ABSTRACT

Title of dissertation: EVALUATING THE EQUILIBRIUM WELFARE IMPACTS OF THE 1990 CLEAN AIR ACT AMENDMENTS IN THE LOS ANGELES AREA

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This dissertation develops a discrete choice equilibrium model to evaluate the benefits of the air quality improvements that occurred in the Los Angeles area following the 1990 Clean Air Act Amendments (CAAA). Large improvements in air quality will change the desirability of different neighborhoods, disrupting the equilibrium of the housing market. The discrete choice equilibrium approach accounts for the fact that air quality improvements brought about by the 1990 CAAA will change housing choices and prices. The dissertation makes two empirical contributions to public economics. First, the study provides the first application of the discrete choice equilibrium framework (Anas, 1982, Bayer et al., 2005) to the valuation of large environmental changes. Second, the study provides new evidence for the distributional benefits of the 1990 CAAA in the Los Angeles area.

Households' location choices are modeled according to the random utility framework of McFadden (1978) and the differentiated product specification of Berry, Levinsohn and Pakes (1995). The model is estimated with public-use household microdata from the 1990 U.S. Census. Findings suggest that the air quality improvements that occurred in the

Los Angeles area between 1990 and 2000 provided an average equilibrium welfare benefit of $1,800 to households. In contrast, average benefits are $1,400 when equilibrium price effects are not accounted, demonstrating that ignoring equilibrium effects will likely underestimate the benefits of large environmental changes. We find that the equilibrium welfare impacts of the 1990 CAAA in the Los Angeles area varied significantly across income groups. Households in the highest income quartile experienced equilibrium benefits of approximately $3,600 as compared to only $400 for households in the lowest income quartile. We also find that ignoring equilibrium adjustments in housing prices can significantly alter the distribution of relative welfare gains (i.e. welfare gains as a proportion of household income) across households. Indeed, welfare impacts that do not account for equilibrium adjustments suggest that high-income households experience larger relative welfare gains compared to low-income households. However, when accounting for equilibrium adjustments, we find that the distribution of relative welfare gains from the 1990 CAAA is fairly even across income groups.

EVALUATING THE EQUILIBRIUM WELFARE IMPACTS OF THE 1990 CLEAN AIR ACT AMENDMENTS IN THE LOS ANGELES AREA

by

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Dissertation submitted to the Faculty of the Graduate School of the
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DEDICATION

To my Mother, who taught me discipline, and my Father, who always emphasized the importance of education.

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1 Introduction

Environmental regulations such as the Clean Air Act can lead to large air quality changes which cover wide areas and affect many residential communities. These types of widespread non-marginal improvements in air quality will have significant equilibrium welfare effects across local jurisdictions as households re-evaluate their residential location choices and equilibrium housing prices adjust. Traditional approaches to evaluating the impacts of air quality regulation have relied on direct welfare measures. These welfare measures are recovered directly from the estimated preference function of consumers using either the hedonic framework (Rosen, 1974) or the discrete choice framework (McFadden, 1973, 1978). However, these welfare measures do not explicitly account for the adjustments in housing prices which will occur when widespread non-marginal changes lead households to re-sort in the housing market. As a result, they will generally underestimate the full, i.e. equilibrium, welfare gains from regulations that result in widespread non-marginal improvements[1] in environmental amenities (Bartik, 1988).

Recent studies by Sieg et al. (2004) and Smith et al. (2004) have shown that incorporating equilibrium price effects can significantly alter the estimates of welfare benefits from large environmental improvements. For instance, Sieg et al. (2004) find that the reductions in ozone levels during the five years following the implementation of the 1990 Clean Air Act Amendments led to equilibrium price increases ranging from 11% to 20% in the Los Angeles Metropolitan area. These price changes resulted in

[1] These are changes that are large enough to alter the stock of environmental quality in the market. As an example, consider the cleanup of all toxic waste sites in the Los Angeles metropolitan area.

equilibrium welfare gains that were 13 percent higher than the direct benefits estimates that do not account for equilibrium adjustments.

This dissertation develops a discrete choice locational equilibrium model to evaluate the benefits of the 1990 Clean Air Act Amendments (CAAA) to Los Angeles area households. The study makes two empirical contributions to public economics. First, the study provides the first application of the discrete choice equilibrium framework (Anas, 1980, 1982) to the valuation of large environmental changes. Households' location choices are modeled according to the random utility framework of McFadden (1978). The equilibrium model is closely related to the model of Bayer et al. (2005). This, more recent, discrete choice equilibrium model follows the differentiated product specification of Berry, Levinsohn and Pakes (1995), henceforth BLP, by incorporating unobserved attributes of residential locations in the household utility function. The discrete choice equilibrium framework provides an alternative to the framework proposed by Sieg et al. (2004) for evaluating the welfare impacts of large environmental improvements. It also allows for a richer characterization of households' substitution patterns and preference heterogeneity.

Second, the study provides new evidence for the distributional benefits of the CAAA in the Los Angeles area. Using the changes in ozone levels that occurred in the Los Angeles area between 1990 and 2000 we estimate average welfare benefits as well as the distribution of welfare gains across income groups. Recently, Sieg et al (2004) have provided estimates of the benefits of the CAAA based on the changes in ozone levels that took place between 1990 and 1995. With the availability of air quality monitoring data for the year 2000, we are able to evaluate the benefits of the CAAA from 1990 to 2000.

Little is known about the distribution of the benefits among households from the 1990 CAAA regulations. The only attempts at such an analysis have focused on the spatial distribution of welfare gains.[2] In other words, welfare gains in predominantly high-income neighborhoods are compared with those in low-income neighborhoods. This approach, however, fails to capture the distribution of welfare gains and losses across household characteristics such as income and race. It only provides a comparison of the welfare gains across neighborhoods.

The study also sheds new lights on the performance of the representative consumer approach to approximating expected compensating variation (*ECV*) welfare measures in discrete choice random utility models. A general closed form expression for *ECV* does not exist since the compensating variation (*CV*) measure can be a nonlinear function of the stochastic component of the utility. Two numerical approaches have been suggested for recovering *ECV*. Morey et al. (1993) suggested approximating *ECV* by simply computing the *CV* for a representative consumer. McFadden (1999) suggested a Markov chain Monte-Carlo simulation approach for recovering the *ECV* of each individual consumer. McFadden argues that the representative consumer approximation to *ECV* is biased when large changes are considered. However, in a study of fishing mode choices by California anglers, Herriges and Kling (1999) find that the two approaches lead to similar welfare results. We provide additional empirical evidence on the relative performance of these two approaches in the context of measuring equilibrium welfare impacts.

[2] See for example Shadbegian et al. (2004). Smith et al. (2004) investigate the distributional impacts of the 1990 CAAA using the projected air quality changes, in the Los Angeles Area for the year 2000, from the EPA's 1999 prospective study. However, the actual air quality changes between 1990 and 2000 significantly differ from the EPA projections.

Household preferences are estimated using a dataset which includes households and housing units from the 1990 Census Public Use Microdata Sample (PUMS), annual ozone summaries from the California Air Resource Board, school performance data from the California Department of Education, and crime indices from the California Criminal Justice Statistics Center. Households' residential location choices are characterized by a discrete choice model in which equilibrium conditions are enforced. The model captures the heterogeneity of household preferences for location amenities by incorporating observed household characteristics in the utility function. Observed household characteristics include household income, household size, employment location and educational attainment of the household head.

Estimation of the equilibrium welfare impacts incorporates price adjustments that result from the fact that households alter their residential location choice after the changes in air quality throughout the Los Angeles Area. Computation of the equilibrium price adjustments is obtained via simulation. Using 1990 as a benchmark we simulate market clearing prices for the counterfactual locational equilibrium that would have resulted in 1990 if air quality levels were identical to those observed in 2000, while all other housing attributes remained at their 1990 levels. The counterfactual equilibrium reflects the changes in air quality that occurred in the Los Angeles area between 1990 and 2000. Other factors characterizing the Los Angeles area housing market, such as population, household income and housing supply, are assumed fixed in the simulation.

The empirical analysis focuses on the four counties of the Los Angeles area which makeup the South Coast Air Quality Management District. This area experienced significant improvements in air quality during the decade that followed the implementation of the 1990 CAAA. Figure 1 provides a regional map of the area. The neighborhood average ozone concentration fell by nearly 21 percent between 1990 and 1995. By the year 2000, the average reduction in ozone levels was close to 40 percent. The changes in ozone levels also varied widely across the area. The largest ozone reductions occurred in the most polluted neighborhoods located in the south-central and south-eastern portions of Los Angeles County, and the western portions of Riverside County and San Bernardino County. On the other hand, the costal neighborhoods of Los Angeles County and Orange County, which already had low levels of ozone concentrations, experienced minor ozone reductions.

Figure 1.1: The South Coast Air Quality Management District

The empirical analysis suggests that the reductions in ozone concentrations across Los Angeles, Orange, Riverside and San Bernardino counties, provided an average equilibrium benefit of $1,800 to households. In contrast, average benefits are $1,400 when equilibrium price adjustments are not accounted, demonstrating that ignoring equilibrium effects will likely underestimate the benefits of large environmental changes. We find that the equilibrium welfare impacts of the 1990 CAAA, in the Los Angeles area, varied significantly across income groups. Households in the highest income quartile experienced equilibrium benefits of approximately $3,600 as compared to only $400 for households in the lowest income quartile. We also find that ignoring equilibrium adjustments in housing prices can significantly alter the distribution of relative welfare gains (i.e. welfare gains as a proportion of household income). Indeed, welfare impacts that do not account for equilibrium effects suggest that high-income households have larger relative welfare gains compared to low-income households. However, when accounting for equilibrium adjustments, we find that the distribution of relative welfare gains from the 1990 CAAA is fairly even across income groups.

