kind by local government is vulnerable to the acceptance and approval of taxpayers. In fact, a pillar of American democracy is jeopardized if equity is not present. Because of this, equity in the property tax structure is of vital importance and has been the topic of many research endeavors and papers. It shall also be the topic of this thesis, in which property tax inequities will be evaluated, spatially examined and statistically explained. The objective of this research is to synthesize previous research efforts in a methodologically comprehensive paper aimed at examining the social and geographic equity of the property tax structure in Lansing, Michigan.

It was the primary purpose of an international research project to examine the efficacy of market value as a basis of assessment for an equitable property taxation system (McCluskey et al, 1998). While the research effort has not yet concluded, initial findings identify a need for criteria from which the collection of revenues by local government can be measured. One such criterion the group asserts is the status of equity, a term used interchangeably with the phrase, "how well the property tax is administered and assessed."

**Typology of Equity**

Generally, there are two kinds of equity recognized in the literature surrounding property tax equity, *horizontal* and *vertical*. Horizontal equity exists when properties of the same value are, on average, taxed the same. Vertical equity exists when properties of different value are, on average, taxed at the same proportion of market value. These "principles of both horizontal and vertical equity are vital to the perceived equity of any landed property–based tax, and, therefore, its social acceptability" (McCluskey et. al 1998).

Horizontal and vertical equity are very important. They are much discussed in taxation literature and this paper will deal with them. However, spatial equity, which incorporates the principles of both horizontal and vertical inequities, will be the primary target of investigation in this paper. For the purpose of this paper, spatial equity will refer to the situation that exists if all geographic areas of the taxing jurisdiction are taxed at the same rate. This means that if spatial equity exists, properties that are over- or under-taxed are spatially independent or not spatially autocorrelated. Indeed, if spatial equity exists there will be no discernable spatial pattern to the property tax structure.

It is sensible to study spatial equity in addition to horizontal equity and vertical equity, which are generally studied separately and aspatially, because if horizontal or vertical inequity exists, the inequity is likely to be spatial as well. Both vertical and horizontal inequities tend to represent themselves spatially due to the nature of human settlement to organize itself in homogenous neighborhoods within a larger segregated urban area. Furthermore, if equity, regardless of type, is studied spatially, more information is revealed about the tax structure. Spatial equity not only assures both horizontal and vertical equity, it generally assures that a property tax is not regressive, which, as is described in the next section, is most inequitable in a property tax structure.

**Regressive Taxation**

Vertical inequity may be *regressive* or *progressive*. Generally, regressive vertical inequity is defined as a situation in which lower valued properties are taxed at a higher rate or larger proportion of market value than higher valued properties. Conversely, a progressive vertical inequity exists when higher valued properties are taxed at a higher rate or larger proportion of market value than lower valued properties. Because lower valued properties tend to cluster together in a taxing jurisdiction and higher valued properties tend to cluster together, vertical inequity can most often be visualized spatially, revealing a spatial pattern to the over and under assessed areas.

The same spatial distribution might also be true of horizontal inequity. Consider the example of horizontal inequity detected by Beveridge in his research for the *New York Times* (Schemo, 1994). Beveridge found that in forty-four percent of the sixty-one major United States cities and suburbs that he studied, properties of the same value were taxed differentially depending on the race of the property owner. Property owners who are black were taxed significantly more than property owners who are white for similarly valued properties in the same taxing jurisdictions. This is an example of a horizontal inequity, but it also has a spatial pattern due to the strong degree of racial segregation in his study areas. For the purposes of this paper, the inequity described above will also be considered regressive. That is, the definition of a regressive tax will be expanded to include not only regressive vertical inequities but also horizontal inequities like this one discovered by Beveridge.

Thus, the definition of a regressive property tax will be expanded to one in which properties that are of low value, owned by a poor person or person of a marginalized group, or living in an area occupied by poor and or marginalized populations are taxed at a higher proportion of market value than properties of high value, owned by a wealthy person or someone living in an area occupied by wealthy and or politically powerful mainstream populations. In other words, a regressive tax is one that benefits the politically powerful and puts at a disadvantage the poor and marginalized. Conversely, a progressive tax benefits the opposite populations.

Researchers such as Massey recognize this kind of regressive spatial inequity. In his discussion of property tax inequity as one of the problems inherent to segregation by race and/or class, he warns of a "rising inequality and its geographic expression." He sites data that show increasing segregation of both poor and minority populations, as well as affluent populations. Because of this increased geographic segregation, Massey concludes that property tax inequity may become increasingly unequal as well (Massey, 1996).

A regressive tax structure is politically unpopular and exists in contrast to the *ability to pay theory,* one of the historical underpinnings on which the property tax is based. It is an extremely undesirable form of inequity to society (McCluskey et. al, 1998). Therefore, the purpose of this paper is to test for and examine any inequity with an emphasis on any regressive inequity that may exist in the property tax structure.

**Assessment Process**

Throughout the United States and much of the world, property tax is determined by some assessment of the property's market worth. It follows, then, that the status of equity is dependent on the quality of the assessment process. This paper will utilize empirical assessment data from Lansing, Michigan. Lansing will serve as an interesting case study that in some ways typifies the American property tax structure and, in other ways, does not.

The taxing process employed in Lansing, Michigan is representative of that present elsewhere in the United States. Each parcel of land is taxed according to its assessed value multiplied by the municipality's millage rate, which is constant for each property type. A millage rate is defined as the amount of taxation in mills (one tenth of a cent) per dollar of valuation and the assessed value of the property is the property tax assessor's best guess of the market value. The market value can be defined as:

> "the most probable price expressed in terms of money that a property would bring if exposed for sale in the open market, in an arm's length transaction between a willing seller and a willing buyer, both of whom are knowledgeable concerning the uses of the property"(Miles and Wurtzbach, 1987, p. 751).

Clearly, market value is impossible to measure if a property isn't "exposed for open sale" and one could never even say with certainty that a particular transaction was an "arm's length transaction." That is why assessors can only estimate or guess the market value and the result of this estimation is their assessment. Equation 1.1 shows how the property tax for parcel i is calculated.

**Equation 1.1: Property $tax_i = AV_i$ * millage rate**

There are also some ways in which the taxing process in Lansing is different from other taxing bodies. For example, in most tax jurisdictions, the assessor estimates market value and sets their assessment equal to the estimate. In other words the assessment has a theoretical one – to – one relationship with market value. This is not the case in Michigan. Although assessed value is still directly proportional to market value it is not a one – to – one relationship. Instead, state statute dictates that property in Michigan is assessed at half of market value. Therefore, by state law, assessors in Michigan are required to estimate market value of each property and divide their estimate in half to arrive at the assessed value of each property. This does not mean that property taxes are lower in Michigan than in most other places. Michigan simply has higher millage rates to make up for the lower assessments. One could question why this is done. Perhaps the assessment system has something to gain from the smaller assessments. If assessments are half of market value they make the magnitude of the property tax base seem less unpalatable for taxpayers who are then less likely to challenge or dispute the assessments. This could potentially save the assessor's office from having to defend their assessments against questioning taxpayers.

In evaluating the quality of assessments, it is often helpful to express assessed value (AV) as a proportion of market value (MV), or some measure of, and is called the assessment ratio (AR).

**Equation 1.2:** $AV_i/MV_i = AR_i$

Due to the legal reasons stated above, assessment ratios should be 0.50 for all properties in Lansing. Assessment Ratios reveal the accuracy of the assessments. If they are more than 0.50, the assessment is too high. If they are less than 0.50 then the assessment is too low. Because MV is an immeasurable variable (see above definitions of market value), ARs are often constructed with a surrogate for MV – usually the sale amount (S) of the property transaction.

**Equation 1.3:** $AV_i/S_i = AR_i$

Equation 1.3 can be solved for AV to get Equation 1.4.

**Equation 1.4: $AV_i = AR_i * S_i$**

in equation 1.1 to arrive at equation 1.5 as follows:

**Equation 1.5: Property $tax_i = AR_i * S_i *$ millage rate**

Equation 1.5 shows the dependency of the property tax on the assessment ratio. If the assessment ratio is too high, the property tax will be more than it should and if the assessment ratio is too low, the property tax will be less than it should. For example, if the millage rate for a jurisdiction were imposed at 0.075, a properly assessed $100,000 property would be taxed (0.50)*$100,000*(0.075) or $3,750.00. However, the same $100,000 property that is incorrectly under-assessed at 0.45 of market value would only be taxed, (0.45)*$100,000*(0.075) or $3,375.00. The under-assessed property would pay $375.00 less than the correctly assessed property. On the other hand, the same $100,000 property that is incorrectly over-assessed at 0.55 of market value would be taxed, (0.55)*$100,000*(0.075) rate or $4,125.00. The over-assessed property pays $375.00 more than it would if the property were assessed correctly. Worse still, the over-assessed property is charged $750 more than if it were under-assessed at 0.45 of market value.

**Ideal Property Tax Structure**

In a perfect property tax system, all properties in the system would be taxed at the same rate according to their market values. That is, the assessment ratio, AR (commonly calculated by dividing an assessed value, AV, by its measured market price, S) would be uniform across all properties. While deviations from uniformity in the assessment ratio are inevitable and to be expected, these deviations would occur randomly if the system were equitable. Assuming equity, there would be no spatial pattern to the assessment ratio distribution. However, in most cities in the United States, spatial uniformity does not exist in property assessment ratios. Indeed, there is often a geographic distribution, or pattern, in the under and over assessment of residential properties. These patterns that are pervasive in the property tax structure are indicative of inequity.

Taxing administrations do generally evaluate their assessments for equity themselves. The Lansing City Assessor's Office does this by dividing the jurisdiction into neighborhoods. Every year before issuing new assessments, each neighborhood's average assessment ratio, based on sale transaction data, is compared to the mean for the city. If the average neighborhood assessment is too low, each assessment in the neighborhood is adjusted up by some multiplied amount. In the same way, if the average assessment is too high, each assessment in the neighborhood is adjusted down by some multiplied amount. While this method may indeed correct some inequities, individual assessments may become even more skewed. For example, some parcels that are over assessed in a neighborhood that on average is assessed too low will become even more over assessed. However, individual parcel assessment adjustments are too costly for most assessors' offices and can be biased if judged by a non-market sale transaction.

One way some taxing administrations assure greater compliance to standards of equity is by managing and evaluating their assessments using a geographic information system (GIS). A GIS is a database management system that can deal effectively with large amounts of spatially referenced data. The property tax assessment process is an ideal use of GIS because it is inherently geographic. Because of this, several taxing bodies and even entire states have implemented geographic information systems to aid in the administration of the property tax (Castly 1993, Hensley 1993, Rodda 1992 and Wills 1998). Here lies another difference between the Lansing City Assessor's Office and other places in the United States. The city of Lansing has not appropriated the funds necessary to implement a GIS. Therefore, one intent of this thesis is to demonstrate how a detailed computerized spatial evaluation of property tax equity would be important for local assessor's offices like Lansing's.

**Purpose**

The purpose of this research is to test for, describe and explain patterns in the property tax structure by implementing a variety of methodologies and using assessment and sales data for the city of Lansing, Michigan. Several hypotheses will be tested with the end goal of addressing the following research question: What is the extent, nature and future of property tax inequity? The many hypotheses to be tested in this paper fall into three distinct categories. Thus, the thesis research can be divided into three main parts. First, in Chapter 3, the status of equity in the property tax structure will be ascertained and measured by employing several tests for vertical inequity. Second, in Chapter 4, the assessment ratio pattern will be graphically described and evaluated. Finally, in Chapter 5, the geographic patterns in the assessment ratio will be mathematically accounted for or explained. The research questions and hypotheses specific to each chapter's topic will be detailed in their respective chapters. Prior to this, however, Chapter 2 will introduce the data used throughout the thesis and will explain the methods used to prepare it for answering the research questions.

## Chapter 2

## DATA AND PREPARATION

The data for this research came from two sources: the Lansing City Assessor's Office and the U.S. Bureau of the Census.

**Data from the Lansing City Assessor's Office:**

Parcel sale transaction data were obtained from the city assessor for all 8,660 transactions occurring from January 1994 to August 1998. The data, in spreadsheet format, include assessed value at the time of sale (AV), sale amount (S), parcel address, month and year of sale.

**Census Data**

1990 Census Bureau Tiger files containing the street index of Lansing, Michigan were obtained from Environmental Research Institute (ESRI) on its Internet web site (www.esri.com). In addition, census tract boundaries and census tract block group boundaries were obtained from the same web site in shape file format. Finally, several census tract and block group variables were extracted from the 1990 Census of Population and Housing for Lansing, MI. The census variables include measures of race, income and age of housing. They will be used in conjunction with the property sale transaction data later in the paper.

**Data Preparation**

The 1990 Tiger street index of Lansing, MI was imported by Transcad as were the parcel sale transaction data. The parcel sale transaction data were then geo-coded, by the address matching function in Transcad, to the 1990 Tiger Street Index. This was done to obtain decimal degree latitude and longitude geographic coordinates for each sale transaction observation. The address matching was ninety-five percent successful, or about ninety-five percent of the transactions were geocoded. The process leaves 8,227 geocoded sales observations in the sample. The five percent that could not be matched were probably not successful due to errors in the Tiger street index or errors in the street names, zip codes or street numbers of the parcel sale transaction. They have been discarded and will not be used in the following analyses. An assumption is made at this point, for the purposes of this research, that these unmatched addresses are randomly distributed throughout the city of Lansing. Although this assumption is not proven, it is known that the unmatched five-percent of sale transaction observations represented all Lansing zip codes.

Next, assessment ratios (ARs) were calculated for each observation. This was accomplished by dividing each assessed value by its corresponding sale amount. As noted above, Michigan state statute dictates that each assessed value should be half of market value – not sale amount. However, market value is an immeasurable variable so sale amount is measured and will be used in its place in this study as it has in many others (DeCesare, 1998; I.A.A.O, 1990). Market Value may be immeasurable but it is assumed to be a nonstochastic fixed variable while sale amount, S, is viewed as a random variant around the fixed market value (Clapp, 1990).

Unfortunately, sale amount, S, is not always a good indicator of market value. Sometimes S is not representative of an "arm's length market transaction." Occasionally, properties sell for a small nominal value simply to transfer official ownership. For example, an elderly landowner may decide to "sell" a property to a younger relative for a dollar. In this case, the name on the deed may be changed to represent a change in ownership but not a transfer of the property's market worth. This would create an extremely high AR regardless of the quality of the assessment. Another example of a sale that doesn't represent market value, which would result in a false high AR, is that of a land contract sale. Sometimes a parcel is sold by contract at the market value of the day. However, the sale is not finalized and made official until the contract is paid off, in most cases, years later. The official sale amount used to calculate the AR then is the amount on the contract. Inflation and market value increases render the official sale amount very low and the calculated assessment ratio much too high.

There are also instances when an especially low AR is not indicative of a bad assessment but rather an unusual circumstance as well. Perhaps the assessment is done correctly but the property buyer is someone unfamiliar with the local market conditions. For example, someone from California, used to the high cost of housing and living there, suddenly gets transferred to Lansing, Michigan and must buy a house in a short amount of time, might purchase the house at an inflated amount, mistaking it for a bargain. This would result in an especially low assessment ratio not representative of an arm's length market transaction. According to the International Association of Assessing Officers

(I.A.A.O.), sale transaction observations are considered "outliers" if they have very high or low "sales ratios" which are calculated identically to the ARs in this study. The I.A.A.O. believes the outliers may result from 1) "poor or outdated appraisals," 2) "non-arm's-length" sales, or 3) a mismatch between the property sold and the property appraised (I.A.A.O 1990, p. 137).

So it seems, the sale amount (S) is not always a very good surrogate for market value. Because of this, the data are trimmed, using the variable AR, to get rid of data observations that are not representative of market transactions. Such trimming is done in most assessment ratio studies that utilize empirical sale transaction data (Denne 1993).

One such assessment ratio study was done by Gaston, who trimmed any transactions with "market error" which he defined as "discrepancy between sale price and actual market value"(Gaston 1984, p. 182). Although Gaston does not explicitly detail what percent of transactions he eliminated, he does list causes of market error that led him to eliminate as he did. He eliminated transactions with possible departures from market value caused by "inflation/deflation relative to lien date, associated personal property, title transfer instruments, interest rates, and other relevant and estimable transaction factors"(Gaston 1984, p. 182).

The I.A.A.O recommends the following trimming procedures: 1) select "cut–off" points and trim above and below them, or 2) trim the observations that fall more than two standard deviations from the mean ratio, which is usually about five percent of the observations (I.A.A.O. 1990, p. 137). However, the organization suggests that "most sales are usable," and the goal of the researcher should be "not to find reasons to exclude sales." In fact, "in large samples, the accidental inclusion of a few invalid sales will have little effect on ratio studies" (I.A.A.O. 1990, p.138)

For this study the observations were trimmed to get rid of extreme assessment ratios. Each tail of the assessment ratio distribution was trimmed by 1.25 percent. The total trim resulted in the removal of 2.5% of the geocoded sale transaction observations. The trim resulted in a sample population of 8069 observations with a mean of 0.46 and range of (0.236 - 0.846). The following map, Figure 1, shows the locations of the sample observations.

The sample is now prepared for the analysis of Chapter 3 and Chapter 4. However, some of the research in Chapter 5, involves analysis at three geographic scales: census tract scale, census block group scale and parcel scale. The property sale transaction data were prepared in three different ways accordingly. These are described in the next section.

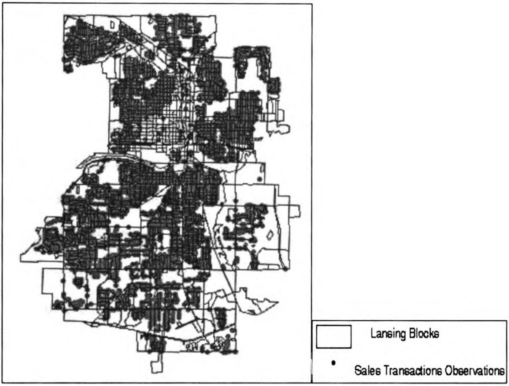


**Figure 1 - Parcel Sale transaction Observations**

**Three Scales of Analysis**

To prepare the data for analysis at the census tract scale, the 8069 geo-coded observations in the trimmed sample were each assigned to a census tract using *ARC/INFO*. This was accomplished by first making the geo-coded observations into a point file and importing their corresponding data into *ARC/INFO* and creating a data coverage. Next, *ARC/INFO* coverages were made of the census tract boundary shape file. Then the points were assigned to tracts using the *Identity* function of *ARC/INFO*. Finally, the census tract variables from the census of population and housing were imported by *ARC/INFO* and joined to the geographic census tract boundaries. The resulting database contained the 8069 parcels with their associated assessed values, assessment ratios, sale amount and their census tract information. The observations were then aggregated to the census tract level. Aggregation was done in an Excel pivot table by averaging the parcel data variables.

The boundary of the city of Lansing contains and cuts through a total of forty-four census tracts. The sale transaction observations are fairly well distributed throughout the city (See Figure 1). However, there are very few observations in the central business district (CBD) located in the middle of the city. This is due to the large amount of government and corporately owned properties that do not turn over very quickly. In addition, the Grand River cuts through this downtown section, and there is a large public park on both sides of the river containing very few privately owned properties. So while forty-one of the tracts in Lansing each have at least one-hundred observations which is convenient statistically, three tracts have only two, three and six observations each. These are the tracts that cover the CBD area of Lansing. They were therefore eliminated from the analysis, as their sample sizes would not lead to unbiased means in statistical analyses. Thus, after the aggregation process, forty-one observations are left in the sample at the census tract scale. Figure 2 shows the Census tract observational unit boundaries and the Census tracts that will not be included in the analysis for lack of data.

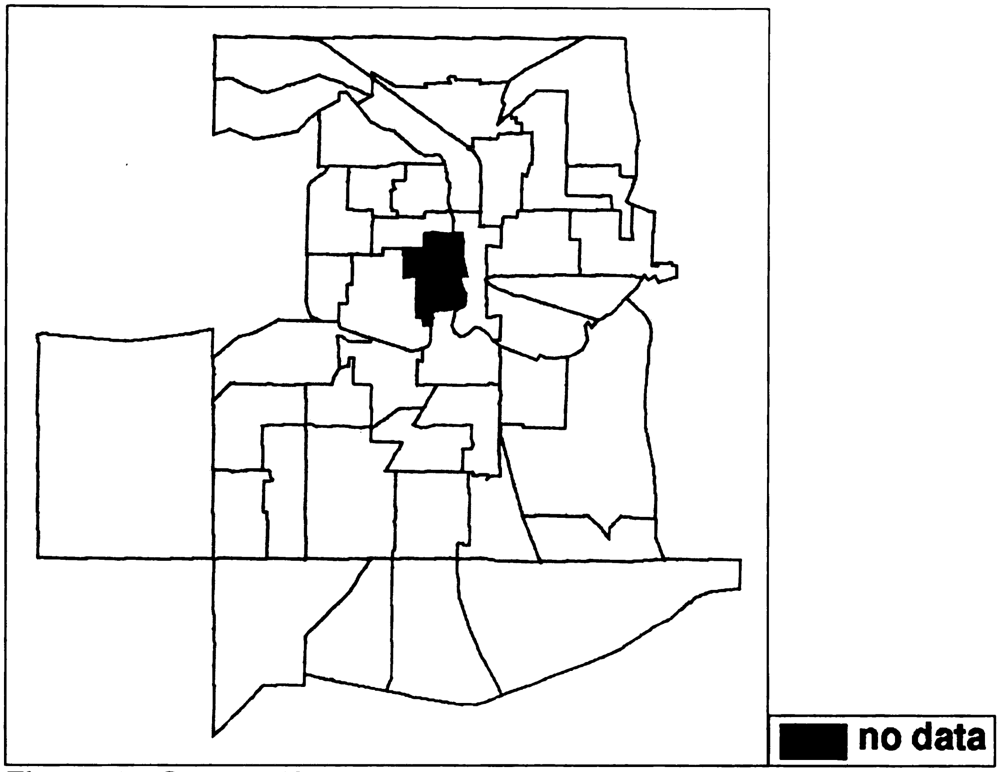

**Figure 2 - Census Tract Boundaries in Lansing, MI**

Preparation of the data for analysis at the census block group scale was done in much the same way. The observations in the trimmed sample of parcel sale transactions were each assigned a block group and then all of the data were aggregated to that scale. All of the block groups within the three tracks that were eliminated due to small sample size at the tract scale were also eliminated at this scale. In addition, some of the remaining block groups had less than twenty parcel sale observations. If so, they were combined to create a group of block groups with at least twenty observations. This was done for statistical purposes. Otherwise the means could be biased. In all, there are 117 block group observations or group of block groups observations in the sample at this scale of analysis.

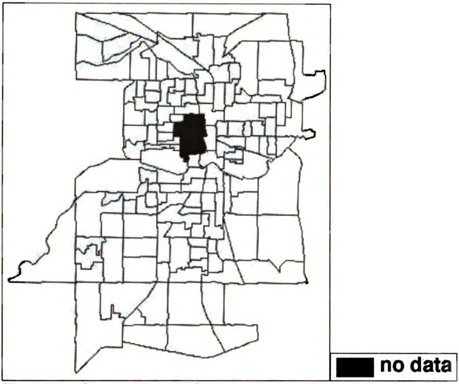


**Figure 3 - Census Block Group Boundaries in Lansing, MI**

No aggregation was necessary to prepare the data for analysis at the parcel scale. However, since census variables could not be collected at the parcel scale, each parcel took on the characteristics of its block group, so, all that had to be done was to assign each parcel to a block group. At this scale all parcels in the same block group will take on the same values for the variables collected at the block group scale. For instance, all of the parcels in block group one will have the same percentage black population and the same median household income. However, the month and year of the transaction will vary within the observations of the block group. The observations that were eliminated for statistical purposes at the other scales will also not be included in the analysis done at the parcel scale. Hence, the sample size decreased from 8069 to 8056.

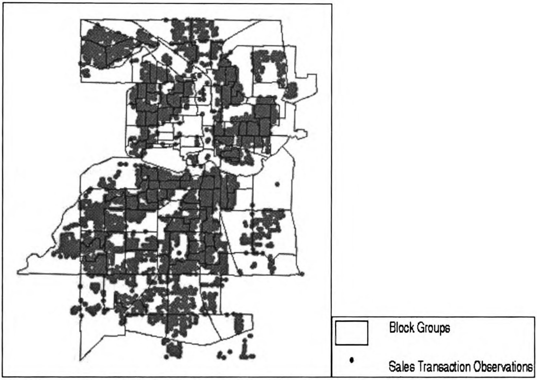


**Figure 4 - Parcel Sale Transaction Observations on Block Groups**

Although the data are further manipulated and subjected to various and many methods, these will be noted and discussed in the bodies of the next three chapters where appropriate.

# Chapter 3

## VERTICAL EQUITY TESTING

According to the International Association of Assessing Officers (I.A.A.O.), "Vertical inequities are differences in appraisal levels for groups of properties defined by value." (I.A.A.O 1990, p.516)

As was stated in Chapter 1, vertical inequity exists if properties are taxed differentially depending on their values. Recall that a regressive (progressive) vertical inequity exists if the assessment ratio decreases (increases) with an increase in property value or increases (decreases) with a decrease in property value. There are many different models in the tax and business literature that serve to test for vertical equity in property taxes. The purpose of this chapter is to employ some of these models to test for vertical inequity in the property tax structure using the assessment data for Lansing, Michigan. There are two general research questions that are addressed in this chapter. First, is the property tax structure of Lansing, Michigan vertically inequitable? The null hypothesis of this question is that no vertical inequity exists. The primary test hypothesis is that the property tax structure has regressive vertical inequity. The other alternative hypothesis is that progressive vertical inequity exists. This question will be addressed by employing four vertical equity tests.

The second research question asks, does the status of equity vary from year to year? The null hypothesis is that there is no variation in the status of equity from year to year. A rejection of this null will lead to the conclusion that in some years the assessment process leads to a more equitable situation than in others. This question will be addressed by modifying the models to control for year of sale and assessment. This issue involving dynamics in the property tax structure will also be addressed in Chapter 4.

In 1972, Paglin and Fogarty developed the first econometric model to test for vertical property tax inequity. It consists of a simple linear regression of assessed value on sale amount (Paglin and Fogarty 1972). Other researchers such as Edelstein (1979) tested this model with empirical data for various study areas. In these studies a regressive property tax structure was concluded most often. Soon after its development, a variation of the vertical equity test was developed by Cheng in 1974. Cheng assumed a different functional form. He thought the relationship between Assessed Value and Sale amount should be exponential, or log–linear. Other researchers added their own slight changes to the vertical equity test model, but they left assessed value as the dependent variable and sale amount as the independent variable.

The literature changed direction when the hypothesized relationship between assessed value and sale amount was reversed by Kochin and Parks in 1972. They believed that sale amount should be the dependent variable and assessed value the independent variable. Kochin and Parks assert that if market values were fixed and nonstochastic and assessed values were perfectly proportional to market values (their were no misassessments), then assessment ratios would appear regressive if sale amounts were distributed randomly around market value. So, they argued, if a property sold above market value the assessment ratio would appear lower and if a property sold below market value, the assessment ratio would appear higher, incorrectly detecting regressivity. For example, assume that all market values are $100,000 and assessed values are $50,000. If one parcel sells for $110,000 its calculated AR would be 0.45. If another parcel sells for $90,000 its calculated AR is 0.55. Any of the traditional tests for vertical inequity would label this example one of regressive vertical inequity because the parcel that sold for more has a lower AR and the parcel that sold for less, has a higher AR. Kochin and Parks would argue that in this example, there is no inequity because only the sale prices have errors, not the assessments. Indeed, empirical results of their test largely revealed progressive property tax structures and they declared previous results from the old models were biased toward finding regressivity.

However, the assumptions made by Kochin and Parks have been challenged. After the Kochin and Parks paper was published, the literature was inundated with arguments for and against their model. Several papers were written that showed statistical evidence against the Kochin and Parks model and successfully defended the traditional models. These included work by Kennedy (1984), Gaston (1984), and Clapp (1990). It is now generally accepted that market value is a fixed non-stochastic variable and both assessed value and sale amount are subject to error.

Clapp not only showed that Kochin and Parks model was plagued by bias, he developed his own model that would incorporate the benefits of Kochin and

Parks and those of the traditional model. In doing so he removed the biases of the former models (Clapp 1990).

In this chapter, four models, the Pagin and Fogarty, the Cheng, the I.A.A.O, and the Clapp model will be employed to show whether there are patterns of vertical inequity in the property tax structure in Lansing. In all four models, the null hypothesis is that the property tax structure is vertically equitable. The test hypothesis is that the property tax structure is regressive and vertical inequity is present. An alternative situation, that the property tax structure is progressive, might also be concluded from the test results.

**Paglin and Fogarty Model**

The first model, by Paglin and Fogarty was developed in 1972. It is a simple linear regression of sale amount on assessed value. The model is estimated by the Ordinary Least Squares method. A t–test will be used to determine the significance of the difference between hypothesized and actual coefficients. The model is formally stated in the following equation:

$$\mathbf{AV} = \beta_0 + \beta_1 \mathbf{S} + \varepsilon.$$

If the property tax structure behaved equitably, as it theoretically should, the mean assessment ratio would be 0.5 and accordingly the slope of the line should also be 0.5 with an intercept of zero. Therefore under the null hypothesis, that no vertical inequity exists, the slope of the line is 0.5 and the intercept is zero:

$$\mathbf{H_0}: \beta_0 = 0 \text{ and } \beta_1 = 0.5.$$

However, if the line goes through the origin, there is no vertical inequity regardless of slope. If this is the situation, it doesn't matter what the sale price is because the corresponding estimated assessed value will be half of sale price and all parcels will be taxed at the same rate. Hence, the test for regressivity hinges on the intercept. If the intercept is zero, equity exists. If the intercept is more than zero, regressive vertical inequity exists and if the intercept is less than zero, progressive vertical inequity exists. Figure 5 graphically shows the Paglin and Fogarty regression under the null hypotheses of equity. It is the line:

**AV = 0 + 0.5 S.**

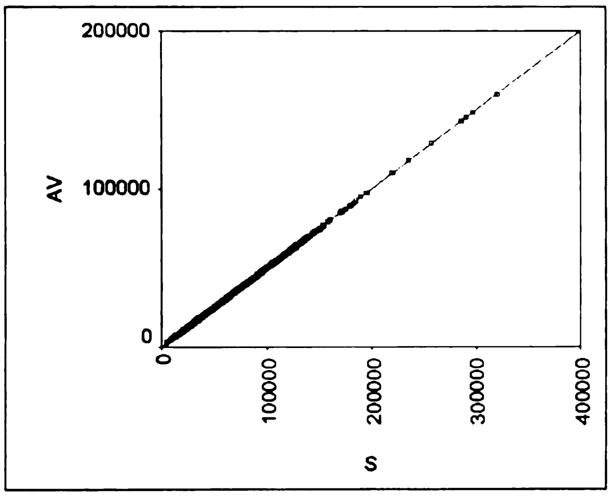


**Figure 5 - Paglin and Fogarty Model (under the null)**

There are two test hypotheses. First, that the property tax structure is regressive. In this case the intercept will be more than zero. In addition, since the mean of all assessment ratios in the sample is known to be 0.46, the slope is expected to be less than 0.5 under conditions of regressivity.

**$H_1$: $\beta_0 > 0$ and $\beta_1 < 0.5$.**

The second hypothesis is that the property tax structure is progressive. In this case the intercept will less than zero and the slope is expected to be more than 0.5.

**$H_1$: $\beta_0 < 0$ and $\beta_1 > 0.5$.**

**Results**

The estimated Paglin and Fogarty equation is displayed in Table 1. The estimated equation is also shown graphically in Figure 6a. The t-test on the intercept coefficient shows it is significantly greater than zero and the t-test on the slope shows the estimated $\beta_1$ is significantly less than 0.5. Therefore, the null hypothesis is rejected at the 99% confidence level. The result of the Paglin and Fogarty test for vertical inequity is consistent with the first test hypothesis of a regressive property tax structure. For comparison, the estimated or actual relationship between AV and S is shown in Figure 6b on the same graph as the theoretical line under equity (slope, 0.5, and intercept, 0,) and another hypothetical linear relationship between AV and S that is also indicative of equity. This line has a slope equal to the sample mean of 0.46 and intercept of zero.

**Table 1 – Estimated Paglin and Fogarty Equation**

| AV | = | $\beta_0$ | + | $\beta_1$*S |
|---|---|---|---|---|
| **Estimated AV** | **=** | **2217.79** | **+** | **0.412 S** |
| s.e. | = | 118.272 | | 0.002 |
| t-stat for hypothesis test | = | 18.752 | | -46.809 |
| R Squared = 0.926 | | | | |

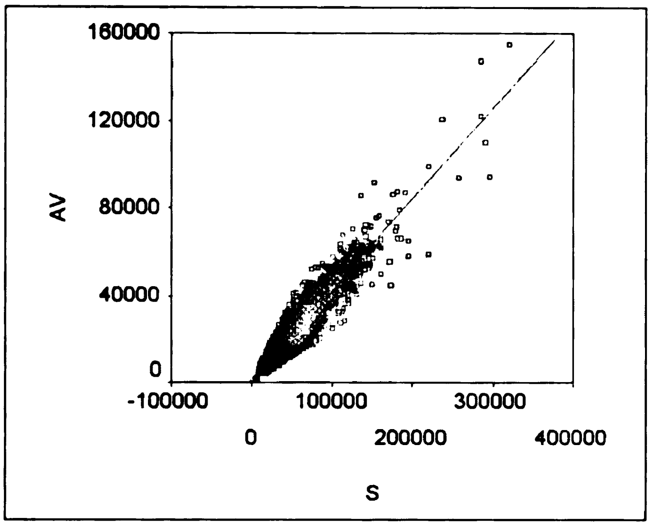


**Figure 6 - Estimated Paglin and Fogarty Model**

As can be seen by the estimated Paglin and Fogarty model and Figure 6, lower valued properties are taxed at a higher rate than higher valued properties. For example, given the results of the test, a property that sold for $75,000 has an estimated assessed value of $33,117.79 and therefore an estimated assessment ratio of 0.442. A higher valued property, one that sold for $175,000, has an estimated assessed value of $74,317.79 and therefore an estimated assessed value of 0.425. This example shows that the higher valued property pays a lower estimated rate of taxes and the lower valued property pays a higher estimated rate of taxes.

**Cheng Model**

The Cheng model was developed in 1974 as an improved alternative to the Paglin and Fogarty model. The Cheng model allows a non-linear relationship to exist between assessed value, the dependent variable, and sale amount, the independent variable:

$$\mathbf{AV = \beta_0 S^{\beta}{}_1 * \varepsilon.}$$

It is log transformed to a linear form for ease of estimation:

**$\ln AV = \ln \beta_0 + \beta_1 \ln S + \ln\varepsilon$**

The log - log form is then estimated by ordinary least squares. Again, a t–test will be employed to test the estimated coefficients for significance. Like the Paglin and Fogarty test, the null hypothesis is no inequity. Under the null, the untransformed slope is 0.5 or $H_0$: $\beta_0 = 0.5$. However, when the equation is log transformed the log is taken of $\beta_0$ and the null hypothesis is modified so that the transformed intercept is the log of 0.5 or

**$H_0$: $\ln\beta_0 = \ln 0.5 = -0.693$**

Also under the null, the power of S, or the coefficient of lnS, is one:

**$H_0$: $\beta_1 = 1$**

Unlike the Paglin and Fogarty model, regressivity in this test hinges on the elasticity, $\beta_1$, or the power of S in the untransformed exponential model. If $\beta_1$ proves to be more than one, progressive inequity exists, or higher valued properties are taxed higher rates. If $\beta_1$ proves to be less than one, then regressive inequity exists and lower valued properties are taxed at higher rates. Figure 7 shows the Cheng equation graphically under the null of equity.

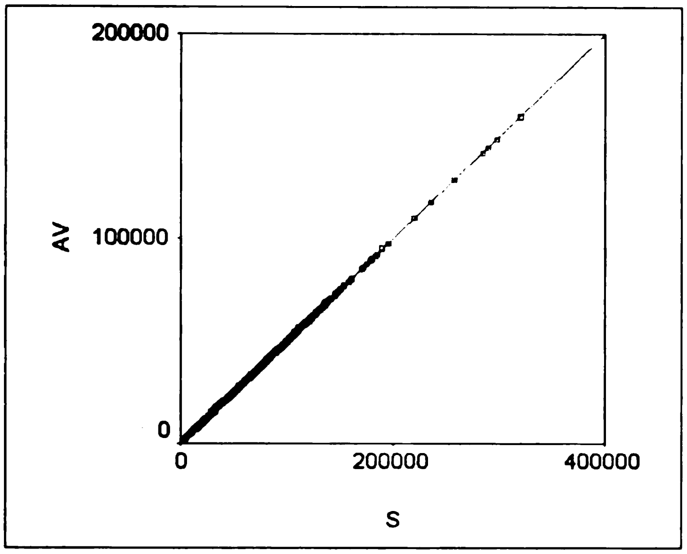


**Figure 7 – The Cheng Model (under the null)**

The test hypotheses are verbally the same here as they were for the Paglin and Fogarty model. The first test hypothesis is that the property tax structure is regressive. In this case, taxes are regressive if the power of S, $\beta_1$, is less than one. In the transformed model, the power becomes the coefficient of the log of S and if the taxes are regressive it will be less than one. **$H_1$: $\beta_1 < 1$.** The other alternative is progressivity. **$H_1$: $\beta_1 > 1$.** There is no test hypothesis about the intercept term and it will not be interpreted because to interpret the intercept is to interpret beyond the data set.

