INVESTIGATING INEQUITIES IN APPRAISED RESIDENTIAL PROPERTY VALUES

FOR DALLAS COUNTY, TEXAS, FROM 2004 – 2014:

USING AN INSTRUMENTAL VARIABLE APPROACH

by

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Research suggests that effective administration of property tax assessment is challenging under conditions of rapidly fluctuating house prices, lack of comparable sales, and use of informed guesses for value judgments. The literature catalogues tools for identifying inequities yet there is still debate over the appropriate approach. This research builds upon Cheng's (1976) model specification to vertical inequity estimation by employing hedonic house price characteristics in the first stage of a two-stage least squares estimation. This specification generalizes into temporal and spatial models using indicator variables for sale years and market areas, respectively. Results find full expression using a graphical plot of inequity estimates in the original scale. Single-family, residential dwellings exhibit a mixture of progressive, equitable, and regressive patterns before, during, and after a period of volatile housing market dynamics in Dallas County, Texas.

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CHAPTER 1

INTRODUCTION

1.1 Problem Statement

In the United States, various levels of governments rely on taxation to provide public services. The primary tax levied by the federal government is the income tax whereby individuals, married couples or corporations are required to provide a percentage of their total earnings defined by the tax code. Similarly, many state governments issue a tax on income as a major financing resource. Not all state governments levy income taxes. States seeking revenue development that do not have an income tax may pursue other avenues to finance public services such as sales tax and/or property tax. Non-income tax reliant states may fund public services at the local government level (e.g., county, city, school district) through (1) property and/or sales taxes, (2) federal grants and (3) some combination of items (1) and (2). One challenge states may face is identifying an optimal taxation strategy that provides a balance of various qualities supporting the well-being of their residents and their state's economy.

1.1.1 Optimal Taxing Systems

An optimal taxation system can benefit a taxing authority and taxpayers simultaneously. Stiglitz (2000, 458) defines five essential principles as the foundation for a good taxation system.

1. "Efficiency", relates to the improvement and benefit of the system to the economy.
2. Tax regimes that have "administrative simplicity" do not exhaust valuable resources.
3. Where such systems are "flexible", legislative or economic changes are not debilitating.
4. A "transparent" taxation system demonstrates "political responsibility".

5. The nature and perception of the taxation system should be “fair”, giving all an equal burden in proportion to their ability to pay.

The principle of *fairness* is the primary focus of this research regarding property tax assessment uniformity.

The property tax system should be fair and fit within Stiglitz’ optimal taxation framework. Property taxes are the vehicle for revenues for many local governments in the Unites States. Local governments include school districts, municipalities, local utility districts, community colleges, and county governments and hospitals. Figure 1.1 shows total revenues compared with property tax revenues for local governments in Texas. Total statewide revenues consist of state taxes, licensing fees, interest earnings, property sales, and other miscellaneous sources. Property tax revenues encompass funds paid by levies on real and personal property to local governments. The U.S. Census Bureau estimates that in 2011 the property tax consisted of almost one-third of total local government revenues in Texas (U.S. Census Bureau 2011; Malm and Kant 2013).

The Texas legislature recognized the critical nature of fairness in property taxes. According state law[1], appraisal districts are required to produce estimates of each property’s market value as of January 1st. This requires that assessed value represent 100% of its market value. If assessed above or below 100% of market value, non-compliance is apparent. The law[2] also requires market value estimates be obtained during a “declining economy”. Regardless of

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[1] Texas Constitution Sec 23.01.

[2] Texas Constitution Sec. 23.01c, clause 2.

the statutory mandate for fairness, appraisal districts may experience challenges in adhering perfectly to this law.

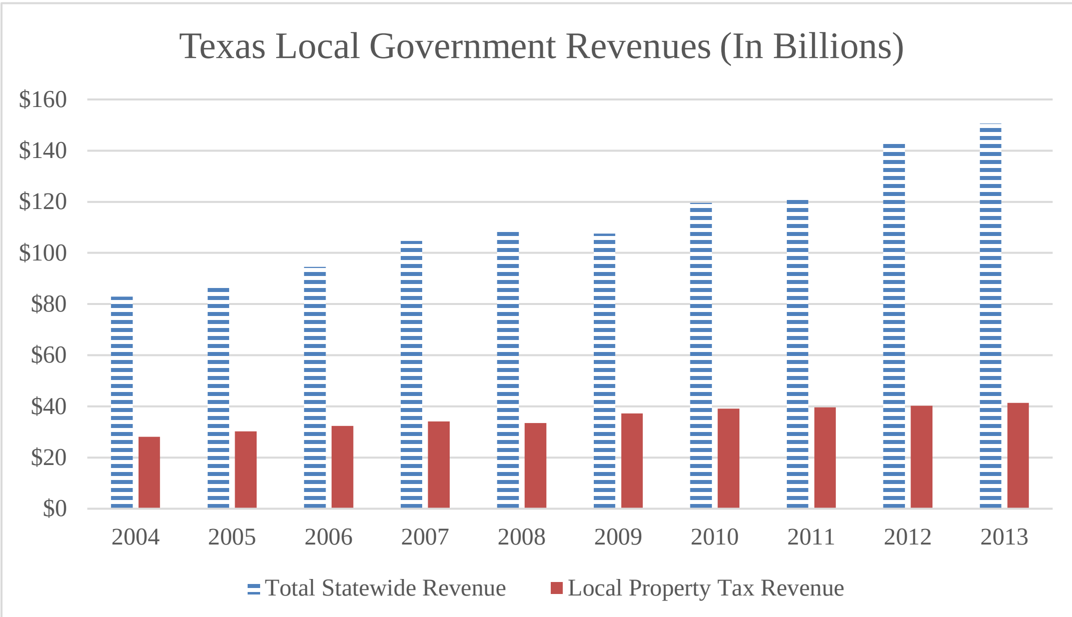

Figure 1.1. These estimates for the State of Texas provide information on total revenue in comparison to the portion of revenues derived from property taxes alone. Data from the U.S. Census of State and Local Government Finances, accessed 01/01/2015, https://www.census.gov/govs/local/historical_data_2011.html.

1.1.2 Challenges to Property Tax Assessment

Homeowners pay annual property taxes based on the assessed value of their real estate. The property tax assessor or appraisal district inventories real estate for an entire assessment jurisdiction and provides an opinion of market value based on property characteristics, neighborhood amenities, and local housing market dynamics. In most cases, many characteristics of the appraisal process are objective and standardized. Evidence suggests however, that some uncertainty exists in the appraisal process, which challenges objectively identifying home or land values.

Appraisers are employed by the appraisal district and are trained to make “value judgements” within defined geographic areas (Cypher and Hansz 2003). These judgements, though based on objective measures such as raw material costs and comparable sales comparisons, have uncertain elements. These elements include a lack of information, unique appraiser perspectives, and local and global housing market volatility.

During the appraisal process, characteristics of the land and dwelling are recorded to aide in identifying an appropriate value for the property. Not all property characteristics are easily accessible however. Appraisers are unable to enter homes for inspections of dwelling quality and construction. This precludes identifying any features of the lot not visible from the property’s public right of way. In many cases, building plans and permits are available to appraisers, yet, as is often the case, remodeling or other property updates are unknown. Another uncertain element related to the appraiser’s unique perspective is selecting the overall condition of the property (Spahr and Sunderman 1998, 379). When appraiser’s estimates are based on information including informed guesses, they may not accurately reflect the market value of real estate (Kennedy 1984, 287; Decesare and Ruddock 1998, 5). For example, if an indicator is used to categorize an appraiser’s opinion of the overall quality of the property, several factors may influence their decision. One example may include difficulty of selecting a quality opinion when a neighbor has poorly maintained property. Another example includes a lack of criteria for selecting a quality indicator. Both circumstances may lead appraisers to record property quality based on their unique perspectives. Independent of objective evidence, these decisions could lead to deviations of assessed value from market value.

Another difficulty that assessors face is the volatility of the housing market. Assessors provide an estimate of market value for real estate from a specific assessment date. Their estimates rely on relevant sales transactions before the assessment date. Appraisers find that effectively monitoring and assessing market trends in a dynamic housing market can be difficult (Jacobus 2012, 374; Hyman 2005, 645). These challenges may inhibit appraisers from applying an objective measure of property condition or quality as prices decline. For example, studies have found that home owners are less likely to maintain properties in distressed housing markets (Been et al. 2011, 408; Leonard and Murdoch 2009, 331; Harding, Rosenblatt, and Yao 2009, 165; Katz, Wallace, and Hedberg 2013, 362).

Instability of housing economies are detrimental to accurate property valuation because transaction prices are questionable. Precise appraisal methods require sales prices of homes that accurately reflect true market value (Pagourtzi et al. 2003, 386). In volatile housing markets, buyer and seller motivations and types of sale introduce uncertainty in transaction prices. A buyer or seller may be pressured to alter purchase or asking prices depending on the nature of the housing market. In a seller’s market, transaction volume and completion time pressure buyers to purchase outside of their expected price to obtain their housing objective. In these cases, prices may become inflated. Alternatively, buyer’s markets pressure sellers to lower their asking prices to attract consumers. Nearby property prices influence local house values (Gillen et al. 2001, 5). This extends to alternative transaction types (e.g., foreclosures, short sales, REO properties, etc.). Subsequently, research has found that nearby foreclosures discount neighborhood sales prices (Zhang and Leonard 2014, 134).

Questionable sales prices do not always depend on the economy's health. Buyer and seller relationships and sales price add-ons (e.g., rolling closing cost, real estate fees) also introduce uncertainty. Familial bonds most likely induce discounts on transaction prices (Benson et al. 1997, 239). Add-on features to sales price may include personal property not always reported by multiple listing agencies (Clapp and Giacotto 1992, 301). External to the appraiser's control, these circumstances contribute to the uncertainty associated with the appraisal estimate.

1.1.3 Property Tax Assessment Uniformity

Challenges to the appraisal process and uncertainty from market dynamics may produce *assessment inequities* or departures of the appraiser's estimate from market value. Such deviations from *assessment uniformity* are categorized into *horizontal* and *vertical inequity*.

- *Horizontal inequity* exists when there is a deviation of assessed value from the market value of a property within one, distinct price class (Allen and Dare 2002, 154).
- *Vertical inequity* exists when there is variation of assessed value from market value for properties within different price classes. There are two forms of vertical inequity: *regressivity* and *progressivity* (Benson and Schwartz 1997; Benson and Schwartz 2000).
    1. *Regressivity* is exhibited by high-priced properties that are under-valued in comparison to low-priced properties.
    2. *Progressivity* results when lower-priced properties are under-valued in comparison to high-priced properties.

It is important to quantify assessment inequities because of the negative impacts for homeowners in both the upper and lower house price distribution. Another negative impact involves unintentional, property tax revenue discounts or premiums for funding of public services. When local governments receive a fraction of property taxes for services, potential shortfalls in annual budgets may pose a problem. One example that illustrates the importance of consistent and uniform funding of local public services (i.e., primary or secondary public education) is the use of equalization studies. States conduct equalization studies to detect assessments that are considerably different from market value. Other oversight agencies may be required to conduct additional studies to verify assessment uniformity. A re-appraisal order is required for cases when study results identify acute inequities. Despite the importance of conducting regular studies to quantify assessment uniformity, the appropriate method is still under debate in academia (Fairbanks et al. 2013, 21) and professionals in assessment practice continue to explore more accurate techniques (Gloudemans 2011; Denne 2011; Denne 2015).

1.1.4 Academic Debate over Vertical Inequity Estimation

Assessment uniformity is typically measured using assessment ratios (i.e., assessed value divided by sales price), measures of central tendency, or statistical models that describe how assessed values and sales prices covary. More recently, the literature has paid particular attention to vertical inequity methods (Fairbanks et al. 2013, Carter 2016). There are two streams of argument related to the appropriate method for vertical inequity estimation within a linear regression framework:

1. error-in-variables (Krupa 2014, 560 – 561)
2. causality direction (Fairbanks et al. 2013, 9)

The econometric framework is appropriate for measuring vertical inequity because of the uncertainty inherent in assessed values and sales prices. Each may be considered a random variable measured with some degree of error. Hence, the first argument regarding error-in-variables is an econometric issue identifying the independent variable as an endogenous regressor (Wald 1940, 285). The second argument relates to direction of causality; specifically, whether assessed value or sales price should be the dependent variable. In a linear regression framework, the dependent variable should be explained by the independent variable. Two issues are related to this argument. First, the causality direction should reflect economic theory. Typically, appraisers use sales prices to derive assessments, or in other words, sales *cause* assessments. This theoretical framework places assessments as the dependent variable. Since inequity estimation identifies uncertainty in assessments, this research applies an alteration to this framework by pre-dating assessments to their respective sales. Otherwise, it would be easy for the appraiser to judge property value, reducing the probability of inequity. Second, vertical inequity research identifies cases where switching causality flows on similar data sets produces contradictory results (Twark et al. 1989, 185; Fairbanks et al. 2013, 9).

1.2 Research Objectives

The focus of this dissertation is to evaluate the appraiser's accuracy of single-family dwelling, value predictions in both temporal and spatial dimensions. The appropriate method should be free of bias. This goal is obtained through three, specific objectives.

The first objective is to identify whether vertical inequity can be estimated without bias. Increasing uncertainty of appraisal estimates and transaction prices, exacerbated by volatile housing markets, requires statistical controls for error in ***both*** market value indicators, the sales price and the appraised home value. This research investigates the appropriate econometric approach to addressing uncertainty that removes bias from parameter estimates. While methods addressing the error-in-variables problem and appraiser uncertainty exist, some have questioned technical aspects of their use in practice. This research attempts to build upon the work of these seminal authors by identifying econometric tools addressing theoretical and practical concerns.

The second objective is to validate vertical equity estimates across a volatile housing market period. While the literature includes research investigating temporal vertical inequities addressing error-in-variables, it does not report model results or relevance and exogeneity diagnostics (Krupa 2014, 569). Such investigations are of particular interest because they highlight vertical inequity during episodes of increased doubt related to the validity of assessed values and sales prices. Temporal indices of vertical inequity provide empirical evidence fueling theories regarding appraiser behavior under increased economic uncertainty.

The final objective is to produce spatial indices of vertical inequity. Recent literature offers examples of vertical inequity measures for subdivisions of assessment jurisdictions; however, error-in-variables (Hodge et al. 2017, 246) and appropriate diagnostic tests are overlooked (Smith 2008, 215). While global estimates provide useful indicators at the assessment jurisdiction level, introducing local variation accents regions of concern where oversight agencies and assessors may focus investigations.

1.3 Data Description: Study Area and Study Period

The study area for this research is Dallas County, Texas, USA shown in Figure 1.3. It is approximately 908 square miles with approximately 871 square miles of land area. The 2010 population (U.S. Census Bureau 2017) was approximately 2.37 million and increased by almost 150,000 between 2000 and 2010 (U.S. Census Bureau 2011b). Residents appear to be concentrated in central and northern portions of the county. It contains Dallas, the 9th most populated U.S. city in 2017 according to the U.S. Census Bureau (2018).

Dallas County was selected for the analysis because rich appraisal, housing transaction, and geospatial data sources are available. The Dallas Central Appraisal District (DCAD) is the assessor for Dallas County, Texas and provided property characteristics, sales transactions, and public school tax rates for single-family dwellings in the study area. Housing market statistical reports were obtained from the North Texas Real Estate Information System, LLC (NTREIS). Public school quality in the form of elementary school ratings were available from the Texas Education Agency. Geospatial datasets were gleaned from various local municipalities and national, governmental organizations.

The study duration overlaps a period of volatile housing markets between 2004 and 2014 categorized into theoretical, recession phases: (1) pre-recession, (2) in-recession, and (3) post-recession. Each episode begins on January 1st and ends on December 31st. Although the Great Recession of 2007 did not begin on January 1st, phases are defined this way because the date of the dependent variable is representative of properties on this date. Figure 1.2 superimposes these theoretical recession phases on the Dallas-Plano-Irving metropolitan statistical division house price index between 2003 and 2015. This not only demonstrates the housing market volatility over the study duration, but also supports derivation of theoretical phases.

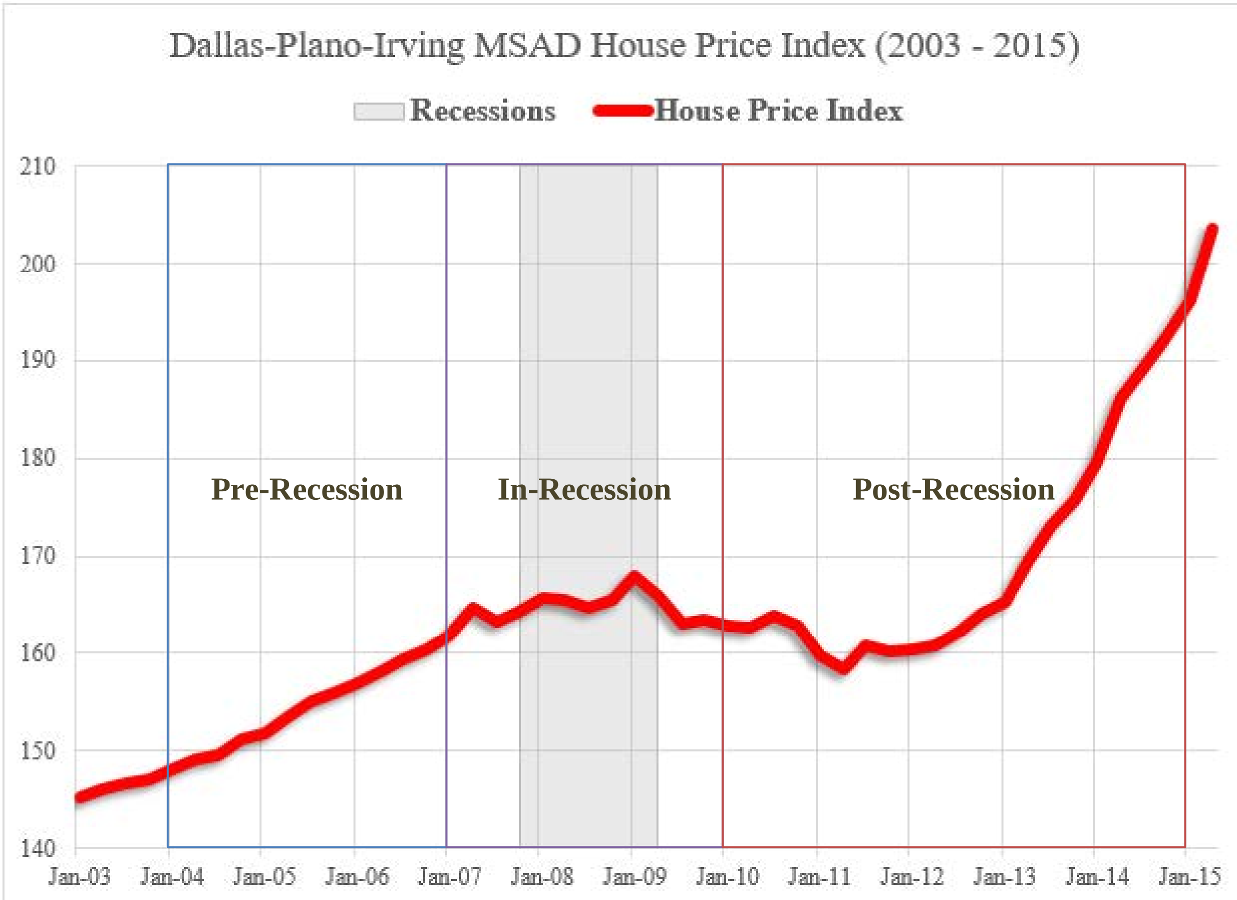

Figure 1.2. House Price Index for the Dallas-Plano-Irving MSAD from 2003 to 2015 with theoretical recession phases superimposed. Data from, "All-Transactions House Price Index for Dallas-Plano-Irving, TX (MSAD)", accessed 10/30/2015, https://research.stlouisfed.org/fred2/series/ATNHPIUS19124Q/.

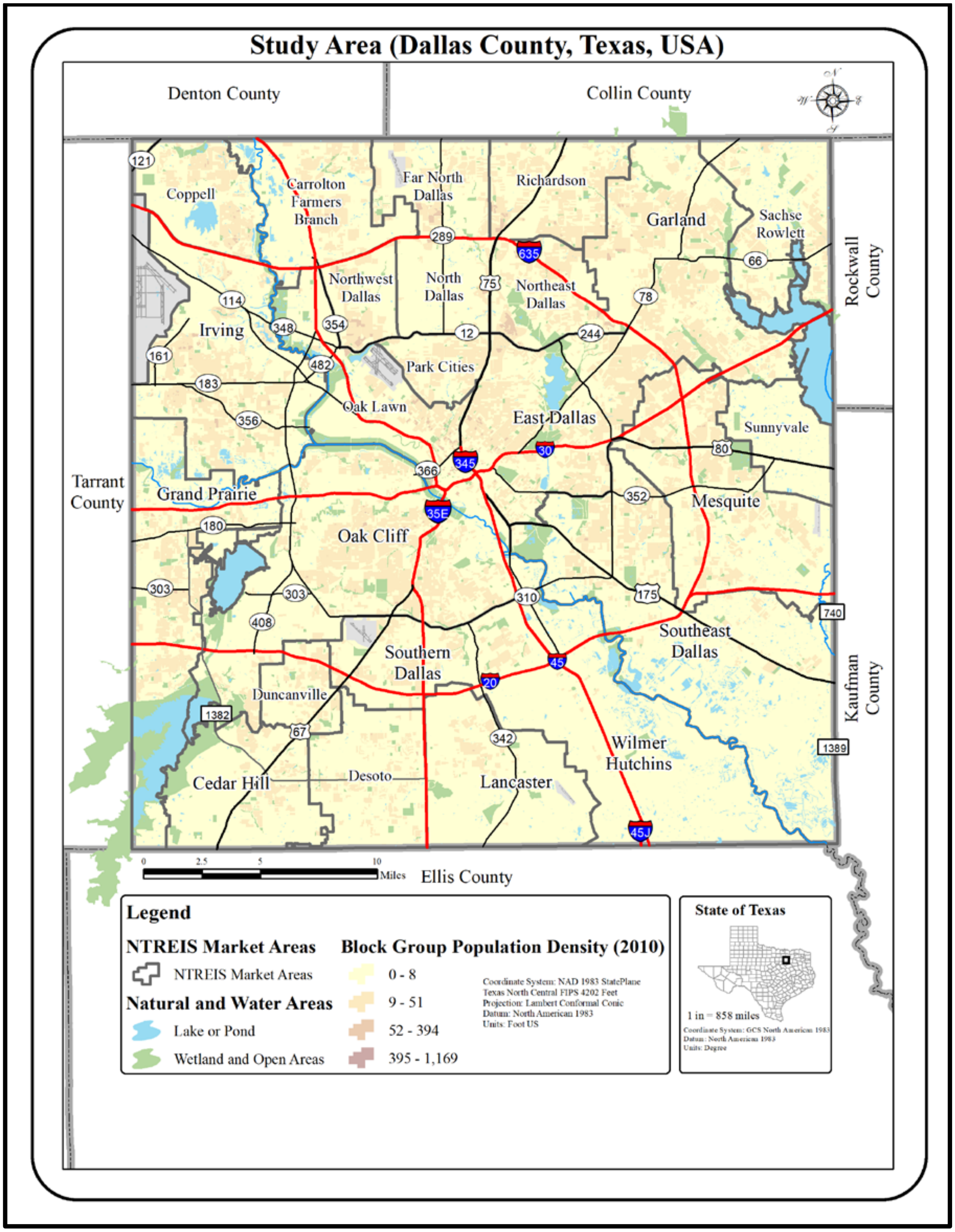

Figure 1.3. Map of Dallas County, Texas, USA and NTREIS housing market areas.

1.4 Methodology Overview

The development of the specific research objectives emerged in five phases. The first phase encompasses data collection and conversion to formats appropriate for linear regression. Hedonic house price variables that explained the current $\log(sales\ price)$ were operationalized and refined in a preliminary, ordinary least squares model during the second and third phases respectively. Variables include a variety of structural, neighborhood, locational, and environmental features translated from Sirmans, Macpherson, and Zietz (2005) taxonomy of commonly used hedonic house price variables in the literature. Novel specifications were employed for a subset of these variables. Sales and foreclosure activity were represented by a bi-variate normal distribution. Dwelling age was interacted with building class groups to model the appropriate price-age relationship. Additionally, spatial indices were created using a combination of existing data sets and published sources. The final variable set was adjusted using appropriate data transformations and residual analysis, ultimately improving model fit.

A global two-stage least squares model (over all temporal episodes and market areas) was specified and appropriate diagnostics used to validate instruments in the fourth phase. Here, the temporal lag between the appraisal estimates and the revealed sales prices was controlled for via house price indices obtained from NTREIS statistical reports. Potential causality flows were expressed as bi-directional influences based on comparable sale use in the appraisal process and negative property tax capitalization theory. In the fifth and final phase, the global specification was generalized with indicator variables and interaction terms to identify inequity trends for each study year and areal heterogeneity in a temporal model and a spatial model, respectively. A flow-chart outlines the employed research methodology in Figure 1.4.

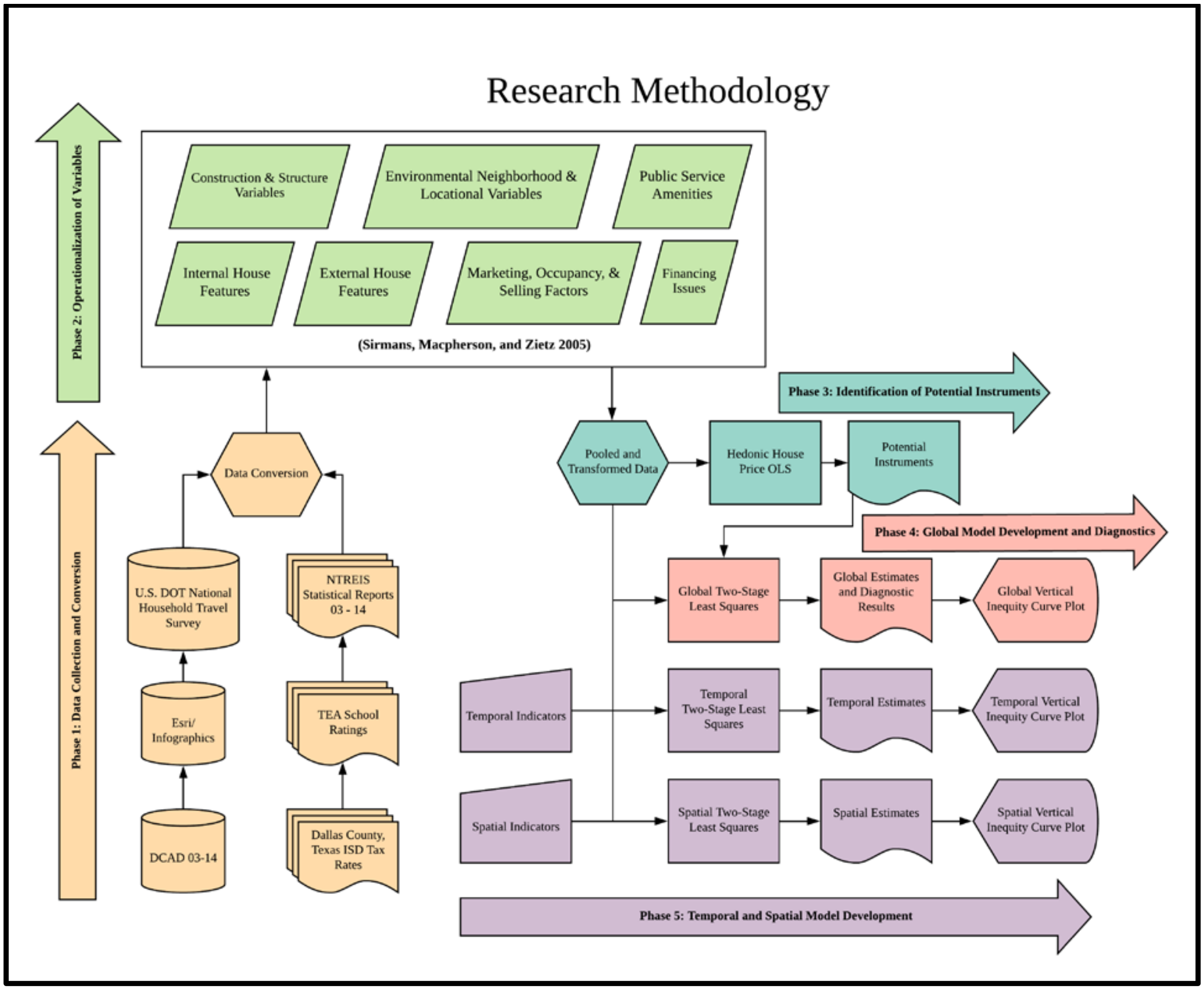

Figure 1.4. Research methodology divided into five logical steps.

1.5 Dissertation Outline

The dissertation is organized into eight chapters. Following this introduction are four chapters comprising the literature review. Chapter 2 sets the empirical background for Dallas County, Texas residential markets, forming of the real estate bubble, and eventual housing market crash with its subsequent market boom. Implications for housing market volatility and assessment uniformity provide a meaningful transition for the following chapter on uncertainty in market value indicators assessed value and sales price. Chapter 4 explores the assessment uniformity literature including methods addressing error-in-variables and causality direction. Additionally, Chapter 4 reviews theoretical background for instrumental variables and other statistical methods. The research methodology is expanded in Chapters 5 – 7. Detailed data descriptions and theoretical arguments for hedonic house price instruments are contained in Chapter 5. Chapter 6 provides the preliminary, hedonic house price, ordinary least squares model identifying potential instruments later used in a global, two-stage least squares specification. Associated instrumental variable diagnostics are then presented. Causality direction is adjusted according to the theoretical linkage between assessed values and sales prices. To evaluate appraiser accuracy effectively, this relationship is modified to use the lag of appraised value as the dependent variable to incorporate appraiser uncertainty about future sales prices. Graphical plots, house price indices, and horizontal inequity adjustments are introduced here. Temporal and spatial specifications with associated graphical plots are shown in Chapter 7. Chapter 8 summarizes findings, makes policy recommendations, reveals limitations, and offers future research opportunities. Appendices provide assessment processes, spatial unit details, and other documentation.

CHAPTER 2

THE DALLAS HOUSING MARKET AND ITS ECONOMY BEFORE, DURING AND AFTER THE 2007 RECESSION

To provide a foundation for understanding housing dynamics as they relate to the research problem, this chapter will first discuss the general structure of the housing market in Dallas County, Texas. The following section reviews the national, housing regulatory environment and its implications before the Great Recession of 2007. The next section provides an overview of Dallas County's economic housing stability before the recession and its subsequent volatility during and after the recession. The chapter concludes by discussing some implications of the study area's local housing market across volatile economic cycles for the assessment process.

2.1 Empirical Background of Dallas County, Texas Housing Market Economy Before 2007

Understanding the nature of Dallas County's housing market requires knowledge of local sales price distribution across its urban landscape. Research reveals that Dallas County's urban structure does not conform to the monocentric model. The monocentric city model (O'Sullivan 2012, 174), is a representation of a municipality that has one central business district and portrays house price distributions in terms of distance decay from the central city node. Waddell, Berry, and Hoch (1993b) analyze distance decay, or house price gradients, in the multi-nodal urban landscape of Dallas County, Texas. They also investigate spatial externalities such as the house price effects of distance to major highways, employment sub-centers, intersection of land with floodplains and ethnic clusters. To quantify these externalities, they employ a hedonic model that regresses the log of sales price on a battery of indicator variables that capture socioeconomic, spatial and temporal effects. To capture the price gradient effect from each employment center, authors divide distances into three categories: zero to one mile, two to five miles, and five to ten miles (Waddell, Berry, and Hoch 1993b, 122). They find evidence of an "asymmetric and non-linear" price gradient from the primary central business district (Waddell, Berry, and Hoch 1993b, 127–28). These price gradients reflect striking differences in prices between the area immediately north and south of the central business district. They explain this price gradient using resident income levels. The wealthy, "high-status" municipalities of university and highland park demonstrate price homogeneity while south of the central business district some gentrified areas contrast with low-income housing (Waddell, Berry, and Hoch 1993b, 128). Satellite employment sub-centers (e.g., "Las Colinas" and "Galleria-LBJ") limit the central business district price gradient from 10 to 15 miles (Waddell, Berry, and Hoch 1993b, 129–30).

Another study evaluates house price distributions in relation to dwelling age. Rubin (1993) argues that buyers are willing to pay more for recently built homes rather than older homes. Waddell, Berry, and Chung (1996) reveal some weaknesses in Rubin's approach and propose improvements to his methods. They seek to understand the effect of house price depreciation across residential submarkets within Dallas County, Texas. Authors collect approximately 15,000 single-family dwelling transactions occurring in 1993 across 44 different submarkets within Dallas County, Texas. To provide context for analytical results, they merged the data set with socioeconomic variables from the 1990 block-level census. Single-family dwelling age in Dallas County, Texas, exhibits a non-linear relationship to price (Waddell, Berry, and Hoch 1993a, 15; Goodman and Thibodeau 1995; Waddell, Berry, and Hoch 1993b, 126–27). To control for this non-linearity, they include linear, quadratic and cubic transformations of the dwelling age variable in their ordinary least squares specification (Waddell, Berry, and Chung 1996, 270–71). They identify “significant heteroscedasticity” in estimated housing price throughout the county, so they weight observations across different submarket region clusters (Waddell, Berry, and Chung 1996, 271) They find that different clusters demonstrate varying house price depreciation patterns, which suggests that “premiums” are paid with respect to the age of the dwelling (Waddell, Berry, and Chung 1996, 279).

Another key component to understanding the Dallas County housing market is the behavior of sales prices across economic business cycles. House prices are known to fluctuate in parallel with economic recession and expansionary periods. These fluctuations are expressed in different equilibrium levels of supply and demand. Supply refers to the number of homes that are available for sale at a given price. This supply is sorted into heterogeneous market segments compartmentalized by age of the housing stock, housing style and building materials. Supply may also be categorized into *new construction* or *pre-existing homes*. The total number of buyers actively looking to buy a home drive housing demand. Just as housing supply is heterogeneous, buyers’ housing preferences are also heterogeneous. Buyers interact in the market with their own unique preferences for housing. A 2013 – 2014 survey conducted by the National Association of Realtors (2014a; 2014b) identified characteristics of groups that purchased real estate. It categorizes home buyers into profiles such as: 1) “first-time home buyers”, 2) “repeat buyers”, 3) “married couples with kids”, 4) “unmarried couples”, 5) “multi-generational buyers”, 6) “single females”, 7) “single males”, 8) “senior-housing buyers”, 9) “commuters” and 10) “downsizers”.

When supply and demand are in equilibrium supply matches demand at a given price. Increased demand produces more sales in the housing marketplace. When houses are selling frequently this is considered in the literature as a “broad” or thick market (Jacobus 2012, 384–85). This kind of economic environment yields many comparable sales, improving accuracy of market value estimates. Reduced demand translates into fewer sales and possibly, increasing supply. A thin market prevails when few buyers and sellers are interacting with one another for the purchase of property. Accurately identifying market value of real estate is more challenging under thin market conditions because there are fewer comparable sales. Accuracy suffers from a lack of reference points on which to judge the value of housing characteristics and local amenities. This condition may contribute to horizontal or vertical inequity.

Disequilibrium in supply and demand produces an alternative set of market conditions: 1) supply is high and demand is low or 2) supply is low and demand is high. These conditions are also known as a buyer’s market and a seller’s market respectively. In a “buyer’s market”, high volumes of initial supply are sold at a fraction of the cost because few buyers are willing to pay the asking price (Jacobus 2012, 384). Sellers compete for the buyer’s bid in this kind of market by lowering prices. As supply remains longer and longer on the market, the listing price continues to drop to attract a willing buyer. In a “seller’s market”, low volumes of available housing supply sell at a premium because the buyers are now competing against one another for the purchase of real estate (Jacobus 2012, 384). In these markets, buyers may find that they are required to increase their bid to purchase property that attracts other bidders. Both types of markets reflect a transition in a buyer’s willingness to pay. In a buyer’s market, they pay less for housing because there are more options that meet their specific housing preferences. On the contrary, in a seller's market buyers are willing to pay a premium for housing because there are fewer options that meet their housing preferences. This phenomenon of buying and selling behavior and the potential sales price of homes is what appraiser's try to estimate. Identifying the market value of homes can be challenging when supply and demand patterns change drastically. Drastic changes in supply and demand patterns may follow economic business cycles. Drastic economic business cycles are expressed by recessions and expansions.

Berry, Chung, and Waddell (1995) perform an empirical investigation to observe price variation in local housing submarkets during periods of recession and expansion. Authors produce house price indices using hedonic house price models for 50 housing submarkets within Dallas County, Texas. Approximately 185,000 single-family dwelling sales transactions were merged with structural, geographic and socioeconomic attributes over the period between 1979 and 1993. Authors initiate the viewpoint of housing as a "multidimensional good" expressed as a bundle of services, each varying in magnitude and value (Berry, Chung, and Waddell 1995, 722–23). Hedonic model parameter estimates represent implicit prices, revealed by supply and demand, expressed within the dependent variable (house transaction price). Authors fit hedonic house price models of structural, geographic, and socioeconomic attributes over the study period (Berry, Chung, and Waddell 1995, 722). Temporal indicators are included within regression models for expressing fluctuations in price indices. The authors include a note on the creation of 67 market areas, typically used for the purpose of "Appraisal Ratio Studies", to estimate price indices for their study (Berry, Chung, and Waddell 1995, 732–33). These market areas were defined by UTD's Bruton Center as aggregations of DCAD neighborhoods. DCAD neighborhoods originate from digitized polygons combined with attributes in the appraisal database. These polygons were aggregated based on adjacency, municipal boundaries, school district boundaries and similarity in characteristics such as appraisal value, area of the improvement, age of the dwelling, distance to freeways and floodplain participation. Homogeneity within these submarkets was subsequently validated using Wald tests. Cases that failed the null hypothesis of the Wald test were aggregated into a larger market area. This process refined 67 market areas to a total of 50 that exhibited asymptotic homogeneity. While these market areas were considered for application in this research, they were later replaced by more recently created market boundaries commonly visible in the public eye.

To provide context for study results, Figure 2.1 shows the trend of the Dallas-Plano-Irving house price index over the study period. The gray bars represent national recession cycles as defined by the National Bureau of Economic Research. The red line is based on data from the U.S. Federal Housing Finance Agency (2015) representing house price indices[3] for the Dallas-Plano-Irving metropolitan statistical area division from April 1976 to December 1993. The figure displays prices appreciating from April 1976 until April 1986 when prices begin to decline.

[3] House price indices reveal changes in house prices based on repeat sales and refinancing of single-family residences. The y-axis in the following house price figures represent percentage points from the initial period when the index was recorded. For example, the index in Figure 2.1 begins the index at about 45 index points. These data are not seasonally adjusted and are reported by quarters.

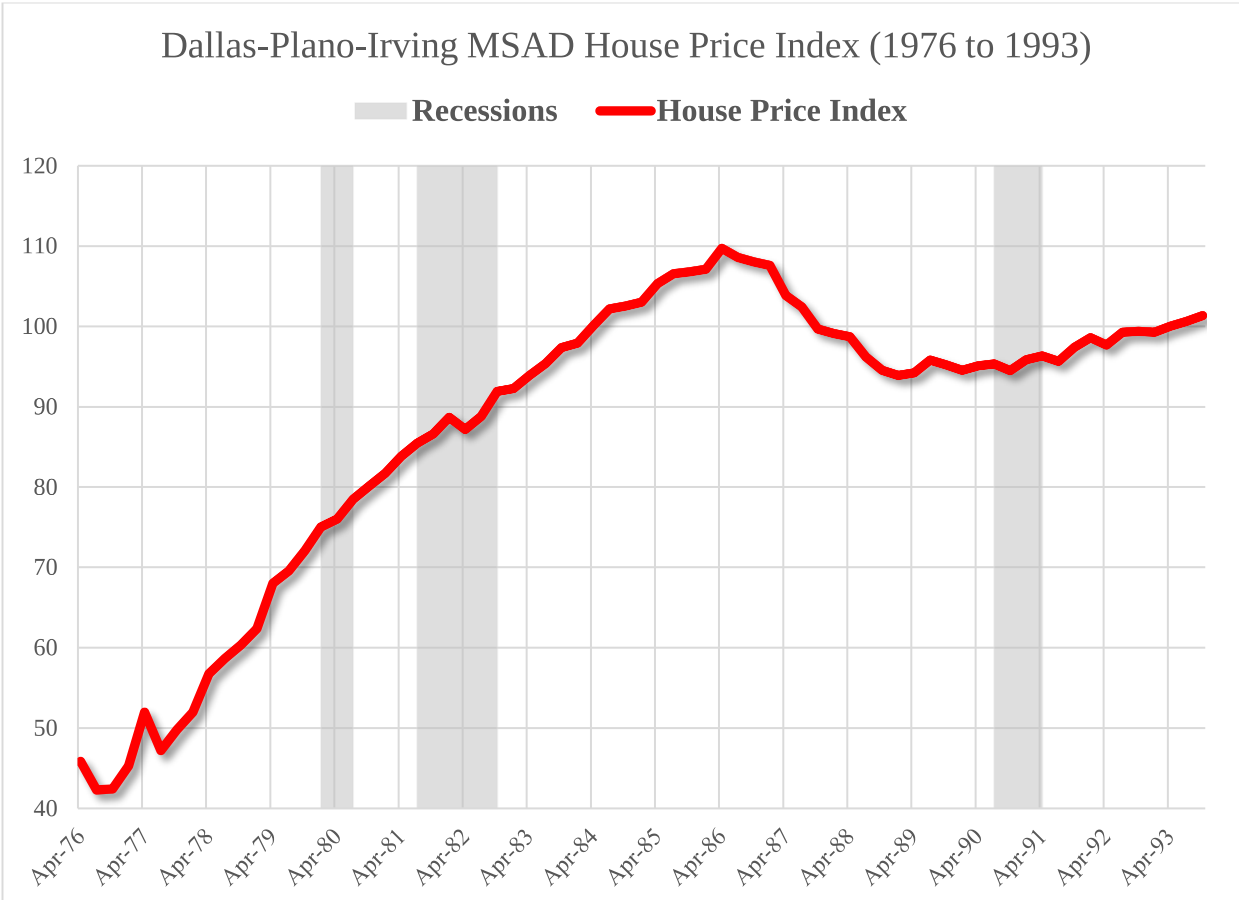

Figure 2.1. House Price Index for the Dallas-Plano-Irving MSAD from 1976 to 1993. Data from, "All-Transactions House Price Index for Dallas-Plano-Irving, TX (MSAD)", accessed 10/30/2015, https://research.stlouisfed.org/fred2/series/ATNHPIUS19124Q/.

To facilitate interpretation of house price indices, authors combined market areas into nine groups identified alphabetically with the letters A through I. One area, primarily containing industrial and manufacturing properties, was omitted from the study. Berry, Chung, and Waddell (1995, 731) identify prominent patterns throughout Dallas County business cycles. Figure 2.2

illustrates the pre-2008 DCAD assessment region[4] showing the 50 submarkets and their group clusters used in the analysis. A description of housing market activity in these areas is provided in Table 2.1.

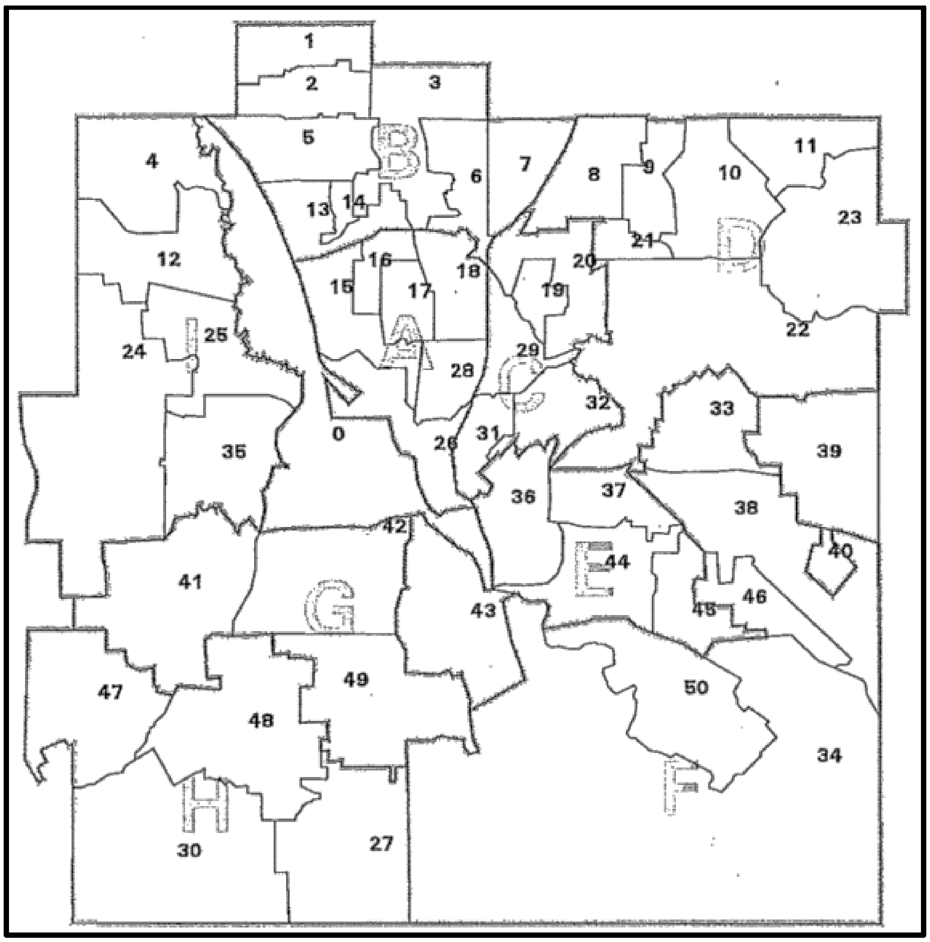

Figure 2.2. Housing submarkets and group clusters in the pre-2008 DCAD region. Adapted from "Widening gaps: The behavior of submarket housing price indexes in the Dallas area, 1979-1993" by Berry, Brian J. L., Chung, Kyoun-Sup and Waddell, Paul, 1995, *Urban Geography*, 16, pg. 724. Copyright 1995 by the Taylor and Francis Group. Included with permission.

[4] Prior to 2008, the DCAD assessed some areas outside of Dallas County, Texas.

Table 2.1. Marketa area group label and description.

Market Area Group Label	Description
A	Highest income in study region. Markets experienced greatest appreciation and stability.
B	Suburban neighborhoods experienced moderate appreciation with some markets struggling due to competition between new and existing homes.
C	Heterogeneous culture, housing stock, and quality. Wealthy pockets of older homes rimmed by subsidized government housing. Steady appreciation throughout the study period.
D	Suburban neighborhoods with a major rural section. With the exception of area 11’s volatility, markets experienced similar appreciation to Group B.
E	Lowest income in study region. Depreciation reduced house prices below initial levels and recovery was more gradual than in other groups.
F	Suburban neighborhoods with a rural mix similar to group D. Homes appreciate and decline moderately as other groups. After alternating gains and losses, indicative of group E, market area 50 ended the study period below initial levels.
G	Suburban neighborhoods with wealthy pockets of older homes. Price patterns are reflective of group F, except for market area 42 rising well above other markets early in the study period.
H	Suburban neighborhoods with moderate appreciation and decline as in groups F and G.
I	Suburban neighborhoods with moderate appreciation and decline in markets 24 and 35, and little appreciation in markets 12 and 25. Market area 4 maintained positive appreciation later during the study, possibly due to positive perception of local public schools.

This study is informative because of the rich set of local, market area characteristics under variable, economic stability levels. Wealthy housing markets experienced less of a negative impact from the recessionary cycle and recovered more quickly, even exceeding price levels at the start of the study period. Poor market areas exhibited detrimental price impacts during the market decline and took much longer to recover. Authors refer to “widening gaps” in this study as increasing price disparities between the lower- and higher-income markets of Group

E and A respectively, from the beginning of the study period to its completion (Berry, Chung, and Waddell 1995, 731). Although informal adaptations of these market areas may exist, future research would benefit from a contemporary market analysis.

2.2 The Forming of the Real Estate Bubble

Shortly following the period of house-price appreciation and decline in Dallas County examined by Berry, Chung, and Waddell (1995), national real estate economic cycles changed in scope and magnitude. A prolonged period of appreciation may have been the result of an economic "bubble" (Wheaton and Nechayev 2008, 2). Theories regarding the national housing bubble suggest that house prices appreciated rapidly beginning in the $1990s$. Despite these rapid price gains, Dallas County house price appreciation remained well below the national level (Wheaton and Nechayev 2008, 4).

An economic bubble is a drastic increase in the price of some commodity that suggests promising growth to investors. Such sharp increases eventually result in sinking prices based on unmatched expectations as dire as they were optimistic at the outset. These declines may result in economic disasters (Smith and Smith 2006, 2). As house prices continued to increase sharply borrowers felt confident in the ability to pay off mortgages beyond budgetary constraints (Jarsulic 2010, 2). Inquiry into the causes of this spike focuses our attention on policy interventions that, perhaps inadvertently, opened loopholes for unwise lending practices.

2.2.1 Low Interest Rates

According to Zandi (2009, 9) events such as 9-11, conflict in Iraq and the decline in the technology stock market triggered economic concern that encouraged the federal reserve to lower interest rates to "a record low" at 1% in 2003. As is typical of banks, they followed the example of the Federal Reserve by reducing their own interest rates. Amidst the Federal Reserve's fears of inflation, they employed periodic, interest rate increases (Gieve and Provost, 2012, 68). Despite this federal intervention, lenders were allowed to suppress interest rates through alternative mortgage products (Gieve and Provost 2012, 69). The Financial Crisis Inquiry Commission (2011, 85–86) found that interest rates for adjustable rate mortgages were among the lowest and these lending tools began to increase rapidly in popularity and use.