The remainder of this dissertation is organized as follows. Chapter 2 provides some background information on the 1990 CAAA and the changes in air quality that occurred in the Los Angeles area. Chapter 3 reviews the current body of literature on the valuation of housing amenities. Chapter 4 characterizes the locational equilibrium model. Chapter 5 describes the various datasets used to estimate the empirical model. Chapter 6 estimates the parameters of households' preferences. Chapter 7 discusses the measurement of welfare impacts and reports the welfare results. Chapter 8 concludes the analysis.

2 Background and Policy Setting

This chapter discusses the main policy context for this study, the 1990 Clean Air Act Amendments (CAAA). The chapter also presents some background information on ozone air pollution, and provides an overview of the air quality changes that occurred in the Los Angeles area between 1990 and 2000.

2.1 The 1990 Clean Act Amendments[3]

The Clean Air Act Amendments of 1990 addressed three major environmental issues in the United States: acid rain, urban air pollution, and toxic air emissions. The amendments are organized in seven titles. Title I established new provisions for the attainment and maintenance of the National Ambient Air Quality Standards (NAAQS). Title II introduced new provisions regarding air pollution from mobile sources. Title III expanded the regulation of hazardous air pollutants, while Title IV set new requirements for power plant emissions to control for acid rain. Title V mandated the use of tradable pollution permits to reduce pollution from major sources and Title VI implemented new provisions for the protection of the ozone layer. Finally, Title VII introduced new provisions expanding the authority of the U.S. Environmental Protection Agency (EPA) in the enforcement of air pollution regulations.

Titles I and II of the amendments provide the main provisions relating to air quality regulation. Title I addresses the urban air pollution problems arising from ozone, carbon monoxide and particulate matter (PM-10). Areas for which ambient levels of these pollutants were above the target levels were designated as non-attainment areas by EPA.

[3] Based on U.S. Environmental Protection Agency (2006a).

Non-attainment areas for ozone were divided into five categories: marginal, moderate, serious, severe and extreme. These areas were then required to implement control measures that vary with the severity of the non-attainment status. For carbon monoxide and particulate matter, areas that did not meet the federal health standards were classified into either moderate or serious non-attainment status. Areas exceeding carbon monoxide standards were required to introduce oxygenated fuels programs and/or implement enhanced emission inspections. Depending on the severity of their status, particulate matter non-attainment counties were either required to implement reasonably available control measures (RACM) or best available control measures (BACM).

Title II tightened emission standards from automobiles and trucks, two of the major sources for ozone and carbon monoxide emissions in urbanized areas. The new standards intended to curb tailpipe emissions of hydrocarbons, carbon monoxide, and nitrogen oxide on a phased-in basis starting with 1994 models. Additional provisions for improving fuel quality were also introduced. A new reformulated gasoline program was to be initiated in 1995 for the nine cities with the worst ozone problems. In addition, higher levels of alcohol-based oxygenated fuels were to be introduced during winter months in the 41 areas that exceeded the federal standards for carbon monoxide. The new regulation also introduced a clean fuel car pilot program in California, calling for the establishment of tighter emission controls for 15,000 vehicles in model year 1996 and 300,000 by the model year 1999.

2.2 Ground-level Ozone Air Pollution [4]

Ozone (O_3) is a gas which is found in the earth's atmosphere. Its chemical configuration is made of three oxygen atoms. The chemical structure of ozone is the same regardless of whether it occurs miles above the earth surface or at ground-level. However, the function of ozone will depend on where it occurs in the atmosphere. When it occurs in the in the stratosphere, approximately 10 to 30 miles above the earth's surface, ozone forms the layer that protects all life forms from the sun's ultraviolet (UV) rays. When ozone occurs in the troposphere, the lowest portion of the earth's atmosphere, it is a major air pollutant that can have damaging effects on human respiratory health, as well as plants and ecosystems.

While stratospheric ozone occurs naturally in the atmosphere, tropospheric or ground-level ozone is generally the result of urban activity. Emissions from industrial facilities, motor vehicle exhaust, and chemical solvents produce nitrogen oxide (NO_X) and volatile organic compounds (VOCs). The chemical reaction between NO_X and VOCs in the presence of sunlight produces ground-level ozone. Though ground-level ozone is primarily an urban air pollutant, it may also occur in less populated areas when NO_X and VOCs are transported over long distances by prevailing winds.

Ground-level ozone can irritate the human respiratory system, causing chest pain, throat irritation, and coughing. Repeated short-term exposure in children can lead to reduced lung function in adulthood. Ground-level ozone can also aggravate asthma and other chronic lung diseases, such as emphysema and bronchitis, and reduce the immune system's response to bacterial infections in the respiratory system.

[4] Based on U.S. Environmental Protection Agency (2007)

In addition to its effect on respiratory health, ground-level ozone can damage plants and ecosystems. It can limit the ability of certain sensitive plants to produce and store food, making them more vulnerable to diseases, insects, competition, and harsh weather. Ground-level ozone can also damage the leaves of plants and trees, negatively impacting the appearance of urban vegetation, national parks, and recreation areas. High concentration of ground-level ozone can also reduce crop yields and forest growth, thereby impacting species diversity in ecosystems.

2.3 Air Quality Standards for Ground-level Ozone [5]

Under the Clean Air Act, EPA is required to set National Ambient Air Quality Standards (NAAQS) for pollutants that are considered to be harmful to public health and the environment. The Clean Air Act established primary and secondary national air quality standards. Primary standards were designed to protect the health of the general population, as well as the health of sensitive groups such as asthmatics, children and the elderly. Secondary standards, on the other hand, were intended to preserve public welfare. They set limits to protect against decreased visibility and damage to animals, crops, vegetation, and buildings.

Currently, two primary standards are used to regulate ozone levels in the U.S. The national 1-hour standard for ozone, set at 0.12 parts per million (ppm) by volume, was established in 1979. It is achieved when the expected number of days per calendar year with maximum hourly concentrations above 0.12 ppm does not exceed 1. In 1996, EPA established a new national 8-hour ozone standard which was set at 0.08 ppm by volume.

[5] Based on U.S. Environmental Protection Agency (2006b)

This standard is attained when the 3-year average of the fourth highest daily maximum 8-hour ozone concentration measured at each monitor within an area is less than 0.08 ppm.

On June 15, 2005 the 1-hour ozone standard was revoked in all areas and replaced by the 8-hour standard, except in the fourteen 8-hour ozone non-attainment areas that were part of EPA's Early Action Compacts program. Early Action Compacts give local communities the flexibility to develop their own approach to meeting the 8-hour ozone standard, provided the communities control emissions from local sources earlier than the Clean Air Act would otherwise require.

In addition to setting the NAAQS, EPA designates areas as either non-attainment, attainment or unclassified. The designation process plays an important part in the implementation of air pollution control measures by states and local governments. Currently, an area is designated as non-attainment if it violates the national 8-hour ozone standard over a three-year period. An area will be designated as attainment if it has air quality monitoring data showing that the area has not violated the ozone standard over a period of three years. Areas are designated as unclassified if there is not enough data to determine ozone levels.

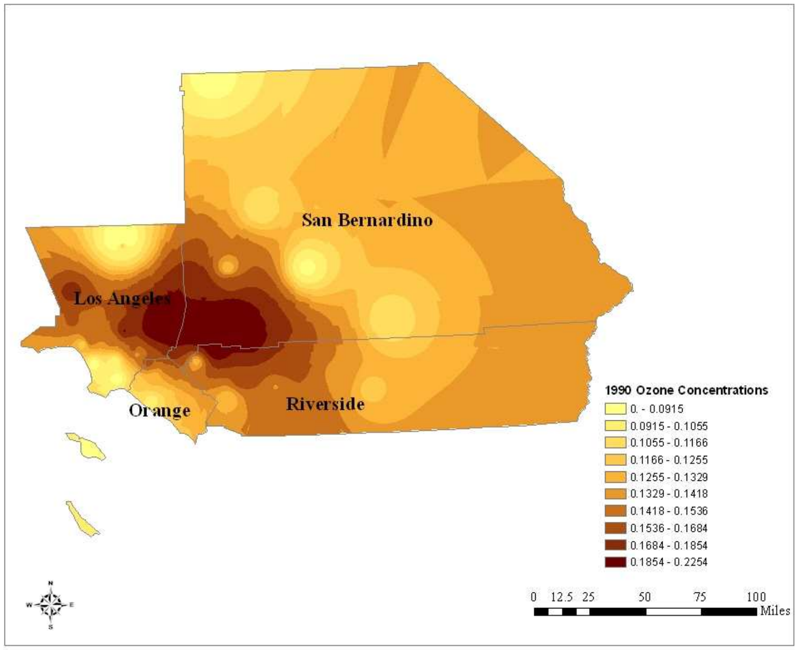
2.4 Air Quality Improvements in the Los Angeles Area