**Results**

The estimated Cheng equation is displayed in Table 2 and it is shown graphically in Figure 8. As can be seen from Figure 8, the data fit the estimated Cheng model better than they do the estimated Paglin and Fogarty model shown in Figure 6a. The t – test shows the estimated $\beta_1$ is significantly less than one and the null hypothesis is rejected at the 99% confidence level. The results are consistent with the first test hypothesis of a regressive property tax structure.

The estimated model can be transformed to solve for AV by taking the antilog of both sides of the equation:

**Estimated AV = 1.586 $S^{0.884}$**

As an example, to see how the estimated Cheng model shows a regressive vertically inequitable property tax structure, let S equal $50,000 and $100,000 respectively. When S equals $50,000, AV is expected to be $22,604.38 and therefore the expected AR is 0.452. When S equals $100,000, AV is expected to be $41716.05 and therefore the expected AR is 0.417. As can be seen, as S increases, AR decreases. Clearly, the estimated Cheng model reveals a regressive vertical inequity. Table 2 and Figure 8 show the estimated Cheng model.

**Table 2 - Estimated Cheng Model**

| | | | | |
|---|---|---|---|---|
| lnAV | = | $\ln\beta_0$ | + | $\beta_1 \ln S$ |
| **Estimated lnAV** | **=** | **0.461** | **+** | **0.884 lnS** |
| s.e. | = | 0.048 | | 0.004 |
| t-stat for hypothesis test | = | 24.042 | | -26.304 |
| R Squared = 0.833 | | | | |

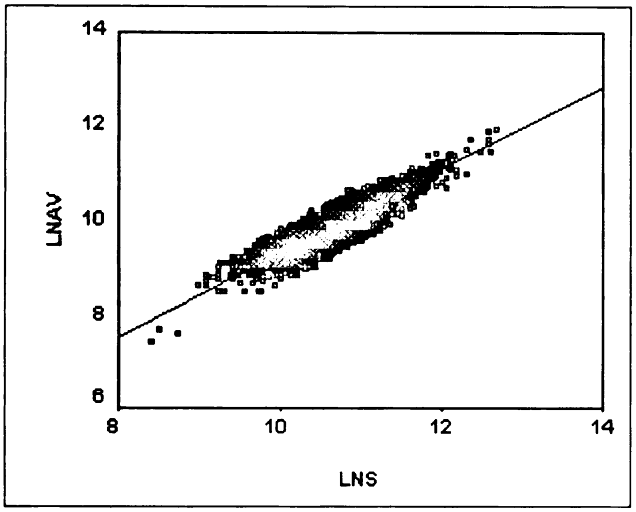


**Figure 8 - Estimated Cheng Model**

**The International Association of Assessing Officers Model**

The third model is endorsed by the International Association of Assessing Officers (I.A.A.O). Its dependent variable is the assessment ratio instead of the assessed value. It too is estimated by the Ordinary Least Squares Method. The equation is as follows:

$\mathbf{AR} = \beta_0 + \beta_1 \mathbf{S} + \varepsilon$

Under the null of no regressivity, the assessment ratio (AR) should be 0.5 for all properties. Thus, under the null, the slope of the line, (the coefficient of S,) is zero. $\mathbf{H_0}$: $\beta_1$**=0**. In addition, if the property taxes are assessed as they should be, the intercept is 0.50 $\mathbf{H_0}$: $\beta_0$**=0.5.** Figure 9 shows the I.A.A.O model graphically under the null of equity.

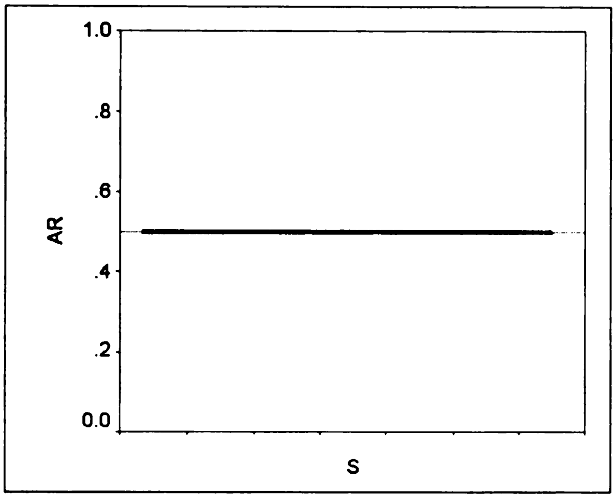


**Figure 9 - The I.A.A.O. model (under the null)**

Again, in this model the test hypotheses are, first, that the property tax structure is regressive: **$H_1$: $\beta_1 < 0$,** and second, that the property tax structure is progressive, **$H_1$: $\beta_1 > 0$.**

**Results**

The estimated I.A.A.O. equation is shown in Table 3. It is graphically depicted in Figure 10. The t-test shows the intercept is significantly more than 0.5 and the slope is significantly different from zero. This means that the lowest valued properties are being assessed above the legally mandated proportion of market value and as value increase assessment ratio decreases. However, as can be seen from Figure 10, the intercept is outside the data range and therefore not consequential. Regardless, the null hypothesis of equity is rejected at the 99% confidence level. The results are consistent with the first test hypothesis of regressivity. Note that even though the null hypothesis is rejected, the low R squared and Figure 10 show that the model does not fit the data well.

**Table 3 - Estimated I.A.A.O Model**

| | | | | |
|---|---|---|---|---|
| AR | = | $\beta_0$ | + | $\beta_1 S$ |
| estimated AR | = | 0.511 | - | -8.75E-07 S |
| s.e. | = | 0.002 | | 3.71E-08 |
| t-stat for hypothesis test | = | 5.5 | | -23.607 |
| R Squared = 0.254 | | | | |

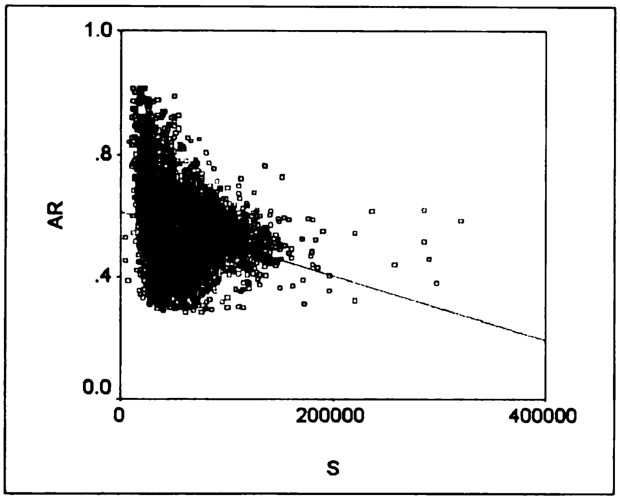


**Figure 10 - Estimated I.A.A.O model**

**Clapp Two – Stage Least Squares Simultaneous Equations Model**

The first three models used so far, have been criticized, most notably by Kochin and Parks, to be biased toward finding regressivity. The fourth model was created with the goal of eliminating the bias of the previous models. It is the Clapp Two-Stage Least Squares Simultaneous Equations Model. It acknowledges that sale amount is not a perfect predictor of market value and assumes that assessed value and market value are interdependent. Included in the model is an instrumental variable, Z, that is highly correlated to both market value and assessed value. Z, a binary variable, is equal to one if the observation is in both the top third of all sale values and in the top third of all assessed values. Z is set equal to negative one if the observation is in both the bottom third of all sales values and in the bottom third of all assessed values. Z is set equal to zero otherwise. Unlike an ordinary regression model that may be estimated using ordinary least squares, this model does not assume a one-way causal relationship. In this model, assessed value is both an independent and a dependent variable. Because AV is mutually dependent, not independent, it is an endogenous variable.

The model is a set of two simultaneous equations. It must be estimated using the Two-Stage-Least-Squares method. In this method, the parameters of one of the equations are estimated taking into account the information given in both equations. Ordinary Least Squares (OLS) can not be used in this case because not all of the information known about AV would be taken into account. For this reason, the coefficients, if estimated using OLS, would be inconsistent or biased even in large samples. OLS coefficients would not converge to their true population values and would be inefficient resulting in very large variances (Gujarati 1995, part 4). This model was developed in 1990.

$$\mathbf{Ln\ S} = \beta_0 + \beta_1 \,\mathbf{ln\ AV} + \varepsilon_1$$

$$\mathbf{Ln\ AV} = \alpha_0 + \alpha_1 \mathbf{Z} + \varepsilon_2$$

Under the null hypothesis of no inequity, $\beta_1$ is statistically equal to one, **$H_0$: $\beta_1 = 1$**. The test hypotheses are as follows: 1)The property tax structure is regressive, **$H_1$: $\beta_1 > 1$**, and 2) The property tax structure is progressive, **$H_1$: $\beta_1 < 1$**.

**Results**

The estimated coefficients of the Clapp equation are in Table 4. T-test results lead to a rejection of the null hypothesis at the 99% confidence level. Results are consistent with the first test hypothesis, a regressive property tax structure.

**Table 4 - Estimated Clapp 2SLS Simultaneous Equation Model**

| LnS | = | $\beta_0$ | + | $\beta_1$lnAV |
|---|---|---|---|---|
| Estimated lnS | = | 0.556039 | + | 1.023555 lnAV |
| s.e. | = | 0.062991 | | 0.006252 |
| t-stat for hypothesis test | = | 8.827 | | 3.77 |

R Squared = 0.76892

**Controlling for Year**

The above models were estimated with the entire sample of property transactions that occurred over five different years. Because properties are given a new assessment every year, it seems logical to question whether the amount of inequity varies from year to year. To test this question, the year of the sale and assessment must be controlled. To this end, dummy variables representing years, are inserted in the Cheng Model. The following dummy variables were created from the data:

D1994 equals one if the observation was collected in 1994, zero otherwise.

D1995 equals one if the observation was collected in 1995, zero otherwise.

D1996 equals one if the observation was collected in 1996, zero otherwise.

D1997 is set equal to one if the observation was collected in 1997, zero otherwise.

Note that there is not a dummy variable for every year as that would cause perfect colinearity making Ordinary Least Squares estimation impossible. As can be seen, there is a dummy variable for 1994, 1995, 1996 and 1997 but there is no D1998 for 1998. Nevertheless, observations from 1998 are accounted for. If an observation occurred in 1998, all other dummies are set to zero and it can be assumed that the remaining model coefficients are valid for 1998. The dummy variables are entered into the Cheng model as intercept dummies. They are also used in multiplicative dummies or slope dummies by multiplying each by S.

The Cheng model with the intercept and slope dummies is stated as,

$$\mathbf{lnAV = \beta_0 + \beta_1 lnS + \beta_2 D1997 + \beta_3 lnSD1997 + \beta_4 D1996 + \beta_5 lnSD1996 + \beta_6 D1995 + \beta_7 lnSD1995 + \beta_8 D1994 + \beta_9 lnSD1994 + \varepsilon.}$$

The estimated Cheng model with dummies is as follows:

$$\mathbf{lnAV = .113 + .913\, lnS + .289\, D1997 + .028\, lnSD1997 + .370\, D1996 - .031\, lnSD1996 + .239\, D1995 - .018\, lnSD1995 + .287\, D1994 - .017\, lnSD1994}$$

Assuming all coefficients are significantly different from zero, the year specific relationship between lnAV and lnS can be calculated by adding the coefficient on lnS, $\beta_1$, to the specific year's slope dummy. To calculate the year specific intercept, the intercept, $\beta_0$, is added to the specific year's intercept dummy. For example, in 1997, all variables except the intercept, lnS and the 1997 dummies are set equal to zero and the estimated relationship between lnAV and lnS is $lnAV = (\beta_0 + \beta_2 D1997) + (\beta_1\, lnS + \beta_3\, lnSD1997)$. The year specific Cheng model results are in Table 5.

**Table 5 – Year Specific Cheng Model Results**

| | | | | |
|---|---|---|---|---|
| $LnAV_{1994}$ | = | 0.397 | + | 0.896 $lnS_{1994}$ |
| $LnAV_{1995}$ | = | 0.352 | + | 0.895 $lnS_{1995}$ |
| $LnAV_{1996}$ | = | 0.483 | + | 0.882 $lnS_{1996}$ |
| $LnAV_{1997}$ | = | 0.402 | + | 0.885 $lnS_{1997}$ |
| $LnAV_{1998}$ | = | 0.113 | + | 0.913 $lnS_{1998}$ |

### Results

Results show that equity does vary from year to year. 1996 has the smallest slope indicating the most regressive inequity. 1998 has the slope closet to one and the least inequity.

### Conclusion

All four models, Paglin and Fogarty, Cheng, I.A.A.O., and Clapp, show vertical inequity that is statistically significant. The results in each case lead to a rejection of the null of equity. All results are consistent with a regressive property tax structure. Each test assumes a different functional relationship between AV and S. Some of these functional forms fit the data better than others. As can be seen by Figures 2.4 through 2.6, the estimated Cheng model (Figure 2.5) fits the data quite well. The I.A.A.O model (Figure 2.6) on the other hand, clearly doesn't fit the data well at all, and the residuals have heteroskedasticity problems.

When dummy variables are included in the Cheng model to control for year variations in equity, it is clear that although the level of equity changes slightly from year to year, inequity is pervasive throughout. The yearly variations in assessment equity will be further examined in the next chapter. This chapter's results have great significance, demonstrating inequitable and undesirable non-uniform assessments across properties. In Lansing, MI, higher priced properties pay property taxes at a lower rate than lower priced properties. The finding that property taxes are regressive with respect to sale values justifies the following examination of the nature and spatial distribution of the assessment ratio. This examination could reveal more information about the groups of people that are most negatively affected by the regressive nature of the property tax structure.

## Chapter 4

## SPATIAL AUTOCORRELATION AND SURFACES OF INEQUITY

It has now been asserted that regressive vertical inequity is present in the property tax structure of Lansing, Michigan. The test results of the previous chapter show that higher valued properties are taxed at a smaller proportion of market value than lower valued properties and than is legally permitted. Because cities are made up of neighborhoods of like characteristics of which housing value is one, it seems likely that the vertical inequity previously detected only econometrically, manifests itself spatially as well. In addition, as was discussed in Chapter 1, the assessor's office divides Lansing into neighborhood units to deal with assessments and assessment adjustments. If the average assessment ratio of an assessor-designated neighborhood is too low or two high the whole neighborhood is adjusted up or down accordingly. Because of this, it is likely that residual or boundary effects of this process can be seen in the spatial patterns of assessment. Are some areas of the city taxed more than other areas? The subsequent chapters deal with this question of spatial inequity.

There has not been very much literature on the description of spatial patterns in property taxation. Perhaps this is due to the absence of geographers participating in the body of literature surrounding social equity and the property tax. Most researchers in this field have come from real estate disciplines and econometrics. Many of the geographers who have studied spatial inequity have done so statistically and econometrically using cross sectional data with little spatial referencing. If maps were created, they were usually based on data that had been aggregated to relatively large areas. They did not tend to examine spatial patterns visually in attempt to create hypotheses with sophisticated surface maps. This is likely because when most of the geography literature in this subject was created, computer GIS was just being developed and was in an inaccessible, time-consuming stage. There is one notable exception. Thrall, a geographer who has worked on this topic, has looked at map patterns in two studies. The first was in done in 1978 (Thrall 1978). He had to manually locate the addresses of the sale transactions on a map and then write code to create a crude trend surface map of the assessment ratio. In 1993, Thrall did a similar study to see if "geographic equity" was present in the tax structure of St. Lucie County (Thrall 1993). This time he had use of the best GIS equipment made for personal computers. However, Thrall did not create surface maps or even analyze spatial autocorrelation. Instead, he simply mapped the locations of the over assessed properties (properties with assessment ratios at least one standard deviation over the mean) and under assessed properties (properties with assessment ratios at least one standard deviation under the mean) and then compared their patterns visually (Thrall 1993).

The purpose of this chapter is to display and describe any spatial patterns that may exist in the property tax structure of Lansing, Michigan. To accomplish this, the data will be subjected to several procedures. First the property tax structure will be formally modeled and tested for spatial inequity by using semivariance analysis and *Moran's I* tests respectively. Next, spatial patterns of tax inequity will be displayed in *kriged* surface maps. The process of kriging is explained in detail later in this chapter. Finally, those maps will be graphically compared and tested for correlation to identify any dynamic patterns that occur in the data. The contents of the chapter will be organized around the four research questions in Table 6 and each will be addressed in a section of this chapter. The methodologies used to test each of the research questions will be explained in the beginnings of these chapter sections.

**Table 6 – Chapter 4 Research Questions**

| | **Research Questions** | **Null Hypotheses** | **Test Hypotheses** |
|---|---|---|---|
| 1 | Is the assessment ratio (AR) spatially autocorrelated? | There is no spatial autocorrelation in AR. | AR is spatially autocorrelated. |
| 2 | What do the spatial patterns in the data look like? | There are concentric ring patterns. | There are other patterns. |
| 3 | Do the patterns vary or shift from year to year? | The patterns do not change. | The patterns are dynamic. |
| 4 | Is an assessment correction process apparent in the data? | No assessment correction process is apparent. | A correction process is apparent. |

**Research Question 1: Is the Assessment Ratio Spatially Autocorrelated?**

This is the first research question partly because, if the null hypothesis is accepted, there is really no need to discuss spatial inequity and the rest of the chapter, and partly because the methodology used to answer this question is also needed to answer the subsequent research questions. There will be two methods used to address this question; semivariance analysis and *Moran's I*. However, it is first important to establish just what the first research question is asking.

As was defined in previous chapters, the assessment ratio, AR, for a particular parcel, is the proportion of market value at which that parcel is assessed. All assessment ratios are supposed to be 0.50. Therefore, there shouldn't be any pattern to the assessment ratio surface. However, since vertical regressive inequity was detected in Chapter 3, it is already known that the assessment ratio does not behave as it theoretically should and it is likely that the vertical regressive inequity manifests itself spatially as well. If the vertical regressive inequity does have spatial implications, then the variable AR will have a spatial pattern and its high and low values will be spatially autocorrelated. Spatial autocorrelation is the dependence of a value of a variable at any point on the values of the variable at near by points. Spatial autocorrelation is present, "when similar values cluster together on a map" (Odland 1988, p. 7). Spatial autocorrelation will result in some areas in the city averaging lower ARs and some areas averaging higher ARs. Spatial autocorrelation may be positive or negative. If positive spatial autocorrelation exists between two points, then their values will be similar. If negative spatial autocorrelation exists between two points, their values will be dissimilar. Both kinds of spatial autocorrelation will result in distinct spatial patterns. If there is no spatial inequity, then AR will not be spatially autocorrelated and there will be no spatial pattern to the assessment ratio. The first step taken in testing for spatial patterns is a graphical approach that models any spatial autocorrelation that exists in the variable AR. The method employed in this paper to model the spatial autocorrelation of AR is semivariance analysis.

**Semivariance Analysis**

One way to examine spatial patterns and spatial autocorrelation is by semivariance analysis. Semivariance is mathematically defined as:

$\gamma$ **(h) = [N(h)/2] * $_{i}{}^{n}\Sigma[z_i - z_{i+h}]^2$**

Where:

$\gamma$ (h) is the average semivariance of a pair separated by a lag distance of h

h = the lag distance

N(h) = the number of pairs separated by h

$z_i$ = the value of the variable (in this study z is AR) at location i.

$Z_{i+h}$ = the value of the variable at the location a lag away from i.

Essentially, semivariance is the average difference between the values of a pair of points that are separated by a given distance or lag. So, in this study, $\gamma$(h) is the difference in the values of AR for a pair of locations that are separated by a lag of specified distance.

If positive spatial autocorrelation exists, the difference between values of pairs that are closer together will be smaller than the difference between values of pairs that are farther apart. Put differently, under classic spatial autocorrelation circumstances, the semivariance will be less at smaller lag values and increase until there is no spatial autocorrelation (dependence) between pairs of points or until negative spatial autocorrelation is present.

The software *GS+* will calculate the average semivariance for all pairs (of points) in a lag class for all lags up to a specified *active lag distance*. The active lag distance is specified by the researcher and is the longest distance by which a pair will be separated in the analysis. Its greatest value may be as much as the distance between the pair of points that are the farthest away from each other in the study area, or it may be any distance shorter. Often, a researcher will not be interested in the difference between values of pairs that are extremely far apart (spatially) because it is hypothesized that they will have little effect on each other (pairs are not spatially autocorrelated after a certain distance).

In addition, *GS+* lets the researcher specify the lag distances. The lag distances may be at equal intervals or uneven intervals. That is, the active lag distance may be divided evenly into lags, or the lags may vary in distance. Specifying the appropriate lag interval – or the number of lags, is something of an art form because spatial structure may become apparent at different lags for different kinds of data. Usually the researcher undergoes a trial and error process in choosing a lag that best represents the spatial dependence of the data. At the beginning of the process it is beneficial to study the dependence of the variable in question at the maximum active lag distance and with very short lag intervals. Therefore, in this thesis, semivariance analysis will first be conducted at the maximum active lag distance which is the length of the distances between the pairs of points that are the farthest apart. The maximum active lag distance for the Lansing study area is approximately 13,600 map units,[1]which is about 13.6 kilometers, or 8.5 miles. The actual maximum active lag distance varies slightly between years of data because the locations of sample points vary from year to year. In addition, the semivariance analysis will first be done with very small lag classes. The active lag distance will be broken into approximately 136 lags creating lag classes of 100 map units or 110 yards. This will show information at the neighborhood scale.

A semivariance analysis is done for each year of data separately and the results are found in tabular form in Appendices A through E. The data are examined year by year because of the dynamic nature of the research questions listed in Table 6.

The results in the appendices are shown in four columns. The first column identifies the lag class. As was stated above, the lag classes are 100 map units, and since the maximum lag distance is about 13,600 map units, there are approximately 136 lags in the tables. The next column is "average distance," which is the average length of separation of points in the lag. For example, in the first lag not all of the pairs are separated by exactly 100 map units. Instead, each pair is separated by some distance up to 100 map units. The "average distance" is the average of the distances between pairs in the first lag class. For example, in Appendix A (1994 data), the average distance in the first lag is 56.47 map units (approximately 62 yards). The third column in the tables is the "average semivariance," or the difference between the assessment ratios in each pair, and the last column indicates the number of pairs in each lag class.

**Semivariance Results**

Recall from Table 6, that the null hypothesis of the first research question is no spatial autocorrelation, and the test or alternative hypothesis is that spatial

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[1] The map units are in UTM, Universal Transverse Mercator meters, units. The latitude and longitude units derived from geocoding in Transcad were reprojected to UTM coordinates in a

autocorrelation does exist. The results of this first semivariance analysis shown in the tables in Appendices A through E reveal a pattern of autocorrelation, which is consistent with the test hypothesis. The first few lag classes have smaller average semivariances indicating that values closest together are more similar. The semivariances increase with lags until they begin to decrease again at about 50 lags. Actually, the values in the tables reveal that pairs of points that are about 1000 map units apart are the most autocorrelated. Their semivariances are even smaller than the pairs that are the closest together in the first couple of lags. The significance of these patterns will be further examined and tested in the next section, *Moran's I* Tests. Semivariance analysis will also be revisited later in this chapter in a section called Semivariograms.

The results of this first semivariance analysis indicate that within small areas or neighborhoods the assessment ratios are similar. In addition, these results suggest that neighborhoods separated by great distances also have similar assessment ratios. This analysis gives reason to reject the null hypothesis of the first research question and conclude that the semivariance analysis is so far consistent with spatial autocorrelation in the assessment ratio. However, a more formal test for spatial autocorrelation, *Moran's I*, has also been performed and will be described in the next section to confirm the hypothesis test for the first research question.

### ***Moran's I* Tests**

*Moran's I* is an autocorrelation statistic that is constructed to test for spatial autocorrelation. It is a "product moment" statistic that is similar in nature

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coordinate conversion program called *Corpscon For Windows*.

and purpose to the Pearson's Correlation statistic. *Moran's I* varies from negative one to positive one. Positive values of *Moran's I* represent the presence of positive spatial autocorrelation. A variable is said to have positive spatial autocorrelation when similar values are clumped together. If *Moran's I* is zero, no spatial autocorrelation exists and the variable exihibits randomness. It follows logically then, that negative values of *Moran's I* represent the presence of negative spatial autocorrelation. Negative spatial autocorrelation exists when disimilar values are consistently located in close proximity to one another.

The process of calculating *Moran's I* involves applying a spatial weighting function to the map of values of the variable in question. According to Odland, a spatial weighting function is a set of rules for assigning values to pairs of places in a way that represents their arrangement in space (Odland 1988, p. 9). When the function is applied to the map, a set of weights in matrix form can be calculated. The weights are the relative locations of the places on the map. Generally, if places are closer together they have more effect on each other's variable values than places that are further apart. Weights can be simply binary and are in this thesis. For instance, if an adjacency rule were applied, the weight for a pair of locations that are adjacent to each other would be one while the weight for a pair of locations that are not adjacent to each other would be zero. In this paper, the weights will be binary based on distance lags. So if a pair is separated by the lag for which the statistic is being calculated, the weight is one. Otherwise, the weight of the pair will be zero.

The Moran's I test statistic is mathematically defined as follows:

$\mathbf{I = n/\sum\sum w_{ij} * [\sum\sum w_{ij}(z_i - z)(z_j - z) / {}_i^n\sum(z_i - z)^2]}$ (Odland 1988, p. 10)

$Z_i$ = the value of the variable in question (AR for the purposes of this study) at location i. The double summation indicates summation over all pairs and lag distances.

The null hypothesis of a *Moran's I* test is always that no spatial autocorrelation exists and that the variable in question is distributed either normally or randomly. In this thesis, it is assumed that the assessment ratio under the null is distributed normally. This is because it is known that the assessment ratio should have a mean of 0.50 and any deviations from the mean should not result in spatial patterns. Therefore, it is assumed that under the null, there is no spatial autocorrelation in the variable assessment ratio at any lag, and it is distributed throughout the study area in a normal way.

The value of *Moran's I* under the null approaches zero for large samples and is asymptotically normal. Spatial autocorrelation can affect pairs of locations at different lags or distances apart. Because of this, a separate *Moran's I* statistic is calculated for every lag that is tested for spatial autocorrelation. For example, if it is desirable to test for spatial autocorrelation at three lags: between locations that are less than one mile apart, less than two miles apart and less than three miles apart, then *Moran's I* must be calculated and tested three times. The program, *GS+*, will be used to calculate the *Moran's I* statistic. *GS+* calculates the statistic for every lag of specified length in the *active lag distance* described above in the section on semivariance analysis. The lags used in this test will be 100 map units and the active lag distance will be set to the maximum possible for the study area, approximately 13,600 map units. The calculated Moran's I statistics are listed in Appendices F through J.

The null hypotheses of no spatial autocorrelation are tested using a z test of significance. A separate significance test is done for each lag. The sample sizes are relatively large in this analysis and are equal to the number of pairs in each lag class. Because of this and the asymptotically normal characteristic of *Moran's I*, significance will be decided by comparing a z statistic (1.645) to z scores. Many steps are taken to calculate the z scores. First, the expected *Moran's I* under the null is calculated using the following formula:

**E(I) = -1/(n-1)**

Where: E(I) is the expected Moran's I under the null and approaches zero when the sample size gets very large. Then, the expected *Moran's I* standard deviation is calculated. It approaches one when the sample size gets very large. The standard deviation is calculated as follows:

**SD = SQRT $((n^2-n+9)/(n^2-1))$**

Next, the standard error for the calculated Moran's I is estimated as follows:

**s.e. = SD/SQRT(n)**

Finally, z scores are calculated for each lag as follows:

**Z score = (I – E(I))/s.e.**

The null hypotheses were rejected at the 95% confidence level if the absolute values of the z scores were greater than 1.645.

**Moran's I Results**

The hypothesis test results, standard error, z score and the expected Moran's I under the null for each lag of each year are listed in the Appendices F through J along side the calculated Moran's I for the lag class and the number of pairs in the lag class.

**Table 7- Null Hypothesis Rejections by Year**

| Year | Number of Lags with Spatial Autocorrelation (Rejections of null hypothesis) | Lags with Positive Spatial Autocorrelation (number of lags with significant negative *I*s) | Lags with Negative Spatial Autocorrelation (number of lags with significant positive *I*s) |
|---|---|---|---|
| 1994 | 22 of 135 | 10 | 12 |
| 1995 | 14 of 135 | 9 | 5 |
| 1996 | 51 of 134 | 29 | 22 |
| 1997 | 30 of 135 | 13 | 17 |
| 1998 | 15 of 130 | 7 | 8 |

It is interesting to note that at the smallest lags there are many instances of positive spatial autocorrelation. This indicates that within small areas or within neighborhoods, the assessment ratios are similar. This is expected, because it is known that assessors adjust the ratios of entire neighborhoods up or down at once. It is also interesting to note that there are almost as many negative spatially autocorrelated lags as there are positive. This too, is not unexpected. The fact that both kinds of spatial autocorrelation exist simply means that some areas in the city are alike and some are different. If all of the lags had positive spatial autocorrelation, the assessment ratio wouldn't differ from neighborhood to neighborhood or from area to area.

The results of the Moran's I analysis leads to a formal rejection of the null hypothesis of the first research question. The results are consistent with the existence of spatial autocorrelation in the assessment ratio.

**Research Question 2: What do the spatial patterns in the data look like?**

It is apparent from rejecting the first research question hypothesis that the data are spatially autocorrelated and that there are spatial patterns in the data. To address research question two, the spatial patterns shall be viewed in surface maps. The process used in this thesis to create the surfaces is kriging, which is described in detail later on in this chapter. In order to create the kriged surfaces however, the spatial autocorrelation must be modeled and described with parameters. The semivariance analysis that has been done will be used to create semivariograms that are in turn used in the kriging process to create surface maps.

**Semivariograms**

A semivariogram is a graph of the autocorrelation present in the data structure; that is, a semivariogram shows the semivariance of the data. The software package, *GS+*, is used as a research tool in this paper to construct semivariograms. A semivariogram plots the difference between values (in this case the difference between AR in a pair of points) versus the distance between points (pairs of values.) Typically the difference between values increases with distance. This is as expected according to distance decay.

However, the semivariance analysis described above reveals that the difference between values of AR does increase with distance until they begin to decrease again. Semivariograms have been constructed from the data in Appendices A through E and they appear in Figures 11-15.

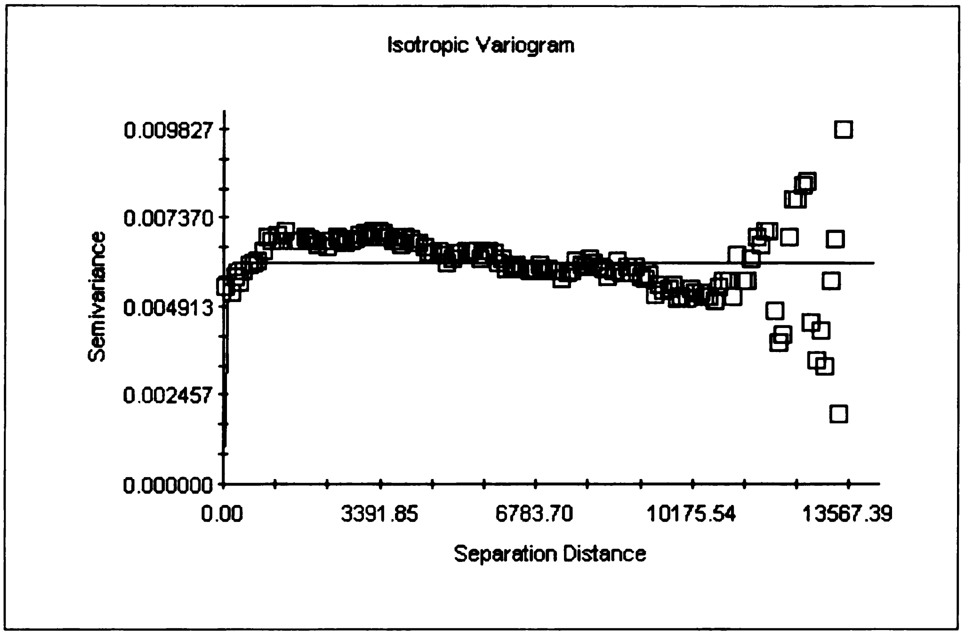


**Figure 11 – 1994 Semivariogram with Maximum Active Lag Distance**

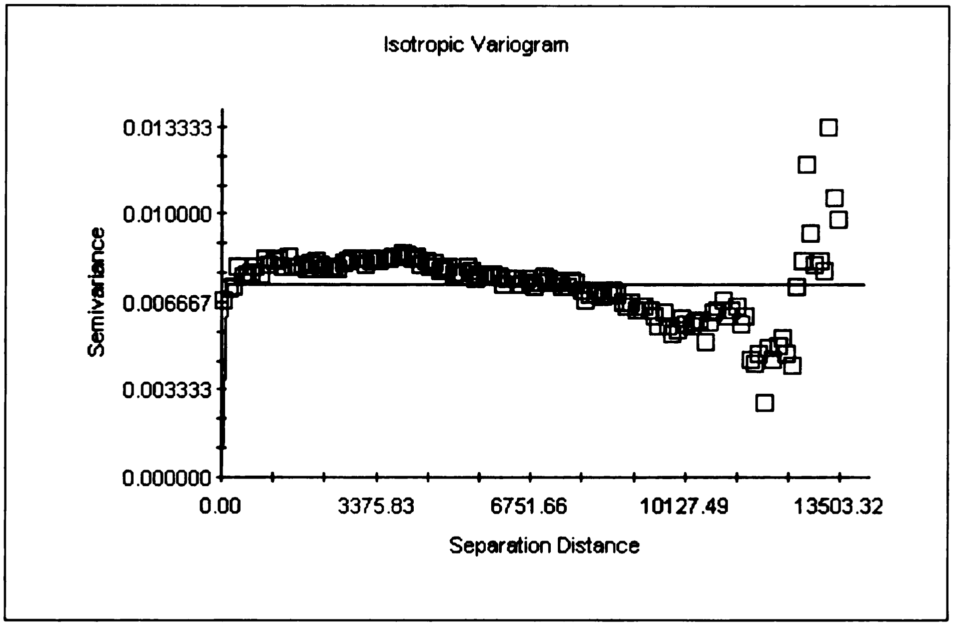


**Figure 12 – 1995 Semivariogram with Maximum Active Lag Distance**

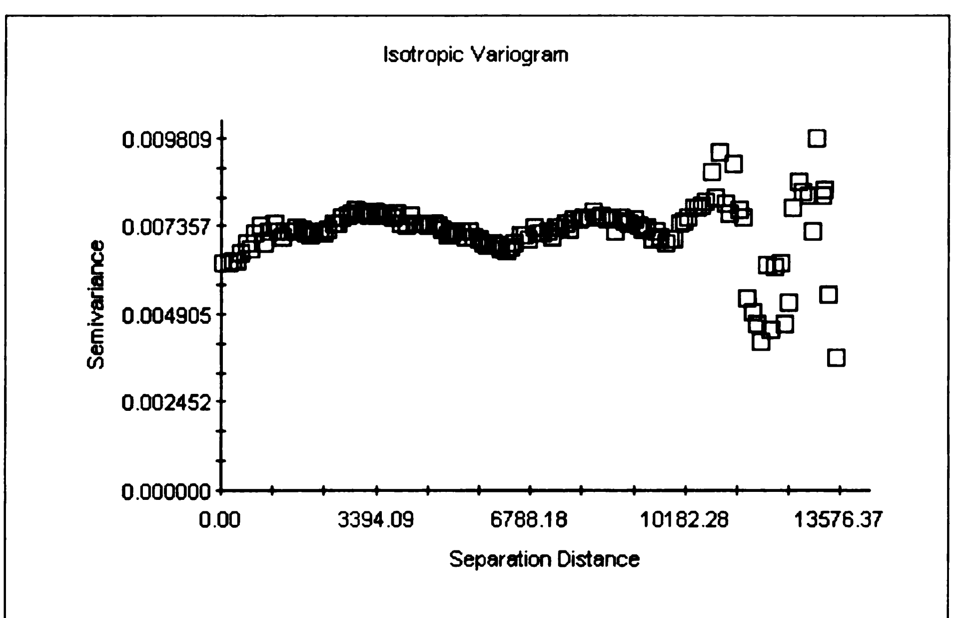


**Figure 13 – 1996 Semivariogram with Maximum Active Lag Distance**

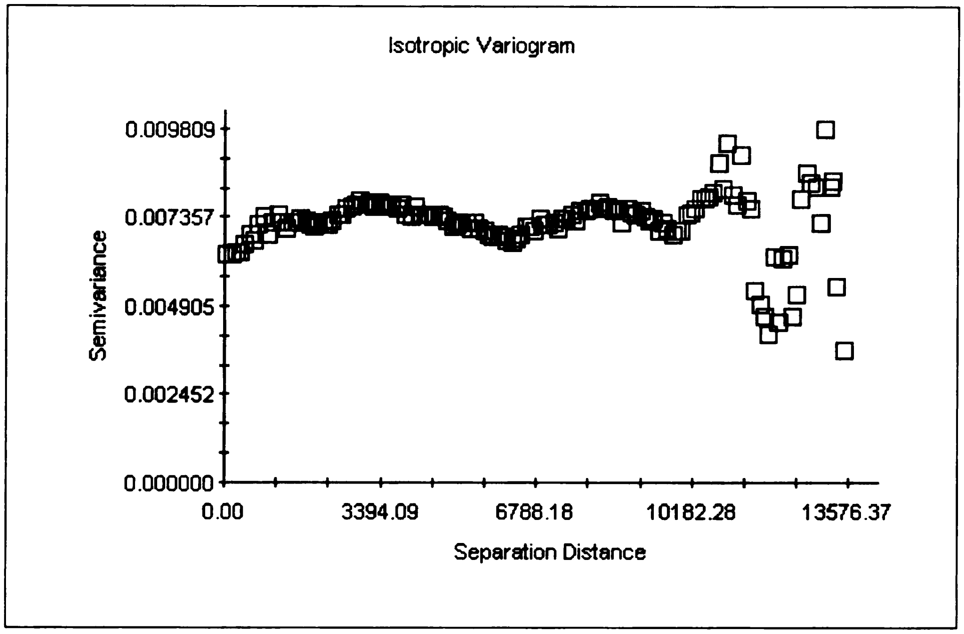


**Figure 14 – 1997 Semivariogram with Maximum Active Lag Distance**

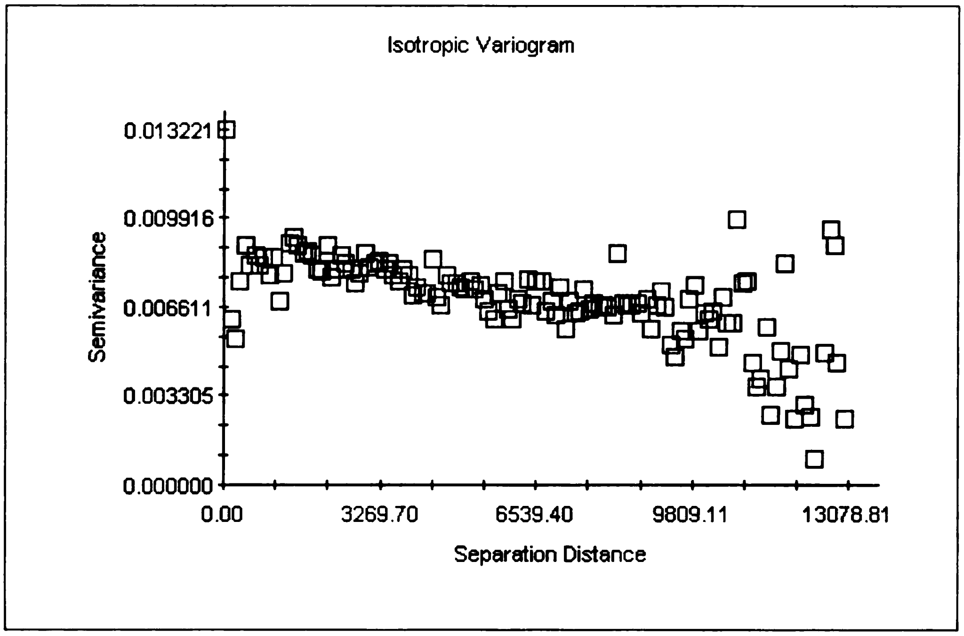


**Figure 15 – 1998 Semivariogram with Maximum Active Lag Distance**

Figure 11 is a graph of the data in Appendix A. The semivariogram clearly shows that pairs closest together, in the very first lags have more similar values than those do in the middle lags, but that those pairs farthest apart are the most alike in terms of AR value.