2.2.2 Government Sponsored Entities: Fannie Mae and Freddie Mac

The two organizations Federal National Mortgage Association (i.e., Fannie Mae) and Federal Home Loan Mortgage Corporation (i.e., Freddie Mac), also known as Government Sponsored Entities, were instituted to purchase and manage portfolios of federally insured mortgage loans (MacDonald 1995, 55). These organizations marketed portfolios using a new method to introduce and liquidate capital into mortgage lending mechanisms called *securitization* (Peicuti 2013, 444-445). With the inception of the Secondary Mortgage Market Enhancement Act in 1984, securitization was opened up to the private sector unfettering their investment options (MacDonald 1995, 59). Historically, mortgage portfolios were a long-term asset, but through the process of securitization, originators could liquidize loans quickly (Peicuti 2013, 446). In the face of compelling evidence against lenders from studies based on the Home Mortgage Disclosure Act data, the Community Reinvestment Act was amended to introduce stricter controls to balance loan approval across ethnic backgrounds (MacDonald 1995, 61). The Affordable Housing Act of the early 1990s also imposed lending quotas for Fannie Mae and

Freddie Mac to provide mortgages to applicants that did not meet previously established guidelines for good credit ratings (McCoy and Renuart 2008, 9; Lucas et al. 2013, 2).

2.2.3 The Rise of Sub-Prime Lending

Loans sold to applicants with substandard credit were considered “subprime” (Agarwal, Ambrose, and Yildirim 2015, 891). As banks and other private lenders entered the arena, the reduced risk from securitization and the loopholes left open from federal policy instruments set the stage for “regulatory arbitrage” in the mortgage industry (Acharya, Schnabl, and Suarez 2013, 516; Karolyi and Taboada 2015, 2396). This allowed banks to distribute risky investments, inhibited by local regulation, into foreign, less-regulated credit markets. These lucrative instruments outshined traditional bonds that were waning in their yield. A report from the International Monetary Fund identified a transition from investment in U.S. treasury bonds “towards riskier and more complex investments” (International Monetary Fund 2005). At the same time, national house prices were growing and reached their peak in July of 2006 according to the S&P/Case Shiller house price index (S&P Dow Jones Indices LLC 2018). On the expectation of increasing house prices, lenders grew more confident in providing risky mortgages for unqualified candidates. Since appreciating house prices made it more difficult for typical buyers to purchase housing with traditional mortgages (Byun 2010, 3), appealing products such as Alt-A and other subprime derivatives began to enter the lending market. These loans allowed for exorbitant loan-to-value ratios (Agarwal, Ambrose, and Yildirim 2015, 898), options to pay interest-only, and low-interest rates with longer re-payment periods (Peicuti 2013, 447). Vulnerable populations, which lending policies were meant to support and guide to homeownership, were now being targeted for loans that were outside of their ability to repay

(Nofsinger 2012, 172). Over concerns of “predatory lending” in Illinois, legislators initiated a 2006 pilot project (i.e., HB 4050) to control against such practices (Blagojevich 2007). Researchers used this pilot program as an experiment to determine if predatory lending was one of the stimulants of the subprime mortgage crisis (Agarwal et al. 2014, 30). While the author’s findings were inconclusive[5], in the pilot project treatment area they did determine that market activity was reduced by 40% and defaulting loans were reduced by $6-7\%$. This was in part by lenders specializing in unsafe mortgage products and consumers of such loans exiting treatment areas. Although “predatory lending” may not have been a primary cause for the crisis, authors suggest further investigations should look into “reckless lending” practices (Agarwal et al. 2014, 50).

An empirical study by Keys et al. (2010) questioned whether securitization permitted relaxed lending regulations on subprime mortgage loans. Not only do authors identify an increase in subprime loan origination after 2003 when the Federal reserve began increasing the interest rate, but also that applicants experienced “lax screening” (Keys et al. 2010, 308). Authors investigate loan applications between 2001 and 2006 and find that applicants with FICO scores just above 620 required less stringent credit checks (Keys et al. 2010, 353). This is based on Fannie Mae and Freddie Mac’s “rule of thumb” denying loan approval for borrowers having FICO scores below 620 (Keys et al. 2010, 309). For pre-crash lenders, this score gave the illusion of creditworthiness while undermining capital verification for potential borrowers. Their experiment proves that lenders succeeded in forcing loans for at-risk borrowers meeting the

[5] This is primarily a function of the inability to measure the lender’s information advantage over the borrower’s (Agrawal et al. 2014, 30).

FICO borrowing threshold without sufficiently investigating their income and other assets. Frame (2015, 809) suggests escalating house prices led lenders to believe subprime mortgages were less risky for these "low documentation" clients.

2.2.4 Indications of Failure

For the time period between 1999 and 2006 the amount of home mortgage debt nearly doubled in 2006 dollars (Ashton 2009, 1432). This ever increasing debt, with a substantial percentage established on subprime type loans (Lucas et al. 2013, 9), began to have repercussions upon the housing market. The prosperity of the housing market amid increasing supply and diminishing demand began to wane and decreasing prices of homes left many subprime mortgage holders underwater (Greene et al. 2012, 161). No longer able to maintain homes with negative equity[6] many suffered from loan default and foreclosure (Ellen and Dastrup 2012, 1). These impacts also affected banks. Their desire to fund mortgages vanished amidst and ever increasing backlog of poorly maintained properties (Leonard and Murdoch 2009, 331).When a property enters default on a mortgage, it ultimately results in a foreclosure. At some point, the bank that retains equity in the property attempts to sell the property but usually at a fraction of the original loan.

2.3 The 2007 Housing Market Crash

Exploring Dallas County house prices across latter recession and expansion periods of the 20th century gives the reader an indication of local housing market behavior through volatile

[6] Negative equity refers to the value of the property being less than the total amount owed for the mortgage. This is also known as an underwater mortgage.

economic periods. The most recent recession in 2007, has been quoted by some to have paralleled the Great Depression in its impact on the housing market (Nofsinger 2012, 164; Lutz, Molloy, and Shan 2011, 306). Employment levels dropped significantly in many areas and households out of work could not afford to make their mortgage payments. Mortgage delinquencies increased from 0.9% in 2006 to 8.9% in 2010 (Kumhof, Rancière, and Winant 2015, 1224). When foreclosures and short sales increase in a neighborhood, it had a destabilizing effect. Households in foreclosure were required to move to other locations having a negative impact on local social capital[7]. Regions and neighborhoods affected by a weakened economy were eligible for special government grants to help revitalize neighborhood property values and encourage households to move in. Dallas County received approximately 12 million in government funding through the "Neighborhood Stabilization Program", a component of the 2008 Housing and Economic Recovery Act (Blum 2009, 6–7).

2.4 The Dallas County, Texas Housing Market Before, During, and After the Great Recession

This section explores the nature of the housing market in Dallas County before, during, and after the 2007 recession. The national bureau of economic research believes that the recession began in December of 2007 and ended approximately in June of 2009 making it the longest post-world war II recession (Financial Crisis Inquiry Commission 2011, 1). To provide context for house price fluctuations before, during, and after the recession Figure 2.3 shows the trend of the Dallas-

[7] Social capital refers to the relationships among neighborhood residents giving them a sense of belonging and unity that strengthen individual ties to the location.

Plano-Irving house price index between 2003 and 2015. The gray bar represents the recession period as defined by the National Bureau of Economic Research. The red line is based on data from the St. Louis Federal Reserve displaying the Dallas-Plano-Irving metropolitan statistical area division, house price index from January 2003 to April 2015.

House prices[8], according to the graph in Figure 2.3, are appreciating from early 2003 until the end of 2007 when the recession officially began. This is indicative of what economists have called the "housing bubble" (Smith 2005, Hardaway 2011, and Mayock 2014). During the recession period, homebuilders began to stall in their production. This drop in housing volume subsequently lowers the house price index. Even for a short period after the official recession ended, prices continued to decline. Then several fluctuations occur demonstrating housing market volatility until early 2012 when the market stabilized and prices began to rise rapidly due to an increase in demand outpacing available supply. In this post-recession period, there was a lack of new housing. Slowly builders were able to increase housing volumes. Prices then rose rapidly, even past levels before the recession, perhaps because the market aimed at making up for losses during recession years.

[8] The y-axis represents percentage points from the initial period when the index was recorded. For example, Figure 2.3 begins the index at about 145 index points.

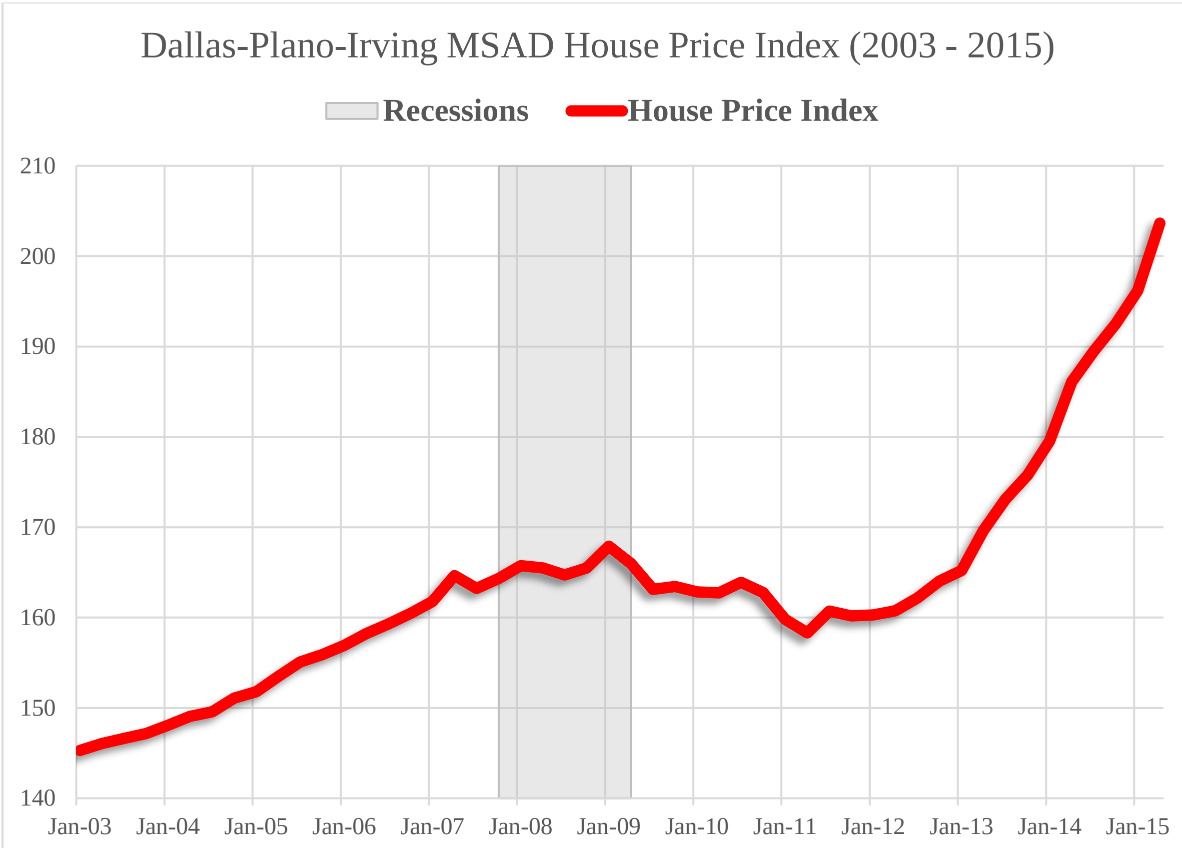

Figure 2.3. House Price Index for the Dallas-Plano-Irving MSAD from 2003 to 2015. Data from, "All-Transactions House Price Index for Dallas-Plano-Irving, TX (MSAD)", accessed 10/30/2015, https://research.stlouisfed.org/fred2/series/ATNHPIUS19124Q/.

Supply and demand indicators reveal the kind of market that prevailed during recessionary economic cycles. NTREIS provides information regarding single-family home sales for various counties in the North Texas region. Two indicators of supply and demand they provide are summary statistics of average number of days on the market and total homes sold for a given county. These statistics are available by quarter for Dallas County between 2004 and 2014 in Figure 2.4. The red line indicates total homes sold during the quarter. This value gives some insight into Dallas County housing demand over the data series. The grey dashed line represents the average number of days listed homes remained on the market during the quarter. Average number of days listed on the market provides some indication of supply. The axis on the right side of the graph displays the average number of days that listed homes are on the market while the axis on the left side of the graph displays the total number of homes. The light grey recession bar approximates the period of the 2007 recession. The date interval represents quarters between economic cycles.

Before the recession, Figure 2.4 shows a constant to gradually increasing demand, despite seasonal fluctuations. There is also a gradual increase in average number of days on the market. As the recession period begins, approximately $Q1{:}\,2008$, housing demand slows down as indicated by fewer sales and sharper increases in the average number of days on the market. Economic conditions here reflect a thin market. In this environment, many existing homes fell into foreclosure and banks were placing them on the market for sale. Demand may have dropped due to Dallas County residents losing employment, businesses cutting budgets, and banks becoming more reluctant to fund mortgage loans.

After the 2^{nd} quarter of 2013, the supply and demand pattern reveals that the number of homes sold sharply increases and the average number of days on the market decreases. This pattern exhibits a seller's market where demand exceeds the level of supply, ultimately driving up. This may indicate the steep climb in the house price index after 2012 in Figure 2.2. Here builders are trying to add to existing volumes but the recessionary housing market may have caused laborers and builders to relocate. In this pattern, a thin market could result if supply continues to drop.

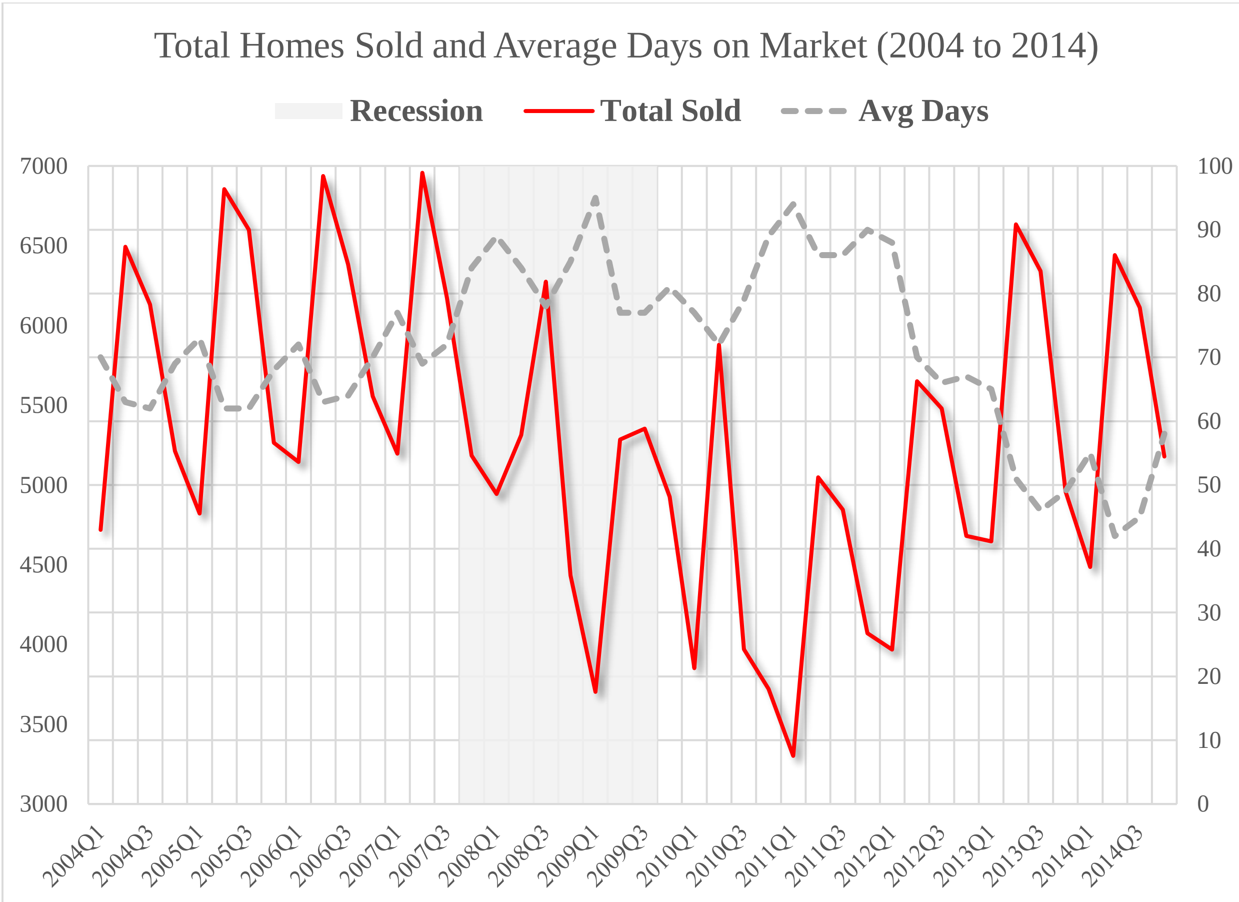

Figure 2.4. Total Homes Sold and Average Days on the Market from 2004 to 2014. Data from the North Texas Real Estate Information System, accessed 08/19/2013, http://www1.ntreis.net/ntreis/resources/statisticsarchive.asp.

2.5 Volatile Housing Markets Challenge Assessment Uniformity

Reflecting on local housing economy indicators from the viewpoint of supply and demand provides some indication of the dynamic characteristics of the Dallas County housing market. Thin markets, such as those indicated during the recession period, challenge the appraiser because there are fewer representative comparable sales to establish an opinion of value. Appraiser’s estimates may be biased in thin market conditions and assessment inequities may result (McMillen and Weber 2008, 654; Weber and McMillen 2010, 79).

Sharp changes from a buyer's market to a seller's market, such as those indicated after the recession period, also challenge the appraiser in identifying market value. This difference between an appraiser's estimate and market value is known as *assessment lag* in the property tax assessment literature (Bowman and Mikesell 1978, 140; Levine 1983, 109). It refers to appraisers trying to catch up with the housing market. Assessment lags may vary in magnitude depending on the volatility of property markets. This phenomenon, among others, constitutes a challenge to assessment uniformity.

One of the goals of this research was to identify how assessment uniformity changed before, during, and after the 2007 Great Recession. This research proposes that challenges were greater for the appraiser to establish unbiased estimates during periods of housing market instability. When bias exists in either appraiser estimates or market value, then measurement error becomes an issue. Measurement error translates as an error-in-variables problem in econometric analysis. The next section defines assessed values, sales prices, and their inherent uncertainties.

CHAPTER 3

MARKET VALUE, ASSESSED VALUE AND SALES PRICE

3.1 Assessed Value and Sales Price Versus Market value

An understanding of the *unknowns* inherent in market value is essential before one employs benchmarks for its accurate measurement. The unobservable nature and uncertainty of market value is introduced. This discussion defines assessed value, sales price and their components. Although not central to this research, insurance value is also mentioned. The assessed value and sales price literature is reviewed. Following a comparison of the two variables sales price is distinguished as a more accurate depiction of market value. This chapter ends by relating uncertainty in assessed value and sales price with the error-in-variables problem.

3.1.1 Market Value Defined

According to Jacobus (2012, 356), *market value*, also known as *fair market value*, is the maximum, monetary amount for which real estate is worth under ideal market conditions[9]. A paramount issue in identifying market value is the inability to measure it precisely. This variable is considered to be unobservable by some authors (Robins and West 1977, 290; Kochin and Parks 1982, 527; Clapp 1990, 233). Direct measurement of market value is impossible given the universe of preferences a buyer may have about their willingness to pay for real estate. Evans (1995, 12) suggests that there is no "true market value", but, rather a "range of prices". *Assessed*

[9] See Appendix E for a list of these conditions within the market value definition.

value (Clapp and Giaccotto 1992, 301) and *sales price* (Dare, Goebel, and Isett 2011, 23) are two observable measures that may be used as proxies for market value.

3.1.2 Assessed Value Defined

Jacobus (2012, 626) defines assessed value as, “a value placed on property for the purpose of taxation.” This value is a final estimate that public service providers use to tax residents. Revenues generated from property taxes fund public services (e.g., public education, municipalities, and utility districts). Assessed values represent a taxable amount that public service providers may use to estimate annual budgets. The taxable amount for each property is multiplied by the tax rate published by the local government. The result is the amount owed in property taxes by the homeowner provided on the homeowner’s annual tax bill.

Assessed value is comprised of the appraiser’s estimate of a property’s[10] value (land and buildings). The appraised value is an opinion or estimate of market value of an appraiser for a portion of land and improvements based on property characteristics and real estate market indicators (FDIC 1990).

The appraised value is not always equivalent to the assessed value in some cases. Property exemptions are discounts subtracted from the appraised value. Many states provide taxpayers with the option to apply for exemptions based on their qualifications. For example, in the state of Texas, if a taxpayer owns a property and it is their primary residence, it qualifies for a homestead exemption. Other homeowners may qualify for exemptions[11] based on their age,

[10] The term property refers to the market value of the land and the buildings or improvements that exist on the land.

[11] State laws vary on the requirements and availability of exemptions for real property (Haveman and Sexton 2008, 11).

disability and veteran status. Appraised value may be further reduced when a homeowner or their representative participates in an appeal or protest. Reductions occur if the decision of an unbiased panel of real estate professionals determines based on the evidence provided, that the appraisal should be lowered. In these panel hearings, appraisers represent the appraisal district and defend the value applied to the property.

3.1.3 The Appraiser's Role

The licensed appraiser's role is to estimate a property's value based on federally mandated standards of professional appraisal practice. These standards allow appraisers to use expert knowledge to make value judgements on real estate for the purposes of estimating market value. They produce reports and document findings that support their value judgements. To the extent possible they are to make judgements as "impartially" and "objectively" as possible (The Appraisal Foundation 2010, U-6). Appraisers do all they can to "protect the overall public trust" in the appraisal profession (The Appraisal Foundation 2010, U-6). They have a responsibility to the public to ensure their valuation is of the highest quality and adheres to uniform standards of appraisal practice. On occasion, they may be asked to defend these judgements before a property tax assessment review panel or within a court of law.

The role of the appraiser has a lot of bearing upon the purpose of the employer. Appraisal districts employ appraisers for the purpose of property tax assessment. The Bureau of Labor and Statistics (2015) names this kind of appraiser an "assessor". These assessments form the basis of local government property taxation. Appraisal services are also required for mortgage lenders, providers of homeowner's insurance, and real estate investment firms. Members of this latter group are commonly known as "independent fee appraisers" (Cypher and Hansz 2003, 307) and produce an appraised value as the basis for a mortgage or insurance coverage amount.

Although acting under similar rules and standards, there are some differences between each appraiser group. There are certain conditions that allow/restrict the appraiser to enter the property to be valued. Some states have laws that allow assessors to enter commercial property during normal business hours but have no laws related to residential property (e.g., Texas). Independent fee appraisers are usually given access to any property when providing services to mortgage lenders and insurance providers/adjustors. Assessors may spend more time working in the field to determine values of properties grouped by neighborhood (U.S. Bureau of Labor Statistics and U.S. Department of Labor 2015). This occurs because of their requirement to perform mass appraisal for property tax assessment purposes. Independent fee appraisers may spend a greater amount of time in the office compiling more extensive documentation and reports. Rather than visiting many properties in the field, they make case-by-case site visits.

These two groups, assessors and independent fee appraisers, will be distinguished thenceforth as appraisers to avoid confusion. Standards exists for both groups and are required by federal law in order to promote uniformity in appraisal practice. These standards were established by reforms resulting after economic declines in the aftermath of the Savings and Loan crisis that occurred in the late 1980s (Robinson 2013).

3.1.4 Formation of Federally Mandated Appraisal Standards

One of these federal reform efforts was the passing of the Financial Institutions Reform, Recovery, and Enforcement Act of 1989, hereafter Act. Title XI of the Act established the Appraisal Subcommittee under the auspices of the Federal Financial Institutions Examination

Council. It was originally established to ensure uniformity in appraisal standards of transactions of federal institutions. In addition, specific, real estate appraisal obligations were established under the Act that the Appraisal Subcommittee enforces. The Appraisal Subcommittee subsumes the Appraiser Qualifications Board and the Appraiser Standards Board. The Appraiser Qualifications Board defines the requirements for individuals to be licensed at the state level. The Appraiser Standards Board ensures that standards of appraisal practice are adopted. They oversee the Appraisal Foundation, a non-profit organization that defines standards for professional appraisal practice. These standards are published and updated by the Appraisal Foundation and are called the Uniform Standards of Professional Appraisal Practice (Jacobus 2012, 375).

In the state of Texas, the Texas Appraiser Licensing and Certification Board, in conjunction with the Texas Real Estate Commission, oversees "real estate brokerage, real property appraisals, inspections, home warranties and timeshare opportunities" (Texas Appraiser Licensing and Certification Board 2015a). This oversight organization requires a residential appraiser to receive education in federally mandated appraisal practice outlined by Uniform Standards of Professional Appraisal Practice in order for state certification and licensure (Jacobus 2012, 380). Various certifications and licenses are available through the Texas Appraiser Licensing and Certification Board each requiring specific levels of education and experience. For example, to become a state-licensed real estate appraiser in Texas, an applicant must complete 150 hours of approved education courses and 2,000 hours of work-related experience (Texas Appraiser Licensing and Certification Board 2015b). Other states may also adopt these standards and require similar training for state-licensed appraisers.

3.1.5 Sales Price Defined

Sales price (i.e., settlement price, transaction price) is a variable commonly used in the real estate literature as a proxy for the market value of real property. The price is finalized when the seller accepts an offer from the buyer. It should not be confused with the asking or listing price as found in most multiple listing services provided by local real estate boards. In the case of single-family dwellings, the sales price includes the price of the land in addition to the improvement.

Sales prices may be considered an observed random variable because multiple listing services, lenders, and other authorized agencies record this value. In states such as Texas, no law exists requiring disclosure of the sales price to any third party of the real estate transaction. Liability exists in the inherent loyalty required as part of the fiduciary duty owed to a principal by a licensed real estate broker. This duty proscribes the agent from disclosing a principal's information, such as the sales price, without their knowledge and consent.

3.1.6 Insurance Value Defined

Insurance value should be considered in conjunction with assessed value and sales price. It is not used in this research, but is another estimate of market value used by insurance companies to replace impaired structures. Jacobus (2012, 384) defines insurance value as the liability related to improvement damage. Insurance usually covers the replacement cost of the improvement alone. The replacement cost is the amount required "to rebuild or repair your home, based on current construction costs" (Texas Department of Insurance 2017). In this regard, it is different from market value. Although the land may be negatively affected, land is considered indestructible and is not covered.

3.2 Uncertainty in Assessed Value

Uncertainty in assessed values, or appraisal bias, is defined as the variable's deviation from market value. An exhaustive review of appraisal bias was performed by Yiu et al. (2006). They classified appraisal bias into "systematic" and "random" components (Yiu et al. 2006, 322). The authors contend that systematic appraisal bias is of greater concern to the real estate profession because it involves deviations from market value that occur consistently (Yiu et al. 2006, 321). Their investigation may be grouped into the following appraisal bias categories: 1) information available to the appraiser, 2) features of the appraiser's judgement, and 3) factors related to market dynamics.

3.2.1 Uncertainty Related to Lack of Information

The appraiser forms an opinion of market value based on information they receive from various sources. Kochin and Parks (1982, 512) suggest that this information comprises a "specific information set." The authors seek to identify assessment inaccuracies by considering whether the appraiser uses the existing information set effectively or not and if additional information might improve the accuracy of the appraisal estimate. They later suggest that deviations from correct market value assessments can occur when independent fee appraisers are privy to property flaws unavailable to assessors (Kochin and Parks 1984, 283). Such deviations are possible because assessors cannot enter the property or improvement of a residential dwelling to investigate its features. This is one advantage independent fee appraisers have in achieving a better estimate of market value for homes.

McMillen and Weber (2008, 654) add lack of comparable sales to the list of missing information. Sales prices of nearby homes provide information about the current market value in a particular locale. When this information is missing, appraisers are required to rely more upon their judgement rather than on comparable sales.

3.2.2 Uncertainty Related to Appraiser Judgement

Lack of information can lead to additional bias when the appraiser makes a value judgement based on incomplete or incorrect information. Without adequate information, appraisers may need, in part, to rely upon informed guesses rather than objective evidence regarding property value. Hyman (2005, 465) supports this idea stating that *specific aspects* of the appraisal process are subjective. Many others hold a similar view (Clapp 1990; Fairbanks et al. 2013; Decesare and Ruddock 1998; Krupa 2014; Smith 2000). Northcraft and Neale (1987, 86) identify three possible sources of this subjectivity: 1) differences in selection criteria for comparable sales, 2) identifying property and neighborhood quality and 3) restriction of the number of characteristics included in the adjustment process of the market approach to appraisal. They argue that even though a standard formula may be used to estimate an appraisal on a similar property, the set of conditions for each of these avenues may be different for each appraiser (Northcraft and Neale 1987, 86). Smith (2000) provides an empirical example of the challenges associated with defining housing and neighborhood quality. He finds that assessed values reflect the market more closely in areas that are newer and more homogenous. Smith explains that the method of calculating depreciation, or the monetary loss due to aging of the dwelling, is not accurate for either newer or older homes (Smith 2000). When older residential neighborhoods exhibit more variety in their physical composition, Smith adds, they are categorized with less quality by appraisers.

3.2.3 Uncertainty Related to Housing Market Volatility

A body of research investigates appraisal bias that is independent of appraisal practices. Dynamic economic markets and homeowner decisions trigger this bias. Independent of seasonal fluctuations, sales prices are known to be stable over time, but in the short-term, can be described as volatile. As shown previously in Figure 2.3 and Figure 2.4, fluctuations demonstrate that house prices are constantly changing. Despite periods of rapid house price appreciation, there are occasional periods of steady and stable growth as well as periods of decline. Assessment jurisdictions are required to follow market values even in dynamic markets. There is evidence that these efforts are slow to catch up with rapid changes in the market. In an empirical investigation Lutz (2008) uses Metropolitan Statistical Area data to identify the relationship between appreciating house prices and property taxes. The estimation for this research uses a time series model, which can isolate the amount of increase or decrease of property taxes in relation to house prices from 1985 to 2005. Lutz (2008, 565) finds that assessed values lag behind the housing market (i.e., house prices) by approximately three years.

3.3 Uncertainty in Sales Prices

How closely sales price reflects market value has been a subject of concern for some researchers (Vandell 1991, 217; Clapp 1990, 235). Their concerns are founded in the myriad conditions that could alter the ultimate cost agreed upon for the sale of the subject property. The following sections discuss conditions that can introduce differences between the final sales price of a home and its market value.

3.3.1 Uncertainty Related to Lack of Information

The agreement on a purchase price between a buyer and seller is founded upon reference information about the subject property's market value. Reference information includes comparable sales, construction costs, building permits, professional appraisals and real estate investor knowledge (Shih-MingYou 2009, 307). When reference information is not available to the buyer or seller, then they *lack information* about the current housing market. This is a similar issue for the appraiser. Lack of information may also result from limited searching for other homes for sale or not having knowledge about the local housing market (e.g., from a local real estate agent). When individuals lack information they may rely upon methods to simplify what may be perceived as a complex task with a lack of reference information. Tversky and Kahneman (1974, 1124) suggest that individuals simplify difficult, value estimation tasks using "heuristic principles". These heuristics provide workarounds for individuals to identify their estimate, but, occasionally result in "severe and systematic errors" (Tversky and Kahneman 1974, 1124). The following list describes, in brief, these heuristic principles:

- **"Representativeness"** is a method typically employed when an individual is asked to express a probability of association between two objects (Tversky and Kahneman 1974, 1124). The probability is based on the individual's perception of how much object C "resembles" object D (Tversky and Kahneman 1974, 1124).

- **"Availability"** is a tool for evaluating how frequently or likely an event may occur based on the speed which it can be recalled (Tversky and Kahneman 1974, 1127).
- **"Anchoring and adjustment"** is an approach using some initial value as an "anchor" forming a basis to derive an "adjusted" estimate ultimately biased towards the initial value (Tversky and Kahneman 1974, 1128).

Northcraft and Neale (1987, 85) suggest that this latter human decision tool, "anchoring and adjustment", is applicable to estimation of market value of residential real estate because of two conditions: 1) market value is unobserved and 2) residential real estate purchases require the buyer and seller to settle on a transaction price. They support this claim with an example negotiation between a buyer and seller anchoring subsequent offers/bids on the original listing price.

Another concept related to sales price uncertainty is "information asymmetry"(Smith 2000). When the seller has more information than the buyer, and vice-versa, information asymmetry may exist. An example of this asymmetric relationship is in the case of the seller being a real estate investor or agent. Levitt and Syverson (2008, 600) analyze 100,000 house transaction prices, of which approximately 3% are owned by real estate agents. They find that sellers that were real estate agents profited approximately 3.7% more than non-real estate agents did.

3.3.2 Uncertainty Related to Buyer and Seller Motivations

The second condition, price settlement, also involves uncertainties. Buyer and seller motivations may influence deviations of the transaction amount from market value (Quan and Quigley 1991, 129). If an interested party is trying to relocate, a certain premium or discount may be applied to the final selling price because they are eager to move. In contrast, sellers may be motivated to increase the listing period. Haurin and Jensen (1988, 16) suggest that transaction price is a function of time on the market. To attract the ideal transaction price, sellers may resort to waiting for a better bid, based on prevailing market dynamics.

3.3.3 Uncertainty Related to Bargaining Power of Buyer and Seller

Oldman and Aaron (1965, 47) suggest that the process of bargaining on a final transaction price is "arbitrary" and subject to unlimited "chance elements" that would lead to market value estimation errors. Both buyer and seller, with higher incomes, may choose to employ brokers to reduce "opportunity costs" (Zumpano, Elder, and Baryla 1996, 173; Stelk and Zumpano 2017, 53). Buyer opportunity costs may include longer house-hunting periods. For the seller, similar costs may involve greater time on the market. Greater opportunity costs for buyers place the seller in a position to encourage buyers to purchase above their original budget to avoid further bargaining or searching (Evans 1995, 23). Should listing prices be far from expectations, a potential side effect is greater bargaining room for the buyer. Consequently, some researchers believe that differential opportunity costs contribute substantially to transaction prices (Asabere, Huffman, and Johnson 1996, Carillo 2012).

3.3.4 Uncertainty Related to Real Estate Broker Influence

Although not every home sale involves the use of a real estate broker, transactions involving brokerage of one type or another may influence the ultimate selling price. In the United States, it is traditionally the obligation of the seller to pay the broker's commission (Roark and Roark

2006, 16). In some instances, the buyer may be responsible for broker's fees, which are included in the home selling price (IAAO 2010, 17). This fee is independent of any property's market value and introduces uncertainty or noise into the sales price variable. Two related, critical issues are variation in broker fees and degree of influence.

Carillo (2012) states that real estate agent fees may vary. Depending on the experience of the agent or other factors, Carillo (2012, 205) finds that fees may alter the transaction price by 1%. Zumpano, Elder, and Baryla (1996) and Elder, Zumpano, and Baryla (2000) empirically test the influence of the use of a seller's broker on the ultimate transaction price. They do not find any significant impacts on selling price, but they do identify lower "search duration" for buyers (Zumpano, Elder, and Baryla 1996, 170). Stelk and Zumpano (2017) provide empirical evidence of broker influence under volatile housing market conditions. They suggest that seller brokerage fees may have been capitalized into higher house prices for the buyer during prosperous circumstances (Stelk and Zumpano 2017, 64). Higher house prices in a buyer's market may have occurred because brokers were more selective in their choice of homes to list.

3.3.5 Uncertainty Related to Type of Sale

Another challenge to the seller's bargaining ability may be sale characteristics. Some sales occur after the borrower defaults on a mortgage loan. There are several options afforded to the lender to recuperate any losses. The property may be listed as a short sale, which is a pre-foreclosure attempt to gain some of the lost principal to default. If the borrower forecloses[12] on the property,

[12] Some research has linked reduced offers for distressed property sold in auctions to uncertainty in the transaction process, property condition of distressed property, and holding company investment (Chinloy et al. 2017, 194).

then the lender must undergo a lengthy process in obtaining documentation through legal proceedings to assume ownership. Once ownership is assumed, the property is then considered *real estate owned* (i.e., REO). Lenders attempt to sell real-estate owned property as soon as possible to recuperate any outstanding debts.

Pennington-Cross (2006, 201) suggests that this places lenders in a "weak bargaining position" and may lead to acceptance of offers well below their asking price. He collects data for over 12,000 single-family homes between 1995 and 1999. His goal was to identify the total discount for real estate owned property and the effect that duration of the real estate owned status had on the discount. He specifies an OLS regression model with a dependent variable representing the difference between the percentage change in the metropolitan house price index and the percentage change of the house value from the loan's initiation to its foreclosure (Pennington-Cross 2006, 209). He regresses real estate owned duration on indicator variables expressed as two month cohorts (e.g., between two and four months). He finds that homes that were real estate owned between two and four months were discounted by 14%. Properties that were categorized as real estate owned greater than 12 months received a 25% discount and higher depending on the duration of ownership by the lender.

3.3.6 Uncertainty Related to Physical Condition of the Property

When disposed[13] of, short sale or real-estate-owned property may have been poorly maintained. Improperly maintained homes reap lower premiums. Clauretie and Daneshevry (2009)

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[13] Empirical research suggests that many lenders dispose of distressed property as quickly as possible through auctions (Lee and Immergluck 2012, 1103; Lichtenstein and Weber 2013, 1; Zhang and Leonard 2014, 135).

investigate the effects of property condition, length of listing period and occupancy status on the log of selling price. Their observations consist of 1,302 foreclosed and 8,498 non-foreclosed single-family dwellings within Clark County, NV between 2004 and 2007. They employ a generalized spatial two-stage least squares estimator to model the endogeneity between selling price and length of the listing period. The authors find that real estate owned properties that were poorly maintained sold at a greater discount than those in better condition (Clauretie and Daneshvary 2009, 60). Leonard (2013, 53) investigates property maintenance investment for owners with increased default risk (i.e., low loan-to-value ratios) between 2001 and 2009. Reduced property maintenance was observed for homeowners with poor loan-to-value ratios and inadequate monthly income to support lenders fees. If a property is not required to be sold quickly, a typical homeowner will perform at least minor updates to the property. These updates may include, for example, painting, landscaping, minor repairs, or installing new carpeting. When these updates are made, the seller may ask for a higher price than they would if property improvements were not made.

3.3.7 Uncertainty Related to the Buyer and Seller Relationship

The relationship between buyer and seller may also influence sales prices (IAAO 2010, 11). When buyer and seller have a formal relationship, not affected by personal or familial connection, both parties seek to maximize their monetary gain. This condition is reflective of a market sale (i.e., arm's length transaction). If, however, owners such as aging parents deed property to a son with a young family, they may choose to alter the transaction price to a fraction of what they would sell to an unknown buyer. Real estate transactions between "corporate affiliates" may also deviate from market value (IAAO 2010, 11). Sales involving these kinds of relationships should be validated to see if they meet the conditions of market value as defined in section 3.1.1.

3.3.8 Uncertainty Related to Sales Price Add-Ons

When a property is purchased, there may be several additional charges added to the final transaction price. These add-ons may take the form of mortgage financing options, fees owed to participants of the transaction, and personal property purchased along with the real estate. An example of a mortgage finance option is the "discount point" (Jacobus 2012, 216). This financing tool diverts the interest paid on a mortgage from the interest rate itself and is added to the purchase price (Harris Jr. and Sirmans 1987, 97). Interest that would have been paid throughout the life of the loan is now paid at the beginning, thus adding an arbitrary interest percentage to the sales price.

When a real estate transaction is closed, there are several fees, or closing costs, that are required. These closing costs comprise an added amount to the initial sales price. Closing costs include, but are not limited to appraisals, courier services, deed transcription, escrow payments, discount points, realtor fees, insurance, surveys, inspections, underwriting services and document preparation (Jacobus 2012, 142). The party that pays these fees is decided upon during negotiations. Exclusively, the buyer may pay closing costs, or, in some cases, the seller may contribute payment. If the buyer pays closings costs then it is applied to the purchase price. However, if the seller pays the closing costs then it may not become part of the final transaction price. Uncertainty is introduced through the arbitrary addition of closing costs to the sales price of the home.

Finally, in some cases, the purchase of personal property may accompany the transfer of real estate. Personal property may consist of furniture, vehicles or any asset that is not permanently attached to the land or improvement. Jacobus (2012, 14) urges that this transfer be executed through a bill of sale, separate from the deed for the real estate.

Although many of these items are typically itemized and recorded separately on real estate contracts, closing statements and lender agreements, it is not always clear how these prices are included with the sales price. Real estate professionals and researchers interested in using sales price to follow housing market trends would be wise to ignore, or at the least, deliberately distinguish these add-ons from final real estate transaction amounts.

3.4 A More Accurate Measurement

Despite indications that both assessed value and sales price contain some unknown degree of error, researchers and practitioners alike agree that sales price represents a more reliable depiction of market value. The International Association of Assessing Officers (IAAO) (2013, 7) states that sales prices are "more objective" measurements of market value than assessed values. Payton (2006, 183) recommends that assessed value should be compared with sales price to measure for uniformity. Decesare and Ruddock (1998, 9) recognize that sales prices are commonly employed in ratio studies and use sales price in their model estimating assessment equity to represent "full cash value". Ihlandfeldt and Vasquez-Martinez (1986) examine sample selection bias in sales prices and subsequently analyze measurement error in relation to assessed values and owner estimates of house value. They collect American Housing Survey responses data from April 1978 to March 1979. Their sample of 540 sales observations and 3,276 non-sale observations is restricted to the county containing Atlanta, Georgia and its four adjacent neighboring counties. Authors specify a log-linear model regressing a vector of physical housing attributes, geographic indicators, and variables describing the head of the household on the log of selling price. Ihlandfeldt and Martinez-Vasquez (1986, 367) determine that sales price produces estimates with less bias than owner estimates and assessed values.

Before sales prices can be considered a more objective measurement of market value, they must reflect, to the extent possible, an arm's length transaction. It is evident that housing sales transactions may occur under varying conditions that disqualify them from a market value classification. Much of the research reviewed initiates a rigorous screening of sale transaction characteristics before considering cases for the market value population (IAAO 2010).

3.5 Uncertainty in Assessed Values and Sales Prices Represents an Error-In-Variables Problem

Assessed value and sales prices are estimates of unobserved market value. Any error in these estimates indicates a departure or bias from market value. The uncertainty or bias in assessed value has been expressed as "measurement error" by real estate researchers (Ihlanfeldt and Martinez-Vazquez 1986, 357; Robins and West 1977, 290; Shilling, Sirmans, and Dombrow 1991, 373). Sales prices may also be measured with some degree of error (McMillen and Weber 2008, 659; Case and Shiller 1988, 15).

When researchers use variables measured with error in linear regression, a problem in estimation of regression parameters may result. This problem is termed "error-in-variables" or the "measurement error model" in the econometrics literature (Cheng and Van Ness 1998, 3). The error-in-variables model consists of two random variables measured with error, x and y.

These may be expressed as observed random variables x and y consisting of the components measured without error x^* and y^* and the measurement error u and v.

$$x = x^* + u \tag{3.1}$$

$$y = y^* + v \tag{3.2}$$

Furthermore, both measurement errors u and v may be correlated when they rely, to some degree, on the same, missing information or biasing influences. These variables may be formalized in a linear regression model where the dependent variable is y and the independent variable is x and v represents the unexplained error in y.

$$y^* = x^* + v \tag{3.3}$$

One problem with equation (3.3) is the missing error term or measurement error associated with x, namely u. Adding the missing error term to equation (3.3) results in a new specification, (3.4), including all elements identified in equations (3.1) and (3.2).

$$y^* = x^* + u + v \tag{3.4}$$

When correlated with v, this error term, u, causes ordinary least squares to be become biased. This bias results from errors in the u direction violating the ordinary least squares assumption (i.e., $Cov(x, [u + v]) = 0$) that the independent variables are not correlated with the error term. This problem has implications in measuring uniformity in property tax assessments. The implications are inherent in specific methods for measuring property tax inequities. After a general taxonomy of assessment inequities, a treatise on the methods for their measurement follows.

CHAPTER 4

CONCEPTUAL MODEL SPECIFICATION

4.1 Property Tax Assessment Inequity

Within the past fifty years, there has been a substantial body of literature discussing theories and applications relating to uniformity of property tax assessment. Much of the early work is based on the unfairness of the property tax. One problem is that the property tax is considered the backbone of local government income yet is the subject of embittered polemic (Thorndike and Ventry 2002, 221). Many have been concerned about the equitable distribution of the property tax and have been vocal about whether it meets a uniform standard. Researchers have investigated the challenges associated with producing an equitable assessment. Some of these are listed in Table 4.1. This has led to government legislation and regulation of assessment practices seeking to identify inequities. One example is the requirement for the State of Texas comptroller’s office to perform a biennial property value study (Hegar 2018b). The study investigates assessment inequities for each appraisal district in Texas. Understanding uniformity in property tax assessment requires the identification of two distinct measures: horizontal and vertical equity.

While this research briefly introduces horizontal inequity, the primary focus is on identifying vertical inequity. This chapter reviews the principal literature on the topic, particularly in measuring uncertainty in vertical inequity. Two prevalent arguments linked to measuring vertical inequity is whether assessed value and sales price constitute an error-in-variables problem and are subject to simultaneity. Properly addressing theoretical and methodological issues in these areas requires further investigation in the statistical background of instrumental variables. The chapter concludes by discussing a gap in the literature and reviewing the research objectives.

Table 4.1. Common challenges facing real estate appraisers that compromise assessment uniformity.

Challenges	**Authors**
Sophistication of Real Estate Legislation	O'Sullivan, Sheffrin, and Sexton 1994; Lang and Jian 2004; Moore 2008
Fractional Assessment	Epley 1974; Bowman and Butcher 1986; Eom 2008; Hultquist and Petras 2012
Abrupt Fluctuations in Property Values	Engle 1975; Benson and Schwartz 1997, 220; Gaffney 2009; Krupa 2014; Payton 2015
Dynamic Socioeconomic Landscape	Fuerst and Ditton 1975; Thrall 1979; Ellis, Combs, Weber 1983
Age of the Dwelling	Bowman and Mikesell 1978, 140; Berry and Bednarz 1975; Payton 2013
Subjective Elements of the Appraisal Process	Decesare and Ruddock 1998, 5; Shih-MingYou 2009; Jacobus 2012, 374; Fairbanks et al. 2013, 3; Cornia and Slade 2005, 18
Limited Number of Comparable sales	Netzer 1966; Harris and Lehman 2001, 883; McMillen and Weber 2008

4.2 Horizontal Inequity

Horizontal equity is achieved when assessed values for similar[14] properties are divided by their respective sales prices and they do not deviate too far from one (Payton 2013, 3; Horne and Felsenstein 2010, 1183; Weber and McMillen 2010, 75). *Horizontal inequity* occurs when

[14] The similarity referred to here is in physical structure, raw materials, age and locational influences

assessment ratios (i.e., assessed values divided by respective sales prices) are *more divergent* from one for similar properties.

4.3 Vertical Inequity

Other authors present research that highlights the excess property tax burden in neighborhoods with lower income levels (Engle 1975, Baar 1981). When these burdens are disproportionately prevalent for different income levels and property types, *vertical inequity* may be evident (Sunderman et al. 1990, 320; Allen, Dare, and Riegel 2010, 364). A political dimension to vertical inequity lies in its dualistic nature. When lower-valued properties carry a greater property tax burden compared to higher-priced properties, this is called *regressivity* (McMillen 2011, 9). Its opposite, *progressivity*, exists when higher-priced properties carry the greater burden (Twark, Everly, and Downing 1989, 184).

4.3.1 Property Tax Regressivity

Netzer (1966, 56) introduces the notion that property tax regressivity (property tax in relation to income) is related to property tax assessments. His explanation for property tax regressivity is that residential property assessments for greater value properties are lower compared to market sales prices than are assessments for lower valued properties compared to market sales. Netzer assumes that this type of regressivity occurs because low-value properties are not as difficult to assess with accuracy because they tend to be sold more frequently than high-value properties. In contrast, Netzer assumes assessors undervalue to evade protests from owners of high-valued properties lacking sufficient market transactions. Netzer supports this claim by referring to the U.S. Census of Governments of 1957 and 1962. These reports revealed that most assessment jurisdictions assessed expensive properties at a smaller proportion than low-priced homes. However, these inequities were not as noticeable in larger metropolitan areas (Netzer 1966, 56 – 57).

Paglin and Fogarty (1972) suggest that assessment inequities may be divided into various component parts. These parts include “intrinsic” and “administrative” inequity (Paglin and Fogarty 1972, 557). The intrinsic inequity component relates to the random variation that may occur in assessed value to sales price ratios. Administrative components represent a “systematic…related bias in the appraisal process” (Paglin and Fogarty 1972, 557). In other words, the authors want to identify inequity resulting from methods of assessment, their procedures, and practices. Households at the lowest income level were over burdened by 29.6% based on “vertical administrative inequity”[15] and the highest income class experienced 11.9% in under-assessed homes. Authors theorize that “assessment error” results from assessing higher priced homes at a lower percentage of market value in relation to lower priced homes (Paglin and Fogarty 1972, 563). Part of this argument is because accurate assessment of high-income homes might be challenging because of unique characteristics of the dwelling. In their article, they admit that specific reasons for disproportionate assessment of low-income households remained unclear. They also suggest that inequities occur because reappraisal cycles are scheduled infrequently and lag behind the true market value of properties (Paglin and Fogarty 1972, 563). In other words, while high quality neighborhoods demonstrate increases in house price over the assessment lag period, lower-priced properties decline in market value. Authors

[15] *Vertical Administrative Inequity* – An artifact of appraisal jurisdiction procedures that reveals a comparative dissimilarity of appraised value and market value as it relates to cost of housing.

recommend isolating these factors to alleviate sources of vertical administrative inequity (Paglin and Fogarty 1972, 560).

In his study, Thrall (1979, 280) echoes Netzer's proposition, that assessors will apply a lower than necessary estimation of home value for properties having a higher price for fear of assessment appeals. Benson and Schwartz (1997, 224) agree with Paglin and Fogarty (1972) positing that assessors undervalue high priced properties based on the challenge of accurately estimating rare or luxurious features, e.g., scenic vistas, atypical landscaping. Allen (2003, 182) found regressivity among small size multi-family housing units. Furthermore, Lin (2010, 517) identified variation in the magnitude of vertical inequity levels among different property types, e.g., single-family dwellings, and low-level to high-level condominiums. Weber and McMillen (2010, 94) revealed that owners of high-priced homes have a greater tendency to appeal their assessed value, more so than appealers owning homes in different price classes. They also found that the majority of protesters successful in receiving an adjustment to their assessed value owned smaller and older homes. The authors conclude, based on the lack of significance on the successful and unsuccessful coefficients of their probit model, that appeal results are not strong indicators of regressivity (Weber and McMillen 2010, 95). Ross (2012, 33) suggested that his findings correlating senior citizens with a high incidence of regressivity might be related to these homeowners having paid off their mortgages, leaving their housing budget consisting primarily of property taxes. In addition, they may receive an additional property tax exemption on top of the homeowner's exemption in states that provide these political adjustments to the property tax. His findings also showed a slight correlation with an assortment of ethnicities present (Ross 2012, 40).