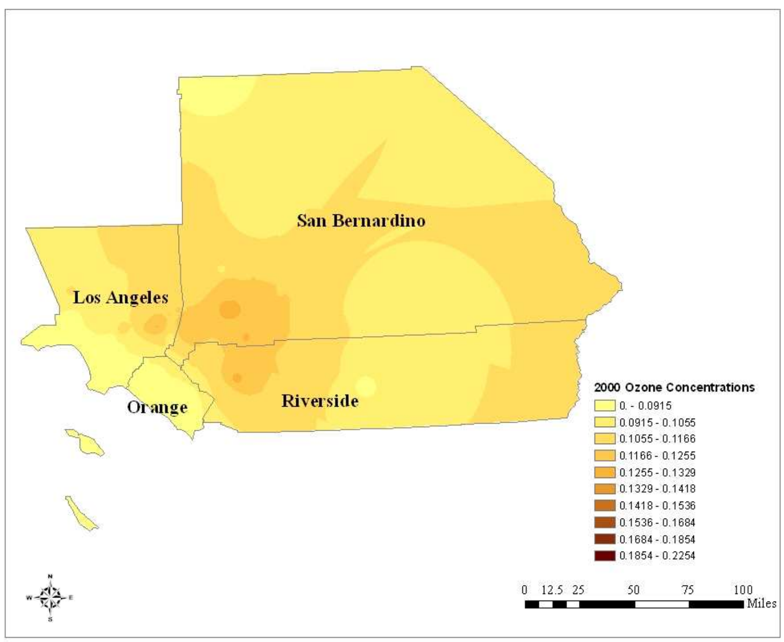
The South Coast Air Quality Management District (AQMD) is the main regulatory body for air pollution in the Los Angeles area. It encompasses Orange County and the urban areas of Los Angeles, Riverside and San Bernardino County. The area is the most densely populated urban center of the state of California and is home to over 16 million people.

The South Coast Air Quality Management District has historically exhibited some of the worst ambient levels of air quality in the nation and is currently designated by EPA as a severe ozone non-attainment area (U.S. EPA, 2006c). Every three years AQMD develops an air quality management plan which identifies implementation measures designed to bring the area in compliance of state and federal air quality standards. Figure 2.1 provides maps of ozone concentrations in 1990 and 2000 for the four counties which makeup the South Coast AQMD. The 1990 map shows a wide variation in ozone levels across the area. Specifically, ozone concentrations were lowest in the coastal areas of Los Angeles and Orange County. Average 1-hour ground-level ozone concentrations, in those areas, were below the federal 1-hour standard (0.12 ppm). On the other hand, the areas east of the San Bernardino Mountains and south of the San Gabriel Mountains exhibited the highest ozone concentrations in 1990. Average 1-hour ground-level ozone concentrations in these areas ranged from 0.185 ppm to as high as 0.225 ppm.

The South Coast AQMD counties experienced significant reductions in ozone concentrations between 1990 and 2000. Table 2.1 reports average ozone concentrations from monitoring stations across the area. The average 1-hour ground-level ozone reading in 2000 was roughly 0.10 ppm, compared to 0.14 ppm in 1990. In addition, the number of days exceeding the federal 1-hour standard significantly decreased between 1990 and 2000. The average number of recorded exceedences across the area was about 3.5 days in 2000, compared to nearly 36 days in 1990. Figure 2.1 also shows that the ozone reductions were highest in areas with the worst ground-level ozone concentrations in 1990. Average ozone concentrations fell by nearly 62 percent at monitoring stations with a recorded 1990 ozone level above the federal 1-hour standard (0.12 ppm). On the other hand, monitors with a recorded 1990 ozone level below the federal 1-hour standard experienced an average reduction of only 28 percent.

Figure 2.1: 1990 and 2000 Ozone[6] Concentrations for the Greater Los Angeles Area





[6] Ozone concentrations are obtained via interpolation. We generate a pollution surface for the entire study area using 100 meter-by-100 meter grid cells. We then assign to each grid cell a distance-weighted average of the readings from the 3 closest monitors.

Table 2.1: Average† Monitor Readings for Ground-Level Ozone

		Study area	Los Angeles County	Orange County	Riverside County	San Bernardino County
Ozone concentration*	1990	0.144	0.15	0.116	0.137	0.154
	2000	0.097	0.089	0.078	0.111	0.109
Ozone exceedences**	1990	35.7	37.1	11.2	33.2	46.9
	2000	3.5	2	0.3	5.4	6

* Average top 30 1-hour daily maximum readings at monitors (parts per million).
** Average number of days exceeding the federal 1-hour ozone standard at monitors.
† 3-year centered average.
Source: California Ambient Air Quality Data. 2004 Data CD

3 Valuing Amenities in Housing Markets: A Review

The idea that urban amenities will be capitalized into property values has provided economists with a powerful tool for valuing local public goods. (Cropper, 1999) The empirical evidence on this approach goes back to Ridker and Henning (1967) who estimate the willingness to pay for sulphate air pollution in St Louis, Missouri during the 1960s using house values across Census tracts. Since then, a large number of studies have investigated the benefits of various types of amenity changes using observed household decisions in housing markets. This class of models is known as property value models.

This chapter reviews the current empirical evidence on the property value approach to valuing changes in environmental quality. The chapter is organized in three parts. Section 3.1 provides a review of the behavioral approaches that are used in property value models. In Section 3.2 we discuss the various approaches to valuing changes in local housing amenities. This discussion will also highlight the types of datasets that are required to carry out these methods. Section 3.3 surveys a special class of models, referred as locational equilibrium models, which have been used to value large and spatially dispersed amenity changes. A more comprehensive exposition of the theory and methods presented in this chapter can be found in Palmquist (2006) (see also Freeman, 2003 and Bockstael and McConnell, 2007).

3.1 Behavioral Approaches to Modeling Housing Choice

Property value models are generally concerned with characterizing the behavior of households in a residential housing market. In these models the housing good or residential location is treated as a differentiated product, i.e. a bundle of characteristics.

Two behavioral frameworks have been used to characterize households' residential location choice. The hedonic framework (Rosen, 1974) characterizes the household's decision in terms of choosing the optimal levels for continuous characteristics of the housing location. On the other hand, the discrete choice or random utility framework (McFadden, 1978) characterizes the household location decision as a choice among discrete housing bundles.

The Hedonic Framework

The hedonic framework postulates that a household's optimal housing choice will reveal their demand for environmental quality as well as other location amenities. In equilibrium, the price of each housing bundle is a function of the levels of the characteristics which make up the bundle. The mathematical representation of this mapping is referred as the hedonic price function (HPF). The formal treatment of the theory behind the hedonic approach is due to Rosen (1974).

Consider a consumer with income y and idiosyncratic taste α choosing a housing location with vector of continuous characteristics $X = (x_1,..,x_J)$. These characteristics will include housing attributes such as number of bedrooms, age, as well as neighborhood attributes such as air quality, school quality, and public safety. Let $u = u(X, b; \alpha)$ represent the value that the consumer derives from the consumption of a non-housing good (b) and the housing characteristics (X). The consumer chooses the optimal combination of X and the consumption of the non-housing good (b) to maximize her utility,

$$u = u(x_1,...,x_J, b; \alpha), \tag{3.1}$$

subject to the budget constraint

$$y = P(X) + b \, . \tag{3.2}$$

Where, *P(X)* represents the equilibrium HPF for the housing market. The price of the non-housing good is normalized to \$1. Letting λ represent the marginal utility of income, the first order necessary conditions for an interior solution are given by

$$\partial u / \partial x_j = \lambda \cdot \partial P / \partial x_j \, , \qquad j=1,\ldots, n, \tag{3.3}$$

$$\partial u / \partial b = \lambda \, , \tag{3.4}$$

$$y - P(X) - b = 0 \, . \tag{3.5}$$

Combining equations (3.3), (3.4) and (3.5) yields

$$\frac{\partial u(X, y - P(X)) / \partial x_j}{\partial u(X, y - P(X)) / \partial b} = \partial P / \partial x_j \, , \qquad j=1,\ldots, J. \tag{3.6}$$

The left hand side of equation (3.6) is the marginal rate of substitution between the j^{th} characteristic and the numeraire non-housing good. This marginal rate of substitution represents the implicit price or the marginal willingness to pay (MWTP) for characteristic *j* in the housing market equilibrium. Equation (3.6) implies that, in equilibrium, the implicit price of a characteristic *j* is given by the slope of the HPF. It also characterizes the marginal willingness to pay function for the amenity x_j.

We can also characterize Rosen's bid function which represents a household's willingness to pay for a housing location with a set of characteristics $X = (x_1,..,x_J)$. This willingness to pay will be function of the characteristic vector, the household's income, the household's taste, and the level of utility provided by the housing location. It will later be used to characterize the household's valuation of a non-marginal amenity change. The household's bid function, $\theta = \theta(X, \bar{u}, y; \alpha)$, is implicitly defined as:

$$u(X, y-\theta; \alpha) = \bar{u} \ . \tag{3.7}$$

Implicit differentiation of equation (3.7) provides additional insights on the shape of the household bid function. Differentiating the bid function with respect to amenity *j*, holding other characteristics constant, yields:

$$\frac{\partial u}{\partial x_j} - \frac{\partial u}{\partial b}\frac{\partial \theta}{\partial x_j} = 0 \ . \tag{3.8}$$

Rearranging equation (3.8) we obtain the slope and curvature of the bid function in the price-amenity space:

$$\frac{\partial \theta}{\partial x_j} = \frac{\partial u / \partial x_j}{\partial u / \partial b} = \frac{\partial P(X)}{\partial x_j} > 0 \, , \tag{3.9}$$

$$u_{jj}u_b^2 + u_{bb}u_j^2 - u_{jb}u_b u_j < 0 \ . \tag{3.10}$$

Equation (3.9) holds from the first order conditions. It implies that the household bid function has a positive slope in the bid-amenity space. Holding income constant, an increase in the quantity of one characteristic will result in a higher bid. Equation (3.9) also implies that the household bid function is tangent to the HPF at the chosen amenity level, x_j^*. Equation (3.10) says that the household's bid function is quasi-concave in the bid-amenity space, suggesting that the marginal bid for an amenity decreases as the quantity of the amenity increases.