After the semivariogram is plotted, it is modeled by a known distribution such as a gausian, spherical, linear or exponential. Obviously, none of these known distributions resemble any of the maximum active lag distance semivariograms seen plotted in Figures 11 through 15. Because of this, a smaller active lag distance is chosen. For example, if the semivariogram only displays semivariances for pairs separated by up to one quarter of the total extent of the map unit distance, or about 43,000 map units, the known distributions will fit the pattern better.

Therefore, the active lag distance is truncated before the semivariances decrease, and new semivariograms showing just a portion of the maximum active lag distance are created. The known distributions are then fit to the semivariogram plots, and the errors are calculated between the actual plot and the known distributions. The distribution with the lowest mean square error is then chosen to model the semivariogram plot. Figures 17 through 21, are the truncated semivariograms with the best-fit distributions modeling the semivariances.

Three parameters, the nugget, sill, and range are used to summarize the modeled semivariogram plot. The nugget is the y-intercept of the model. The sill is the y-value or semivariance value at which the model levels off and the range is the distance over which spatial dependence is apparent in the modeled semivariogram. Figure 16 is an idealized semivariogram with nugget, sill and range shown.

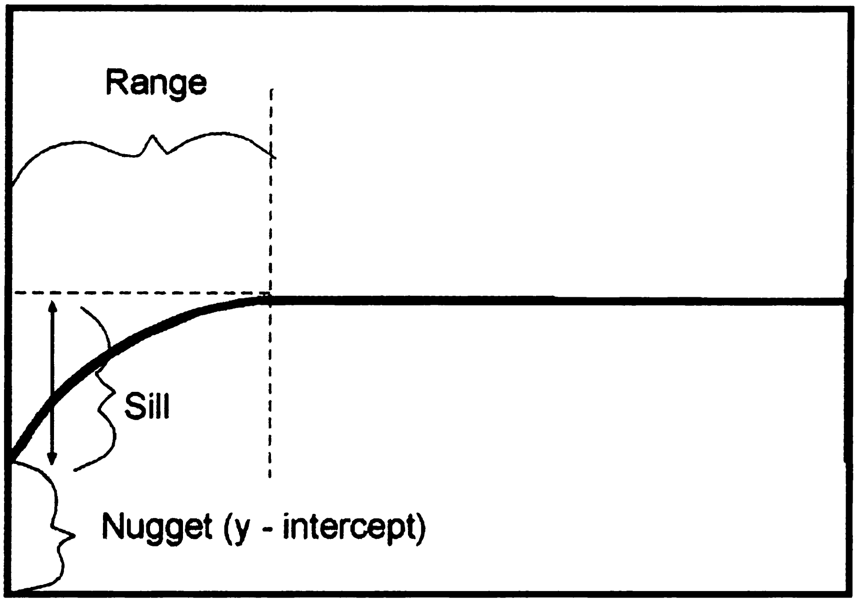


**Figure 16 – Idealized Semivariogram with Parameters**

Figures 17 through 21 are the truncated semivariograms with active lag distance of approximately 4,300 map units or about one third of the maximum active lag distance. The most appropriate lag intervals for these semivariograms are found by iteratively examining how well semivariograms fit the established models. The following semivariograms have larger lags, like 500 map units instead of only 100 map units. This allows the exponential distribution, the best-fit model for these semivariograms, to better model the spatial dependence of the assessment ratio.

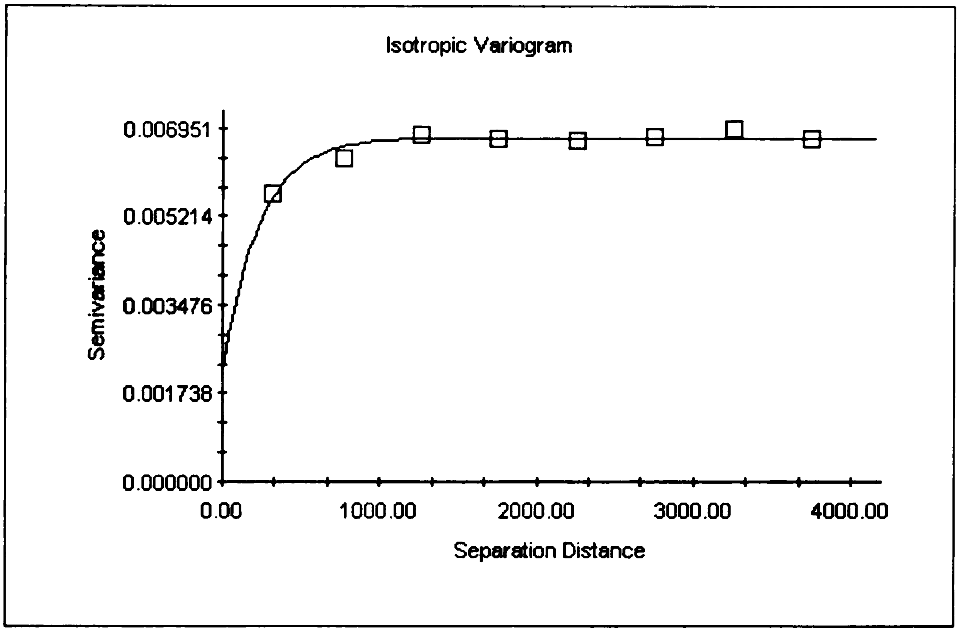


**Figure 17 – 1994 Truncated Semivariogram with Exponential Model**

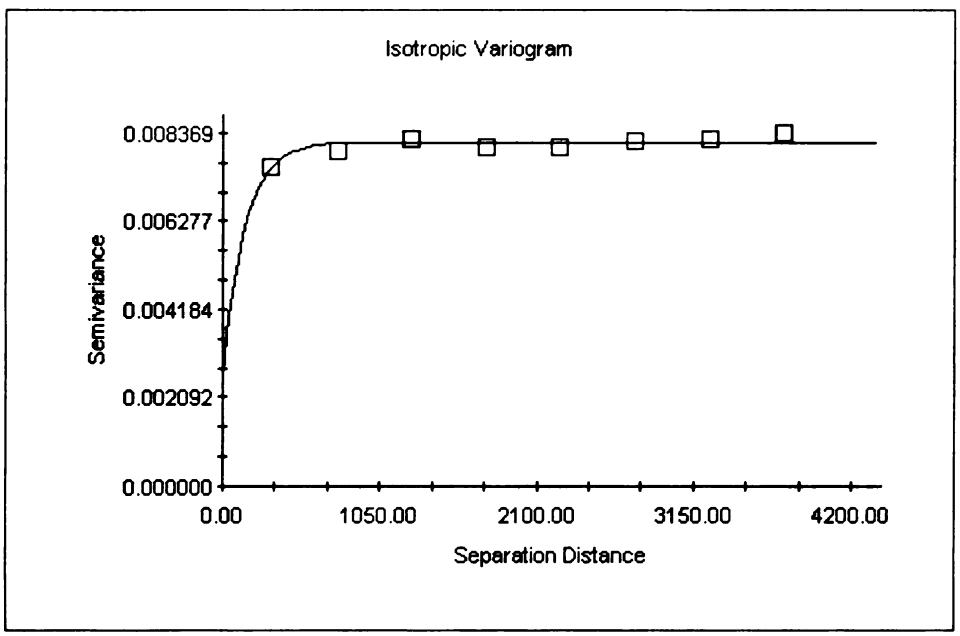


**Figure 18 – 1995 Truncated Semivariogram with Exponential Model**

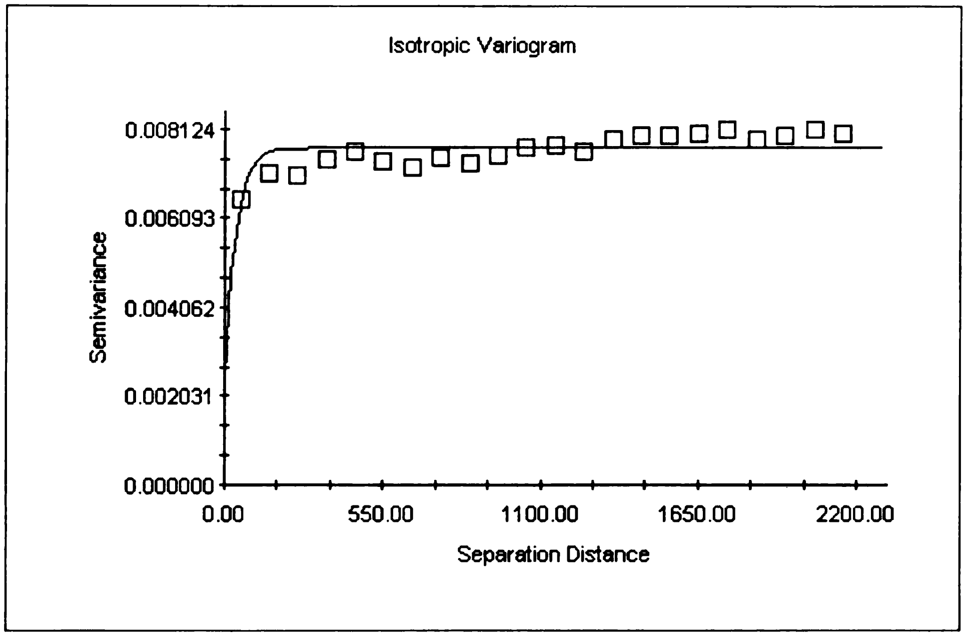


**Figure 19 – 1996 Truncated Semivariogram with Exponential Model**

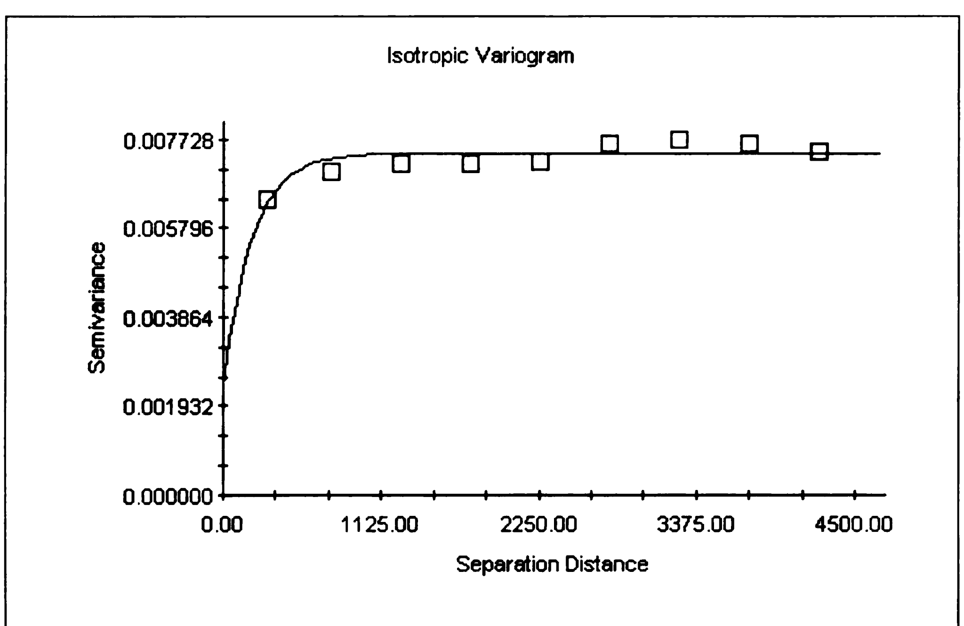


**Figure 20 – 1997 Truncated Semivariogram with Exponential Model**

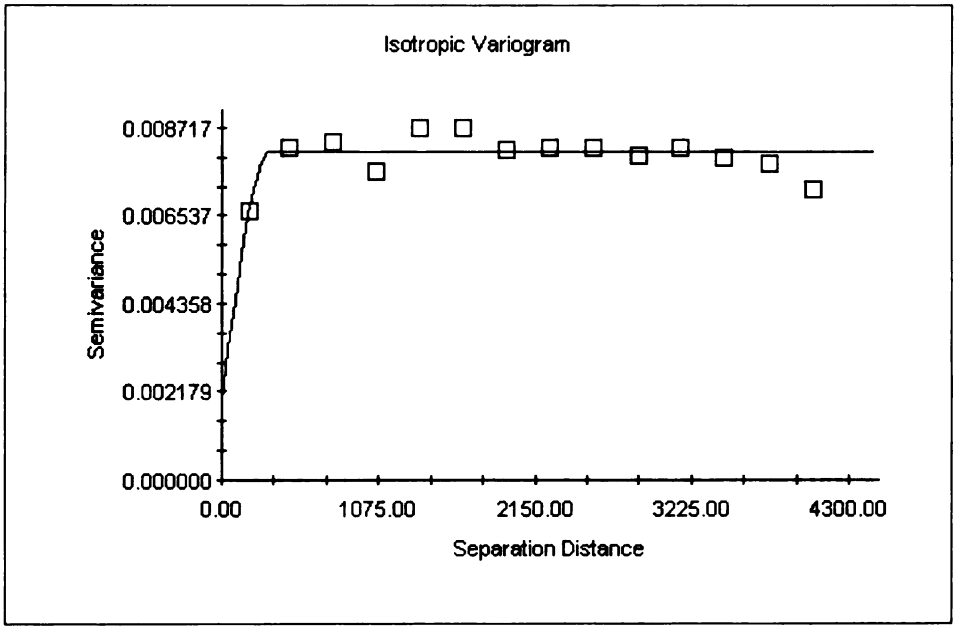


**Figure 21 – 1998 Truncated Semivariogram with Spherical Model**

Now, the known models fit the data much better, and parameters (nugget, sill, and range) describing the model will more accurately describe the data. The nugget is how much difference between AR is observed at zero distance between points. The sill is how much difference between AR is observed when the semivariogram levels off and the range is the distance between pairs of values when the difference between the values is at its highest – or when the semivariogram levels off. At distances less than the range, there exists positive spatial autocorrelation between points, and at distances greater than the range, there is assumed no dependence between the values of points. Autocorrelation is assumed to be the same between pairs of the same lag regardless of where the pairs are located. These semivariograms are a necessary step in the creation of the kriged surfaces that will be used to examine and describe the spatial patterns in the assessment ratio.

The model parameters and fit of the semivariograms that will be entered into the kriging process are listed in Table 8.

**Table 8 - Semivariogram Results**

| Semivariogram | Model Type | Nugget | Sill | Range | R Squared | RSS |
|---|---|---|---|---|---|---|
| 1994 | Exponential | 0.0022 | 0.0068 | 700 map units | 0.92 | 1.01E-07 |
| 1995 | Exponential | 0.0026 | 0.0082 | 441 map units | 0.73 | 1.26E-07 |
| 1996 | Exponential | 0.0024 | 0.0077 | 111 map units | 0.41 | 1.78E-06 |
| 1997 | Exponential | 0.0023 | 0.0074 | 606 map units | 0.7 | 3.09E-03 |
| 1998 | Spherical | 0.0019 | 0.0081 | 326 map units | 0.49 | 2.01E-06 |

**Kriged Surfaces**

Kriged surfaces are constructed to describe the spatial assessment ratio distribution. Kriged surfaces are superior to other surfaces such as trend surfaces because they can measure the error associated with each estimated value on the surface. The most likely value at each point is known as well as how likely that value is to occur there. Kriging is a distance weighting method that calculates estimated values of the variable – in this case the assessment ratio – at all points in the study area, sampled and unsampled. The parameters for the method are determined by interpreting the semivariograms shown in Figures 17 through 21.

The parameters, nugget, sill, and range, from the semivariograms derived in the previous section and listed in Table 8, are entered into the kriging model to estimate the weights that should be applied to each point to estimate the value of the assessment ratio at any unknown location. So kriging calculates the weighted average of neighboring known values and assigns it as the value at any given point in the study area. *GS+* will once again be employed, this time to create the kriged surfaces. The kriged surfaces are then brought into *ARC/INFO* and converted to raster grids.

The raster grids are helpful for two reasons. First, in raster format, the patterns in the maps are clear and discernable, and second, the patterns can be compared more readily from year to year. These raster grids of the kriged surfaces are shown in Figures 22 through 26. In all of the maps, darker colors represent higher assessment ratios, and lighter colors represent lower assessment ratios.

**Expected Map Patterns**

Recall from Table 7 that the null hypothesis of the second research question, "What do the spatial patterns in the data look like?" is that concentric patterns will appear radially out from the center of the city. This is an expected pattern that comes from the literature. It is widely acknowledged that the oldest parts of cities tend to be over assessed due to the depreciation of the housing stock and the amount of rented property. It is also accepted that lower assessment ratios tend to congregate in the newer parts of the city near the edges of the city or closer to the suburbs. One reason is because assessments usually err toward the mean, and newly developed properties that tend to be worth more are therefore underassessed (Paglin and Fogarty 1972). The actual patterns in the data will be described in the next section. Figures 22 through 26 show the raster grids of the kriged surfaces for each year from 1994 to 1998.

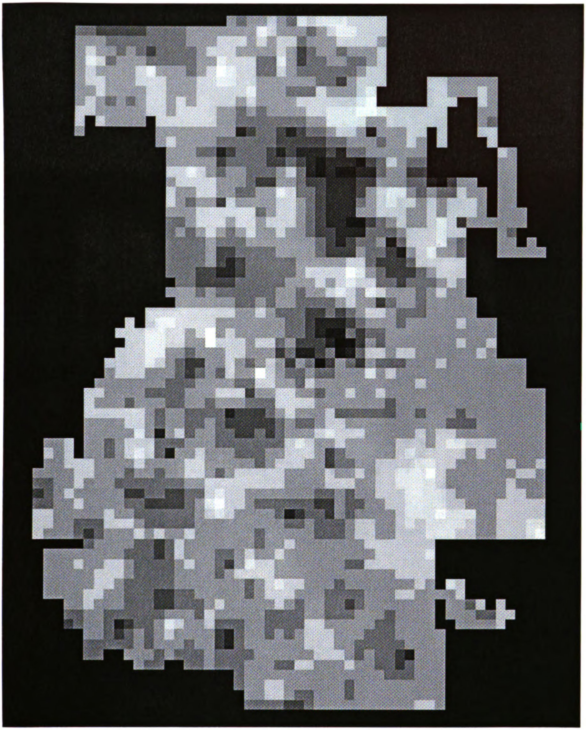

**Figure 22 - Grid of  Kriged Surface of AR from 1994 Sale transaction Data**

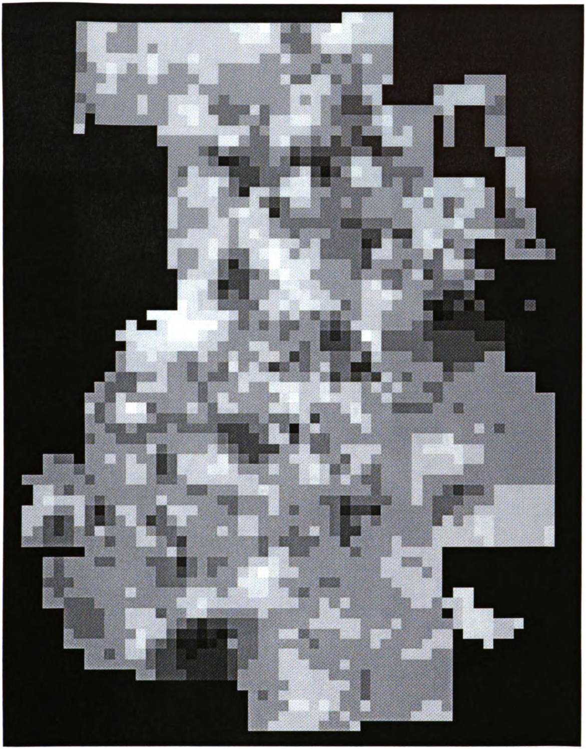

**Figure 23 - Grid of Kriged AR surface from 1995 Sale transaction Data**

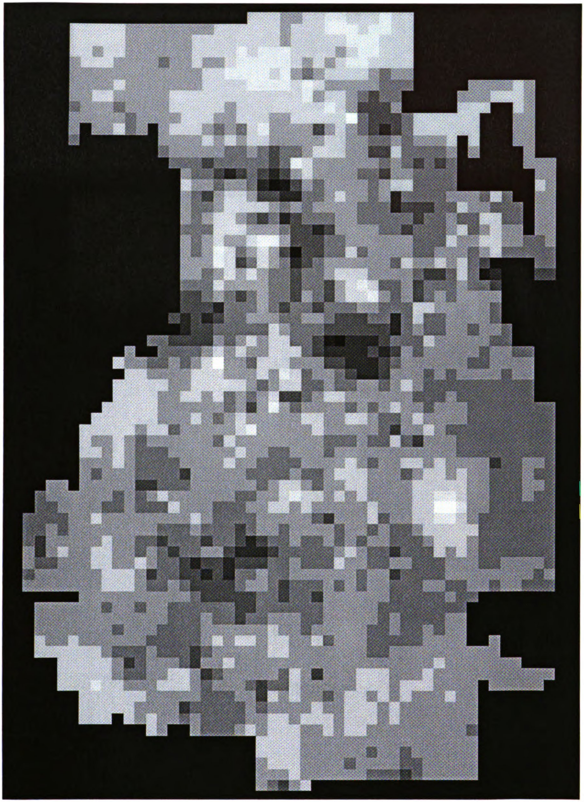

**Figure 24 - Grid of Kriged AR surface from 1996 Sale transaction Data**

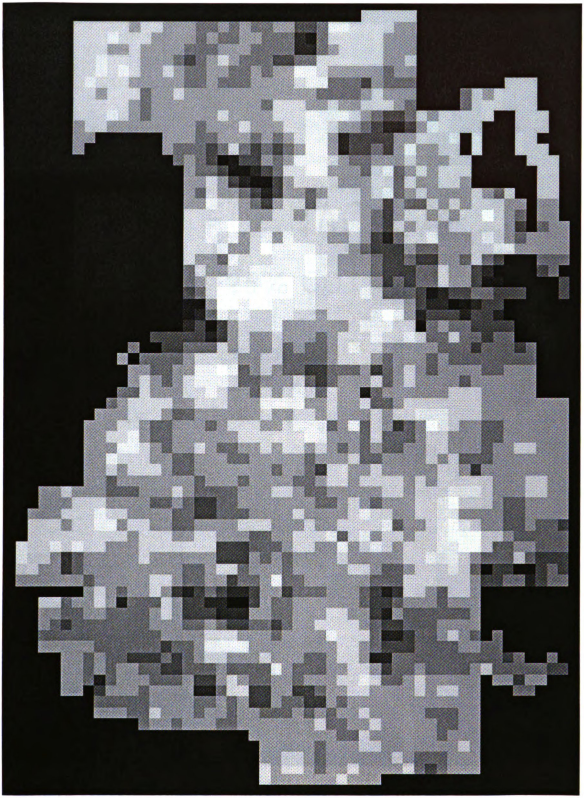

**Figure 25 - Grid of Kriged AR surface from 1997 Sale transaction data**

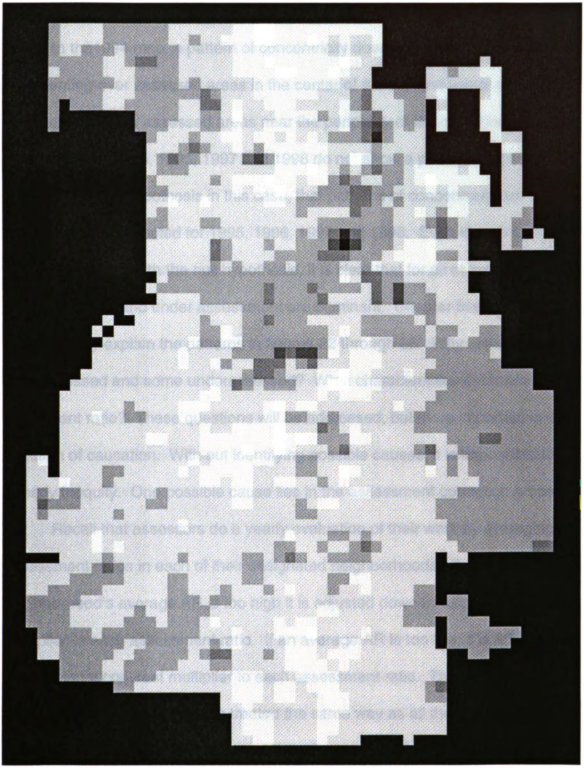

Figure 26 - Grid of Kriged AR surface from 1998 data

**Description of Map Patterns**

In the1994 map, a pattern of concentricity does appear with darker colors representing over assessed areas in the center of the city and lighter colors representing under assessed areas near the periphery of the city. However, the other maps for 1995, 1996, 1997 and 1998 do not show a pattern of concentricity clearly. The null hypothesis in this case, that patterns of concentricity are present, may be rejected for 1995, 1996, 1997 and 1998. Even though the 1994 map is consistent with the null hypothesis, it is clear that for all of the maps, other patterns of over and under assessment are dominant. Chapter five will attempt to statistically explain the patterns in figures 22 through 26. Why are some areas over assessed and some underassessed? What characteristics determine assesment ratio? These questions will be addressed, but more important is the question of causation. With out identifying possible causes, it is impossible to remedy inequity. One possible cause lies in the assessment correction process.

Recall that assessors do a yearly evaluation of their work by averaging assessment ratios in each of their designated neighborhoods. If a neighborhood's average AR is too high it is adjusted down by applying a constant multiplier to each assessment ratio. If an average AR is too low, it is adjusted up by applying a constant multiplier to each assessment ratio. Therefore, each parcel within a neighborhood is treated the same way as all the others in the neighborhood regardless of its actual individual value. Thus, if the average AR in a neighborhood happens to be too low, even the assessments that are too high in that neighborhood are adjusted still higher and if the average AR in a neighborhood is too high, even the assessments that are too low are adjusted still lower. It can be shown that this process would lead to a boundary effect, that is, properties on the edges of neighborhoods would be most likely to have extreme values of assessment ratios. This process may actually cause more spatial inequity and indeed the patterns of over and underassessment seen in the maps.

**Research Question 3: Do the patterns vary or shift from year to year?**

This next research question will be addressed by graphically comparing each year's raster grid to the previous year's grid. The comparison is done in *ARC/INFO* by subtracting the value of each cell in the later year by the corresponding cell in the earlier year. The resulting grid maps are shown in Figures 27 through 32. The null hypothesis for this research question is that the patterns do not change. Under the null then, areas that are over and under assessed in 1994 will remain so in ensuing years. The test hypothesis is that the map patterns from Figures 27- 32 are dynamic – areas that are under and over assessed do change from year to year.

**Map Interpretation and Results**

In these maps, the darkest colors are areas where the later year's assessment ratio was much higher than the earlier year, so darker areas represent areas where the assessment ratio has increased. The lightest colors are areas where the later year's assessment ratio was much lower than the earlier year, so the lighter areas represent places where the assessment ratio has decreased. The medium gray colors represent places where the assessment ratio has changed little from the earlier year to the later year.

So under the null hypothesis of no change in the patterns of over and under assessed areas, the map patterns will be boring, mostly gray maps with out areas of great change. Conversely, if the null hypothesis is rejected, the map patterns will be distinct with areas of great change represented by dark and light colors.

This research question will not be tested by means of statistics, only by a subjective viewing of the maps. Because the maps do show distinct areas of dark and light colors, the null hypothesis – that the patterns do not change – is rejected, and it will be concluded that the assessment ratio is dynamic.

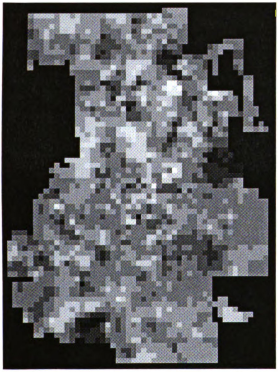

**Figure 27 – 1995 Surface Subtracted by 1994 Surface**

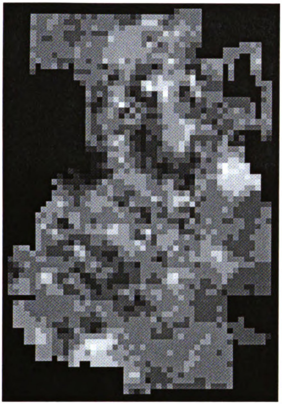

**Figure 28 – 1996 Surface Subtracted by 1995 Surface**

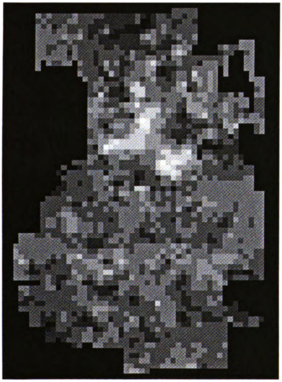

**Figure 29 – 1997 Surface Subtracted by 1996 Surface**

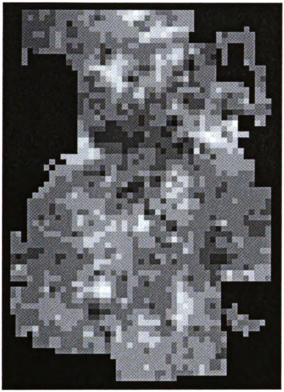

**Figure 30 – 1998 Surface subtracted by 1997 Surface**

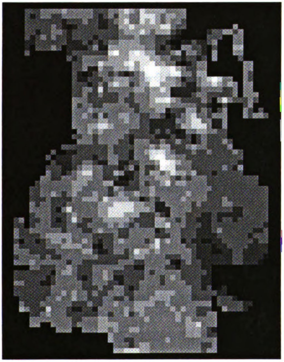

**Figure 31 – 1998 Surface subtracted by 1994 Surface**

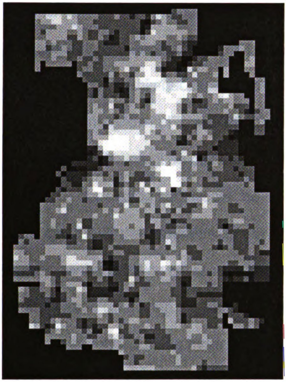

**Figure 32 – 1997 Surface subtracted by 1994 Surface**

**Research Question 4: Is an Assessment Correction Process Present?**

The results of the previous section indicate that the patterns of over and under assessment are not static but do change from year to year. This research question asks whether or not these dynamics in the property tax structure are the products of correction processes or other forces. There are two kinds of correction processes that could be present. The first comes from the assessor's office. The assessment process does attempt to target neighborhoods that are under or over assessed and adjust them with the goal of achieving more equity. The other kind of correction could come from the market. In this case, the assessments are assumed to be correct, and it is the sale prices that are assumed to be too high or too low. If there were a market correction at work, the sale prices would be adjusting back to true market values, thereby correcting assessment ratios. This question will test to see if the dynamics result from an assessment correction or a market correction.

To answer this question, a correlation statistic will be generated by correlating the grids in Figures 22 through 26 in *ARC/INFO*. A separate correlation statistic will be calculated for each year and its subsequent year. In addition a correlation statistic will be calculated for 1994, the earliest year of the data, and 1998, the latest year of the data. The null hypothesis is that no assessment correction process is apparent. Under the null, spatial inequities are getting worse or staying the same. Thus, under the null, the property tax structure is not becoming more equitable. Under the null, the correlation statistic r will be zero or positive. If the correlation statistic is zero there is no correlation between the values of cells in the grids from year to year. If the correlation statistic is positive, then cells with high values correspond to high values and cells with low values correspond to low values indicating the spatial inequities are worsening. The test hypothesis is that the property tax structure is becoming more equitable. If this is the case, then the correlation statistics will be negative. If the correlation statistic is negative, then cells with high values correspond to low values and vice versa.

**Correlation Results**

The correlation statistics are listed in Table 9. Because the statistic is calculated by means of a cell to cell comparison, the sample size of each correlation is 3283, the number of cells the grids have in common. With such a large sample size, the standard error of the statistic will be very low and the statistics are likely to be significant. However, this test is biased because the correlations (like the grids) are based on interpolated data, and there are only a few thousand actual measured observations in each year's data. Regardless, five of the six correlations are positive and thus consistent with the null hypothesis. However, the correlation between 1994 and 1998, the first and last years of the analysis, is negative. Although this correlation is the smallest in magnitude, it does indicate that perhaps inequities correct themselves over a lag of a few years. Nonetheless, it is clear that over all, the results are consistent with the null hypothesis – that there is no apparent corrective process in the data and in fact, patterns of inequity are getting worse.

**Table 9 – Correlation Statistics**

| | 1994 | 1995 | 1996 | 1997 | 1998 |
|---|---|---|---|---|---|
| 1994 | | 0.24648 | | 0.05492 | -0.00383 |
| 1995 | | | 0.14745 | | |
| 1996 | | | | 0.15218 | |
| 1997 | | | | | 0.09061 |

## Conclusion

The goal of this chapter was to see if the vertical regressive inequities detected in Chapter 3 manifest themselves spatially, and if so, do patterns of under and over assessment change from year to year and is this change the result of an assessment correction? The results of the hypothesis testing are as follows; the assessment ratio is spatially autocorrelated because over and under assessments are clustered together. The spatial patterns are dynamic, changing from year to year. However, there is apparently no correction of the inequity. Unfortunately, it seems that inequity is either becoming more concentrated or at best, it is not getting any less concentrated. The next chapter, Chapter 5, will attempt to explain the spatial inequities and patterns in the assessment process that have been shown in this chapter as well as identify other biases that may exist in the property tax structure.

# Chapter 5

## EXPLANATION OF THE ASSESSMENT RATIO VARIATION

The purpose of this chapter is to attempt to explain the property tax inequities identified in Chapters 3 and 4, as well as to identify further inequities and possible biases in the property tax structure. Already known is that the property tax structure is regressive with respect to sale amounts (sale amount, S, is inversely linearly related to AR). Are there any other regressive biases of the property tax structure? Why are some geographic areas over assessed and some under assessed? Are there different forces influencing the assessment process at different scales? These questions will be addressed in this chapter. The hypotheses for this chapter, discussed in the next section, are addressed by testing the significance of cross sectional, geographic variables in explaining the assessment ratio. These hypothetical explanatory variables are derived from the literature on this topic, which is reviewed in the following pages. First the hypotheses will be tested with bivariate Pearson's Correlation tests. However, the primary method used to test hypotheses for explanatory power in this thesis is multiple regression analysis. Throughout Chapter 5, the hypothetical variables will be referred to by their short code names. A description of each can be found in the codebook under "List of Abbreviations" on page xi.

### Framing the Hypotheses

Property tax literature has long recognized a geographic discrepancy in property tax assessment. For example, an article appearing in the National Tax

Journal in 1965 concludes, "the tax burden on real estate and personal property in Iowa varies substantially depending on the location of the property being taxed." (Meyer 1965) Although Meyer was studying the variation in the effective tax rate between counties and did not test determinants of assessment ratio variation, he does speculate that income and the extent that a population uses public services can affect the rate of taxation. Essentially, Meyer implies that the tax structure is regressive with respect to economic group and biased against those on public income. Meyer's speculations will be represented and tested in this chapter by the variables INC and PUBLIC.