4.3.2 Property Tax Progressivity

For some time, researchers believed that the property tax on housing was solely regressive. One author used empirical research to argue that, in general, uniform property tax assessment administration would be equivalent to a progressive structure (Edelstein 1979, 753; Paul 1975, 20). Among the literature reviewed, fewer studies revealed progressivity. Heavey (1983) reviewed assessment ratios for school districts in Pennsylvania. He identified properties in the city that were assessed too high and paying more in property taxes than suburban residents did. His argument for this was that the assessment jurisdiction waited too long to initiate its revaluation cycle, perpetuating outdated values for properties that had changed in market value (Heavey 1978, 181).

Borland (1990, 432) found progressivity in jurisdictions having “complex” property tax structures, a property may have more than one property tax specified for it in a given assessment period (i.e., multiple taxing entities such as schools, municipalities, utility districts, colleges, and hospitals). Smith et al. (2003, 587), following Borland’s results, verified this claim. In addition, they found that dense non-residential properties and urban growth were correlated with progressivity (Smith et al. 2003, 586 – 587).

4.4 Illustration of Vertical Inequity

To conceptualize both facets of vertical inequity, Figure 4.1 shows a coordinate plane with the log of assessed value on the y-axis and the log of sales price on the x-axis. The line going through the origin represents a “perfect equity” line (Paglin and Fogarty 1972, 558). This line represents hypothetical assessments that are uniform. In other words, for every 1% percent change in the log of assessed value there is a 1% change in the log of sales price for all values in the sample. There are two regions identified in the coordinate plane. The low price region represents an area where properties on the low-value portion of the house price spectrum are either over- or under-assessed. The high price region represents high-value properties in terms of house price that are either over- or under-assessed. The location *P* represents a pivot point at which equity changes direction from over-assessment to under-assessment and vice-versa. The solid dashed line represents a progressive property tax structure where low-price properties are under-assessed compared to higher-priced properties. The thinner dotted line symbolizes a regressive property tax structure where low-price properties are over-assessed compared to higher-priced properties. The value of this illustration is its ability to identify minimal, moderate, or extreme inequity by how much regressive or progressive lines deviate from the perfect equity line.

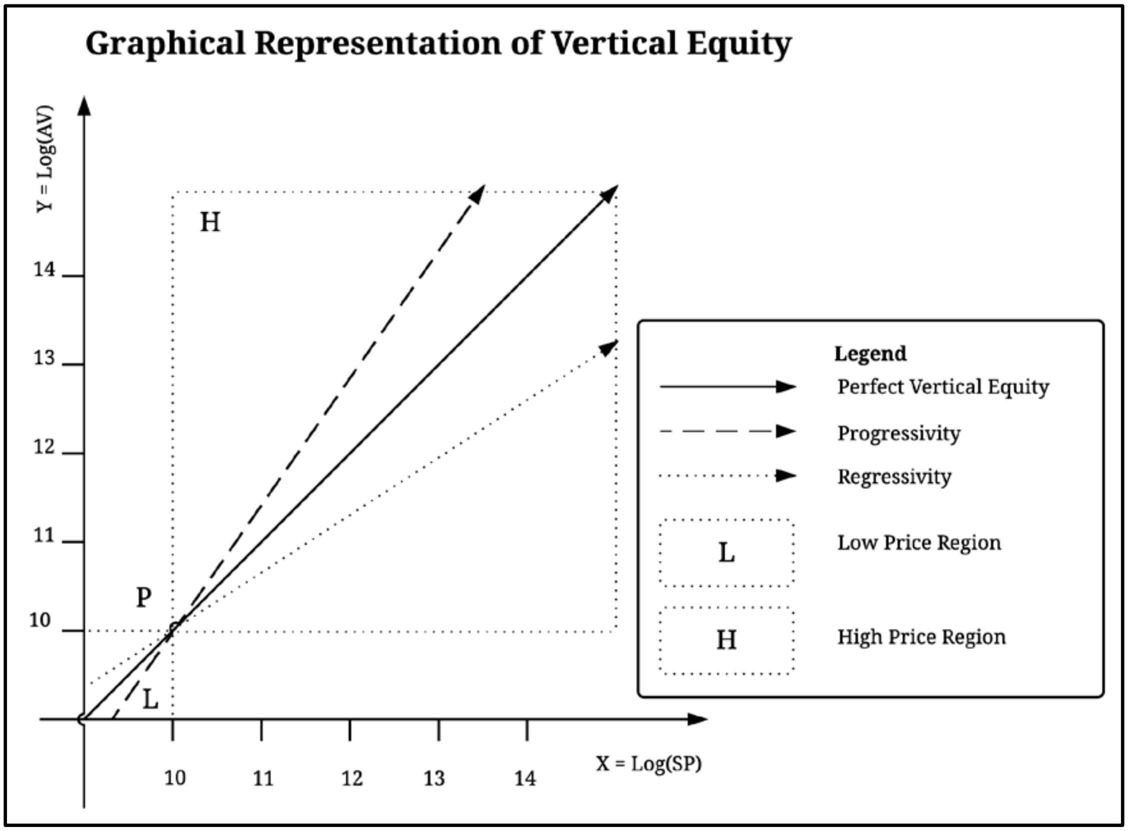

Figure 4.1. Graphical representation of the two types of vertical inequity: progressivity and regressivity.

4.5 Measuring Assessment Uniformity

Many methods identifying inequities in property tax assessment have been developed in the five preceding decades. In the first two decades, the literature focuses on development and testing of different approaches to identify horizontal and vertical inequity. Sirmans, Gatzlaff, and Macpherson (2008) provide a thorough treatise of these approaches. Remaining decades produced research empirically testing methods proposed by these seminal authors (Sunderman et al. 1990; Sirmans, Diskin, and Friday 1995; Spahr and Sunderman 1998; Allen 2003; Cornia and Slade 2005; Fairbanks et al. 2013).

Much of the pre-1970's literature focuses on measures of central tendency and dispersion for both horizontal and vertical inequity. While these measurements provide indications of uniformity, they ignore the inherent uncertainty in judging the fair market value by the assessed value and the sales prices. Ratios, medians, and coefficients of dispersion are helpful when discussing uniformity in general terms, but they lack the ability to make statistical inferences about underlying observations or to scrutinize relationships between random variables. For exposition on such measurements the reader is directed to IAAO and LILP (1977) and Eckert, Gloudemans, and Almy (1990). The purpose of this section is to review linear and non-linear methods for identifying vertical inequity. After reviewing these methods, their limitations will be addressed. Following these limitations, an important gap in the literature is identified that provides a foundation for the method proposed in this research.

4.5.1 Linear Regression for Vertical Inequity

Building upon the foundation of Netzer (1966, 56-58), Paglin and Fogarty (1972, 557) offer a "new conceptual model" to test for vertical inequity in property taxes. The authors introduce the concept of assessment equity being represented by a "perfect equity" line on a scatterplot of assessed values on the Y-axis and sales prices on the X-axis. If assessed values were uniform with sales prices, then the line would go through the origin and the point represented by the weighted mean. Viewing assessment equity in this manner leads the authors to perceive vertical inequities as departures from this perfect equity line. Any departures from perfect equity would be expressed as the ratio of the coefficient of the perfect equity line and the coefficient of the independent variable on the assessment inequity line subtracted from 1 (Paglin and Fogarty

1972, 563). The Paglin and Fogarty model is specified in (4.1), (4.2), and (4.3). The intercept, β_0 goes through the origin, is equal to zero, and is excluded from the equation in (4.1).

$$Y_i = \beta_{vi} X_i + \varepsilon_i \tag{4.1}$$

$$\beta_e = \frac{\sum_{i=1}^{n} AV_i}{\sum_{i=1}^{n} SP_i} \tag{4.2}$$

$$VI = 1 - \frac{\beta_{vi}}{\beta_e} \tag{4.3}$$

Here, the first equation is a regression model in (4.1) representing the empirical observations of the response, assessed value Y_i, and the predictor, market value or sales price X_i, with an intercept β_0 and error term ε_i where i represents each parcel and $i = 1,2,3 \dots N$. The term, β_e, signifies the sum of assessed values divided by the sum of sales prices and is the coefficient of the line representing perfect equity. The equation in (4.2) is a reflection of perfect equity, β_e, using the weighted mean. The empirical model's coefficient, VI, identifies how much vertical inequity exists for the assessment jurisdiction (4.3). The authors execute this model on approximately 400 single-family dwellings having sales transactions occurring in 1968 in Multnomah County, Oregon (Paglin and Fogarty 1972, 561–62). These equations were executed on households with six different price classes between \$5,000 and \$40,000. The lowest two price classes exhibit a positive value for the vertical inequity measure indicating over-assessment while the remaining four higher price classes exhibit a negative value indicating under-assessment (Paglin and Fogarty 1972, 564).

Cheng (1974, 277) adds to the Paglin and Fogarty model by taking the log of the parameters to control for heteroscedasticity in the error term as well as highly positively skewed distributions of the assessed values and the sales prices. Wooldridge (2009, 706–7) defines Cheng's alteration of the Paglin and Fogarty model as a "constant elasticity model". This linear model is expressed in terms of a log transformed dependent and independent variable. The coefficient is an *elasticity*. In relative terms an elasticity is defined as the total "percentage change" in the dependent variable resulting from a 1% increase in the independent variable (Wooldridge 2009, 706). In equation (4.5), the derived relationship is a ratio of percentage change equivalent to β_1. This is the coefficient in a bivariate log-log model or the elasticity. It requires that both variables are strictly positive. In terms of equal relative change in both variables (i.e., sales price and assessed value respectively), $\beta_1 = 1$ represents perfect vertical equity. Many authors following Cheng's work began to test for vertical equity using the hypothesis test of $\beta_1 = 1$.

$$\log y = \beta_0 + \beta_1 \log x \tag{4.4}$$

$$\beta_1 = \frac{\Delta vy}{\Delta x} \times \frac{ux}{y} = \frac{\%\Delta y}{\%\Delta x} = \frac{\Delta \log vy}{\Delta \log x} \tag{4.5}$$

Cheng (1974, 268) addresses the problem of accurately identifying a critical threshold[16] for the dispersion of assessment ratios. Recognizing the implausibility of a single criterion spanning all property strata, he encourages us in the prospect of revealing dispersion limits for

[16] Cheng (1974) refers to this as "critical dispersion" defined as variation in assessment ratios of homogeneous properties where assessment administration does not suffer from a lack of uniformity.

specific property divisions. He posits the integration of "critical dispersion" with aforementioned errors in assessment administration using regression analysis as the research goal of his article (Cheng 1974, 268).

Cheng (1976, 1254) expands on previous work by theorizing a "growth" or "decay rate" in assessed values over time. Assessed values *grow* or *decay* in relation to housing markets identified by sales price distributions. It is critical to correct any temporal disassociation between appraised value and sales price when comparing the two. When ignored, such disassociations translate as outdated estimates or appraisal lags (Heavey 1978, Strumpf 1999, Bowman 2006). Controlling for such lags within a linear regression framework requires an adjustment of assessed value making it contemporaneous with sales occurring at t.

Here, $Q_{i\tau}$ and P_{it} represent assessed values and "settlement prices" (i.e., sales prices) for a parcel i, respectively, on the assessment date τ and sale date t where $i = 1,2, \dots, N_t$ with $\tau < t$ (Cheng 1976, 1251). In this case, the assessment date occurs before the sale date. The benefit of this is that appraisers have no information during τ regarding housing markets at t and estimated home value represents true forecast of the true market value. The parameters α and θ represent indicators of appraisal uniformity. When $\alpha = \theta = 1$, appraisals are uniform within the associated housing market. Cheng (1976, 1254) incorporates the aforementioned exogenous "growth (or decay) rate", g_i, due to, for instance, inflation and defines its value as the difference in price between sale and assessment dates or, $t - \tau$.

$$
\begin{aligned}
\log(Q_{i\tau}) &= \log(\alpha) + \theta \log(P_{it}) - \theta(t-\tau)g_{it} + \varepsilon_{it} \\
&= \log(\alpha) + \theta \cdot (\log(P_{it}) - (t-\tau)g_{it}) + \varepsilon_{it}
\end{aligned} \tag{4.6}
$$

The formula in (4.6) may be reduced to (4.7) by assuming a lag of 1 for assessed values or $t - \tau = 1$.

$$
\log(Q_{i\tau}) = \log(\alpha_t) + \theta_t \log(P_{it}) - \theta_t g_{it} + \varepsilon_{it} \tag{4.7}
$$

Cheng (1976, 1254) discusses the possibility of g_{it} being uniform across all i, that is, constant, and thus the term $\theta_t g_t$ becomes a component of the intercept term. To make this g_{it} value part of the intercept term in the conceptual model specification, the g_{it} term needs to be converted to a global estimate for all i, g_t. As the growth rate increases, the intercept term in the conceptual model decreases further at or below zero. This makes sense since less of the intercept term is explained by variation in inflation. When sales prices increase, the intercept term's standard errors also increase. To properly model growth and decay within the conceptual model, an authoritative source for house price changes, independent of the population's sales prices, is desirable. This data source, provided by NTREIS (2018b) is discussed further in the next chapter.

IAAO (1978) adapted the Cheng model for use in assessment practice manuals to include a ratio of assessed value to sales price. IAAO used this adaptation because of the familiarity of the assessment ratio to the assessor (Sirmans, Gatzlaff, and Macpherson 2008, 172).

4.6 The Large n Problem

One subject worth mentioning within a linear model context is that of the implication of many observations on standard errors and inference. The availability of housing transaction data is growing, and its value is becoming known within the marketplace and in housing research. Particularly with the advent of companies such as Zillow, Trulia, Realtor.com, Redfin, and Homesnap users can access real time sales data within their target search area. As increasing volumes of sales transaction data are made available by data aggregators and vendors, research will involve an increasing number of sales observations to fuel empirical work. Of moderate importance in linear studies with large sample sizes is the "large $p - value$" (Lin, Lucas, and Shmueli 2013) or "large n problem" (Kim 2018).

Wooldridge (2009, 136) cautions empirical researchers of studies with "large samples" to be careful in their interpretation of parameter estimates because such studies suffer from a debilitating "precision". This means that greater sample sizes produce smaller standard errors and subsequently greater probability of a statistically significant result. Research suffers in such cases because "false positives" can occur, leading to conclusions influenced by statistical size rather than power (Kim 2018, 7). Even when analysts reduce the significance level to address the greater precision, problems may still arise when "practical" and "statistical significance" no longer "coincide" (Wooldridge 2009, 136). Practical significance relates to theoretical thresholds or boundaries frequently employed as restrictions in hypothesis tests. Practical significance stresses the critical effect size at which a decision maker will take action. In the case of the literature's linear models estimating vertical inequity, such tests have involved $\beta = 1$.

Gloudemans (2011, 4) warns readers of false positives regarding large sample sizes in vertical inequity calculations.

4.7 Linear Models of Assessment Uniformity and Measurement Error

Table 4.2 gives an overview of pre-2013 linear and non-linear models estimating property tax inequity, but the focus will be on those that address measurement error specifically. The discussion on measurement error in estimation of assessment inequity begins after Paglin and Fogarty's (1972) seminal paper. As previously discussed, they estimate vertical inequity using OLS regression. Paglin and Fogarty (1972, 561) place assessed value as the dependent variable and sales price as the independent variable to estimate variations in assessment uniformity. The methods that authors employ, however, do not consider the measurement error inherent in these random variables. Authors introduce unobserved true values (i.e., market value) in their OLS regression using the random variable of sales price. Sales price, however, only represents a proxy of unobserved market value[17]. The argument, then, is that an additional component is not accounted for in Paglin and Fogarty's model: the difference between the unobserved market value and the measured value in the sales price variable. Namely, measurement error in the sales price random variable.

[17] Gloudemans states that assessment ratios are correlated with sales prices but not with unobserved market value. Any attempt to quantify the relationship between assessment ratios and unobserved market value introduces a positive bias into the estimates. He argues, the estimation is encumbered by the error-in-variables problem. Gloudemans adds that "no completely satisfactory resolution to this problem has been obtained" (IAAO and LILP 1977, 98).

Table 4.2. Overview of vertical inequity regression categorized by linear and non-linear models in chronological order. Adapted from Fairbanks, Joshua C., Paul R. Goebel, Michael D.S. Morris, and William H. Dare. 2013. “A Monte Carlo Exploration of the Vertical Property Tax Inequity Models: Searching for a ‘Best’Model.” Journal of Real Estate Literature 21 (1): 3–24. Copyright 2013 by the American Real Estate Society. Included with permission.

Exhibit 1
Vertical Tax Inequity Models

Model	Null Hypothesis	Regressive Condition	Author (Date)
Panel A: Linear (Log-Linear) Models			
$AV_i = \alpha_0 + \alpha_1 SP_i$	$\alpha_0 = 0$	$\alpha_0 > 0$	Paglin and Fogarty (1972)
$lnAV_i = \alpha_0 + \alpha_1 lnSP_i$	$\alpha_1 = 1$	$\alpha_1 < 1$	Cheng (1974)
$AV_i / SP_i = \alpha_0 + \alpha_1 SP_i$	$\alpha_1 = 0$	$\alpha_1 < 0$	IAOO (1978)
$lnSP_i = \alpha_0 + \alpha_1 \, lnAV_i$	$\alpha_1 = 1$	$\alpha_1 > 1$	Kochin and Parks (1982)
$lnSP_i = \alpha_0 + \alpha_1 lnAV_i$	$\alpha_1 = 1$	$\alpha_1 > 1$	Clapp (1990)
$lnAV_i = \beta_0 + \beta_1 Z$			
Panel B: Nonlinear Models			
$AV_i = \alpha_0 + \alpha_1 SP_i + \alpha_2 SP_i^2$	$\alpha_0 = \alpha_2 = 0$	Initial (intercept): $\alpha_0 > 0$ Becoming more so (quadratic): $\alpha_2 < 0$	Bell (1984)
$AV_i = \alpha_{00} + \alpha_{01} LOW_i + \alpha_{02} HIGH_i + \alpha_{10} SP_i + \alpha_{11} LOWSP_i + \alpha_{12} HIGHSP_i$	$\alpha_{00} = \alpha_{01} = \alpha_{02} = 0$	Low: $\alpha_{00} + \alpha_{01} > 0$ Middle: $\alpha_{00} > 0$ High: $\alpha_{00} + \alpha_{02} > 0$	Sunderman, Birch, Cannady, and Hamilton (1990)

Notes: The null hypothesis states that there is no vertical inequity. *AV* is the assessed value, *SP* is the observed sales price, *Z* is a dichotomous variable equal to 1 if both *AV* and *SV* are in the top third of their respective values and −1 if both *AV* and *SV* are in the bottom third of their respective values. Low is an indicator variable that *SP* is in the bottom third, and High is an indicator variable that *SP* is in the top third.

Cheng (1974) also identifies a similar “market error” representing the difference between assessed value and market value. Cheng continues to cite literature that fails to consider the error involved in assessed and market house prices (Welch 1969, 203 – 214; Peterson et al. 1973). Later, Cheng (1976) builds on the Paglin and Fogarty model, isolating assessed value errors from errors related to sales prices. This approach was meant to differentiate the unique error components forming a composite error term. The structure of his model implies that assessed value errors, intentionally separated from sales price errors, exhibit variation (Cheng 1976). Kochin and Parks (1982, 519) identify the measurement error relationship in their examination of Paglin and Fogarty’s model. Kochin and Parks’ (1982, 523) proposed model seeks to address what they view as the measurement error inherent in the independent variable (sales price) of the Paglin and Fogarty model. They argue that "efficient assessments" (Kochin and Parks 1982, 517) can be derived through multiple samples of observed assessed values and sales prices. Hence, their efficient model creates predictions for assessed value resulting in a more objective measure of market value than sales price. Authors switch the causality of the model by placing sales price as the dependent variable and assessed value as the independent variable. Their argument is that assessed value represents a more objective measure because it is based on more information. Fairbanks et al. (2013, 7) argue against the reversal of causality because a more appropriate specification involves placing sales price on the right hand side of the equation rather than the left hand side. They justify this by stating that sales price explains assessed value better than assessed value explains sales price.

Kochin and Parks (1982, 517) employ the "efficient assessment" assumption to argue that the random variable for assessed value predictions is uncorrelated with the error term. In rebuttal to their claim, Kennedy (1984, 289) argues that multiple samples do not produce assessed value predictions without some degree of error. Furthermore, Kennedy (1984, 289) refers to this error as "subjective assessment error" attributable to elements that do not have an objective method for valuation. Such elements, he suggests, include "quality of construction" and the utility of "view" from any perspective on the property (Kennedy 1984, 289). An instrumental variable estimator is an optional approach to correct these problems (Kennedy 2003, 193; Cheng and Van Ness 1998, 4; Wooldridge 2009, 525). The Clapp (1990) model continues with the reversal of causality but explicitly captures the error in assessed value by an instrumental variable method.

4.8 Instrumental Variable Methods

Uniform administration of the assessment process is problematic and the literature has attempted to improve it through specification of various models. Some of these models are developed to address "econometric issues" related to administration of property tax assessment (Clapp 1990, 233). Before discussing this stream of the vertical property tax inequity literature, establishing a theoretical and methodological foundation in econometrics is critical. The next section develops this foundation by first emphasizing ordinary least squares estimation and its assumptions. Violation of one of these assumptions leads to instrumental variables and its derivation follows. The chapter concludes with empirical instrumental variable methods in the vertical property tax inequity literature.

4.8.1 Ordinary Least Squares Estimation

A bivariate ordinary least squares equation with regressor X_i and dependent variable Y_i is defined in (4.8) for $i = 1,2,3,\ldots,N$.

$$Y_i = \beta_0 + \beta_1 \cdot X_i + \varepsilon_i \tag{4.8}$$

Following Hamilton (1992, 294), if the covariance of X_i and ε_i is $Cov(X_i, \varepsilon_i) = 0$ then X_i is an *exogenous regressor* and the regression coefficient β_1 is unbiased as shown in (4.9), (4.10), and (4.11).

$$Cov(Y_i, X_i) = \beta \cdot Cov(X_i, X_i) + Cov(X_i, \varepsilon_i) \tag{4.9}$$

$$Cov(X_i, X_i) = Var(X_i) \tag{4.10}$$

$$\beta_1 = \frac{Cov(Y_i, X_i)}{Var(X_i)} + 0 \tag{4.11}$$

Wooldridge (2009, 169) explains this condition as the "zero correlation" assumption. When a violation of this assumption occurs, for example when X_i is measured with error (i.e., error-in-variables), it becomes an *endogenous regressor*. In other words, when the predictor X_i in the linear regression model $Y_i = \beta_0 + \beta_1 \cdot X_i + \varepsilon_i$ is correlated with the disturbances ε_i or $Cov(X_i, \varepsilon_i) \neq 0$, *endogeneity* exists. Then equation (4.12) demonstrates a biased β_1 coefficient because the second term in (4.12) is no longer zero as in (4.11). This bias may exist even in large samples (Kennedy 2008, 139).

$$\beta_1 = \frac{Cov(Y_i, X_i)}{Var(X_i)} + \frac{Cov(X_i, \varepsilon_i)}{Var(X_i)} \tag{4.12}$$

If an *instrumental variable*, Z_i, is found that satisfies both (4.13) and (4.14) then an unbiased regression coefficient may be obtained as shown in (4.15) and (4.16). Equations (4.13) and (4.14) satisfy what are known as "instrument exogeneity" and "relevance" conditions respectively (Wooldridge 2009, 508; Watson 2015, 425). To reassure the reader, β_1 contains the effect of X_i on Y_i rather than Z_i on Y_i because Z_i aids in "purging" the endogeneity from X_i (Wooldridge 2009, 522).

$$Cov(Z_i, \varepsilon_i) = 0 \tag{4.13}$$

$$Cov(X_i, Z_i) \neq 0 \tag{4.14}$$

$$Cov(Y_i, Z_i) = \beta \cdot Cov(X_i, Z_i) + Cov(Z_i, \varepsilon_i) \tag{4.15}$$

$$\beta_1 = \frac{Cov(Y_i, Z_i)}{Cov(X_i, Z_i)} + 0 \tag{4.16}$$

4.8.2 Two Stage Least Squares Estimation

The previous section discussed endogeneity of regressors in a bivariate linear regression model. Endogeneity of regressors in the multivariate case may be addressed using a *two-stage least squares* approach. Three categories of variables participate in this procedure. Endogenous regressors, $\mathbf{X}_{EN}$, constitute all regressors correlated with the disturbances. Variables independent of disturbances but included as covariates to endogenous variables comprise the exogenous regressor group, $\mathbf{X}_{EX}$. Instrumental variables, $\mathbf{X}_{IV}$**,** are assumed to be correlated with $\mathbf{X}_{EN}$ but are uncorrelated with the disturbances. For convenience, these categories may be grouped into **Z** and **X** as shown in (4.17) and (4.18).

$$\mathbf{Z} = [\mathbf{X}_{IV} | \mathbf{X}_{EX}] \tag{4.17}$$

$$\mathbf{X} = [\mathbf{X}_{EN}, \mathbf{X}_{EX}] \tag{4.18}$$

Both stages include an ordinary least squares equation. In the first stage, the predicted values, $\widehat{\mathbf{X}}$, required in the second stage, are obtained by regressing the instrumental variables, **Z**, on **X** using a simple OLS estimator in (4.21). Equation (4.20) is also known as the *reduced form equation*. The second stage, or the *structural equation*, employs, $\widehat{\mathbf{X}}$, to obtain the unbiased coefficient as shown in (4.19). These derivations constitute *two-stage least squares* (TSLS) estimation (Kennedy 2008, 148; Wooldridge 2009, 521). Naturally, $\widehat{\boldsymbol{\beta}}_{IV}$ is assumed unbiased because $\boldsymbol{Cov}(\mathbf{Z}, \boldsymbol{\varepsilon}) = \boldsymbol{Cov}\left(\widehat{\mathbf{X}}, \boldsymbol{\varepsilon}\right) = 0$.

$$\mathbf{y} = \widehat{\mathbf{X}} \cdot \widehat{\boldsymbol{\beta}}_{IV} + \boldsymbol{\varepsilon} \tag{4.19}$$

$$\widehat{\mathbf{X}} = \mathbf{Z} \cdot \boldsymbol{\Gamma} \tag{4.20}$$

$$\boldsymbol{\Gamma} = (\mathbf{Z}^T \cdot \mathbf{Z})^{-\mathbf{1}} \cdot \mathbf{Z}^T \cdot \mathbf{X} \tag{4.21}$$

Researchers employing two separate OLS stages will produce a biased standard error of $\boldsymbol{\beta}_{IV}$. Using compact notation, the $\widehat{\boldsymbol{\beta}}_{IV}$ estimator is displayed in (4.22) where the hat matrix, $\mathbf{H}$, is derived in (4.23). The covariance matrix of $\widehat{\boldsymbol{\beta}}_{IV}$ is displayed in (4.25).

$$\widehat{\boldsymbol{\beta}}_{IV} = (\mathbf{X}^T \cdot \mathbf{H} \cdot \mathbf{X})^{-1} \cdot \mathbf{X}^T \cdot \mathbf{H} \cdot \mathbf{y} \tag{4.22}$$

$$\mathbf{H} = \mathbf{Z} \cdot (\mathbf{Z}^T \cdot \mathbf{Z})^{-1} \cdot \mathbf{Z} \tag{4.23}$$

$$\widehat{\mathbf{X}} = \mathbf{H} \cdot \mathbf{X} \tag{4.24}$$

$$Cov\left(\widehat{\boldsymbol{\beta}}_{IV}\right) = \hat{\sigma}^2 \cdot (\mathbf{X}^T \cdot \mathbf{H} \cdot \mathbf{X})^{-1} \tag{4.25}$$

The proper covariance matrix is required when executing the two-stages manually. Researchers interacting dummy variables with endogenous regressors may resort to manual implementation to avoid endogenous interactions.

4.8.3 Test of Instrument Relevance and Exogeneity

The implication of (4.25) is that standard errors may be exacerbated when instrument relevance is poor. Tests for instrument relevance and exogeneity aid in identifying bias in two-stage least squares estimates.

Instrument relevance may be tested using a partial F test. Based on Wooldridge (2009, 145-146), the standard F statistic determines if a model with instruments (i.e., unrestricted model), (4.26) is an improvement compared to a model with no instruments (i.e., restricted model), (4.27).

$$\widehat{\mathbf{X}}_{EN} = [\mathbf{X}_{IV}|\mathbf{X}_{EX}] \cdot [\boldsymbol{\beta}_{IV}^{T}|\boldsymbol{\beta}_{EX}^{T}]^{T} \tag{4.26}$$

$$\widehat{\mathbf{X}}_{EN} = \mathbf{X}_{EX} \cdot \boldsymbol{\beta}_{EX} \tag{4.27}$$

The specific hypotheses are displayed in (4.28) and (4.29). A rejection of the null hypothesis signifies strong instruments.

$$H_0: \boldsymbol{\beta}_{IV} = \mathbf{0} \tag{4.28}$$

$$H_1: \boldsymbol{\beta}_{IV} \neq \mathbf{0} \tag{4.29}$$

Failure to reject the null implies that instruments may be weak. Staiger and Stock (1997, 557) estimate a critical value for weak instrument identification. When the F statistic is greater than 10 the instruments are strong. However, when the F statistic is less than 10 the instruments are weak. *Weak instruments* severely handicap the first stage regression from producing exogenous predictions.

Two exogeneity tests are prevalent in the literature. They examine the correlation of both the endogenous regressor and instruments with the disturbances respectively. The first test verifies if the "troublesome regressor" (Kennedy 2008, 141), **X**, is endogenous. Kennedy (2008, 153) recommends using "the second variant of the Hausman test" for this purpose. Since the first stage residuals, $\mathbf{u}$, filter out the endogenous variation in **X**, including them in the structural equation as shown in (4.30) facilitates a partial F test excluding $\mathbf{u}$ from the restricted model. This translates into a correlation test between $\mathbf{u}$ and $\boldsymbol{\varepsilon}$. If these terms are correlated, then the coefficient on $\mathbf{u}$ will be greater than zero, affirming endogeneity of **X**. Null and alternate hypotheses are display in (4.31) and (4.32) respectively. Rejection of the null hypothesis implies that **X** is endogenous. The alternate hypothesis suggests that **X** is exogenous.

$$\hat{\mathbf{y}} = \widehat{\boldsymbol{\beta}}_{\mathbf{0}} + \mathbf{X} \cdot \widehat{\boldsymbol{\beta}} + \mathbf{u} \cdot \widehat{\boldsymbol{\beta}}_{\mathbf{u}} \tag{4.30}$$

$$H_0 \colon \widehat{\boldsymbol{\beta}}_{\mathbf{u}} = \mathbf{0} \tag{4.31}$$

$$H_1 \colon \widehat{\boldsymbol{\beta}}_{\mathbf{u}} \neq \mathbf{0} \tag{4.32}$$

The second test evaluates "instrument validity" (Doku and Dofour 2008, 2650) and is achieved using a specification test formalized by Sargan (1958). Simply put, this test regresses the instruments, $\mathbf{Z}$, on the second stage residuals $\boldsymbol{\varepsilon}$. Since the exogeneity assumption for instrumental variables is $\boldsymbol{Cov}(\boldsymbol{Z}, \boldsymbol{\varepsilon}) = \mathbf{0}$, the model's R^2 should equal zero. Sargan's statistic $n \cdot R^2$ distributed as a χ_k^2 where k is equal to the number of instruments minus the number of endogenous regressors. Associated hypothesis tests are displayed in (4.33) and (4.34). When the null is rejected, at least one instrument in $\mathbf{Z}$ is endogenous. The alternate hypothesis implies instrument exogeneity. This test is limited because it is unclear which instrument suffers from endogeneity in cases of a rejection of the null (Kennedy 2008, 155). An additional limitation is the test's sensitivity to sample size, suggesting that the rejection region increases with n.

$$H_0: n \cdot R^2 = 0 \tag{4.33}$$

$$H_1: n \cdot R^2 \neq 0 \tag{4.34}$$

4.8.4 The Many Instruments Problem

Anderson and Sawa (1979, 175) find that that standard OLS hypothesis tests may "seriously underestimate the actual significance" of the TSLS estimator when the number of instruments increases. Bound, Jaeger and Baker (1995, 449) confirm this in their empirical findings. The problem of inconsistency of TSLS estimators in relation to the number of instruments has given rise to empirical research identifying solutions (Donald and Newey 2001, Chao and Swanson 2005; Carrasco 2012; Chao et al. 2014).

Greene's (2008, 316 – 317) derivation of the instrumental variables estimator provides a framework to infer a multivariate example of instrument endogeneity.

$$\text{plim}\mathbf{b}_{\mathbf{OLS}} = \beta + \text{plim}\left(\frac{\mathbf{X}'\mathbf{X}^{-1}}{n}\right)\text{plim}\left(\frac{\mathbf{X}'\varepsilon^{-1}}{n}\right) = \beta + \mathbf{Q}_{\mathbf{xx}}^{-1}(\gamma) \neq \beta \tag{4.35}$$

$$\text{plim}\mathbf{b_{IV}} = \beta + \text{plim}\left(\frac{\mathbf{Z'X}}{n}^{-1}\right)\text{plim}\left(\frac{\mathbf{Z'}\varepsilon}{n}^{-1}\right) = \beta + \mathbf{Q_{zx}^{-1}}(\delta) \neq \beta \tag{4.36}$$

The terms $\mathbf{Q_{xx}^{-1}}(\gamma)$ and $\mathbf{Q_{zx}^{-1}}(\delta)$ in equations (4.35) and (4.36) both represent the correlation between independent variables, **X**, or instrumental variables, **Z**, and the error term, ε, respectively. If either of these terms is not equal to zero (i.e., $\gamma = \text{plim}(\frac{\mathbf{X'}\varepsilon^{-1}}{\mathbf{n}}) \neq 0$ or $\delta = \text{plim}(\frac{\mathbf{Z'}\varepsilon^{-1}}{\mathbf{n}}) \neq 0$), then there is some endogeneity between independent or instrumental variables and the error term respectively. When instruments correlate highly with **X,** then this problem is not as severe. When they do not, the problem of instrument endogeneity is exacerbated, even when **Z** is only slightly correlated with ε. Authors have asserted that weak instruments pose a great problem in applied econometrics using instrumental variables (Nelson and Startz 1990; Bound, Jaeger, and Baker 1995; Murray 2006, Murray 2017).

Authors have attempted to mitigate the many, weak instrument problem through factor analysis methods. Bai and Ng (2010, 1578) propose using principal component analysis identifying "common components" in place of their weak instrument counterparts. This way, endogeneity is reduced by restructuring variation explaining the endogenous regressor into fewer instruments. They suggest that the noisy or endogenous part of the instrument is cleaned out through the data reduction process of principal component analysis (Bai and Ng 2010, 1587; Bai and Ng 2008, 12).

4.8.5 Clapp's (1990) Instrumental Variable Specification

Clapp agreed that an econometric approach was warranted, but argues that the underlying theory regarding housing market economy should be the foundation of any approach. The author quotes Edelstein's (1979, 761) theory concerning property taxes being negatively capitalized into sales prices suggests simultaneity between sales price and assessed value. Thus, a link between the two variables exists, implying that the sales price and the assessed value share a common error component. Referring briefly to Edelstein and Oates to discuss negative capitalization will provide a foundation for understanding Clapp's approach to theory behind housing market economy.

Edelstein (1979, 756) refers to Oates' (1969, 968) cross-sectional study on the nature of the link between residential property value, local property taxes (i.e., a percentage of assessed values) and public service provision. His empirical study regressed a vector of independent variables on the median of house price in 1960 dollars divided by 1,000. Oates finds that the selling prices of homes are reduced to compensate for property tax rate increases, holding the amount of public services constant. There is a potential endogeneity issue in using this method because of possible correlation between the dependent variable and the measurement error in the log of tax rate variable. In particular, high property values might be correlated with low property taxes for non-uniform public service distribution. In addition, public school districts in locales with higher disposable income might collect more revenue than low-income public-school districts. He finds that, since families with higher incomes are willing to spend more in housing consumption, there is a potential correlation between house prices and local public service provision in terms of public education. Higher disposable revenues can also translate into housing consumption, which suggests correlation between house prices and local public education costs. To control for these sources of endogeneity, Oates (1969, 965) employs a two-stage least square method to explain the variation in tax rates and public expenditures.

Oates uses the model coefficients to determine changes in property tax capitalization when public service investment increases. The example in his study follows a statutory investment in spending per public student by $100 and he tests the coefficient on the property tax variable after this increase. Oates (1969, 966) finds that positive investment in public services influences the effect of property taxes on housing values negatively. This study assumes that when there is no investment in public services for a given local government jurisdiction, property taxes are negatively capitalized into house values. Here, *capitalization* refers to returns on an investment that increase (or decrease) in value over some length of time. *Negative capitalization* can be described, in terms of Oates' findings, as house value dollars that are lost in the value of a residence based on the impacts of increasing property taxes. In support of Oates and Edelstein's theory of negative property tax capitalization, Clapp suggests that both assessed value and sales price influence one another leading to simultaneity. Clapp (1990, 237) argues that assessed value and sales price are variables both subject to error, and therefore, the side of the regression in which sales price is located is unimportant. If one reflects on the information that explains assessed value, an argument could be made against Clapp's assertion. When appraisers formulate an opinion of value, they employ comparable sales as reference information to that opinion. In other words, previous sales prices explain assessed value. Whether or not these variables contain measurement error, the appropriate direction of causality is that assessed value is explained by sales price, placing them on the right and left hand side of the regression equation respectively.

However, Clapp did introduce negative property tax capitalization theory into assessment inequity models. Theoretically, property tax expenditures capitalize into future sales prices in the form of a discount. In other words, assessed value influences sales price, albeit indirectly and through only a small percentage (e.g., 2%). However, this theory requires the assumption, made by Oates (1969, 966), that local governments do not introduce positive investment in public services. Two directions of causality now become apparent. The first relates to the use of sales prices as reference information in determining assessed value. This influence is strong and positive because of an established practice using comparable sales to determine appraisal estimates. The second direction, although weak and negative, relates to property taxes considered in ultimate sales prices. Consider, now, two directions of causality; the first one is a strong, positive influence, while the other exerts a weak, negative influence. This relationship is conceptualized in Figure 4.2.

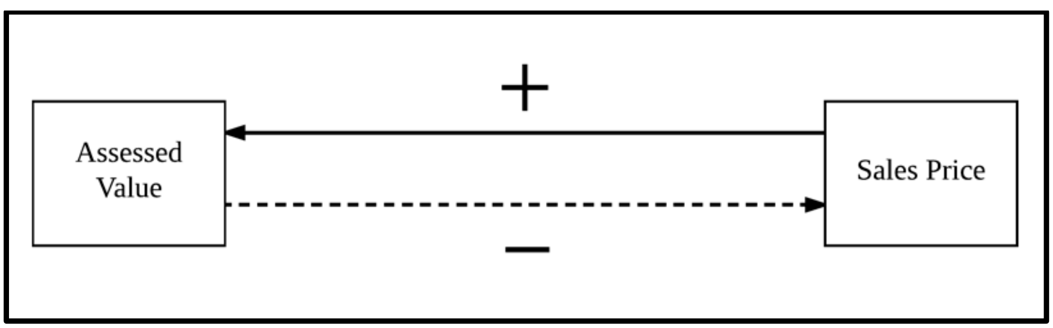

Figure 4.2. Simultaneous causality influences between assessed value and sales price.

This dual causality problem also contributes to endogeneity of the sales price variable. This endogeneity is a result of the weak, negative influence that assessed value has on the independent variable, sales price. Stock and Watson (2015, 424) suggest that an instrumental variable approach may also control for this endogeneity problem.

Clapp (1990, 237) proposes a new perspective of market value as the "most probable price" expressed as an expectation of sales price based on repeated draws. This theory suggests that market value cannot be directly observed. Therefore, any attempt to measure market value, is, consequently, a random variable with an associated error term that expresses deviations from unobserved market value. He follows Kochin and Park's (1982, 518) approach with sales price on the left hand side of the equation and places assessed value on the right hand side.

Clapp empirically explores a new model compared with empirical results from Kochin and Park's model and those of the improved Paglin and Fogarty model. He examines the direction of vertical inequity (e.g., regressivity or progressivity) for each model. If the Kochin and Parks or Paglin and Fogarty model indicate vertical inequity, he reports regressive or progressive results. Clapp argues that, based on the alternatives, the large sample properties of the instrumental variable estimator produces the least amount of bias. The reduced form and structural equation are defined in (4.37) and (4.38).

$$\ln SP_i = \beta_0 + \beta_1 \widehat{\ln AV_i} + \epsilon_i \tag{4.37}$$

$$\ln AV_i = \pi_0 + \pi_1 Z_i + u_i \tag{4.38}$$

The first stage includes AV_i as the assessed value for parcel i where $i = 1,2,3 \ldots n$, π_0 as the intercept term, π_1 as the coefficient for the instrumental variable Z_i, and u_i as the error term. Second stage terms include SP_i as the transaction price for parcel i, β_0 is the intercept term, β_1 is the elasticity coefficient, $\widehat{\ln AV_i}$ represents the fitted values derived in the first stage, and ϵ_i as the disturbances. The elasticity, β_1, is the parameter used for determining the direction and magnitude of vertical inequity. The percentage change below one indicates progressivity and an elasticity above one exhibits regressivity. In the event that the elasticity reports a value exactly equal to one then assessments indicate no vertical inequity (Clapp 1990, 239).

Clapp uses data from approximately 17,000 sales transactions for one- to three-family residential dwellings located in Connecticut municipalities between 1981 and 1987. Clapp (1990, 241) finds that the improved Paglin and Fogarty model reports 37 regressive and 15 uniform municipalities of the 52 tested at a 95% confidence level. He concludes that the model is biased towards regressive results (or that it reports regressivity more than the Paglin and Fogarty model). Clapp (1990, 245) finds that the Kochin and Parks model reports progressivity for 34 of 52 municipalities tested at a 95% confidence level. Remaining municipalities were uniform. This model was seemingly biased towards progressive results. Clapp analyzes the same municipalities using an instrumental variable estimator and finds that 12 municipalities exhibited regressivity while only 6 were progressive. The remainder of the sample demonstrated uniform results.

4.9 Gap in the Literature

In the review of methods for estimating uniformity of property tax assessments, the discussion has focused on the uncertainties inherent in the variables of interest: assessed value and sales price. Though both variables have 1) some degree of measurement error and 2) simultaneous causality, econometric solutions are available. Clapp (1990) has addressed the solution to the first problem with an instrumental variable. However, authors question the causality direction and three-group instrumental variable.

Two arguments support the appropriate causality direction. First, which variable is the endogenous dependent variable and which the endogenous independent variable relates to their degree of uncertainty. As argued in section 3.4, assessed values are substantially more uncertain with regard to the true market value than the revealed sales price. The assessed value is ultimately just an estimate based on uncertain information whereas potential buyers and sellers collect considerably more information about the true market value of a specific property. It is sound practice to make the variable with higher uncertainty a dependent variable. Cheng (1976, 1252) asserts this requirement. And second, Benson and Schwartz (2000, 242) and Fairbanks et al. (2013, 7) argue that assessed value should be the dependent variable because it is derived using sales prices (i.e., using the comparable sale approach). Yet current research proposes that a contrasting relationship is valid (Birch, Sunderman, Radetskiy 2017, 76). Carter (2016, 6) invites the property tax profession and other experts to work together to identify solutions to the causality problem.

Two concerns related to the three-group instrumental variable involve potential exogeneity and omission of observations. First, Clapp's (1990) ranking of assessed value and sales price assumes that the instrumental variable is relevant and exogenous compared to assessed value. Although it likely that the instrumental variable is relevant to its endogenous counterpart, a stronger assumption is that of exogeneity. Clapp's (1990) instrumental variable, Z_i, assumes that grouping both ranked sales price and assessed value into terciles does not violate the condition that Z_i is not correlated with the error term (i.e., $Corr[Z_i, u_i] = 0$) (Cheng and Van Ness 1998, 8). Since a component of Z_i is a ranked adaptation of current year, assessed value, it is probably correlated with X_i. However, the author assumes that this method "averages away" the associated measurement error (Kennedy 2003, 162–63). Neyman and Scott (1951, 358–59) discuss the implication that any error is averaged away only for "some values" of the instrumental variable. These authors indicate that errors are not eradicated with this method. Denne (2011, 10) observes that Clapp's (1990) specific instrumental variable construction ignores a third of the observations because it follows Bartlett's (1949) three group method. Of another concern, is the sensitivity of this approach to grouping by sales price as originally discussed by Schultz (1996). Dare, Goebel, and Isett (2013, 28) hint that this problem may influence Clapp model vertical inequity estimates in their empirical investigation of assessments in Lubbock, Texas between 2001 and 2008.

Finally, simultaneity or a bi-directional influence between assessed value and sales price may introduce endogeneity into the estimation process. Instrumental variables are also a solution to the second problem. This research seeks to fill a gap in the literature related to the appropriate method for estimating vertical property tax inequity. A brief synopsis of the research objectives follows.

4.10 Synopsis of Research Objectives

To address the issues previously discussed within the existing body of knowledge by explicitly addressing the model's uncertainties when identifying vertical inequity, the following research objectives were defined:

- Determine if vertical inequity can be measured without bias. This will be addressed by incorporating hedonic house price instruments that simultaneously control for measurement error and capture the effect of negative property tax capitalization.

Additionally, the appropriate causality direction and temporal lag between appraisals and sales will be incorporated into the model specification.

- Temporally evaluate vertical inequity during volatile economic periods within Dallas County, Texas when market value indicators exhibited greater uncertainty.
- Spatially generate an index of vertical inequity using housing market areas commonly used in real estate circles.

Subsequent chapters identify the methods used to execute these objectives. Chapter 5 lists the data used for the study with supporting theory behind housing characteristic selection for the hedonic house value instruments. The study's global specification follows in Chapter 6, representing an adaptation of Cheng's (1976) constant elasticity model incorporating a growth and decay term. Chapter 7 introduces temporal and spatial indicator variables, which are used to express temporal and spatial fluctuations in vertical inequity. Finally, Chapter 8 summarizes study findings, discusses policy implications, addresses research limitations, and suggests future research opportunities.

CHAPTER 5

DATA AND THEIR CONVERSION TO EVIDENCE

5.1 Introduction

This chapter describes the research methodology's phase one and two shown in Figure 1.4. These phases, *data conversion* and *operationalization of variables*, convey how data was prepared for use in analysis. Subsequent chapters elaborate on the remaining phases. Organized by data source group, preliminary sections first define data variables within the context of research objectives. These include residential, single-family dwelling characteristics collected by the assessor and known in the literature to influence market value. Sales transactions are also included but require additional discussion for three reasons. The first addresses uncertainty regarding how closely sales represent market value. The second pertains to a house price index adjusting lagged appraised values to the same period as sales transactions. Finally, extreme appraisal ratios are trimmed following common practice in applied work. Summary statistics for these critical data variables are provided. Geo-referenced data sources are then identified and discussed. The chapter concludes with a literature review of hedonic house price constructs and approaches used to convert such data sources to evidence.

5.2 Real Property Appraised Value and Characteristics

DCAD annually records property characteristics, housing market sales information, and neighborhood amenities that may trigger a change in property values within Dallas County, Texas. The appraisal estimate, also known as *appraised value*, is applied to properties using one of three valuation approaches in practice at DCAD. The cost and market approach are commonly employed to derive appraised value on owner-occupied, single family dwellings within the study area. These estimation methods are discussed in sections A.5.1 and A.5.3 respectively. Appraisers define appraised value using property characteristics recorded as of the annual assessment date of January 1st each year. This facilitates efficient reporting and taxation. Any changes to property characteristics and location influences after the assessment date are set aside for the following appraisal year. A more detailed description of DCAD's assessment cycle is available in Figure C.1. These property characteristics are available for approximately 650,000 delineated parcel boundaries. Appraisers record information regarding the number of full bathrooms, total floors, presence of a swimming pool, building class, effective age of dwelling, foundation material, interior and exterior walls, trees indicator, and lot area. A detailed list of these and other recorded characteristics may be found in Table C.2 and Table C.3.

Appraised, rather than assessed, values were employed for this study to investigate the original estimate from the appraiser before any statutory discounts[18] were applied. Another purpose is to identify inequity from the perspective of the appraiser rather than the homeowner. One could justify this by stating that statutory property tax limitations are out of the appraisers control and not considered in the estimation. Additionally, lagged, appraised value is used in uniformity calculations to avoid any bias resulting from appraiser knowledge regarding comparable sales. For example, if a sale occurred on a property shortly before the assessment date, then the appraiser has knowledge of the market value. Appraiser estimates matching recent sales prices is known as "sales chasing" and is discouraged in practice (Ihlanfeldt 2004, 8; IAAO

[18] State mandated discounts include property tax exemptions or assessment caps and become effective upon receipt of a valid application from a homeowner.

2013, 43). This is discussed further in section 6.4. Summary statistics for lagged appraised value are provided in Table 5.1.

Table 5.1. Summary statistics for lagged appraised value.

Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum
11	109	146	199	222	9274

5.3 Single-Family Dwelling Transactions

Texas law does not require real estate transactions to report the final price for the purchase of real estate. The law also protects property owners by specifying non-disclosure clauses related to private information (e.g., property sales prices). DCAD (2018a, 14) receives sales information from: 1) surveys mailed to the buyer or seller, 2) from making phone calls, 3) from sales rendered by the taxpayer, 4) annual protest hearings, 5) multiple listing boards, 6) real estate agents, 7) independent fee appraisers and 8) home builders. From these sources, other information related to the sale is gathered. This information includes: 1) the type of sale, 2) sale date, 3) sale price with/without personal property or financing options applied and 4) an indicator reporting sale suitability as a comparable sale or in ratio studies.

5.3.1 Sales Observations Reflective of Fair Market Value

Single-family dwelling transactions were collected from DCAD’s appraisal database. Selection criteria identifies only those sales that represent market value and avoids uncertainties that may exist in sales prices discussed in section 3.3. Criteria is based on common practice in uniformity studies (IAAO 2010). The selection criteria may be found in Table 5.2. Originally, eleven individual samples, one for each year of the study period, were collected. These samples consisted of a property's most recent sale within each study year indicated. With a sale year label applied, these observations were later pooled together in preparation for model estimation.

Table 5.2. This selection criteria represents filtering rules for sampling the observations for the study.