From equation (3.7) we can also obtain additional information on the functional form of the bid function. Differentiating the bid function with respect to income we obtain that the slope of the bid function in the price-income space is given by:

$$\frac{\partial \theta}{\partial y} = \frac{\partial u / \partial b}{\partial u / \partial b} = 1. \tag{3.11}$$

This suggests that the household's bid function is additively separable in the income level *y*. A direct implication of this result is that the bid function can be redefined in the following form:

$$\theta(X, \bar{u}, y; \alpha) = \theta^*(X, \bar{u}; \alpha) + y, \tag{3.12}$$

Where $\theta^*(X, \bar{u}; \alpha)$ is simply the indifference surface which yields the level of utility $\bar{u}$. θ^* can also be interpreted as the household's expenditure on the numeraire non-housing good *b*, holding the level of utility constant. The specification of the bid function in equation (3.12) implies that the marginal bid function $\partial\theta/\partial x_j$ will be independent of the household's income.

Structural parameters for the household's utility function can be recovered by estimating the marginal willingness to pay function, $\partial P(X)/\partial x_j$, in (3.6). Rosen (1974) suggested a two-stage approach for estimating the MWTP function. In the first stage one estimates the HPF via a regression of housing prices on housing characteristics and neighborhood amenities, and obtains the implicit price for each amenity as the gradient of the estimated HPF. The MWTP function for a housing amenity is then estimated by regressing its implicit price on housing attributes and a set of household characteristics.

The majority of applications of the hedonic property value approach have used the first stage estimation of the HPF. Estimation of the HPF requires data on the prices, characteristics and neighborhood amenities of occupied housing units. These data are generally easy to obtain. This estimation does not require information on the households residing in the housing units. However, estimation of the marginal willingness to pay function via the second stage does require the socioeconomic characteristics of the household choosing each housing unit. These data are not typically available, and are not contained in housing transactions data.

Two types of datasets are generally available for the estimation of property value models. These are Census public-use microdata and housing transactions microdata. Census public-use microdata are generally aggregated to large spatial units to protect the confidentiality of households. The main advantage of Census public-use microdata is that they are free and they also provide a detailed set of characteristics of the household choosing each occupied housing unit, which is essential for estimating the marginal willingness to pay functions in the second stage of Rosen's (1974) approach. The main limitation of these data is that the value of an owner-occupied housing unit is given by the owner's assessment instead of the actual transaction price. In addition, they only provide a limited set of characteristics for the housing unit.

Most property value applications of the hedonic first stage estimation have used housing transactions microdata. These data are spatially disaggregated and provide actual sale prices of housing units. Housing transactions data also provide a comprehensive set of characteristics for the housing units. However, these data typically do not include household socioeconomic characteristics which are necessary for the estimation of marginal willingness to pay functions. Transactions data are generally obtainable by purchase from private companies which specialize in real estate data.

The implementation of the two-stage hedonic estimation is complicated by a number of econometric issues which arise in the second stage. The first issue has to do with the identification of the parameters of the marginal willingness to pay function. In general, identification of the amenity demands can be achieved either via *a priori* restrictions on the functional forms of the hedonic price function and demand equations, or data from multiple distinct housing markets. Palmquist (2006) provides an extended discussion of identification strategies that have been used in the empirical literature. Additional identification strategies are proposed by Eckland et al. (2004) and Bajari and Benkard (2002). An endogeneity problem also arises from the fact that implicit prices and quantities of amenities are simultaneously determined in the hedonic equilibrium. As a result amenity prices and quantities will be correlated with the structural errors in the amenity demand functions. The correlation occurs because the structural errors contain omitted characteristics which, by virtue of the hedonic equilibrium, are correlated with the observed prices and quantities. This means that ordinary least-squares (OLS) estimation of the amenity demand functions will produce bias estimates. A number of strategies for valid instruments have been proposed in the literature and are summarized by Palmquist (2006).

The Discrete Choice Framework

An alternative to the hedonic property value approach is the discrete choice random utility (RUM) framework (McFadden, 1978). Unlike the hedonic approach, where households choose continuous characteristics of housing units, this framework assumes that households make discrete housing location choices and their preferences for amenities are known up to an error term. Following the notation introduced in the hedonic approach, the consumer's utility for choosing a house *k* is given by:

$$u_k = u(X_k, b_k, \varepsilon_k; \alpha)\,, \tag{3.13}$$

where the error term ε_k characterizes the fact the true specification of the utility is unknown. Since the choice of the house is a binary decision, the budget constraint is reduced to:

$$y = P_k + b_k\,. \tag{3.14}$$

The consumer then chooses the house which provides her with the highest value. The indirect utility for the chosen house is given by

$$V\ (X\ \ , y-p\ \ , \varepsilon\ \ ; \alpha) = \max\{u(X_1, y-P_1, \varepsilon_1; \alpha), \ldots, u(X_K, y-P_K, \varepsilon_K; \alpha)\}. \tag{3.15}$$

The probability that the household chooses a given house *k* can also be obtained as

$$\Pr(k) = \Pr[u(X_k, y-P_k, \varepsilon_k; \alpha) > u(X_l, y-P_l, \varepsilon_l; \alpha)] \qquad \forall k \neq l\ . \tag{3.16}$$

Pr(*k*) can be viewed as the household's expected demand for the housing location *k*. The final expression of the choice probability will depend on the functional assumption about the error term ε. For a given expression of the choice probability one can estimate the set of structural parameters characterizing the household's random utility function. The expected population demand for housing location *k* is obtained by summing the choice probabilities across the household population.

Estimation of the random utility model is not without econometric issues. In order to estimate household preference parameters, one needs to assume a functional form for the error term which enters the indirect utility function. The estimation is greatly simplified when the errors are assumed independently and identically distributed as Type I Extreme Value (EV). This error structure however gives rise to the multinomial logit model, which assumes Independence from Irrelevant Alternatives (IIA). More general error structures can be used but with a greater computational cost. The nested logit model provides a partial relaxation of the IIA assumption by assuming a Generalized Extreme Value (GEV) distribution for the error term. A full relaxation of the IIA assumption can be achieved with the random parameter or mixed logit model. In this model, the error term is assumed EV but the parameters of the utility are allowed to vary randomly across individuals.

Identification of the parameters of the household's random utility function requires housing prices as well as housing characteristics and neighborhood amenities. These can be obtained either from housing transactions microdata or Census public-use microdata. When the random utility function includes household interaction parameters, identification will also require household socioeconomic characteristics. Currently the most spatially disaggregated microdata which can accommodate this requirement are the Census long form files. Unfortunately, these data are confidential and generally difficult to obtain. An alternative is to use the Census Public-Use Microdata Sample (PUMS) which contain the same information as the long form files but are spatially aggregated to protect the confidentiality of the households.

3.2 Valuing Amenity Changes Using Property Value Models

The goal of most property value studies is to value housing amenities. However, there are a number of ways that this goal may be achieved. First, the researcher might be interested in estimating the marginal value from an amenity change. Second, the researcher may want to estimate the willingness to pay of households for a non-marginal amenity change at their residential location. Finally, the researcher might be interested in measuring the welfare impact from a policy or exogenous event which results in a non-marginal amenity change. Each of these questions requires a different empirical approach. We discuss these approaches and their applications to the valuation of environmental amenities.

3.2.1 Estimating the Marginal Value for an Amenity Change

Given equation (3.4) the valuation of a marginal change in an amenity *j* is a simple task. It amounts to estimating the first stage of Rosen's (1974) two-stage estimation. The MWTP an for amenity *j* is given by the gradient the estimated HPF, $\partial\hat{P}(X)/\partial x_j$. The willingness to pay (WTP) for a marginal change Δx_j is then obtained by multiplying the MWTP, $\partial\hat{P}(X)/\partial x_j$, by Δx_j.

Applications of Rosen's first-stage hedonic approach overwhelmingly dominate the empirical evidence on the valuation of environmental improvements. The majority of the applications to air quality valuation were summarized in the meta-analysis of Smith and Huang (1995). Empirical estimates of the MWTP for air quality vary widely across studies. The MWTP for a one percent change in air quality ranges from $18 to $181. More recent applications of Rosen's first stage estimation to environmental valuation include Beron et al. (2001) and Banzhaf (2005). The former study evaluates the benefits of visibility improvements in the Los Angeles metropolitan area using residential housing sales between 1980 and 1995. Banzhaf (2005) estimates cost-of-living indices for air quality and other local public goods in the Los Angeles area using estimates of implicit prices from a hedonic price function.

A potential limitation of the hedonic price estimation in the context of air quality valuation is due to an omitted variables bias. Certain relevant neighborhood attributes can be omitted from the hedonic price regression as a result of insufficient data. In equilibrium, the provision of such attributes is likely to be correlated with air quality and other observed public goods. As a result the estimated implicit price of air quality will generally be biased and highly sensitive to the choice of functional form for the HPF.