In 1972, Black published an article that aimed to identify and test the determinants of the variation in the assessment ratio (Black 1972). He used regression analysis on data aggregated to census tracts. His dependent variable was equivalent to the AR in this thesis, and his study area was the city of Boston. The results of Black's study reveal that systematic variation in the assessment ratio is positively correlated to the percentage of properties with multiple housing units, inversely related to the median family income of a census tract, and positively related to percent nonwhite. That is, areas with more multiple unit housing, lower median incomes and higher percentages of nonwhite populations were taxed higher. Conversely, areas with more single family housing units, higher median incomes, and higher percent whites were taxed lower. In addition, areas with built environments of poorer quality were also found to be taxed at a higher rate. Black does not offer explanation as to why the above determinants explain the assessment ratio, but he suggests that increased federal or centralized control over the assessment process would alleviate some of the inequity. Some of Black's results will be retested here at three scales with the variables INC, WHITE and RENTOCC.

Black's study prompted similar studies including a comprehensive appraisal of the nature of regressive inequities in the property tax by Edelstein. Although the main purpose of his paper is *measurement* of property tax regressivity, Edelstein also empirically finds "regressivitiy of the property tax is principally caused by its poor and de facto discriminatory administration" (Edelstein 1979). Several possible explanations for the observed regressivity are discussed in the article. First, Edelstein postulates that miss-assessment could be the result of the user-benefits principle which theorizes that households consuming more public goods and/or services should be taxed more to cover their share of the local public expenditures.

Another explanation or cause of regressivity laid out in the Edelstein article is pure discrimination. That is, the assessment process may discriminate against marginalized households in order to "avoid confrontations" caused by advantaged home-owners who are more likely to "protest assessment changes." Both of these possible causes assume that individual assessors are biased against poor, minority and politically unpowerful groups. This explanation is highly unlikely because individual assessors rarely readjust a single parcel's assessment and it would be difficult for them to ascertain what kind of person owns any given parcel.

Finally, Edelstein describes a *market phenomena* explanation of tax inequity. This theory is based on the differential market behavior of geographic sub-areas: that there is an inertial quality to assessed values which cause them to have a delayed reaction to market values. Thus, geographic sub-areas with increasing market values usually have smaller assessment ratios, and geographic subareas with decreasing market values usually have larger assessment ratios (Edelstein 1979). This "market phenomena" will be directly tested in this chapter with the variable SEASON.

Another article, written by Thrall and also published in 1979, dealt with spatial inequities in tax assessment in Hamilton, Ontario. Thrall's findings were consistent with the prior research described above, but his methodological design varied slightly. Instead of using assessment ratios as the dependent variable, he borrows from Paglin and Fogarty's vertical inequity test and postulates that, "the quality of assessment depends upon the relative behavior of AV with respect to MV" (Thrall 1979). He asserts that the ideal assessment system should be characterized by[2]

$AV = a + bMV.$

Where $a = 0.00$ and $b = 1.00$ (although for Michigan this coefficient is 0.50). Thrall then states that,

> "The manner in which the actual assessment system deviates from the ideal may be identified by establishing how the constant and the slope in the equation behave over a set of characteristics: by determining what social, economic, geographic, institutional, and other characteristics lead to variation in the intercept a and slope b (Thrall 1979)."

[2] Thrall uses this linear functional form but stipulates that any two–parameter (intercept and slope) functional forms would be appropriate (Thrall 1979).

However, Thrall did not measure such “characteristics” directly. Instead, he partitioned his study area of Hamilton, Ontario into 16 subareas. He uses dummy variables to represent the 16 area partitions and inserts them into his regression design. If any of the dummy variables have significant coefficients that diverge from the ideal intercept and slope coefficients he concludes that the assessment process is geographically biased. So, Thrall does not test any demographic variables like racial or income variables, directly. However, he does imply that he is testing social, economic, geographic, institutional and other characteristics indirectly because he claims he divided his study area into partitions with similar characteristics. The manner in which he did this is unclear but he asserts that each area is relatively homogenous. He also partitioned the sale prices into three categories: low, medium and high, and created dummy variables to represent the categories inorder to test for vertical regressive inequity.

In this thesis, geographic inequity will not be studied like Thrall does by dividing the study area into dummy variables. Instead, all of the variables are geographically referenced and in the event that they are significant, they represent geographic bias with respect to the characteristic they stand for. In doing so, the geographical bias discussed by Thrall is being implicitly studied.

Thrall found that indeed the assessment process in Hamilton, Ontario was geographically biased. Some of the 16 areas were over taxed and some were under taxed. He concluded that areas near the central business district and industrial areas were over taxed and areas with new subdivisions were under taxed. Thrall's results were also consistent with regressive vertical inequity. Properties with higher sale prices were found to be under taxed, and properties with lower sale prices were found to be over taxed.

**Correlation**

Recall that the data was prepared for analysis at three scales: census tract, block-group and parcel from largest to smallest scales respectively. This was done so that hypotheses can be tested at three distinct scales. If relationships between scales are found to be the same regardless of scale, perhaps the assessment process, which is scale specific, isn't the source of the bias, but rather market interactions are causing assessment discrepancies. In this section, many of the hypotheses and determinants found in the literature will be tested at all three scales with simple Pearson's Correlations. The nature and direction of the determinant relationships are hypothesized in Table 10. Please refer to the "List of Abbreviations" on page xi where descriptions of each variable used in Table 10 and throughout this thesis are located. All of the verbal hypotheses found in Table 10 postulate that areas dominated by marginalized populations are correlated with the highest assessment ratios.

**Table 10 – Hypothesized Correlation with AR**

| Explanatory Variable | Hypothesized Direction | Verbal Hypothesis |
|---|---|---|
| WHITE | - | As white percent increases, AR decreases |
| BLACK | + | As black percent increases, AR increases |
| HISPANIC | + | As Hispanic percent increases, AR increases |
| INC | - | As median household income increases, AR decreases |
| RENTOCC | + | As renter occupancy percent increases, AR increases |
| PUBLIC | + | As public assistance percent increases, AR increases |
| YEAR | - | As median year built increases, AR decreases |
| SEASON (binary variable: summer = 1, winter = 0) | - | AR decreases in the summer |
| VACANT | + | As vacant percent increases, AR increases |

## Correlation Results

**Table 11 - Bivariate Pearson's Correlation Results at Three Scales**

| Explanatory Variable | Census Tract | Census Block-Group | Parcel |
|---|---|---|---|
| WHITE | r = 0.382** | r = 0.341** | r = .063** |
| BLACK | r = -0.273* | r = -0.252* | r = -0.045** |
| HISPANIC | r = 0.480** | r = 0.380** | R = 0.077** |
| INC | r = 0.531** | r = -0.42** | R = 0.087** |
| RENTOCC | r = 0.334* | r = 0.292** | R = 0.057** |
| PUBLIC | r = 0.555** | r = 0.421** | R = 0.087** |
| YEAR | r = -0.027 | r = -0.033 | r = 0.003 |
| SEASON (binary variable: summer = 1, winter = 0) | not applicable | not applicable | r = -0.033** |
| VACANT | r = 0.425** | r = 0.400** | R = 0.067** |

** r is significant at .01 level
* r is significant at .05 level

As can be seen in Table 11, the results are consistent with all of the hypotheses except that with YEAR. There is no significant correlation between the age of housing and the assessment ratio. All other correlations are statistically significant at least at the 95 percent confidence level. The meaning of the results is this; the regressive nature of the property tax structure in Lansing, Michigan goes much farther than just regressive vertical inequity alone. Higher AR values are correlated to areas with larger minority populations. The tax structure is regressive and biased against black and Hispanic populations. AR values are also positively correlated to areas that have larger poor populations so the tax structure is regressive and biased against poor populations. AR values are also positively correlated to politically unpowerful groups like those renting property instead of owning property and those groups on public assistance. Thus, the tax structure is regressive and biased against renters and people on government assistance. The regressive nature of the property tax appears to go much further than being biased against lower valued properties alone.

**OLS Modeling**

Next, the significant variables, identified in the correlation table above, will be used in linear regression models to explain variation in the assessment ratio. In addition, a form of S, sale amount, will be used, because as the I.A.A.O. model in Chapter 3 demonstrated, S is not only correlated to, it also helps to explain the variation in AR. For that reason, the natural log of S will be used as an explanatory variable in some of the following models.[3] Again, linear models will be built at each of the three scales of analysis. However, because many of the hypothesized determinants listed in Table 10 are correlated with each other, and not independent, they can not all be used in the same linear regression models. For this reason, two models are created and displayed for each scale of analysis. Full tables of correlations, which show the linear bivariate relationships between all pairs of variables are located in Appendices K, L and M.

This thesis is concerned with the variation from the expected 0.50 in the assessment ratio. Recall that if the property tax structure were equitable, any variation from the expected 0.50 in the assessment ratio would be randomly distributed. Under equity, the random errors would be both spatially neutral and uncorrelated to other variables with spatial reference. However, it is already known from tests done in Chapter 3 and Chapter 4 that the assessment errors are not completely neutral. In Chapter 3 vertical inequity testing showed that the assessment ratio is biased with respect to sale amount and Chapter 4 showed that instances of deviation from 0.5 in the assessment ratio are not spatially random. Nonetheless, much of the error in the assessment process, which causes AR to deviate from 0.5, is most likely randomly distributed. AR will therefore be used as the dependent variable in the following regression analyses to try to find out what explains the variation in the assessment ratio. Thus, R-Squares are not expected to be very large, and thus, the focus of the

[3] The natural log transformed version of S, LNS, has a better linear relationship with AR than S and LNS will therefore be used in the following linear regression models.

investigation will be on the statistical significance of the hypothesized explanatory variables.

The residuals from one model at each scale will be examined for spatial autocorrelation and possible sources of additional AR explanation. If there appears to be geographic patterns in the residuals, then some explanatory variables related to assessment bias are probably still missing from the models. If the residuals appear to be randomly distributed, (this could be confirmed by formal tests for spatial autocorrelation), then the models can be considered complete, and there are no more spatial variables causing assessment bias.

Alternatively, like Thrall's regression models, assessed value, AV, or its natural log, could also be used as a dependent variable when coupled with sale amount, S, as an independent variable. In this case, R-Squares should be high and S should explain most of the variation in AV; any other variables found to be significant would represent property tax bias. From a model of this nature, the variation of AR is only implicitly examined. The Paglin and Fogarty model as well as the Cheng model, which were discussed in Chapter 3, already demonstrated how regressive vertical inequity could be explained by such a model.

**Census Tract Scale**

Each of the explanatory variables that were found to be significantly correlated to AR are entered as an explanatory variable in a simple, single independent variable, regression model. The results are displayed in Table 12. For organizational purposes, the explanatory variables and their regression models have been divided into three categories: those having to do with racial characteristics of the population, those having to do with income and sale amount of property and those having to do with housing stock.

**Table 12 – Simple Regressions, Dependent Variable = AR, df = 40**

| | Explanatory Variable | Estimated Intercept | Estimated Slope | Beta | t-stat | R Square |
|---|---|---|---|---|---|---|
| Race Variables | **WHITE** | 0.487 | -3.33E-04 | -0.382 | -2.584 | 0.146 |
| | **BLACK** | 0.457 | 2.53E-04 | 0.273 | 1.771 | 0.074 |
| | **HISPANIC** | 0.451 | 1.40E-03 | 0.480 | 3.416 | 0.230 |
| Wealth Variables | **LNS** | 0.757 | -2.71E-02 | -0.622 | -4.957 | 0.371 |
| | **INC** | 0.486 | -8.54E-07 | -0.531 | -3.914 | 0.264 |
| | **PUBLIC** | 0.450 | 2.39E-03 | 0.555 | 4.166 | 0.308 |
| Housing Variables | **VACANT** | 0.451 | 1.81E-03 | 0.425 | 2.934 | 0.181 |
| | **RENTOCC** | 0.453 | 2.51E-04 | 0.334 | 2.212 | 0.111 |

Each of the simple regression models at the tract scale, displayed in Table 12, has significant explanatory power. All of the explanatory variables have significant slope coefficients at the 95% one–tail confidence level. This shows that neighborhood and geographic characteristics do play a role in determining assessment ratios and therefore property taxes of individual taxpayers.

The slope coefficients represent the expected change in AR for a one-unit increase in the explanatory variable. For instance, a one-unit (one percent) increase in HISPANIC will bring about an expected 0.00140 increase in the assessment ratio. In the same way, a one-unit (one percent) increase in population on public assistance (PUBLIC) will bring about an expected 0.00239 increase in the assessment ratio.

The R-Squares in the models vary from 0.07 to 0.37. It is important to recognize the meaning of the magnitude of the explanatory power of these individual variables alone. When regression designs are used to create predictive or forecasting models, it is important that they have large R-Squares and explain a large amount of the variation in the dependent variable. However, the regression models in this chapter are not intended for predictive purposes. They are only used for diagnostic purposes, to test explanatory variables for significance and thus test the property tax structure for geographic bias. In addition, none of the hypothesized determinants should theoretically, under equity, explain any of the variation in AR. For these reasons, low R-Squares are expected and have been realized. Nonetheless, the R-Squares for the models in Table 12 at the tract scale do show explanation of up to 37 percent. In fact, each of the race variables alone explains between nearly 7.5 percent and 23 percent of the variation in AR. A single wealth variable explains between 26 percent and 37 percent of the variation in AR and individual housing variables explain between 11 and 18 percent of the variation in the dependent variable.

To account for even more of the variation in AR, explanatory variables will be used together in multiple regression models. However, they can not all be used in the same model since they are not all independent from each other thereby violating an assumption of linear regression. The variables within each category (race, wealth and housing) are highly interdependent. When variables within each category are used in the same multiple regression model there is likely to be multicolinearity. For this reason, the use of more than one variable from any category will be avoided. However, there is also dependency between the categories making it difficult to include more than any two of the variables in the regression designs especially at the tract scale that has fewest degrees of freedom. Check the full correlation tables in Appendices K-M for information on what the correlation is between variables. The following multiple regression models are an attempt to combine relatively independent explanatory variables in models that explain what is determining the variation in AR. The tolerance of the explanatory variables will be included in the tables that display the multiple regression models. The tolerance is the percent of the explanatory variable that is not explained by the other variables. It ranges between zero and one. Low tolerances represent the presence of multicolinearity, under the presence of which can cause coefficient bias and unefficiency. The variables included in the models were chosen by first entering a wealth variable, and then a race variable and then a housing variable. If the variables were not significant, they were removed from the design.

Another reason for creating multiple regression models is to test for bias holding other variables constant. The bivarite correlations and simple regressions already revealed the explanatory power of the individual independent variables. The multiple regression models will show the effect of individual variables holding other variables constant. For example, the racial variables have shown to significantly explain AR. When combined with a wealth variable in a multiple regression model, the impact of the racial variables will be known holding income or sale amount constant. In addition, since it is known that the property tax structure is biased against racial minority groups, the models will able to distinguish between expected AR values for rich racial minority populations and poor racial minority populations.

**Table 13 – Tract Multiple Regression 1.**

| | | | | |
|---|---|---|---|---|
| **AR** | **=** | **$b_0$ +** | **$B_1$INC +** | **$B_2$WHITE** |
| Estimated AR | = | 0.494 | -1.68E-04 INC | -7.23E-07 WHITE |
| Beta | | | -0.450 | -0.193 |
| t-stat | | 53.62 | -3.033 | -1.299 |
| sig. | | 0.000 | 0.004 | 0.202 |
| tolerance | | | 0.822 | 0.822 |
| R - Square = | 0.313 | | | |
| F-stat = | 8.64 | | | |
| df = | 40 | | | |

Each independent variable coefficient should be interpreted as the marginal expected change in AR, the dependent variable, for a one-unit change in the independent variable holding all other explanatory variables constant. Therefore, as the amount of white population increases by one percent holding median household income constant, the assessment ratio can be expected to decrease by 0.000000723. Likewise, as median household income increases by one dollar, the expected assessment ratio decreases by 0.000168 holding WHITE constant. What impact does this inequity have on the average taxpayer? For example, holding race constant, a \$100,000.00 property that is subjected to a \$100.00 dollar decrease in median household income would increase its estimated AR from 0.494 to 0.510. This could increase the effective property taxes by more than \$50 dollars if the millage rate is 0.033. The results of Tract Multiple Regression 1 in Table 13 show a bias in the property tax structure that financially disadvantages neighborhoods as INC and WHITE decrease. The standardized beta coefficients of the independent variables can be compared to show the relative effects of the independent variables on AR. In this case, the betas show that INC has more than two times the effect on AR than does WHITE. Tract multiple regression 1 shows that not only is the property tax structure biased with respect to income and race, expected AR values are lower for rich white populations than for poor white populations.

**Table 14 – Tract Multiple Regression 2.**

| **AR** | **=** | **$b_0$ +** | **$b_1$LNS +** | **$b_2$BLACK** |
|---|---|---|---|---|
| Estimated AR | = | 0.740 | -2.580E-02 LNS | 1.091E-04 BLACK |
| Beta | | | -0.591 | 0.118 |
| t-stat | | 11.857 | -4.534 | 0.902 |
| sig. | | 0.000 | 0.000 | 0.373 |
| Tolerance | | | 0.931 | 0.931 |
| R – Square = | 0.398 | | | |
| F-stat = | 12.572 | | | |
| df = | 40 | | | |

The results of the second multiple regression model in Table 14 show similar biases. Holding sale amounts constant, as the black population increases by one-unit (percent), the assessment ratio will increase by 0.0001091. While this discrepancy doesn't seem large at first glance, a fifty percent increase in population that is black, can mean more than $24 in effective property tax dollars for a parcel that sold for 100,000 dollars. In addition, results also show that holding other explanatory variables constant, a one- percent increase in sale amount, decreases the assessment ratio by an expected 0.0258.[4] This time the betas show the wealth variable has five times more effect on AR than the race variable.

[4] Notice that the interpretation for the coefficient on LNS is slightly different than for the linear variables. In this situation, the coefficient gives the marginal expected change in the dependent variable for a one percent change in the log linear variable, S, holding all other variables constant.

## Residual Examination – Census Tract Scale

The multiple regression model with the largest R square, shown in Table 14, has been chosen to be tested for completeness by examining its residuals. Residual analysis is very important in model building because the residuals show what the model fails to explain. If the residuals appear spatially autocorrelated, it is likely that there is another geographic factor that explains variation in the assessment ratio. If the residuals appear randomly distributed, it can be assumed that random forces cause the variation that remains unexplained by the multiple regression design. The residuals, the difference between the expected ARs given the model and the actual ARs, are standardized, or made into Z–scores, and mapped in Figure 33. The darker colors represent tracts with large positive residuals where the ARs are higher than the model predicts. The lighter colors represent areas with large negative residuals where the ARs are lower than the model predicts.

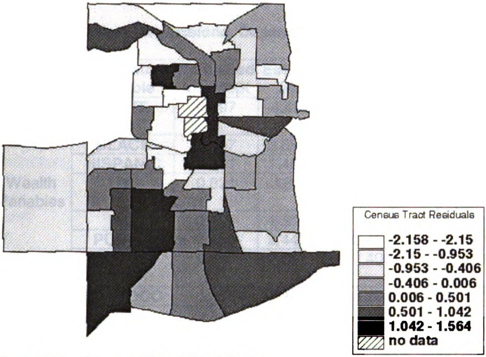


**Figure 33 – Census Tract Residuals**

It appears that large positive residuals are located in the center city tracts and in the southwestern tracts of Lansing, while large negative residuals are located in the north and northwestern tracts of the city. However, the residuals closest to zero, tracts the model explains well, seem to be distributed evenly throughout Lansing. A formal test for spatial autocorrelation is needed to conclude with statistical confidence that the residuals are either clustered or independently distributed. However, it is beyond the scope of this thesis to gather new data and form new explanatory hypotheses and variables. Future research efforts should use residual analysis in an interactive iterative process to examine map patterns, develop new hypotheses from residuals, collect variables to represent the hypotheses, and finally, to create better models that explain more of the variation in the assessment ratio.

**Block Group Scale**

**Table 15 – Simple Regressions, Dependent Variable = AR, df = 116**

| | Explanatory Variable | Estimated Intercept | Estimated Slope | Beta | t-stat | R Square |
|---|---|---|---|---|---|---|
| Race Variables | **WHITE** | 0.497 | -4.49E-04 | -0.341 | -3.894 | 0.117 |
| | **BLACK** | 0.457 | 3.68E-04 | 0.252 | 2.798 | 0.064 |
| | **HISPANIC** | 0.451 | 1.46E-03 | 0.380 | 4.402 | 0.137 |
| Wealth Variables | **LNS** | 0.821 | -3.31E-02 | -0.503 | -6.237 | 0.253 |
| | **INC** | 0.491 | -9.92E-07 | -0.420 | -4.961 | 0.176 |
| | **PUBLIC** | 0.450 | 2.44E-03 | 0.421 | 4.974 | 0.117 |
| Housing Variables | **VACANT** | 0.450 | 2.35E-03 | 0.400 | 4.682 | 0.160 |
| | **RENTOCC** | 0.451 | 3.39E-04 | 0.292 | 3.273 | 0.085 |

The results of simple regression models at the block group scale are very similar to those at the census tract scale. The t-statistics show that each model has significant explanatory power and each of the explanatory variables' coefficients are significantly different from zero at the 99 percent confidence level. Again, this indicates that geographic, social and economic variables do play a role in determining assessment ratios, and the assessment process is biased and inequitable. The move to a smaller scale with more smaller observational units appears not to affect the conclusion of bias in the assessment process.

Differences in the regression models at this scale lie in the R squares. The R squares at the block group level are lower than those at the census tract level. At this scale, each variable only explains between six percent and 25 percent of the variation in the assessment ratio. Again, multiple regression designs are formulated with a combination of the explanatory variables above.

Two of these are displayed at this scale in Tables 16 and 17. The variables were picked arbitrarily, one from each category, and inserted in the design if they proved significant.

**Table 16 – Block Group Multiple Regression 1**

| | | | | |
|---|---|---|---|---|
| **AR** | **=** | **$b_0$+** | **$b_1$INC +** | **$b_2$WHITE** |
| Estimated | = | 0.507 | -8.010E-07 | -2.780E-04 |
| AR | | | INC | WHITE |
| Beta | | | -0.339 | -0.212 |
| t-stat | | 57.165 | -3.771 | -2.355 |
| sig. | | 0.000 | 0.000 | 0.020 |
| Tolerance | | | 0.853 | 0.853 |
| R – Square = | 0.214 | | | |
| F-stat = | 15.564 | | | |
| Df = | 116 | | | |

The model shown in Table 16 is slightly different from its census tract scale counter part in the relative proportions of the betas. In this model at the block group scale INC's beta is only 1.6 times greater than WHITE's beta.

**Table 17 – Block Group Multiple Regression 2**

| | | | | | |
|---|---|---|---|---|---|
| **AR** | **=** | **$b_0$+** | **$B_1$LNS +** | **$B_2$BLACK +** | **$B_3$VACANT** |
| Estimated | = | 0.731 | -2.55E-02 | 1.70E-04 | 9.47E-04 |
| AR | | | LNS | BLACK | VACANT |
| Beta | | | -0.388 | 0.116 | 0.162 |
| t-stat | | 10.533 | -4.091 | 1.404 | 1.696 |
| sig. | | 0.000 | 0.000 | 0.163 | 0.093 |
| Tolerance | | | 0.700 | 0.917 | 0.693 |
| R – Square = | 0.289 | | | | |
| F-stat = | 15.308 | | | | |
| df = | 116 | | | | |

Table 17 shows a significant regression design that includes three of the explanatory variables. The results at this scale are consistent with those at the census tract scale, except the R-Square is lower. The three explanatory variables together explain just less than thirty percent of the variation in AR. The standardized residuals from this model will be mapped and the resulting map patterns will be examined. This model was chosen because it explains more of the variation in AR than the other block group model in Table 16.

**Residual Examination – Block Group Scale**

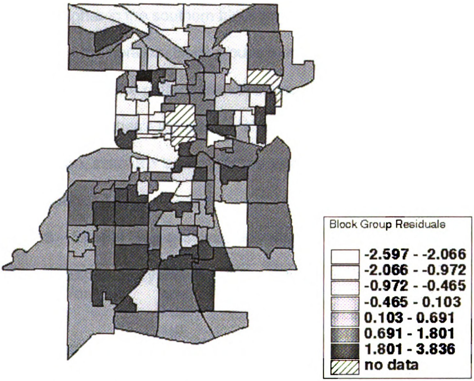


**Figure 34 – Block Group Residuals**

It seems as if there are more positive residuals in the southern half of Lansing, tracts with larger calculated ARs than the model would predict, and more negative residuals in the northern half of Lansing, tracts with smaller calculated ARs than the model would predict. This means there is probably another bias of the assessment ratio that is not represented in the regression model. An example of an appropriate hypothesis for this missing element is as follows; perhaps there is a characteristic of the real estate market, affecting property supply and demand. This hypothetical variable would affect differentially the northern and southern parts of Lansing. If, for example, the real-estate characteristic is correlated with lower demand in the southern block groups, (thus, decreasing sale prices there), and higher demand in the northern block groups, (thus, raising sale prices there), then calculated assessment ratios would be higher in the southern block groups than the model in Table 17 predicts and lower in the northern block groups than the model predicts. This hypothesis is consistent with the pattern seen in the residuals. Unfortunately, it is beyond the scope of this thesis to measure a variable that could explain this phenomenon, instead it is offered here as a suggestion for further research.

**Parcel Scale**

**Table 18 – Simple Regressions, Dependent Variable = AR, df = 8055**

| | Explanatory Variable | Estimated Intercept | Estimated Slope | Beta | t-stat | R Square |
|---|---|---|---|---|---|---|
| Race Variables | **WHITE** | 0.488 | -3.55E-04 | -0.063 | -5.633 | 0.004 |
| | **BLACK** | 0.456 | 2.89E-04 | 0.045 | 4.082 | 0.002 |
| | **HISPANIC** | 0.451 | 1.36E-03 | 0.077 | 6.934 | 0.006 |
| Wealth Variables | **LNS** | 1.133 | -6.19E-02 | -0.322 | -30.519 | 0.104 |
| | **INC** | 0.486 | -8.37E-07 | -0.087 | -7.803 | 0.008 |
| | **PUBLIC** | 0.451 | 8.17E-04 | 0.087 | 7.795 | 0.007 |
| Housing Variables | **VACANT** | 0.452 | 1.73E-03 | 0.067 | 6.032 | 0.004 |
| | **RENTOCC** | 0.452 | 2.83E-04 | 0.057 | 5.164 | 0.003 |
| Season Variable | **SEASON** | 0.464 | -5.76E-03 | -0.033 | -2.934 | 0.001 |

Again, at the parcel scale, all of the simple regressions have significant explanatory power, and all explanatory variables are statistically different from zero at the 99 percent confidence level. The R-Squares are remarkably smaller at this scale. This is because the dependent variable was collected at the parcel scale and the independent variables were collected at the block group scale and then disaggregated to the parcel scale. The models at this scale are called "fixed x" models. Because there is more variation in the dependent variable than in the independent variables, less can be explained by them. However, the concern in this chapter is not how much of the variation in AR is explained, but which variables do explain variation.

Notice at this scale, the explanatory variable SEASON, is included in the analysis. This dummy variable, which denotes the season that the sale transaction took place, can only be used at the parcel scale because dummy variables collected at a smaller scale can not be aggregated to a larger scale. The results of the simple regression show that when SEASON equals one, or in the summer time, AR decreases. This is as expected because more parcels sell in summer, which represents more demand for parcels. More demand drives sale prices up and since sale price is the denominator of AR, the assessment ratio will appear smaller in the summer. Thus, there is an inverse relationship between SEASON and AR.

The following multiple regressions have several significant independent variables. More explanatory variables can be used at the parcel scale because the number of degrees of freedom is high and significance is more easily achieved.

**Table 19 – Parcel Multiple Regression 1**

| AR | = | $b_0$+ | $b_1$WHITE + | $b_2$HISPANIC + | $b_3$INC + | $b_4$SEASON |
|---|---|---|---|---|---|---|
| Estimated AR | = | 0.488 | -1.602E-04 | 5.469E-04 | -5.544E-07 | -4.641E-03 |
| | | | WHITE | HISPANIC | INC | SEASON |
| Beta | = | | -0.028 | 0.031 | -0.057 | -0.026 |
| t-stat | = | 64.742 | -2.288 | 2.209 | -4.198 | -2.370 |
| Sig. | = | 0.000 | 0.022 | 0.027 | 0.000 | 0.018 |
| Tolerance | = | | 0.805 | 0.621 | 0.659 | 0.995 |
| R Square = | 0.010 | | | | | |
| df = | 8055 | | | | | |

The results of this multiple regression model are consistent with those at the other scales of analysis. Because of the large number of degrees of freedom, this model contains two race variables. So the effect of one, holding the other constant may be ascertained. It is apparent that as the percentage of Hispanic people increase, AR increases, even holding the percent of white people, median household income, and season of sale transaction constant. Again, INC is the variable with the largest Beta and the most relative impact on the assessment ratio. The standardized residuals from this model will be kriged and mapped to examine the residual map patterns.

**Residual Examination – Parcel Scale**

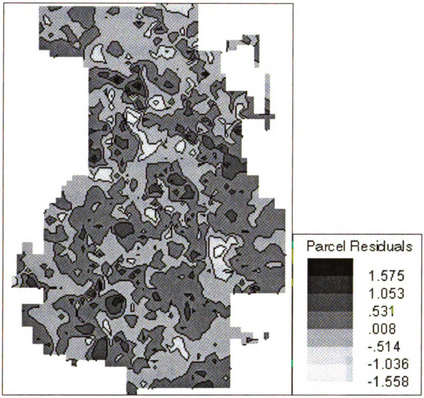


**Figure 35 – Parcel Residuals**

Figure 35 is a kriged surface map of the residuals from the model in Table 19. Recall from Chapter 4 that the process of kriging involves interpolation of the surface based on the parameters of a semivariogram. The semivariance analysis reveals that dependence in the residuals exists only within a very small lag distance. In fact, Moran's I statistics show the residuals are spatially autocorrelated only at lag distances of less than 350 UTM meters (less than .35 kilometers). This means that the model from which the residuals came does not treat large areas of Lansing differentially. In other words, there are not large scale patterns in the residuals from which hypotheses could easily by developed. Because the spatial autocorrelation only exists at very small scales it is very difficult to conjecture what variables, if any, are missing from the model. Another way to see that large and small residuals are fairly well distributed on the map, is to look at a three dimensional representation of the residuals. Figure 36, shows the same surface map in three dimensions. The map is shown as if Lansing is being looked at from west to east. As is shown in this map, it is easy to see that the large positive residuals, shown by dark colored peaks, are often accompanied by large negative residuals, shown by light colored holes. This is further indication that there aren't easily measured variables missing from the model. It is more likely that if there is an element missing, it is a subtle market affect that is highly geographically variable.

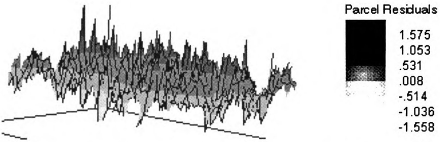


**Figure 36 – Three Dimensional Residual Surface**

**Conclusion**

Under an equitable property tax structure, the variation in the assessment ratio would be unexplainable and randomly distributed. The results of this chapter find nine geographic variables that explain significant variation in the assessment ratio. Eight of these are significant at all three scales. Each significant variable represents a bias in the assessment process. Much of the bias is of a regressive nature. Results of the research in this chapter show that areas dominated by marginalized, low income, minority populations, rented housing or vacant housing are also those areas that are explaining higher assessment ratios. It was also determined that members of poor racial minority groups are the most discriminated against in terms of expected assessment ratios. In addition, a seasonal bias was detected at the parcel scale. Parcels that sell in summer have significantly higher assessment ratios. In general, geographic, economic and demographic variables all play a role in determining assessment ratios.

**Sources of Inequity**

There are three possible sources of the inequity that has been identified throughout this thesis. First, the literature notes that individual assessors are the source of inequity (Edelstein 1979). Second, it could be the assessment process or the fault of the assessment readjustment process. Third, the workings of the real estate market dynamics could be the source of inequity.

The first of these causes can be ruled out due to the three-scaled methodology, which gives some clue as to the cause of the bias. At the small, parcel scale, the neighborhood characteristics have a very small influence on the assessment ratio (as evidenced by the small R square). This indicates that neighborhood characteristics do not play a big role in determining an individual parcel's assessment, giving evidence against the argument that individual assessors are causing inequity. However, at the larger scales, (census tract and block group scales), the parcel data is aggregated to a smaller number of observational units and more variation in the assessment ratio is explained. This indicates that much of the random assessment error tends to be averaged out, and that at these scales neighborhood characteristics do play a big role in determining average assessment ratios. These observations are evidence against the argument that it is individual assessors causing inequity.

It is much more plausible that it is the assessment process and market dynamics causing inequity. Because the biases are most apparent at the neighborhood scale (tract and block group scales) they are most likely caused by processes that are inherently based on neighborhood units and their characteristics. The assessment process and the real-estate market are both such processes.

As has already been discussed, the assessment process involves reassessing entire neighborhoods up or down if the average AR is too low or to high. This process produces a boundary effect that creates areas of extremely high or low AR values. Since geographic areas tend to be demographically homogenous at small scales, the boundary effect could cause certain demographic groups to be differentially affected by the assessment process.

Another likely source of inequity is various real estate market dynamics. The significance of the variable SEASON is already proof that the cyclic market dynamic causes inequity. There are many other dynamics causing supply and demand differentials that could also determine AR values. Part of the reason for this is the extreme segregation of real estate markets. In the United States, real estate markets are as diverse as there are niches of population. Each real estate market caters to a different kind of household. Each market likely has its own ups and downs and supply and demand patterns. It is out of the realm of this thesis to try to correct segregation in the settlement patterns in the United States. However, it can safely be postulated that correcting the market dynamics that cause inequity would be a difficult job indeed. Nonetheless, it is legally incumbent upon the assessment process to correct any inequity, regardless of source. Therefore, bias and inequity in the property tax structure can and should be the responsibility of the property tax assessment process. The next chapter will present an outline for correcting the biases and inequities identified in this chapter.

# Chapter 6

## CONCLUSION

This chapter will begin with a short review of important findings from the research of this thesis. A discussion of the possible causes for the inequity and bias will follow. Next, the limitations of this thesis and ideas for future research are laid out. Ultimately, the purpose of this chapter is to outline related policy implications as well as recommendations for the city of Lansing Assessor's Office.

### Findings

The property tax structure of Lansing, Michigan was first found to be inequitable with respect to sale amounts. Four models tested in Chapter 3; Paglin and Fogarty, Cheng, I.A.A.O. and Clapp all show significant, regressive, vertical inequity. This is a clear demonstration that higher priced parcels are taxed at a lower rate than lower priced parcels.

Inequities with respect to geographic location or distinct neighborhoods in Lansing were also found. This finding comes out of the analyses described in Chapter 4 which show that positive spatial autocorrelation exists between parcels separated by small distance lags and that both positive and negative spatial autocorrelation exist between parcels separated by medium and large distance lags. These results show that some neighborhoods are taxed higher than other neighborhoods. This represents a geographic bias because it shows that taxpayers, on average, pay taxes on different proportions of market value based on where they live.

Results from the linear model testing in Chapter 5 show that the property tax structure in Lansing, Michigan is also inequitable with respect to many demographic, social-economic, and market variables. These biases exist even when sale amounts are held constant. If the property structure were equitable, no measurable variables would explain variation in the assessment ratio because the variation would only consist of random error. Instead, the property tax structure is inequitable. Three racial variables: percentages of black, white, and Hispanic populations, all prove to be property tax biases as they significantly explain variation in the assessment ratio. Also, income variables like median household income and percentage of population on public income are significant variables, revealing bias based on wealth. All of these results were found at three geographic scales. Furthermore, a seasonal dummy variable also shows significant bias of the property tax with respect to the real estate market's seasonal dynamics.

**Causes of Bias**

This thesis sought to identify and examine property tax inequities and biases. However, the question this thesis does not answer directly is what causes the property tax inequities that are persisting. No scientific hypothesis testing will be done to answer that question. Instead, only logical speculation is made here. It seems there are two possible sources or causes of the inequity. First, the assessment process itself could be biased, causing inequity. Second, the dynamics of the real estate market could be such that assessments are unavoidably error prone. It is likely that it is some combination of the two sources causing the identified inequities. Another possibility, one that should be ruled out, is that malicious individuals, who are actively seeking to over assess some parcels while underassessing others, cause the inequities. This supposition, which is mentioned in the literature, is highly unlikely as the assessment process, (see Conclusion section in Chapter 5), would seem to prevent the manifestation of this kind of intent (Edelstein 1979).

The work in this thesis provides evidence for both of the other possible sources of bias. Evidence that the assessment process is causing inequity lies in the work done in Chapter 4. Because the assessors' office has carved Lansing into discrete neighborhoods and uses them as units to adjust up or down, it seems likely that some of the spatial patterns identified in the maps in Figures 22 through 26 are boundary effects produced by this neighborhood assessment technique.

There is also evidence obtained in this study that indicates inequity is caused by real estate market dynamics. The best example of this is the variable SEASON. SEASON equals one if the parcel sold in the summer and zero if the parcel sold in the winter this dummy variable is inversely linearly correlated to AR[5]. The result reflects a supply and demand effect that raises sale amounts in the summer making the assessment ratio appear lower for those parcels. Certainly, it is not the assessment process assessing parcels sold in the summer

[5] This variable is measured at the parcel scale and therefore is only tested at that scale in the linear models.

lower than those sold in the winter. This is the only variable in the study that is necessarily independent of the assessment process so that it only describes a market dynamic. Nonetheless, its' significance indicates that market dynamics do, to some degree, determine assessment ratios.