Selection Criteria for Annual Sample Observations
The property type is a single-family, detached, owner-occupied dwelling
The most recent sale is coded as an arm's length transaction by the appraiser
There are no improvement permits issued between the date of the sale and the assessment
The property is not sold by a government or financial institution that typically sells *real estate owned* property
The most recent sale is not part of a multi-property transaction
The improvement is not newly constructed within the last five years
The improvement is considered **100%** complete at the time of the assessment
The property did not change in its land use before the most recent sale (e.g., from commercial to residential)
There was no change in property characteristics between the date of the sale and the assessment

5.3.2 Sales Price Summary Statistics

Sales prices (and appraised values) are collected in single dollar values but are later converted to $1,000's. They are similar to lagged appraised value in their distribution only slightly larger. Summary statistics for sales price is provided in Table 5.3.

Table 5.3. Summary statistics for sales price.

Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum
11	116	157	222	249	11700

5.3.3 Case-Shiller Index

Individual and composite S&P CoreLogic Case-Shiller house price indices provide general information about single-family house price fluctuations for major metropolitan statistical areas. Repeat single-family dwelling transactions from a base time period (i.e., January 2000) beginning at 100 indicate how housing market values increase or decrease, on average, from month-to-month (CoreLogic 2017). CoreLogic reports house value movements using an individual and composite price index for twenty major MSA's in the United States. Individual indices for 16 major U.S. cities are also available. They derive these indices using two-stage least squares regression because sales correlate with the error term.

Economists Case and Shiller's methodology using house price indices derived from a three-month moving average of single-family sales prices was investigated for adjusting lagged appraised value in the structural equation; however, growth and decay estimates were much too conservative given the larger geographic area (i.e., Dallas-Forth Worth-Arlington MSA). Rather, disaggregate estimates of average house price by zip code, allowed for greater precision.

5.3.4 NTREIS Sales Information

NTREIS (2018) is a solution provider for multiple listing boards within the North Texas region. Not only does NTREIS maintain a repository of real estate transactions within the study area, they also report sales statistics. Reports include data such as number of transactions, average sales prices and its percentage change from previous periods, and number of days the property remained on the market. Quarterly reports detailing sales statistics by county and zip code are available for the entire study period and were used in calculation of a local house price index. Derivation of the price index is provided in the next section.

To determine the representativeness of the study population, NTREIS total homes sold for Dallas County, Texas from statistical reports were compared to those included in DCAD's sales database. NTREIS reports a total of approximately $232{,}000$ transactions while DCAD reports approximately $225{,}000$ with a difference of approximately $7{,}000$ transactions. Compared to NTREIS, the DCAD database maintains a reasonably representative sales database differing by less than 4%.

5.3.5 NTREIS House Price Index

The value, ψ_{jt}, shown in (5.1), is an NTREIS house price index for Dallas County, Texas single-family house prices. The index is constructed by subtracting the average house price, $\bar{p}$, for zip code j in the first quarter, q_{t-1}, from the average house price for the zip code and quarter in which the sale occurred. This difference is then divided by the original average, $\bar{p}_{jq_{t-1}}$. Once ψ_{jt} is defined, the growth rate, γ_{jt}, is constructed in (5.2). The growth rate makes lagged appraised values and sales prices contemporaneous.

$$\psi_{jt} = \frac{\left(\bar{p}_{jq_t} - \bar{p}_{jq_{t-1}}\right)}{\bar{p}_{jq_{t-1}}} \tag{5.1}$$

$$\gamma_{jt} = \frac{\psi_{jt}}{100} \tag{5.2}$$

When the growth rate is specified in this way, γ_{jt} expresses positive or negative changes between $t-1$ and t in the appropriate measurement scale. These changes, represented by γ_{jt}, act as a component of the dependent variable Y_{it-1} in the model specification. Equation (5.3) corrects the value of lagged, $\log(appraisedvalue)$ for sales price fluctuations by applying the rate as a product. If sales prices declined by -0.215% from $t-1$ to t in zip code j and $t = 2008$ for example, where $\frac{\psi_{jt}}{100} = -0.00215$ then $\left(\frac{\psi_{jt}}{100} + 1\right) = 0.99785$. Lagged appraised value or $Y_{it-1} = \$150{,}000$ changes as shown in (5.3) to log($149,678).

$$
\begin{aligned}
\log\left(Y_{it-1} \times \gamma_{jt} + 1\right) &= \log(\$150{,}000 \times 0.99785) \\
&= \log(\$149{,}678)
\end{aligned}
\tag{5.3}
$$

5.4 Trimming of Outlier Ratios

As discussed in section 5.3.1, sales screening techniques were used to extract arm's-length transactions meeting the industry's standard of fair market value (IAAO 2010; IAAO 2013). Trimming of assessment ratios was also employed according to industry guidelines (IAAO 2013, 53). Ratios were filtered from the observations if they fell below $1.5 \times IQR(\frac{AV}{SP}) -$ the first ratio quartile or above $1.5 \times IQR(\frac{AV}{SP}) +$ the fourth ratio quartile. Here, IQR is the inter-quartile range. The trimming process removed 2,633 observations that were saved for a post-hoc investigation.

After initial matching of sales transactions with parcel ids, various typos were corrected. In addition, a balanced grouping design was defined to arrange building classes into categories by sales price. Two observations were removed because the properties had more than two floors. The final sample size was 55,206.

5.5 Independent School District Information

Appropriate indicators were required to control for *public service provision* and *negative property tax capitalization*. The following sections identify indicators expressing these concepts and their data sources within the study region. Their operationalization is discussed in section 5.7.

5.5.1 Independent School District Dallas County, Texas Tax Rates

Property tax rates levied by independent school districts give an indication of property tax capitalization. Rate values determine the percentage of taxable assessed value for annual tax bills. These nominal tax rates vary by school district and are used as an instrument in the first stage of the two-stage least squares vertical inequity model. The rate applies to each $100 in property value. DCAD (2016) maintains a record of historic independent school district tax rates for the entire study period. Because of the amount of services provided, public school tax rates are among the highest of all local governments within the study region.

5.5.2 Texas Education Agency School Ratings

Each K-12 public school within the state of Texas requires oversight for the quality of education it provides. Legislators gave oversight authority to the Texas Education Agency[19]. The agency

[19] Texas Constitution, sec. 39.053

reports status indicators based on average test scores in various subjects for each school district (Texas Education Agency, 2016). Status indicators are available for all years within the study period except for 2012[20]. Before 2012, the rating system in Table 5.4 was used and starting in 2013 a more general rating system was introduced. The general rating system identified whether districts met the TEA standard or if improvement was required.

Table 5.4. Nominal ranking status and interpretation of the TEA's school accountability rating system.

Rating Description	**Rating Code**	**Rating Interpretation**
Exemplary	E	90% of tested students passed all subjects
Recognized	R	70% of tested students passed all subjects
Academically Acceptable	A	Reading/ELA (50% passed), Writing (50% passed), Social Studies (50% passed), Math (35% passed), Science (25% passed)
Academically Un-Acceptable	L	None of the criteria for academically acceptable was met
Not Rated	P	Non-public and non-charter schools are not rated (e.g., private)

5.6 Geo-referenced Data Sources

Geospatial data for parcel boundaries, market areas, and local amenities are available for the study area. These data were provided in a format compatible with most GIS software. In many cases, study data was processed to include observations that only exist within the study region.

5.6.1 DCAD Parcel Boundaries

Parcel boundaries refer to the legal description of the property recorded at the Dallas County clerk's office. Parcel polygons change regularly. They contain an identifier for linking spatial polygons to property characteristics available in the appraisal roll. Parcel boundaries are only

[20] TEA status indicators for this year were imputed from the preceding years using an ordinary least squares prediction.

used to reveal the centroid location of properties to associate them with their respective market areas.

5.6.2 NTREIS Market Areas

NTREIS has historically maintained market areas. NTREIS also maintains and reports sales data for the Dallas Fort-Worth metroplex and its local realtor organizations. NTREIS no longer maintains georeferenced, market area boundaries; however, recently delineated NTREIS market boundaries are published in periodic real estate articles by the Dallas Morning News (Brown 2017, D). The newspaper publishes maps defining real estate market statistics. These published maps were used to digitize NTREIS market areas for analysis purposes in the study. These market areas provided relatively[21] homogeneous localities for use in estimating vertical inequity coefficients across the study area. The vintage of market areas is unknown, but is believed to be the most up to date available in print media.

5.6.3 Zip Code Tabulation Areas

The U.S. Census Bureau (2000, 2010) provides zip code tabulation areas that assisted in calculation of the house price index used to derive lagged appraised values contemporaneous with sales prices. Also known as ZCTAs, these regions provided locations for average sales prices to be matched from NTREIS statistical reports. Two ZCTA datasets from the decennial censuses of 2000 and 2010 were used at the parcel centroid observation level for $2004 - 2009$ and $2010 - 2014$ respectively. Percentage change estimates were applied to each ZCTA and

[21] As indicated in sections 7.11.3 and 7.11.4, some market areas exhibit heterogeneity in vertical inequity estimates.

coded to parcel centroids using GIS software. Few differences existed between 2000 and 2010 vintages. Only one 2000 vintage ZCTA polygon was split into two in the 2010 ZCTA dataset. Where the zip code did not exist for 2000 census ZCTAs, the house prices for shared zip codes found in both census ZCTA data sets were propagated for the appropriate year and quarter (e.g., 75254 for ZCTA 2010 and 75240 for ZCTA 2000 and 2010). Additionally, two observations were contained in ZCTAs that did not have a matching NTREIS average sales price. These price calculations were derived using an ordinary kriged surface based on average ZCTA sales prices. The kriging function K-Bessell with a 95% confidence interval produced the smallest RMSE value. Lag sizes were between $16000 - 19000$ for a total of 12 lags.

5.6.4 Recreational Amenities and Shopping Facilities

Locations where homeowners gather for recreation include places such as lakes, hiking or bike trails, and fitness centers. Spatial areal, linear, and point features are used to represent such places in a geographic context. Such places are represented spatially with areal, linear, and point features respectively. I discuss their influence on house prices in section 5.7.5. Spatial, amenity data sources within the study area included parks (NCTCOG 2014), lakes (U.S. Geological Survey 2014), trails (City of Dallas 2016; OpenStreetMap contributors 2016; City of Richardson 2016), and recreational facilities (Esri and Infogroup 2015). Shopping mall locations were another important influence discussed in section 5.7.6. Commercial shopping sites existing in 2015 were spatially represented by point features and from these, mall locations were obtained for this study (NCTCOG 2015).

5.6.5 Other Geo-referenced Data Sources

Various georeferenced data sources were employed in providing context to published maps within the study. Reference material regarding population (TNRIS 2017), water features (USGS 2014), open spaces (USGS 2016), and transportation arteries (TNRIS 2016) acted as important background features in understanding patterns of sales price activity and inequity within market areas.

5.7 Converting Data to Evidence: Hedonic House Price Variables

Instrumental variables are required for the appropriate estimation of vertical inequity. The instruments contained in the first stage regression control for measurement error and simultaneity. Instruments controlling for measurement error identify the unobserved market value with observed characteristics. One author, Can (1992) employs an instrumental variable approach for estimating unobserved market value or hedonic house price to consider spatial effects in prediction. One of Can's (1992, 472) models includes instruments as interaction terms with the spatial lag of the dependent variable, which is the property's sales price. These interaction terms combine the spatial lag with construction material of the residential dwelling façade, number of bathrooms, area of the parcel the improvement is built on, a fireplace indicator, two-car garage indicator, and an air conditioning and heating unit indicator. Interaction terms in Can's implementation are comprised of dwelling characteristics typically included as independent variables in hedonic house price models. Although Can's particular use of instruments is not to control for measurement error, but to produce an estimator with desirable large sample properties in lieu of maximum likelihood estimation, I considered their use of hedonic house price variables appropriate for this research (Can 1992, 469).

The goal of hedonic house price models is to identify how specific housing characteristics, expressed as a bundle describing an ideal house, contribute individually to the ultimate selling price. This approach helps to determine the marginal willingness to pay for specific house price characteristics within distinct housing markets. Rosen (1974) expressed this concept in terms of utility maximization theory. This theory represents a homebuyer making their selection based on choices producing the greatest utility among the set of dwelling options available to them, subject to budget constraints. Utility, in this context, means that individual buyers want to gain the most benefit from the housing purchase.

To address homebuyer, utility maximization theory, the hedonic house price function attempts to estimate housing feature prices through linear estimation of selling price on a collection of observed units. Unit characteristics are expressed as independent variables in linear estimation. Model coefficients translate to “implicit” prices derived from explanatory power of the characteristic’s contribution to collective selling prices of homes (Sirmans, Macpherson, and Zietz 2005, 4). McFadden (1978, 75) lists some of these housing characteristics or “attributes” that home buyers consider when attempting to maximize their housing utility. McFadden’s (1978, 75) characteristics includes the following attributes:

1. Environmental and neighborhood characteristics such as neighborhood quality and provision of public services.
2. Cost related characteristics such as price of housing and property taxes.

3. Accessibility measures such as distance to retail, education and employment locations.
4. Dwelling specific characteristics such as age of the building and total number of rooms.

Although many authors have recommended lists such as McFadden's to be incorporated into empirical hedonic price models, selection of these attributes is seemingly arbitrary. Sirmans, Macpherson, and Zietz (2005) highlight this issue in their review of contemporary hedonic house price literature. These authors compile evidence assigning specific housing characteristics into categories by comparing empirical work in hedonic modelling. Authors generate a list of housing characteristics grouped by category that were frequently included in hedonic price models and significant. Among these categories were (1) "construction and structure variables", (2) "internal house features", (3) "external house features", (4) "natural and environmental characteristics", (5) "environmental neighborhood and location factors", (6) "public service amenities", (7) "marketing occupancy and selling factors", and (8) "financing issues" (Sirmans, Macpherson, and Zietz 2005). I identify the mode of operationalizing measurement and categorical variables into these eight categories for determining a proxy for market value in the following sections.

5.7.1 Construction and Structure Variables

Two of these variables include square footage of lot and living space. According to Sirmans, Macpherson, and Zietz (2005, 11), these variables are the most frequently found in hedonic house price model research and almost always have a positive sign. This makes sense because more land and larger buildings sell for a premium[22]. Living space may increase when the number of floors or stories also increases. Yet surprisingly, the literature more commonly associates a greater number of floors with a negative relationship to house price. Sirmans, Macpherson, and Zietz (2005, 10) find that number of stories demonstrated a negative sign in 7 empirical studies compared to 4 reporting a positive sign. DCAD parcel boundaries were used to generate the total lot size in square feet of the property for each observation in the study. Living area was collected from DCAD's appraisal database in units of square feet. Number of floors information was also gleaned from this database and compiled as a numeric variable comprising the sum of each full floor as 1.0 and half floors as 0.5.

Dwelling age is also heavily regarded in the literature. There are two different age variables to consider in DCAD's appraisal database, the first being actual age and the second effective age. Actual age represents the total amount of time since the improvement was built; however, this is not always interpreted as a true housing-age measurement. Effective age is defined as the number of years since the dwelling experienced substantial remodeling. Substantial remodeling translates to upgrades on the property sufficient to change the appraiser's calculation of depreciation or how much value is lost due to physical wear, obsolete features, or economic forces (Jacobus 2012, 368–69). The appropriate age variable used in the hedonic model is effective age because it correctly accounts for depreciation in relation to age.

[22] Lot size does not always have a linear relationship with sales price in some cases. Particularly in cases where large lots are in rural areas compared to smaller lots in urban areas with larger buildings. This becomes more evident when looking at the coefficients of the hedonic house price model in Table 6.1. The lot size coefficient is much smaller than the living area coefficient.

Some authors suggest that the age variable has a possible non-monotonic (Hill 2012, 24–25) or polynomial relationship to price. Others have found that dwelling-age price distributions may follow a third-order polynomial shape (Goodman and Thibodeau 2003; Thibodeau 1995; Beron, Thayer, and Murdoch 1999; Waddell, Berry, and Chung 1996). Figure 5.1 illustrates causes for this polynomial relationship. One reason, non-linearity between price and age occurs is because of the dwelling's life cycle. Depreciation[23] causes the price to decline as the dwelling ages. At some point, owners invest and remodel thereby increasing the home's appeal, and ultimately, the selling price. Other reasons for increased price with increased age are suggested in Waddell, Berry, and Chung (1996, 279).

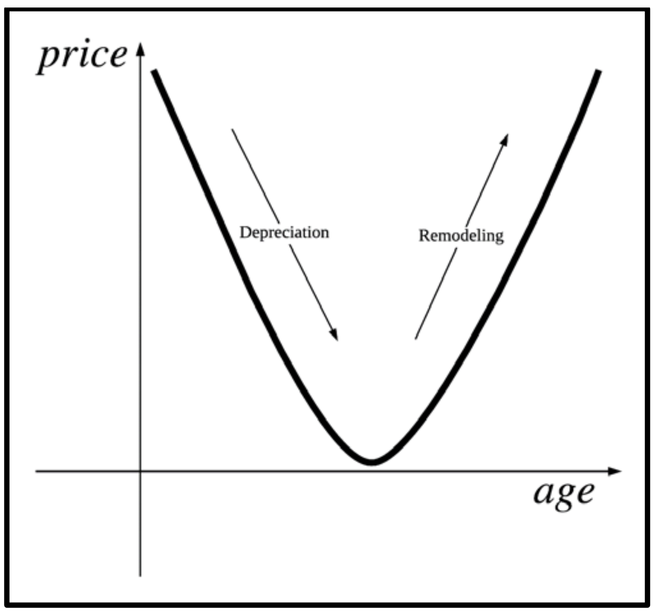

Figure 5.1. An illustration of the aging effect on house prices. As dwellings age they experience wear and obsolescence. This causes the homes' value to decline. Remodeling remedies wear and obsolescence increasing the homes' value.

[23] For a definition of depreciation and its various types, see section A.5.1.

Researchers provide statistical evidence of a non-linear price to age relationship, yet there are issues in interpreting the polynomial's coefficient (Fox and Weisberg 2011, 177–78; Hamilton 1992, 152). One solution for avoiding challenging regression polynomials while capturing non-linear age effects on price is to employ a variable that has a relationship with both price and age. Appraiser assigned building classes are used to identify age effects across different dwelling types. These classes are categorical designations of dwellings with unique qualities selling for different house price premiums. Although classes are not perfect divisions of house price ranges, interaction effects facilitate interpretation of building class' relationship to price.

DCAD defines building class categories to distinguish type of housing style, construction material, and special features of the dwelling. Classifying buildings into pre-defined groups of construction quality and other features simplifies the process of recording property characteristics. Not all building classes will have the same features and such deviations are expected. These deviations are listed and valued along with the final estimate. There are approximately 20 different building classes with unique qualities ranging from number of fireplaces, material of building exterior, foundation type, plumbing and existence of amenity features (e.g., wet bars, saunas). To adhere to the principle of parsimony in linear regression, building classes were aggregated into groups based on three criteria: foundation type and both exterior and interior wall material. Remaining features were so unique they precluded a more consolidated regime and were not included. Table 5.5 lists building class groupings based on the aforementioned criteria.

The interaction effect between age and building class group expresses how groups vary by age, and, ultimately how its variation explains price. For example, a dwelling in building class 25 or 26 has a concrete foundation and is made of brick exterior with wooden or plaster interior walls. One may expect buildings in these class groups to sell at a premium because of higher quality construction. In contrast, dwellings in building class 1 or 2 have wooden exterior walls, sheetrock interior walls and a post and girder foundation. These homes have poorer quality construction, and, therefore, do not sell at a premium. In this sense, building class groupings provide, to some degree, a better understanding of price variation with age than polynomial regressors do.

For the hedonic model, the building-class group variable was coded as a categorical variable. Using the R software package, categorical variables may be constructed using the *factor* command. This command generates indicator variables or contrasts for each category, omitting the first (i.e., default) contrast included in a list parameter. There are nine, total, unordered contrasts representing nine building class groups within this factor: “BCG1”, “BCG2”, “BCG3”, “BCG4”, “BCG5”, “BCG6”, “BCG7”, “BCG8”, and “BCG9”. Not all building class groups are well represented in the underlying data. If any building class groups are represented by less than 3 or 4 observations, then they were removed from the population and therefore, not included in the model nor its graphical outputs. Contrasts for all model variables were ordered based on an observed relationship with house price identified in the preliminary calibration phase. In the case of building class groups, group 7 had the greater number of building classes and, therefore, had the larger number of observations. This qualified the group as the most efficient default contrast and a similar approach was followed for other categorical variables in each model. Coefficient interpretation for these factors should be made in the context of the default contrast. If the coefficient for the default contrast has a value of $+0.50$, then this becomes the initial value above or below which remaining coefficients are to be interpreted. Based on the data processing shown in Table 5.5, the construction quality of group 7 is of high quality and thus has a high and positive relationship with house price. Other contrasts will have a lower relationship with selling prices in comparison.

Table 5.5. Building Class (BC) is grouped based on foundation type, exterior, and interior wall material. Construction quality is also provided to give an indication of the premium that may be paid for higher quality classes.

BC Grp	**BC**	**Foundation**	**Exterior Wall**	**Interior Wall**	**Construction**
1	1	Post/Girder	Wood	Sheetrock	Poor
1	2	Post/Girder	Wood	Sheetrock/Shiplap	Fair
2	3	Concrete	Wood	Sheetrock	Fair
2	4	Concrete	Wood	Sheetrock	Average
2	5	Concrete	Wood	Sheetrock	Good
3	6	Concrete	Wood	Sheetrock/Paneling	Good
3	7	Concrete	Wood	Sheetrock/Paneling	Excellent
4	8	Concrete	Brick Veneer	Paper/Canvas/Shiplap	Fair
4	9	Concrete	Brick Veneer	Paper/Canvas/Shiplap	Good
5	10	Concrete	Brick Veneer	Sheetrock	Good
6	11	Concrete	Concrete Block	Sheetrock	Fair
5	12	Concrete	Brick Veneer	Sheetrock	Fair
5	13	Concrete	Brick Veneer	Sheetrock	Average
5	14	Concrete	Brick Veneer	Sheetrock	Average
5	15	Concrete	Brick Veneer	Sheetrock	Good
7	16	Concrete	Brick Veneer	Sheetrock/Paneling	Average-Plus
7	18	Concrete	Brick Veneer	Sheetrock/Paneling	Good
7	21	Concrete	Brick Veneer	Sheetrock/Paneling	Good
7	23	Concrete	Brick Veneer	Sheetrock/Paneling	Good
7	24	Concrete	Brick Veneer	Sheetrock/Paneling	Excellent
8	25	Concrete	Brick Veneer	Plaster	Excellent
9	26	Concrete	Brick/Stone Veneer	Hardwood/Ceramic Tile	Excellent

5.7.2 Sales Price Effects of Age and Building Class

The scatterplot in Figure 5.2 demonstrates the increase in sales price for each building class group categorized by age. A loess line fits through each point cloud representing a different building class group. Starting from building class group 9 (i.e., "BCG9") and ending at group 1 (i.e., "BCG1"), each group is in a lower price class. A non-linear price to age relationship is evident for most building class groups. The most striking are among building class groups 5 and 7 with homes greater than 50 years old exhibiting nearly exponential price increases.

Figure 5.2. Price-age relationship by building class group. Colors represent unique building class groups and matching colored lines are a loess fit through the data point cloud.

5.7.3 Internal House Features

In respect to the interior of the dwelling, certain housing characteristics add value to the ultimate selling price. According to Sirmans, Macpherson, and Zietz's (2005, 17) review, variables for air conditioning, number of fireplaces, and bathrooms are frequently used and have a positive sign on the coefficient, indicating they are important to the purchaser. The number of fireplaces is represented by an integer value of 0, 1 or 2. A value of 2 means there are two or more fireplaces in the dwelling. Not all homes have fireplaces, but air conditioning, in Texas, may be considered more of a necessity. Sirmans, Macpherson, and Zietz (2005, 31) show that air conditioning is more important in terms of buyer preference in the Midwest and South than in northern climes. Appraisers catalogue multiple types of residential air conditioning units. For simplicity, this variable is constructed as 1 if the dwelling contains a full, central air conditioning unit and 0 if it does not. Bathrooms may consist of two types: a full bath or a half bath. A half bath contains only a sink and lavatory, while, typically, a full bath includes a bathtub or shower. Most homes have at least one full bath but not all contain a half bath. To simplify, I express this variable as an integer by counting two half baths as one full bath.

5.7.4 External House Features

External features are located on the property but outside of the main dwelling and refer to those elements that contribute to the ultimate selling price. Some examples include decks, tennis courts, pools, and garages. Variables for the square footage of garage area and a swimming pool indicator are included in the model. Sirmans, Macpherson, and Zietz (2005, 19) show they are frequently found in the hedonic house price literature and exhibit a positive sign. If a swimming pool exists on the property, then the pool indicator variable is equal to 1 and 0 otherwise. Landscaping quality is also featured in Sirmans, Macpherson, and Zietz’s review, but is less frequently analyzed. Hoch and Waddell (1993, 31) find that it has a positive effect on house prices in the Dallas area and since DCAD records landscape quality it is also included. Landscaping quality pertains to the level of maintenance and visual appearance of plants, trees and outdoor ornamentation. DCAD appraisers assign an ordinal category of *poor*, *typical* and *excellent* to properties that have visible landscaping on the property. If there is no landscaping, then it is *unassigned*.

If one or more attached or detached garages exist on the property, then the variable represents the natural log of total garage area in square feet. Many properties reported 0 size garage area when a garage was not present. To execute a log transformation on the entire garage area variable, zero values were increase by the minimum garage area available in the population.

5.7.5 Environmental Characteristics

Buyers are interested in the neighborhood and its surroundings when considering potential home purchases. Positive or negative externalities within a neighborhood's environment have been shown to increase or decrease local house prices respectively (Li and Brown 1980; Orford 2002). Externalities influence house prices because they contribute to processes that shape public perceptions whether good or bad. This section discusses environmental characteristics that pertain to not only a neighborhood's quality and local appeal, but also its infrastructure and developed residential form. Sirmans, Macpherson, and Zietz (2005, 9–12) classify hedonic house price literature involving environmental characteristics further into three distinct categories. Environmental characteristics of the Sirmans, Macpherson, and Zietz (2005) taxonomy are categorized into the following groups: (1) natural environment, (2) neighborhood and its location, and (3) neighborhood's public amenities.

Natural Environment, Neighborhood and its Location

Landscapes that contribute to a homeowner's natural environment include lake and ocean views. Characteristics of a resident's neighborhood and location include trees and golf courses that ultimately increase property appeal.

These features may be considered *recreational amenities* because they provide a desirable venue for a variety of leisure pursuits. Empirical research finds that dwellings in close proximity to lakes add value to residential property (Lansford and Jones 1995, 217; Benson et al. 1998, 68; Bourassa, Hoesli, and Sun 2004, 1443). Similar findings exist for neighborhood parks and green spaces (Morancho 2003, 39; Sander and Polasky 2009, 843; Hui and Liang 2016, 32). In support of their results, Sirmans, Macpherson, and Zietz (2005, 19–21) reveal that studies including "lake-front", "lake view", and "golf course" model variables have positive and significant coefficients. Research also indicates that recreational facilities may have a positive impact on house prices (Alexandrakis and Berry 1994, 18; Tse 2002, 1174; Asabere and Huffman 2009, 418).

To control for recreational amenity effects in the hedonic house price model, a measurement variable identifying accessibility to recreation was required. Recreational accessibility was quantified using a measurement variable, *recreational accessibility score*, α_i, generated for each subject property, i. This score was calculated by identifying each recreational amenity location, j, within a specified driving distance threshold, δ_{ij}, from each i. Recreational amenity locations within a radius of this distance threshold comprised the feasible set of accessible opportunities, J.

Recreational amenity locations were created from GIS shapefiles discussed in section 5.6.4. Recreational facilities were defined using the North American Industry Classification System's code for fitness and recreational sports centers. These centers include, but are not limited to, tennis courts, sports facilities, neighborhood swimming pools, fitness centers, skating rinks, and dance halls. A large number of recreational amenity locations exist within the study area; consequently, to minimize computational complexity when calculating accessibility scores, each amenity location was determined using a set of convenience criteria. First, areal features less than 10 acres were represented by the polygon's centroid. Second, line features and areal features greater than 10 acres were represented by the feature's boundary shape point[24], which is closest to subject property, i, in terms of Euclidean distance. Finally, point features were represented by their amenity location, j.

Recreation accessibility scores were formed using a three step process. The first step evaluated Euclidean distance from each subject property, i, to each amenity location, j, in the feasible set of accessible opportunities, J. Next, a preliminary accessibility score, α_{ij}, determined the measure of recreational accessiblity from i to j. Preliminary scores were derived using a triangular kernel function illustrated by Figure 5.3. The kernel function diminished accessibility scores as δ_{ij} increased and allowed for a maximum score where $\delta_{ij} = 0$. This function was employed here because it allowed for a well-defined cut-off distance δ_{max}. Possible scores were constrained to the grey area as shown in Figure 5.3. The triangular kernel function is formulated in equation (5.4).

[24] Shape points are locations that make up the polygon boundary and are also known as vertices.

$$\alpha_{ij} = \begin{cases} \left(\alpha_{max} - \left[\dfrac{\alpha_{max}}{\delta_{max}} \cdot \delta_{ij}\right]\right), & if\ \delta_{ij} \leq \delta_{max} \\ 0, & otherwise \end{cases} \tag{5.4}$$

Finally, preliminary accessibility scores were aggregated for each subject property, i. Aggregation occurred by taking the sum of all α_{ij}'s as in equation (5.5).

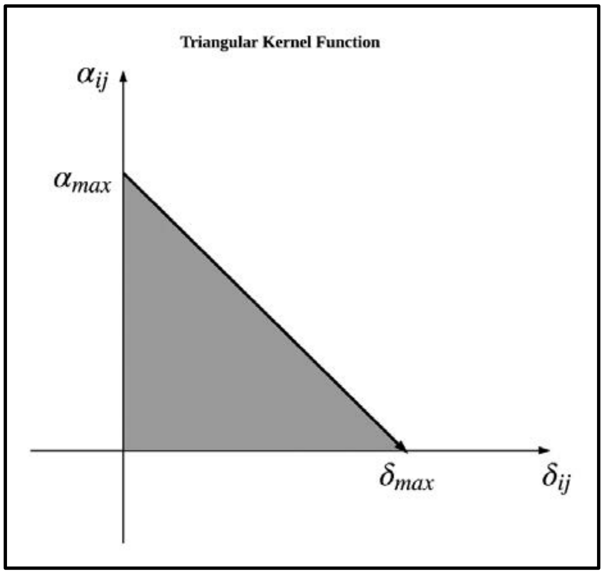

Figure 5.3. The triangular kernel function produced an accessibility score that diminished as distance increased. When distance was equal to zero accessibility score was at its maximum.

$$\alpha_i = \sum_{j=1}^{J} \alpha_{ij} \tag{5.5}$$

The value of $\alpha_{max} = 1$ and $\delta_{max} = 5.0$ miles were selected for this study. The value for α_{max} was designated for convenience[25], but the value of δ_{max} was based on research determining a person's willingness to travel for recreation (Alexandrakis and Berry 1994, 18; Spinney and Millward 2013, 483). I expected, *ceteris paribus*, that as recreational accessibility score, α_i, increased, house price at property, i, would also increase. Because the summary score estimated in (5.5) was positively skewed, a log transformation was applied to produce a distribution seemingly more normal in shape.

Other neighborhood and location characteristics not related to recreation included in this study are properties adjacent to a back-alley and residences with trees on the lot. Guttery (2002) investigated the impact of back-alleys on house prices in the Denton, Texas area between 1989 and 1995. The author finds that they had a negative impact on house prices and the coefficient was only slightly significant at the 1% confidence level (Guttery 2002, 270). He suggests that such alleys represent dis-amenities because they attract crime, accumulate refuse and restrict or infringe on lot area (Guttery 2002, 271). Sirmans, Macpherson, and Zietz (2005, 21) also support a negative sign on the alley coefficient, and report two other studies indicating insignificant results. For this study, I expected the alley variable to have a negative sign on the coefficient and to be only slightly significant. The appraisal database provides data on properties with back-alleys. The alley indicator variable included in this model was equal to 1 if the property has a back-alley and 0 otherwise.

[25] Future research could identify appropriate measures for α_{max} based on the size or type of amenity location.

Research shows that trees have positive impacts on house prices, representing a positive externality in the homebuyer's decision. Dombrow, Rodriguez, and Sirmans (2000, 42) studied the impact of adult trees on property values in Baton Rouge, Louisiana, between 1985 and 1994, finding that they had a positive and slightly significant effect. Sirmans, Macpherson, and Zietz (2005, 22) report five additional studies that have a similar outcome. To understand the potential impact on house values, wooded lots are expressed as an indicator variable in my study's hedonic model, as reported by the DCAD appraisal database. A wooded lot translates to an indicator equal to 1 and 0 otherwise.

5.7.6 Public Service Amenities

The term "public service amenities" represents another category in Sirmans, Macpherson, and Zietz's (2005, 23–24) environmental characteristics nomenclature because of their integral association with location. Public services are provided by local governments through funding instruments such as taxes, fees, and bond programs (City of Arlington, 2018). Many of the public service amenity variables Sirmans, Macpherson, and Zietz (2005) identify in the hedonic house price literature are related to public school quality (e.g., standardized test scores). They also classify "adequate shopping area" and "commercial activities" as residential amenities (Sirmans, Macpherson, and Zietz 2005, 24). Although such amenities are not public services per se, they are not constrained by service area. The literature and measurement approach associated with these variables are discussed hereafter.

Public School Quality

Many authors have investigated the impact school quality has on house prices. Nguyen-Hoang and Yinger (2011) provide a comprehensive review of the methodological approaches to measuring educational quality influences on property values since 1999. Authors conclude, for studies both inside and outside the U.S., that house prices increase between 1 and 4% for each one-unit increase in the standard deviation of student achievement test scores (Nguyen-Hoang and Yinger 2011, 46). Supporting Nguyen-Hoang and Yinger's claim, Zabel (2015, 83) produces results showing that high test scores increase house prices by 3.5%. Sirmans, Macpherson, and Zietz (2005, 23) list two studies in which empirical findings reveal that public schools with higher than average math and reading test scores have positive impacts on sales values. These empirical results are supported by many of the practices of main stream real estate websites such as Trulia.com that report school quality information (Gee 2010, 112–14) to help visitors identify desirable property.

School test scores are used as proxy for school quality in this study because of their pervasiveness in the empirical literature (Li and Brown 1980, 128–29; Jud and Watts 1981, 465; Black 1999, 578). The state of Texas reports public school test scores through the Texas Education Agency's (2004) Academic Excellence Indicator System (AEIS). The system applies a nominal ranking status for school campuses and districts that have a pre-defined achievement rate in cumulative test scores. This rating system is discussed in section 5.5.2.

To operationalize status indicators, this study used the nominal rating code shown in Table 5.4 to give an indication of school quality within each school district. Observations for in the study population was coded with this nominal rating code for their respective public school district. The only exception is the Wilmer-Hutchins Independent School District because it was consolidated into the Dallas Independent School District in 2006. Cases in Wilmer-Hutchins

ISD prior to the consolidation date were coded as being in Dallas ISD. For study years 2013 and 2014, only the numerical, achievement test passing rates were available. This information was used to identify the appropriate rating code in Table 5.4 for each observation. For two cases, academic rating codes were not observed during specific study years. In the first case, rating code *L*, was only observed in 2009. For the second case, the *E* academic rating code was not observed in 2004 despite its presence in the remaining study years. The *A* academic rating code was the omitted factor for this variable.

Shopping Accessibility

Akin to school quality, is the public amenity of accessibility to shopping centers. Empirical research indicates disparate impacts of nearby shopping centers on local house prices (Colwell, Gujral, and Coley 1985; Sirpal 1994; Des Rosiers et al. 1996; Yu, Cho, and Kim 2012).

Colwell, Gujral, and Coley (1985) is one of the first to investigate the influence nearby shopping centers have on house prices. The study identifies 43 single-family dwellings and condominium residences that were purchased between 1976 and 1982 less than a mile away from a proposed shopping center. The shopping center was comprised of five small retail stores and a disconnected grocery store. Living area, lot size, and number of bathrooms and fireplaces are attributes included as independent variables in regression models with varying functional form each using household selling price as the dependent variable. To measure impacts on shopping center proximity, distance variables were also included in regression models. These variables were constructed as a product of distances in linear feet of each residential property and an indicator representing whether the property was sold before or after the new shopping center was publicized for opening. A common pattern revealed among diverse analyses shows positive and significant coefficients for homes greater than a mile away from the proposed shopping center. In contrast, negative and significant coefficients were demonstrated for dwellings less than a mile[26] away from the proposed shopping center. Results indicate that shopping centers in close proximity to residential properties produced negative externalities based on the marginal willingness to pay of housing consumers.

Sirpal (1994) supports Colwell, Gujral, and Coley's (1985) findings in his research exploring how shopping center size and distance from neighborhood residences impact house prices. He argues that property values are less for dwellings in proximity to shopping centers because negative externalities would far outweigh the benefits (Sirpal 1994, 489). Empirically, his results indicate otherwise, at least for large shopping centers. Sirpal employs a similar approach to Colwell, Gujral, and Coley's (1985, 37–38) use of a battery of hedonic regression models with different functional forms for 143 dwellings in Gainesville, Florida. Results based on radial distance alone do not indicate a significant impact on house values, yet he consistently finds evidence supporting higher house prices near large[27] shopping centers (Sirpal 1994, 493). Des Rosiers et al. (1996) confirm Sirpal's conclusions in a Canadian context. Yu, Cho, and Kim (2012) also support previous authors' results using network distance for a large shopping center in Knoxville, Tennessee.

Based on the aforementioned evidence, I anticipated that large shopping malls had a positive and significant impact on house prices. Commercial business location data was collected

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[26] Authors employ accessibility measures within such a small distance because of theory suggesting that any negative impacts in relation to "land use externalities may be localized so that they are next door phenomena" (Grether and Mieszkowski 1980, 3).

[27] The author measures size of shopping centers using "gross leasable-area" in square feet (Sirpal 1994, 492) .

from the North Central Texas Council of Government Regional Data Center (NCTCOG 2015). Shopping malls were identified by selecting point locations categorized as *malls* or *shops*. Mall point locations for a seven county accessibility area, shown in Figure 5.4, were used as the population for kernel density estimation to produce a surface raster. Appropriate for the estimation procedure, was the mean travel time based on Texas shopping trip distance from the 2001 National Household Travel Survey (U.S. Department of Transportation 2001). This mean travel distance was used to identify an approximate kernel bandwidth (8.11 miles) based on the assumption that consumers travel, on average, $40\ mph$ to shopping mall destinations. The estimated surface produces a variable for shopping mall density per square mile within the study region.

5.7.7 Marketing, Occupancy, and Selling Factors

To reiterate, housing consists of a bundle of goods and services for which willing buyers place a value (Rosen 1974, 37). Yet some characteristics, other than a home's structural or environmental qualities, have been shown to influence selling prices. These characteristics relate to economic stimuli and local housing market dynamics. Researchers have found negative relationships between selling price and number of days on the market and how motivated a buyer or seller is to close a transaction (Springer 1996, 246; Harding, Knight, and Sirmans 2003, 612; Allen, Fraser, and Swaleheen 2016, 95). Sometimes sellers are motivated to close a transaction for vacant property quickly to transfer financial liabilities. Such motivations may arise from a lower return on investment for vacant properties. Vacant properties have been found to sell for less than occupied dwellings (Turnbull and Zahirovic-Herbert 2011, 33; Fan, Hansz, and Yang 2015, 260).

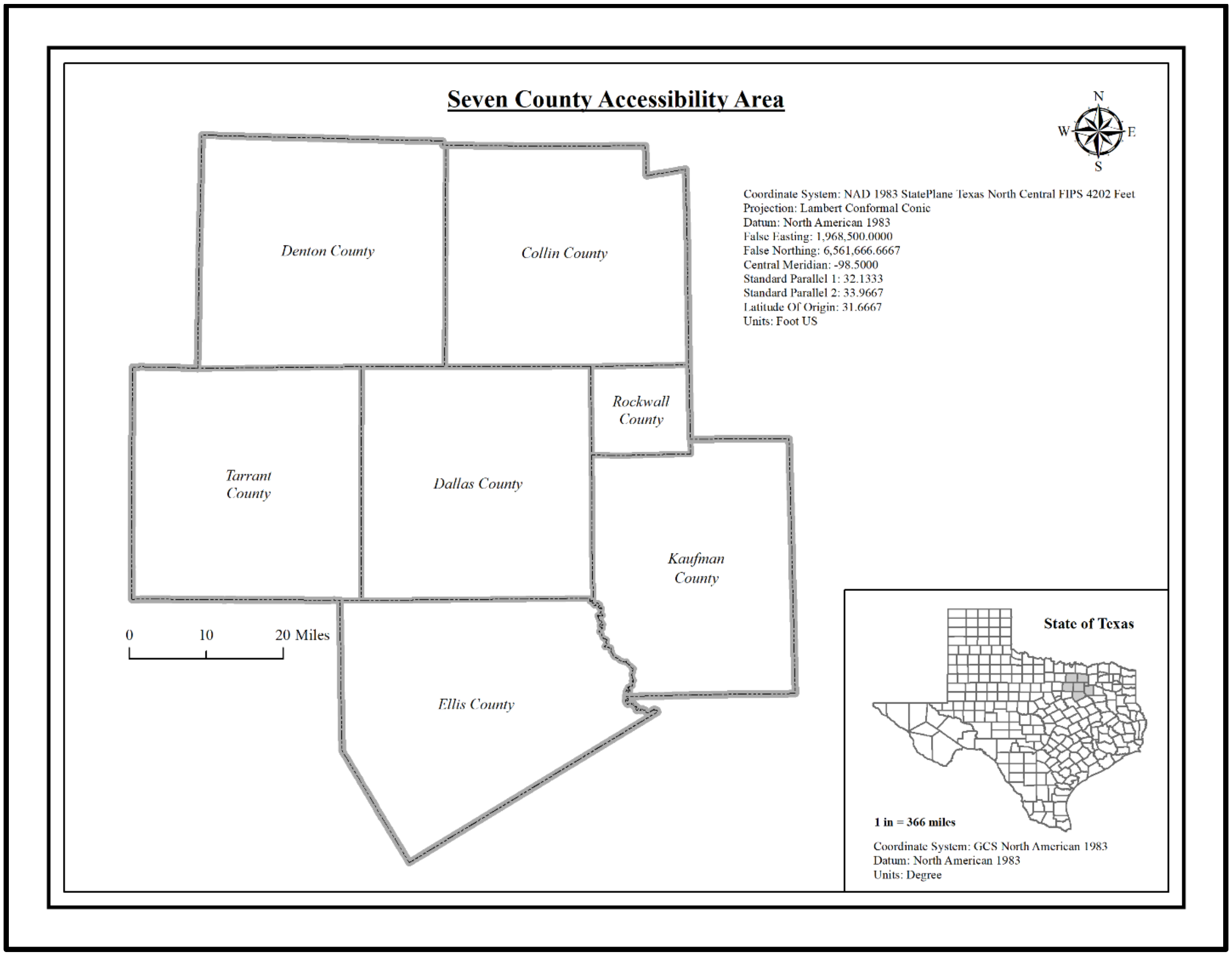

Figure 5.4. Seven county accessibility area used in calculating kernel density for shopping malls.

Properties may become vacant because homeowners cannot make monthly mortgage payments or pay property taxes. When payments are delinquent properties enter foreclosure, residents vacate the premises, and without a resident to maintain the property, its condition deteriorates (Schuetz et al. 2008, 309). When banks take over ownership, property condition may suffer because of the high maintenance costs. This cycle of delinquency-to-foreclosure-tovacancy has been observed in light of the recent housing market crash (Harding, Rosenblatt, and Yao 2009, 172; Whitaker and Fitzpatrick IV 2013, 80). Depressed housing markets reduce demand for housing goods and services, fewer homes sell, and property prices decrease. In these conditions, real estate professionals have fewer comparable sales for deriving property value estimates, introducing bias and lowering prices (Forgey, Rutherford, and VanBuskirk 1994, 318).

Property Condition

Sirmans, Macpherson, and Zietz's (2005, 24–26) marketing, occupancy, and selling factor category includes characteristics such as occupancy status, time on the market, and property condition. Property condition was the only measure in this category for which data was available. Property condition represents the overall quality of the dwelling and land together. Sirmans, Macpherson, and Zietz (2005, 25) report that property condition labeled, "good", had a positive sign and was significant for 4 out of 5 empirical studies. Similar results were found for "assessor quality" and "assessed condition" variables (Sirmans, Macpherson, and Zietz 2005, 24). The DCAD appraiser's record of condition, desirability, and utility, or CDU code was used as quality variables for this research. These codes, though measured using a nominal scale, represent an ordered degree of dwelling and land quality with a seemingly unknown magnitude and interval, as illustrated in Figure 5.5. Excellent condition represents the highest quality and undesirable represents the lowest quality.

Each observation was supplied with the appraiser-defined property condition code, to see the effect increasing or decreasing quality had on house prices. It was expected that greater property condition would correlate with higher house prices. The undesirable category was suppressed in Leonard and Murdoch (2009, 329). Only a few observations were identified as "very poor" and were included in the "poor" category.

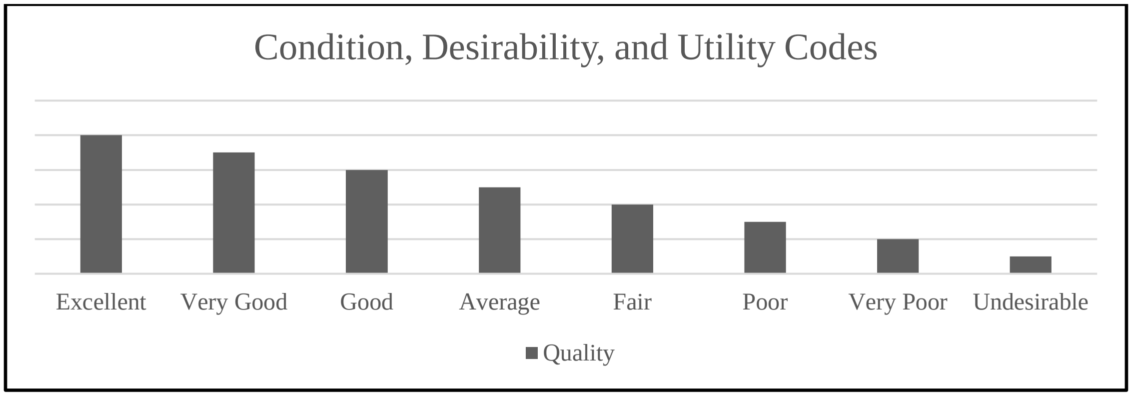

Figure 5.5. Condition, desirability, and utility codes represent a nominal measurement scale of ordered quality.

Market Conditions during Sale

It has already been established that comparable sales and foreclosures influence selling prices because they give the real estate professional insight into current housing market dynamics. Knowledge of these dynamics is imperative to produce a "comparative market analysis" (Jacobus 2012, 380) or market value estimate for a subject property. The process for estimating market value using nearby comparable sales is to first, identify sold properties with similar characteristics to the subject property. Then, based on similarities and differences of the comparable properties, they adjust the estimate downward or upward. Once total estimate adjustments are derived, professionals weight each comparable property based on its similarity to the subject. The weighted total is then calculated for the subject property (Jacobus 2012, 356-362). Professionals may need to rely on sub-optimal information for estimating market value when a housing market involves foreclosures or fewer comparable sales.

Metric variables of comparable sale and foreclosure influence were included to control for housing market performance in the hedonic house price model. These metric variables were generated using a statistical probability distribution combining two characteristics commonly used by professionals to produce market value estimates. The first is proximity to the subject-property and second is difference between comparable and subject property transaction dates. The former characteristic captures influences because of the inherent spatial autocorrelation between a house's selling price and that of its neighbors (Can 1992; Dubin 1998). Concerning proximity, authors suggest this occurs because adjacent properties are more likely to share neighborhood amenities and positive and negative externalities (Basu and Thibodeau 1998, 63). Similarly, a comparable sale's transaction date is commonly used in judging its influence on subject property value estimates (Pagourtzi et al. 2003). When comparable sale transaction dates are closer to subject property query dates, professionals are more likely to produce listing prices more reflective of the current housing market. On the contrary, older sales cloud professional judgement because they represent transactions occurring with seemingly different housing market conditions and property characteristics. Although infrequent sales occasionally warrant such circumstances, professionals consider nearby and recently sold comparable sales as ideal reference properties.

Having laid the foundation for influences of both comparable sale proximity and transaction dates, the methodological literature will now be set forth. Then, how the influences of comparable sales were expressed in the study's hedonic house price model will be addressed. For brevity, comparable sale proximity and transaction date are hereafter referred to as *spatial* and *temporal distance* respectively. Inclusion of these comparable sale influences in the model provided information regarding housing market sales activity around observations under study. Influences were conveyed as a weight measure because such metric weights commonly quantify a comparable sale's relevance to subject properties in the property appraisal literature. Comparable sale selection has been researched avidly in the context of automated valuation models. Automated valuation models use statistical methods, such as hedonic house price models, to produce a market value estimate. Isakson (1986, 276–77) suggests an improvement to existing models with what he labels, the "nearest neighbors appraisal technique". This method extracts the Mahalanobis (1936) distance between subject properties, comparable sales, and unsold properties. It bases distance on scores derived from factor analysis on each property's vector of housing attributes. Then, it selects the set of k households that might influence the market value of the subject property. Shih-MingYou (2009, 307) adapts Isakson's approach for comparable sale selection and considers "proximity of transaction dates" between the subject property and comparable sale, consistent with real estate practice, for estimating weights using ordinary least squares. Krause and Kummerow (2011, 45) adopt Isakson's approach and employ Mahalanobis distance for an automated valuation model's comparable sale selection component. These authors increase the Mahalanobis distance by one for every 0.25 miles that separates the comparable sale from the subject property. Comparable sales with the smallest Mahalanobis distance are selected to produce weighted adjustments to the automated value estimation formula.

Building upon Isakson (1986) , Shih-MingYou (2009), and Krause and Kummerow (2011), influence weights were generated to quantify a comparable sale's relevance with study observations, measuring the study area's housing market transaction volume. The greater the comparable sale weight the more relevant it was for its paired study observation. An aggregate weight value was calculated for each sale observation by taking the sum of relevant comparable sale weights. It was anticipated that larger weights (i.e., more relevant comparable sales) would be associated with higher sale prices, indicated by a positive sign, reflecting a competitive housing market. Lower weights were linked with lower sale prices, indicated by a negative sign, demonstrating a stalled housing market potentially impacted by foreclosures.