Recently, Chay and Greenstone (2005) have estimated the WTP for total suspended particulates (TSP) from a hedonic price regression that makes use of the non attainment status of counties as an instrumental variable (IV). The study finds that IV estimates of the WTP for air quality are more robust to various specifications of the HPF.

3.2.2 Estimating the WTP for a Non-Marginal Change

Valuing Non-Marginal Changes

Though the valuation of marginal changes is generally a simple task, most environmental policies lead to non-marginal amenity changes. Unlike marginal changes, non-marginal changes do alter the distribution of an amenity in the housing market. As a result households may adjust their residential location choice which may cause the equilibrium HPF to shift. Following Bockstael and McConnell (2007), two non-marginal welfare measures can be defined. The first welfare measure characterizes the household's willingness to pay for the change in amenity at their residential location. This welfare measure, termed "pure" WTP by Bockstael and McConnell, captures the direct welfare impact of a non-marginal change on households while ignoring the fact that the equilibrium HPF may shift. The full, i.e. equilibrium, welfare impact from a non-marginal amenity change must account for the shifting of the HPF. This welfare measure can be used to characterize the welfare gains and losses from a policy or exogenous event which leads to a non-marginal change in environmental quality.

Estimating the "Pure" WTP via the Hedonic Approach

Measuring the household's willingness to pay for a non-marginal change requires estimating the parameters of the household's bid function. Knowledge of the gradient of the HPF is no longer sufficient as the non-marginal change would lead to a movement along the household bid curve. The household's willingness to pay for a non-marginal improvement in an amenity *j* at its current housing location can be defined as the change in income which allows the household to consume the same level of the numeraire non-housing good *b* as before the improvement. Because the bid function is separable in income, the WTP can be directly obtained as the change in the household's expenditures on the numeraire (see equation 3.12):

$$WTP = \theta^*(x_j^1, x_{-j}^0, u^0; \alpha) - \theta^*(x_j^0, x_{-j}^0, u^0; \alpha) . \tag{3.17}$$

The willingness to pay in equation (3.17) can also be defined in terms of the household's marginal bid function as:

$$WTP = \int_{x_j^0}^{x_j^1} \frac{\partial \theta^*(x_j, x_{-j}^0, u^0; \alpha)}{\partial x_j} dx_j . \tag{3.18}$$

The "pure" willingness to pay can be empirically recovered by estimating the marginal willingness to pay function,

$$\frac{\partial P}{\partial x_j} = \frac{\partial u / \partial x_j}{\partial u / \partial b} .$$

The marginal willingness to pay function is recovered via the two-stage estimation procedure suggested by Rosen (1974), which is described in the previous section.

Applications of the hedonic demand estimation to the valuation of environmental amenities are limited. Cropper et al. (1993) estimate WTP for non-marginal changes in housing amenities using data from a simulated housing market. The welfare estimates are then compared to those from a discrete choice model. The amenity demand functions are identified via a linear box-cox hedonic price function. Chattopadyay (1999) uses data from the Chicago area housing market to estimate the WTP for clean air in terms of particulate matter (PM-10) and sulfur dioxide (SO_2). The identification of the second stage is achieved via functional form restrictions on the hedonic price equation and consumer preferences. A multi-market hedonic estimation is used by Palmquist and Israngkura (1999). The study uses housing data from thirteen metropolitan areas in the United States to value particulates (TSP), nitrogen oxide (NO_2) and sulfur dioxide (SO_2) air pollution.

Estimating the "Pure" WTP via the Random Utility Approach

The random utility framework can also be used to characterize households' willingness to pay for a non-marginal amenity change at their residential location. The willingness to pay defined in equation (3.17) can be equivalently stated in terms of the change in income necessary to bring the household to their original utility level after an exogenous change in an amenity *j*. (Bockstael and McConnell, 2005) Noting that that θ^* is merely the indifference surface $u(x_j, x_{-j}, b; \alpha) = \bar{u}$ solved for the numeraire $b = y - \theta$, and inverting equation (3.17) yields:

$$u(x_j^0, x_{-j}^0, y - p_j^0; \alpha) = u(x_j^1, x_{-j}^0, y - p_j^0 - WTP; \alpha)\ . \tag{3.19}$$

The willingness to pay in equation (3.19) is commonly referred as the compensating variation (CV). Given estimated parameters of the household's random utility function in equation (3.15) the WTP in (3.19) can be estimated.

Like the hedonic demand approach, the discrete choice approach to valuing non-marginal changes has seen few applications to the valuation of environmental amenities. One of the earliest applications was by Cropper et al. (1993), who estimate preferences for housing attributes using a multinomial logit model and compare the WTP for non-marginal changes with the hedonic demand approach. Palmquist and Israngkura (1999) also compare benefit estimates, for air pollution reduction, from a multinomial logit with hedonic demand estimates. However, the comparison was unsuccessful as they could not obtain reliable welfare estimates from the multinomial logit model. Chattopadyay (2000) uses a nested logit model to value PM-10 air pollution in the Chicago area. He finds that benefit estimates from the discrete choice model where consistently lower than the estimates from the two-stage hedonic approach. More recently, Bayer, Keohane and Timmins (2007) use a discrete choice model, which incorporates unobserved housing attributes and household mobility constraints, to provide an estimate of the WTP for reductions in PM-10 concentrations.

3.2.3 Measuring the Welfare Impact from a Policy or Exogenous Event

The "pure" willingness to pay measure will reveal how much households are willing to pay for a non-marginal amenity change at their residence, all other things held constant. While this is an important question, it does not provide an answer to the broader welfare question that is the welfare impact on households from a policy or exogenous event which results in a non-marginal amenity change across housing locations. The welfare impact from such a change may not coincide with the “pure” WTP measure. This is because households are likely to re-evaluate their location choice, which may lead to a shifting of the equilibrium HPF. Household choices may change because the underlying distribution of the amenity across housing locations will change when large changes occur. As a result, the “pure” WTP measure, which uses the *ex-ante* equilibrium HPF, will be misleading. The “pure” WTP measure from the random utility framework will also be incorrect as it still relies on *ex-ante* housing prices.

Bartik (1988) shows that the “pure” WTP will underestimate the welfare impact from non-marginal policy changes. This is because the welfare measure restricts households to choose the same housing location in the *ex-post* equilibrium. The full, i.e. equilibrium, welfare impact of the improvement allows the household to re-optimizing their choice. In the absence of mobility constraints, households will be made at least better off as a result of this adjustment. This follows from the LeChatelier optimization principle (Bockstael and McConnell, 2007). Hence the “pure” WTP provides a lower bound to the full welfare impact. It will generally underestimate the welfare gains and overestimate the welfare losses from a non-marginal improvement.

There is a special case when evaluation of the welfare impact from a non-marginal amenity change can be carried out in a simple way using the *ex-ante* equilibrium HPF. This occurs when the amenity change is localized, i.e. confined to a small set of neighboring houses. For such a change the equilibrium HPF will not change since only a small number of houses are affected. The implication is that the gains and losses to renters will be pecuniary. Assuming costless mobility, renters will move along the HPF until the marginal WTP for the change equals the increase in rent. Any welfare gains (losses) resulting from the amenity change will be offset by an increase (decrease) in the housing price. As a result, the welfare impact from the localized amenity change will be confined to landowners and is given by sum of the changes in housing prices at each of the affected housing locations. A complete conceptual proof of this result appears in Bartik (1988). Bockstael and McConnell (2007) provide additional intuition on this result.

To evaluate the welfare gains or losses from large amenity changes affecting many housing locations within a market, we need to explicitly account for the *ex-post* changes in equilibrium housing prices that would result from the re-sorting of households. The two-stage hedonic estimation and random utility models are only able to recover household preferences and characterize the *ex-ante* equilibrium in the housing market. Recently, models have been developed to explicitly incorporate equilibrium concepts with the estimation of household preferences. This class of models, referred as locational equilibrium models, is discussed in the next section.

3.3 Locational Equilibrium Models

In contrast to the standard hedonic and discrete choice models, locational equilibrium models are able to incorporate price adjustments that result from the re-sorting of households across housing locations in response to a policy change. These models use estimated structural housing demands to simulate a counterfactual equilibrium outcome for a policy change. The concept of locational (or sorting) equilibrium can be traced back to the early work of Tiebout (1956). Tiebout was the first to postulate that households take account of the tax and expenditure policies of local jurisdictions when making their residential location choice. (Epple and Sieg, 1999) However, until recently, there have been very few empirical attempts to estimate locational equilibrium models. (Ferreyra, 2003)

Currently two classes of locational equilibrium models appear in the empirical literature. One class of models is derived from the urban sorting equilibrium model of Epple and Sieg (1999). This class of equilibrium models has been recently applied to the evaluation of welfare impacts from non-marginal environmental changes by Sieg et al. (2004). The second class of locational equilibrium models is derived from stochastic discrete choice models of housing demand (McFadden, 1978 and Quigley, 1976). These models have been mostly applied to evaluate urban and transportation policy problems. Anas (1982) developed the first locational equilibrium model based on the discrete choice theory of housing demand.