**Future Research**

Future research should concentrate on further isolating the root(s) of the inequities. One of the limitations of this thesis is the short time frame over which the observations were collected. A longer time frame could perhaps reveal dynamic spatial patterns in the property tax structure that would indicate market characteristics causing bias. In addition, a longer time study could reveal if the assessment correction process already being used by Lansing assessors was actually correcting inequity.

**Implementing Geographic Process and Methodology**

Regardless of what is at fault concerning the inequity of the property tax structure, there are some clear policy implications that come from the research in this thesis. The policy implications involve changing the assessment process rather than the real-estate market, for two reasons. First, and obviously, the workings of the real-estate market can not be changed, and ultimately, it is incumbent on the assessment process to overcome market forces that cause bias and inequity anyway. Second, the policy implications are aimed at improving the assessment process so that it can correct its *own* errors and alleviate its biases more efficiently. In general, the policy implication is this: to incorporate geographic evaluation at all stages in the assessment process. The best and most efficient way to deal with large amounts of geographic data and analyses is to create and use a GIS database management system. Please note that an introductory GIS textbook should be consulted for in depth discussion of what a GIS is and how specific spatial operations could be performed. With that said, GIS is a powerful tool that could probably eliminate inequity in the property tax structure of Lansing, Michigan. The next paragraphs will outline a step-by-step procedure that could be used by the city of Lansing to implement a GIS and a more precise spatial evaluation of the property tax structure.

GIS should be used at the very beginning of the cyclic assessment process in the data storage stage. GIS is a powerful tool for managing large quantities of geographically referenced data and Assessment data are just that. The assessor's office already stores its data in databases. But these non-spatial databases do not allow assessors to perform spatial analyses, spatial queries, or view assessments spatially. This is a huge limitation of the current assessment process since anything related to real-estate markets is inherently spatial. This limitation is even more severe, in light of the findings of this thesis that the property tax structure is inequitable with respect to geographically distinct areas. If the assessment data were transferred to a GIS database management system, then the data could be used for assessment purposes more efficiently. There are many different ways GIS should be used in the assessment process. The first, and most elementary of these, is for *organization* and *display* data purposes.

A GIS platform could help the assessor organize the multitudes of data that are collected for the purposes of assessment. Usually, the first step to implementing a GIS for municipal and assessment purposes is to enter the city's plat maps in digital format. Next, aerial photos of the city should be taken and made digital. Plat maps and digital air photos would together make up the base map for the GIS. Together they would have the parcel boundaries, street network, sidewalk delineation, hydrology, electrical and sewer lines, parks and public lines etc. Next, each parcel will be geographically referenced, not only with address and zip code as is done now, but also by latitude and longitude. As was done for the purposes of this research and discussed in Chapter 2, each parcel can then be assigned to other geographic scales to allow for multiple scale analysis. For instance, an assessor could easily bring up all parcels located within a two-block radius from the capital or any other point. The main advantage of this is the elimination of the assessor neighborhood.

After the data has been stored, geo-reference and organized, GIS can be used for display and queries. GIS would aid in the assessment of new parcels or recently altered parcels through spatial analyses and queries. Existing databases in the assessment process can do aspatial queries, but GIS is intended for doing spatial queries. For example, if an assessor wanted information on how a certain kind of property was assessed in the past, he/she could query to find all similar parcels with respect to designated characteristics and perhaps within certain geographic boundaries and then use statistics on the query to guide the assessment. Other layers of data could also be geographically referenced and assigned / attached to each parcel. So, for example, parcels could be selected based on the census characteristics surrounding them. Of course, GIS can also be used for easy mapping and viewing of assessments, parcels and related data. There are many ways GIS would make the actual assessing more efficient and accurate. However, as this thesis has demonstrated, perhaps the most important role for GIS in the assessment process comes at the evaluation stages of the assessment cycle. GIS is most powerful when used as a mode for analysis rather than just data collection and storage.

The assessors do evaluate the assessments on a yearly basis. However, they do so completely aspatially. The techniques used in this thesis that identified many inequities could be easily implemented by the assessor's office for evaluation. Once the evaluation was over, precise adjustments could be made to the property tax structure that would alleviate inequity.

Currently, all assessment analyses and adjustments are done based on static neighborhood designations. Each parcel was manually assigned to a neighborhood and then, the neighborhood designations were entered into the database. A GIS would give the analyses much more flexibility. Instead of using discrete boundaries for readjustment, a *moving window* sometimes called a "neighborhood smoothing" techniques, could be passed over Lansing and each of an infinite number of windows (areas of a designated size) could be readjusted (Chrisman 1997, p.179).[6] This technique would rid the assessment structure of

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[6] A moving window, or a moving average, can be thought of as a box or circle that is layed over each part of the study area, the average assessment ratio could be taken for each moving window and adjusted. Moving windows do away with discrete boundaries, moving window boundaries are also changing.

the boundary affects, seen to cause geographic inequity, caused by the assessor neighborhood boundaries.

Another way GIS could be used to readjust assessments to get rid of inequity is through surface analysis and functions. The assessment ratio surfaces could be smoothed by some function that would eliminate all major peaks and valleys. Then, the surface could be ungenerated to arrive at new assessments for each parcel. This process is only theoretical and would have to be adjusted for the particular software and resources of the implemented GIS. But, in doing these more detailed adjustments and analyses, GIS would be used to correct the inequities caused by the real estate market in addition to correct any remaining inequities overlooked by the assessment process.

Naturally, the implementation of any municipal GIS takes a lot of capital in the form of time, hardware, software and human resources. This would require an overhaul of the current assessment office structure and a large financial commitment from the city.

In addition, the implementation of a GIS and the methods used to assess and correct assessments that are described above, would require a paradigm shift on the part of the assessor's office, but more importantly, a paradigm shift for tax payers. Currently, taxpayers compare their assessments to other assessments on their block, or in their neighborhood. If the systems described above were implemented, taxpayers could do some querying of their own and compare their assessments to those of parcels with similar characteristics and circumstance as well as to the sale amounts of similar parcels.

The city of Lansing, must decide if the costs and changes involved with the implementation of a GIS are worth the increased precision and equity it would bring to the property tax structure.

# APPENDICE

## APPENDIX A

SEMIVARIANCE VALUES FOR 1994 DATA

| Lag | Average Distance | Average Semi-variance | Pairs |
|---|---|---|---|
| 1 | 56.47 | 0.005450 | 1338 |
| 2 | 152.05 | 0.005294 | 3402 |
| 3 | 253.27 | 0.005716 | 4950 |
| 4 | 351.83 | 0.005547 | 6279 |
| 5 | 450.51 | 0.005903 | 7426 |
| 6 | 550.81 | 0.006078 | 8343 |
| 7 | 650.21 | 0.006128 | 9044 |
| 8 | 750.15 | 0.006158 | 9800 |
| 9 | 850.06 | 0.006467 | 10302 |
| 10 | 951.16 | 0.006855 | 11435 |
| 11 | 1050.21 | 0.006719 | 12036 |
| 12 | 1150.01 | 0.006902 | 12317 |
| 13 | 1250.60 | 0.006721 | 12759 |
| 14 | 1350.57 | 0.007017 | 13070 |
| 15 | 1450.59 | 0.006741 | 14159 |
| 16 | 1550.93 | 0.006755 | 14668 |
| 17 | 1650.01 | 0.006756 | 15168 |
| 18 | 1750.46 | 0.006847 | 15732 |
| 19 | 1849.82 | 0.006779 | 16405 |
| 20 | 1949.71 | 0.006705 | 17100 |
| 21 | 2050.45 | 0.006645 | 17582 |
| 22 | 2150.45 | 0.006720 | 18084 |
| 23 | 2250.10 | 0.006573 | 18233 |
| 24 | 2349.83 | 0.006721 | 18922 |
| 25 | 2449.65 | 0.006825 | 19225 |
| 26 | 2550.31 | 0.006808 | 19827 |
| 27 | 2650.44 | 0.006659 | 20429 |
| 28 | 2750.07 | 0.006726 | 20649 |
| 29 | 2850.32 | 0.006767 | 21084 |
| 30 | 2950.03 | 0.006899 | 21719 |
| 31 | 3050.09 | 0.006931 | 22169 |
| 32 | 3150.22 | 0.006831 | 22479 |
| 33 | 3249.84 | 0.007023 | 22653 |
| 34 | 3349.92 | 0.007019 | 22658 |
| 35 | 3449.90 | 0.006952 | 23058 |
| 36 | 3549.86 | 0.006828 | 23510 |
| 37 | 3649.97 | 0.006729 | 23381 |
| 38 | 3750.26 | 0.006755 | 23545 |
| 39 | 3850.68 | 0.006629 | 23927 |
| 40 | 3949.70 | 0.006816 | 23522 |
| 41 | 4049.68 | 0.006762 | 23812 |
| 42 | 4150.37 | 0.006651 | 24122 |
| 43 | 4250.08 | 0.006669 | 23815 |
| 44 | 4349.81 | 0.006570 | 23462 |
| 45 | 4449.26 | 0.006376 | 23604 |
| 46 | 4550.05 | 0.006404 | 22558 |
| 47 | 4649.78 | 0.006480 | 22489 |
| 48 | 4749.68 | 0.006364 | 22140 |
| 49 | 4850.37 | 0.006141 | 21806 |
| 50 | 4949.98 | 0.006231 | 21408 |
| 51 | 5049.82 | 0.006407 | 20840 |
| 52 | 5149.93 | 0.006398 | 20367 |
| 53 | 5249.45 | 0.006463 | 19980 |
| 54 | 5349.83 | 0.006468 | 19619 |
| 55 | 5449.31 | 0.006434 | 19309 |
| 56 | 5549.85 | 0.006236 | 19060 |
| 57 | 5650.04 | 0.006328 | 19295 |
| 58 | 5750.02 | 0.006431 | 18795 |
| 59 | 5849.47 | 0.006386 | 18791 |
| 60 | 5950.35 | 0.006151 | 18149 |
| 61 | 6050.31 | 0.006220 | 17709 |
| 62 | 6149.53 | 0.005960 | 17478 |
| 63 | 6249.52 | 0.006034 | 17175 |
| 64 | 6349.89 | 0.006043 | 16854 |
| 65 | 6449.30 | 0.005967 | 16622 |
| 66 | 6549.89 | 0.005961 | 16113 |
| 67 | 6650.11 | 0.005882 | 15833 |
| 68 | 6750.25 | 0.005940 | 15664 |
| 69 | 6849.60 | 0.006079 | 15201 |

| | | | |
|---|---|---|---|
| 70 | 6949.47 | 0.005920 | 14641 |
| 71 | 7049.99 | 0.005932 | 13754 |
| 72 | 7149.96 | 0.005904 | 13416 |
| 73 | 7249.39 | 0.005922 | 12770 |
| 74 | 7349.83 | 0.005702 | 12161 |
| 75 | 7449.15 | 0.005841 | 11691 |
| 76 | 7549.35 | 0.005895 | 11185 |
| 77 | 7649.20 | 0.006158 | 10667 |
| 78 | 7748.91 | 0.006078 | 10380 |
| 79 | 7850.35 | 0.005989 | 9982 |
| 80 | 7949.46 | 0.006249 | 9903 |
| 81 | 8049.78 | 0.006131 | 9097 |
| 82 | 8149.97 | 0.006023 | 8754 |
| 83 | 8250.01 | 0.005945 | 8585 |
| 84 | 8349.09 | 0.005756 | 8151 |
| 85 | 8449.60 | 0.005879 | 7868 |
| 86 | 8549.78 | 0.006169 | 7739 |
| 87 | 8649.88 | 0.005875 | 7418 |
| 88 | 8749.21 | 0.006000 | 7234 |
| 89 | 8849.79 | 0.005861 | 7049 |
| 90 | 8949.76 | 0.006032 | 6739 |
| 91 | 9049.60 | 0.005734 | 6335 |
| 92 | 9149.38 | 0.005702 | 5699 |
| 93 | 9248.95 | 0.005798 | 5761 |
| 94 | 9349.63 | 0.005216 | 5121 |
| 95 | 9449.11 | 0.005492 | 4981 |
| 96 | 9550.18 | 0.005329 | 4796 |
| 97 | 9648.77 | 0.005414 | 4534 |
| 98 | 9749.55 | 0.005538 | 4320 |
| 99 | 9848.94 | 0.005110 | 4256 |
| 100 | 9950.26 | 0.005194 | 3996 |
| 101 | 10048.34 | 0.005116 | 3797 |
| 102 | 10150.61 | 0.005384 | 3422 |
| 103 | 10249.93 | 0.005288 | 3164 |
| 104 | 10350.27 | 0.005324 | 3008 |
| 105 | 10448.91 | 0.005183 | 2704 |
| 106 | 10547.90 | 0.005173 | 2548 |
| 107 | 10649.06 | 0.005049 | 2223 |
| 108 | 10748.07 | 0.005459 | 2047 |
| 109 | 10850.27 | 0.005654 | 1810 |
| 110 | 10948.05 | 0.005651 | 1589 |
| 111 | 11049.32 | 0.005207 | 1464 |
| 112 | 11149.84 | 0.006329 | 1257 |
| 113 | 11250.55 | 0.005646 | 1112 |
| 114 | 11348.42 | 0.005636 | 1020 |
| 115 | 11448.23 | 0.006215 | 820 |
| 116 | 11548.29 | 0.006859 | 686 |
| 117 | 11648.98 | 0.006615 | 621 |
| 118 | 11745.48 | 0.007018 | 492 |
| 119 | 11849.32 | 0.006991 | 445 |
| 120 | 11947.85 | 0.004777 | 351 |
| 121 | 12045.70 | 0.003925 | 336 |
| 122 | 12147.93 | 0.004127 | 323 |
| 123 | 12245.27 | 0.006859 | 227 |
| 124 | 12346.91 | 0.007897 | 160 |
| 125 | 12446.56 | 0.007906 | 121 |
| 126 | 12553.91 | 0.008281 | 73 |
| 127 | 12647.90 | 0.008361 | 50 |
| 128 | 12741.99 | 0.004452 | 36 |
| 129 | 12846.82 | 0.003445 | 32 |
| 130 | 12951.89 | 0.004222 | 26 |
| 131 | 13050.27 | 0.003254 | 18 |
| 132 | 13155.17 | 0.005605 | 15 |
| 133 | 13242.74 | 0.006771 | 6 |
| 134 | 13337.97 | 0.001918 | 3 |
| 135 | 13442.00 | 0.009827 | 2 |

## APPENDIX B

### SEMIVARIANCE VALUES FOR 1995 DATA

| Lag | Average Distance | Average Semi-variance | Pairs |
|---|---|---|---|
| 1 | 54.53 | 0.006720 | 1448 |
| 2 | 152.82 | 0.007180 | 3937 |
| 3 | 253.29 | 0.007225 | 5352 |
| 4 | 352.09 | 0.008031 | 6969 |
| 5 | 451.38 | 0.007672 | 8558 |
| 6 | 551.39 | 0.007734 | 9523 |
| 7 | 650.91 | 0.007810 | 10585 |
| 8 | 750.71 | 0.008037 | 11693 |
| 9 | 850.88 | 0.007709 | 12450 |
| 10 | 951.06 | 0.008318 | 13657 |
| 11 | 1049.98 | 0.008070 | 14307 |
| 12 | 1150.35 | 0.008202 | 15163 |
| 13 | 1250.37 | 0.008321 | 15671 |
| 14 | 1350.54 | 0.008047 | 16215 |
| 15 | 1450.27 | 0.008350 | 17687 |
| 16 | 1550.28 | 0.007980 | 17875 |
| 17 | 1649.72 | 0.008020 | 19019 |
| 18 | 1750.09 | 0.008088 | 18967 |
| 19 | 1849.87 | 0.007961 | 19747 |
| 20 | 1950.38 | 0.008127 | 20461 |
| 21 | 2050.28 | 0.008213 | 20957 |
| 22 | 2150.81 | 0.008104 | 21343 |
| 23 | 2250.16 | 0.007950 | 21944 |
| 24 | 2349.97 | 0.008018 | 22695 |
| 25 | 2450.39 | 0.007996 | 24060 |
| 26 | 2549.95 | 0.007945 | 24643 |
| 27 | 2650.17 | 0.008173 | 25039 |
| 28 | 2750.58 | 0.008222 | 25815 |
| 29 | 2849.83 | 0.008279 | 26215 |
| 30 | 2950.07 | 0.008285 | 26792 |
| 31 | 3050.23 | 0.008308 | 26984 |
| 32 | 3149.65 | 0.008084 | 27215 |
| 33 | 3250.02 | 0.008226 | 27386 |
| 34 | 3350.17 | 0.008295 | 27957 |
| 35 | 3449.87 | 0.008208 | 28119 |
| 36 | 3550.42 | 0.008289 | 27969 |
| 37 | 3650.14 | 0.008281 | 28251 |
| 38 | 3750.01 | 0.008361 | 28234 |
| 39 | 3850.04 | 0.008400 | 28335 |
| 40 | 3950.50 | 0.008513 | 28096 |
| 41 | 4049.81 | 0.008423 | 28208 |
| 42 | 4150.07 | 0.008277 | 27847 |
| 43 | 4249.94 | 0.008373 | 26700 |
| 44 | 4349.49 | 0.008049 | 26349 |
| 45 | 4449.57 | 0.008260 | 25695 |
| 46 | 4549.93 | 0.007974 | 25349 |
| 47 | 4649.49 | 0.008167 | 24849 |
| 48 | 4749.91 | 0.007834 | 24828 |
| 49 | 4850.22 | 0.007955 | 24262 |
| 50 | 4950.00 | 0.007994 | 23673 |
| 51 | 5049.80 | 0.007713 | 22775 |
| 52 | 5149.47 | 0.007813 | 22479 |
| 53 | 5249.60 | 0.007769 | 21925 |
| 54 | 5349.92 | 0.007981 | 21494 |
| 55 | 5449.54 | 0.007874 | 21325 |
| 56 | 5549.38 | 0.007551 | 21131 |
| 57 | 5649.75 | 0.007700 | 20987 |
| 58 | 5750.07 | 0.007660 | 20545 |
| 59 | 5850.05 | 0.007663 | 20628 |
| 60 | 5950.08 | 0.007686 | 19846 |
| 61 | 6049.87 | 0.007630 | 19285 |
| 62 | 6149.13 | 0.007317 | 19042 |
| 63 | 6249.25 | 0.007579 | 18513 |
| 64 | 6349.64 | 0.007542 | 18340 |
| 65 | 6449.73 | 0.007553 | 17526 |
| 66 | 6549.92 | 0.007368 | 16966 |
| 67 | 6650.17 | 0.007533 | 16300 |
| 68 | 6749.94 | 0.007377 | 15765 |
| 69 | 6849.47 | 0.007268 | 15454 |
| 70 | 6949.92 | 0.007408 | 14891 |
| 71 | 7049.20 | 0.007634 | 14501 |
| 72 | 7149.39 | 0.007554 | 13290 |
| 73 | 7249.85 | 0.007488 | 13313 |
| 74 | 7349.41 | 0.007378 | 12707 |
| 75 | 7450.28 | 0.007286 | 12100 |

| | | | |
|---|---|---|---|
| 76 | 7549.77 | 0.007254 | 11420 |
| 77 | 7649.61 | 0.007511 | 10892 |
| 78 | 7749.70 | 0.007399 | 10681 |
| 79 | 7849.61 | 0.007130 | 10261 |
| 80 | 7950.47 | 0.006738 | 10088 |
| 81 | 8049.44 | 0.006989 | 9477 |
| 82 | 8149.58 | 0.006963 | 9119 |
| 83 | 8249.68 | 0.007144 | 8922 |
| 84 | 8349.58 | 0.006889 | 8413 |
| 85 | 8449.93 | 0.006939 | 7906 |
| 86 | 8550.22 | 0.007101 | 7551 |
| 87 | 8649.81 | 0.006989 | 7341 |
| 88 | 8749.03 | 0.006678 | 7087 |
| 89 | 8848.19 | 0.006538 | 6512 |
| 90 | 8949.28 | 0.006659 | 6106 |
| 91 | 9049.68 | 0.006359 | 5739 |
| 92 | 9149.11 | 0.006512 | 5180 |
| 93 | 9248.78 | 0.006486 | 4842 |
| 94 | 9349.78 | 0.006346 | 4448 |
| 95 | 9448.76 | 0.006144 | 4239 |
| 96 | 9549.31 | 0.005799 | 3907 |
| 97 | 9648.32 | 0.006253 | 3649 |
| 98 | 9749.75 | 0.005754 | 3377 |
| 99 | 9848.91 | 0.005462 | 3195 |
| 100 | 9950.00 | 0.005631 | 2955 |
| 101 | 10049.33 | 0.006035 | 2615 |
| 102 | 10150.56 | 0.005838 | 2441 |
| 103 | 10248.82 | 0.005736 | 2320 |
| 104 | 10349.07 | 0.005905 | 2107 |
| 105 | 10449.22 | 0.006020 | 1855 |
| 106 | 10548.53 | 0.005188 | 1769 |
| 107 | 10649.00 | 0.005923 | 1421 |
| 108 | 10748.35 | 0.006256 | 1176 |
| 109 | 10847.76 | 0.006379 | 916 |
| 110 | 10949.76 | 0.006747 | 842 |
| 111 | 11049.79 | 0.006156 | 745 |
| 112 | 11148.14 | 0.006394 | 611 |
| 113 | 11248.08 | 0.006537 | 546 |
| 114 | 11350.26 | 0.005803 | 523 |
| 115 | 11449.17 | 0.006147 | 548 |
| 116 | 11550.17 | 0.004476 | 445 |
| 117 | 11646.84 | 0.004377 | 421 |
| 118 | 11747.94 | 0.004723 | 406 |
| 119 | 11847.75 | 0.002825 | 323 |
| 120 | 11946.19 | 0.004965 | 229 |
| 121 | 12050.44 | 0.004517 | 201 |
| 122 | 12149.97 | 0.004981 | 170 |
| 123 | 12247.08 | 0.005347 | 122 |
| 124 | 12350.22 | 0.004692 | 144 |
| 125 | 12440.03 | 0.004298 | 97 |
| 126 | 12542.02 | 0.007232 | 58 |
| 127 | 12653.95 | 0.008262 | 24 |
| 128 | 12749.86 | 0.011914 | 24 |
| 129 | 12844.64 | 0.009285 | 22 |
| 130 | 12950.21 | 0.008062 | 11 |
| 131 | 13063.09 | 0.008229 | 11 |
| 132 | 13154.26 | 0.007866 | 11 |
| 133 | 13237.50 | 0.013333 | 1 |
| 134 | 13350.33 | 0.010594 | 9 |
| 135 | 13435.40 | 0.009782 | 2 |

# APPENDIX C

## SEMIVARIANCE VALUES FOR 1996 DATA

| Lag | Average Distance | Average Semi-variance | Pairs |
|---|---|---|---|
| 1 | 54.44 | 0.006535 | 1954 |
| 2 | 152.94 | 0.007132 | 4922 |
| 3 | 252.45 | 0.007050 | 7022 |
| 4 | 351.08 | 0.007437 | 8773 |
| 5 | 451.18 | 0.007633 | 10401 |
| 6 | 551.00 | 0.007407 | 11630 |
| 7 | 650.95 | 0.007244 | 13097 |
| 8 | 750.92 | 0.007459 | 13986 |
| 9 | 851.43 | 0.007352 | 14790 |
| 10 | 951.03 | 0.007521 | 15723 |
| 11 | 1050.07 | 0.007701 | 16573 |
| 12 | 1150.63 | 0.007740 | 17841 |
| 13 | 1250.54 | 0.007638 | 18732 |
| 14 | 1350.51 | 0.007881 | 19235 |
| 15 | 1450.45 | 0.007971 | 20334 |
| 16 | 1550.13 | 0.007992 | 21418 |
| 17 | 1650.17 | 0.008019 | 22408 |
| 18 | 1750.27 | 0.008120 | 23069 |
| 19 | 1850.15 | 0.007894 | 23738 |
| 20 | 1950.58 | 0.008001 | 24824 |
| 21 | 2050.37 | 0.008124 | 25087 |
| 22 | 2150.61 | 0.008011 | 26295 |
| 23 | 2250.50 | 0.008245 | 26639 |
| 24 | 2350.11 | 0.008261 | 27115 |
| 25 | 2449.91 | 0.008076 | 28065 |
| 26 | 2550.64 | 0.008018 | 28608 |
| 27 | 2650.31 | 0.007946 | 29526 |
| 28 | 2750.02 | 0.007982 | 30010 |
| 29 | 2850.12 | 0.008075 | 31189 |
| 30 | 2950.47 | 0.008366 | 31460 |
| 31 | 3049.96 | 0.008082 | 32673 |
| 32 | 3150.08 | 0.008191 | 32618 |
| 33 | 3250.20 | 0.008385 | 32900 |
| 34 | 3350.12 | 0.008166 | 33596 |
| 35 | 3450.08 | 0.008239 | 34274 |
| 36 | 3550.11 | 0.008177 | 33877 |
| 37 | 3649.85 | 0.008122 | 33713 |
| 38 | 3750.00 | 0.007990 | 33472 |
| 39 | 3849.77 | 0.007935 | 33785 |
| 40 | 3950.16 | 0.007780 | 33581 |
| 41 | 4050.03 | 0.007864 | 33972 |
| 42 | 4150.24 | 0.007921 | 33758 |
| 43 | 4250.25 | 0.007820 | 33762 |
| 44 | 4349.85 | 0.007868 | 33712 |
| 45 | 4449.65 | 0.007673 | 33266 |
| 46 | 4550.20 | 0.007792 | 33247 |
| 47 | 4649.86 | 0.007889 | 32836 |
| 48 | 4749.71 | 0.007918 | 31596 |
| 49 | 4849.80 | 0.007762 | 30982 |
| 50 | 4949.97 | 0.007945 | 30001 |
| 51 | 5049.40 | 0.007815 | 29319 |
| 52 | 5150.07 | 0.007731 | 28262 |
| 53 | 5250.09 | 0.007499 | 27984 |
| 54 | 5349.35 | 0.007564 | 27379 |
| 55 | 5449.55 | 0.007278 | 27094 |
| 56 | 5550.10 | 0.007420 | 27207 |
| 57 | 5649.98 | 0.007302 | 26516 |
| 58 | 5749.98 | 0.007434 | 25926 |
| 59 | 5850.15 | 0.007273 | 25443 |
| 60 | 5950.02 | 0.007281 | 25116 |
| 61 | 6049.57 | 0.007217 | 24434 |
| 62 | 6149.61 | 0.007171 | 23872 |
| 63 | 6249.81 | 0.007188 | 23266 |
| 64 | 6349.88 | 0.007286 | 22762 |
| 65 | 6449.88 | 0.007166 | 21785 |
| 66 | 6549.87 | 0.007106 | 21305 |
| 67 | 6650.18 | 0.006885 | 21242 |
| 68 | 6750.23 | 0.007182 | 20960 |
| 69 | 6850.15 | 0.007115 | 20393 |
| 70 | 6949.91 | 0.007216 | 19760 |
| 71 | 7049.66 | 0.007364 | 19073 |
| 72 | 7149.78 | 0.007328 | 18365 |
| 73 | 7249.61 | 0.007287 | 17827 |
| 74 | 7349.94 | 0.007283 | 16776 |
| 75 | 7449.76 | 0.007330 | 16169 |

| | | | |
|---|---|---|---|
| 76 | 7549.88 | 0.007391 | 15634 |
| 77 | 7650.20 | 0.007237 | 14941 |
| 78 | 7749.76 | 0.007242 | 15090 |
| 79 | 7849.84 | 0.007294 | 14316 |
| 80 | 7949.79 | 0.007282 | 13940 |
| 81 | 8049.62 | 0.007257 | 13579 |
| 82 | 8150.20 | 0.007579 | 12874 |
| 83 | 8249.65 | 0.007401 | 12626 |
| 84 | 8349.75 | 0.007477 | 12043 |
| 85 | 8449.01 | 0.007547 | 12086 |
| 86 | 8549.57 | 0.007447 | 11621 |
| 87 | 8649.59 | 0.007389 | 10953 |
| 88 | 8749.30 | 0.007322 | 10627 |
| 89 | 8849.29 | 0.007213 | 9673 |
| 90 | 8949.58 | 0.007324 | 9295 |
| 91 | 9049.32 | 0.006980 | 8685 |
| 92 | 9149.97 | 0.006961 | 7858 |
| 93 | 9249.02 | 0.006897 | 7517 |
| 94 | 9349.26 | 0.006789 | 7066 |
| 95 | 9449.67 | 0.006758 | 6407 |
| 96 | 9549.79 | 0.006454 | 6186 |
| 97 | 9649.65 | 0.006053 | 5851 |
| 98 | 9749.31 | 0.005862 | 5492 |
| 99 | 9849.00 | 0.005982 | 5142 |
| 100 | 9949.65 | 0.005823 | 4996 |
| 101 | 10049.58 | 0.005699 | 4727 |
| 102 | 10149.65 | 0.005981 | 4479 |
| 103 | 10249.45 | 0.005573 | 4181 |
| 104 | 10349.46 | 0.005422 | 3917 |
| 105 | 10448.77 | 0.005553 | 3616 |

| | | | |
|---|---|---|---|
| 106 | 10549.49 | 0.005368 | 3212 |
| 107 | 10649.36 | 0.005480 | 2861 |
| 108 | 10748.95 | 0.005423 | 2559 |
| 109 | 10850.39 | 0.005581 | 2201 |
| 110 | 10950.16 | 0.005678 | 1862 |
| 111 | 11047.09 | 0.005246 | 1682 |
| 112 | 11149.61 | 0.004583 | 1600 |
| 113 | 11251.17 | 0.004306 | 1379 |
| 114 | 11348.99 | 0.004245 | 1239 |
| 115 | 11448.14 | 0.004342 | 1060 |
| 116 | 11547.46 | 0.004312 | 871 |
| 117 | 11647.29 | 0.004207 | 837 |
| 118 | 11747.94 | 0.003836 | 728 |
| 119 | 11848.96 | 0.004065 | 714 |
| 120 | 11949.03 | 0.003476 | 554 |
| 121 | 12050.33 | 0.004099 | 502 |
| 122 | 12149.52 | 0.003981 | 384 |
| 123 | 12247.75 | 0.004659 | 325 |
| 124 | 12351.49 | 0.003746 | 280 |
| 125 | 12445.10 | 0.004936 | 226 |
| 126 | 12547.81 | 0.004397 | 139 |
| 127 | 12646.64 | 0.006301 | 99 |
| 128 | 12748.35 | 0.004511 | 65 |
| 129 | 12848.13 | 0.006767 | 29 |
| 130 | 12944.03 | 0.004301 | 21 |
| 131 | 13048.78 | 0.002397 | 22 |
| 132 | 13134.73 | 0.004838 | 5 |
| 133 | 13248.78 | 0.001558 | 11 |
| 134 | 13354.52 | 0.000542 | 5 |

# APPENDIX D

## SEMIVARIANCE VALUES FOR 1997 DATA

| Lag | Average Distance | Average Semi-variance | Pairs |
|---|---|---|---|
| 1 | 56.78 | 0.006328 | 1618 |
| 2 | 153.66 | 0.006311 | 4037 |
| 3 | 252.69 | 0.006400 | 5958 |
| 4 | 351.89 | 0.006377 | 7436 |
| 5 | 450.71 | 0.006604 | 8738 |
| 6 | 551.17 | 0.006858 | 10112 |
| 7 | 651.21 | 0.006717 | 11253 |
| 8 | 750.45 | 0.007156 | 12300 |
| 9 | 850.55 | 0.007403 | 13084 |
| 10 | 950.47 | 0.006912 | 14006 |
| 11 | 1050.23 | 0.007197 | 14839 |
| 12 | 1150.15 | 0.007418 | 15108 |
| 13 | 1250.66 | 0.007197 | 15745 |
| 14 | 1350.90 | 0.007062 | 16698 |
| 15 | 1450.64 | 0.007235 | 17343 |
| 16 | 1550.40 | 0.007240 | 18019 |
| 17 | 1650.73 | 0.007348 | 19048 |
| 18 | 1750.69 | 0.007252 | 19251 |
| 19 | 1850.23 | 0.007167 | 20168 |
| 20 | 1950.19 | 0.007102 | 20998 |
| 21 | 2050.54 | 0.007235 | 21168 |
| 22 | 2150.23 | 0.007184 | 21744 |
| 23 | 2250.20 | 0.007153 | 22338 |
| 24 | 2350.11 | 0.007261 | 23036 |
| 25 | 2449.94 | 0.007446 | 23782 |
| 26 | 2550.50 | 0.007418 | 24641 |
| 27 | 2650.16 | 0.007608 | 25623 |
| 28 | 2750.03 | 0.007646 | 26177 |
| 29 | 2850.01 | 0.007727 | 26566 |
| 30 | 2950.07 | 0.007838 | 27529 |
| 31 | 3050.41 | 0.007725 | 27380 |
| 32 | 3149.92 | 0.007765 | 27941 |
| 33 | 3250.33 | 0.007661 | 28701 |
| 34 | 3350.26 | 0.007784 | 28922 |
| 35 | 3449.99 | 0.007704 | 29258 |
| 36 | 3550.07 | 0.007675 | 29546 |
| 37 | 3649.85 | 0.007674 | 29495 |
| 38 | 3749.68 | 0.007618 | 29737 |
| 39 | 3849.83 | 0.007712 | 29441 |
| 40 | 3950.26 | 0.007459 | 29704 |
| 41 | 4050.11 | 0.007388 | 29713 |
| 42 | 4150.15 | 0.007658 | 29197 |
| 43 | 4249.67 | 0.007454 | 29513 |
| 44 | 4349.56 | 0.007441 | 28845 |
| 45 | 4449.96 | 0.007456 | 28186 |
| 46 | 4550.05 | 0.007376 | 27737 |
| 47 | 4649.71 | 0.007450 | 26796 |
| 48 | 4749.82 | 0.007359 | 26535 |
| 49 | 4849.86 | 0.007287 | 26091 |
| 50 | 4949.52 | 0.007128 | 25121 |
| 51 | 5049.87 | 0.007182 | 24064 |
| 52 | 5149.60 | 0.007200 | 23623 |
| 53 | 5249.36 | 0.007199 | 22939 |
| 54 | 5349.73 | 0.007061 | 22530 |
| 55 | 5449.86 | 0.007233 | 22223 |
| 56 | 5549.62 | 0.007040 | 21869 |
| 57 | 5649.97 | 0.006997 | 21363 |
| 58 | 5749.95 | 0.006898 | 20415 |
| 59 | 5850.07 | 0.006848 | 20379 |
| 60 | 5950.00 | 0.006881 | 20039 |
| 61 | 6049.81 | 0.006824 | 19500 |
| 62 | 6149.33 | 0.006718 | 19288 |
| 63 | 6249.44 | 0.006644 | 18949 |
| 64 | 6349.67 | 0.006790 | 18743 |
| 65 | 6449.75 | 0.006876 | 17837 |
| 66 | 6549.97 | 0.007079 | 17552 |
| 67 | 6650.36 | 0.007115 | 17286 |
| 68 | 6750.00 | 0.007021 | 16435 |
| 69 | 6849.52 | 0.007304 | 16257 |
| 70 | 6949.51 | 0.007172 | 15472 |
| 71 | 7049.88 | 0.007153 | 14933 |
| 72 | 7149.89 | 0.007208 | 14247 |
| 73 | 7250.37 | 0.007074 | 13994 |
| 74 | 7349.67 | 0.007309 | 13340 |
| 75 | 7449.46 | 0.007334 | 12929 |

| | | | |
|---|---|---|---|
| 76 | 7550.02 | 0.007409 | 12353 |
| 77 | 7649.46 | 0.007248 | 11673 |
| 78 | 7749.41 | 0.007562 | 11333 |
| 79 | 7849.70 | 0.007557 | 10759 |
| 80 | 7949.40 | 0.007619 | 10228 |
| 81 | 8049.98 | 0.007603 | 10302 |
| 82 | 8149.97 | 0.007775 | 9649 |
| 83 | 8249.75 | 0.007606 | 9137 |
| 84 | 8348.72 | 0.007638 | 8655 |
| 85 | 8449.67 | 0.007535 | 8145 |
| 86 | 8549.54 | 0.007578 | 7883 |
| 87 | 8649.96 | 0.007228 | 7408 |
| 88 | 8750.27 | 0.007617 | 7099 |
| 89 | 8848.83 | 0.007502 | 6692 |
| 90 | 8949.23 | 0.007429 | 6569 |
| 91 | 9050.08 | 0.007520 | 6176 |
| 92 | 9149.84 | 0.007379 | 5831 |
| 93 | 9248.44 | 0.007278 | 5502 |
| 94 | 9349.64 | 0.007321 | 5384 |
| 95 | 9450.14 | 0.007018 | 4831 |
| 96 | 9549.08 | 0.007220 | 4570 |
| 97 | 9649.97 | 0.007074 | 4304 |
| 98 | 9748.78 | 0.006904 | 3926 |
| 99 | 9849.26 | 0.006979 | 3634 |
| 100 | 9949.57 | 0.006970 | 3513 |
| 101 | 10048.82 | 0.007417 | 3324 |
| 102 | 10150.38 | 0.007518 | 3009 |
| 103 | 10249.55 | 0.007625 | 2826 |
| 104 | 10348.36 | 0.007895 | 2562 |
| 105 | 10448.67 | 0.007867 | 2421 |
| 106 | 10549.97 | 0.007946 | 2114 |
| 107 | 10647.60 | 0.008052 | 1882 |
| 108 | 10748.00 | 0.008855 | 1641 |
| 109 | 10848.03 | 0.008174 | 1337 |
| 110 | 10949.46 | 0.009410 | 1150 |
| 111 | 11049.32 | 0.007976 | 1035 |
| 112 | 11146.86 | 0.007687 | 797 |
| 113 | 11247.30 | 0.009068 | 758 |
| 114 | 11350.77 | 0.007822 | 627 |
| 115 | 11450.52 | 0.007603 | 456 |
| 116 | 11549.25 | 0.005356 | 435 |
| 117 | 11647.69 | 0.004955 | 367 |
| 118 | 11747.92 | 0.004636 | 331 |
| 119 | 11849.54 | 0.004133 | 345 |
| 120 | 11949.63 | 0.006301 | 271 |
| 121 | 12045.86 | 0.004441 | 221 |
| 122 | 12150.83 | 0.006205 | 211 |
| 123 | 12251.67 | 0.006325 | 171 |
| 124 | 12345.10 | 0.004614 | 146 |
| 125 | 12444.26 | 0.005256 | 120 |
| 126 | 12545.93 | 0.007896 | 66 |
| 127 | 12652.70 | 0.008590 | 51 |
| 128 | 12739.81 | 0.008297 | 44 |
| 129 | 12855.38 | 0.008221 | 30 |
| 130 | 12943.35 | 0.007202 | 44 |
| 131 | 13056.74 | 0.009809 | 33 |
| 132 | 13161.80 | 0.008219 | 26 |
| 133 | 13224.42 | 0.008363 | 21 |
| 134 | 13325.71 | 0.005460 | 10 |
| 135 | 13463.19 | 0.003678 | 8 |