Spatial and temporal distance were elements that determined how relevant comparable sales, j, were to a subject property, i. A bi-variate normal distribution, with δ_{ij} being spatial distance, and τ_{ij} being temporal distance[28], was used to obtain the weight $\omega_{ij} \sim f(\delta_{ij},\ \tau_{ij})$. The bi-variate normal distribution weight was beneficial because its peak was located at the origin i where $(\delta_{ij} = 0, \tau_{ij} = 0)$ and values decrease as spatial or temporal distances increase. This mirrored the intent of the comparable sale influence weight, which diminished with greater spatial and temporal distance from the subject property. The weight is hereafter known as the *comparable sale influence weight*, ω_{ij}, for subject property i and comparable sale j. Figure 5.6 is a two-dimensional plot illustrating how ω_{ij} modeled comparable sale influences of hypothetical spatial distances up to 0.5 miles and hypothetical temporal distances up to 20 months. As values on each axis increase, the comparable sale influence weight decreases. The maximum weight value is at the origin $(\delta_{ij} = 0, \tau_{ij} = 0)$.

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[28] To operationalize temporal distance for this research, two transaction dates were used, namely 1) the subject property's most recent transaction date and 2) the comparable sale's transaction date.

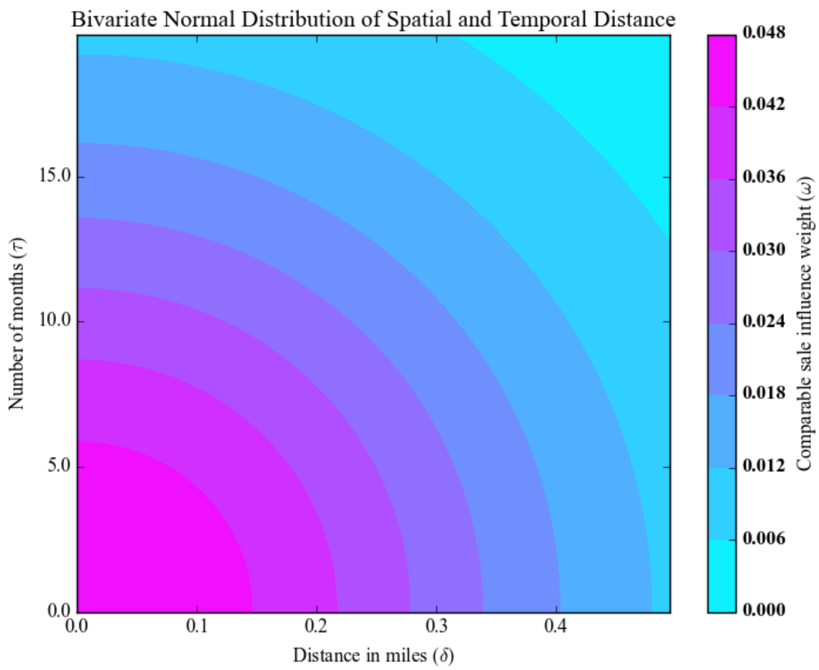

Figure 5.6. Graph depicts the increasing comparable sale influence weight (ω_{ij}) expressed as a bi-variate normal distribution that increases the closer it gets to the sale observation at the coordinates $(\delta_{ij} = 0,\ \tau_{ij} = 0)$.

Spatial distance for this study may be expressed as linear distances, δ_{ij}, in miles, from the subject property, i, to comparable sale j, up to Krause and Kummerow's (2011, 43) distance threshold of 0.25 miles. Its counterpart, temporal distance, τ_{ij}, may be expressed as integers representing the time difference in transaction dates in number of months, as shown in equation (5.6). Temporal distance was calculated as the absolute value of the difference between the subject property i's and comparable j's sale date between 0 and 18 months[29].

[29] Standards for time influence of comparable sales varies across professional, educational, and governmental agencies (see Table C.1). For this research, the time window used by the DCAD is used for convenience.

$$\tau_{ij} = \begin{cases} |\tau_i - \tau_j|, & 0 \le \tau_{ij} \le 18 \\ 0, & otherwise \end{cases} \tag{5.6}$$

Two distance and time standard deviations, equivalent to 0.5 miles and 36 months respectively, were employed in the calculation of ω_{ij} to incorporate 95% of the possible spatial and temporal distance cases within the probability density function. The valid range of values of spatial and temporal distance for calculation of ω_{ij} in the case of comparable sales is shown in (5.7).

$$f(\omega) = \begin{cases} \omega_{ij}, & \delta_{ij} \le 0.25 \ and \ \tau_{ij} \le 18 \\ 0, & otherwise \end{cases} \tag{5.7}$$

The above may be generalized to the foreclosure[30] case shown in (5.8). Notice that foreclosure weight calculation employs a similar[31] spatial distance but a different[32] temporal distance.

$$f(\theta) = \begin{cases} \theta_{ij}, & \delta_{ij} \le 0.25 \ and \ \tau_{ij} \le 12 \\ 0, & otherwise \end{cases} \tag{5.8}$$

[30] Sirmans, Macpherson, and Zietz (2005, 29) categorize foreclosures as financing issues discussed in the next section. They are mentioned here to more easily describe methods employed in estimating their influence on subject properties.

[31] This study used approximate distance thresholds to Leonard and Murdoch (2009, 323) and Zhang and Leonard (2014, 134), up to 1,500 feet .

[32] A 12 month threshold was used here because Zhang and Leonard (2014, 139) and Zhang, Leonard, and Murdoch (2016, 138) use this period in empirical research related temporal foreclosure impacts within the same study area.

The influence weight, ω_{ij}, represents one of J possible weight values. To identify the total comparable sale and foreclosure influence weight at subject property i, the sum of these weights is necessary. This can be accomplished in equations (5.9) and (5.10).

$$\omega_i = \sum_{j=1}^{J} \omega_{ij} \tag{5.9}$$

$$\theta_i = \sum_{j=1}^{J} \theta_{ij} \tag{5.10}$$

Comparable sale and foreclosure information was gleaned from DCAD's sales file incorporated into the appraisal database discussed in section 5.3.1. Sales are categorized by staff members based on type: (1) as a qualifying market sale, (2) foreclosure, or (3) other type of sale. The distribution of the number of market sales or non-distressed sales and foreclosures or distressed sales are shown in Figure 5.7. As we would expect within the study area, market sales increased until the housing market crash occurred in late December 2007. At this point, the number of foreclosures began to increase and the number of market sales decreased. By 2013, the number of market sales began to increase and the number of foreclosures started to decrease by 2011. The comparable sale influence weight was calculated for all sales that were considered a comparable sale by DCAD staff. A comparable sale is indicated by an indicator field in the DCAD sales file. During the housing market crash, some distressed sales had to be considered a comparable sale if they comprised 20% or more of the sales within the market area (IAAO 2010, 13). Foreclosures were identified in the DCAD sales file if coded FORECLOSURE in the sales type field.

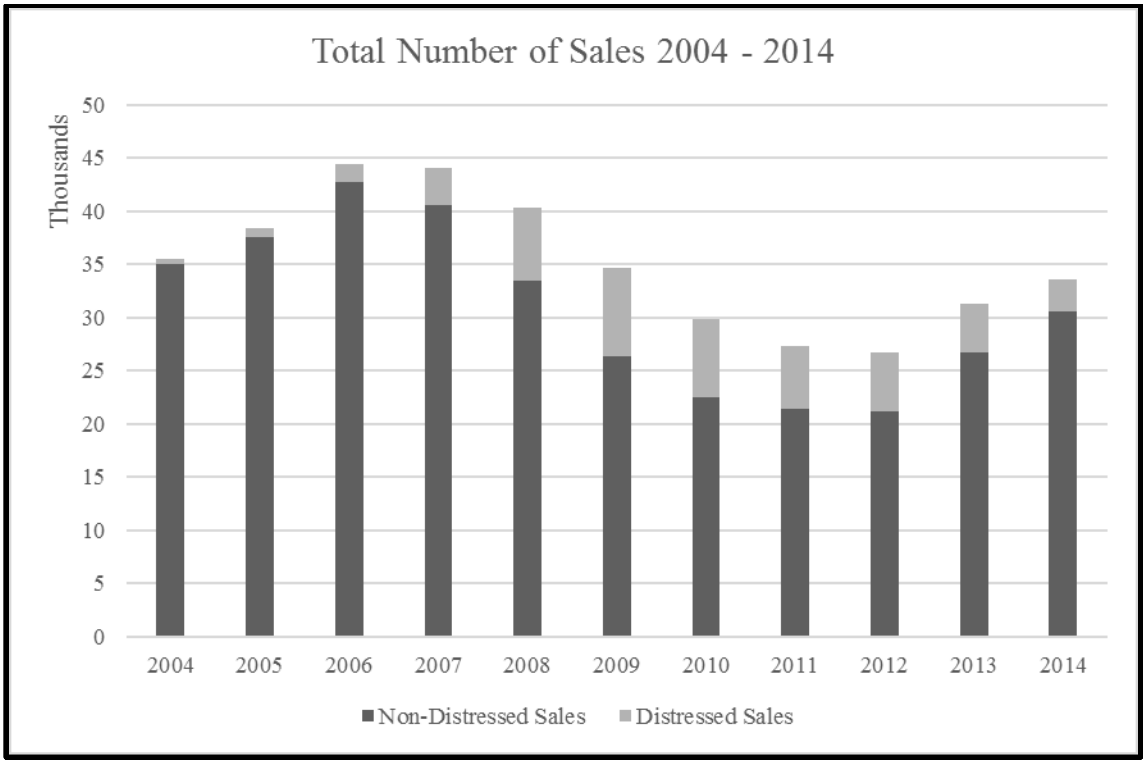

Figure 5.7. Graph of total sales distribution by sale type. Non-distressed sales represent a market sale and distressed sales represent foreclosures.

The measurement variables generated by influence weights represent the level of comparable sale and foreclosure activity surrounding a subject property. It was expected that as comparable sales increased house prices would remain high. On the other hand, when there were fewer comparable sales, prices would decline. The opposite would be true for nearby foreclosures. If the number of foreclosures increased, house prices would slightly decline. On the other hand, when foreclosures decreased, prices would be slightly higher. Since the study area was comprised of multiple housing markets with variable quality of housing stock, the coefficient for these variables would represent the mean of markets with greatest activity. For example, if a housing market with a mean sales price of $100,000 dollars reports few sales, then this will not be an active part of the study area's housing market. Other segments may experience greater sales activity and these were be reflected in the comparable sale or foreclosure-influence weight variable's coefficient.

5.7.8 Financing Issues

This section addresses house price influences related to financial and legal agents in funding a home. These include the terms upon which a mortgage agreement is realized or how settlement costs (i.e., closing costs) are handled. To qualify for a mortgage, homes within a flood zone may require flood insurance, further increasing the ultimate purchase price. Other examples are related to controls and fees levied by local governments for property already owned. Such controls and fees include eminent domain and property taxes respectively. The property tax is of interest in this study because of its relationship with house prices. Property tax rates influence house prices. Yinger (1988, 51) suggests that, *ceteris paribus*, home buyers are "willing to pay more for a house the lower the property taxes on that house." This section will briefly review the empirical literature supporting Yinger's argument, motivations for including the variable in the hedonic model, and coefficient results over the study period.

Property Taxes

Property taxes are the vehicle for local governments to procure revenues that fuel public services. Local governments establish property taxes according to the level of service required for any given jurisdiction. When jurisdictions (e.g., public schools) require a specific level of service, the property tax rate must meet the required service demand. Before discussing the importance of property taxes in the hedonic house price model, it is essential to highlight first the connection with public school quality, one of the model variables. In a previous section, public school quality was measured using a model variable related to state mandated academic test scores by school district. School quality is considered a public amenity or service provided by local governments. Such services, when of higher quality, sell for a premium in terms of house price. Black (1999), employs a hedonic house price study to identify a relationship between house prices and school quality in Boston, Massachusetts between $1993 - 1995$. Study results reveal that Boston residents were willing to pay 2.1% more for homes within school districts where achievement scores were 5% higher than other school districts on average (Black 1999, 595). In addition, Black (1999, 579) suggests that including academic test achievement and public school spending as model variables in hedonic house prices remedies an omitted variables problem at the school district level.

Studies that include property tax rates and public service provision (e.g., public school quality) as independent variables within a hedonic model produce an estimate of *property tax capitalization*. This term is based on the theory that house prices decrease or increase in proportion to the local property tax. Ross and Yinger (1999, 2032) find that all, well designed studies produce a negative and significant estimate, suggesting *negative* property tax capitalization. In other words, when property taxes increase, house prices decrease. Recent research findings support this theory (Cebula 2009; Charlot, Paty, and Visalli 2013; Coombs, Sarafoglou, and Crosby 2012).

Measures for public service provision (e.g., public school quality) and negative property tax capitalization (e.g., nominal school district property tax rate[33]) were included as independent

[33] The nominal property tax rate variable was used here because Haurin and Brasington (1996, 359) and Yinger (1988, 101) consider it to be exogenous. This is a desirable property for instrumental variable candidates.

variables in the hedonic model for this study. The nominal school district property tax rate is recorded by DCAD (2016). Appropriate property tax rates were associated with each observation based on the school district where they were located. As discussed in the literature review, this helped to address the issue of simultaneity between appraised values and market values when estimating vertical inequity (Clapp 1990; Edelstein 1979).

5.7.9 Independent Variable Transformations

The variables listed in Table 5.6 and their associated descriptions provided information on the operationalized measurement and categorical variables. The distinction between continuous and factor variables is provided in the *type* column. The *description* column indicates transformation parameters (if applicable) and information the variable represents. For example, *livarea* is the name of the measurement variable for total living area in square feet. A box cox transformation was applied to *livarea* with a $\lambda = -0.34$ (Velilla 1993). Measurement variables were candidates for a box cox transformation if they exhibited extreme, positive skew and if their distribution improved after executing a Shapiro-Wilk test (Shapiro and Wilk 1965). Though a more technical matter than theoretical, the dependent variable, sales price, was log transformed because it is the endogenous regressor in the structural equation discussed in the next chapter.

Table 5.6. Variable name,description, and type with associated lambda transformation parameters.

Variable Name	Description	Type
livarea	Box cox transformed total living area ($\lambda = -0.34$)	continuous
lotarea	Box cox transformed total lot area ($\lambda = -0.53$)	continuous
floors	Total number of stories of dwelling	continuous
age	Duration in years since last major remodel	continuous
bcgrp	Building class group in ascending order by sales price	factor
fullac	A full central air conditioner exists in the dwelling	factor
age x bcgrp	Age/building class group interaction term	continuous/factor
		continued on next page

Table 5.6 continued from previous page		
firepl	Total number of fireplaces $(0, 1, 2 \text{ where} \geq 2)$	continuous
baths	Total number of full bathrooms (2 half baths $=$ 1 full bath)	continuous
gararea	Total garage area in square feet	continuous
pool	A pool exists on the property	factor
recacc	Recreational accessibility score	continuous
alley	A back alley exists on the property	factor
woods	The property has a wooded lot	factor
schlqlty	School quality based on TEA test scores	factor
shopacc	Box cox transformed shopping accessibility score ($\lambda = 0.45$)	continuous
propcond	Property condition according to appraiser	factor
compsw	Box cox transformed bivariate comparable sale weight (distance and sale duration) ($\lambda = 0.22$)	continuous
foreclw	Yeo-Johnson transformed bivariate foreclosure sale weight (distance and sale duration) ($\lambda = -11.54$)	continuous
tax	Nominal school district tax rate	continuous

CHAPTER 6

GLOBAL VERTICAL PROPERTY TAX INEQUITY MODEL ESTIMATION

6.1 Introduction

Building upon Cheng's (1976) approach with the logarithm of the appraised value as dependent variable, this research attempts to address uncertainty in market value indicators when estimating vertical property tax inequity. I expand upon Cheng's work by addressing two problems previously mentioned (1) questions concerning the three-group instrumental variable and (2) a correction for reverse causality. Having surveyed the pertinent literature regarding these issues, the appropriate methodology is set forth. First, I start by introducing the identification of potential instruments used in the reduced form equation. Then I establish the global econometric framework comprising the reduced form and structural equations. Prior to discussing the structural equation, I mention the approach for interpreting model results using vertical inequity curve plots, and horizontal inequity adjustment factors. I conclude this section with an explanation of the global model's diagnostic test results and their implications. The following chapter includes the temporal and spatial model specifications and their results.

6.2 Identification of Potential Instruments

The previous chapter listed available data and their operationalization into measurement and categorical variables for hedonic house price modelling. I also reviewed how these variables potentially influence house prices. This section introduces phase 3 of the methodology, which includes the preliminary, ordinary least squares regression identifying potential instruments included in the reduced form equation.

Care was taken to ensure parsimony in variable selection without employing popular search methods such as stepwise regression. Search methods introduce risk of identifying coincidental “patterns” within the population without substantive validity or producing deceivingly low p-values (Hamilton 1992, 83). Rather, the empirical literature discussed in section 5.7 supports inclusion of model variables. Additionally, variables having a significant impact in terms of low p-values (i.e., an α-error less than 5%) become candidates for instruments in the reduced form equation discussed previously.

6.2.1 Potential Instrument OLS Model Results

One global, ordinary least squares model was specified for all years and market areas of available data. Output from the model estimation is provided in Table 6.1. For ease of interpretation, regressors are labeled using the independent variable names provided in Table 5.6. Capitalized text following label names describes unique factors for categorical variables (e.g., **pool1** represents the contrast for properties with or without a swimming pool, **bcgrpBCG4** represents the contrast for properties in building class group 4 against the other building class groups, **age:bcgrpBCG4** represents the interaction term between **age** and **bcgrpBCG4**, etc.). Differing scales for the metric variables required a z transformation to derive meaningful coefficient values and standard errors. Coefficients are listed next to regressor labels and standard errors are in parentheses just to the left of the reported t-statistics.

With few exceptions, most t-statistics were significant at the 99% confidence level (Fox and Weisberg 2011, 153). Ultimately, they help to explain sales prices fairly well. The reported R^2 and residual standard error are comparable to existing empirical research in the same study area (Thibodeau, 1990; Waddell, Berry, and Hoch 1993a; Waddell, Berry, and Hoch 1993b; Hoch and Waddell 1993; Goodman and Thibodeau 1995; Chung, Waddell, and Berry 1997; Goodman and Thibodeau 1998; Diaz et al. 2008; Leonard and Murdoch 2009).

Table 6.1. Potential instruments linear regression results

Potential Instruments OLS Model (All Years)			
	Dependent variable:		
	$\log(sp)$		
	Coef.	Std. Err.	t - statistic
Intercept	4.90182	(0.00635)	771.53620***
$livarea$	0.26229	(0.00203)	129.30670***
$livarea^2$	0.04292	(0.00091)	47.12702***
$lotarea$	0.03339	(0.00123)	27.18215***
$floors$	-0.00311	(0.00120)	-2.59602***
age	-0.05873	(0.00223)	-26.37020***
$bcgrpBCG9$	0.55026	(0.04092)	13.44622***
$bcgrpBCG8$	0.49547	(0.02656)	18.65556***
$bcgrpBCG4$	0.33123	(0.01005)	32.94722***
$bcgrpBCG3$	0.24054	(0.03030)	7.93848***
$bcgrpBCG2$	0.02414	(0.00882)	2.73746***
$bcgrpBCG5$	0.02277	(0.00259)	8.79416***
$bcgrpBCG1$	-0.23516	(0.03617)	-6.50092***
$fullac1$	0.08905	(0.00549)	16.22791***
$firepl$	0.04682	(0.00120)	38.96102***
$baths$	0.02018	(0.00184)	10.97373***
$baths^2$	0.00658	(0.00058)	11.35987***
$gararea$	0.01759	(0.00106)	16.64433***
$pool1$	0.05849	(0.00260)	22.47826***
$lscpqltyUN$	-0.01973	(0.00221)	-8.92857***
$lscpqltyPR$	-0.04280	(0.00995)	-4.30157***
$lscpqltyEX$	0.08129	(0.00547)	14.86550***
$recacc$	0.01594	(0.00102)	15.63987***
$alley1$	-0.02106	(0.00213)	-9.89054***
$woods1$	0.05582	(0.00253)	22.02769***
$schlqltyL$	-0.25218	(0.04835)	-5.21541***
$schlqltyR$	-0.00471	(0.00230)	-2.04500**
continued on next page			

Table 6.1 continued from previous page			
$schlqltyE$	0.34502	(0.00604)	57.07957***
$shopacc$	0.21983	(0.00130)	169.42310***
$shopacc^2$	0.07077	(0.00096)	73.95847***
$propcondPR$	-0.07711	(0.01468)	-5.25255***
$propcondFR$	-0.03992	(0.00514)	-7.76436***
$propcondAV$	-0.03106	(0.00251)	-12.38306***
$propcondVG$	0.04462	(0.00231)	19.28916***
$propcondEX$	0.07836	(0.00326)	24.00831***
$compsw$	0.06281	(0.00102)	61.58468***
$foreclw$	-0.05884	(0.00099)	-59.18440***
tax	-0.06312	(0.00109)	-58.07278***
$age{:}bcgrpBCG4$	0.05206	(0.00505)	10.31423***
$age{:}bcgrpBCG2$	0.06459	(0.00537)	12.02570***
$age{:}bcgrpBCG9$	0.06182	(0.02889)	2.14003**
$age{:}bcgrpBCG3$	0.08242	(0.01462)	5.63888***
$age{:}bcgrpBCG1$	0.08384	(0.01635)	5.12802***
$age{:}bcgrpBCG8$	0.08444	(0.01353)	6.24111***
$age{:}bcgrpBCG5$	0.09524	(0.00257)	37.04422***
Observations	55,206		
R^2	0.87706		
Adjusted R^2	0.87696		
Residual Std. Error	0.21052		
F Statistic	8,943.87000***		
Note:	$*p < .1$ $**p < .05$ $***p < .01$		

6.2.2 Potential Instrument Model Diagnostics

The estimates reported in Table 6.1 were obtained after successive refinements to measurement variables in the global model. Investigating residual plots proved helpful in achieving this. These plots identify “lack-of-fit” for potential instrument model parameters (Fox and Weisberg 2011, 289). Each plot displays the Pearson residuals for each regressor. The curved red lines represent “fitted quadratic regressions” for continuous variables on the residuals (Fox and Weisberg 2011, 289). A curved line indicates a need for a transformation of the measurement variable. The final plot has the Pearson residuals on the y-axis and the fitted values on the x-axis. Overall, the model fits fairly well with most predictors demonstrating a quadratic relationship straight red line indicating a reasonable fit. This is underscored by the significant Tukey (1949, 263) tests in Table 6.2.

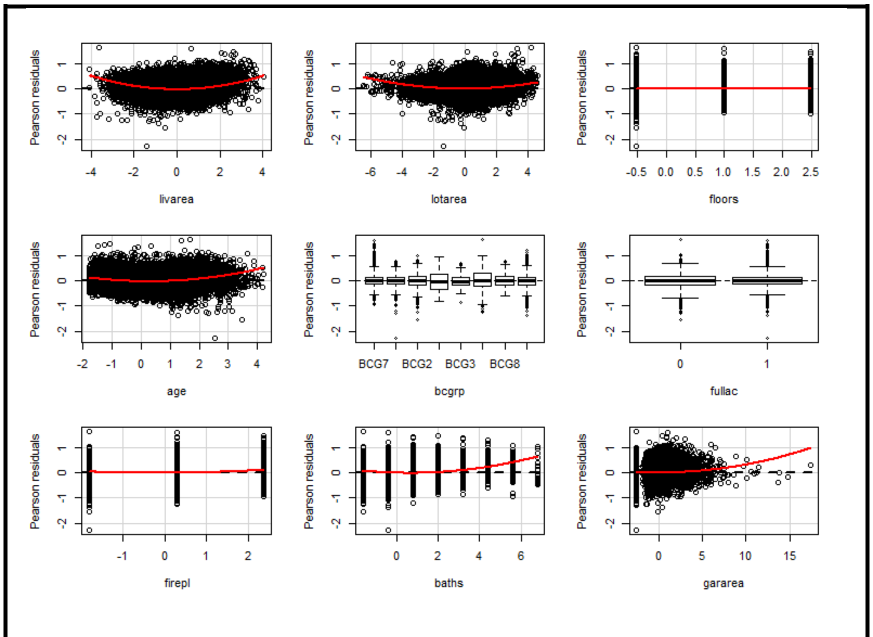

Figure 6.1. Pearson Residual plots displaying predicted values against measurement variables. Curved red lines indicate a need for varible transformation.

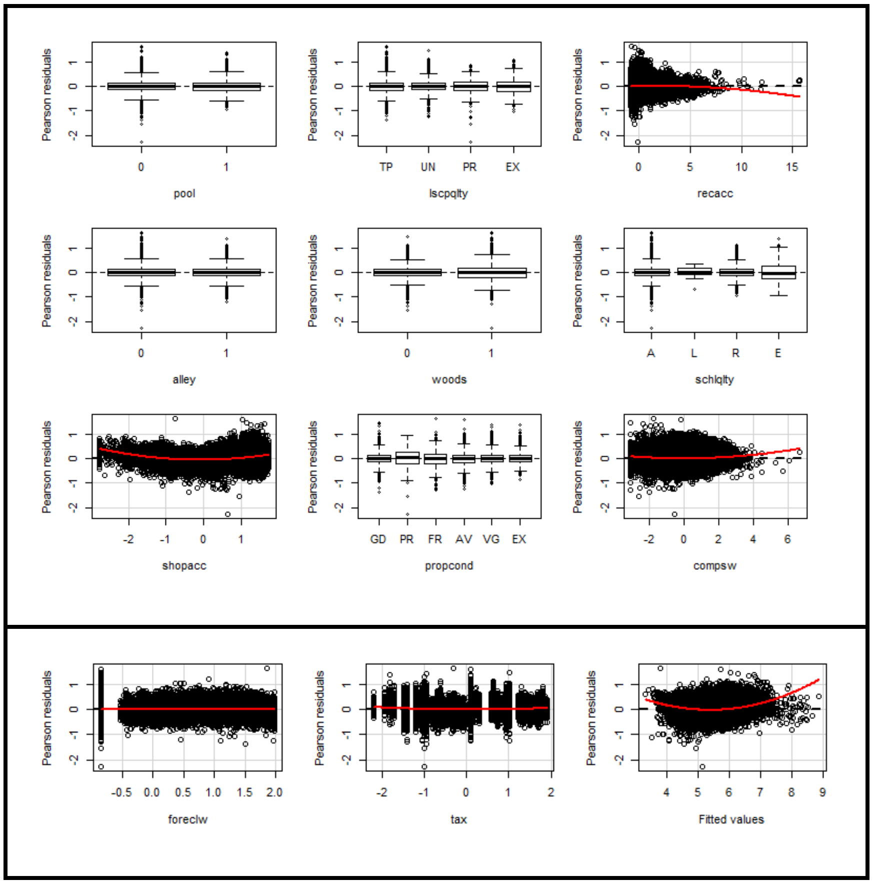

Figure 6.1 (continued). Pearson Residual plots displaying predicted values against measurement variables. Curved red lines indicate a need for varible transformation.

Results in Table 6.2 for the original model indicate the need to add a quadratic term for the significant measurement variables. After adding the relevant quadratic terms, almost all relationships approached linearity.

Table 6.2. Tukey test from original potential instrument model before quadratic terms were applied.

Variable Name	Test Statistic	Pr(>|t|)
livarea	63.904	0
lotarea	27.338	0
floors	5.768	0
age	57.421	0
bcgrp	NA	NA

continued on next page

Table 6.2 continued from previous page		
fullac	NA	NA
firepl	33.332	0
baths	40.76	0
gararea	11.96	0
pool	NA	NA
lscpqlty	NA	NA
recacc	-6.461	0
alley	NA	NA
woods	NA	NA
schlqlty	NA	NA
shopacc	71.526	0
propcond	NA	NA
compsw	14.285	0
foreclw	-6.204	0
tax	15.692	0
Tukey Test	76.099	0

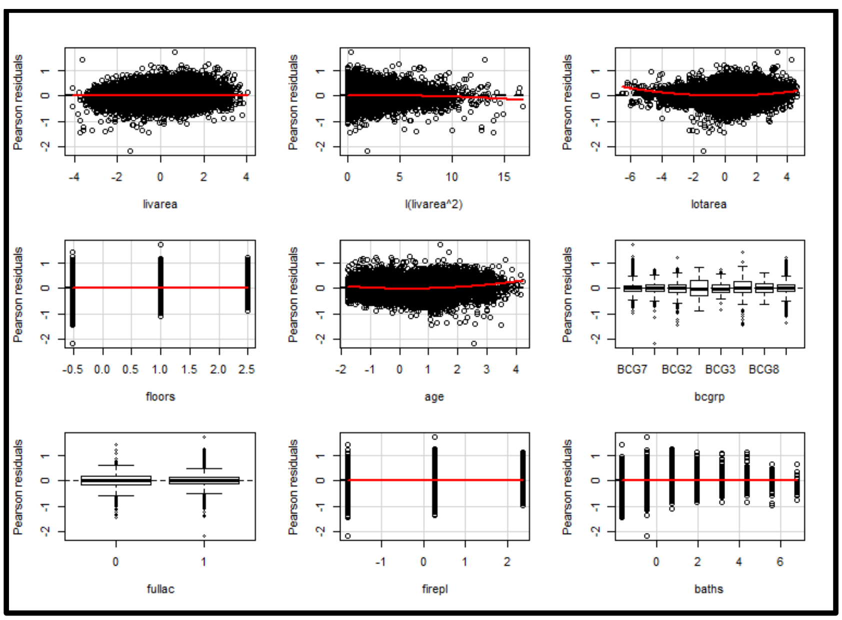

Figure 6.2. A second iteration of pearson residual plots indicate an improved model fit.

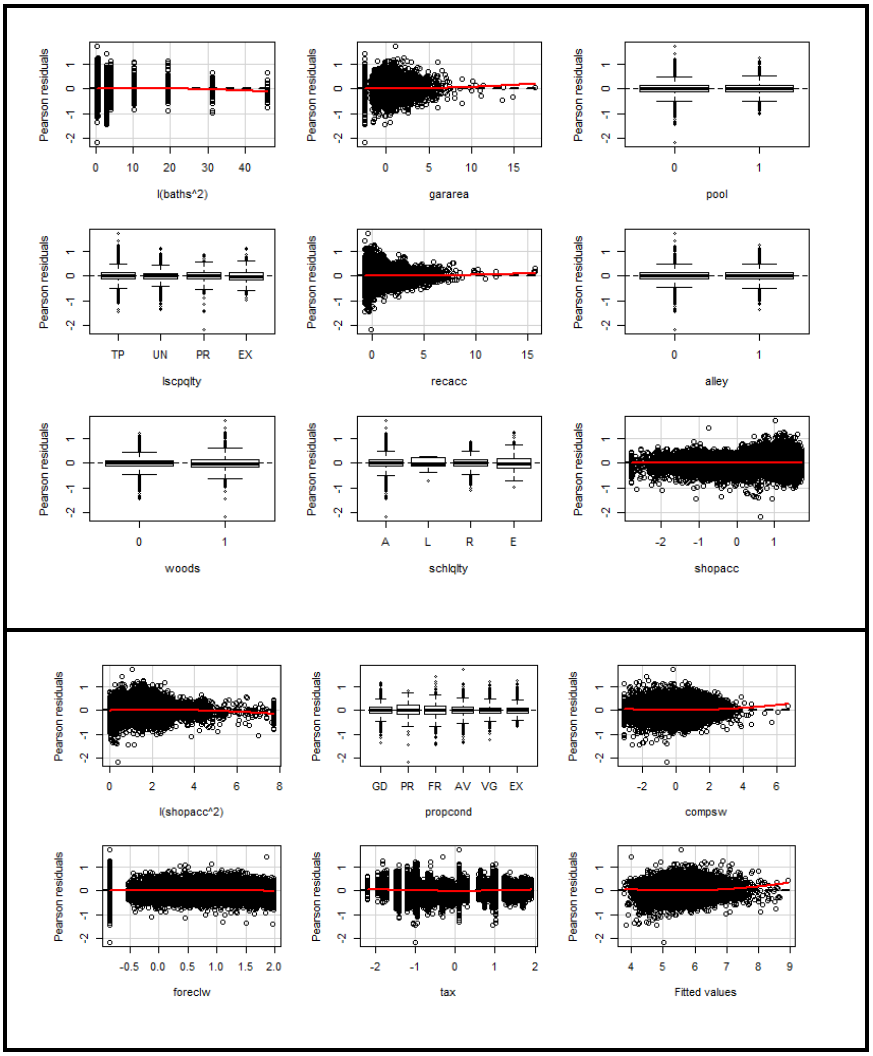

Figure 6.2 (continued). A second iteration of pearson residual plots indicate an improved model fit.

To avoid complexity in the potential instrument model specification, only the regressors with the three largest Tukey test statistics had a quadratic term applied (i.e., livarea, shopacc, and baths). The results are displayed in Pearson residual plots in Figure 6.2. The regressors obtained in the potential instruments ordinary least squares model, after appropriate diagnostics were performed, became the selected set of instruments, Z_{kit}. These will be employed in the reduced form equation discussed in the next section.

6.3 Global Econometric Model Framework

Phase 4, global model development and diagnostics, of the research methodology will be detailed in the remaining sections in this chapter. This section establishes the foundation for the two-stage least squares approach for estimating global vertical property tax inequity for all years and market areas. Having identified potential instruments that explain market value relatively well in section 6.2.1, I will now proceed to describe the reduced form equation which generates the instrumental variable that was used in the second stage or structural equation. Prior to discussing the structural equation, the method for interpreting the model results and two important adjustments to the dependent variable are explained. I conclude this section by discussing results from the global model's instrumental variable diagnostic tests that were introduced in section 4.8.3.

6.4 Reduced Form Equation

For review, to address potential endogeneity in vertical inequity estimation resulting from measurement error or simultaneity, a two-stage least squares approach is sufficient. Here, the second stage endogenous variable is $\log(X_{it})$ or the natural log of current sales price for parcel i in sale year t where $\mathrm{i} = 1, 2, \cdots, 55{,}206$ and $\mathrm{t} = 2004, 2004, \cdots 2014$ respectively and is placed on the left hand side as the dependent variable. I derived regressors, shown in equation (6.1) from the set of selected instruments discussed in section 6.2.1. For a more detailed description of selected instruments, see Table 5.6.

$$
\begin{aligned}
\log(\hat{X}_{it}) = \pi_1\, livarea_{it} &+ \pi_2\, (livarea_{it})^2 + \pi_3\, lotarea_{it} + \pi_4\, age_{it} \\
&+ \pi_5\, floors_{it} + \pi_6\, bcgrp4_{it} + \pi_7\, bcgrp2_{it} + \pi_8\, bcgrp9_{it} \\
&+ \pi_9\, bcgrp3_{it} + \pi_{10}\, bcgrp1_{it} + \pi_{11}\, bcgrp8_{it} \\
&+ \pi_{12}\, bcgrp5_{it} + \pi_{13}\, age_{it} \times bcgrp4_{it} + \pi_{14}\, age_{it} \\
&\times\, bcgrp2_{it} + \pi_{16}\, age_{it} \times bcgrp1_{it} + \pi_{17}\, age_{it} \times\, bcgrp8_{it} \\
&+ \pi_{14}\, age_{it} \times\, bcgrp9_{it} + \pi_{15}\, age_{it} \times\, bcgrp3_{it} + \pi_{18}\, age_{it} \\
&\times\, bcgrp5_{it} + \pi_{19}\, firepl_{it} + \pi_{20}\, baths_{it} + \pi_{21}\, (baths_{it})^2 \\
&+ \pi_{22}\, pool_{it} + \pi_{23}\, gararea_{it} + \pi_{24}\, alley_{it} + \pi_{25}\, woods \\
&+ \pi_{26}\, schlqltyL_{it} + \pi_{27}\, schlqltyR_{it} + \pi_{28}\, schlqltyE \\
&+ \pi_{29}\, recacc_{it} + \pi_{30}\, shopacc_{it} + \pi_{31}\, (shopacc_{it})^2 \\
&+ \pi_{32}\, propcondPR_{it} + \pi_{33}\, propcondFR_{it} \\
&+ \pi_{34}\, propcondAV_{it} + \pi_{35}\, propcondVG_{it} \\
&+ \pi_{36}\, propcondEX_{it} + \pi_{37}\, propcondFR_{it} + \pi_{38}\, compsw_{it} \\
&+ \pi_{39}\, foreclw_{it} + \pi_{40}\, tax_{it}
\end{aligned}
\tag{6.1}
$$

The second stage of the model includes the dependent variable, Y, representing appraised value of parcel i and appraisal year $t-1$ where $\mathrm{i} = 1, 2, \cdots, 55{,}206$ and $\mathrm{t} = 2004, 2004, \cdots\ 2014$ respectively. I introduce the lag $(t-1)$ to compare appraisals that must pre-date sales prices according to common practice mentioned in section 5.2. I incorporate price fluctuations between the assessment and sale dates related to inflation using an adaptation of Cheng's (1976) growth and decay parameter, g_i. Growth and decay then become a growth rate by using the NTREIS house price index as an annual percentage change for each Dallas County zip code. Converting the g_i value to a constant for all i at time t within zip code j, the growth rate then becomes γ_{jt}, conveniently incorporated as a component of the dependent variable (see section 5.3.5). This helps to control for inflation between the dependent variable, $\log(Y_{it-1})$ at period $t-1$, and the endogenous regressor, $\log(\hat{X}_{it})$ at the subsequent year t. Continuing the second stage explanation requires a brief foray into the model interpretation approach.

6.5 Vertical Inequity Curve Plot

Cheng's (19976) original model produced an elasticity, β_1, to understand the degree of vertical inequity. This elasticity identifies the percentage change in sales price for a one percent change in assessed value and is the parameter of interest in his bi-variate, double-log or constant elasticity model. Elasticities between 0 and 1 reflect regressive property taxes. Perfect equity results when elasticities are equal to one. Values greater than one indicate a progressive tax structure. Iterative model refinement identified potential difficulties with this approach. Estimated $\hat{\beta}_1$ elasticity and estimated intercept $\hat{\alpha}_0$values different from zero were observed in most cases. These can occur in the double-log functional form. Since the intercept term in a constant elasticity model represents the value of $\log(y)$ when $\log(x) = 0$, values other than zero are hard to interpret. Interpretation becomes trivial in the original scale

$$Y_{it-1} \cdot \gamma_{jt} = \exp(\alpha_0) \cdot \hat{X}_{it}^{\beta_1} \tag{6.2}$$

and in the context of Cheng's (1976) constant elasticity model. Cheng (1976, 1252) defines vertical equity as having both coefficients equal to unity, (i.e., $\exp(\alpha_0) = \beta_1 = 1$). From the exponential model perspective, the intercept is a multiplier in the original scale and is another essential indicator of vertical inequity that aids model interpretation. A mathematical exploration illustrates this concept when $\exp(\alpha_0) = \beta_1 = 1$ in equation (6.3) where α_0 is the model's constant term and β_1 the elasticity coefficient of the instrumental variable $\log(\hat{X}_{it})$ at the second stage.

$$\begin{aligned} \log(Y_{it-1} \cdot \gamma_{jt}) &= \log\left(\exp(\alpha_0) \cdot \hat{X}_{it}^{\beta_1} \cdot \varepsilon_{it}\right) \\ \Leftrightarrow \log(Y_{it-1}) + \underbrace{\log(\gamma_{jt})}_{\text{offset}} &= \alpha_0 + \beta_1 \cdot \log(\hat{X}_{it}) + \log(\varepsilon_{it}) \end{aligned} \tag{6.3}$$

Consequently, Cheng's (1974, 275) graphical displays were adapted to decipher uniformity implications by expressing model parameters in their anti-log or exponential form as shown in equation (6.2). This equation is a general specification for all years that is missing the horizontal inequity adjustment, λ_g discussed in section 6.6.

I name adapted, graphical displays, *vertical inequity curves* because they demonstrate the exponential distribution's inherent curvature. When $\exp(\alpha_0) = \beta_1 = 1$ the relationship approaches linearity and vertical equity because lagged appraised value and estimated sales price are similar. Inequity curves may exhibit a variety of patterns depending on the nature of uniformity in the property tax system. Cheng's (1974, 275) original patterns are adapted for this study and displayed in Figure 6.3. Block A in Figure 6.3 includes a legend defining the dashed red line as the vertical inequity line (i.e., curve) and the solid green line as the perfect equity line.

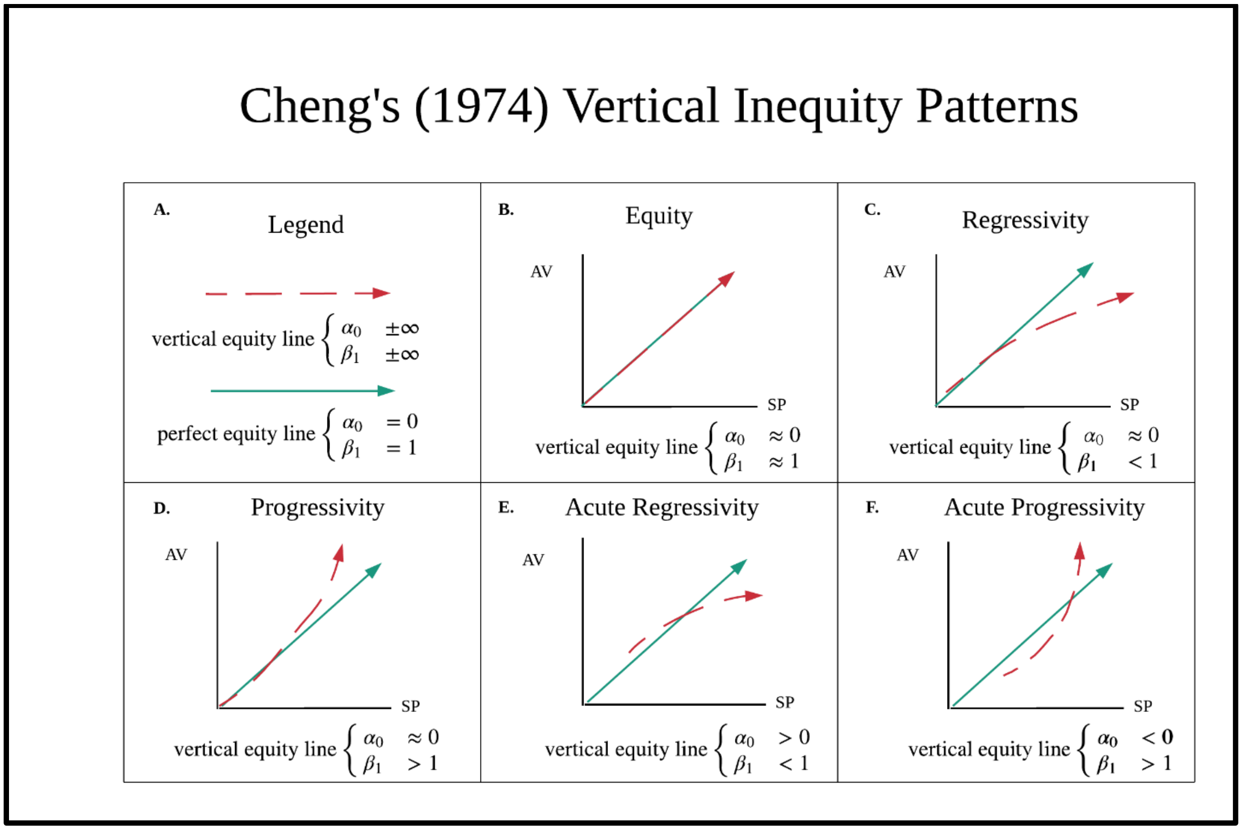

Figure 6.3. Adaptations of Cheng's (1974, 275) possible vertical inequity patterns in appraisal systems.

The pattern shown in block B displays a red vertical inequity curve that is nearly identical to the green perfect equity line when $\alpha_0 \approx 0$ and $\beta_1 \approx 1$. This makes sense because appraisal and sales price distributions are nearly the same. Block C's pattern shows a vertical inequity curve that follows the perfect equity line near lower prices and curving below equity at higher prices. This places the vertical inequity curve below the perfect equity line when $\alpha_0 \approx 0$ and $\beta_1 < 1$ indicating lower priced homes receiving a lower property tax discount than higher priced homes. The pattern in block D reveals a vertical inequity curve that follows the perfect equity line near lower prices and curving above equity at higher prices. This places the vertical inequity curve above the perfect equity line when $\alpha_0 \approx 0$ and $\beta_1 > 1$. Here lower priced homes receive a larger property discount than higher priced homes. Inequities demonstrated in block C and D patterns are exacerbated when $\alpha_0 > 0$ or $\alpha_0 < 0$. This condition is demonstrated in blocks E and F. In such cases lower priced homes are either extremely over- (e.g., block E) or under-appraised (e.g., block F) in comparison to higher priced homes. This generates a noticeable gap between the minimum (lower) values of the vertical inequity curve and the perfect equity line.

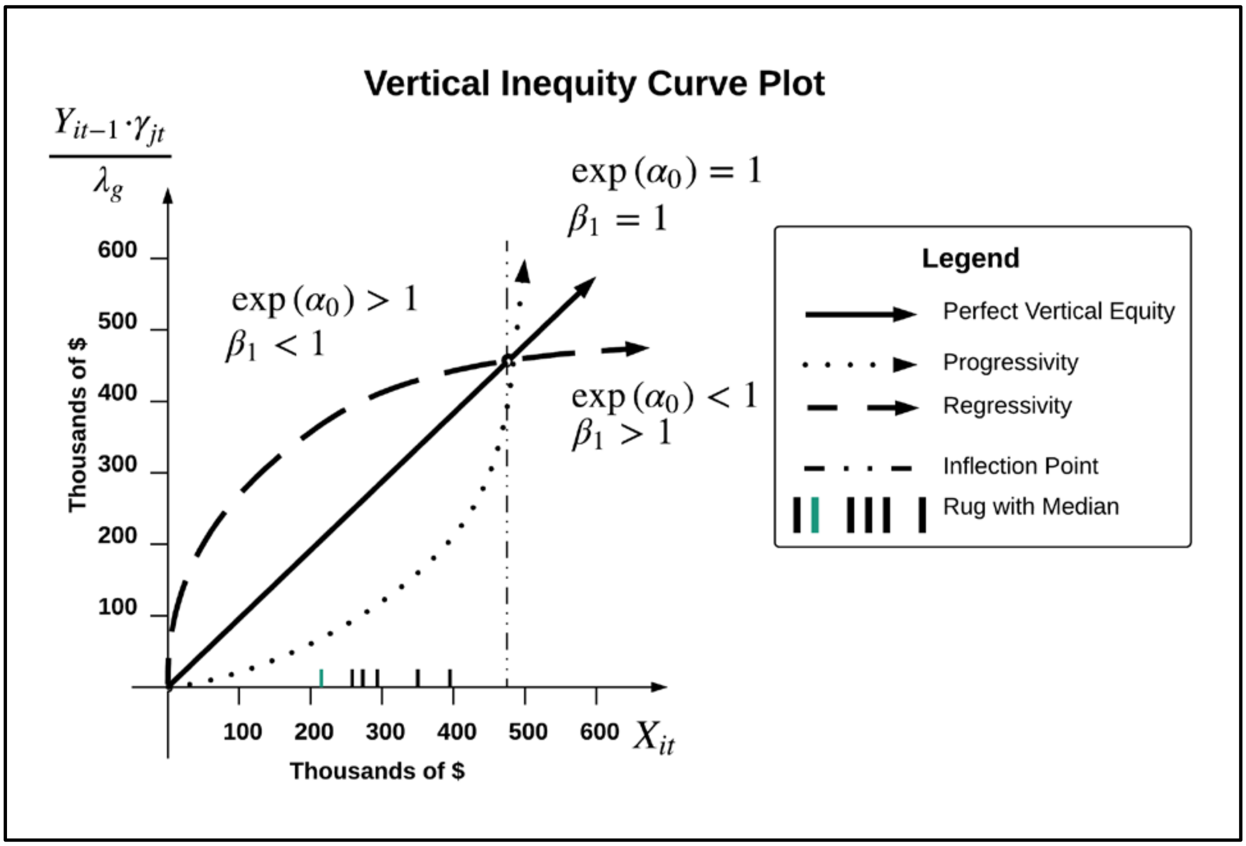

Figure 6.4. Vertical inequity curve plot with legend.

Vertical inequity curve plots, as displayed in Figure 6.4, were implemented in graphical displays expressing predicted values from the model in anti-log form. The horizontal and vertical axes are plotted in increments of $1,000. Red dashed lines identify the *inflection point* at which the vertical inequity curve (solid red line) crosses the perfect equity line (thin black line). The economic meaning of this is that each additional 1% increase in lagged appraised value relates to a greater than 1% increase in sales price until the vertical inequity shifts at the inflection point and this relationship changes to the alternative case. In other words, a progressive relationship exists under-appraising properties to the left of the inflection point. To the right of the inflection point the alternative case is that each 1% increase in appraised value translates to a lower sales price. Specifically, the progressive system over-appraises properties right of the inflection point. The inflection point acts as an estimated pivot point between low- and high-priced properties defining the vertical inequity shift. Derivation of the inflection point is shown in (6.4).

$$inflection\ point = \alpha_0^{\left(\frac{1}{1-\beta_1}\right)} \tag{6.4}$$

It is arguable that one need only test if $\exp(\alpha_0) = \beta_1 = 1$ to verify vertical equity. This is a true statement, yet hypothesis tests such as these are meaningful when statistical and practical significance are congruent. In this case, no standard thresholds exist for reasonably equitable values of $\exp(\alpha_0)$ and β_1.

6.6 Horizontal Inequity Adjustment Factors

It is possible for a population to exhibit both horizontal and vertical inequity. Without adjusting for horizontal inequity initially, vertical inequity curves will demonstrate results that display the curve above or below the x-axis. Under these circumstances, the reader may be able to identify horizontal inequity from curve plots upon visual inspection; however, inflection points are challenging to estimate.