3.3.1 The Epple-Sieg Equilibrium Approach

Epple and Sieg (1999) provide a unified framework of theory and empirics for estimating urban equilibrium models that arise from the sorting of households in a system of local jurisdictions. The housing market is formed by a fixed set of communities, i.e. local jurisdictions, which constitute a metropolitan area. Each community provides housing services and local public goods including school quality, public safety and environmental amenities. The price and quantity of housing in each community is determined by a competitive market equilibrium. Provision of the public goods is financed by a local tax on housing, and households are assumed to move freely across local jurisdictions.

Households have preferences over a private good, b, a local housing good, h, and a local public good index g which is assumed to be a composite function capturing all locally provided public goods. In other words, for a given community j, $g_j = g(X_j)$ where

X_j is a vector of community-specific public goods. Households differ in their income endowment, y, and their taste α for the public good g. The Epple-Sieg framework incorporates aspects of the hedonic and the discrete choice framework. Households make discrete choices among communities differentiated by their provision of the public good g. Conditional on their community choice, households select housing as a continuous, homogeneous good. Given the community-specific gross of tax housing price p, the household maximizes its utility

$$u = u(\alpha, g, h, b) \tag{3.10}$$

subject to the budget constraint

$$ph = y - b \, . \tag{3.11}$$

The indirect utility derived from the household's optimization problem is given by

$$V(\alpha, g, p, y) = u(\alpha, g, h(p, y, g(X); \alpha), y - ph(p, y, g(X); \alpha)) \, . \tag{3.12}$$

It is assumed that the slope of the household's indifference curves in the (g, p) plane is globally monotonically increasing in α and y.[7] As a result, indifference curves in the (g, p) plane satisfy the single crossing property. It turns out that a sorting equilibrium emerging from preferences that satisfy the single crossing property will exhibit three properties which are: boundary indifference, stratification, and ascending bundles. These three properties will characterize the necessary conditions for the locational equilibrium.

[7] The slope of the indifference curve in the (g, p) is defined as $\left.\frac{dp}{dg}\right|_{V=\bar{V}}$.

The following proposition outlines the necessary conditions which characterize the locational equilibrium. Epple and Sieg (1999) provide a proof.

Proposition 3.1 (Epple and Sieg, 1999):

Consider an equilibrium allocation in which no two communities have the same housing prices. For such an allocation to be a locational equilibrium there must be an ordering of community pairs, $\{(g_1, p_1), \ldots, (g_J, p_J)\}$, such that the following conditions hold:
(i) Boundary indifference: Individuals on the "border" between any two communities are indifferent between the two communities. The set of these individuals is characterized by the following expression:

$$I_j = \{(\alpha, y) \,|\, V(\alpha, g_j, p_j, y) = V(\alpha, g_{j+1}, p_{j+1}, y)\}, \qquad j = 1, \ldots, J\text{-}1. \tag{3.13}$$

(ii) Stratification: Let $y_j(\alpha)$ be the implicit function defined by equation (3.13). Then, for each α, the residents of community j consist of those with income y, given by:

$$y_{j-1}(\alpha) < y < y_j(\alpha)\,. \tag{3.14}$$

(iii) Increasing bundles: Consider two communities j and k such that $p_j > p_k$. Then $g_j > g_k$ if and only if $y_j(\alpha) > y_k(\alpha)$.

The necessary conditions for the locational equilibrium are used to estimate a parameterized version of the household indirect utility function. Estimation of the preference parameters can be carried out using housing transactions microdata. The Epple-Sieg equilibrium model allows one to evaluate the welfare impact of policies that lead to non-marginal changes in local public goods. This is because the estimated household indirect utility function can be used to simulate a new sorting equilibrium in which households adjust their locations and equilibrium housing prices change.

The main advantage of the Epple-Sieg model is that the estimation of preference parameters does not require household socioeconomic characteristics. In addition, the computational burden required by the estimation, simulation and welfare computation is relatively low. However, these advantages come at a cost. The necessary conditions for the locational equilibrium require a very tight parameterization of the indirect utility function. The main limitations of the framework result from the fact that housing amenities enter the utility via a single index g and preference heterogeneity for housing amenities is represented by the single parameter α. We discuss these limitations in the context of an application to environmental valuation.

Valuing Non-Marginal Environmental Changes in the Epple-Sieg Framework

Sieg, Smith, Banzhaf and Walsh (2004) apply Epple and Sieg's (1999) locational equilibrium model to environmental valuation. The study provides the first empirical analysis of the equilibrium welfare impacts of non-marginal environmental improvements.[8] The set of communities is characterized by 91 school districts. Communities differ in their provision of the public good index g, which is a function of community-specific amenities (including air quality), and housing. The properties of the locational equilibrium defined in proposition 3.1 are then used to estimate a parameterized version of the household indirect utility function, which is in turn used to simulate alternative equilibrium outcomes for changes in air quality at the school district level.

The estimation of the model relies on a specific parameterization of the indirect utility function. The specification of the indirect utility uses a Constant Elasticity of Substitution (CES) functional form which is separable in the public good (g) and the market goods (h, b). In addition, the optimal housing consumption is assumed to be log-linear in income and housing price. The local public good index g is assumed to be a linear function of the

[8] See also Smith et al. (2004) and Walsh (2003) for other environmental applications of the Epple-Sieg equilibrium approach.

community-specific amenities. The CES separable form allows the housing demand to have constant non-unitary income and price elasticities. Indifference curves from this indirect utility are monotonically increasing in α and y and hence satisfy the single crossing property. This allows the characterization of the three necessary conditions (boundary indifference, stratification and ascending bundles) for the locational equilibrium defined by proposition 3.1.

Using the parameterized version of the household indirect utility, one can characterize the distribution of household income y, the provision of the public good index g and the demand for housing within each community j in the sorting equilibrium. The stratification property is used to define the set of households residing in each community j in the sorting equilibrium. The distribution of household income within community j is obtained by integrating the joint distribution of income and tastes over the set of households residing in j. By ordering the communities with respect to the housing price, the ascending bundle property can be used to define the public good index g_j in community j as a function of the community size, its own housing price p_j, and the housing price p_{j+1} and public good level g_{j+1} in community $j+1$. By normalizing the public good index in the lowest community, the implied levels of the public good index in the remaining $J-1$ communities can be computed numerically via a recursive algorithm similar to the contraction mapping proposed by Berry, Levinsohn and Pakes (1995). The consumption of housing by a household with income y located in community j is derived via Roy's identity. The distribution of housing consumption within community j is obtained by integrating the individual household demands over the marginal distribution of income in community j.

Household preference parameters are estimated via a Generalized Method of Moments (GMM) approach. The estimation makes use of housing transactions microdata from five counties in southern California: Los Angeles, Orange, Riverside, San Bernardino and Ventura. The GMM estimation procedure entails searching for the values of the preference parameters that minimize the weighted distance between the between the moments predicted by the model and the corresponding sample moments observed in the data. Given the distribution of household income *y*, the provision of the public good index *g*, and the demand for housing within each community *j*, three sets of moment conditions are formed. The first set of moment conditions matches the 25th, 50th and 75th quantiles of the parameterized distribution of household income in each community, i.e. school district, *j* with those observed in the housing sample. Empirical quantiles of the income distribution for each school district are obtained from the 1990 U.S. Census. The second set of moments matches the 25th, 50th and 75th quantiles of the parameterized distribution of housing expenditures in each school district with their empirical counterparts. The final set of moments matches the levels of the public good index, in each community, implied by the locational equilibrium with the value predicted by the parameterized functional form. The parameterized form of the public good index is given by a linear function of the air quality, school quality and crime level in each community.

The estimated indirect utility function is used to evaluate the welfare impacts of the changes in air quality between 1990 and 1995. Changes in air quality are converted into changes in the public good index *g* via the estimated linear functional form for the community public good index. The new community public good indices are then used to simulate a counterfactual locational equilibrium for 1995. For a given exogenous change in the public good index g, Sieg et al. define the partial and general equilibrium willingness to pay of a household located in a community *j*. The partial equilibrium WTP is computed by holding prices and household location choices at their 1990 levels. This is the "pure" WTP measure defined in section 3.2. It will characterize the household's WTP for the change in air quality in community *j*. The general equilibrium WTP makes use of the new housing prices and household locations from a simulated counterfactual equilibrium. This measure represents the welfare impact, on the household, of the changes in air quality across the communities. The community-level mean WTP measures are obtained by integrating the household-level WTP measures over the joint distribution of income and tastes for the set of households residing in each community.

Sieg et al. (2004) apply this framework to investigate the welfare benefits of the 1990 CAAA in the Los Angeles area. They find that equilibrium benefits that account for adjustments in housing prices differ substantially from direct benefit estimates. The average equilibrium welfare gain from the reductions in ozone concentrations, which occurred between 1990 and 1995 in the Los Angeles area, was estimated at $1,371. This compares with the average direct benefit of $1,210. In addition, the study finds a significant amount of heterogeneity in welfare gains across counties. Equilibrium benefits were found to be highest in Los Angeles County ($1,556) and lowest in San Bernardino County ($367). The study also finds considerable variation in benefits across school districts, within each county. For example, the equilibrium benefits in Los Angeles County ranged from $486 in the Compton Unified school district to $9,000 in the Beverly Hills school district.