## APPENDIX E

### SEMIVARIANCE VALUES FOR 1998 DATA

| Lag | Average Distance | Average Semi-variance | Pairs |
|---|---|---|---|
| 1 | 50.80 | 0.013221 | 43 |
| 2 | 152.47 | 0.006199 | 161 |
| 3 | 252.08 | 0.005455 | 172 |
| 4 | 349.56 | 0.007545 | 246 |
| 5 | 450.45 | 0.008892 | 280 |
| 6 | 551.71 | 0.008131 | 292 |
| 7 | 650.74 | 0.008526 | 319 |
| 8 | 747.79 | 0.008144 | 361 |
| 9 | 851.83 | 0.008473 | 365 |
| 10 | 949.46 | 0.007761 | 383 |
| 11 | 1051.24 | 0.008459 | 436 |
| 12 | 1149.71 | 0.006826 | 504 |
| 13 | 1250.10 | 0.007885 | 506 |
| 14 | 1352.80 | 0.008997 | 511 |
| 15 | 1451.31 | 0.009171 | 555 |
| 16 | 1551.82 | 0.008871 | 591 |
| 17 | 1649.62 | 0.008586 | 617 |
| 18 | 1749.74 | 0.008700 | 657 |
| 19 | 1849.30 | 0.008571 | 650 |
| 20 | 1949.94 | 0.007994 | 699 |
| 21 | 2050.44 | 0.007979 | 648 |
| 22 | 2149.52 | 0.008910 | 681 |
| 23 | 2250.20 | 0.007721 | 658 |
| 24 | 2347.38 | 0.008048 | 700 |
| 25 | 2450.57 | 0.008523 | 699 |
| 26 | 2548.89 | 0.008242 | 748 |
| 27 | 2651.64 | 0.007990 | 810 |
| 28 | 2749.69 | 0.007504 | 792 |
| 29 | 2850.32 | 0.007847 | 844 |
| 30 | 2949.90 | 0.008635 | 962 |
| 31 | 3049.95 | 0.008060 | 950 |
| 32 | 3149.84 | 0.008230 | 934 |
| 33 | 3249.09 | 0.008342 | 941 |
| 34 | 3349.99 | 0.007991 | 935 |
| 35 | 3447.07 | 0.008225 | 879 |
| 36 | 3548.23 | 0.007806 | 946 |
| 37 | 3649.86 | 0.007602 | 909 |
| 38 | 3749.54 | 0.008026 | 907 |
| 39 | 3850.00 | 0.007809 | 914 |
| 40 | 3949.91 | 0.007071 | 919 |
| 41 | 4050.43 | 0.007348 | 881 |
| 42 | 4148.16 | 0.007161 | 925 |
| 43 | 4249.61 | 0.007160 | 870 |
| 44 | 4348.86 | 0.008353 | 841 |
| 45 | 4449.26 | 0.006955 | 908 |
| 46 | 4549.16 | 0.006663 | 901 |
| 47 | 4650.07 | 0.007812 | 899 |
| 48 | 4750.60 | 0.007527 | 820 |
| 49 | 4850.08 | 0.007500 | 708 |
| 50 | 4951.26 | 0.007326 | 737 |
| 51 | 5050.37 | 0.007310 | 700 |
| 52 | 5150.44 | 0.007563 | 697 |
| 53 | 5249.11 | 0.007275 | 690 |
| 54 | 5348.73 | 0.007434 | 646 |
| 55 | 5449.42 | 0.006877 | 629 |
| 56 | 5551.31 | 0.006450 | 684 |
| 57 | 5649.73 | 0.006135 | 702 |
| 58 | 5749.31 | 0.007159 | 667 |
| 59 | 5849.05 | 0.007596 | 657 |
| 60 | 5951.62 | 0.006549 | 616 |
| 61 | 6048.85 | 0.006125 | 572 |
| 62 | 6150.42 | 0.006905 | 587 |
| 63 | 6249.52 | 0.006740 | 588 |
| 64 | 6348.97 | 0.007625 | 581 |
| 65 | 6453.25 | 0.006649 | 517 |
| 66 | 6547.94 | 0.007600 | 574 |
| 67 | 6651.56 | 0.007591 | 557 |
| 68 | 6751.05 | 0.006448 | 525 |
| 69 | 6848.44 | 0.006835 | 484 |
| 70 | 6950.83 | 0.006310 | 479 |
| 71 | 7047.35 | 0.007371 | 434 |
| 72 | 7151.60 | 0.005800 | 411 |
| 73 | 7252.25 | 0.006845 | 425 |
| 74 | 7350.15 | 0.006383 | 351 |
| 75 | 7451.43 | 0.006435 | 383 |

| | | | |
|---|---|---|---|
| 76 | 7550.21 | 0.007290 | 381 |
| 77 | 7648.32 | 0.006547 | 368 |
| 78 | 7749.53 | 0.006757 | 350 |
| 79 | 7848.86 | 0.006592 | 375 |
| 80 | 7949.50 | 0.006678 | 323 |
| 81 | 8050.90 | 0.006587 | 280 |
| 82 | 8148.48 | 0.006317 | 283 |
| 83 | 8247.92 | 0.008611 | 287 |
| 84 | 8347.80 | 0.006757 | 264 |
| 85 | 8445.55 | 0.006695 | 279 |
| 86 | 8546.27 | 0.006718 | 280 |
| 87 | 8648.73 | 0.006746 | 235 |
| 88 | 8749.81 | 0.006364 | 220 |
| 89 | 8846.47 | 0.006890 | 225 |
| 90 | 8949.99 | 0.005789 | 224 |
| 91 | 9051.14 | 0.006684 | 194 |
| 92 | 9149.06 | 0.007211 | 169 |
| 93 | 9244.44 | 0.006591 | 171 |
| 94 | 9344.17 | 0.005203 | 175 |
| 95 | 9452.39 | 0.004765 | 164 |
| 96 | 9551.44 | 0.005680 | 164 |
| 97 | 9652.24 | 0.005407 | 146 |
| 98 | 9744.00 | 0.006899 | 126 |
| 99 | 9848.24 | 0.007435 | 97 |
| 100 | 9945.92 | 0.005724 | 108 |
| 101 | 10052.65 | 0.006407 | 99 |
| 102 | 10150.69 | 0.006143 | 112 |
| 103 | 10255.53 | 0.006449 | 87 |
| 104 | 10352.05 | 0.005087 | 92 |
| 105 | 10443.64 | 0.006996 | 78 |
| 106 | 10543.66 | 0.006019 | 52 |
| 107 | 10648.42 | 0.006013 | 46 |
| 108 | 10748.07 | 0.009880 | 43 |
| 109 | 10840.73 | 0.007471 | 44 |
| 110 | 10950.47 | 0.007570 | 35 |
| 111 | 11052.07 | 0.004531 | 32 |
| 112 | 11155.73 | 0.003609 | 24 |
| 113 | 11251.51 | 0.003947 | 14 |
| 114 | 11345.14 | 0.005832 | 22 |
| 115 | 11458.77 | 0.002577 | 15 |
| 116 | 11551.40 | 0.003613 | 19 |
| 117 | 11646.84 | 0.005005 | 29 |
| 118 | 11736.57 | 0.008245 | 15 |
| 119 | 11835.58 | 0.004289 | 22 |
| 120 | 11953.33 | 0.002439 | 18 |
| 121 | 12050.47 | 0.004813 | 14 |
| 122 | 12150.82 | 0.002949 | 9 |
| 123 | 12259.14 | 0.002537 | 13 |
| 124 | 12349.18 | 0.000990 | 6 |
| 125 | | | 0 |
| 126 | 12550.86 | 0.004926 | 6 |
| 127 | 12683.99 | 0.009524 | 4 |
| 128 | 12784.15 | 0.008910 | 2 |
| 129 | 12838.04 | 0.004494 | 2 |
| 130 | 12964.58 | 0.002484 | 2 |

## APPENDIX F

1994 MORAN'S I

| Lag | Moran's I | Pairs (n) | E(I) | SD | s.e. | Z score | Hypothesis Test |
|---|---|---|---|---|---|---|---|
| **1** | **0.100755** | **1338** | **-7.5E-04** | **0.99963** | **0.027328186** | **3.7142** | **Reject Null** |
| 2 | 0.026976 | 3402 | -2.9E-04 | 0.99985 | 0.017142304 | 1.5908 | No Reject |
| **3** | **0.041947** | **4950** | **-2.0E-04** | **0.99990** | **0.014211948** | **2.9657** | **Reject Null** |
| **4** | **0.050301** | **6279** | **-1.6E-04** | **0.99992** | **0.012618863** | **3.9988** | **Reject Null** |
| 5 | 0.005232 | 7426 | -1.3E-04 | 0.99993 | 0.011603615 | 0.4625 | No Reject |
| 6 | 0.009738 | 8343 | -1.2E-04 | 0.99994 | 0.010947448 | 0.9005 | No Reject |
| 7 | 0.012273 | 9044 | -1.1E-04 | 0.99994 | 0.010514672 | 1.1777 | No Reject |
| **8** | **0.022854** | **9800** | **-1.0E-04** | **0.99995** | **0.010101011** | **2.2726** | **Reject Null** |
| 9 | 0.008704 | 10302 | -9.7E-05 | 0.99995 | 0.009851859 | 0.8933 | No Reject |
| **10** | **-0.019313** | **11435** | **-8.7E-05** | **0.99996** | **0.009351105** | **-2.0560** | **Reject Null** |
| 11 | 0.002029 | 12036 | -8.3E-05 | 0.99996 | 0.009114669 | 0.2317 | No Reject |
| 12 | -0.013916 | 12317 | -8.1E-05 | 0.99996 | 0.009010106 | -1.5355 | No Reject |
| 13 | 0.000597 | 12759 | -7.8E-05 | 0.99996 | 0.008852678 | 0.0763 | No Reject |
| **14** | **-0.038004** | **13070** | **-7.7E-05** | **0.99996** | **0.008746728** | **-4.3362** | **Reject Null** |
| 15 | -0.01178 | 14159 | -7.1E-05 | 0.99996 | 0.008403658 | -1.3934 | No Reject |
| **16** | **-0.015119** | **14668** | **-6.8E-05** | **0.99997** | **0.008256572** | **-1.8229** | **Reject Null** |
| **17** | **-0.018865** | **15168** | **-6.6E-05** | **0.99997** | **0.008119355** | **-2.3153** | **Reject Null** |
| 18 | 0.005242 | 15732 | -6.4E-05 | 0.99997 | 0.007972495 | 0.6655 | No Reject |
| 19 | 0.001576 | 16405 | -6.1E-05 | 0.99997 | 0.00780726 | 0.2097 | No Reject |
| 20 | 0.0063 | 17100 | -5.8E-05 | 0.99997 | 0.007646968 | 0.8315 | No Reject |
| 21 | 0.009782 | 17582 | -5.7E-05 | 0.99997 | 0.007541427 | 1.3046 | No Reject |
| 22 | 0.006472 | 18084 | -5.5E-05 | 0.99997 | 0.007436023 | 0.8778 | No Reject |
| **23** | **0.014225** | **18233** | **-5.5E-05** | **0.99997** | **0.007405579** | **1.9283** | **Reject Null** |
| 24 | 0.006411 | 18922 | -5.3E-05 | 0.99997 | 0.007269508 | 0.8892 | No Reject |
| 25 | -0.011295 | 19225 | -5.2E-05 | 0.99997 | 0.007211997 | -1.5589 | No Reject |
| 26 | -0.004429 | 19827 | -5.0E-05 | 0.99997 | 0.007101671 | -0.6166 | No Reject |
| 27 | 0.007234 | 20429 | -4.9E-05 | 0.99998 | 0.006996258 | 1.0410 | No Reject |
| 28 | 0.004306 | 20649 | -4.8E-05 | 0.99998 | 0.00695889 | 0.6257 | No Reject |
| **29** | **-0.011919** | **21084** | **-4.7E-05** | **0.99998** | **0.006886732** | **-1.7238** | **Reject Null** |
| 30 | 0.001057 | 21719 | -4.6E-05 | 0.99998 | 0.006785316 | 0.1626 | No Reject |
| 31 | -0.001484 | 22169 | -4.5E-05 | 0.99998 | 0.0067161 | -0.2142 | No Reject |
| 32 | -0.009303 | 22479 | -4.4E-05 | 0.99998 | 0.006669632 | -1.3882 | No Reject |
| 33 | -0.007449 | 22653 | -4.4E-05 | 0.99998 | 0.006643968 | -1.1145 | No Reject |
| 34 | -0.009463 | 22658 | -4.4E-05 | 0.99998 | 0.006643235 | -1.4178 | No Reject |
| 35 | -0.005407 | 23058 | -4.3E-05 | 0.99998 | 0.006585364 | -0.8145 | No Reject |
| 36 | -0.003466 | 23510 | -4.3E-05 | 0.99998 | 0.006521755 | -0.5249 | No Reject |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 37 | -0.00793 | 23381 | -4.3E-05 | | 0.99998 | 0.00653972 | -1.2060 | No Reject |
| 38 | -0.00208 | 23545 | -4.2E-05 | | 0.99998 | 0.006516906 | -0.3127 | No Reject |
| 39 | 0.003276 | 23927 | -4.2E-05 | | 0.99998 | 0.006464677 | 0.5132 | No Reject |
| **40** | **-0.014816** | **23522** | **-4.3E-05** | | **0.99998** | **0.006520091** | **-2.2658** | **Reject Null** |
| 41 | -0.001922 | 23812 | -4.2E-05 | | 0.99998 | 0.006480268 | -0.2901 | No Reject |
| 42 | -0.003594 | 24122 | -4.1E-05 | | 0.99998 | 0.006438495 | -0.5518 | No Reject |
| 43 | -0.003268 | 23815 | -4.2E-05 | | 0.99998 | 0.00647986 | -0.4979 | No Reject |
| 44 | 0.006025 | 23462 | -4.3E-05 | | 0.99998 | 0.006528422 | 0.9294 | No Reject |
| 45 | 0.000532 | 23604 | -4.2E-05 | | 0.99998 | 0.006508756 | 0.0882 | No Reject |
| 46 | 0.001182 | 22558 | -4.4E-05 | | 0.99998 | 0.006657943 | 0.1842 | No Reject |
| 47 | -0.000504 | 22489 | -4.4E-05 | | 0.99998 | 0.006668149 | -0.0689 | No Reject |
| 48 | 0.009513 | 22140 | -4.5E-05 | | 0.99998 | 0.006720497 | 1.4222 | No Reject |
| **49** | **0.017861** | **21806** | **-4.6E-05** | | **0.99998** | **0.006771768** | **2.6443** | **Reject Null** |
| 50 | 0.01097 | 21408 | -4.7E-05 | | 0.99998 | 0.006834422 | 1.6119 | No Reject |
| 51 | -0.000968 | 20840 | -4.8E-05 | | 0.99998 | 0.006926929 | -0.1328 | No Reject |
| 52 | 0.002387 | 20367 | -4.9E-05 | | 0.99998 | 0.007006898 | 0.3477 | No Reject |
| 53 | 0.001478 | 19980 | -5.0E-05 | | 0.99997 | 0.007074429 | 0.2160 | No Reject |
| 54 | -0.000254 | 19619 | -5.1E-05 | | 0.99997 | 0.007139216 | -0.0284 | No Reject |
| 55 | -0.010476 | 19309 | -5.2E-05 | | 0.99997 | 0.007196294 | -1.4486 | No Reject |
| 56 | -0.006111 | 19060 | -5.2E-05 | | 0.99997 | 0.007243145 | -0.8365 | No Reject |
| 57 | -0.009011 | 19295 | -5.2E-05 | | 0.99997 | 0.007198904 | -1.2445 | No Reject |
| **58** | **-0.02092** | **18795** | **-5.3E-05** | | **0.99997** | **0.007294026** | **-2.8608** | **Reject Null** |
| **59** | **-0.024516** | **18791** | **-5.3E-05** | | **0.99997** | **0.007294802** | **-3.3535** | **Reject Null** |
| 60 | 0.002088 | 18149 | -5.5E-05 | | 0.99997 | 0.007422696 | 0.2887 | No Reject |
| 61 | -0.006278 | 17709 | -5.6E-05 | | 0.99997 | 0.007514338 | -0.8280 | No Reject |
| 62 | 0.002552 | 17478 | -5.7E-05 | | 0.99997 | 0.007563829 | 0.3450 | No Reject |
| 63 | -0.000045 | 17175 | -5.8E-05 | | 0.99997 | 0.007630254 | 0.0017 | No Reject |
| 64 | 0.003284 | 16854 | -5.9E-05 | | 0.99997 | 0.00770257 | 0.4341 | No Reject |
| 65 | 0.00557 | 16622 | -6.0E-05 | | 0.99997 | 0.007756134 | 0.7259 | No Reject |
| 66 | 0.009362 | 16113 | -6.2E-05 | | 0.99997 | 0.00787768 | 1.1963 | No Reject |
| **67** | **0.028326** | **15833** | **-6.3E-05** | | **0.99997** | **0.007947027** | **3.5723** | **Reject Null** |
| **68** | **0.014835** | **15664** | **-6.4E-05** | | **0.99997** | **0.00798978** | **1.8647** | **Reject Null** |
| 69 | -0.012028 | 15201 | -6.6E-05 | | 0.99997 | 0.008110538 | -1.4749 | No Reject |
| 70 | 0.006397 | 14641 | -6.8E-05 | | 0.99997 | 0.008264181 | 0.7823 | No Reject |
| 71 | 0.002831 | 13754 | -7.3E-05 | | 0.99996 | 0.008526479 | 0.3406 | No Reject |
| 72 | -0.006685 | 13416 | -7.5E-05 | | 0.99996 | 0.00863321 | -0.7657 | No Reject |
| 73 | -0.00431 | 12770 | -7.8E-05 | | 0.99996 | 0.008848865 | -0.4782 | No Reject |
| 74 | -0.003478 | 12161 | -8.2E-05 | | 0.99996 | 0.009067708 | -0.3745 | No Reject |
| 75 | -0.011205 | 11691 | -8.6E-05 | | 0.99996 | 0.009248166 | -1.2023 | No Reject |
| 76 | -0.008081 | 11185 | -8.9E-05 | | 0.99996 | 0.009455023 | -0.8452 | No Reject |
| 77 | -0.010528 | 10667 | -9.4E-05 | | 0.99995 | 0.009681854 | -1.0777 | No Reject |
| 78 | -0.001537 | 10380 | -9.6E-05 | | 0.99995 | 0.009814777 | -0.1468 | No Reject |
| 79 | 0.001328 | 9982 | -1.0E-04 | | 0.99995 | 0.010008511 | 0.1427 | No Reject |
| 80 | -0.013652 | 9903 | -1.0E-04 | | 0.99995 | 0.010048349 | -1.3486 | No Reject |
| 81 | 0.003041 | 9097 | -1.1E-04 | | 0.99995 | 0.010484001 | 0.3005 | No Reject |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 82 | 0.003357 | 8754 | -1.1E-04 | 0.99994 | 0.010687397 | 0.3248 | No Reject |
| 83 | -0.000399 | 8585 | -1.2E-04 | 0.99994 | 0.010792066 | -0.0262 | No Reject |
| 84 | 0.017771 | 8151 | -1.2E-04 | 0.99994 | 0.011075617 | 1.6156 | No Reject |
| 85 | 0.00427 | 7868 | -1.3E-04 | 0.99994 | 0.01127302 | 0.3901 | No Reject |
| 86 | 0.004513 | 7739 | -1.3E-04 | 0.99994 | 0.011366573 | 0.4084 | No Reject |
| 87 | 0.003986 | 7418 | -1.3E-04 | 0.99993 | 0.01160987 | 0.3549 | No Reject |
| 88 | 0.011322 | 7234 | -1.4E-04 | 0.99993 | 0.011756574 | 0.9748 | No Reject |
| 89 | 0.014655 | 7049 | -1.4E-04 | 0.99993 | 0.011909828 | 1.2424 | No Reject |
| 90 | 0.006564 | 6739 | -1.5E-04 | 0.99993 | 0.01218064 | 0.5511 | No Reject |
| 91 | 0.005793 | 6335 | -1.6E-04 | 0.99992 | 0.012562974 | 0.4737 | No Reject |
| 92 | 0.008206 | 5699 | -1.8E-04 | 0.99991 | 0.013245325 | 0.6328 | No Reject |
| 93 | -0.008069 | 5761 | -1.7E-04 | 0.99991 | 0.013173872 | -0.5993 | No Reject |
| **94** | **0.027661** | **5121** | **-2.0E-04** | **0.99990** | **0.013972698** | **1.9936** | **Reject Null** |
| 95 | 0.007953 | 4981 | -2.0E-04 | 0.99990 | 0.014167663 | 0.5755 | No Reject |
| 96 | 0.007189 | 4796 | -2.1E-04 | 0.99990 | 0.014438272 | 0.5124 | No Reject |
| 97 | -0.020655 | 4534 | -2.2E-04 | 0.99989 | 0.014849487 | -1.3761 | No Reject |
| 98 | -0.019239 | 4320 | -2.3E-04 | 0.99988 | 0.015212759 | -1.2494 | No Reject |
| 99 | 0.008908 | 4256 | -2.4E-04 | 0.99988 | 0.015326687 | 0.5965 | No Reject |
| 100 | 0.015055 | 3996 | -2.5E-04 | 0.99988 | 0.015817325 | 0.9676 | No Reject |
| 101 | 0.003635 | 3797 | -2.6E-04 | 0.99987 | 0.016226418 | 0.2403 | No Reject |
| 102 | -0.020801 | 3422 | -2.9E-04 | 0.99985 | 0.017092151 | -1.1999 | No Reject |
| 103 | -0.009434 | 3164 | -3.2E-04 | 0.99984 | 0.017775153 | -0.5130 | No Reject |
| 104 | -0.022557 | 3008 | -3.3E-04 | 0.99983 | 0.018230103 | -1.2191 | No Reject |
| 105 | -0.004237 | 2704 | -3.7E-04 | 0.99982 | 0.019227226 | -0.2011 | No Reject |
| 106 | 0.003536 | 2548 | -3.9E-04 | 0.99980 | 0.019806849 | 0.1983 | No Reject |
| 107 | 0.018668 | 2223 | -4.5E-04 | 0.99978 | 0.021204743 | 0.9016 | No Reject |
| 108 | -0.007999 | 2047 | -4.9E-04 | 0.99976 | 0.022097111 | -0.3399 | No Reject |
| 109 | -0.011169 | 1810 | -5.5E-04 | 0.99973 | 0.023498567 | -0.4518 | No Reject |
| 110 | -0.012357 | 1589 | -6.3E-04 | 0.99969 | 0.025078538 | -0.4676 | No Reject |
| 111 | 0.00247 | 1464 | -6.8E-04 | 0.99966 | 0.026126552 | 0.1207 | No Reject |
| **112** | **-0.064208** | **1257** | **-8.0E-04** | **0.99961** | **0.028194274** | **-2.2491** | **Reject Null** |
| 113 | 0.019601 | 1112 | -9.0E-04 | 0.99955 | 0.029974642 | 0.6839 | No Reject |
| 114 | 0.032819 | 1020 | -9.8E-04 | 0.99951 | 0.031296013 | 1.0800 | No Reject |
| 115 | -0.012843 | 820 | -1.2E-03 | 0.99940 | 0.034900474 | -0.3330 | No Reject |
| **116** | **-0.074235** | **686** | **-1.5E-03** | **0.99928** | **0.038152745** | **-1.9075** | **Reject Null** |
| 117 | -0.012073 | 621 | -1.6E-03 | 0.99921 | 0.040096816 | -0.2609 | No Reject |
| 118 | -0.003 | 492 | -2.0E-03 | 0.99900 | 0.045038574 | -0.0214 | No Reject |
| **119** | **-0.142692** | **445** | **-2.3E-03** | **0.99890** | **0.047352451** | **-2.9658** | **Reject Null** |
| 120 | -0.025001 | 351 | -2.9E-03 | 0.99862 | 0.053302131 | -0.4154 | No Reject |
| **121** | **0.104749** | **336** | **-3.0E-03** | **0.99856** | **0.054475649** | **1.9777** | **Reject Null** |
| 122 | 0.080309 | 323 | -3.1E-03 | 0.99850 | 0.055557959 | 1.5014 | No Reject |
| **123** | **-0.183431** | **227** | **-4.4E-03** | **0.99789** | **0.066232427** | **-2.7027** | **Reject Null** |
| 124 | -0.121673 | 160 | -6.3E-03 | 0.99707 | 0.07882498 | -1.4638 | No Reject |
| 125 | 0.07798 | 121 | -8.3E-03 | 0.99620 | 0.0905638 | 0.9531 | No Reject |
| 126 | -0.093424 | 73 | -1.4E-02 | 0.99407 | 0.116347123 | -0.6836 | No Reject |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 127 | 0.122192 | 50 | -2.0E-02 | | 0.99196 | 0.140284967 | 1.0165 | No Reject |
| 128 | -0.017457 | 36 | -2.9E-02 | | 0.98991 | 0.164985082 | 0.0674 | No Reject |
| 129 | 0.084539 | 32 | -3.2E-02 | | 0.98919 | 0.17486554 | 0.6679 | No Reject |
| 130 | -0.115275 | 26 | -4.0E-02 | | 0.98808 | 0.193777856 | -0.3885 | No Reject |
| 131 | 0.106116 | 18 | -5.9E-02 | | 0.98754 | 0.232765046 | 0.7086 | No Reject |
| 132 | -0.000362 | 15 | -7.1E-02 | | 0.98878 | 0.255300943 | 0.2784 | No Reject |
| 133 | -0.067886 | 6 | -2.0E-01 | | 1.05560 | 0.430945804 | 0.3066 | No Reject |
| 134 | 0.326682 | 3 | -5.0E-01 | | 1.36931 | 0.790569415 | 1.0457 | No Reject |
| 135 | -0.277577 | 2 | -1.0E+00 | | 1.91485 | 1.354006401 | 0.5335 | No Reject |

# APPENDIX G

## 1995 MORAN'S I

| Lag | Moran's I | pairs (n) | E(I) | SD | s.e. | Z score | Hypothesis Test |
|---|---|---|---|---|---|---|---|
| **1** | **0.065807** | **1448** | **-6.9E-04** | **0.9997** | **0.02627** | **2.531** | **Reject Null** |
| **2** | **0.041966** | **3937** | **-2.5E-04** | **0.9999** | **0.015935** | **2.649** | **Reject Null** |
| **3** | **0.046781** | **5352** | **-1.9E-04** | **0.9999** | **0.013668** | **3.436** | **Reject Null** |
| 4 | -0.00632 | 6969 | -1.4E-04 | 0.9999 | 0.011978 | -0.515 | No Reject |
| 5 | 0.003711 | 8558 | -1.2E-04 | 0.9999 | 0.010809 | 0.354 | No Reject |
| 6 | 0.007416 | 9523 | -1.1E-04 | 0.9999 | 0.010247 | 0.734 | No Reject |
| 7 | -0.00472 | 10585 | -9.4E-05 | 1.0000 | 0.009719 | -0.476 | No Reject |
| 8 | -0.00342 | 11693 | -8.6E-05 | 1.0000 | 0.009247 | -0.361 | No Reject |
| 9 | 0.00226 | 12450 | -8.0E-05 | 1.0000 | 0.008962 | 0.261 | No Reject |
| 10 | -0.01156 | 13657 | -7.3E-05 | 1.0000 | 0.008557 | -1.343 | No Reject |
| 11 | -0.01187 | 14307 | -7.0E-05 | 1.0000 | 0.00836 | -1.411 | No Reject |
| 12 | -0.0069 | 15163 | -6.6E-05 | 1.0000 | 0.008121 | -0.841 | No Reject |
| **13** | **-0.01746** | **15671** | **-6.4E-05** | **1.0000** | **0.007988** | **-2.178** | **Reject Null** |
| 14 | -0.00505 | 16215 | -6.2E-05 | 1.0000 | 0.007853 | -0.635 | No Reject |
| 15 | -0.01051 | 17687 | -5.7E-05 | 1.0000 | 0.007519 | -1.390 | No Reject |
| 16 | 0.011078 | 17875 | -5.6E-05 | 1.0000 | 0.007479 | 1.489 | No Reject |
| 17 | 0.010225 | 19019 | -5.3E-05 | 1.0000 | 0.007251 | 1.417 | No Reject |
| 18 | -0.0031 | 18967 | -5.3E-05 | 1.0000 | 0.007261 | -0.420 | No Reject |
| 19 | 0.001367 | 19747 | -5.1E-05 | 1.0000 | 0.007116 | 0.199 | No Reject |
| 20 | 0.011271 | 20461 | -4.9E-05 | 1.0000 | 0.006991 | 1.619 | No Reject |
| 21 | -0.00211 | 20957 | -4.8E-05 | 1.0000 | 0.006908 | -0.298 | No Reject |
| 22 | 0.000956 | 21343 | -4.7E-05 | 1.0000 | 0.006845 | 0.147 | No Reject |
| 23 | -0.00794 | 21944 | -4.6E-05 | 1.0000 | 0.00675 | -1.169 | No Reject |
| 24 | -0.00213 | 22695 | -4.4E-05 | 1.0000 | 0.006638 | -0.315 | No Reject |
| 25 | 0.00421 | 24060 | -4.2E-05 | 1.0000 | 0.006447 | 0.659 | No Reject |
| 26 | -0.00582 | 24643 | -4.1E-05 | 1.0000 | 0.00637 | -0.907 | No Reject |
| 27 | -0.00711 | 25039 | -4.0E-05 | 1.0000 | 0.00632 | -1.118 | No Reject |
| 28 | -0.0055 | 25815 | -3.9E-05 | 1.0000 | 0.006224 | -0.877 | No Reject |
| 29 | -0.0037 | 26215 | -3.8E-05 | 1.0000 | 0.006176 | -0.592 | No Reject |
| 30 | 0.002041 | 26792 | -3.7E-05 | 1.0000 | 0.006109 | 0.340 | No Reject |
| 31 | -0.00551 | 26984 | -3.7E-05 | 1.0000 | 0.006087 | -0.899 | No Reject |
| 32 | 0.003483 | 27215 | -3.7E-05 | 1.0000 | 0.006062 | 0.581 | No Reject |
| 33 | 0.00045 | 27386 | -3.7E-05 | 1.0000 | 0.006043 | 0.081 | No Reject |
| 34 | 0.004205 | 27957 | -3.6E-05 | 1.0000 | 0.005981 | 0.709 | No Reject |
| 35 | -0.00434 | 28119 | -3.6E-05 | 1.0000 | 0.005963 | -0.722 | No Reject |
| **36** | **-0.01186** | **27969** | **-3.6E-05** | **1.0000** | **0.005979** | **-1.977** | **Reject Null** |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 37 | 0.00882 | 28251 | -3.5E-05 | 1.0000 | 0.005949 | 1.488 | No Reject |
| 38 | 0.00093 | 28234 | -3.5E-05 | 1.0000 | 0.005951 | 0.162 | No Reject |
| **39** | **0.009986** | **28335** | **-3.5E-05** | **1.0000** | **0.005941** | **1.687** | **Reject Null** |
| 40 | 0.005255 | 28096 | -3.6E-05 | 1.0000 | 0.005966 | 0.887 | No Reject |
| 41 | -0.00151 | 28208 | -3.5E-05 | 1.0000 | 0.005954 | -0.248 | No Reject |
| 42 | 0.005184 | 27847 | -3.6E-05 | 1.0000 | 0.005992 | 0.871 | No Reject |
| 43 | -0.0073 | 26700 | -3.7E-05 | 1.0000 | 0.00612 | -1.186 | No Reject |
| 44 | -0.00508 | 26349 | -3.8E-05 | 1.0000 | 0.00616 | -0.818 | No Reject |
| 45 | -0.00245 | 25695 | -3.9E-05 | 1.0000 | 0.006238 | -0.386 | No Reject |
| 46 | 0.004651 | 25349 | -3.9E-05 | 1.0000 | 0.006281 | 0.747 | No Reject |
| **47** | **-0.01347** | **24849** | **-4.0E-05** | **1.0000** | **0.006344** | **-2.117** | **Reject Null** |
| 48 | 0.002747 | 24828 | -4.0E-05 | 1.0000 | 0.006346 | 0.439 | No Reject |
| 49 | 0.00037 | 24262 | -4.1E-05 | 1.0000 | 0.00642 | 0.064 | No Reject |
| **50** | **0.014049** | **23673** | **-4.2E-05** | **1.0000** | **0.006499** | **2.168** | **Reject Null** |
| **51** | **0.013965** | **22775** | **-4.4E-05** | **1.0000** | **0.006626** | **2.114** | **Reject Null** |
| 52 | 0.002025 | 22479 | -4.4E-05 | 1.0000 | 0.00667 | 0.310 | No Reject |
| 53 | 0.005229 | 21925 | -4.6E-05 | 1.0000 | 0.006753 | 0.781 | No Reject |
| 54 | -0.00158 | 21494 | -4.7E-05 | 1.0000 | 0.006821 | -0.224 | No Reject |
| 55 | -0.0033 | 21325 | -4.7E-05 | 1.0000 | 0.006848 | -0.474 | No Reject |
| 56 | -0.00548 | 21131 | -4.7E-05 | 1.0000 | 0.006879 | -0.790 | No Reject |
| 57 | -0.00044 | 20987 | -4.8E-05 | 1.0000 | 0.006903 | -0.056 | No Reject |
| **58** | **-0.01636** | **20545** | **-4.9E-05** | **1.0000** | **0.006976** | **-2.337** | **Reject Null** |
| 59 | -0.00507 | 20628 | -4.8E-05 | 1.0000 | 0.006962 | -0.721 | No Reject |
| 60 | -0.00949 | 19846 | -5.0E-05 | 1.0000 | 0.007098 | -1.330 | No Reject |
| 61 | -0.00386 | 19285 | -5.2E-05 | 1.0000 | 0.007201 | -0.528 | No Reject |
| 62 | 0.003877 | 19042 | -5.3E-05 | 1.0000 | 0.007247 | 0.542 | No Reject |
| 63 | -0.00571 | 18513 | -5.4E-05 | 1.0000 | 0.007349 | -0.770 | No Reject |
| 64 | 0.00341 | 18340 | -5.5E-05 | 1.0000 | 0.007384 | 0.469 | No Reject |
| 65 | -0.00296 | 17526 | -5.7E-05 | 1.0000 | 0.007553 | -0.385 | No Reject |
| 66 | 0.000761 | 16966 | -5.9E-05 | 1.0000 | 0.007677 | 0.107 | No Reject |
| 67 | 0.007216 | 16300 | -6.1E-05 | 1.0000 | 0.007832 | 0.929 | No Reject |
| **68** | **0.01432** | **15765** | **-6.3E-05** | **1.0000** | **0.007964** | **1.806** | **Reject Null** |
| 69 | 0.008208 | 15454 | -6.5E-05 | 1.0000 | 0.008044 | 1.028 | No Reject |
| **70** | **0.015479** | **14891** | **-6.7E-05** | **1.0000** | **0.008195** | **1.897** | **Reject Null** |
| 71 | -0.00573 | 14501 | -6.9E-05 | 1.0000 | 0.008304 | -0.681 | No Reject |
| 72 | -0.00925 | 13290 | -7.5E-05 | 1.0000 | 0.008674 | -1.058 | No Reject |
| 73 | -0.00285 | 13313 | -7.5E-05 | 1.0000 | 0.008667 | -0.321 | No Reject |
| 74 | -0.00961 | 12707 | -7.9E-05 | 1.0000 | 0.008871 | -1.075 | No Reject |
| 75 | -0.00114 | 12100 | -8.3E-05 | 1.0000 | 0.009091 | -0.116 | No Reject |
| 76 | -0.00283 | 11420 | -8.8E-05 | 1.0000 | 0.009357 | -0.293 | No Reject |
| 77 | -0.00559 | 10892 | -9.2E-05 | 1.0000 | 0.009581 | -0.573 | No Reject |
| 78 | -0.00225 | 10681 | -9.4E-05 | 1.0000 | 0.009676 | -0.223 | No Reject |
| 79 | 0.000754 | 10261 | -9.7E-05 | 1.0000 | 0.009872 | 0.086 | No Reject |
| 80 | 0.008261 | 10088 | -9.9E-05 | 1.0000 | 0.009956 | 0.840 | No Reject |
| 81 | -0.00369 | 9477 | -1.1E-04 | 0.9999 | 0.010272 | -0.349 | No Reject |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 82 | 0.012732 | 9119 | -1.1E-04 | 0.9999 | 0.010471 | 1.226 | No Reject |
| 83 | -0.01212 | 8922 | -1.1E-04 | 0.9999 | 0.010586 | -1.135 | No Reject |
| 84 | -0.00459 | 8413 | -1.2E-04 | 0.9999 | 0.010902 | -0.410 | No Reject |
| 85 | 0.002212 | 7906 | -1.3E-04 | 0.9999 | 0.011246 | 0.208 | No Reject |
| 86 | -0.00414 | 7551 | -1.3E-04 | 0.9999 | 0.011507 | -0.348 | No Reject |
| 87 | -0.00142 | 7341 | -1.4E-04 | 0.9999 | 0.011671 | -0.110 | No Reject |
| 88 | -0.01398 | 7087 | -1.4E-04 | 0.9999 | 0.011878 | -1.165 | No Reject |
| 89 | -0.00172 | 6512 | -1.5E-04 | 0.9999 | 0.012391 | -0.126 | No Reject |
| 90 | -0.0111 | 6106 | -1.6E-04 | 0.9999 | 0.012796 | -0.855 | No Reject |
| 91 | -0.00147 | 5739 | -1.7E-04 | 0.9999 | 0.013199 | -0.098 | No Reject |
| 92 | -0.01822 | 5180 | -1.9E-04 | 0.9999 | 0.013893 | -1.297 | No Reject |
| **93** | **-0.02537** | **4842** | **-2.1E-04** | **0.9999** | **0.01437** | **-1.751** | **Reject Null** |
| 94 | -0.00518 | 4448 | -2.2E-04 | 0.9999 | 0.014992 | -0.330 | No Reject |
| 95 | 0.000583 | 4239 | -2.4E-04 | 0.9999 | 0.015357 | 0.053 | No Reject |
| 96 | 0.006334 | 3907 | -2.6E-04 | 0.9999 | 0.015996 | 0.412 | No Reject |
| 97 | -0.01572 | 3649 | -2.7E-04 | 0.9999 | 0.016552 | -0.933 | No Reject |
| 98 | 0.005103 | 3377 | -3.0E-04 | 0.9999 | 0.017206 | 0.314 | No Reject |
| **99** | **0.029529** | **3195** | **-3.1E-04** | **0.9998** | **0.017689** | **1.687** | **Reject Null** |
| 100 | 0.000247 | 2955 | -3.4E-04 | 0.9998 | 0.018393 | 0.032 | No Reject |
| 101 | -0.01231 | 2615 | -3.8E-04 | 0.9998 | 0.019552 | -0.610 | No Reject |
| 102 | -0.00117 | 2441 | -4.1E-04 | 0.9998 | 0.020236 | -0.037 | No Reject |
| 103 | -0.00188 | 2320 | -4.3E-04 | 0.9998 | 0.020757 | -0.070 | No Reject |
| 104 | -0.00106 | 2107 | -4.7E-04 | 0.9998 | 0.02178 | -0.027 | No Reject |
| 105 | -0.01923 | 1855 | -5.4E-04 | 0.9997 | 0.023212 | -0.805 | No Reject |
| 106 | 0.028018 | 1769 | -5.7E-04 | 0.9997 | 0.023769 | 1.203 | No Reject |
| 107 | -0.00173 | 1421 | -7.0E-04 | 0.9997 | 0.026519 | -0.039 | No Reject |
| 108 | 0.006468 | 1176 | -8.5E-04 | 0.9996 | 0.029148 | 0.251 | No Reject |
| 109 | -0.02159 | 916 | -1.1E-03 | 0.9995 | 0.033023 | -0.621 | No Reject |
| 110 | 0.021869 | 842 | -1.2E-03 | 0.9994 | 0.034442 | 0.669 | No Reject |
| 111 | 0.00394 | 745 | -1.3E-03 | 0.9993 | 0.036613 | 0.144 | No Reject |
| 112 | -0.00765 | 611 | -1.6E-03 | 0.9992 | 0.040423 | -0.149 | No Reject |
| 113 | -0.03677 | 546 | -1.8E-03 | 0.9991 | 0.042758 | -0.817 | No Reject |
| 114 | -0.02401 | 523 | -1.9E-03 | 0.9991 | 0.043686 | -0.506 | No Reject |
| 115 | -0.06356 | 548 | -1.8E-03 | 0.9991 | 0.04268 | -1.446 | No Reject |
| 116 | -0.00715 | 445 | -2.3E-03 | 0.9989 | 0.047352 | -0.104 | No Reject |
| 117 | 0.017908 | 421 | -2.4E-03 | 0.9988 | 0.04868 | 0.417 | No Reject |
| 118 | 0.045792 | 406 | -2.5E-03 | 0.9988 | 0.04957 | 0.974 | No Reject |
| 119 | 0.063189 | 323 | -3.1E-03 | 0.9985 | 0.055558 | 1.193 | No Reject |
| 120 | -0.00833 | 229 | -4.4E-03 | 0.9979 | 0.065944 | -0.060 | No Reject |
| 121 | -0.00243 | 201 | -5.0E-03 | 0.9976 | 0.070368 | 0.037 | No Reject |
| 122 | 0.027186 | 170 | -5.9E-03 | 0.9972 | 0.076484 | 0.433 | No Reject |
| 123 | 0.0668 | 122 | -8.3E-03 | 0.9962 | 0.090194 | 0.832 | No Reject |
| 124 | 0.053125 | 144 | -7.0E-03 | 0.9968 | 0.083064 | 0.724 | No Reject |
| 125 | 0.031776 | 97 | -1.0E-02 | 0.9954 | 0.101064 | 0.417 | No Reject |
| 126 | -0.01406 | 58 | -1.8E-02 | 0.9928 | 0.130366 | 0.027 | No Reject |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 127 | 0.031879 | 24 | -4.3E-02 | 0.9878 | 0.201624 | 0.374 | No Reject |
| 128 | -0.13606 | 24 | -4.3E-02 | 0.9878 | 0.201624 | -0.459 | No Reject |
| 129 | 0.243041 | 22 | -4.8E-02 | 0.9875 | 0.210536 | 1.381 | No Reject |
| 130 | 0.072382 | 11 | -1.0E-01 | 0.9958 | 0.300252 | 0.574 | No Reject |
| 131 | 0.176853 | 11 | -1.0E-01 | 0.9958 | 0.300252 | 0.922 | No Reject |
| 132 | 0.224948 | 11 | -1.0E-01 | 0.9958 | 0.300252 | 1.082 | No Reject |
| 133 | -0.71575 | 1 | #DIV/0! | #DIV/0 | #DIV/0! | #DIV/0! | No Reject |
| 134 | 0.0483 | 9 | -1.3E-01 | 1.0062 | 0.33541 | 0.517 | No Reject |
| 135 | -0.13056 | 2 | -1.0E+00 | 1.9149 | 1.354006 | 0.642 | No Reject |