The adjustment factor, also known as the "weighted mean" (IAAO 2013, 13) or "aggregate ratio", gives an estimate of horizontal inequity. Adjustment factors are constructed for different subgroups λ_g, λ_t, and λ_s listed in equations (6.5), (6.6), (6.7) for global, temporal, and spatial indices respectively. These adjustment factors are necessary overall because of a mismatch between appraised values and sales prices. Usually, the appraised value will be slightly less than the sales prices, thus the adjustment factor will be slightly less than one. This chapter uses only the global adjustment factor, whereas the space and time specific factors are employed in the next chapter. The global subgroup, (g), represents a weighted mean across study years and market areas. Indices representing each study year, are expressed by the subgroup, (t). Finally, indices for market areas comprise spatial subgroup, (s). Subscripts are for parcel $= 1,2,\ldots,n$, period $t = 2004,2005,\ldots,T$, and spatial market $s = 1,2,\ldots,S$ where $n = 55{,}206$, $T = 2014$, and $S = 21$.

$$\lambda_g = \frac{\sum_{i=1}^{n} Y_{it-1} \times \gamma_{jt}}{\sum_{i=1}^{n} X_{it}} \tag{6.5}$$

$$\lambda_t = \frac{\sum_{i=1}^{n_t} Y_{it-1} \times \gamma_{jt}}{\sum_{i=1}^{n_t} X_{it}} \tag{6.6}$$

$$\lambda_s = \frac{\sum_{i=1}^{n_s} Y_{it-1} \times \gamma_{jt}}{\sum_{i=1}^{n_s} X_{it}} \tag{6.7}$$

Horizontal inequity may be considered *a priori* information to models estimating vertical inequity. It can be derived with a trivial calculation such as that in (6.5) independent of the two-stage least squares model. Without altering its interpretation in any way, the adjustment factor may be introduced into the structural equation of the vertical property tax inequity model as an *offset* term. Knudsen (1992, 203) specifies an offset term representing *a priori* information within a Poisson regression context but emphasizes its application to any linear regression model. Consequently, for linear model specifications in this research, the offset term is subtracted from and acts as denominator to the dependent variable for logarithmic and exponential forms respectively[34].

6.7 Structural Equation

I estimate a pooled, two-stage least squares model over all years and markets for parcel i and sale year t, with accompanying instrument relevance and exogeneity diagnostics, to validate the use of instruments in the first stage regression. The structural equation for the global model is specified in (6.8) and represents an adaptation of Cheng's (1976, equation 15) specification for identifying vertical inequity. The dependent variable, $\log\left(Y_{it-1} \times \left(\gamma_{jt} + 1\right)\right)$ expresses lagged appraised value that is contemporaneous to t using the price index adjustment, which was discussed in 5.3.5. A horizontal inequity adjustment factor, $\log(\lambda_g)$, is subtracted from the left hand side and applied as an offset term to isolate inequities in the vertical direction. The endogenous regressor, $\log(X_{it})$, is replaced in this stage by the instrumental variable, $\widehat{\log(X_{it})}$, derived in the reduced form equation in (6.9). The coefficients, α_0 and β_1, represent estimates of vertical inequity. The term α_0 is a multiplier to the elasticity, β_1, in the anti-log form. The terms ε_i and u_i represent the disturbances in both structural and reduced form equations respectively.

[34] See equations (6.8) and (6.10).

The reduced form equation was originally specified in (6.1) of section 6.4 and is included here for convenience.

$$\log\left(Y_{it-1} \times \left(\gamma_{jt} + 1\right)\right) - \log\left(\lambda_g\right) = \alpha_0 + \beta_1 \widehat{\log X_{it}} + \varepsilon_i \tag{6.8}$$

$$\log(X_{it}) = \pi_0 + \mathbf{Z} \cdot \boldsymbol{\pi} + u_i \tag{6.9}$$

When employed in vertical inequity curve plots, the anti-log form of (6.8) was used as expressed in (6.10).

$$\frac{Y_{it-1} \cdot \gamma_{jt}}{\lambda_g} = \exp(\hat{\alpha}_0) + \hat{X}_{it}^{\hat{\beta}_1} \tag{6.10}$$

6.8 Global Vertical Inequity Model Output

The two-stage least squares model output across all years and market areas is provided in Table 6.3. This reveals the nature of vertical inequity for the entire study region and period. The pooled model indicates only slight regressivity based on the value of $\beta_1 = 0.984 < 1$.

Table 6.3. Global vertical property tax inequity model output for all years and markets.

Global Vertical Inequity Model (All Years and Markets)			
	Dependent variable:		
	$\log\left(Y_{it-1} \times \left(\gamma_{jt} + 1\right)\right) - \log\left(\lambda_g\right)$		
Parameter	Coef.	Std. Err.	t - statistic
α_0	0.08824	(0.00638)	13.83289***
β_1	**0.98400**	(0.00123)	-13.05343***
Observations	55,206		
			continued on next page

Table 6.3 continued from previous page	
$\boldsymbol{R^2}$	0.92663
Adjusted $\boldsymbol{R^2}$	0.92663
Residual Std. Error	0.16191
Note:	$*\,p < .1$ $**\,p < .05$ $***\,p < .01$
$\boldsymbol{\lambda_g}$	0.9540552

6.8.1 Relevance of Hypothesis Tests

One problem identified from the estimation was that such a large sample size may have distorted standard errors and subsequently the associated t-statistics. I performed a systematic investigation concerning this possibility. The question to be answered by the investigation was "At which hypothetical sample size does the p-value become larger than the error probability (e.g., $\alpha = 0.05$) so one cannot reject the null hypothesis anymore?" This sample size investigation is necessary to evaluate the *practical* relevance of the deviation of the elasticity estimate $\hat{\beta}_{IV}$ from its expected value under the null hypothesis $H_0\colon \beta_{IV} = 1$.

Multiple global vertical inequity models were executed with various samples descending in size from $n_{sample} = 10{,}000$ to determine how the p-value would be affected. The structural equation in (6.8) is generalized to (6.11), where $\hat{X}$ is the instrumental variable, to better explain the simulation. The p-value was derived using a one-tailed t test defined by equation (6.12) where alpha level $\alpha = 0.05$ and residual degrees of freedom $n - k$ where $k = 1$. I expected the global model to produce an estimate of $\beta_{IV} < 1$, and therefore selected the t-statistic equation for a one-tailed test for this direction as shown in (6.13). The associated hypothesis tests are provided in (6.14). The IV standard errors, SE_{IV}, following Wooldridge (2009, 511), are defined in (6.15) where $TSS_{\hat{X}}$ is the total sum of squares of $\hat{X}$, or $TSS_{\hat{X}} = \sum_{i=1}^{n}\left(\hat{X}_i - \bar{\hat{X}}\right)^2$. Values of $\hat{\sigma}$ and $R^2$are described in (6.16) and (6.17) respectively.

$$\hat{Y} = \hat{\beta}_0 + \hat{\beta}_{IV} \cdot \hat{X} \tag{6.11}$$

$$Prob(|t| \geq t_{\alpha,n-k}) \tag{6.12}$$

$$t = \frac{\hat{\beta}_{IV} - 1}{SE_{IV}} \tag{6.13}$$

$$\begin{aligned} H_0&: \beta_{IV} < 1 \\ H_1&: \beta_{IV} \geq 1 \end{aligned} \tag{6.14}$$

$$SE_{IV}\left(\hat{\beta}_{\hat{X}}; n|n_{sample}\right) = \sqrt{\frac{\hat{\sigma}}{TSS_{\hat{X}} \cdot R^2}} \cdot \sqrt{\frac{1}{\frac{n}{n_{sample}}}} \tag{6.15}$$

$$\hat{\sigma} = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}{n-2}} \tag{6.16}$$

$$R^2 = corr^2\left(X, \hat{X}\right) \tag{6.17}$$

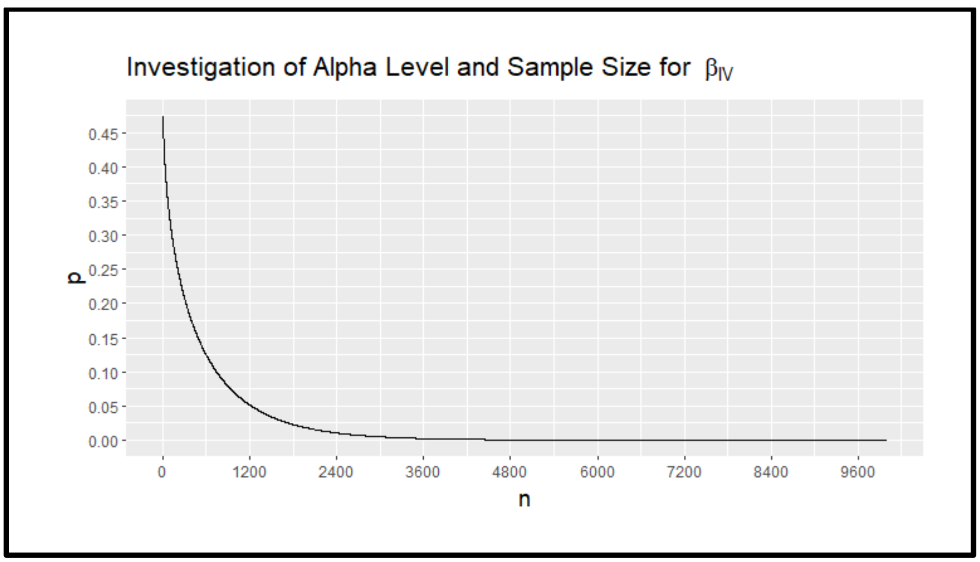

Figure 6.5. The effect of decreasing sample sizes on the significance of the coefficient β_{IV} in the global vertical inequity model.

Figure 6.5 demonstrates how the p-value for the β_1 coefficient (i.e., β_{IV}) is influenced by increasing sample size. As the sample size n decreases to approximately $n = 1{,}200$, we fail to reject the null hypothesis $H_0 \colon \beta_{IV} < 1$. If $n_{sample} \approx 1{,}200$ and $\alpha = 0.05$ the results may not reject the H_0. One may then conclude the significant result is unique to this sample size. These results underscore all test results in the global model and, from a statistical point of view, are biased towards rejecting null hypotheses due to the *large* sample size. This large n problem is still the subject of ongoing research in the statistical sciences.

6.9 Global Model Diagnostics

Table 6.4 provides the common names, test statistics, and interpretations for various instrumental variable diagnostics discussed in section 4.8.3. Based on the p-value of the weak instruments test, instruments are considered strong and relevant to model the endogenous variable. The Wu-Hausman statistic has a low p-value indicating a need for a two-stage least squares approach because the endogenous regressor truly is endogenous. Sargan test results indicate a lack of exogeneity in at least some of the instruments. While the first two diagnostics support the use of selected instruments for the first stage regression, the final test does not. The next section investigates concerns regarding the use of the Sargan test with application to the observed data.

Table 6.4. Diagnostic tests for the global vertical inequity model.

Diagnostic Test	Statistic Type	Test Statistic	Interpretation
Weak Instrument	***F***	8944	Instruments explain the endogenous variable, X_{it}, well.
			continued on next page

Table 6.4 continued from previous page			
Wu-Hausman	χ^2	2984	The variable, X_{it}, is endogenous and would benefit from a two-stage least squares approach.
Sargan	χ^2	3001	The instruments, Z_{kit}, have coefficients that are significantly different from zero when regressed on the reduced form equation's residuals. In other words, there may be some endogeneity in the instruments.

6.9.1 Reliability of Sargan J statistic test

The concerns addressed in section 4.8.3 relate to the implausibility of using the Sargan J statistic test for identifying exogenous instrumental variables. The J-statistic's rejection probability increases with sample size. This section investigates how sample size influences the test statistic, illustrating that the use of this diagnostic in empirical work, with strong instruments and in large samples, is questionable.

Table 6.5 displays the J-statistic for the global vertical inequity model with random sample sizes starting with $n = 5{,}000$ and increasing at increments of $5{,}000$ up to $55{,}000$. The J-statistic nearly doubles, almost at the same rate as n for each subsequent sample. This leads one to question how reliable the J-statistic may be in large samples with strong instrumental variables. This behavior is due to the calculation of the J-statistic shown in (6.18) were $R^2_{u_i,Zkit}$ is the goodness of fit of the second stage residuals, ε_i, regressed on the instruments, **Z**. The J-statistic increases proportionally to the sample size. For example, the J-statistc in the first sample, s_1, in Table 6.5 is approximately 372. If the sample size increases by a factor of 10 (i.e., $50{,}000$), the J-statistic increases by a factor of ${}^{2678}/_{372} \approx 7$ where $j_{s_{10}} = 2678$. This makes sense since $R^2_{u_i} = 0.0544$. Being a function of the sample size brings the J-statistic into scrutiny because even an $R^2_{u_i}$ value just slightly different from zero produces a significant result in large samples.

$$J = n \cdot R^2_{u_i,Zkit} \tag{6.18}$$

According to the diagnostic tests, the selected instruments are strong and highly correlated with the error term. Resorting to a reduction in the number of instruments in an attempt to satisfy the J-statistic test requirement jeopardizes critical variation required to make instruments a viable proxy for the endogenous variable. In the context of property tax assessment uniformity, this risk may be more than oversight agencies are willing to take. Greene (2008) alludes to this issue of simultaneously identifying strong and exogenous instruments. He states, "The choice of $\boldsymbol{Z}$ is often ad hoc. There is a bit of a dilemma in this result. It would seem to suggest that the best choices of instruments are variables that are highly correlated with $\boldsymbol{X}$. But the more highly correlated a variable is with the problematic columns of $\boldsymbol{X}$, the less defensible the claim that these same variables are uncorrelated with the disturbances" (Greene 2008, 320).

Table 6.5. Sample size influence on Sargan J statistic test.

Sample	Sample Size	J statistic	P-value	Degrees of Freedom
s_1	5000	371.6789	6.52E-054	43
s_2	10000	519.322	5.21E-083	43
s_3	15000	850.6891	1.38E-150	43
s_4	20000	1113.714	2.63E-205	43
s_5	25000	1407.953	4.07E-267	43
				continued on next page

Table 6.5 continued from previous page				
s_6	30000	1650.787	1.96E-318	43
s_7	35000	1951.534	0.00E+000	43
s_8	40000	2150.485	0.00E+000	43
s_9	45000	2448.822	0.00E+000	43
s_{10}	50000	2677.614	0.00E+000	43
s_{11}	55000	2998.645	0.00E+000	43

6.9.2 Addressing the Many Instruments Problem

An investigation was initiated in an attempt to mitigate the J-statistic problem, perhaps relating to parameter estimates that involved many instrumental variables. Following an example from Bai and Ng (2010), principal component analysis was used to reduce instruments into smaller subsets. This approach provided favorable results with instruments less prone to be correlated with the error term, but at the expense of instrument relevance. Frequently, relevant instruments such as lot size and living area failed to load on prominent factors. While a careful algorithm investigated all possible combinations of principal component instruments, only semi-relevant subsets continued to produce results that passed the J-statistic test. These subsets brought into question the relevance of fitted values used as a proxy for the endogenous sales price variable. With greater housing market value relevance driving the decision, the full battery of instruments replaced principal component subsets in the final analysis.

6.10 Global Vertical Inequity Curve Plot

The vertical inequity curve, (solid red line), for the global model is displayed in Figure 6.6. The legend in the graph lists values for α_0, β_1, and λ_g being within the range of 1 ± 0.10. The vertical inequity estimate indicates slight regressivity across all years and market areas.

The shift in the property tax burden, based on the inflection point, (dashed red line), begins at approximately \$248,000. It is interesting to note that the vertical inequity curve begins to more sharply deviate from the perfect equity line, (solid black line), at approximately \$2,000,000. Consequently, at this value, the rug in the plot begins to demonstrate more sparse observations. The summary statistics in Table 5.3 reveal that $\frac{1}{4}$ of the observations are above the inflection point. These clues suggest observations in the upper quartile of the data may highly influence the vertical inequity curve's shape. An additional vertical inequity curve plot paints a different picture for observations in the lower three quartiles.

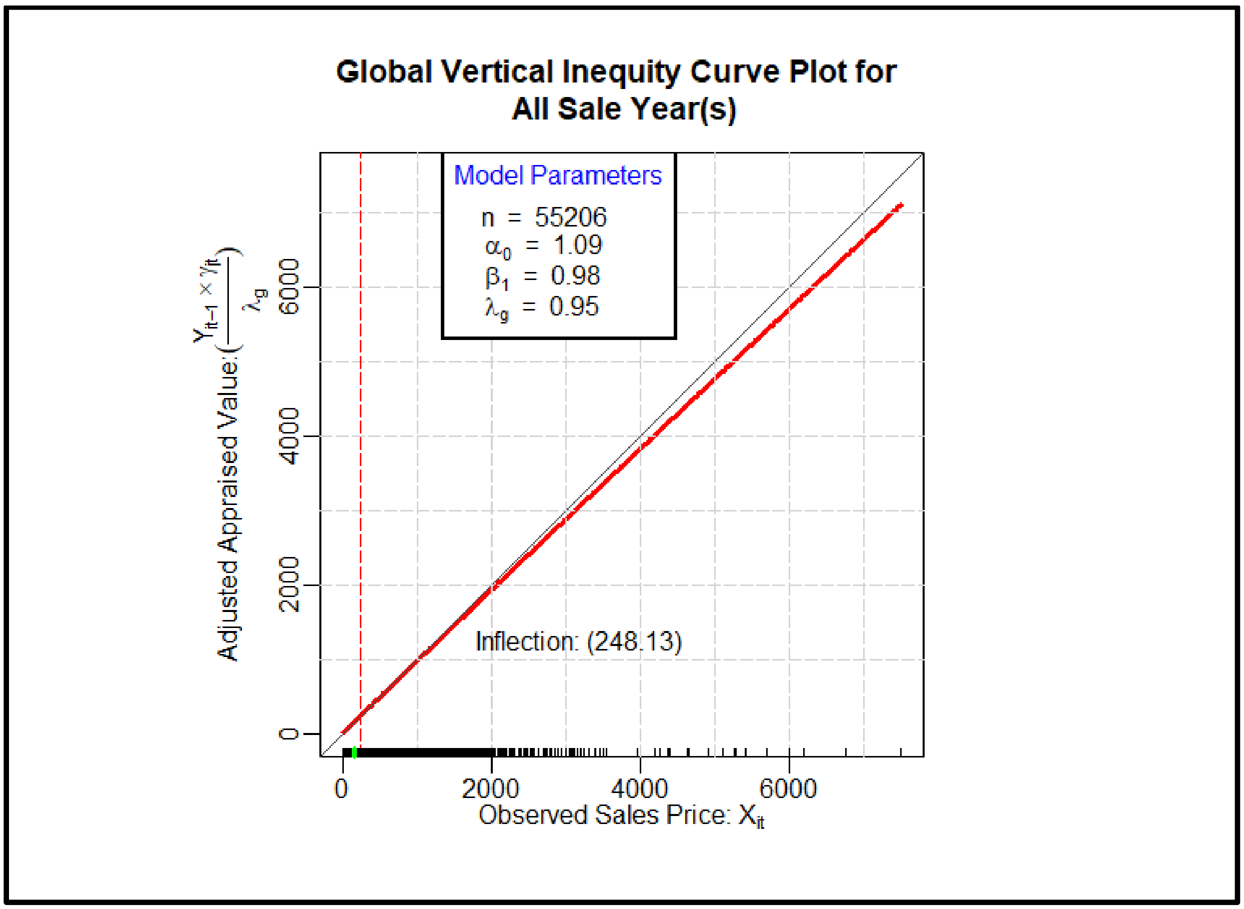

Figure 6.6. Global vertical inequity curve plot for all years and markets.

Figure 6.7 zooms to just those observations with sales prices less than $2,000,000. The vertical inequity curve is now closer to the perfect equity line. The median, green line in the rug is near the origin. Scaling the vertical inequity curve graph's horizontal axis this way provides a meaningful indication of vertical inequity for the majority of the observed homes sales. Given the wide range in the sales prices, grid lines in $500,000 increments were added to the inequity plot.

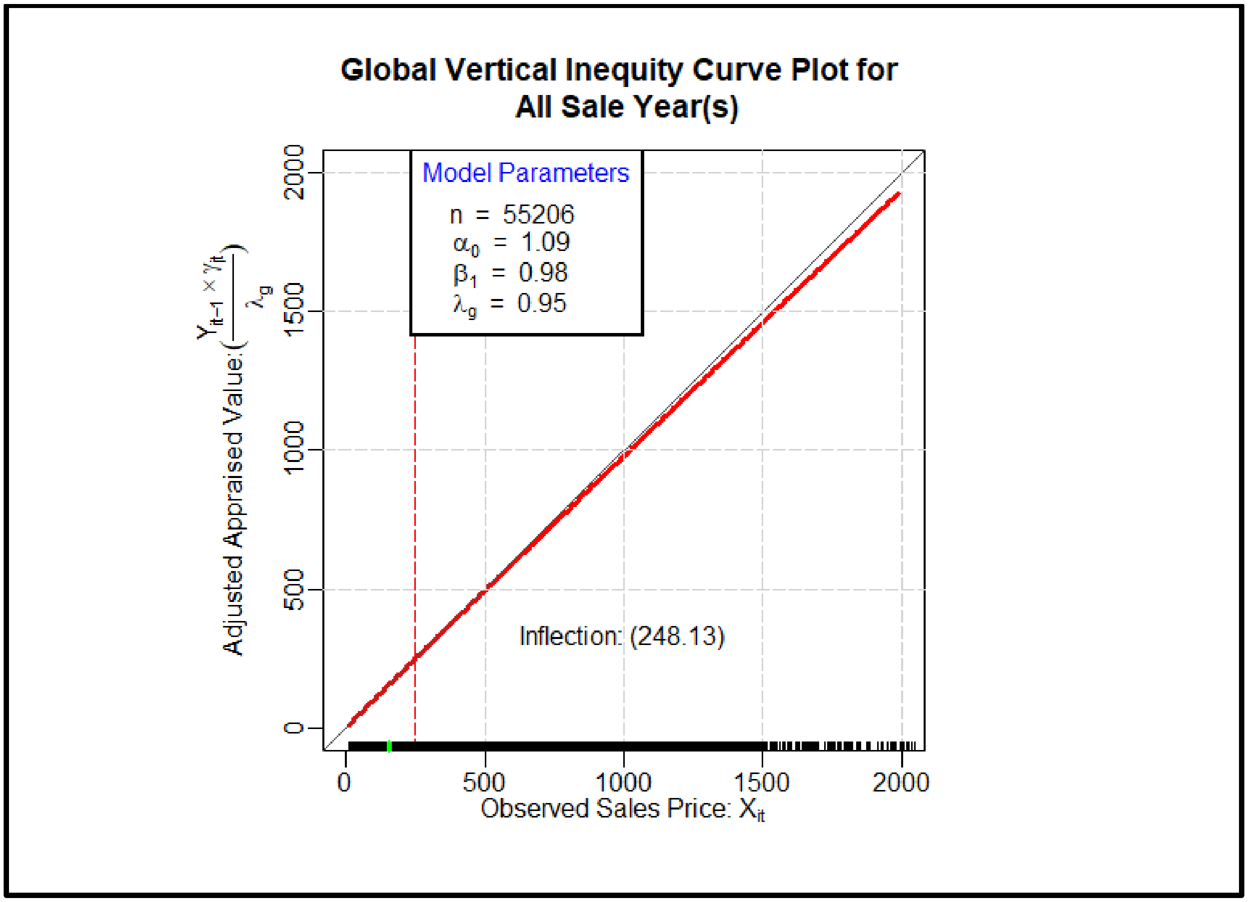

Figure 6.7. Global vertical inequity curve plot for all years and markets for home with sales prices less than $2,000,000.

CHAPTER 7

TEMPORAL AND SPATIAL VERTICAL INEQUITY MODELS

7.1 Introduction

While the global model provided a means for validating the instruments, calibrating the model response, and adjusting the vertical inequity curve plot, temporal and spatial models address more detailed research objectives and provide richer insights into vertical property tax inequity using specific subpopulations of observed sales. The opening sections describe pre-, during-, and post-recession periods. These periods set the framework and provide results for the temporal model, illustrate the horizontal inequity adjustment patterns over time, and display the temporal inequity curve plots. Following the temporal model discussion, spatial model sections elaborate on NTRIES market areas introduced in section 5.6.2, categorize them into price classes, and describe their relationship within the context of the study area's topographic, urban, and social landscapes. The final sections include the spatial model framework, output, and spatial vertical inequity curve plots.

7.2 The 2007 Great Recession Periods

Framing study years within time windows surrounding the 2007 Great Recession facilitates the discussion about the model results and permits formulating theory-based assumptions regarding economic activities in the unique periods. Using the information presented in section 2.4, three theoretical recession periods between January 1st and December 31st for each study year were defined. Recession periods represent study year aggregates of unequal duration. While not intentional, this imbalanced scheme ensures a sufficient amount of observations within each group and accentuates comparison with the critical *in-recession* period. Figure 7.1 shows the organization of study years within recession periods, supported by the number of observations and their totals.

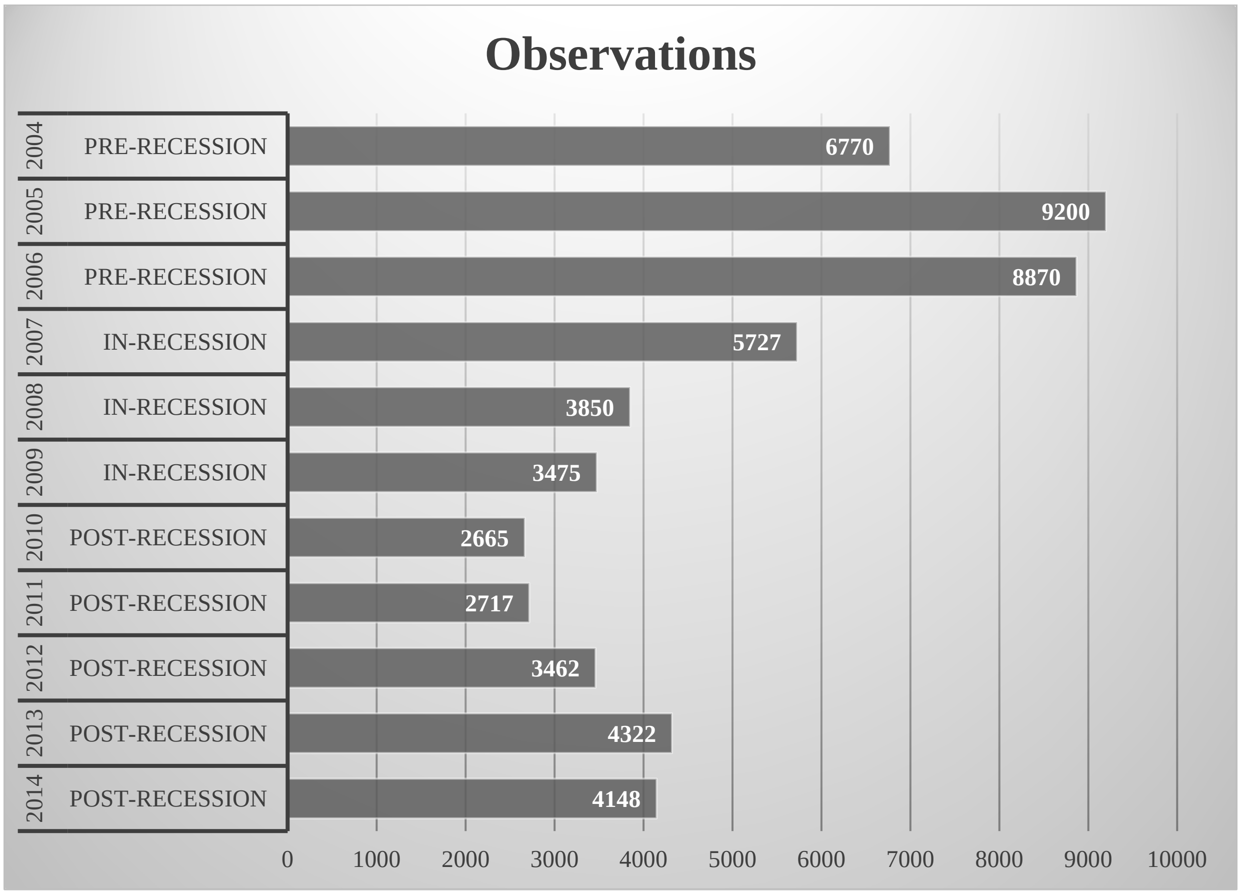

Figure 7.1. Recession period groupings by study year and number of observations.

The *pre-recession* period represents the duration of the study before the 2007 Great Recession occurred between January 1st, 2004 and December 31st, 2006. According to the Financial Crisis Inquiry Commission (2011, 1), the "Great Recession" began in December 2007 and ended in June 2009. This theoretical recession period is labeled *in-recession*. Since dividing years was not part of the study design, the in-recession period included the 2009 year in its entirety. *Post-recession* years are between January 1st, 2010 and December 31st, 2014.

Reviewing the number of observations alone gives an indication of the recession's influence on housing sales activity. The pre-recession period has the lion's share of observations while the in-recession years demonstrate fewer sales. The peak of low sales activity occurs in the early post-recession years and housing markets begin to recover by the end of this period.

7.3 Temporal Vertical Inequity Model Framework

Temporal patterns in vertical inequity were derived using a generalization of (6.8) as shown in (7.2). This specification reveals inequity movements within each study year. The temporal model's first stage is identical to (6.1). The structural equation in (7.2) becomes a varying intercept and slope model. Using this approach, an α_t and β_t coefficient are created for each study year, t. These parameters are required to generate annual vertical inequity curves, divided into panels, and compared across theoretical recession periods.

The variable, δ_t, is an "effect coded" indicator for the year of the sale with the zero-sum property (Wendorf 2004, 54). Parameters of un-suppressed indicators salvage suppressed indicators. In other words, information from the omitted reference indicator is not lost in the intercept, α_0, because additional intercept terms, α_t, reflect positive or negative deviations from α_0. The properties of the time period indicator, δ_t, are defined in (7.1) where t_0 is the matching sale year, t, is the sale year for parcel i, and T, is the final sale year, 2014.

$$\delta_t = \begin{cases} 1\ if\ t = t_0 \\ 0\ if\ t \neq t_0 \\ -1\ if\ t = T \end{cases} \tag{7.1}$$

$$\log\left(Y_{it-1} \times \left(\gamma_{jt} + 1\right)\right) - \log(\lambda_t)$$
$$= \alpha_0 + \beta_1 \widehat{\log X_{\iota t}} + \alpha_t \delta_t + \beta_t \widehat{\log X_{\iota t}} \times \delta_t + \varepsilon_i \tag{7.2}$$

Varying slope effects require an interaction term. Hamilton (1992, 84) defines an interaction as the dependence of variable $\widehat{\log X_{\iota t}}$'s effect on the values of variable, δ_t. Summing main effects, (α_0, β_1) with their companion temporal effects, (α_t, β_t), produces temporal vertical inequity estimates, (α_t^*, β_t^*), as shown in (7.3) and (7.4) respectively.

$$\begin{array}{ccccc} \alpha_0 & + & \alpha_{t=04} & = & \alpha_{04}^* \\ \alpha_0 & + & \alpha_{t=05} & = & \alpha_{05}^* \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \alpha_0 & + & \alpha_{t=T} & = & \alpha_T^* \end{array} \tag{7.3}$$

$$\begin{array}{ccccc} \beta_1 & + & \beta_{t=04} & = & \beta_{04}^* \\ \beta_1 & + & \beta_{t=05} & = & \beta_{05}^* \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \beta_1 & + & \beta_{t=T} & = & \beta_T^* \end{array} \tag{7.4}$$

7.4 Temporal Vertical Inequity Model Output

Including varying intercepts and interaction terms in the global model by year provides an indication of how vertical inequity changed for each year in the study period. The two-stage least squares model estimates for each year across all markets is provided in Table 7.1. This gives an indication of annual vertical inequity for the entire study region. The parameters α_0 and β_1 represent the intercept and elasticity main effects respectively. Additionally, parameters $\alpha_t \delta_t$ and $\beta_t \widehat{\log X_{\iota t}} \times \delta_t$ represent annual intercept and interaction term effects respectively.

There is little deviation of main effects, α_0 and β_1, from the global model and, as mentioned in section 6.8, the main effects are slightly regressive. Annual intercepts and elasticities with significant t-statistics indicate a variety of intermittent patterns above or below the main effects. Year intercepts with insignificant t-statistics are close to main effect values, which are only slightly regressive and practically equitable. Inequity patterns and their implications were more easily interpreted using vertical inequity curve plots in section 7.6.

7.5 Temporal Horizontal Inequity Plot

The plot displayed in Figure 7.2 displays λ_t, or horizontal inequity, for each study year. These values express the level of under- or over-estimation for each study year t. The grey bar in the plot designates the recession period between 2007 and 2009. The volatility of λ_t may be a result of the housing market effects of the recession lasting through 2012. As one might expect, appraisals suffer from greater under-estimation during in-recession and early post-recession years. At the end of post-recession years, estimation returned to pre-recession levels. Interestingly, for the year 2009 the appraised values were rapidly readjusted and thus overshooting to realized recovery.

Table 7.1. Temporal vertical property tax inequity model output for all markets.

	Dependent variable:		
	$\log\left(Y_{it-1} \times \left(\gamma_{jt} + 1\right)\right) - \log(\lambda_t)$		
Parameter	Coef.	Std. Err.	t - statistic
α_0	0.07175	(0.00999)	7.18169***
β_1	0.98893	(0.00190)	520.49000***
α_{04}	-0.23840	(0.02595)	-9.18674***
α_{05}	0.19446	(0.02275)	8.54787***
α_{06}	-0.03862	(0.02318)	-1.66625*
α_{07}	0.13683	(0.02775)	4.93079***
α_{08}	0.13094	(0.03398)	3.85330***
α_{09}	0.08302	(0.03611)	2.29916**
α_{10}	-0.26482	(0.03704)	-7.14964***
α_{11}	-0.46734	(0.03859)	-12.11030***
α_{12}	0.18277	(0.03492)	5.23401***
α_{13}	0.30137	(0.03018)	9.98570***
α_{14}	-0.02021	(0.03196)	-0.63245
β_{04}	0.04111	(0.00506)	8.12506***
β_{05}	-0.03607	(0.00445)	-8.10571***
β_{06}	0.00593	(0.00449)	1.32037
β_{07}	-0.03192	(0.00533)	-5.98871***
β_{08}	-0.02712	(0.00650)	-4.17178***
β_{09}	-0.00982	(0.00697)	-1.40841
β_{10}	0.05703	(0.00702)	8.12392***
β_{11}	0.07996	(0.00731)	10.93810***
β_{12}	-0.04675	(0.00658)	-7.10534***
β_{13}	-0.03921	(0.00560)	-7.00106***
β_{14}	0.00685	(0.00597)	1.14803
Observations	55,206		
R^2	0.85257		
Adjusted R^2	0.85252		
Residual Std. Error	0.22079		
Note:	$*\,p < .1 \quad **\,p < .05 \quad ***\,p < .01$		

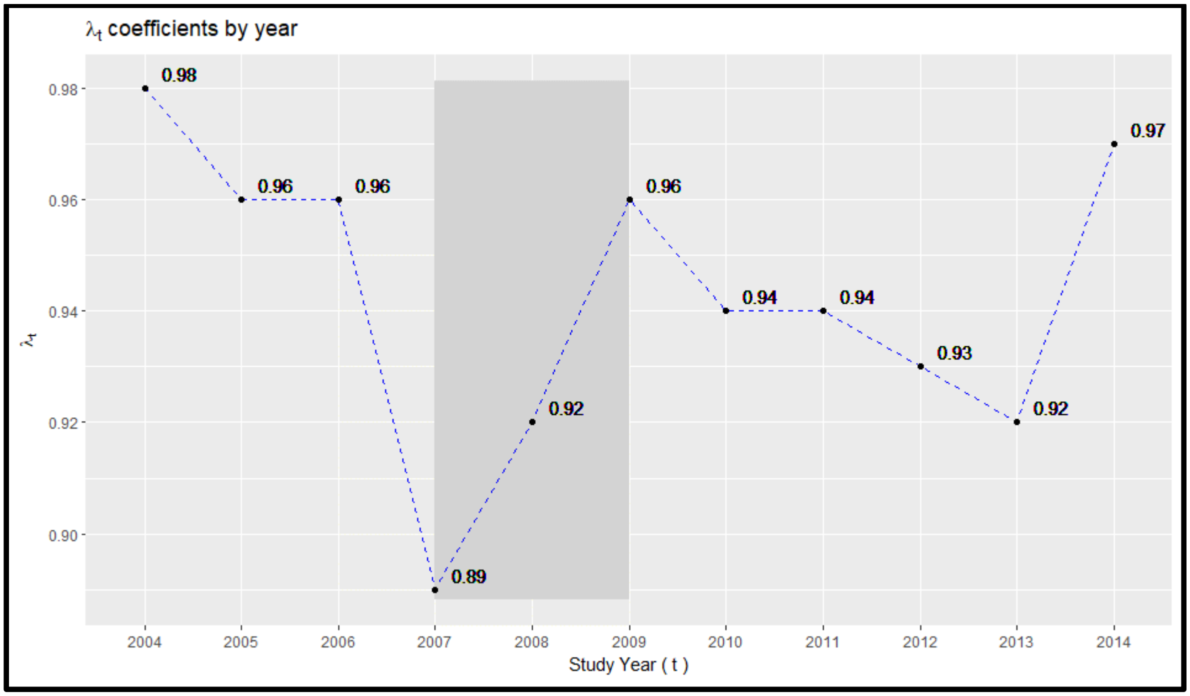

Figure 7.2. Temporal lambda (λ_t) coefficient plot.

7.6 Temporal Vertical Inequity Curve Plots

Vertical inequity curve plots give full expression to the temporal model output. To minimize curve distortion for upper quartile observations as shown in Figure 6.7 the data are only displayed for a sales price up to $2,000,000. The calculations, however, were performed on the untruncated data set. Although the result of summing temporal intercepts and slopes, with their companion main effects are equivalent to (α_t^*, β_t^*), for simplicity, each annual plot denotes intercepts and slopes in the model parameters legend by α_0 and β_1 respectively. Temporal plots are organized into groups or panels by recession period. Figures Figure 7.3 - Figure 7.5 display annual inequity curve plots for each recession phase.

Annual model results are more meaningful when compared to house prices fluctuations across the study period as shown in Figure 2.3. In some locations throughout the U.S., recessionary effects continued throughout the beginning of 2012 and began to improve in 2013 (Langley 2015, 177;Rioja 2017, 19). This appears to be the case in the Dallas area, where after a period of volatility between 2007 and 2012, prices began to increase gradually.

7.6.1 Pre-Recession Period

Figure 7.3 displays pre-recession period, temporal vertical inequity curve plots. During this period, only slight deviations from equity were evident and the inflection point remained close to the median distribution of sales over each year. In the final year, appraisals were equitable with a high inflection point.

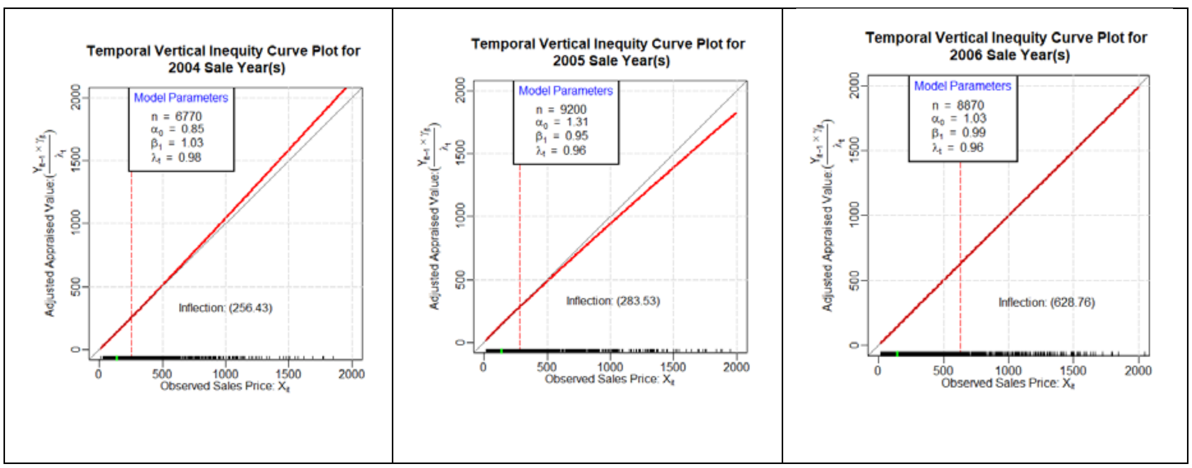

Figure 7.3. Pre-Recession Temporal Vertical Inequity Curve Plots.

7.6.2 In-Recession Period

In-recession phase curves, shown in Figure 7.4, demonstrate the greatest inequity in 2007. The inflection point was lowest for this phase. Additionally, the horizontal inequity, adjustment factor $\lambda_t = 0.89$, is lowest for all phases. From $2008 - 2009$, appraisals demonstrate an increasingly equitable pattern. One possible explanation for these patterns is the 2007 peak in house prices just before the bursting of the housing bubble causing prices to drop as shown in

Figure 2.3. This peak was much sharper than the gradual prices appraisers were experiencing nearly three years prior. Price index fluctuations appear to be generally moderate until the end of 2009 when Dallas area prices dropped again drastically and continued to decline on into the post-recession period.

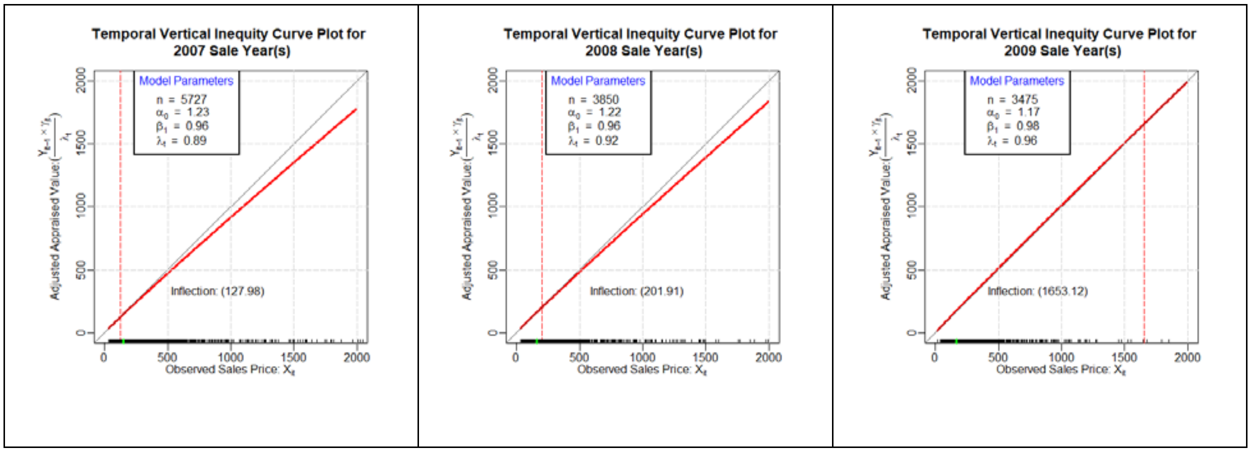

Figure 7.4. In-recession vertical inequity plots identify uniformity patterns during the Great Recession.

7.6.3 Post-Recession Period

End-of-recession declines possibly contribute to the progressive pattern shown in 2010 − 2011 inequity curves displayed in Figure 7.5. When prices drop drastically, house price estimation is a greater challenge for the appraiser (Appraisal Practices Board 2014). In 2012, a transition to a regressive inequity pattern is apparent. Here, house prices were beginning to increase, and such a pattern indicates appraisals were below what the sharp rising market indicated. The small inflection point, (i.e., 81.59) shows that this occurred for the majority of observations for the study year. House prices for observations below this inflection point may have been affected little during this transition period. Although still regressive in 2013, appraisals transition to a more equitable pattern. The full range, inequity curve plot for 2013 revealed higher-priced observations influencing the regressivity pattern. Observations in the lower three quartiles appear to be more equitable as shown by the high inflection point (i.e., 1671.59) in the bottom left panel of Figure 7.5. As house prices improve after recessionary aftershocks in 2014, an equitable pattern appears.

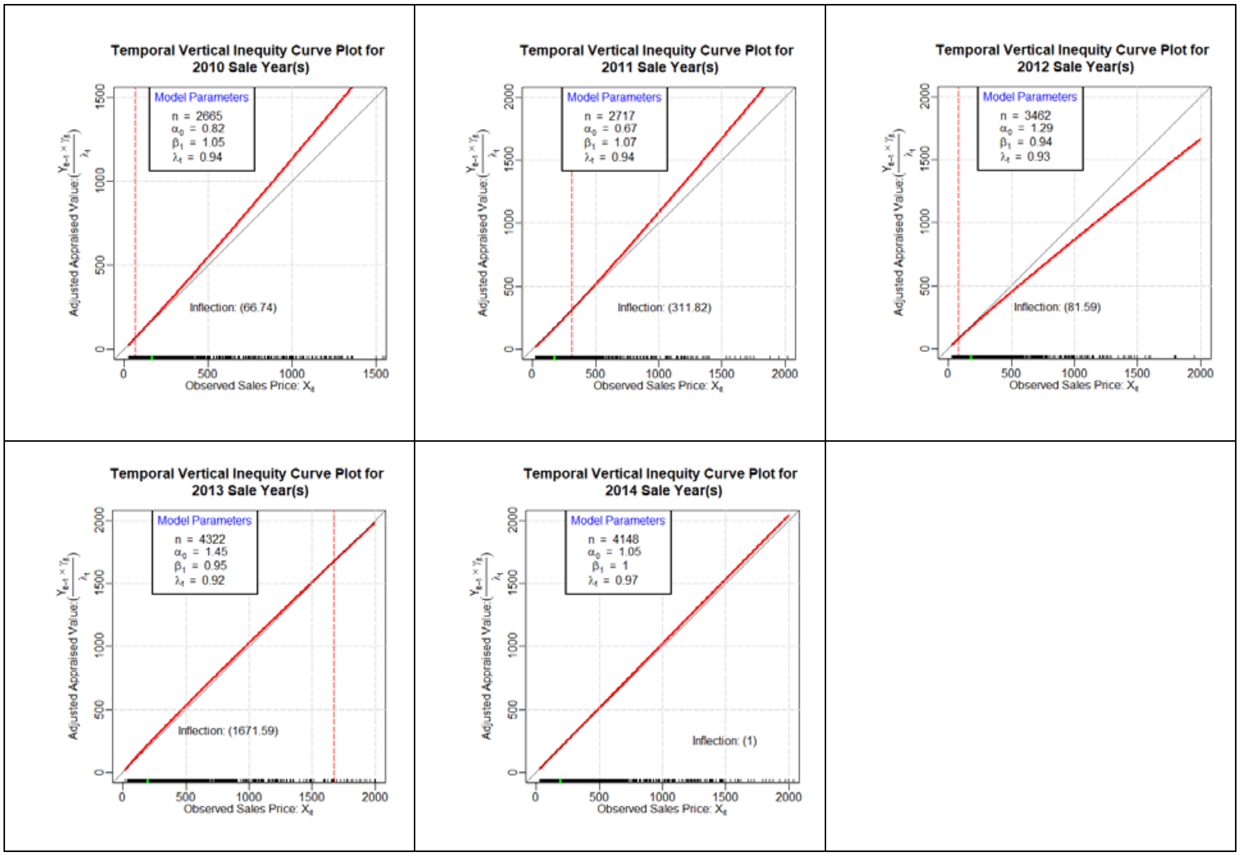

Figure 7.5. Post-recession vertical inequity plots identify uniformity patterns following the Great Recession.

7.7 Spatial Indicators: NTREIS Market Areas

Before discussing the spatial vertical property tax inequity model, elaborating on market area indicators is essential. As previously discussed, market areas were originally defined by NTREIS and published by the Dallas Morning News (Brown 2017, D). Boundaries were digitized using rubber sheeted, printed maps from the newspaper. Many boundaries followed existing transportation arteries, city boundaries established by ordinance, and water features. To avoid the "finite sample bias" that can occur with two-stage least squares estimation methods, markets with less than 400 sales observations were merged with neighboring areas with comparable price distributions (Wooldridge 2009, 510). Table 7.2 provides a list of combined market areas with their respective number of observations before and after merging.

Table 7.2. Market area combinations used to avoid TSLS finite sample bias.

1st Market Area Name	**# of Obs**	**2nd Market Area Name**	**# of Obs**	**Combined Market Area Name**	**Total # of Obs**
Wilmer-Hutchins	6	Southeast Dallas	1100	SE Dallas-Wilm-Hutch	1106
Oak Lawn	133	Northwest Dallas	1753	Oak Lwn-NW Dallas	1886
Sunnyvale	84	Mesquite	4386	Mesquite-Sunnyvale	4470

After combining regions, there were a total of 21 market areas as shown in Figure 7.6. Market areas are labeled with their names and the total number of observations in parentheses. Pie graphs indicate percentage of total observations for each recession period. With two exceptions, Southern Dallas (post-recession – 81) and Lancaster (in-recession – 75), each market area had at least 100 observations in each recession period. Natural features and population density by census block were included in the map to illustrate the topographic and social landscape of each market area respectively. Markets with limited land for residential neighborhoods (e.g., Southeast Dallas-Wilm-Hutch) are highlighted by these elements. Airport areas and the corner market area incorporating the City of Grapevine were excluded from the spatial estimation model because there were no sales transactions for these areas.

7.8 Market Area Sales Price Box Plots

Sales price is distributed unevenly across the study area. These distinct market distributions are grouped by observations having similar sales price ranges. Box plots illustrating these patterns are shown in Figures Figure 7.7 – Figure 7.10. Sales price in thousands of dollars is displayed on the y-axis, while individual market box plots are labeled on the x-axis. To compare market price distributions across groups, a $\$5{,}000{,}000$ reference line is included in each box plot.

7.9 Spatial Vertical Inequity Model Framework

Spatial and temporal vertical inequity model frameworks are similar. The spatial indicator, ω_s, is analogous to, δ_t, shown in (7.1). The properties of the market area indicator, ω_s, are defined in (7.5) where s_0 is the initial market area, s, is the market area for parcel i, and S, is the final market area in the population. Observations over all years are included in each market area group. Essentially, vertical inequity curves include sales occurring over the entire study period within market area, s.