In a subsequent study, Smith et al. (2004) evaluated the benefits of the 1990 CAAA in the Los Angeles area for 2000 and 2010. Using the EPA's projected changes in ozone levels for 2000 and 2010 together with the estimated household preferences from Sieg et al. (2004), the study measures the equilibrium WTP for the policy scenarios developed for EPA's prospective study (EPA, 1999) as they relate to the households of the Los Angeles area. The study also investigates the distribution of equilibrium benefits across income groups. They present the benefits associated with the 25th, 50th and 75th income percentile, for selected school districts in the Los Angeles Area. The estimated equilibrium welfare estimates vary significantly across the household income distribution. The distribution of the welfare estimates also varies across school districts. In the lowest income community, San Juacinto Unified school district, the welfare estimates are -$59 annually at the 25th income percentile as compared to -$28 at the 75th percentile. The welfare estimates in Beverly Hills school district, the highest income community, are $3899 at the 25th income percentile as compared to $7406 at the 75th percentile.

Sieg et al. (2004) provide a major contribution to the valuation of large widespread changes in environmental amenities. The study provides the first explicit characterization of the equilibrium impact of non-marginal amenity changes on household choices and housing prices. Also, because it is based on the Epple-Sieg framework, the Sieg et al. model is quite simple to implement empirically. However the specification of household preferences, which is needed to ensure that the necessary conditions for the equilibrium are met, gives rise to a number of limitations.

First, the characterization of the public good index leads to patterns of substitution across location amenities that are somewhat restrictive. This is because location amenities enter the household's indirect utility function through the single index *g*. This can be shown by looking at the marginal rate of substitution between community characteristics. For the sake of simplicity, let's assume that there are two community characteristics (i.e. $X = [x_1, x_2]$). Taking the total differential of the utility function in the (x_1, x_2) space we get

$$\frac{\partial U}{\partial g}\frac{\partial g}{\partial x_1}dx_1 + \frac{\partial U}{\partial g}\frac{\partial g}{\partial x_2}dx_2 = 0\,. \tag{3.13}$$

The slope of a household's indifference curve the (x_1, x_2) space is then given by

$$\frac{dx_1}{dx_2} = -\frac{\partial g / \partial x_2}{\partial g / \partial x_1}\,. \tag{3.14}$$

Equation (3.14) defines the marginal rate of substitution (MRS) between the two amenities. It is clear from equation (3.14) that the MRS between the two community amenities does not depend on either household's taste, α, or the household income, y. As a result, households are forced to have the same ranking of communities in the amenity space. This vertical differentiation of communities simplifies the estimation of preference parameters and the computation of the locational equilibrium. However, one would generally expect households to have different relative preferences for community-specific amenities such as air quality, education, and crime. For instance, other things equal, one would expect that households with children enrolled in a secondary public school will have higher preferences for communities with good secondary public schools.

A second limitation of the Sieg et al. model relates to the characterization of the heterogeneity in households' preference for location amenities such as air quality, school quality and crime. Heterogeneity in households' preference for the public good index is characterized by the single taste parameter, α, whose marginal distribution is assumed normal. Hence a household's marginal valuation for a given community amenity is only a function of the household's income and does not depend on other household characteristics. Households' preferences for community-specific attributes are, however, likely to vary across other household characteristics such as household size, the presence of children and educational attainment. For instance, highly educated household are likely to have a higher marginal valuation for school quality. As a result, a preference specification which incorporates an interaction between neighborhood school quality and household educational attainment would allow the model to better fit the data. In addition, when investigating welfare gains from an amenity change, a researcher is able to provide an analysis of the distributional impacts across household characteristics other than income. For instance, one may investigate the differential impact of an improvement in air quality on senior households.

3.3.2 The Discrete Choice Equilibrium Approach

An alternative to the Epple-Sieg equilibrium framework is the discrete choice equilibrium framework. This is the equilibrium approach adopted in this dissertation. Anas (1980, 1982) developed a theory of locational housing market equilibrium based on the discrete housing choice model of McFadden (1978). In recent years this framework has been extended to incorporate advances in urban economics and empirical industrial organization. One such model was proposed by Bayer and Timmins (2005). Their model incorporates endogeneous social interaction effects as well as unobserved location attributes.

The discrete choice equilibrium approach provides for a richer characterization of preference heterogeneity and more general patterns of substitution. The discrete-choice modeling of the housing choice allows community-specific amenities to enter directly the utility function. This provides for more general substitution patterns across communities. In addition, the researcher can provide a richer characterization of the observed heterogeneity in households' tastes for location amenities by incorporating interactions of household characteristics and location amenities into the utility function. This would allow the researcher to evaluate the impact of a policy change on various socio-economic subgroups of the household population.

To date, discrete choice equilibrium models have been mostly used to analyze urban and transportation policy changes. Anas (1982) evaluates the impact of public transportation projects proposed for the Chicago area in the early 1980s. Bayer et al. (2005) use an equilibrium model similar to the Bayer and Timmins (2005) model to investigate the impacts of an increase in income inequality in the San Francisco bay area. Timmins (2007) applies the equilibrium concept from Bayer and Timmins (2005) to evaluate the welfare costs of rainfall changes in Brazil using labor market data. The equilibrium model in this dissertation is based on the specification of Bayer et al. (2005).

Two main distinctions arise between our equilibrium model and the model used by Sieg et al. (2004). First, according to the Sieg et al. specification households value community amenities through a single public good index. As a result, households will have the same preference ordering of communities in the amenity space. This type of preference structure generates substitution patterns that can be restrictive since households are forced to have the same ranking of communities in the amenity space. In our specification, substitution patterns are determined by the interaction of household characteristics and location attributes. Hence, households will have different relative preferences for community-specific amenities such as air quality, education, and crime.

Second, the interaction of household characteristics and location attributes also provide a richer characterization of the heterogeneity in household preferences for location amenities. The taste heterogeneity with respect to the community air quality level is captured by interaction with the household income. Heterogeneity in preferences for school quality is captured via interaction with the household's educational attainment. This approach differs from the Sieg et al. (2004) model where heterogeneity in preferences for amenities is characterized by a single unobserved taste parameter, α.

4 A Locational Equilibrium Model for the Los Angeles Area

This chapter develops the discrete choice equilibrium model used to evaluate the welfare impacts of the 1990 Clean Air Act amendments in the Los Angeles area. We model households' location decisions according to the framework of Bayer et al. (2005). The characterization of the locational equilibrium follows Anas (1982). Section 4.1 models the residential location choice of households. Section 4.2 defines the locational equilibrium.

4.1 Modeling Households' Location Choice

The location model postulates that households choose their residential location *h* from a discrete set of housing types (*H*). A housing type is defined as a collection of houses with identical observed characteristics and located within the same neighborhood. The utility that a household *i* derives from a residential location *h* is given by:

$$v_{ih} = \alpha \log(y^i - p_h) + \gamma d_{ih} + \sum_k x_{hk} \beta_{ik} + \xi_h + \varepsilon_{ih}, \qquad (4.1)$$

where y^i represents household *i*'s monthly income and p_h is the monthly rental price of house *h*. d_{ih} is a dummy variable which equals 1 if the residential location is within the household's employment zone. It is intended to capture the household's preference for housing locations that are closer to its workplace. The k^{th} element of the vector of observed attributes for residential location *h* is given by x_{hk}. These are the housing and neighborhood attributes that are present in the researcher's data. Housing characteristics include bedrooms, age, dwelling type, and tenure status. Neighborhood characteristics include ozone concentration, 8th grade math score, crime index, elevation, proximity to the pacific coastline, housing density and proportion of Hispanics. Other attributes of the residential location that are observed by the household but not observed in the data enter the household's utility via the location-specific error term ξ_h. This term will capture the household's average valuation of the unobserved attributes. The last term, ε_{ih}, is a mean-zero stochastic error which captures the unobserved taste heterogeneity among households.

Each household chooses the residential location which provides it with the highest utility. The household's indirect utility derived from this maximization problem is given by:

$$V_{ih} = \underset{h \in H}{\text{Max}} \ \alpha \log(y^i - p_h) + \gamma d_{ih} + \sum_k x_{hk} \beta_{ik} + \xi_h + \varepsilon_{ih}, \tag{4.1a}$$

where α, γ and β_i are parameters of the household's preference function. α characterizes the household's marginal utility of the log of income[9] while β_{ik} captures the household's taste for location attribute k. The parameter γ characterizes the household's disutility for commuting to work. We explicitly account for the heterogeneity in households' preferences for location characteristics by allowing the taste parameters to vary systematically across households. The specification of the heterogeneous taste parameters uses interactions between location characteristics and observed characteristics of households. These observed household characteristics include household income,

[9] So that the marginal utility of income is given by α / (y_i - p_h).

household size, the presence of children under the age of 18, and whether the household head is college educated. The functional form for the household's taste (β_{ik}) for an attribute k is given by:

$$\beta_{ik} = \beta_{0k} + \sum_{r} z_{ir}\beta_{1kr} \, , \tag{4.2}$$

where z_{ir} represents the r^{th} characteristic of household i. The first term captures the mean component of the household's taste for the attribute k, which is common across all households. The second term is intended to capture systematic differences in tastes which can be attributed to the household's observed characteristics.

The final form of the indirect utility function is obtained by substituting equation (4.2) into equation (4.1a) for the chosen location. It is given by:

$$V_{ih} = \delta_h + \alpha \log(y^i - p_h) + \gamma d_{ih} + \sum_{kr} x_{hk} z_{ir}\beta_{1kr} + \varepsilon_{ih} \, , \tag{4.3}$$

where,

$$\delta_h = \sum_{k} x_{hk}\beta_{0k} + \xi_h \, . \tag{4.4}$$

Equation (4.3) outlines the two main components of the household's valuation of its chosen location. The first component, represented by the constant term (δ_h), captures households' common valuation of location attributes. This valuation is shared by households regardless of their characteristics. For instance, all else equal, households would prefer a house with more bedrooms, less pollution, better schools, less crime, etc. This common valuation represents the average utility that households derive from the residential location *h*. The second component captures the household's individual valuation of the location attributes. These individual valuations are assumed to arise from differences in the observed characteristics of households. For instance, all other things equal, households of larger size are likely to choose houses with more bedrooms.