## APPENDIX H

1996 MORAN'S I

| Lag | Moran's I | Pairs (n) | E(I) | SD | s.e. | Z score | Hypothesis Test |
|---|---|---|---|---|---|---|---|
| **1** | **0.092965** | **1954** | **-5.1E-04** | **0.9997** | **0.022617** | **4.133** | **Reject Null** |
| **2** | **0.061403** | **4922** | **-2.0E-04** | **0.9999** | **0.014252** | **4.323** | **Reject Null** |
| **3** | **0.03803** | **7022** | **-1.4E-04** | **0.9999** | **0.011933** | **3.199** | **Reject Null** |
| 4 | 0.005044 | 8773 | -1.1E-04 | 0.9999 | 0.010676 | 0.483 | No Reject |
| 5 | -0.00925 | 10401 | -9.6E-05 | 1.0000 | 0.009805 | -0.934 | No Reject |
| **6** | **0.031717** | **11630** | **-8.6E-05** | **1.0000** | **0.009272** | **3.430** | **Reject Null** |
| **7** | **0.02418** | **13097** | **-7.6E-05** | **1.0000** | **0.008738** | **2.776** | **Reject Null** |
| 8 | 0.013048 | 13986 | -7.2E-05 | 1.0000 | 0.008455 | 1.552 | No Reject |
| 9 | 0.009387 | 14790 | -6.8E-05 | 1.0000 | 0.008222 | 1.150 | No Reject |
| 10 | -0.00454 | 15723 | -6.4E-05 | 1.0000 | 0.007975 | -0.561 | No Reject |
| **11** | **0.014652** | **16573** | **-6.0E-05** | **1.0000** | **0.007768** | **1.894** | **Reject Null** |
| 12 | 0.005036 | 17841 | -5.6E-05 | 1.0000 | 0.007486 | 0.680 | No Reject |
| **13** | **0.014317** | **18732** | **-5.3E-05** | **1.0000** | **0.007306** | **1.967** | **Reject Null** |
| 14 | -0.00358 | 19235 | -5.2E-05 | 1.0000 | 0.00721 | -0.489 | No Reject |
| 15 | -0.00163 | 20334 | -4.9E-05 | 1.0000 | 0.007013 | -0.226 | No Reject |
| 16 | 0.009959 | 21418 | -4.7E-05 | 1.0000 | 0.006833 | 1.464 | No Reject |
| 17 | -0.00601 | 22408 | -4.5E-05 | 1.0000 | 0.00668 | -0.893 | No Reject |
| 18 | -0.00467 | 23069 | -4.3E-05 | 1.0000 | 0.006584 | -0.702 | No Reject |
| 19 | -0.00634 | 23738 | -4.2E-05 | 1.0000 | 0.00649 | -0.970 | No Reject |
| 20 | 0.002392 | 24824 | -4.0E-05 | 1.0000 | 0.006347 | 0.383 | No Reject |
| 21 | 0.001356 | 25087 | -4.0E-05 | 1.0000 | 0.006313 | 0.221 | No Reject |
| 22 | -0.00497 | 26295 | -3.8E-05 | 1.0000 | 0.006167 | -0.799 | No Reject |
| 23 | -0.00072 | 26639 | -3.8E-05 | 1.0000 | 0.006127 | -0.112 | No Reject |
| **24** | **-0.01412** | **27115** | **-3.7E-05** | **1.0000** | **0.006073** | **-2.319** | **Reject Null** |
| 25 | -0.00642 | 28065 | -3.6E-05 | 1.0000 | 0.005969 | -1.070 | No Reject |
| **26** | **-0.01104** | **28608** | **-3.5E-05** | **1.0000** | **0.005912** | **-1.861** | **Reject Null** |
| **27** | **0.010427** | **29526** | **-3.4E-05** | **1.0000** | **0.00582** | **1.798** | **Reject Null** |
| 28 | 0.000384 | 30010 | -3.3E-05 | 1.0000 | 0.005772 | 0.072 | No Reject |
| 29 | 0.000748 | 31189 | -3.2E-05 | 1.0000 | 0.005662 | 0.138 | No Reject |
| **30** | **-0.02257** | **31460** | **-3.2E-05** | **1.0000** | **0.005638** | **-3.998** | **Reject Null** |
| 31 | -0.00312 | 32673 | -3.1E-05 | 1.0000 | 0.005532 | -0.559 | No Reject |
| 32 | -0.00763 | 32618 | -3.1E-05 | 1.0000 | 0.005537 | -1.372 | No Reject |
| **33** | **-0.00965** | **32900** | **-3.0E-05** | **1.0000** | **0.005513** | **-1.745** | **Reject Null** |
| 34 | -0.00237 | 33596 | -3.0E-05 | 1.0000 | 0.005456 | -0.430 | No Reject |
| 35 | -0.00554 | 34274 | -2.9E-05 | 1.0000 | 0.005401 | -1.020 | No Reject |
| 36 | -0.00301 | 33877 | -3.0E-05 | 1.0000 | 0.005433 | -0.549 | No Reject |
| 37 | -0.00742 | 33713 | -3.0E-05 | 1.0000 | 0.005446 | -1.358 | No Reject |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 38 | 0.003065 | 33472 | -3.0E-05 | 1.0000 | 0.005466 | 0.566 | No Reject |
| 39 | -0.0083 | 33785 | -3.0E-05 | 1.0000 | 0.00544 | -1.519 | No Reject |
| 40 | 0.005786 | 33581 | -3.0E-05 | 1.0000 | 0.005457 | 1.066 | No Reject |
| **41** | **-0.00939** | **33972** | **-2.9E-05** | **1.0000** | **0.005425** | **-1.725** | **Reject Null** |
| 42 | -0.00558 | 33758 | -3.0E-05 | 1.0000 | 0.005443 | -1.019 | No Reject |
| 43 | -0.00659 | 33762 | -3.0E-05 | 1.0000 | 0.005442 | -1.206 | No Reject |
| 44 | -0.00868 | 33712 | -3.0E-05 | 1.0000 | 0.005446 | -1.589 | No Reject |
| **45** | **0.013164** | **33266** | **-3.0E-05** | **1.0000** | **0.005483** | **2.406** | **Reject Null** |
| 46 | -0.00429 | 33247 | -3.0E-05 | 1.0000 | 0.005484 | -0.777 | No Reject |
| **47** | **-0.01049** | **32836** | **-3.0E-05** | **1.0000** | **0.005518** | **-1.895** | **Reject Null** |
| **48** | **-0.01093** | **31596** | **-3.2E-05** | **1.0000** | **0.005626** | **-1.938** | **Reject Null** |
| 49 | 0.008212 | 30982 | -3.2E-05 | 1.0000 | 0.005681 | 1.451 | No Reject |
| **50** | **-0.01107** | **30001** | **-3.3E-05** | **1.0000** | **0.005773** | **-1.912** | **Reject Null** |
| **51** | **-0.01277** | **29319** | **-3.4E-05** | **1.0000** | **0.00584** | **-2.181** | **Reject Null** |
| **52** | **-0.01896** | **28262** | **-3.5E-05** | **1.0000** | **0.005948** | **-3.182** | **Reject Null** |
| 53 | -0.00213 | 27984 | -3.6E-05 | 1.0000 | 0.005978 | -0.350 | No Reject |
| 54 | -0.00433 | 27379 | -3.7E-05 | 1.0000 | 0.006043 | -0.710 | No Reject |
| 55 | 0.001988 | 27094 | -3.7E-05 | 1.0000 | 0.006075 | 0.333 | No Reject |
| 56 | -0.00265 | 27207 | -3.7E-05 | 1.0000 | 0.006062 | -0.432 | No Reject |
| **57** | **0.011625** | **26516** | **-3.8E-05** | **1.0000** | **0.006141** | **1.899** | **Reject Null** |
| 58 | 0.009968 | 25926 | -3.9E-05 | 1.0000 | 0.00621 | 1.611 | No Reject |
| **59** | **0.014226** | **25443** | **-3.9E-05** | **1.0000** | **0.006269** | **2.275** | **Reject Null** |
| **60** | **0.016168** | **25116** | **-4.0E-05** | **1.0000** | **0.00631** | **2.569** | **Reject Null** |
| 61 | 0.007464 | 24434 | -4.1E-05 | 1.0000 | 0.006397 | 1.173 | No Reject |
| **62** | **0.021142** | **23872** | **-4.2E-05** | **1.0000** | **0.006472** | **3.273** | **Reject Null** |
| 63 | 0.010032 | 23266 | -4.3E-05 | 1.0000 | 0.006556 | 1.537 | No Reject |
| **64** | **0.017329** | **22762** | **-4.4E-05** | **1.0000** | **0.006628** | **2.621** | **Reject Null** |
| **65** | **0.019716** | **21785** | **-4.6E-05** | **1.0000** | **0.006775** | **2.917** | **Reject Null** |
| 66 | 0.007459 | 21305 | -4.7E-05 | 1.0000 | 0.006851 | 1.096 | No Reject |
| **67** | **0.02376** | **21242** | **-4.7E-05** | **1.0000** | **0.006861** | **3.470** | **Reject Null** |
| **68** | **0.013156** | **20960** | **-4.8E-05** | **1.0000** | **0.006907** | **1.912** | **Reject Null** |
| **69** | **0.011774** | **20393** | **-4.9E-05** | **1.0000** | **0.007002** | **1.688** | **Reject Null** |
| **70** | **0.012056** | **19760** | **-5.1E-05** | **1.0000** | **0.007114** | **1.702** | **Reject Null** |
| 71 | 0.005253 | 19073 | -5.2E-05 | 1.0000 | 0.007241 | 0.733 | No Reject |
| 72 | -0.00331 | 18365 | -5.4E-05 | 1.0000 | 0.007379 | -0.441 | No Reject |
| 73 | 0.003498 | 17827 | -5.6E-05 | 1.0000 | 0.007489 | 0.475 | No Reject |
| 74 | 0.007754 | 16776 | -6.0E-05 | 1.0000 | 0.00772 | 1.012 | No Reject |
| 75 | 0.008128 | 16169 | -6.2E-05 | 1.0000 | 0.007864 | 1.041 | No Reject |
| 76 | -0.00187 | 15634 | -6.4E-05 | 1.0000 | 0.007997 | -0.226 | No Reject |
| 77 | -0.01015 | 14941 | -6.7E-05 | 1.0000 | 0.008181 | -1.233 | No Reject |
| 78 | 0.002393 | 15090 | -6.6E-05 | 1.0000 | 0.00814 | 0.302 | No Reject |
| 79 | -0.00252 | 14316 | -7.0E-05 | 1.0000 | 0.008357 | -0.293 | No Reject |
| 80 | -0.00294 | 13940 | -7.2E-05 | 1.0000 | 0.008469 | -0.338 | No Reject |
| 81 | 0.001604 | 13579 | -7.4E-05 | 1.0000 | 0.008581 | 0.196 | No Reject |
| **82** | **-0.01965** | **12874** | **-7.8E-05** | **1.0000** | **0.008813** | **-2.221** | **Reject Null** |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 83 | -0.0074 | 12626 | -7.9E-05 | 1.0000 | 0.008899 | -0.822 | No Reject |
| 84 | -0.00885 | 12043 | -8.3E-05 | 1.0000 | 0.009112 | -0.963 | No Reject |
| **85** | **-0.0271** | **12086** | **-8.3E-05** | **1.0000** | **0.009096** | **-2.970** | **Reject Null** |
| **86** | **-0.02466** | **11621** | **-8.6E-05** | **1.0000** | **0.009276** | **-2.649** | **Reject Null** |
| **87** | **-0.02765** | **10953** | **-9.1E-05** | **1.0000** | **0.009555** | **-2.885** | **Reject Null** |
| **88** | **-0.04229** | **10627** | **-9.4E-05** | **1.0000** | **0.0097** | **-4.350** | **Reject Null** |
| **89** | **-0.02628** | **9673** | **-1.0E-04** | **0.9999** | **0.010167** | **-2.575** | **Reject Null** |
| **90** | **-0.04212** | **9295** | **-1.1E-04** | **0.9999** | **0.010372** | **-4.051** | **Reject Null** |
| **91** | **-0.0285** | **8685** | **-1.2E-04** | **0.9999** | **0.01073** | **-2.645** | **Reject Null** |
| **92** | **-0.02118** | **7858** | **-1.3E-04** | **0.9999** | **0.01128** | **-1.866** | **Reject Null** |
| **93** | **-0.02129** | **7517** | **-1.3E-04** | **0.9999** | **0.011533** | **-1.835** | **Reject Null** |
| **94** | **-0.02548** | **7066** | **-1.4E-04** | **0.9999** | **0.011895** | **-2.130** | **Reject Null** |
| **95** | **-0.03305** | **6407** | **-1.6E-04** | **0.9999** | **0.012492** | **-2.633** | **Reject Null** |
| 96 | -0.01913 | 6186 | -1.6E-04 | 0.9999 | 0.012713 | -1.492 | No Reject |
| 97 | -0.00486 | 5851 | -1.7E-04 | 0.9999 | 0.013072 | -0.358 | No Reject |
| 98 | -0.00172 | 5492 | -1.8E-04 | 0.9999 | 0.013493 | -0.114 | No Reject |
| 99 | 0.002477 | 5142 | -1.9E-04 | 0.9999 | 0.013944 | 0.192 | No Reject |
| 100 | 0.001268 | 4996 | -2.0E-04 | 0.9999 | 0.014146 | 0.104 | No Reject |
| 101 | 0.001101 | 4727 | -2.1E-04 | 0.9999 | 0.014543 | 0.090 | No Reject |
| 102 | 0.001538 | 4479 | -2.2E-04 | 0.9999 | 0.01494 | 0.118 | No Reject |
| 103 | 0.006406 | 4181 | -2.4E-04 | 0.9999 | 0.015464 | 0.430 | No Reject |
| 104 | 0.011375 | 3917 | -2.6E-04 | 0.9999 | 0.015976 | 0.728 | No Reject |
| 105 | 0.015433 | 3616 | -2.8E-04 | 0.9999 | 0.016627 | 0.945 | No Reject |
| 106 | 0.023872 | 3212 | -3.1E-04 | 0.9998 | 0.017642 | 1.371 | No Reject |
| **107** | **0.033281** | **2861** | **-3.5E-04** | **0.9998** | **0.018692** | **1.799** | **Reject Null** |
| 108 | 0.006826 | 2559 | -3.9E-04 | 0.9998 | 0.019764 | 0.365 | No Reject |
| 109 | 0.025714 | 2201 | -4.5E-04 | 0.9998 | 0.02131 | 1.228 | No Reject |
| 110 | 0.009923 | 1862 | -5.4E-04 | 0.9997 | 0.023168 | 0.451 | No Reject |
| **111** | **0.042587** | **1682** | **-5.9E-04** | **0.9997** | **0.024376** | **1.772** | **Reject Null** |
| **112** | **0.054363** | **1600** | **-6.3E-04** | **0.9997** | **0.024992** | **2.200** | **Reject Null** |
| **113** | **0.050044** | **1379** | **-7.3E-04** | **0.9996** | **0.026919** | **1.886** | **Reject Null** |
| **114** | **0.070634** | **1239** | **-8.1E-04** | **0.9996** | **0.028398** | **2.516** | **Reject Null** |
| **115** | **0.066531** | **1060** | **-9.4E-04** | **0.9995** | **0.0307** | **2.198** | **Reject Null** |
| **116** | **0.092052** | **871** | **-1.1E-03** | **0.9994** | **0.033864** | **2.752** | **Reject Null** |
| 117 | 0.049087 | 837 | -1.2E-03 | 0.9994 | 0.034545 | 1.456 | No Reject |
| **118** | **0.069078** | **728** | **-1.4E-03** | **0.9993** | **0.037037** | **1.902** | **Reject Null** |
| 119 | 0.048413 | 714 | -1.4E-03 | 0.9993 | 0.037398 | 1.332 | No Reject |
| 120 | 0.065772 | 554 | -1.8E-03 | 0.9991 | 0.042448 | 1.592 | No Reject |
| 121 | 0.044608 | 502 | -2.0E-03 | 0.9990 | 0.044589 | 1.045 | No Reject |
| **122** | **0.086935** | **384** | **-2.6E-03** | **0.9987** | **0.050966** | **1.757** | **Reject Null** |
| 123 | -0.00546 | 325 | -3.1E-03 | 0.9985 | 0.055387 | -0.043 | No Reject |
| **124** | **0.096965** | **280** | **-3.6E-03** | **0.9983** | **0.059658** | **1.685** | **Reject Null** |
| 125 | -0.04718 | 226 | -4.4E-03 | 0.9979 | 0.066378 | -0.644 | No Reject |
| 126 | 0.124838 | 139 | -7.2E-03 | 0.9967 | 0.084535 | 1.562 | No Reject |
| 127 | -0.15894 | 99 | -1.0E-02 | 0.9954 | 0.100046 | -1.487 | No Reject |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 128 | -0.00694 | 65 | -1.6E-02 | 0.9935 | 0.123225 | 0.070 | No Reject |
| 129 | -0.19716 | 29 | -3.6E-02 | 0.9886 | 0.183583 | -0.879 | No Reject |
| 130 | -0.08152 | 21 | -5.0E-02 | 0.9874 | 0.215473 | -0.146 | No Reject |
| 131 | -0.0121 | 22 | -4.8E-02 | 0.9875 | 0.210536 | 0.169 | No Reject |
| 132 | -0.10838 | 5 | -2.5E-01 | 1.0992 | 0.491596 | 0.288 | No Reject |
| 133 | 0.153176 | 11 | -1.0E-01 | 0.9958 | 0.300252 | 0.843 | No Reject |
| 134 | 0.18821 | 5 | -2.5E-01 | 1.0992 | 0.491596 | 0.891 | No Reject |

# APPENDIX I

1997 MORAN'S I

| Lag | Moran's I | Pairs (n) | E(I) | SD | s.e. | Z score | Hypothesis Test |
|---|---|---|---|---|---|---|---|
| 1 | 0.069013 | 1618 | -6.2E-04 | 0.9997 | 0.024853 | 2.802 | Reject Null |
| 2 | 0.076283 | 4037 | -2.5E-04 | 0.9999 | 0.015737 | 4.863 | Reject Null |
| 3 | 0.036198 | 5958 | -1.7E-04 | 0.9999 | 0.012954 | 2.807 | Reject Null |
| 4 | 0.056766 | 7436 | -1.3E-04 | 0.9999 | 0.011596 | 4.907 | Reject Null |
| 5 | 0.008137 | 8738 | -1.1E-04 | 0.9999 | 0.010697 | 0.771 | No Reject |
| 6 | -0.0104 | 10112 | -9.9E-05 | 1.0000 | 0.009944 | -1.036 | No Reject |
| 7 | 0.033149 | 11253 | -8.9E-05 | 1.0000 | 0.009426 | 3.526 | Reject Null |
| 8 | -0.00692 | 12300 | -8.1E-05 | 1.0000 | 0.009016 | -0.758 | No Reject |
| 9 | 0.00463 | 13084 | -7.6E-05 | 1.0000 | 0.008742 | 0.538 | No Reject |
| 10 | 0.016788 | 14006 | -7.1E-05 | 1.0000 | 0.008449 | 1.995 | Reject Null |
| 11 | -0.00171 | 14839 | -6.7E-05 | 1.0000 | 0.008209 | -0.200 | No Reject |
| 12 | 0.000413 | 15108 | -6.6E-05 | 1.0000 | 0.008135 | 0.059 | No Reject |
| 13 | 0.0011 | 15745 | -6.4E-05 | 1.0000 | 0.007969 | 0.146 | No Reject |
| 14 | -0.00202 | 16698 | -6.0E-05 | 1.0000 | 0.007738 | -0.253 | No Reject |
| 15 | -0.0003 | 17343 | -5.8E-05 | 1.0000 | 0.007593 | -0.031 | No Reject |
| 16 | -0.00094 | 18019 | -5.6E-05 | 1.0000 | 0.007449 | -0.119 | No Reject |
| 17 | -0.01893 | 19048 | -5.3E-05 | 1.0000 | 0.007245 | -2.606 | Reject Null |
| 18 | -0.00477 | 19251 | -5.2E-05 | 1.0000 | 0.007207 | -0.655 | No Reject |
| 19 | 0.004216 | 20168 | -5.0E-05 | 1.0000 | 0.007041 | 0.606 | No Reject |
| 20 | 0.008372 | 20998 | -4.8E-05 | 1.0000 | 0.006901 | 1.220 | No Reject |
| 21 | -0.00678 | 21168 | -4.7E-05 | 1.0000 | 0.006873 | -0.979 | No Reject |
| 22 | 0.009283 | 21744 | -4.6E-05 | 1.0000 | 0.006781 | 1.376 | No Reject |
| 23 | 0.004111 | 22338 | -4.5E-05 | 1.0000 | 0.006691 | 0.621 | No Reject |
| 24 | 0.000992 | 23036 | -4.3E-05 | 1.0000 | 0.006589 | 0.157 | No Reject |
| 25 | -0.00207 | 23782 | -4.2E-05 | 1.0000 | 0.006484 | -0.312 | No Reject |
| 26 | 0.007415 | 24641 | -4.1E-05 | 1.0000 | 0.00637 | 1.170 | No Reject |
| 27 | -0.01078 | 25623 | -3.9E-05 | 1.0000 | 0.006247 | -1.719 | Reject Null |
| 28 | -0.0099 | 26177 | -3.8E-05 | 1.0000 | 0.006181 | -1.595 | No Reject |
| 29 | -0.01575 | 26566 | -3.8E-05 | 1.0000 | 0.006135 | -2.562 | Reject Null |
| 30 | -0.01297 | 27529 | -3.6E-05 | 1.0000 | 0.006027 | -2.145 | Reject Null |
| 31 | -0.01433 | 27380 | -3.7E-05 | 1.0000 | 0.006043 | -2.365 | Reject Null |
| 32 | -0.01099 | 27941 | -3.6E-05 | 1.0000 | 0.005982 | -1.831 | Reject Null |
| 33 | -0.00061 | 28701 | -3.5E-05 | 1.0000 | 0.005903 | -0.097 | No Reject |
| 34 | 0.002767 | 28922 | -3.5E-05 | 1.0000 | 0.00588 | 0.476 | No Reject |
| 35 | -0.00818 | 29258 | -3.4E-05 | 1.0000 | 0.005846 | -1.394 | No Reject |
| 36 | -0.00854 | 29546 | -3.4E-05 | 1.0000 | 0.005818 | -1.462 | No Reject |
| 37 | -0.01315 | 29495 | -3.4E-05 | 1.0000 | 0.005823 | -2.252 | Reject Null |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 38 | -0.00229 | 29737 | -3.4E-05 | 1.0000 | 0.005799 | -0.389 | No Reject |
| **39** | **-0.01503** | **29441** | **-3.4E-05** | **1.0000** | **0.005828** | **-2.572** | **Reject Null** |
| 40 | 0.004089 | 29704 | -3.4E-05 | 1.0000 | 0.005802 | 0.711 | No Reject |
| 41 | 0.00434 | 29713 | -3.4E-05 | 1.0000 | 0.005801 | 0.754 | No Reject |
| 42 | -0.00331 | 29197 | -3.4E-05 | 1.0000 | 0.005852 | -0.559 | No Reject |
| 43 | -0.00823 | 29513 | -3.4E-05 | 1.0000 | 0.005821 | -1.408 | No Reject |
| 44 | -0.00565 | 28845 | -3.5E-05 | 1.0000 | 0.005888 | -0.954 | No Reject |
| 45 | 0.00143 | 28186 | -3.5E-05 | 1.0000 | 0.005956 | 0.246 | No Reject |
| 46 | 0.002473 | 27737 | -3.6E-05 | 1.0000 | 0.006004 | 0.418 | No Reject |
| 47 | 0.003722 | 26796 | -3.7E-05 | 1.0000 | 0.006109 | 0.615 | No Reject |
| **48** | **0.015114** | **26535** | **-3.8E-05** | **1.0000** | **0.006139** | **2.468** | **Reject Null** |
| 49 | -0.00836 | 26091 | -3.8E-05 | 1.0000 | 0.006191 | -1.343 | No Reject |
| 50 | 0.001174 | 25121 | -4.0E-05 | 1.0000 | 0.006309 | 0.192 | No Reject |
| **51** | **0.012661** | **24064** | **-4.2E-05** | **1.0000** | **0.006446** | **1.971** | **Reject Null** |
| **52** | **0.012** | **23623** | **-4.2E-05** | **1.0000** | **0.006506** | **1.851** | **Reject Null** |
| 53 | 0.000485 | 22939 | -4.4E-05 | 1.0000 | 0.006602 | 0.080 | No Reject |
| **54** | **0.015464** | **22530** | **-4.4E-05** | **1.0000** | **0.006662** | **2.328** | **Reject Null** |
| 55 | 0.006635 | 22223 | -4.5E-05 | 1.0000 | 0.006708 | 0.996 | No Reject |
| 56 | 0.006586 | 21869 | -4.6E-05 | 1.0000 | 0.006762 | 0.981 | No Reject |
| 57 | 0.0044 | 21363 | -4.7E-05 | 1.0000 | 0.006842 | 0.650 | No Reject |
| 58 | 0.00797 | 20415 | -4.9E-05 | 1.0000 | 0.006999 | 1.146 | No Reject |
| 59 | 0.008482 | 20379 | -4.9E-05 | 1.0000 | 0.007005 | 1.218 | No Reject |
| 60 | 0.00917 | 20039 | -5.0E-05 | 1.0000 | 0.007064 | 1.305 | No Reject |
| **61** | **0.016697** | **19500** | **-5.1E-05** | **1.0000** | **0.007161** | **2.339** | **Reject Null** |
| **62** | **0.012555** | **19288** | **-5.2E-05** | **1.0000** | **0.0072** | **1.751** | **Reject Null** |
| 63 | 0.001576 | 18949 | -5.3E-05 | 1.0000 | 0.007264 | 0.224 | No Reject |
| 64 | -0.00964 | 18743 | -5.3E-05 | 1.0000 | 0.007304 | -1.312 | No Reject |
| **65** | **-0.01541** | **17837** | **-5.6E-05** | **1.0000** | **0.007487** | **-2.050** | **Reject Null** |
| 66 | 0.006569 | 17552 | -5.7E-05 | 1.0000 | 0.007548 | 0.878 | No Reject |
| 67 | -0.00608 | 17286 | -5.8E-05 | 1.0000 | 0.007606 | -0.791 | No Reject |
| 68 | -0.00305 | 16435 | -6.1E-05 | 1.0000 | 0.0078 | -0.383 | No Reject |
| 69 | -0.01286 | 16257 | -6.2E-05 | 1.0000 | 0.007843 | -1.632 | No Reject |
| 70 | 0.001922 | 15472 | -6.5E-05 | 1.0000 | 0.008039 | 0.247 | No Reject |
| 71 | 0.004932 | 14933 | -6.7E-05 | 1.0000 | 0.008183 | 0.611 | No Reject |
| 72 | 0.01145 | 14247 | -7.0E-05 | 1.0000 | 0.008378 | 1.375 | No Reject |
| 73 | -0.00044 | 13994 | -7.1E-05 | 1.0000 | 0.008453 | -0.044 | No Reject |
| **74** | **-0.0144** | **13340** | **-7.5E-05** | **1.0000** | **0.008658** | **-1.655** | **Reject Null** |
| 75 | 0.001135 | 12929 | -7.7E-05 | 1.0000 | 0.008794 | 0.138 | No Reject |
| 76 | -0.00549 | 12353 | -8.1E-05 | 1.0000 | 0.008997 | -0.601 | No Reject |
| **77** | **-0.01893** | **11673** | **-8.6E-05** | **1.0000** | **0.009255** | **-2.036** | **Reject Null** |
| 78 | 0.006715 | 11333 | -8.8E-05 | 1.0000 | 0.009393 | 0.724 | No Reject |
| **79** | **-0.02119** | **10759** | **-9.3E-05** | **1.0000** | **0.00964** | **-2.188** | **Reject Null** |
| 80 | 0.002486 | 10228 | -9.8E-05 | 1.0000 | 0.009887 | 0.261 | No Reject |
| 81 | 0.00432 | 10302 | -9.7E-05 | 1.0000 | 0.009852 | 0.448 | No Reject |
| 82 | -0.01514 | 9649 | -1.0E-04 | 0.9999 | 0.01018 | -1.477 | No Reject |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 83 | 0.010556 | 9137 | -1.1E-04 | 0.9999 | 0.010461 | 1.020 | No Reject |
| **84** | **0.021661** | **8655** | **-1.2E-04** | **0.9999** | **0.010748** | **2.026** | **Reject Null** |
| 85 | 0.013212 | 8145 | -1.2E-04 | 0.9999 | 0.01108 | 1.204 | No Reject |
| 86 | 0.010267 | 7883 | -1.3E-04 | 0.9999 | 0.011262 | 0.923 | No Reject |
| 87 | 0.00597 | 7408 | -1.4E-04 | 0.9999 | 0.011618 | 0.525 | No Reject |
| 88 | -0.00254 | 7099 | -1.4E-04 | 0.9999 | 0.011868 | -0.202 | No Reject |
| **89** | **-0.03446** | **6692** | **-1.5E-04** | **0.9999** | **0.012223** | **-2.807** | **Reject Null** |
| 90 | -0.01272 | 6569 | -1.5E-04 | 0.9999 | 0.012337 | -1.019 | No Reject |
| 91 | -0.01365 | 6176 | -1.6E-04 | 0.9999 | 0.012724 | -1.060 | No Reject |
| 92 | -0.02012 | 5831 | -1.7E-04 | 0.9999 | 0.013095 | -1.523 | No Reject |
| 93 | -0.00392 | 5502 | -1.8E-04 | 0.9999 | 0.01348 | -0.277 | No Reject |
| 94 | -0.00398 | 5384 | -1.9E-04 | 0.9999 | 0.013627 | -0.279 | No Reject |
| 95 | 0.022597 | 4831 | -2.1E-04 | 0.9999 | 0.014386 | 1.585 | No Reject |
| 96 | -0.0161 | 4570 | -2.2E-04 | 0.9999 | 0.014791 | -1.074 | No Reject |
| 97 | 0.013369 | 4304 | -2.3E-04 | 0.9999 | 0.015241 | 0.892 | No Reject |
| 98 | -0.00548 | 3926 | -2.5E-04 | 0.9999 | 0.015958 | -0.328 | No Reject |
| 99 | -0.02408 | 3634 | -2.8E-04 | 0.9999 | 0.016586 | -1.435 | No Reject |
| 100 | -0.00336 | 3513 | -2.8E-04 | 0.9999 | 0.016869 | -0.183 | No Reject |
| 101 | -0.02516 | 3324 | -3.0E-04 | 0.9999 | 0.017342 | -1.433 | No Reject |
| 102 | -0.02709 | 3009 | -3.3E-04 | 0.9998 | 0.018227 | -1.468 | No Reject |
| 103 | -0.02065 | 2826 | -3.5E-04 | 0.9998 | 0.018808 | -1.079 | No Reject |
| 104 | -0.00469 | 2562 | -3.9E-04 | 0.9998 | 0.019753 | -0.218 | No Reject |
| 105 | -0.00935 | 2421 | -4.1E-04 | 0.9998 | 0.02032 | -0.440 | No Reject |
| 106 | -0.01108 | 2114 | -4.7E-04 | 0.9998 | 0.021744 | -0.488 | No Reject |
| **107** | **-0.04459** | **1882** | **-5.3E-04** | **0.9997** | **0.023045** | **-1.912** | **Reject Null** |
| **108** | **-0.05373** | **1641** | **-6.1E-04** | **0.9997** | **0.024678** | **-2.152** | **Reject Null** |
| 109 | -0.04232 | 1337 | -7.5E-04 | 0.9996 | 0.027338 | -1.520 | No Reject |
| **110** | **-0.05051** | **1150** | **-8.7E-04** | **0.9996** | **0.029476** | **-1.684** | **Reject Null** |
| 111 | 0.002939 | 1035 | -9.7E-04 | 0.9995 | 0.031069 | 0.126 | No Reject |
| 112 | -0.03192 | 797 | -1.3E-03 | 0.9994 | 0.0354 | -0.866 | No Reject |
| **113** | **-0.09627** | **758** | **-1.3E-03** | **0.9993** | **0.036298** | **-2.616** | **Reject Null** |
| 114 | 0.012108 | 627 | -1.6E-03 | 0.9992 | 0.039905 | 0.343 | No Reject |
| 115 | -0.07146 | 456 | -2.2E-03 | 0.9989 | 0.046779 | -1.481 | No Reject |
| 116 | -0.01819 | 435 | -2.3E-03 | 0.9989 | 0.047892 | -0.332 | No Reject |
| 117 | 0.054 | 367 | -2.7E-03 | 0.9987 | 0.05213 | 1.088 | No Reject |
| 118 | 0.042165 | 331 | -3.0E-03 | 0.9985 | 0.054884 | 0.823 | No Reject |
| 119 | 0.017391 | 345 | -2.9E-03 | 0.9986 | 0.053762 | 0.378 | No Reject |
| 120 | -0.02589 | 271 | -3.7E-03 | 0.9982 | 0.060638 | -0.366 | No Reject |
| 121 | 0.043118 | 221 | -4.5E-03 | 0.9978 | 0.067122 | 0.710 | No Reject |
| 122 | -0.04203 | 211 | -4.8E-03 | 0.9977 | 0.068687 | -0.543 | No Reject |
| 123 | -0.00919 | 171 | -5.9E-03 | 0.9972 | 0.076261 | -0.043 | No Reject |
| 124 | 0.06923 | 146 | -6.9E-03 | 0.9968 | 0.082496 | 0.923 | No Reject |
| 125 | 0.031726 | 120 | -8.4E-03 | 0.9962 | 0.090938 | 0.441 | No Reject |
| 126 | -0.07505 | 66 | -1.5E-02 | 0.9935 | 0.122298 | -0.488 | No Reject |
| 127 | -0.06887 | 51 | -2.0E-02 | 0.9921 | 0.13892 | -0.352 | No Reject |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 128 | 0.091303 | 44 | -2.3E-02 | 0.9912 | 0.149425 | 0.767 | No Reject |
| 129 | -0.00868 | 30 | -3.4E-02 | 0.9888 | 0.180532 | 0.143 | No Reject |
| 130 | 0.009625 | 44 | -2.3E-02 | 0.9912 | 0.149425 | 0.220 | No Reject |
| 131 | 0.039202 | 33 | -3.1E-02 | 0.9894 | 0.172228 | 0.409 | No Reject |
| 132 | -0.09827 | 26 | -4.0E-02 | 0.9881 | 0.193778 | -0.301 | No Reject |
| 133 | 0.006994 | 21 | -5.0E-02 | 0.9874 | 0.215473 | 0.265 | No Reject |
| 134 | -0.02469 | 10 | -1.1E-01 | 1.0000 | 0.316228 | 0.273 | No Reject |
| 135 | -0.10592 | 8 | -1.4E-01 | 1.0157 | 0.359122 | 0.103 | No Reject |