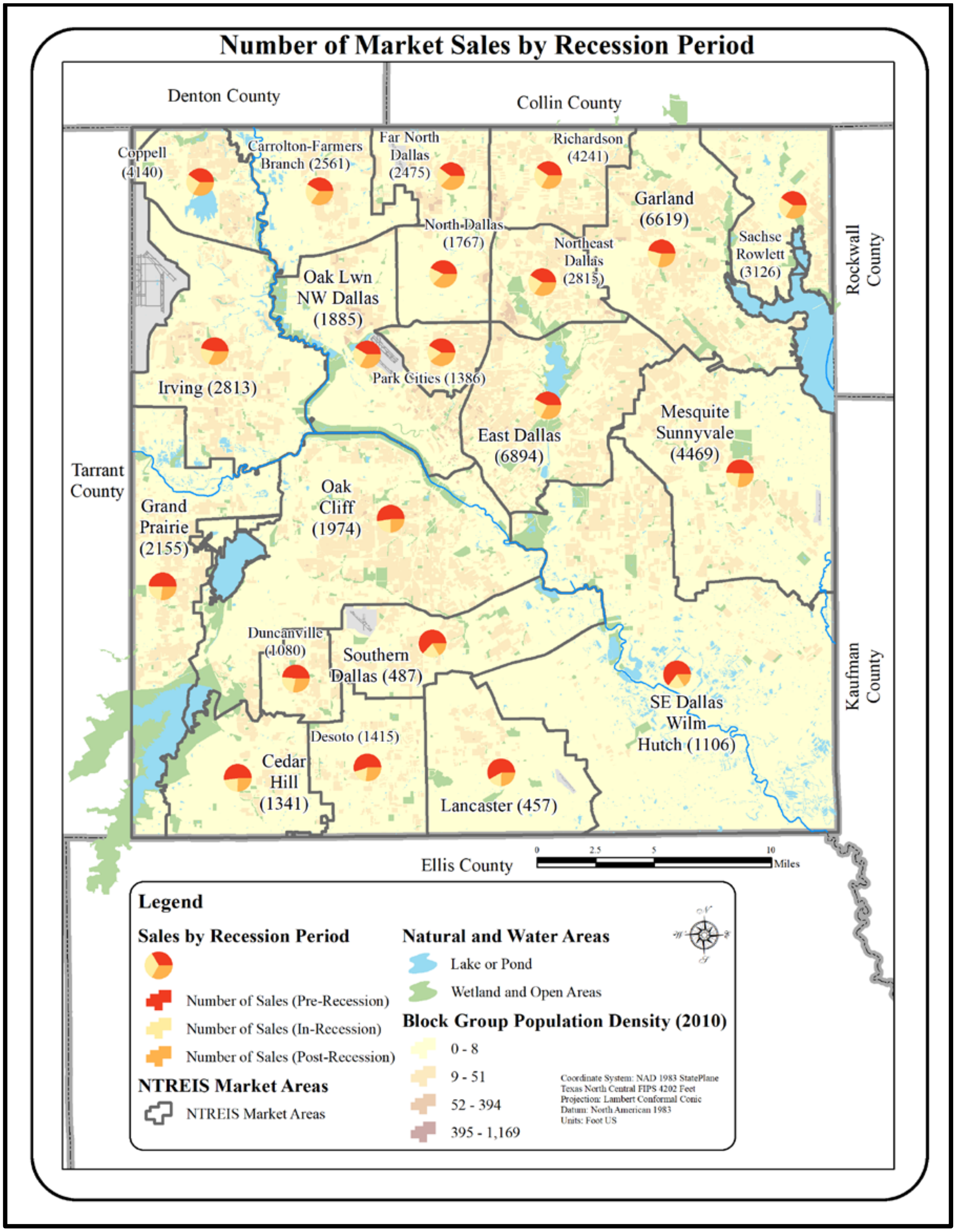

Figure 7.6. Map of NTREIS market areas with number of sales by recession period.

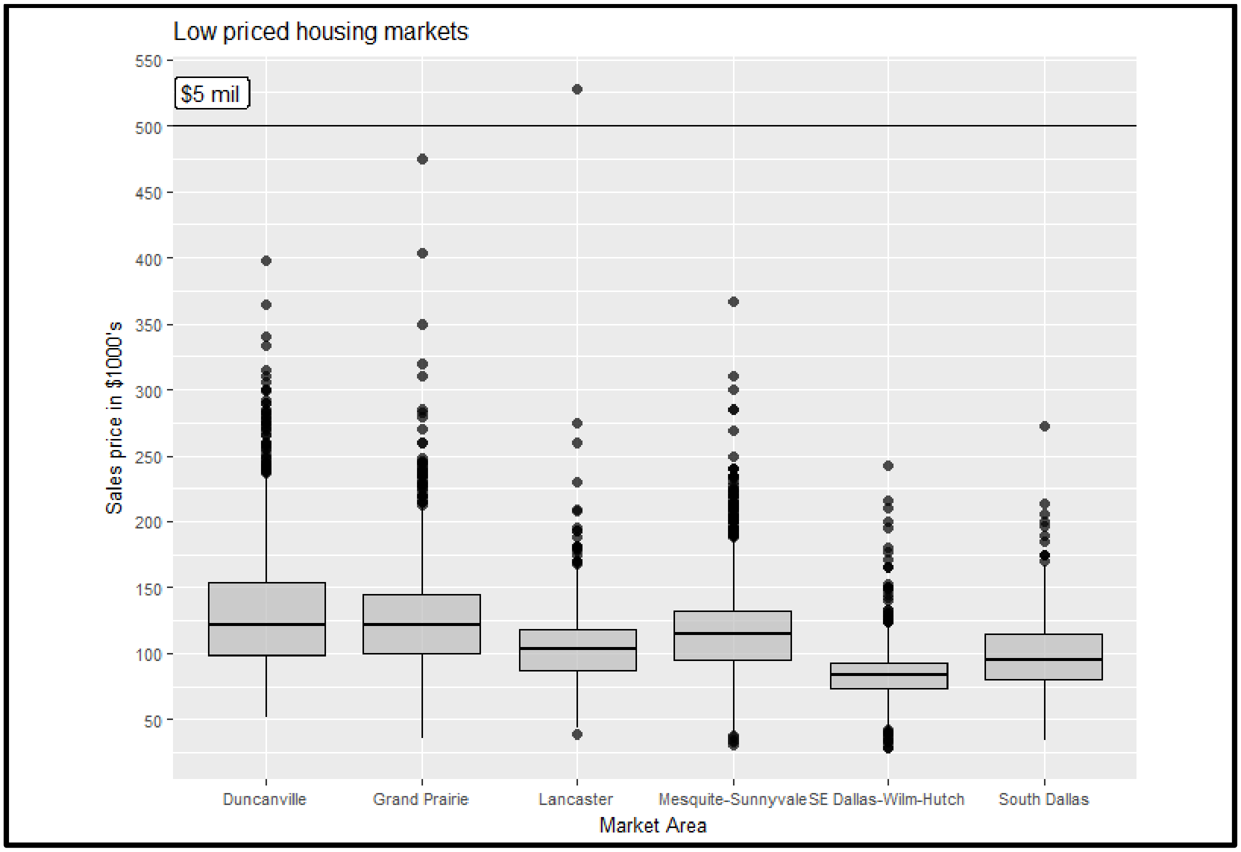

Figure 7.7. Box plot for low priced market sales.

The index s represents the market area identifier as defined by NTREIS. Identifiers are not sequentially labeled for two reasons. First, areas are uniquely assigned within the entire Dallas Fort-Worth metroplex. Second, as shown in Table 7.2, some market areas were combined to improve their degrees of freedom. A table with the complete list of market area names and sector ids may be found in Table D.1. Spatial vertical inequity estimates (α_s^*, β_s^*) are shown in (7.7) and (7.8) respectively.

$$\omega_s = \begin{cases} 1 \; if \; s = s_0 \\ 0 \; if \; s \neq s_0 \\ -1 \; if \; s = S \end{cases} \tag{7.5}$$

$$\log\left(Y_{it-1} \times \left(\gamma_{jt} + 1\right)\right) - \log(\lambda_s)$$
$$= \alpha_0 + \beta_1 \widehat{\log X_{\iota t}} + \alpha_s \omega_s + \beta_s \widehat{\log X_{\iota t}} \times \omega_s + \varepsilon_i \quad (7.6)$$

$$\begin{array}{ccccc} \alpha_0 & + & \alpha_{s=1} & = & \alpha_1^* \\ \alpha_0 & + & \alpha_{s=2} & = & \alpha_2^* \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \alpha_0 & + & \alpha_{s=S} & = & \alpha_S^* \end{array} \quad (7.7)$$

$$\begin{array}{ccccc} \beta_1 & + & \beta_{s=1} & = & \beta_1^* \\ \beta_1 & + & \beta_{s=2} & = & \beta_2^* \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \beta_1 & + & \beta_{s=S} & = & \beta_S^* \end{array} \quad (7.8)$$

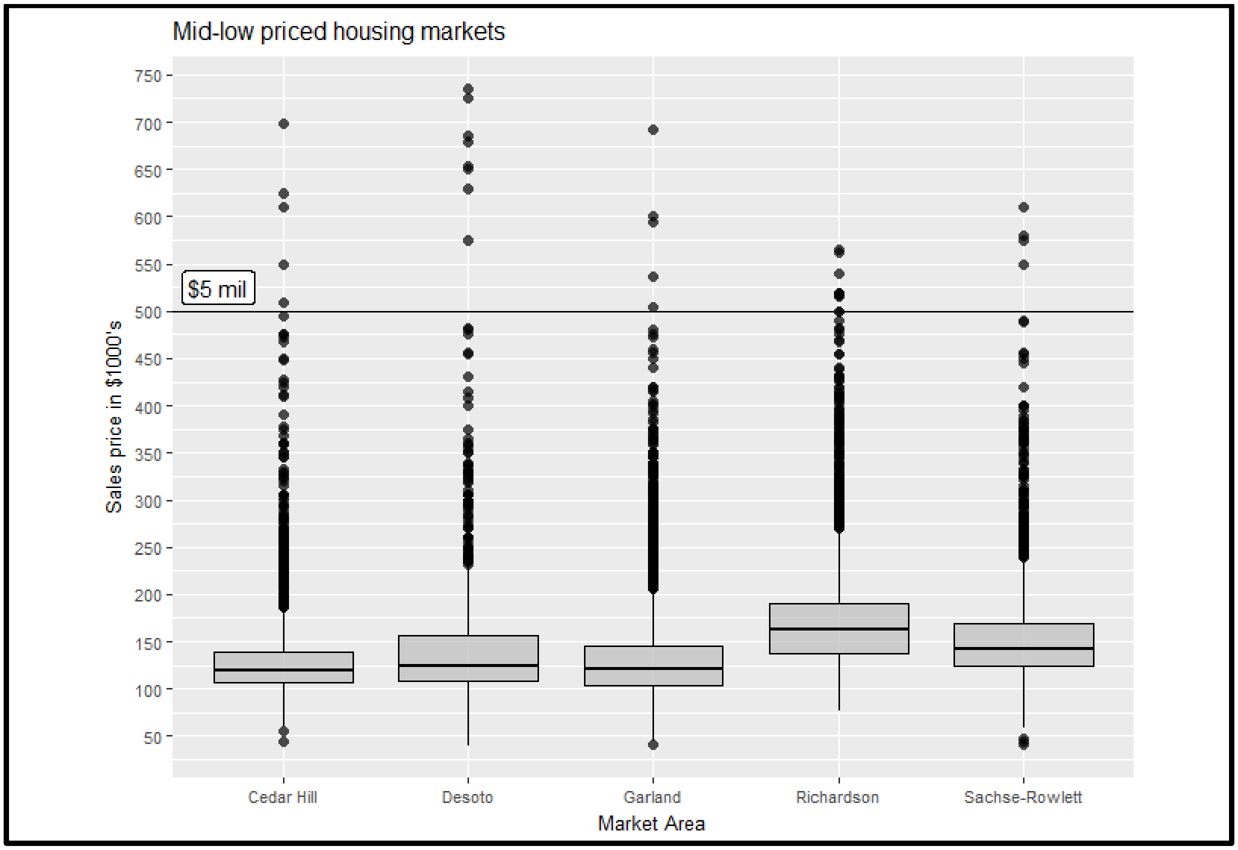

Figure 7.8. Box plot for lower range, mid priced market sales.

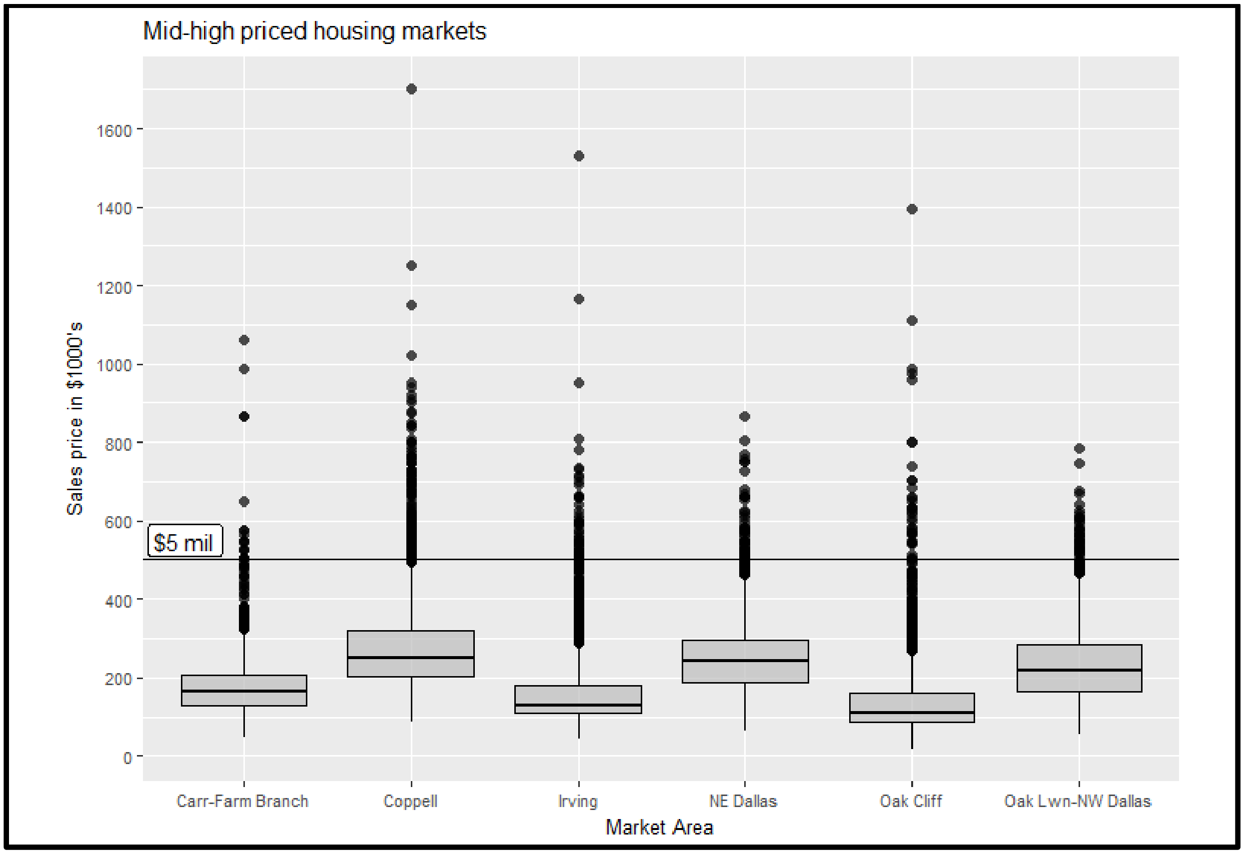

Figure 7.9. Box plot for upper range, mid priced market sales.

7.10 Spatial Vertical Inequity Model Output

The spatial model output is displayed in Table 7.3. Parameters $\alpha_s\omega_s$ and $\beta_s \log\widehat{X_{\iota t}} \times \omega_s$ represent market area intercept and interaction term effects respectively. The parameters α_0 and β_1 are the model's main effects. The main effect β_1 elasticity parameter should not be confused with the term $\beta_1 \log\widehat{X_{\iota t}} \times \omega_1$, which represents the coefficient parameter for the interaction term of market area $s = 1$.

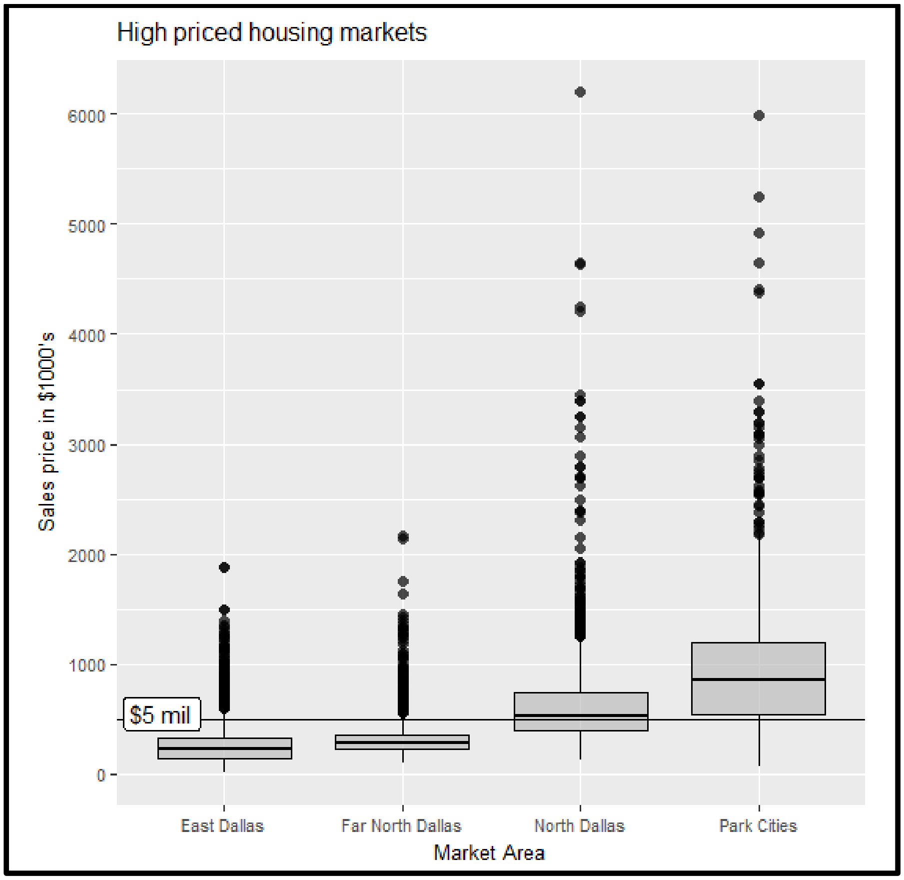

Figure 7.10. Box plot for high priced market sales.

7.10.1 Sum of Spatial Indicator Coefficients

Since indicator variables, ω_s, are expressed in the effect or deviation-coding scheme their coefficients should sum to zero. Both intercept and slope coefficients in the model summed to zero as shown in Table 7.4. As with the temporal adjustment factor, λ_t, spatial horizontal inequity, λ_s, is best expressed within its population's context. In other words, rather than representing λ_s using a timeline, as was done with λ_t, a choropleth map differentiating market area boundaries by λ_s values was more appropriate. In the next section, a discussion about the map of λ_s reveals theoretical implications of the observed pattern.

Table 7.3. Spatial vertical property tax inequity model output for all years

	Dependent variable:		
	$\log\left(Y_{it-1} \times \left(\gamma_{jt} + 1\right)\right) - \log(\lambda_s)$		
Parameter	Coef.	Std. Err.	t - statistic
α_0	0.37352	(0.01803)	20.71680***
β_1	0.92358	(0.00368)	250.97300***
α_1	-0.04934	(0.08414)	-0.58640
α_2	-0.26931	(0.08467)	-3.18073***
α_3	0.12328	(0.16895)	0.72970
α_5	0.00707	(0.05139)	-0.13757
α_8	0.26028	(0.06469)	4.02351***
α_{10}	-0.55521	(0.06936)	-8.00472***
α_{11}	0.17262	(0.06251)	2.76150***
α_{12}	-0.57529	(0:03303)	-17.41730***
α_{13}	0.64106	(0.11332)	5.65711***
α_{14}	-1.06869	(0.05413)	-19.74300***
α_{15}	0.12468	(0.14890)	0.83734
α_{16}	-0.65906	(0.07130)	-9.24343***
α_{18}	-0.82732	(0.06042)	13.69280***
α_{21}	0.52563	(0.04980)	10.55480***
α_{22}	0.05991	(0.06468)	0.92627
α_{23}	0.49890	(0.05732)	8.70377***
α_{24}	-0.33457	(0.04298)	-7.78433***
α_{25}	0.82056	(0.05453)	15.04790***
α_{26}	-0.31995	(0.04574)	-6.99487***
α_{27}	-0.12876	(0.07595)	-1.69538*
α_{28}	−0.08700	(0.08852)	−0.98284
β_1	0.01730	(0.01746)	0.99071
β_2	0.03928	(0.01704)	2.30512**
β_3	-0.04176	(0.03599)	-1.16035
β_5	-0.00677	(0.01075)	-0.62950
β_8	-0.04744	(0.01300)	-3.64947***
β_{10}	0.09244	(0.01218)	7.58918***
β_{11}	0.00030	(0.01022)	0.02926
β_{12}	0.12916	(0.00636)	20.30850***
β_{13}	-0.17513	(0.02500)	-7.00539***
β_{14}	0.21131	(0.01115)	18.95170***

continued on next page

Table 7.3 continued from previous page			
β_{15}	-0.05903	(0.03174)	-1.85974*
β_{16}	0.09780	(0.01290)	7.58168***
β_{18}	-0.13144	(0.01130)	-11.63200***
β_{21}	-0.08338	(0.00915)	-9.11216***
β_{22}	-0.05241	(0.01213)	-4.32047***
β_{23}	-0.09788	(0.01121)	-8.73178***
β_{24}	0.07018	(0.00889)	7.89462***
β_{25}	-0.07042	(0.00878)	-8.02021***
β_{26}	0.06909	(0.00916)	7.54307***
β_{27}	0.02574	(0.01582)	1.62680
β_{28}	0.01306	(0.01822)	0.71661
Observations	55,206		
R^2	0.87499		
Adjusted R^2	0.87491		
Residual Std. Error	0.20631		
Note:	$*\,p < .1$ $\;\; **\,p < .05$ $\;\; ***\,p < .01$		

7.10.2 Map of Spatial Horizontal Inequity λ_s

This choropleth map in Figure 7.11 provides the horizontal inequity distribution for the market areas, λ_s, (i.e., weighted mean). A value indicating how close appraised value and observed sales price are for sales observations over all years. The varying colors represent appraised value's deviation from the weighted sales price. Darker colors reveal where appraisers were able to estimate properties, on average, close to their weighted sales price. Lighter colors reveal locations where, on average, appraisals were less than their weighted sales price. This could indicate a lack of fairness in terms of discounts to selected areas. Discounted areas seemingly include markets with relatively high and low house prices, conditions that are challenging to the appraisal process.

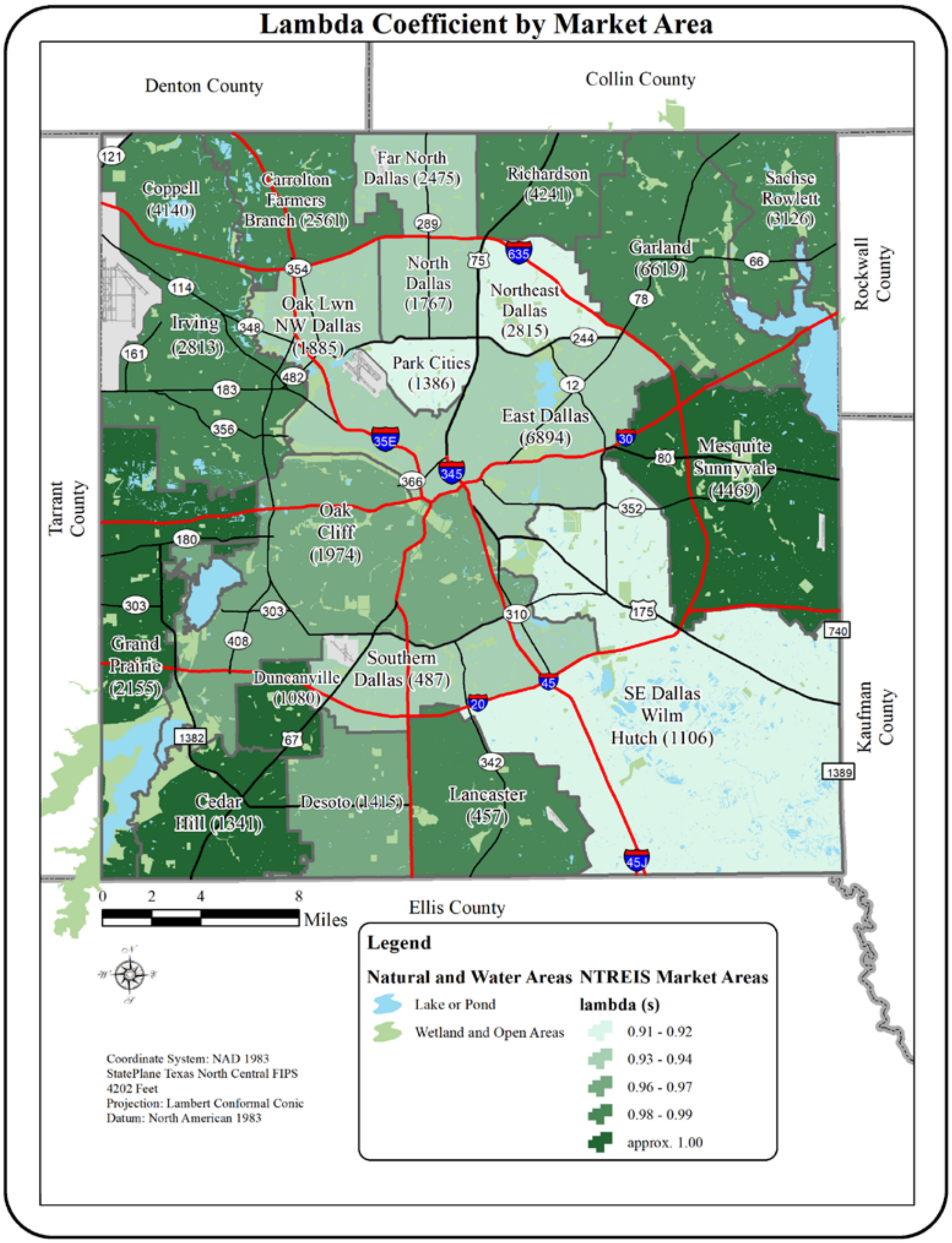

Figure 7.11. Map of coefficient, λ_s, indicating horizontal inequity across market areas.

Table 7.4. Spatial indicator coefficient sums and adjustment factor by market area

Market	Market Area	α_s	β_s	λ_s
Cedar Hill	1	-0.04934	0.01730	1.00
Carr-Farm Branch	22	0.05991	-0.05241	0.98
Coppell	21	0.52563	-0.08338	0.97
Desoto	2	-0.26931	0.03928	0.96
Duncanville	28	-0.08700	0.01306	1.00
East Dallas	12	-0.57529	0.12916	0.93
Far North Dallas	10	-0.55521	0.09244	0.94
Garland	24	-0.33457	0.07018	0.99
Grand Prairie	27	-0.12877	0.02574	1.00
Irving	26	-0.31995	0.06909	0.98
Lancaster	3	0.12328	-0.04176	0.98
Mesquite-Sunnyvale	5	-0.00707	-0.00677	1.00
NE Dallas	18	0.82732	-0.13144	0.92
North Dallas	11	0.17262	0.00029	0.94
Oak Cliff	14	-1.06869	0.21131	0.97
Oak Lwn-NW Dallas	16	-0.65906	0.09780	0.95
Park Cities	25	0.82056	-0.07042	0.91
Richardson	23	0.49890	-0.09788	0.98
Sachse-Rowlett	8	0.26028	-0.04744	0.99
SE Dallas-Wilm-Hutch	13	0.64106	-0.17513	0.92
South Dallas	15	0.12468	-0.05903	0.94
Total		0.00	0.00	

7.11 Spatial Vertical Inequity Curve Plots

For convenience in interpreting vertical inequity curve plots, they are grouped using box plot distributions of sales price in ascending order displayed in Figures Figure 7.7 - Figure 7.10. Four groups of low, mid-low, mid-high, and high-priced market areas follow the spatial model output in Figures Figure 7.12 - Figure 7.15. Here the gray bars representing $500,000 increments more easily assist the reader in determining the adjusted appraised value for its associated sales price because the smaller range of the x-axis facilitates visual intersections. The full range of x-axis values are presented in each of the panels. These vary depending on the sales distribution for each market area. As with temporal vertical inequity curve plots, spatial curve plots display intercepts and slopes that are sums of main and spatial effects equivalent to (α_s^*, β_s^*). Again, for simplicity, each spatial plot designates intercepts and slopes in the model parameters legend as α_0 and β_1 respectively.

7.11.1 Low-Priced Market Area Vertical Inequity Curve Plots

Figure 7.12 vertical inequity curve plots depict a regressive pattern with the lower priced markets having steeper curves. These results would indicate that the lower the house price, the more challenging the appraisal process. It is possible that there were fewer comparable sales for homes in the lowest price range. Another interesting pattern in this panel is the relationship that the increasing median house price has with the inflection point. With the exception of the South Dallas market area, all other inflection points increase with house price. Low inflection points indicate that greater house prices receive a greater benefit or burden whether the pattern is progressive or regressive respectively. It is also important to note, there is the gap between the inequity curve and the perfect equity line to the left of the inflection point. For regressive patterns in Figure 7.12, this gap indicates larger property tax burdens for homes on the lower-price spectrum of the population. These gaps appear greater for lower priced markets (e.g., SE Dallas-Wilm-Hutch and South Dallas); however, differences from the perfect equity line seem minimal. It also appears that the three lowest-priced markets have curves influenced by extreme observations.

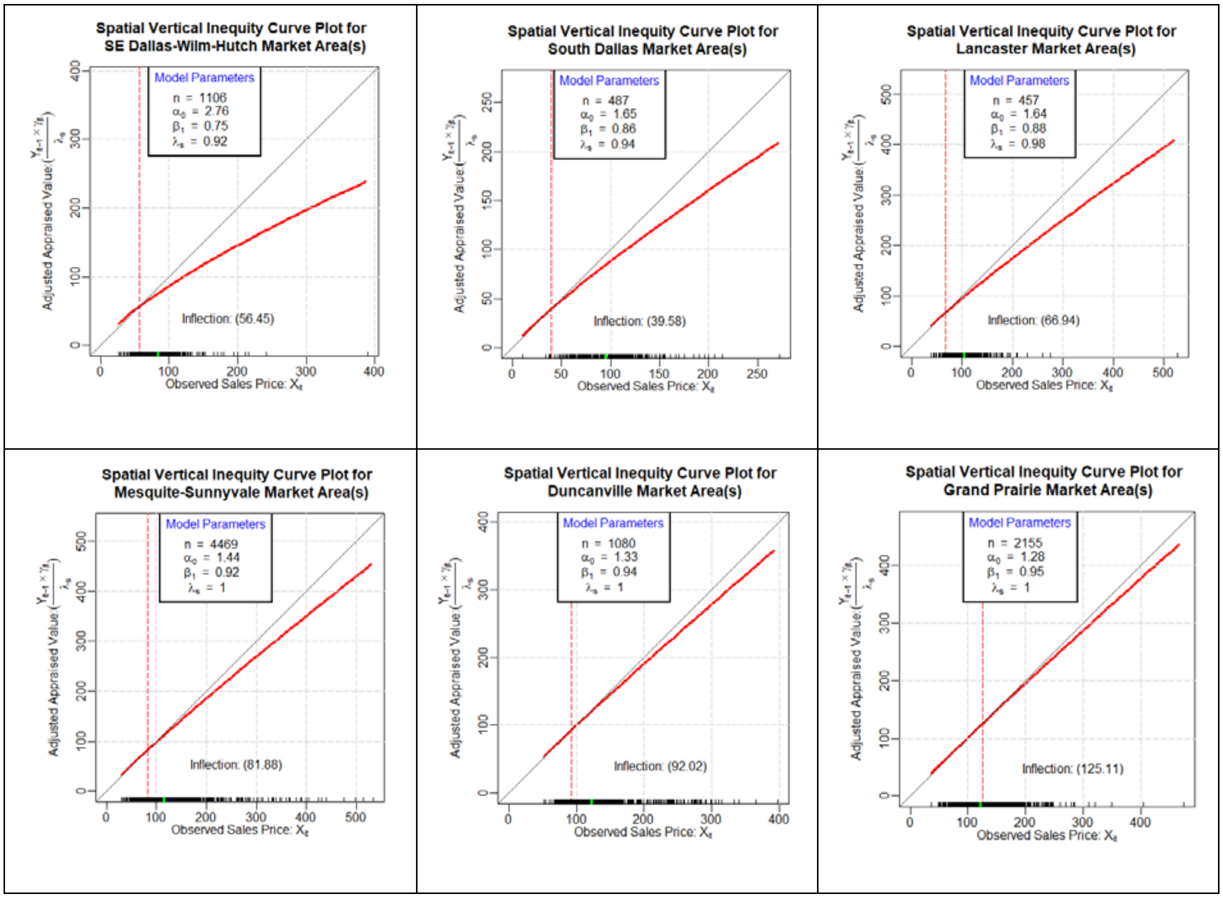

Figure 7.12. Low-priced housing market area vertical inequity curve plots.

7.11.2 Mid Low-Priced Market Area Vertical Inequity Curve Plots

Figure 7.13 results indicate a mix of equitable and regressive patterns. The Garland inequity curve is close to the perfect equity line. Sachse-Rowlett and Richardson markets have seemingly steeper curves.

7.11.3 Mid High-Priced Market Area Vertical Inequity Curve Plots

Figure 7.14 inequity curve plots have a mix of progressive, equitable, and regressive patterns. The Oak Cliff market has the majority of its observations below $500,000 which is defined by the gray dashed line in the plot. The difference between adjusted appraised value and sales price here may be \$10,000 or \$15,000 for homes in this price range. Beyond this price range, the curve indicates greater inequity.

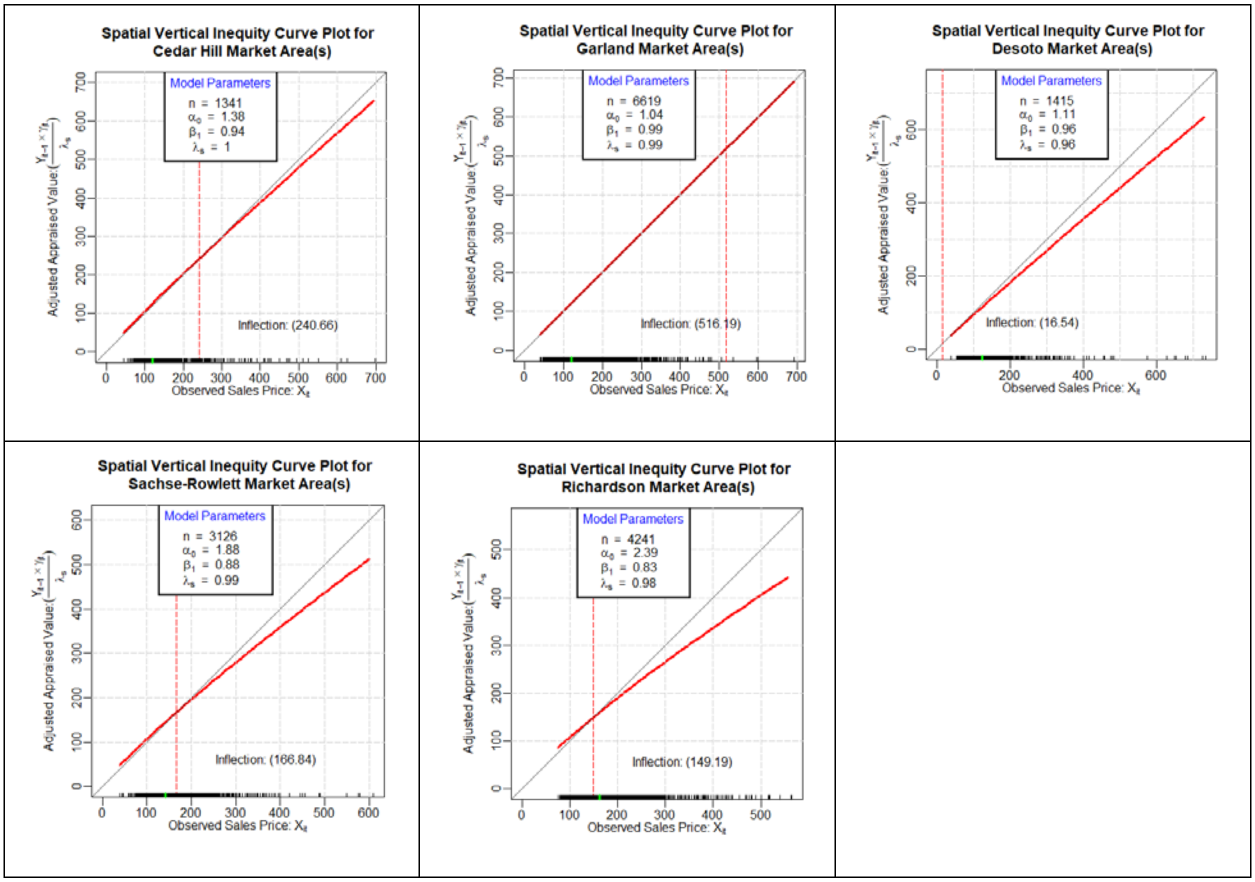

Figure 7.13. Mid low-priced housing market area vertical inequity curve plots.

This unique inequity pattern may be the result of heterogeneity of sales prices within the Oak Cliff market. Figure 7.16 displays a map highlighting the Oak Cliff market's heterogeneous sales distribution. Kessler Park, an affluent community in the heart of Oak Cliff, has high-priced sales that may influence vertical inequity curve estimates when compared with adjacent, low-priced homes. The Oak Lawn –Northwest Dallas market area does not have a visible inflection point visible because it exceeds the bounds of the horizontal axis.

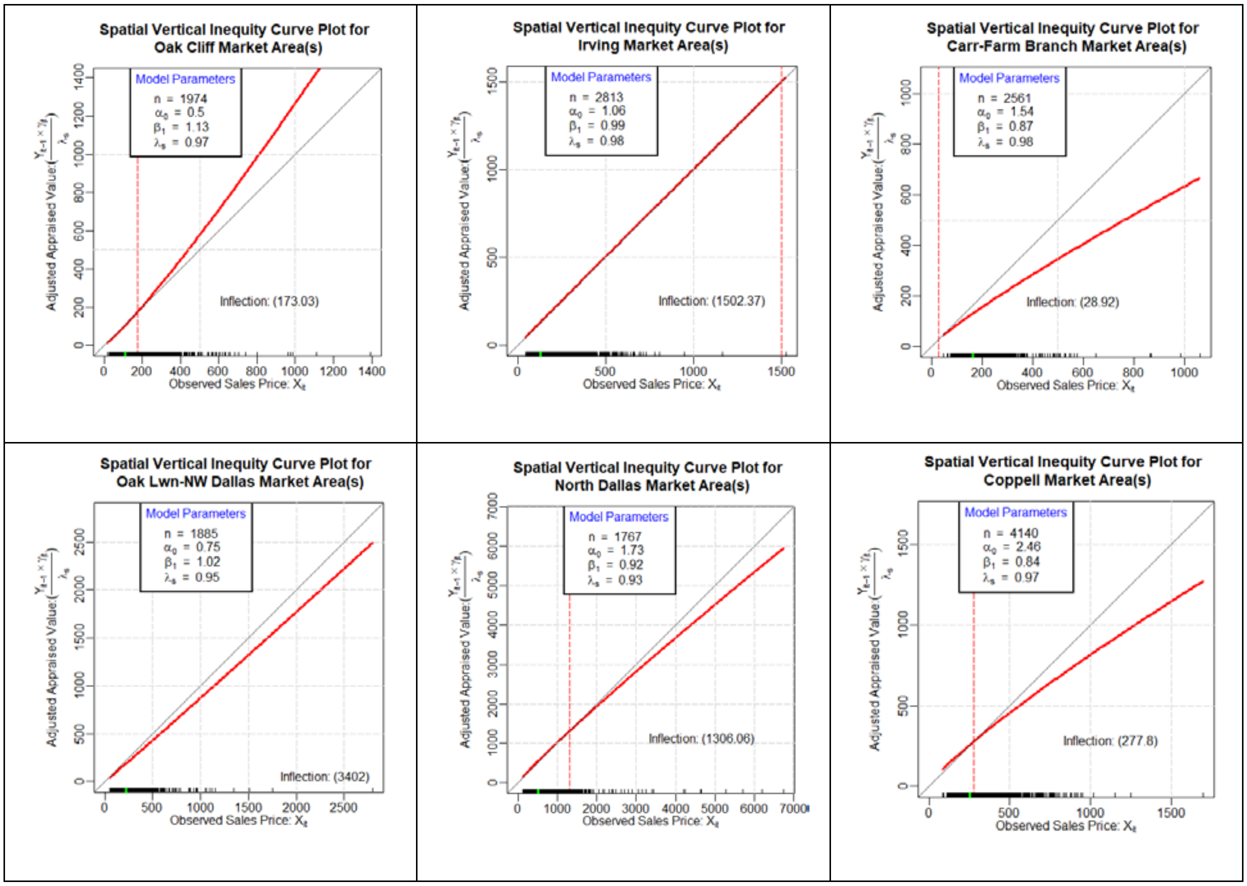

Figure 7.14. Mid-high priced housing market area vertical inequity curve plots.

7.11.4 High-Priced Market Area Vertical Inequity Curve Plots

Figure 7.15 also contains a mix of progressive and regressive patterns. Similar to the Oak Cliff market, East Dallas has a steep curve beyond the $500,000 delimeter. The housing market landscape is comparable to that of Oak Cliff because of the high-priced residences surrounding White Rock Lake and bordering the influential Park Cities area as shown in Figure 7.17. Lower-priced homes to the south and east may lead to market heterogeneity subsequently affecting inequity curves. The vertical inequity curve plot for the Park Cities market has the largest gap to the left of the inflection point for all curves. This may relate to the extremely high-priced homes to the right of the inflection point. This handful of sales are two and three times greater than observations in the lower three quartiles.

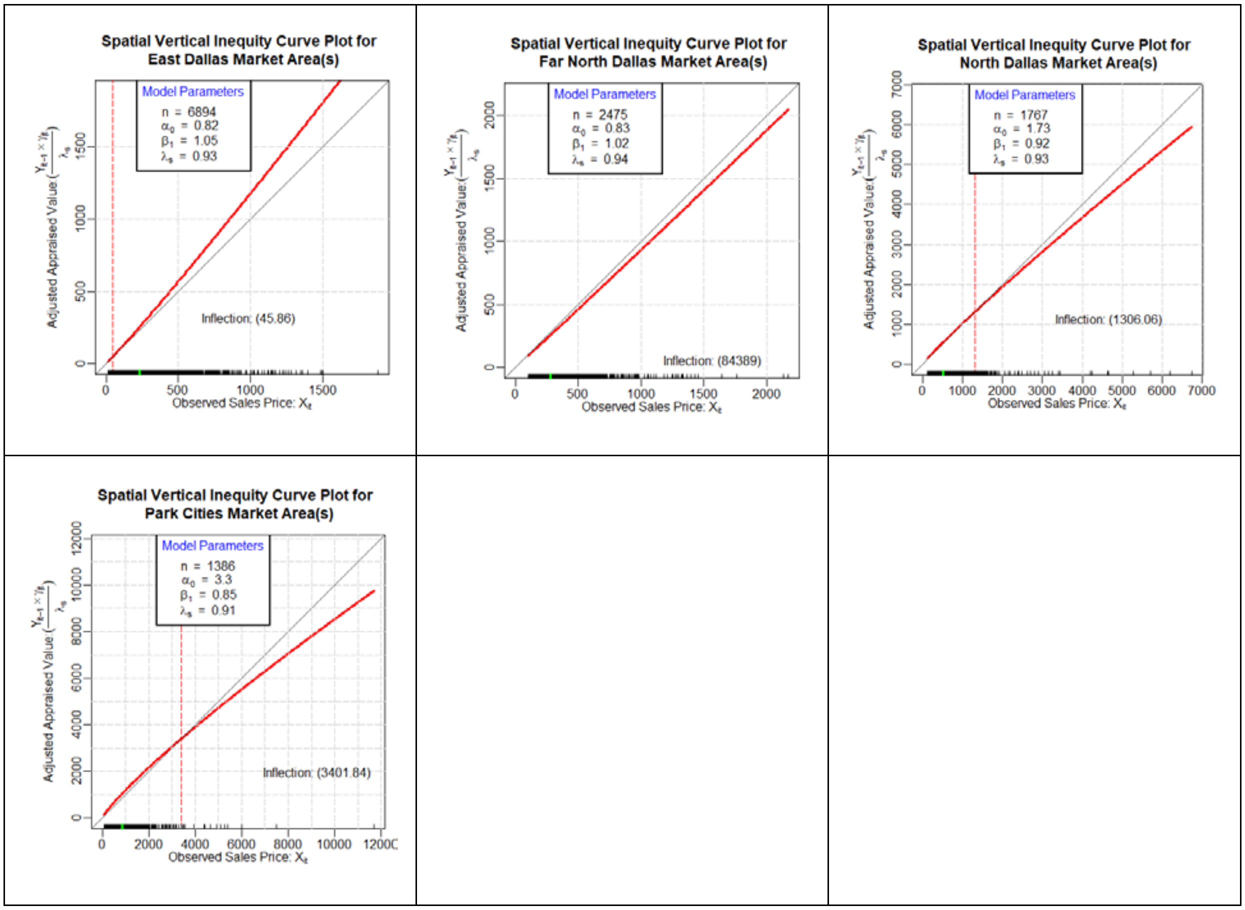

Figure 7.15. High priced housing market area vertical inequity curve plots.

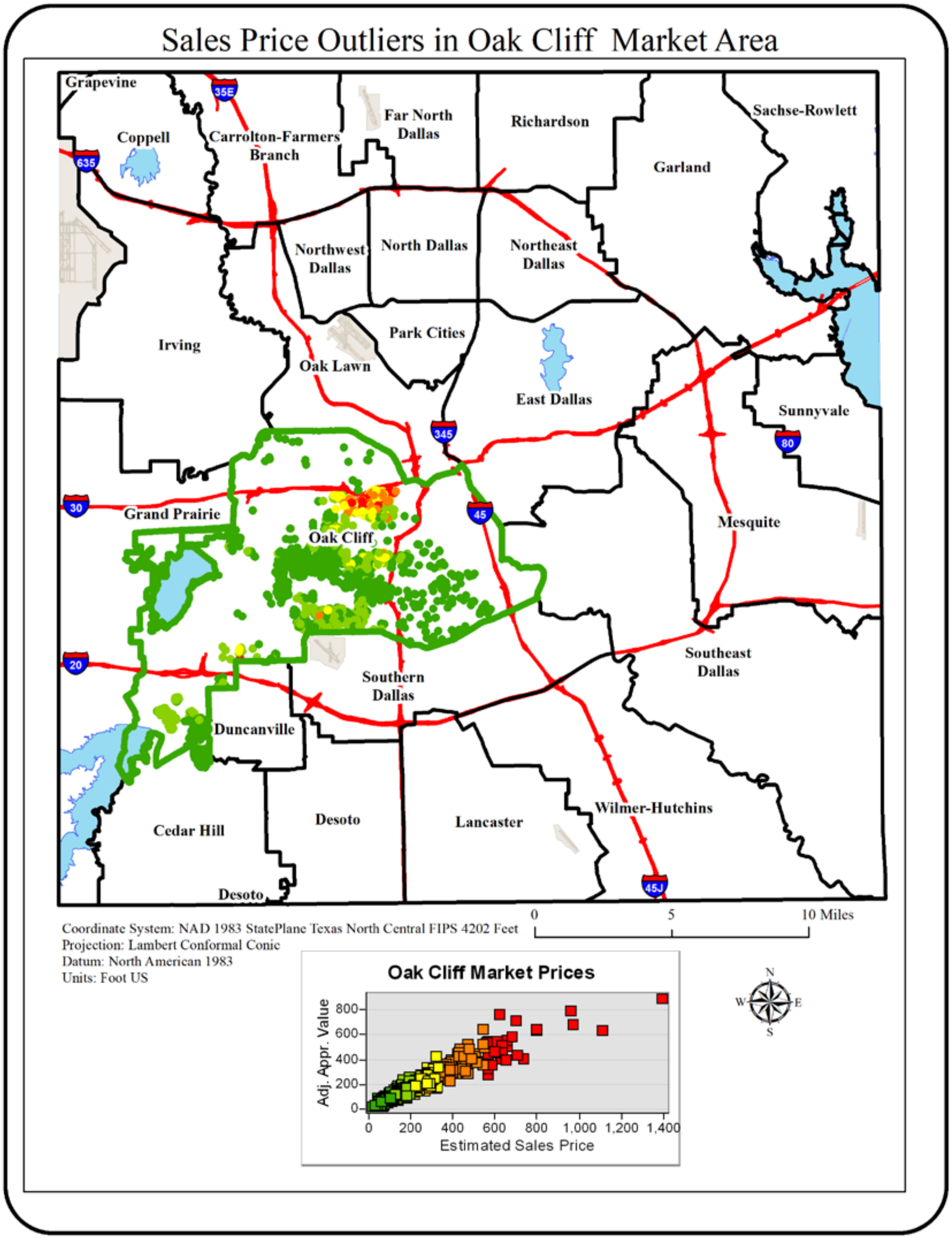

Figure 7.16. Map of NTREIS market areas highlighting the Oak Cliff market with sales observations color-coded by sales price. Higher-priced sales in the elite, Kessler Park area may distort vertical inequity curve estimates when surrounded by lower-priced sales.