## APPENDIX J

1998 MORAN'S I

| Lag | Moran's I | Pairs (n) | E(I) | SD | s.e. | Z score | Hypothesis Test |
|---|---|---|---|---|---|---|---|
| **1** | **-0.30732** | **43** | **-2.4E-02** | **0.9910** | **0.151131** | **-1.876** | **Reject Null** |
| 2 | 0.023046 | 161 | -6.3E-03 | 0.9971 | 0.078581 | 0.373 | No Reject |
| **3** | **0.154391** | **172** | **-5.8E-03** | **0.9973** | **0.07604** | **2.107** | **Reject Null** |
| 4 | 0.083922 | 246 | -4.1E-03 | 0.9980 | 0.063633 | 1.383 | No Reject |
| 5 | 0.014157 | 280 | -3.6E-03 | 0.9983 | 0.059658 | 0.297 | No Reject |
| 6 | -0.07067 | 292 | -3.4E-03 | 0.9983 | 0.058424 | -1.151 | No Reject |
| **7** | **-0.10698** | **319** | **-3.1E-03** | **0.9985** | **0.055904** | **-1.857** | **Reject Null** |
| 8 | -0.0212 | 361 | -2.8E-03 | 0.9987 | 0.052561 | -0.350 | No Reject |
| 9 | 0.018491 | 365 | -2.7E-03 | 0.9987 | 0.052273 | 0.406 | No Reject |
| **10** | **-0.09171** | **383** | **-2.6E-03** | **0.9987** | **0.051033** | **-1.746** | **Reject Null** |
| 11 | -0.0801 | 436 | -2.3E-03 | 0.9989 | 0.047838 | -1.626 | No Reject |
| 12 | 0.031669 | 504 | -2.0E-03 | 0.9990 | 0.0445 | 0.756 | No Reject |
| 13 | 0.036761 | 506 | -2.0E-03 | 0.9990 | 0.044412 | 0.872 | No Reject |
| **14** | **-0.08724** | **511** | **-2.0E-03** | **0.9990** | **0.044195** | **-1.930** | **Reject Null** |
| 15 | -0.04177 | 555 | -1.8E-03 | 0.9991 | 0.04241 | -0.942 | No Reject |
| 16 | -4.9E-05 | 591 | -1.7E-03 | 0.9992 | 0.0411 | 0.040 | No Reject |
| 17 | 0.006067 | 617 | -1.6E-03 | 0.9992 | 0.040226 | 0.191 | No Reject |
| 18 | 0.055809 | 657 | -1.5E-03 | 0.9993 | 0.038984 | 1.471 | No Reject |
| 19 | 0.000165 | 650 | -1.5E-03 | 0.9992 | 0.039194 | 0.044 | No Reject |
| 20 | 0.027171 | 699 | -1.4E-03 | 0.9993 | 0.037797 | 0.757 | No Reject |
| 21 | 0.060449 | 648 | -1.5E-03 | 0.9992 | 0.039254 | 1.579 | No Reject |
| 22 | 0.008086 | 681 | -1.5E-03 | 0.9993 | 0.038292 | 0.250 | No Reject |
| 23 | -0.03045 | 658 | -1.5E-03 | 0.9993 | 0.038955 | -0.743 | No Reject |
| **24** | **-0.06821** | **700** | **-1.4E-03** | **0.9993** | **0.03777** | **-1.768** | **Reject Null** |
| 25 | 0.027359 | 699 | -1.4E-03 | 0.9993 | 0.037797 | 0.762 | No Reject |
| 26 | -0.05681 | 748 | -1.3E-03 | 0.9993 | 0.036539 | -1.518 | No Reject |
| 27 | -0.00218 | 810 | -1.2E-03 | 0.9994 | 0.035115 | -0.027 | No Reject |
| 28 | 0.018382 | 792 | -1.3E-03 | 0.9994 | 0.035511 | 0.553 | No Reject |
| 29 | 0.006612 | 844 | -1.2E-03 | 0.9994 | 0.034401 | 0.227 | No Reject |
| **30** | **-0.06125** | **962** | **-1.0E-03** | **0.9995** | **0.032225** | **-1.868** | **Reject Null** |
| 31 | 0.006059 | 950 | -1.1E-03 | 0.9995 | 0.032427 | 0.219 | No Reject |
| 32 | 0.005373 | 934 | -1.1E-03 | 0.9995 | 0.032704 | 0.197 | No Reject |
| 33 | -0.04708 | 941 | -1.1E-03 | 0.9995 | 0.032582 | -1.412 | No Reject |
| **34** | **0.053097** | **935** | **-1.1E-03** | **0.9995** | **0.032686** | **1.657** | **Reject Null** |
| 35 | -0.02796 | 879 | -1.1E-03 | 0.9994 | 0.03371 | -0.796 | No Reject |
| 36 | 0.025814 | 946 | -1.1E-03 | 0.9995 | 0.032496 | 0.827 | No Reject |
| 37 | 0.003247 | 909 | -1.1E-03 | 0.9995 | 0.03315 | 0.131 | No Reject |
| 38 | -0.03238 | 907 | -1.1E-03 | 0.9995 | 0.033186 | -0.943 | No Reject |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 39 | 0.007373 | 914 | -1.1E-03 | 0.9995 | 0.033059 | 0.256 | No Reject |
| 40 | 0.036672 | 919 | -1.1E-03 | 0.9995 | 0.032969 | 1.145 | No Reject |
| 41 | 0.022617 | 881 | -1.1E-03 | 0.9994 | 0.033672 | 0.705 | No Reject |
| 42 | -0.00014 | 925 | -1.1E-03 | 0.9995 | 0.032862 | 0.029 | No Reject |
| 43 | -0.00815 | 870 | -1.2E-03 | 0.9994 | 0.033884 | -0.207 | No Reject |
| 44 | -0.05502 | 841 | -1.2E-03 | 0.9994 | 0.034462 | -1.562 | No Reject |
| 45 | 0.00319 | 908 | -1.1E-03 | 0.9995 | 0.033168 | 0.129 | No Reject |
| 46 | 0.032541 | 901 | -1.1E-03 | 0.9995 | 0.033297 | 1.011 | No Reject |
| 47 | -0.01167 | 899 | -1.1E-03 | 0.9994 | 0.033334 | -0.317 | No Reject |
| 48 | -0.04249 | 820 | -1.2E-03 | 0.9994 | 0.0349 | -1.182 | No Reject |
| 49 | -0.03057 | 708 | -1.4E-03 | 0.9993 | 0.037556 | -0.776 | No Reject |
| 50 | -0.01061 | 737 | -1.4E-03 | 0.9993 | 0.036811 | -0.251 | No Reject |
| 51 | -0.05794 | 700 | -1.4E-03 | 0.9993 | 0.03777 | -1.496 | No Reject |
| 52 | -0.01676 | 697 | -1.4E-03 | 0.9993 | 0.037851 | -0.405 | No Reject |
| 53 | 0.006491 | 690 | -1.5E-03 | 0.9993 | 0.038042 | 0.209 | No Reject |
| 54 | 0.009332 | 646 | -1.6E-03 | 0.9992 | 0.039314 | 0.277 | No Reject |
| 55 | 0.016761 | 629 | -1.6E-03 | 0.9992 | 0.039841 | 0.461 | No Reject |
| 56 | 0.026188 | 684 | -1.5E-03 | 0.9993 | 0.038208 | 0.724 | No Reject |
| **57** | **0.062292** | **702** | **-1.4E-03** | **0.9993** | **0.037716** | **1.689** | **Reject Null** |
| 58 | -0.00771 | 667 | -1.5E-03 | 0.9993 | 0.038692 | -0.160 | No Reject |
| 59 | -0.00795 | 657 | -1.5E-03 | 0.9993 | 0.038984 | -0.165 | No Reject |
| 60 | 0.041778 | 616 | -1.6E-03 | 0.9992 | 0.040259 | 1.078 | No Reject |
| 61 | -0.02844 | 572 | -1.8E-03 | 0.9991 | 0.041776 | -0.639 | No Reject |
| 62 | -0.01319 | 587 | -1.7E-03 | 0.9992 | 0.04124 | -0.279 | No Reject |
| 63 | -0.00407 | 588 | -1.7E-03 | 0.9992 | 0.041205 | -0.057 | No Reject |
| 64 | -0.05184 | 581 | -1.7E-03 | 0.9992 | 0.041452 | -1.209 | No Reject |
| 65 | -0.04433 | 517 | -1.9E-03 | 0.9991 | 0.043938 | -0.965 | No Reject |
| 66 | -0.01619 | 574 | -1.7E-03 | 0.9991 | 0.041703 | -0.346 | No Reject |
| 67 | -0.05008 | 557 | -1.8E-03 | 0.9991 | 0.042334 | -1.141 | No Reject |
| 68 | 0.020336 | 525 | -1.9E-03 | 0.9991 | 0.043603 | 0.510 | No Reject |
| 69 | 0.047994 | 484 | -2.1E-03 | 0.9990 | 0.045409 | 1.103 | No Reject |
| 70 | 0.054733 | 479 | -2.1E-03 | 0.9990 | 0.045644 | 1.245 | No Reject |
| 71 | -0.01964 | 434 | -2.3E-03 | 0.9989 | 0.047947 | -0.361 | No Reject |
| **72** | **0.096656** | **411** | **-2.4E-03** | **0.9988** | **0.049268** | **2.011** | **Reject Null** |
| 73 | 0.013296 | 425 | -2.4E-03 | 0.9989 | 0.048451 | 0.323 | No Reject |
| 74 | -0.01862 | 351 | -2.9E-03 | 0.9986 | 0.053302 | -0.296 | No Reject |
| **75** | **0.102741** | **383** | **-2.6E-03** | **0.9987** | **0.051033** | **2.065** | **Reject Null** |
| 76 | -0.05773 | 381 | -2.6E-03 | 0.9987 | 0.051166 | -1.077 | No Reject |
| 77 | 0.011362 | 368 | -2.7E-03 | 0.9987 | 0.05206 | 0.271 | No Reject |
| 78 | -0.00376 | 350 | -2.9E-03 | 0.9986 | 0.053378 | -0.017 | No Reject |
| 79 | 0.006808 | 375 | -2.7E-03 | 0.9987 | 0.051573 | 0.184 | No Reject |
| 80 | -0.07051 | 323 | -3.1E-03 | 0.9985 | 0.055558 | -1.213 | No Reject |
| 81 | -0.03654 | 280 | -3.6E-03 | 0.9983 | 0.059658 | -0.552 | No Reject |
| 82 | 0.051508 | 283 | -3.5E-03 | 0.9983 | 0.059342 | 0.928 | No Reject |
| 83 | -0.01786 | 287 | -3.5E-03 | 0.9983 | 0.058929 | -0.244 | No Reject |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 84 | 0.043182 | 264 | -3.8E-03 | 0.9982 | 0.061433 | 0.765 | No Reject |
| 85 | 0.043408 | 279 | -3.6E-03 | 0.9983 | 0.059765 | 0.787 | No Reject |
| 86 | -0.00244 | 280 | -3.6E-03 | 0.9983 | 0.059658 | 0.019 | No Reject |
| 87 | 0.014153 | 235 | -4.3E-03 | 0.9980 | 0.0651 | 0.283 | No Reject |
| 88 | 0.0446 | 220 | -4.6E-03 | 0.9978 | 0.067274 | 0.731 | No Reject |
| **89** | **-0.12742** | **225** | **-4.5E-03** | **0.9979** | **0.066525** | **-1.848** | **Reject Null** |
| 90 | -0.02758 | 224 | -4.5E-03 | 0.9979 | 0.066673 | -0.346 | No Reject |
| 91 | -0.00696 | 194 | -5.2E-03 | 0.9976 | 0.07162 | -0.025 | No Reject |
| 92 | -0.0725 | 169 | -6.0E-03 | 0.9972 | 0.076709 | -0.868 | No Reject |
| 93 | -0.01423 | 171 | -5.9E-03 | 0.9972 | 0.076261 | -0.109 | No Reject |
| 94 | 0.033785 | 175 | -5.7E-03 | 0.9973 | 0.075389 | 0.524 | No Reject |
| 95 | 0.051661 | 164 | -6.1E-03 | 0.9971 | 0.077863 | 0.742 | No Reject |
| 96 | 0.020284 | 164 | -6.1E-03 | 0.9971 | 0.077863 | 0.339 | No Reject |
| **97** | **0.131212** | **146** | **-6.9E-03** | **0.9968** | **0.082496** | **1.674** | **Reject Null** |
| 98 | 0.01185 | 126 | -8.0E-03 | 0.9963 | 0.088761 | 0.224 | No Reject |
| 99 | -0.04232 | 97 | -1.0E-02 | 0.9954 | 0.101064 | -0.316 | No Reject |
| 100 | -0.06618 | 108 | -9.3E-03 | 0.9958 | 0.09582 | -0.593 | No Reject |
| 101 | 0.087114 | 99 | -1.0E-02 | 0.9954 | 0.100046 | 0.973 | No Reject |
| 102 | -0.10381 | 112 | -9.0E-03 | 0.9959 | 0.094106 | -1.007 | No Reject |
| 103 | 0.117165 | 87 | -1.2E-02 | 0.9949 | 0.106664 | 1.207 | No Reject |
| 104 | 0.034414 | 92 | -1.1E-02 | 0.9951 | 0.103751 | 0.438 | No Reject |
| 105 | -0.17875 | 78 | -1.3E-02 | 0.9944 | 0.112593 | -1.472 | No Reject |
| 106 | -0.0328 | 52 | -2.0E-02 | 0.9922 | 0.137593 | -0.096 | No Reject |
| 107 | 0.06158 | 46 | -2.2E-02 | 0.9915 | 0.146182 | 0.573 | No Reject |
| **108** | **-0.29661** | **43** | **-2.4E-02** | **0.9910** | **0.151131** | **-1.805** | **Reject Null** |
| 109 | 0.066982 | 44 | -2.3E-02 | 0.9912 | 0.149425 | 0.604 | No Reject |
| 110 | -0.2221 | 35 | -2.9E-02 | 0.9897 | 0.167296 | -1.152 | No Reject |
| 111 | -0.04213 | 32 | -3.2E-02 | 0.9892 | 0.174866 | -0.056 | No Reject |
| 112 | 0.103687 | 24 | -4.3E-02 | 0.9878 | 0.201624 | 0.730 | No Reject |
| 113 | 0.347942 | 14 | -7.7E-02 | 0.9897 | 0.264506 | 1.606 | No Reject |
| 114 | -0.07501 | 22 | -4.8E-02 | 0.9875 | 0.210536 | -0.130 | No Reject |
| 115 | 0.16843 | 15 | -7.1E-02 | 0.9888 | 0.255301 | 0.940 | No Reject |
| 116 | -0.00323 | 19 | -5.6E-02 | 0.9874 | 0.22653 | 0.231 | No Reject |
| 117 | -0.11062 | 29 | -3.6E-02 | 0.9886 | 0.183583 | -0.408 | No Reject |
| 118 | -0.26904 | 15 | -7.1E-02 | 0.9888 | 0.255301 | -0.774 | No Reject |
| 119 | 0.024517 | 22 | -4.8E-02 | 0.9875 | 0.210536 | 0.343 | No Reject |
| **120** | **0.561431** | **18** | **-5.9E-02** | **0.9875** | **0.232765** | **2.665** | **Reject Null** |
| 121 | -0.1349 | 14 | -7.7E-02 | 0.9897 | 0.264506 | -0.219 | No Reject |
| 122 | 0.131594 | 9 | -1.3E-01 | 1.0062 | 0.33541 | 0.765 | No Reject |
| 123 | 0.315564 | 13 | -8.3E-02 | 0.9910 | 0.274863 | 1.451 | No Reject |
| 124 | 0.067272 | 6 | -2.0E-01 | 1.0556 | 0.430946 | 0.620 | No Reject |
| 125 | | 0 | 1.0E+00 | #NUM! | #NUM! | #NUM! | No Reject |
| 126 | 0.209432 | 6 | -2.0E-01 | 1.0556 | 0.430946 | 0.950 | No Reject |
| 127 | 0.019853 | 4 | -3.3E-01 | 1.1832 | 0.591608 | 0.597 | No Reject |
| 128 | -0.23952 | 2 | -1.0E+00 | 1.9149 | 1.354006 | 0.562 | No Reject |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 129 | -0.13529 | 2 | -1.0E+00 | 1.9149 | 1.354006 | 0.639 | No Reject |
| 130 | 0.008527 | 2 | -1.0E+00 | 1.9149 | 1.354006 | 0.745 | No Reject |

# APPENDIX K

## Pearson's Bivariate Correlations at the Census Tract Scale n = 41

| | | AV | LNAV | AR | S | LNS | WHITE | BLACK |
|---|---|---|---|---|---|---|---|---|
| **AV** | r | 1.000 | 0.975 | -0.537 | 0.996 | 0.975 | 0.433 | -0.252 |
| | P | . | 0.000 | 0.000 | 0.000 | 0.000 | 0.005 | 0.112 |
| **LNAV** | r | 0.975 | 1.000 | -0.552 | 0.963 | 0.995 | 0.472 | -0.278 |
| | P | 0.000 | . | 0.000 | 0.000 | 0.000 | 0.002 | 0.079 |
| **AR** | r | -0.537 | -0.552 | 1.000 | -0.588 | -0.622 | -0.382 | 0.273 |
| | P | 0.000 | 0.000 | . | 0.000 | 0.000 | 0.014 | 0.084 |
| **S** | r | 0.996 | 0.963 | -0.588 | 1.000 | 0.971 | 0.420 | -0.241 |
| | P | 0.000 | 0.000 | 0.000 | . | 0.000 | 0.006 | 0.129 |
| **LNS** | r | 0.975 | 0.995 | -0.622 | 0.971 | 1.000 | 0.460 | -0.263 |
| | P | 0.000 | 0.000 | 0.000 | 0.000 | . | 0.002 | 0.097 |
| **WHITE** | r | 0.433 | 0.472 | -0.382 | 0.420 | 0.460 | 1.000 | -0.955 |
| | P | 0.005 | 0.002 | 0.014 | 0.006 | 0.002 | . | 0.000 |
| **BLACK** | r | -0.252 | -0.278 | 0.273 | -0.241 | -0.263 | -0.955 | 1.000 |
| | P | 0.112 | 0.079 | 0.084 | 0.129 | 0.097 | 0.000 | . |
| **HISPANIC** | r | -0.680 | -0.731 | 0.480 | -0.680 | -0.748 | -0.287 | 0.022 |
| | P | 0.000 | 0.000 | 0.001 | 0.000 | 0.000 | 0.069 | 0.892 |
| **VACANT** | | -0.575 | -0.631 | 0.425 | -0.553 | -0.618 | -0.441 | 0.265 |
| | P | 0.000 | 0.000 | 0.006 | 0.000 | 0.000 | 0.004 | 0.094 |
| **RENTOCC** | r | -0.546 | -0.566 | 0.334 | -0.527 | -0.548 | -0.345 | 0.219 |
| | P | 0.000 | 0.000 | 0.033 | 0.000 | 0.000 | 0.027 | 0.169 |
| **LNINC** | r | 0.808 | 0.860 | -0.528 | 0.793 | 0.851 | 0.461 | -0.269 |
| | P | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.002 | 0.089 |
| **INC** | r | 0.889 | 0.899 | -0.531 | 0.879 | 0.894 | 0.421 | -0.225 |
| | P | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.006 | 0.156 |
| **PUBLIC** | r | -0.724 | -0.798 | 0.555 | -0.710 | -0.798 | -0.640 | 0.453 |
| | P | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.003 |
| **YEAR** | r | 0.378 | 0.375 | -0.027 | 0.354 | 0.362 | 0.055 | 0.052 |
| | P | 0.015 | 0.016 | 0.869 | 0.023 | 0.020 | 0.733 | 0.745 |

## CensusTract Scale Pearson Bivariate Correlations contd.

| | | HISPANIC | VACANT | RENTOCC | LNINC | INC | PUBLIC | YEAR |
|---|---|---|---|---|---|---|---|---|
| AV | r | -0.680 | -0.575 | -0.546 | 0.808 | 0.889 | -0.724 | 0.378 |
| | P | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.015 |
| LNAV | r | -0.731 | -0.631 | -0.566 | 0.860 | 0.899 | -0.798 | 0.375 |
| | P | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.016 |
| AR | r | 0.480 | 0.425 | 0.334 | -0.528 | -0.531 | 0.555 | -0.027 |
| | P | 0.001 | 0.006 | 0.033 | 0.000 | 0.000 | 0.000 | 0.869 |
| S | r | -0.680 | -0.553 | -0.527 | 0.793 | 0.879 | -0.710 | 0.354 |
| | P | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.023 |
| LNS | r | -0.748 | -0.618 | -0.548 | 0.851 | 0.894 | -0.798 | 0.362 |
| | P | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.020 |
| WHITE | r | -0.287 | -0.441 | -0.345 | 0.461 | 0.421 | -0.640 | 0.055 |
| | P | 0.069 | 0.004 | 0.027 | 0.002 | 0.006 | 0.000 | 0.733 |
| BLACK | r | 0.022 | 0.265 | 0.219 | -0.269 | -0.225 | 0.453 | 0.052 |
| | P | 0.892 | 0.094 | 0.169 | 0.089 | 0.156 | 0.003 | 0.745 |
| HISPANIC | r | 1.000 | 0.501 | 0.312 | -0.599 | -0.638 | 0.654 | -0.433 |
| | P | . | 0.001 | 0.047 | 0.000 | 0.000 | 0.000 | 0.005 |
| VACANT | r | 0.501 | 1.000 | 0.775 | -0.815 | -0.778 | 0.720 | -0.219 |
| | P | 0.001 | . | 0.000 | 0.000 | 0.000 | 0.000 | 0.169 |
| RENTOCC | r | 0.312 | 0.775 | 1.000 | -0.774 | -0.770 | 0.590 | 0.143 |
| | P | 0.047 | 0.000 | . | 0.000 | 0.000 | 0.000 | 0.374 |
| LNINC | r | -0.599 | -0.815 | -0.774 | 1.000 | 0.967 | -0.888 | 0.187 |
| | P | 0.000 | 0.000 | 0.000 | . | 0.000 | 0.000 | 0.241 |
| INC | r | -0.638 | -0.778 | -0.770 | 0.967 | 1.000 | -0.832 | 0.263 |
| | P | 0.000 | 0.000 | 0.000 | 0.000 | . | 0.000 | 0.096 |
| PUBLIC | r | 0.654 | 0.720 | 0.590 | -0.888 | -0.832 | 1.000 | -0.290 |
| | P | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | . | 0.066 |
| YEAR | r | -0.433 | -0.219 | 0.143 | 0.187 | 0.263 | -0.290 | 1.000 |
| | P | 0.005 | 0.169 | 0.374 | 0.241 | 0.096 | 0.066 | . |

## APPENDIX L

### Pearson Bivariate Correlations at the Block Group Scale n = 117

| | | AV | LNAV | AR | S | LNS | WHITE | BLACK |
|---|---|---|---|---|---|---|---|---|
| AV | r | 1.000 | 0.976 | -0.364 | 0.993 | 0.967 | 0.395 | -0.220 |
| | P | . | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.017 |
| LNAV | r | 0.976 | 1.000 | -0.395 | 0.966 | 0.991 | 0.437 | -0.243 |
| | P | 0.000 | . | 0.000 | 0.000 | 0.000 | 0.000 | 0.008 |
| AR | r | -0.364 | -0.395 | 1.000 | -0.451 | -0.503 | -0.341 | 0.252 |
| | P | 0.000 | 0.000 | . | 0.000 | 0.000 | 0.000 | 0.006 |
| S | r | 0.993 | 0.966 | -0.451 | 1.000 | 0.972 | 0.391 | -0.217 |
| | P | 0.000 | 0.000 | 0.000 | . | 0.000 | 0.000 | 0.019 |
| LNS | r | 0.967 | 0.991 | -0.503 | 0.972 | 1.000 | 0.438 | -0.243 |
| | P | 0.000 | 0.000 | 0.000 | 0.000 | . | 0.000 | 0.008 |
| WHITE | r | 0.395 | 0.437 | -0.341 | 0.391 | 0.438 | 1.000 | -0.948 |
| | P | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | . | 0.000 |
| BLACK | r | -0.220 | -0.243 | 0.252 | -0.217 | -0.243 | -0.948 | 1.000 |
| | P | 0.017 | 0.008 | 0.006 | 0.019 | 0.008 | 0.000 | . |
| HISPANIC | r | -0.679 | -0.746 | 0.380 | -0.680 | -0.754 | -0.396 | 0.120 |
| | P | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.196 |
| VACANT | r | -0.478 | -0.533 | 0.400 | -0.475 | -0.537 | -0.418 | 0.261 |
| | P | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.005 |
| RENTOCC | r | -0.442 | -0.469 | 0.292 | -0.437 | -0.465 | -0.382 | 0.250 |
| | P | 0.000 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 | 0.007 |
| LNINC | r | 0.702 | 0.736 | -0.436 | 0.701 | 0.736 | 0.438 | -0.271 |
| | P | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.003 |
| INC | r | 0.758 | 0.769 | -0.420 | 0.758 | 0.769 | 0.383 | -0.215 |
| | P | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.020 |
| PUBLIC | r | -0.650 | -0.710 | 0.421 | -0.650 | -0.715 | -0.612 | 0.461 |
| | P | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| YEAR | r | 0.463 | 0.462 | -0.033 | 0.432 | 0.437 | 0.046 | 0.059 |
| | P | 0.000 | 0.000 | 0.727 | 0.000 | 0.000 | 0.621 | 0.526 |

**Block group scale Pearson Bivariate Correlation contd.**

| | | HISPANIC | VACANT | RENTOCC | LNINC | INC | PUBLIC | YEAR |
|---|---|---|---|---|---|---|---|---|
| **AV** | r | -0.679 | -0.478 | -0.442 | 0.702 | 0.758 | -0.650 | 0.463 |
| | P | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| **LNAV** | r | -0.746 | -0.533 | -0.469 | 0.736 | 0.769 | -0.710 | 0.462 |
| | P | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| **AR** | r | 0.380 | 0.400 | 0.292 | -0.436 | -0.420 | 0.421 | -0.033 |
| | P | 0.000 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 | 0.727 |
| **S** | r | -0.680 | -0.475 | -0.437 | 0.701 | 0.758 | -0.650 | 0.432 |
| | P | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| **LNS** | r | -0.754 | -0.537 | -0.465 | 0.736 | 0.769 | -0.715 | 0.437 |
| | P | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| **WHITE** | r | -0.396 | -0.418 | -0.382 | 0.438 | 0.383 | -0.612 | 0.046 |
| | P | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.621 |
| **BLACK** | r | 0.120 | 0.261 | 0.250 | -0.271 | -0.215 | 0.461 | 0.059 |
| | P | 0.196 | 0.005 | 0.007 | 0.003 | 0.020 | 0.000 | 0.526 |
| **HISPANIC** | r | 1.000 | 0.475 | 0.369 | -0.555 | -0.561 | 0.584 | -0.364 |
| | P | . | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| **VACANT** | r | 0.475 | 1.000 | 0.739 | -0.742 | -0.714 | 0.665 | -0.222 |
| | P | 0.000 | . | 0.000 | 0.000 | 0.000 | 0.000 | 0.016 |
| **RENTOCC** | r | 0.369 | 0.739 | 1.000 | -0.753 | -0.740 | 0.615 | 0.074 |
| | P | 0.000 | 0.000 | . | 0.000 | 0.000 | 0.000 | 0.428 |
| **LNINC** | r | -0.555 | -0.742 | -0.753 | 1.000 | 0.973 | -0.804 | 0.241 |
| | P | 0.000 | 0.000 | 0.000 | . | 0.000 | 0.000 | 0.009 |
| **INC** | r | -0.561 | -0.714 | -0.740 | 0.973 | 1.000 | -0.760 | 0.259 |
| | P | 0.000 | 0.000 | 0.000 | 0.000 | . | 0.000 | 0.005 |
| **PUBLIC** | r | 0.584 | 0.665 | 0.615 | -0.804 | -0.760 | 1.000 | -0.235 |
| | P | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | . | 0.011 |
| **YEAR** | r | -0.364 | -0.222 | 0.074 | 0.241 | 0.259 | -0.235 | 1.000 |
| | P | 0.000 | 0.016 | 0.428 | 0.009 | 0.005 | 0.011 | . |

## APPENDIX M

### Pearson Bivariate Correlations – Parcel Scale n = 8056

| | | AV | LNAV | AR | S | LNS | WHITE | BLACK |
|---|---|---|---|---|---|---|---|---|
| AV | r | 1.000 | 0.949 | 0.083 | 0.926 | 0.868 | 0.281 | -0.158 |
| | p | . | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| LNAV | r | 0.949 | 1.000 | 0.088 | 0.876 | 0.913 | 0.309 | -0.171 |
| | p | 0.000 | . | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| AR | r | 0.083 | 0.088 | 1.000 | -0.254 | -0.322 | -0.063 | 0.045 |
| | p | 0.000 | 0.000 | . | 0.000 | 0.000 | 0.000 | 0.000 |
| S | r | 0.926 | 0.876 | -0.254 | 1.000 | 0.940 | 0.282 | -0.159 |
| | p | 0.000 | 0.000 | 0.000 | . | 0.000 | 0.000 | 0.000 |
| LNS | r | 0.868 | 0.913 | -0.322 | 0.940 | 1.000 | 0.317 | -0.180 |
| | p | 0.000 | 0.000 | 0.000 | 0.000 | . | 0.000 | 0.000 |
| WHITE | r | 0.281 | 0.309 | -0.063 | 0.282 | 0.317 | 1.000 | -0.952 |
| | p | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | . | 0.000 |
| BLACK | r | -0.158 | -0.171 | 0.045 | -0.159 | -0.180 | -0.952 | 1.000 |
| | p | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | . |
| HISPANIC | r | -0.499 | -0.548 | 0.077 | -0.506 | -0.552 | -0.418 | 0.160 |
| | p | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| VACANT | r | -0.362 | -0.405 | 0.067 | -0.362 | -0.407 | -0.381 | 0.235 |
| | p | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| RENTOCC | r | -0.329 | -0.355 | 0.057 | -0.332 | -0.357 | -0.414 | 0.293 |
| | p | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| LNINC | r | 0.552 | 0.576 | -0.093 | 0.561 | 0.582 | 0.396 | -0.235 |
| | p | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| INC | r | 0.597 | 0.603 | -0.087 | 0.606 | 0.606 | 0.353 | -0.196 |
| | p | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| PUBLIC | r | -0.501 | -0.546 | 0.087 | -0.507 | -0.553 | -0.652 | 0.509 |
| | p | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| YEAR | r | 0.395 | 0.400 | 0.003 | 0.372 | 0.376 | -0.019 | 0.117 |
| | p | 0.000 | 0.000 | 0.810 | 0.000 | 0.000 | 0.082 | 0.000 |

**Parcel Scale Pearson Bivariate Correlations contd.**

| | | HISPANIC | VACANT | RENTOCC | LNINC | INC | PUBLIC | YEAR |
|---|---|---|---|---|---|---|---|---|
| **AV** | r | -0.499 | -0.362 | -0.329 | 0.552 | 0.597 | -0.501 | 0.395 |
| | p | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| **LNAV** | r | -0.548 | -0.405 | -0.355 | 0.576 | 0.603 | -0.546 | 0.400 |
| | p | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| **AR** | r | 0.077 | 0.067 | 0.057 | -0.093 | -0.087 | 0.087 | 0.003 |
| | p | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.810 |
| **S** | r | -0.506 | -0.362 | -0.332 | 0.561 | 0.606 | -0.507 | 0.372 |
| | p | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| **LNS** | r | -0.552 | -0.407 | -0.357 | 0.582 | 0.606 | -0.553 | 0.376 |
| | p | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| **WHITE** | r | -0.418 | -0.381 | -0.414 | 0.396 | 0.353 | -0.652 | -0.019 |
| | p | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.082 |
| **BLACK** | r | 0.160 | 0.235 | 0.293 | -0.235 | -0.196 | 0.509 | 0.117 |
| | p | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| **HISPANIC** | r | 1.000 | 0.491 | 0.389 | -0.575 | -0.570 | 0.631 | -0.327 |
| | p | . | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| **VACANT** | r | 0.491 | 1.000 | 0.674 | -0.701 | -0.674 | 0.602 | -0.271 |
| | p | 0.000 | . | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| **RENTOCC** | r | 0.389 | 0.674 | 1.000 | -0.721 | -0.711 | 0.566 | 0.056 |
| | p | 0.000 | 0.000 | . | 0.000 | 0.000 | 0.000 | 0.000 |
| **LNINC** | r | -0.575 | -0.701 | -0.721 | 1.000 | 0.972 | -0.744 | 0.333 |
| | p | 0.000 | 0.000 | 0.000 | . | 0.000 | 0.000 | 0.000 |
| **INC** | r | -0.570 | -0.674 | -0.711 | 0.972 | 1.000 | -0.714 | 0.336 |
| | p | 0.000 | 0.000 | 0.000 | 0.000 | . | 0.000 | 0.000 |
| **PUBLIC** | r | 0.631 | 0.602 | 0.566 | -0.744 | -0.714 | 1.000 | -0.285 |
| | p | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | . | 0.000 |
| **YEAR** | r | -0.327 | -0.271 | 0.056 | 0.333 | 0.336 | -0.285 | 1.000 |
| | p | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | . |

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