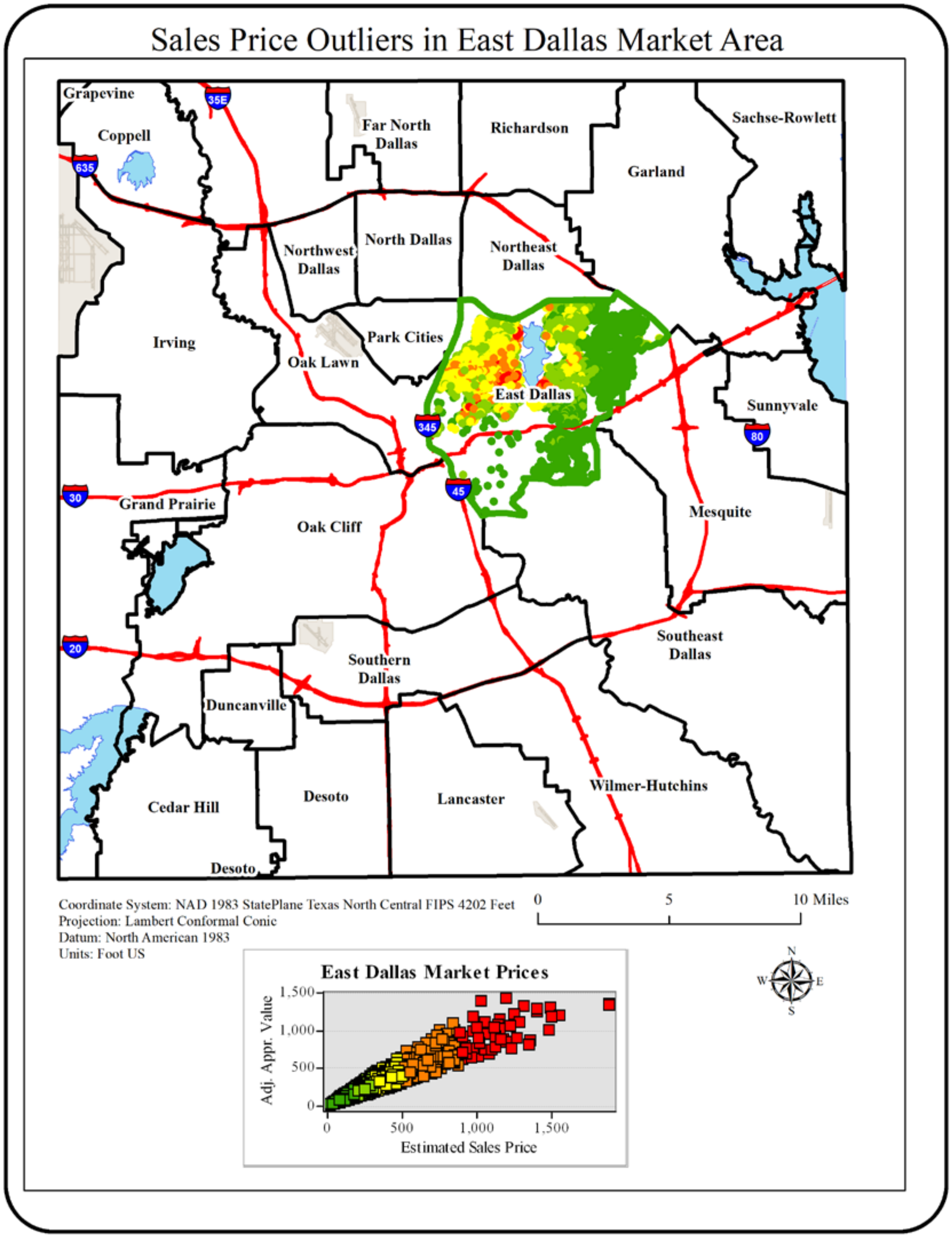

Figure 7.17. Map of NTREIS market areas highlighting the East Dallas market with sales observations color-coded by sales price. Higher-priced sales in surrounding White Rock Lake and the neighboring Park Cities introduce sales price heterogeneity with adjacent low-priced homes to the south and east.

CHAPTER 8

CONCLUSIONS

8.1 Summary of Findings

Despite few investigations in vertical property tax inequity during unstable economic periods, little research has explored the appropriate econometric methods for integrating stochastic endogeneity in these environments. Questions were identified in the literature regarding reliability of the commonly used approaches for estimating vertical inequity under uncertainty, and some inconsistencies were considered. This work tried to address these inconsistencies using a modified Cheng (1976) specification comprised of calibrated instruments explaining $\log(sales\ price)$ in Dallas County, Texas between $2004 - 2014$. This specification included an adjustment for horizontal inequity and contemporaneous sales prices on the dependent variable, $\log(lagged\ appraised\ value)$.

Chapter 2 reviewed literature and data sources discussing the housing market in Dallas County, Texas. Dallas County house price indices and market volatility indicators were obtained from various data sources and analyzed. House prices appreciated up until the recession period. Recession prices were only moderately volatile. Sales prices fell after the recession's official end in July 2009. Moderate supply and demand indicators, average days on the market, and total number of homes sold indicated semi-favorable housing markets. The opposite case was observed shortly after the recession. This post-recession housing market volatility foreshadowed concurrent, temporal vertical inequity patterns discussed in Chapter 7.

Upon establishing the definitions for assessed value and sales price in Chapter 3, the historical background behind current appraisal standards, rules, and governing entities was established. The need for such standards is highlighted by potential causes of uncertainty in assessed values. More such causes exist for sales price. Measurement error in both assessed value and sales prices translates into an “error-in-variables” problem (Cheng and Van Ness 1998, 3). This measurement error introduces potential biases into linear models and thus misleading conclusions of property tax assessment uniformity.

After reviewing the theoretical literature of horizontal and vertical inequity, regressivity and progressivity were illustrated in Chapter 4. Econometric theory supporting instrumental variables helps bring to light the utility of this method for vertical inequity estimation in the face of error-in-variables. The vertical property tax inequity literature identified an existing debate and other deficiencies. The first was in regards to grouping instruments for market value. Another related to frequently used approaches suffering from reverse causality (e.g., Kochin and Parks (1982) and Clapp (1990)). These weaknesses constitute a gap in the literature for addressing uncertainty in vertical inequity estimation. The methodology used for this research integrated three components used to fill this gap. These include (1) an instrumental variable comprised of hedonic house price variables, (2) diagnostics testing for weak instruments and endogeneity, and (3) a two-stage least squares specification that places market value indicators within the appropriate causal relationship. The approach used in (1) addresses the problem of omitted observations and ranked price variables. Methods applied in (2) and (3) assess instrument relevance and exogeneity, control for simultaneity, and correct the reversal of causality.

Chapter 5 summarizes and describes data sources for market value indicators. For evaluation purposes, a lagged appraised value was used and compared to subsequent sales prices.

In this case, the previous year's estimate, adjusted for current year change in average sales prices for the zip code, becomes the subject under evaluation. House price index adjusted, lagged, appraised value, compared with fitted values extracted from a reduced form equation of appropriate property characteristics were regressed on filtered sales prices. This approach improves the evaluation of appraiser estimates within the context of their uncertainty about future housing markets. Relevant data sources were categorized into the Sirmans, Macpherson, and Zietz (2005) taxonomy of single-family house price variables typically used in the real estate literature. Once categorized, variables were operationalized for inclusion in the preliminary hedonic model, initiated to identify potential instruments.

Preliminary hedonic model fit was improved through incremental variable transformation and residual analysis in Chapter 6. Estimates were comparable to similar specifications in the real estate literature for the study area. Hedonic model regressors were employed as instruments in the reduced form equation of the two-stage least squares specification. The sheer number of observations distorted the precision of hypothesis test results to the degree that vertical inequity was identified in every case. Considering the sensitivity of two-stage least squares methods to finite sample bias, the degrees of freedom were retained, precluding any determination of inequity through statistical inference. Furthermore, the appraisal industry has not identified appropriate thresholds of vertical inequity estimates (α_0 and β_1) for a two-stage least squares approach, preventing any appeal to industry standards. A graphical approach to vertical inequity identification, originally suggested by Cheng (1974), engaged an exponential curve to remedy these issues. Preliminary plots were seemingly flawed because systematic under-appraisal was identified. Incorporating horizontal inequity adjustments to the dependent variable improved vertical inequity curve presentation allowing for interpretation of change in appraisal estimates for each increasing dollar value of homes. Placing horizontal and vertical dashed lines at intervals supported visual identification of over- and under-appraisal. Additionally, the price at which property tax burdens shift from under-appraisal to over-appraisal and vice versa, was highlighted using an *inflection point* on the exponential curve. Global model diagnostic results indicated that instruments were relevant and the sales price variable was indeed endogenous. Exogeneity of instruments was difficult to test because of a flaw in the Sargan, J statistic test of over-identifying restrictions. Despite efforts to remedy a potential, many instruments problem, this test statistic's (i.e., $n \cdot R^2$) explicit dependence on the sample size n while having constant degrees of freedom casts doubt on reasonably relevant instruments in large sample studies. Global model vertical inequity curves indicated slight regressivity across the entire range of sales prices.

The global model was disaggregated into two additional specifications incorporating temporal and spatial indicators respectively in Chapter 7. Dummy variables constructed in the effect-coding scheme translated model output into deviations of temporal and spatial effects from main effects. Summing main effects with their respective temporal and spatial effects allowed individual, graphical plots to be produced for each study year and market area. Temporal model results were grouped by recession periods, facilitating comparison with reported, house price index movements in Chapter 2. Moderate progressivity and regressivity were reported before the Great Recession. During the recession, seemingly more regressivity was indicated for early years, exceeding the pre-recession period. Surprisingly, the final year of the Great Recession reported nearly perfect vertical equity. As indicated by increased volatility in house price indices, the post-recession period revealed greater vertical inequities between $2010 - 2012$. Vertical equity increased during the end of this post-recession period. As vertical inequity curves approached equity, inflection points are non-existent as in the case of the 2014 temporal, vertical inequity curve plot in Figure 7.5. A timeline revealed horizontal inequity estimates comparable to their vertical counterparts, with the exception of greater inequity occurring at the onset of the Great Recession. It is interesting to note that both horizontal and vertical inequity follow a similar volatile pattern over the study period.

Vertical inequity curve plots for each market and price group reveal regressive patterns in the low-priced category. While this group's regressive markets appear to be influenced by extreme cases, those in the mid-low group do not, suggesting a more systematic problem. The mid-high-priced group revealed a mix of regressive and progressive patterns with progressivity possibly stemming from extreme market heterogeneity. The high-priced group exhibits a similar inequity pattern to the mid-high-priced group possibly influenced by both market heterogeneity and extreme observations. The spatial distribution of horizontal inequity across the study area suggests markets, within mid-price groups, received less of a discount than low and high-priced groups. Some reasons for this may be greater homogeneity of housing stock, richer comparable sales, and lower incidence of unique features in these markets.

8.2 Policy Recommendations

Findings from this research are beneficial for both the academic and the professional communities. They introduce insights that reveal an improved approach to vertical inequity estimation. Additionally, the information is useful to agencies and stakeholders concerned with vertical and horizontal property tax inequity. Temporal model results reveal that market volatility does influence vertical inequity. Stable markets produce less inequity; however, some inequity is still evident. Assessors and those with oversight should agree on an acceptable threshold for vertical inequity for two-stage least squares estimates of α_0 and β_1 as it is unlikely that any housing market and appraisal district will be completely free from some degree of inequity. It appears that greater volatility and lower house prices increase inequity. During periods of extremely depressed house prices, additional efforts should be made to ensure that every possible market transaction is obtained and verified with an additional source. Some third party vendors sell this information at a reasonable cost making transaction validation possible. Additionally, market heterogeneity is of concern. Market area vertical inequity estimates should account for any market heterogeneity in areas where low house prices are adjacent to high house prices. Finally, markets with steep vertical inequity curves with strong positively skewed distributions of home values should receive further investigation. These include markets influenced by hundreds of properties contributing to inequity estimates rather than just a handful of observations. Lastly, an appraisal district must work diligently to achieve a homogenous spatial distribution of horizontal inequity estimates to avoid disadvantaging their clientele in specific market areas

8.3 Limitations

While this research has introduced some meaningful contributions to addressing uncertainty in vertical property tax inequity estimation, there are some limitations. These limitations include sample size issues and market heterogeneity.

Large sample size introduces two issues. The first relates to the power and size problem in statistics. A fine line exists between selection of a "critical region" that controls type I error and diminishes the probability of a type II error at a given effect size (Miller and Miller 2004, 377). To increase the sample size and avoid finite sample bias one runs the risk of emphasizing statistical significance over the practical relevance of the results. One possible approach to overcome this problem is to adjust all standard errors to reasonable small hypothetical sample size. Another problem related to sample size is the reliance of the Sargan J statistic on the sample size n. Larger sample sizes increase the probability of a rejection of the null hypothesis that instruments are exogenous. The sample size problem has been ignored in the econometric literature. Concerns over this statistic's reliability causes this study's exogeneity diagnostics to be questionable, despite favorable results from other relevance and exogeneity tests. Until researchers identify and empirically validate a viable test for instrument exogeneity, it is unclear if this study's vertical inequity estimates are unbiased.

The approach of using the predicted log sales prices from the global instrumental variable model in the temporally and spatial disaggregated models is somewhat *ad hoc*. A conceptually more sound approach would have been to add spatio-temporal indicator variables in the structural form estimation during the second stage of the two-stage estimation procedure. However, in doing so one would have introduced statistical interaction terms between endogenous regressors, such as the log sales price, and the indicator variables. Ultimately, this would have led to an endogenous interpretation of the indicator variables, which is counterintuitive because the time and location of sales almost certainly are recorded error-free.

Market areas used in this study may suffer from sales price heterogeneity. High-priced homes within a market area may demonstrate a specific vertical inequity pattern that is influenced by a large number of low-priced observations. When observed within their own group, a completely different vertical inequity pattern may be presented. Two study markets exhibited this problem where pockets of low and high-priced homes were concentrated within the same area.

8.4 Future Research

Major avenues for future research include selection of appropriate hedonic house price variables and generalizing instrumental variable specifications. While a novel approach to amenity value was employed for this study, further investigation is required for estimating recreational opportunity scores appropriately. Examples include unique estimation for lakes, parks, trails and recreational facilities. An appropriate improvement would include an inventory of how homeowners favor different amenities over others. In other words, how much more desirable is a lake in a nearby location compared to a trail or park. The appropriate means for measuring this appeal would also be beneficial. For convenience, this study's cutoff distance for recreational amenities was five miles. A useful investigation may involve empirical analysis of appropriate walking or driving distance thresholds relating to amenity size and type. For example, it would be interesting to identify how much further residents are willing to drive for large parks with a fishing pond compared to small neighborhood parks with only playground equipment. Considering the vast literature on the subject of real estate characteristics, there may be additional variables to include in the hedonic house price model. Some examples include walkability score (Duncan et al. 2011; Rauterkus and Miller 2011), air quality (Anselin and Le

Gallo 2006; Carriazo and Gomez-Mahecha 2018), and crime density (Lynch and Rasmussen 2001; Gibbons 2004) to name a few.

Another avenue of potential research is the generalization of this study's two-stage least squares approach into the spatio-temporal realm. This approach was not feasible for the current study because of the insufficient sample size. Advancing the temporal and spatial models to a simultaneous, spatio-temporal specification could enrich inequity insights for individual markets over each period. To do this, the number of observations would need to be adequate to support the concept of spatio-temporal horizontal and vertical inequity. Examples of these horizontal and vertical inequity coefficients are presented in (8.1), (8.2), and (8.3). Here, λ_{ts}, α_{ts}, and β_{ts} represent horizontal and vertical inequity (both α_{ts} and β_{ts}) respectively at period t and market area s where $t = 1,2,3, \dots, T$ and $s = 1,2,3, \dots, S$.

$$\begin{bmatrix} \lambda_{11} & \lambda_{12} & \lambda_{13} & \cdots & \lambda_{1S} \\ \lambda_{21} & \lambda_{22} & \lambda_{23} & \cdots & \lambda_{2S} \\ \lambda_{31} & \lambda_{23} & \lambda_{33} & \cdots & \lambda_{3S} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \lambda_{T1} & \lambda_{T2} & \lambda_{T3} & \cdots & \lambda_{TS} \end{bmatrix} \tag{8.1}$$

$$\begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} & \cdots & \alpha_{1S} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} & \cdots & \alpha_{2S} \\ \alpha_{31} & \alpha_{23} & \alpha_{33} & \cdots & \alpha_{3S} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \alpha_{T1} & \alpha_{T2} & \alpha_{T3} & \cdots & \alpha_{TS} \end{bmatrix} \tag{8.2}$$

$$\begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \cdots & \beta_{1S} \\ \beta_{21} & \beta_{22} & \beta_{23} & \cdots & \beta_{2S} \\ \beta_{31} & \beta_{23} & \beta_{33} & \cdots & \beta_{3S} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \beta_{T1} & \beta_{T2} & \beta_{T3} & \cdots & \beta_{TS} \end{bmatrix} \tag{8.3}$$

Identification of appropriate market area boundaries within the study area is needed. While the markets used in this study were published recently, the vintage of their delineation is unknown, as is their application to Dallas County, Texas house prices today. The literature is replete with empirical research delineating and defining housing markets (Islam and Asami 2009). Further research into variables explaining vertical inequity would also be of benefit to the property tax assessment literature. Such findings would be of great value to assessors, oversight agencies, and others striving to improve assessment uniformity.

APPENDIX A

PROPERTY TAX ASSESSMENT AT DCAD

To understand the methods of data collection and analysis an understanding of general procedures for property tax assessment within DCAD is essential. The following section outlines the assessment process, the mass appraisal model, the appraisal review board and certification of appraised values.

A.1 The DCAD Mass Assessment Process

DCAD assesses values for commercial, residential and business personal property within Dallas County, Texas. Taxing entities such as municipalities, public hospitals, community college districts, special districts (e.g., road utility or water reclamation districts) and independent school districts rely on assessment jurisdictions for accurate appraisal of taxable property. These entities determine tax rates sufficient for public service provision based on revenues generated by assessed value totals within their jurisdiction. For the purposes of this research, residential properties (i.e., single-family residences) will be the type of taxable entity under study. Judicious analysis of assessment values and their relation to sales prices requires an understanding of the DCAD assessment workflow. Property tax assessment at DCAD entails the use of state and federally mandated procedures in conjunction with statistical analyses for the derivation[35] of an opinion of value of a residence. The process[36] for the valuation of residential property within

[35] For a summary of the commonly accepted methods for appraisal of property see A.5.

[36] For a timeline of DCAD's assessment year and important dates during the valuation process, see Figure C.1. For an overview of the mass appraisal workflow, see Figure C.2.

DCAD's assessment jurisdiction begins in early August (DCAD 2018a, 66). Municipalities typically require developers, builders and homeowners with the intention to build improvements for commercial or residential real estate purposes to submit building permits. The residential assessment department divides its work among 15 assessors assigned a particular territory within the jurisdiction. Remaining assessment staff receives assignments in any territory as needed. Assessors visit municipalities within their territories to collect copies of building permits. They review the status of completion of the improvement as well as its housing characteristics to derive a value. This value is an estimate of market value as of January 1st. Any property that is not 100% complete by that date will receive a value estimate in proportion to its level of completion. Permit review continues until January 15th to ensure that all permits applicable to the January 1st deadline are received and processed. The residential department begins preliminary neighborhood sales analysis in the middle of October. This analysis includes the processing of properties that have sold within 18 months[37] before the January 1st deadline. During this phase, assessors identify neighborhoods with sales activity indicating assessment ratios that are outside of the 0.90 and 1.15 interval. Ratios outside of this critical range may be indicative of measurement error and require time to investigate the cause of the extreme proportion. Phase two (i.e., second Pass) involves the neighborhood level analysis of assessment ratios between 0.95 and 1.05 (DCAD2018a, 27). Phase 3 is a review and update of neighborhoods selected during Phase 1 applying newly acquired sales. Neighborhoods identified undergo two forms of reappraisal: 1) Conventional and 2) Programmatic. Conventional reappraisal involves

[37] There are diverse opinions on how sales influence varies with time. See Table C.1 for these time windows (Reese 2013).

information gathering and update of property characteristics[38] through on-site inspection. Typically, this form of reappraisal includes every residence within a neighborhood. Programmatic reappraisal employs information gathering and update of property characteristics through using geographic information systems and aerial photography. When an appraiser finds outliers using in-house assessment ratios these will be inspected on-site. The rest of the neighborhood will then be reviewed using an in-car inspection. Local amenities are identified and new location factors[39] calculated. Independent of neighborhood analysis and building permits there are additional criteria that may illicit the physical inspection of a property within the DCAD jurisdiction. If a taxpayer makes an inquiry, outside of the ARB period[40], concerning their property, such that it warrants an appraiser's physical inspection, an update of the appropriate information is possible. Occasionally, properties are damaged (e.g., fire, natural disaster) and such an occurrence necessitates the inclusion in appraisal records. Properties may be included on the assessment roll via rendition as well as deed or building permit. A rendition is a formal statement by a property owner of the existence of taxable property within the assessment jurisdiction. Such statements make it possible for owners to enroll their property into the county appraisal process. State law requires properties to be assessed every three years. A record of the next revaluation year$(t+3)$, where t is equal to the current year in which the property is assessed, is retained for each property on the assessment roll. If a property has the

[38] See Table C.2 for a list of typical property characteristics and their meaning.

[39] A *building class location factor* (BCLF) is a corrective quantity calculated based on current sales within a neighborhood and applied to all properties in the same neighborhood by building class. This variable captures the market influences of the period and specific location of the neighborhood (DCAD 2018a, 15).

[40] For a discussion about the Appraisal Review Board (ARB) see A.3.

next revaluation year listed as the current appraisal year, then the property will be reviewed, either conventionally or programmatically, depending on the opinion of the appraiser.

A.2 The Mass Appraisal Model

Shortly before the mailing of notices of assessed value, all properties undergo a mass appraisal estimation. This algorithm makes mass appraisal possible, since the manual estimation of all properties within the assessment jurisdiction on an annual basis would be beyond the scope and resources of nearly any assessment jurisdiction. The outcome variable of the algorithm is *market value* (MV) or the assessor's opinion of value based on procedures mandated at the federal and state levels. Other elements of the algorithm include *land value (*LV), *replacement cost new* (RCN), *business class location factor* (BCLF) and *depreciation* (D)[41]. First RCN is added to BCLF and the sum is subtracted by D. The result is then added to the LV variable. This calculation is performed on all properties within the assessment roll whether they experienced a change in attributes during the assessment year or not.

A.3 The Appraisal Review Board

Following these phases of the assessment cycle, a notice of appraised value is mailed to the taxpayer[42] . Upon receipt of this notice[43], taxpayers have a legal right to protest[44] the proposed

[41] For a discussion about how land value, replacement cost new and depreciation are derived, see Appendix A.

[42] Taxpayers are notified of assessed value by DCAD if there has been a change in ownership or the property has entered the assessment roll as a new taxable account. In addition, there must be an indication that the market value of the property has increased or that the residential account had a capped value applied in the previous tax year. Renditions filed for the assessment year also merit notification (DCAD 2018b, 17).

[43] Since legislation in 2011, taxpayers residing within an assessment jurisdiction where the population exceeds a half million have the option to retrieve an electronic notice of assessed value. See section 41.415 of the State of Texas property tax code.

[44] See section 41.41 of the state of Texas property tax code.

value during the Appraisal Review Board (ARB). A protest may be filed online, through a protest form or through a written protest letter. These submissions must including the owner's name, account number and reason for protest. There are nine possible reasons[45] for protest that may be provided on these submissions. To file a protest hearing, the form must be filled out and submitted on or before May 31st . Alternatively, a protest is properly scheduled at DCAD when the homeowner submits an application within thirty days of their receiving an appraisal notice. Informal meetings are available with a DCAD appraiser until May 31st. Personnel familiar with assessment practices at the jurisdiction make every attempt to meet informally with taxpayers to answer questions and come to agreement on derivation of the value of the property in question (DCAD 2018b). When visiting the appraisal district to protest a property value the owner is required to provide substantial evidence to remedy and discrepancy of value and must adhere to the standards proposed by DCAD[46]. If an informal meeting does not result in both the taxpayer and the appraiser agreeing upon the value of the subject property, a formal ARB hearing is an available option. Before a taxpayer enters the hearing, they must present themselves at the ARB waiting area and have their evidence scanned. This scanned evidence is made available to all participating in the hearing. Then, taxpayers and appraisers participating in the hearing sign a sworn testimony affidavit of the truthfulness of the arguments and evidence presented. This board consists of a panel of three unbiased[47] real estate professionals with knowledge relative to the housing market within the assessment jurisdiction. Upon entering the hearing room, the rules

[45] For a list of protest reasons, see Figure C.3.

[46] For a list of examples of substantial evidence reflecting the market value of a subject property, see Figure C.4.

[47] For a list of selection criteria for ARB board members see (Hegar 2018a, 5).

pertaining to the following events are explained. Board members consider the arguments of the taxpayer weighed against a defense[48] by knowledgeable assessment personnel to justify a decrease in property value. The panel may then ask questions, if necessary, to make a fair judgment based on the evidence. Three votes are made as to the verdict and the majority vote wins. The panel chair announces the final determination or verdict. The final determination is then sent via certified mail to the taxpayers address on record (DCAD 2018b, 9).

A.4 Certification of the Assessment Roll

Fulfillment of all informal and scheduled hearings precedes certification of the assessment roll. All properties assessed within the jurisdiction are given a certified value on July 25th or before mandated by state law. Any property that is in dispute may be updated on the appraisal roll later. The appraisal district publishes certified assessment values on the website for taxpayers and the public to use for their own purposes.

A.5 Appraisal of Improvements

This section describes the different methods of appraisal for real estate structures. These methods include the cost, income and market data approach to appraisal.

A.5.1 The Cost Approach

The cost approach to appraisal is the most commonly used method by appraisers to place an estimate on the value of a property. This method is based on calculating the land as vacant and

[48] Both taxpayer and appraiser have five to seven minutes to present their evidence.

then the replacement cost of a new improvement (i.e., building or structure on the subject property) based on cost estimates for materials normalized for the location they are typically purchased. One typical manual used for this purpose is the Marshall and Swift handbook[49]. DCAD updates these cost estimates slightly based on local knowledge. Once the land values and new replacement costs are derived, the percentage of depreciation of the improvement must be calculated. DCAD uses a condition/effective age quantity[50] based on the subjective quality of the dwelling based on various physical and environmental factors. The selection of a condition for the property is a subjective judgment made by the appraiser. These judgments are based on physical, functional, and economic obsolescence. Physical obsolescence applies to the structural integrity of the improvement. If there defects or repairs required and features are wearing out the value of the home is reduced. Functional obsolescence applies to the logical utility of housing features rather than physical utility. For example, in older homes one bath would be a normal occurrence. Today, a single-family dwelling with only one bathroom would not be desirable. Economic obsolescence refers to changes in the environment that impact the value of the home (i.e., spillovers). This might include an airport being built close to a residential subdivision. The value of the homes in the neighborhood may suffer from increased noise and pollution spilling over from the air traffic. This may be a subjective assumption given that other home buyers may prefer having an airport transportation hub close by (Jacobus 2012, 369). Depreciation is

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[49] A description can be found at: < http://www.marshallswift.com/p-39-residential-cost-handbook.aspx>.

[50] See Table B.1 for an example of depreciation percentages.

subtracted from the new replacement cost of the improvement with the final result being added to the value of the land (Jacobus 2012, 367).

A.5.2 The Income Approach

The income approach to appraisal is typically used for income producing properties not intended for occupation by the owner. Rental properties of single-family dwellings do not fall into this category. Town homes, condominiums and apartment buildings are subjects for this method of estimation. Values for such dwellings are estimated using Gross Rent Multiplier (GRM) and Direct Capitalization Methods (DCM) not applicable to the unit of study for this research.

A.5.3 The Market Data Approach

This method of appraisal may be used with a sufficient amount of sales within a neighborhood warrant their use in determining a reasonable estimate of value. A typical single-family dwelling may reside in a neighborhood with n number of comparable sales occurring with any period before the date of estimation of the property value. An appraiser wishing to use this method of estimation will select three to five properties that have sold within the statutory time limit that are comparable in various features to the subject property. Any differences from the subject property are identified and adjustments made to comparable features by dollar amount. Once adjusted, a subject weight is applied to all comparable sales based on similarity to the subject property. After weighting, the cumulative total of adjusted prices represent an “indicated value” which may be rounded to the nearest thousand depending on the final estimate (Jacobus 2012, 356–58).

A.5.4 Appraisal of Land

Using this approach, land is divided into value objects called land sections. One property may have more than one land section that differs by various features (i.e., topography, scenery, or environmental factors). These features[51] may render the land uninhabitable, unable to support a building structure or undesirable. Just as improvements, land may also have comparable sales or *land sales* that help derive value based on a sale vacant land only. Land is durable (i.e., it is indestructible) and does not depreciate over time as structures do (Jacobus 2012, 31). Since land is durable, the cost approach to appraisal is not viable. Certain exemptions apply for land used for agricultural purposes. Land may be valued through several various approaches: 1) flat price, 2) front foot, 3) square foot and 4) acre pricing. The flat price approach to valuing land takes the value of the lot as a whole and not in a per unit pricing scheme. The front foot method considers the width of the property in estimating a value. The square foot and acre methods provide a means of calculating value based on a price per square foot or acre scheme respectively.

[51] See Table C. for a list of features recorded by appraisers when inspecting land.

APPENDIX B

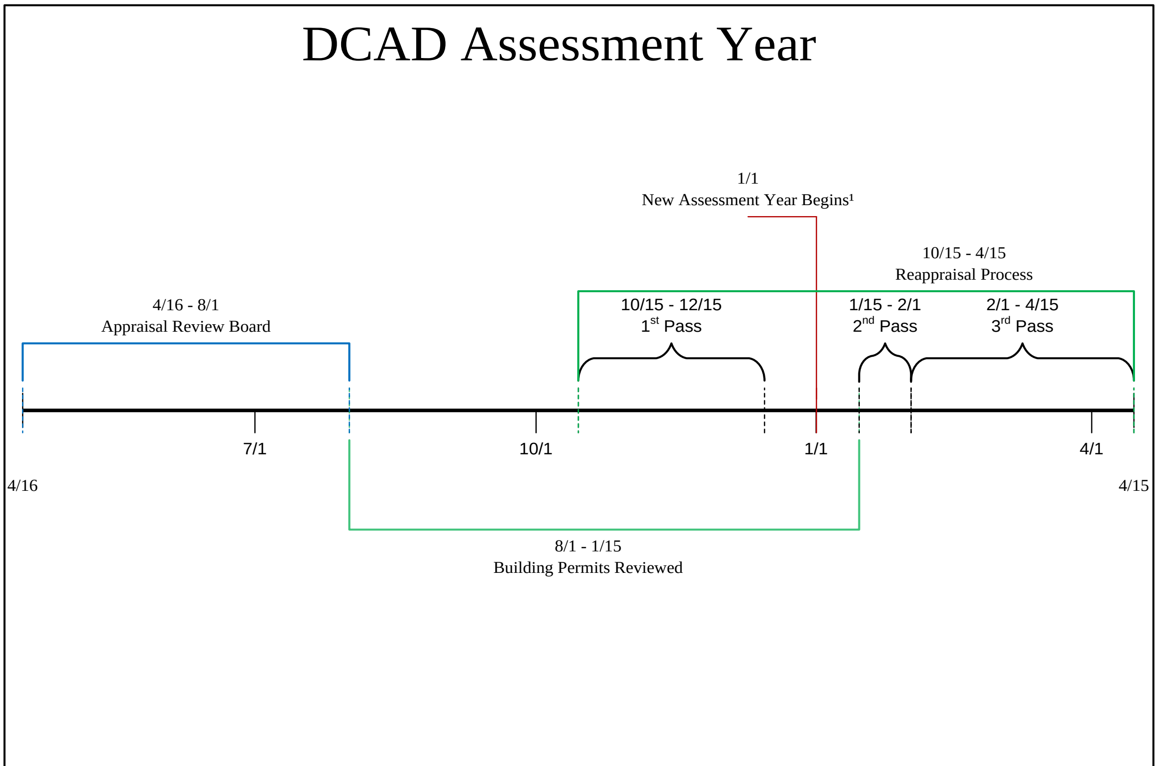
AGE-LIFE DEPRECIATION TABLE

Table B.1. Age-life depreciation table.

Effective Age	Condition, Desirability, and Utility (CDU) Rating							
	Excellent (E)	**Very Good (V)**	**Good (G)**	**Average (A)**	**Fair (F)**	**Poor (P)**	**Poor (R)**	**Undesirable (U)**
0-3	0%	3%	5%	10%	15%	20%	25%	40%
4-8	3	5	10	15	20	25	30	45
9-13	5	10	15	20	25	30	35	50
14-18	10	15	20	25	30	35	40	55
19-23	15	20	25	30	35	40	50	65
24-28	20	25	30	35	40	50	60	75
29-38	25	30	35	40	50	60	65	80
39-49	30	35	40	45	55	65	70	85
50+	35	40	45	50	60	70	75	90

APPENDIX C

ASSESSMENT TIMELINES AND PROCESS



¹The state of Texas property tax code (23.01a) requires appraisal districts to assess all taxable property in proportion to its market value within their respective jurisdictions by January 1 of each year.

Figure C.1. The process of appraisal and review during DCAD's assessment year.

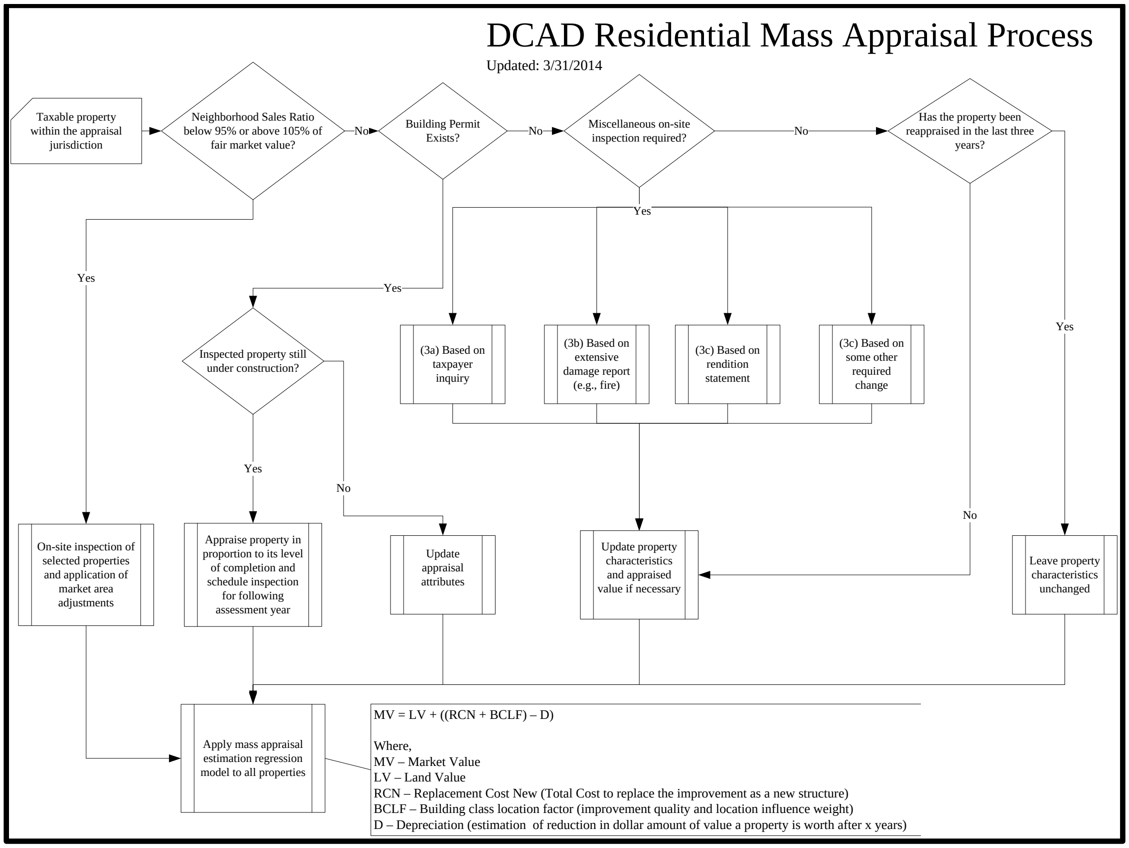


Figure C.2. DCAD's workflow for the appraisal/re-appraisal of a residential property.

Table C.1. Time windows specified by various oversight agencies based on duration of sales influence.

Agency	Time Window of Sales Influence
Property Tax Assistance Division	12 months
University of Texas at Dallas	30 months
Appraisal Foundation	15 months
Dallas Central Appraisal District	18 months

DALLAS CENTRAL APPRAISAL DISTRICT
APPRAISAL REVIEW BOARD (ARB)
NOTICE OF PROTEST FOR
2014

Return Address:
COMMERCIAL DIVISION
P.O. BOX 560448
DALLAS, TX 75356-0448
(214) 905-9406

To be entitled to a hearing and determination of protest, a property owner must file a written Notice of Protest with the ARB. Please review the Information below and make any necessary corrections.

MUST BE POSTMARKED BY U.S. POSTAL SERVICE OR RETURNED ON OR BEFORE: **June 02, 2014**

Account: 00000776533000000
DALLAS CENTRAL APPR DIST

2949 N STEMMONS FWY

DALLAS, TX 752476102

Property Address:
2949 N STEMMONS FWY
Legal Description:
BLK 7910
TRS 19,20 & 21 ACS 4.011

SOUTH OF STEMMONS FWY

It is my desire to file a protest based on the issue(s) checked below. Also, I understand that the Appraisal Review Board (ARB) must notify me of any hearing not later the 15th day before the date of the hearing pursuant to Section 41.46 of the Property Tax Code. The Chief Appraiser is also required by Section 41.67 to inform me at least 14 days before the scheduled hearing of the availability of data, schedules, formulas and other information the Chief Appraiser plans to present at the hearing, and that I may inspect them and obtain copies of them at the offices of the Appraisal District. It is my desire to protest based on the following issue(s) and I have checked the applicable boxes:

- ☐ Value is over market value
- ☐ Value is unequal compared with other properties
- ☐ Property not located in district
- ☐ Exemption was denied or cancelled (Specify ____________________)
- ☐ Ownership is incorrect (Specify ____________________)
- ☐ Ag-use: Change in use of land appraised as agricultural-use, open space, etc.
- ☐ Ag-use: Open-space or other special appraisal denied or cancelled.
- ☐ Property should not be taxed in district or in one or more taxing units
- ☐ Other (Specify ______________________________________)

If you wish to expedite your hearing, waiving the required deadline date under Section 41.46 and 41.67 of the Property Tax Code, please check the following box: ☐

Signature of Owner (or Agent)	Date Filed	(Agent Registration No., if applicable)
Printed Name	Daytime/Cell Phone No.	Fax No./E-Mail Addresses

Additional property that is subject for protest may be listed and attached.

Figure C.3. Protest form required to appeal the value of an owner's property. The owner must find their property with the search tools on the DCAD website to request a protest.

STANDARDS OF DOCUMENTATION
EVIDENCE FOR INFORMAL/FORMAL HEARINGS

Informal hearings will be between an appraiser of the Dallas Central Appraisal District (DCAD) and the property owner. Please provide copies of all evidence to the Appraisal District's appraiser. An original copy of all evidence will be maintained for the official public record.

RESIDENTIAL REAL ESTATE

1. **Sale of Subject Property**
   A signed and dated closing statement is required, if sold during the last 3 years. The closing statement should include a description of the property being transferred. A copy of the sales contract and the instrument number of the recorded deed filing is required in some cases. Photographs of your property are also good forms of evidence.

2. **Sales of Comparable Properties**
   Sales of comparable properties with photographs should include the following information, if available: 1) property address; 2) sales date/sales price; 3) grantor/grantee; 4) instrument number; 5) financing terms/source/confirmed by; and 6) appraisal of subject property, date and reason for sale.

3. **Proof of Physical, Functional or Economic Obsolescence**
   This type of information can be documented in a variety of ways. The best types of documents are usually estimates for repairs from contractors and photographs of physical problems. All documentation should be signed and attested. This means you must furnish "documented" evidence of your property's needs.

4. **The following evidence should be provided concerning inequality of Appraisal issues:**
   The appraisal ratio of the property is more than the median level of appraisal of a reasonable and representative sample of other properties in the appraisal district; the appraisal ratio of the property is more than the median level of appraisal of a sample of properties in the appraisal district consisting of a reasonable number of other properties similarly situated to, or of the same general kind of character as, the property subject to the protest; or the appraised value of the property is more than the median appraised value of a reasonable number of comparable properties appropriately adjusted. This also applies to Commercial real estate.

COMMERCIAL REAL ESTATE

1. **Sale of Subject Property**
   Closing statement or sales contract, signed and dated, including a description of the property being transferred and instrument number, if sold during the last 3 years.

2. **Income Approach**
   Previous year rent roll, rent summary and income statement (typically 3 years of data). Documentation of lease offering rates, lease concessions, effective lease rates and current and historical occupancy, as of January 1 of the current year.

3. **Cost Approach**
   Construction contract(s), signed and dated, including a detailed description of the work to be performed. Certified A.I.A. document G702 or equivalent, with detail. Documentation must reflect all hard and soft costs. IRS RECORDS MAY BE REQUIRED.

4. **Market Approach**
   Provide comparable sales of properties that are of similar construction, use, size and shape, age, amenities, location, zoning, and utility availability.

5. **Independent Fee Appraisal**
   Independent Fee Appraisal: Complete copy of the appraisal report with confirmed sales and photographs of comparable properties. The detail should include: 1) property description; 2) location; 3) land area/building area; 4) year built; 5) grantor/grantee; 6) date of contract/instrument number; 7) sales price; 8) financing terms; 9) basis of sale; and 10) source/confirmed by.

BUSINESS PERSONAL PROPERTY

The Appraisal District or the ARB must have evidence on which to make a ruling in all Business Personal Property cases appearing before them. Normally the form of relevant documents in order of importance are: 1) balance sheets; 2) inventory controls, accounting records, journals, ledgers showing acquisitions by year of purchase; 3) CPA statements of costs; 4) leases pertaining to the property in question; 5) a statement of general accounting policy and procedures, especially concerning the capitalization and expense policy, and should also address inventory methods and whether physical inventory equals book inventory; 6) the basis of depreciation; and 7) a written third party confirmation from a landlord or leasing agent if the business has ceased operations and the assets have been removed prior to January 1.

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Figure C.4. Description of appropriate examples of substantial evidence towards the value of a subject property.

Table C.2. A list of characteristics that a DCAD appraiser will record when making a physical inspection of the subject property.

Physical Attribute	**Description**
Building Class	Class identifier that uniquely identifies an improvement as having a specific style of construction using a specific quality of materials
Number of Stories	Provides the number of floors that an improvement has
Condition	A subjective ranking of the quality of the land and improvement of a property upon which depreciation is estimated
Number of Units	For multi-family residences this provides the number of residential dwellings per building
Year Built	Specifies the year in which the improvement was built
Actual Age	A value based on the current appraisal year minus the year built
Effective Year Built	Calculated based on the scope and completion of recent updates and remodels of the improvement
Effective Age	A value based on the current appraisal year minus the effective year built
Living Area	Amount in square feet of the main improvement
Total Living Area	Amount in square feet of total living area where multiple improvements exist
Foundation	Material that comprises the support the improvement rests on
Basement	Indicates the existence of a basement
Heating	Specifies the type of heating unit within an improvement
Roof Type	Style of roof for the improvement
Roofing	Material that comprises the roof of the improvement
Attached Garage	Indicates the existence of an attached garage
Frame	Material that comprises the frame of the improvement
Exterior Walls	Material that comprises walls that are not adjacent to the inner structure of the improvement
Number of Fireplaces	Provides the number of fireplaces that an improvement has
Number of Bedrooms	Provides the number of bedrooms that an improvement has
Number of Bathrooms	Provides the number of bathrooms that an improvement has
Number of Wet bars	Provides the number of wet bars that an improvement has
Number of Kitchens	Provides the number of kitchens that an improvement has
Number of Full Baths	Provides the number of full baths that an improvement has
Number of Half Baths	Provides the number of half baths that an improvement has
Year Remodeled	Specifies the year the improvement was remodeled or updated
A/C Type	Specifies the type of air conditioning unit within an improvement
Level Finish Out	For use in comparing building quality of the same building class in the same neighborhood
Deck	Indicates the existence of a deck
Security System	Indicates the existence of a security system

continued on next page

Table C.2 continued from previous page	
Porch	Indicates the existence of a porch
Spa	Indicates the existence of a spa
Fence Material	Material that comprises the fence constructed on the land
Sprinkler	Indicates the existence of a sprinkler system
Landscaping	For use in comparing quality of landscaping for properties in the same neighborhood
Wooded Lot	Indicates the improvement is built on a wooded area lot
Quiet Street	Indicates the property is on a quiet street
Data of Inspection	Specifies the date of the last physical inspection of the property

Table C.3. A list of characteristics that a DCAD appraiser will record when making a physical inspection of the land for a subject property.

Land Attribute	**Description**
SPTD	Code used by the State Property Tax Division for classification and reporting purposes (e.g., single family residence)
Zoning	Code applied by municipality lot resides in for zoning purposes
Front	Width of the lot based on the survey plat defining the boundaries
Depth	Length of the lot based on the survey plat defining the boundaries
Area	Total acres of the lot as defined by the metes and bound description on the survey plat
Method	Approach to calculating the value of the land
Unit	Determines the unit for standard method of valuing land (square foot/acre)
Unit/Price	Provides the method of valuing land (front foot, flat price, sq. ft., acre)
Market Adj	Applies adjustments based on environmental qualities
Percent Ownership	Land may be owned by more than one person/entity
Street	Specifies the kind of street surface associated with the land
Sewer	Specifies the type of sewer system associated with the land
Water	Specifies the type of water system associated with the land
	continued on next page

Table C.3 continued from previous page	
Curb	Indicates if a curb is associated with the land
Electricity	Indicates if electricity is available with the land
Gas	Indicates if gas is available with the land
Sidewalk	Indicates if a sidewalk is associated with the land
Alley	Indicates if a sidewalk is associated with the land

APPENDIX D

MARKET AREA INFORMATION

D.1 Market Area Sector and Name Information

The spatial vertical inequity model output reports market area intercepts and interaction terms with the index s. Sector IDs are used in place of market area names to avoid cumbersome output. Table D.1 links market area names with their associated sector ID.

Table D.1. Market area sector ID and name.

Sector ID	Market Area Name
1	Cedar Hill
2	Desoto
3	Lancaster
5	Mesquite-Sunnyvale*
8	Sachse-Rowlett
10	Far North Dallas
11	North Dallas
12	East Dallas
13	Southeast Dallas-Wilmer-Hutchins*
14	Oak Cliff
15	South Dallas
16	Oak Lawn-Northwest Dallas*
18	Northeast Dallas
21	Coppell
22	Carrollton-Farm Branch
23	Richardson
24	Garland
25	Park Cities
26	Irving
27	Grand Prairie
28	Duncanville
	* Combined market areas

APPENDIX E

GLOSSARY

Appraiser – Individual that is in training, having a provisional license, or that is certified to employ state and federally mandated practices to estimate a property's market value for the purposes of taxation.

Assessor – Government organization required to assess property values for the purposes of property taxation.

Depreciation - The cost "for physical deterioration and all relevant forms of obsolescence and optimization" (Ogunba 2011, 191).

Disparities – Refer to over- and under-assessments in the assessment ratio distribution.

Horizontal Inequity – Property assessments are significantly different from market value within the same price class.

Market Value – Also known as *fair market value*, "is the highest price in terms of money that a property will bring if: 1) payment is made in cash or its equivalent, 2) the property is exposed on the open market for a reasonable length of time, 3) the buyer and seller are fully informed as to market conditions and the uses to which the property may be put, 4) neither is under abnormal pressure to conclude a transaction and 5) the seller is capable of conveying marketable title" (Jacobus 2012, 915).

Progressivity – High valued properties receive a property tax assessment that is greater in proportion to that of low valued properties within a specific housing market area.

Property Tax Assessment – The estimation of property value by a certified state appraiser within a jurisdiction. This process may include mass assessment or the estimation of value of many taxable properties throughout a jurisdiction.

Redlining – An illegal practice of mortgage lenders refusing to sell loans to applicants based on property characteristics, religious, ethnic or income related reasons (Jacobus 2012, 244).

Regressivity – Low valued properties receive a property tax assessment that is greater in proportion to that of high valued properties within a specific housing market area.

Single Family Residences – Single-family, detached, owner-occupied residential dwellings.

Subject Property – The individual home or property that is observed in the study. Common real estate practice employs the term when referring to a dwelling for which a price is being estimated through the process of housing market sales, purchase, or appraisal.

Vertical Inequity – Property assessments are significantly different from market value across different price classes.

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BIOGRAPHICAL SKETCH

John Fell was awarded a BS (1999) in Geographic Information Systems from Texas A&M University-Corpus Christi and an MS (2006) in Geospatial Information Sciences from The University of Texas at Dallas. Fell will complete his doctoral degree at The University of Texas at Dallas in Spring 2019. Fell's research analyzes residential vertical property tax inequities in Dallas County, Texas throughout a period of housing market volatility. Fell is currently the GIS Manager at the Dallas Central Appraisal District.

CURRICULUM VITAE

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EDUCATION

2019	PhD, Geospatial Information Sciences, The University of Texas at Dallas Dissertation: *Investigating Inequities in Appraised Residential Property Values for Dallas County, Texas, From 2004 – 2014: Using an Instrumental Variable Approach* Advisor: Dr. Michael Tiefelsdorf
2006	MS, Geospatial Information Sciences, The University of Texas at Dallas
1999	BS, Geographic Information Systems, Texas A&M University-Corpus Christi

PROFFESSIONAL EXPERIENCE

2006 –	**Dallas Central Appraisal District** GIS Manager, Information Technology Department
2009 – 2010	**Brookhaven Community College** Adjunct Faculty Instructor, Department of Science – Geospatial Technology **Programming for GIS** Introductory course in development for geospatial applications **Intermediate Geographic Information Systems (GIS)** Advanced course on the analysis and modelling of multiple spatial data structures using GIS software
2005 – 2006	**City of Grapevine, Texas** GIS Intern, Information Services
2002 – 2004	**Landworks, Inc.** GIS Mapper

AWARDS

2012 – 2018 $600	**Dallas Central Appraisal District Doug Gossom Memorial Education Grant** Award given to five applicants among 200 employees showing merit through exemplary service
2017 $2000	**The Appraisal Institute Education Trust** Awarded based on academic excellence, this scholarship helps finance the educational endeavors of graduate students concentrating in real estate appraisal, land economics, real estate or allied fields.
2016 $1000	**Pioneer Research Grant** Award for purchase of software, hardware, or data supporting doctoral students in Geospatial Information Sciences at the University of Texas at Dallas
2016 $2000	**International Association of Assessing Officers Library Trust Grant** Award to support IAAO members performing graduate level research for inclusion in an IAAO periodical
2016 $1000	**South Central Arc Users Group Memorial Scholarship** Award for full-time working professionals providing exemplary service to the DFW region
2012	**Environmental Systems Research Institute Special Achievement in GIS** Award given to less than 200 recipients worldwide for innovative use of GIS technology

PRESENTATIONS

2018	**Evaluating Inequities in Property Assessments for Single Detached Homes in Dallas County, Texas** Association of American Geographers Conference, New Orleans, Louisiana
2016	**Exploring Assessment Inequity Using Panel Data and Instrumental Variables** GIS/CAMA Technologies Conference, Hyatt Regency Savannah, Savannah, Georgia
2013	**Parcel Fabric Implementation** Metroplex Arc User Group Meeting, Hurst Convention Center