As in Bayer et al. (2005) and Berry et al. (1995), the specification of the indirect utility in equation (4.3) assumes that households have the same valuation for the unobserved attributes. Hence, we are not able to identify heterogeneous preferences for unobserved location attributes. Bayer et al. (2005) suggest a two-stage approach to estimate the parameters of the household location choice model in equation (4.3). In the first stage, one would recover the household-specific taste parameters (α, γ, β_1) and the location-specific constants (δ_h). This stage can be implemented by maximum likelihood estimation. Because of the large number of housing types the alternative constants are estimated using the contraction mapping proposed by Berry et al. (1995). The details of the estimation are provided in Chapter 6. The second stage then estimates the mean taste parameters (β_{0k}) from the regression specification provided by equation (4.4) using the location constants estimated in the first stage.

The household utility in equation (4.3) closely resembles the utility specification in Bayer et al. (2005). However, there are two differences between our specification and that of Bayer et al. (2005). One difference arises from the characterization of the non-housing good. We characterize the household's consumption of the composite non-housing good using the term $log(y_i - p_h)$. This allows the model to capture income effects that are present in the household's choice problem. It also allows us to derive Hicksian welfare measures that are consistent with the household's utility maximization problem. In the Bayer et al. model the indirect utility does not incorporate the composite non-housing good. The household income enters the utility as a linear interaction with location attributes, and the housing price enters the utility linearly as an attribute of the residential location.

The second difference between our model and the model used by Bayer et al. (2005) is that we do not incorporate endogenous social interaction effects. Social interaction effects emerge from the fact that households may care about the average socioeconomic characteristics of their neighborhoods. These social interaction effects are likely to be endogenously determined in the sorting equilibrium when households have heterogeneous preferences. This is because the average socioeconomic makeup of neighborhoods changes each time households resort. In our utility function the social interaction effect is a result of households' homogeneous tastes for the proportion of Hispanics in their neighborhood. Hence the social interaction effect is exogenous since the neighborhood proportion of Hispanics will not change as households resort. This is due to the fact that households' preferences, for the neighborhood proportion of Hispanics, are assumed homogeneous.

Our specification of the household's indirect utility differs fundamentally from Sieg et al. (2004). Sieg et al. specify the indirect utility of a household residing in a community j as:

$$V_{ij} = [\alpha g_j^{\rho} + h(y_i, p_j)^{\rho}]^{1/\rho}, \tag{4.5}$$

where g_j is the public good index for community j and $h(\bullet)$ is a non-linear function characterizing the household's expenditures on housing. y_i represents the household's income while α_i is a parameter characterizing the heterogeneity of the household's valuation for the public good index. p_j represents the housing price index for community j.

Two main distinctions arise between our equilibrium model and the model used by Sieg et al. (2004). First, according to the Sieg et al. specification, households value community amenities through the single public good index g. As a result, households will have the same preference ordering of communities in the amenity space. This type of preference structure generates substitution patterns that can be restrictive since households are forced to have the same ranking of communities in the amenity space. In our specification, substitution patterns are determined by the interaction of household characteristics and location attributes. Hence, households will have different relative preferences for community-specific amenities such as air quality, education, and crime.

Second, the interaction of household characteristics and location attributes also provide a richer characterization of the heterogeneity in household preferences for location amenities. The taste heterogeneity with respect to the community air quality level is captured by interaction with household income. Heterogeneity in preferences for school quality is captured via interaction with the household's educational attainment.

This approach differs from the Sieg et al. model where heterogeneity in preferences for amenities is characterized by the single unobserved taste parameter, α.

4.2 Characterizing the Locational Equilibrium

We now turn to the characterization of the locational equilibrium for the housing market. We first derive the predicted demand for each housing type. The demand side of the market is made of N heterogeneous households. The supply side of the housing market comprises N occupied housing units classified into H housing types. The supply of each housing type h is defined as the measure of housing units of type h in the study area and is assumed fixed. The locational equilibrium defines a set of market clearing prices $\{p_h\}$ and household choice probabilities $\{P_{ih}\}$.

Characterizing the Housing Demand

We will assume that the idiosyncratic error component ε_{ih} is identically and independently distributed and has a Type I Extreme Value (EV) distribution. Given this assumption, the probability that a household chooses a residential location h is defined by:

$$P_{ih}(p, z_i, x) = \Pr[V_{ih} > V_{il, \forall l \neq h}] = \frac{\exp[\delta_h + \alpha \log(y_i - p_h) + \gamma d_{ih} + \sum_{kr} x_{hk} z_{ir} \beta_{1kr}]}{\sum_{m=1}^{H} \exp[\delta_m + \alpha \log(y_i - p_m) + \gamma d_{im} + \sum_{kr} x_{mk} z_{ir} \beta_{1kr}]}, \quad (4.6)$$

The predicted aggregate demand for housing type h is obtained by summing the choice probabilities (P_{ih}) over the household population.

$$d_h(p) = \sum_i P_{ih}(p, z_i, x)\,, \tag{4.7}$$

where p is a vector of housing prices, z_i is a vector of housing characteristics, and x is a matrix of location attributes whose columns are x_h.

Equation (4.6) characterizes a multinomial logit (MNL) choice structure. An implication of the MNL choice structure is the independence from irrelevant alternatives (IIA) property, which has been the subject of much criticism in the discrete choice literature. Using equation (4.6) the ratio of the choice probabilities for two alternatives h and l will be given by:

$$\frac{P_{ih}}{P_{il}} = \frac{\exp[\delta_h + \alpha \log(y_i - p_h) + \gamma d_{ih} + \sum_{kr} x_{hk} z_{ir} \beta_{1kr}]}{\exp[\delta_l + \log(y_i - p_l) + \gamma d_{il} + \sum_{kr} x_{lk} z_{ir} \beta_{1kr}]} = \exp[V_{ih} - V_{il}]\,. \tag{4.8}$$

This implies that, for a given household, the ratio of the choice probabilities for any two alternatives is independent of the household's systematic valuation of the remaining other alternatives in the household's choice set.

The IIA property gives rise to household choice patterns that are somewhat unrealistic. This can be seen from the following example. Suppose that a town has two restaurants, named Big-M and Big-K. Also, suppose that the two restaurants have identical characteristics except that Big-M only serves beef while Big-K only serves chicken. Furthermore, assume that the household choice probabilities are given by: Pr[*choose Big-M*]=Pr[*choose Big-K*]=1/2. Now suppose that a new restaurant, Big-J, also serving only chicken is built in the town. All other characteristics of the new restaurant are identical to the existing ones. Under the MNL choice structure, the new choice probabilities would be: Pr[*choose Big-M*] = Pr[*choose Big-K*] = Pr[*choose Big-J*] = 1/3. But this is somewhat unrealistic as on would expect customers to treat the two chicken serving restaurants as the same choice. This implies that the new choice probabilities are likely to be: Pr[*choose Big-M*] = 1/2 and Pr[*choose Big-K*] = Pr[*choose Big-J*] = 1/4.

It should be noted that while IIA is a property of the individual household choice probabilities in our model, it is not a property of the housing demands. This can be easily seen by looking at the ratio of the predicted demands for housing alternatives k and l:

$$\frac{d_h(p)}{d_l(p)} = \frac{\sum_i P_{ih}}{\sum_i P_{il}} = \frac{\sum_i 1 \Big/ \left(1 + \sum_{m \neq h} \exp[V_{im}]\right)}{\sum_i 1 \Big/ \left(1 + \sum_{m \neq l} \exp[V_{il}]\right)}. \tag{4.9}$$

It is clear that this ratio is not independent of the remaining housing alternatives in the choice set. The only instance when this ratio can be independent of the remaining alternatives is when households have identical characteristics. In this case the ratio equals one. Hence, the inclusion of household characteristics in the indirect utility function ensures that the housing demands derived from the model will exhibit realistic substitution patterns.

Defining the Locational Equilibrium

The supply of housing units of type h, s_h, is assumed fixed and is given by the number of housing units of type h in the data. The locational equilibrium is such that the demand for each housing type equals its supply. It is characterized by a vector of H housing prices p and a set of NH household location choice probabilities $\{P_{ih}\}$. More specifically, the vector of market-clearing prices p is defined by:

$$d_h(p) = s_h \qquad h = 1,\ldots, H. \tag{4.10}$$

Equation (4.10) defines a system of H equations in H variables.

Existence and Uniqueness of the Locational Equilibrium

The existence of a unique vector of market-clearing prices follows under fairly general conditions. The following proposition establishes the uniqueness and stability of the equilibrium price vector.

Proposition 4.1 (Anas, 1982).
Let $ed_h(p) = d_h(p) - s_h$ define the excess demand for each residential location (i.e. housing type) h. The vector of housing prices (p^*) which solves the system in (4.10) is unique and satisfies Hicksian stability conditions if for each h,

$$\frac{\partial ed_h}{\partial p_m} = \begin{cases} < 0 & \text{for } h = m, \quad -\infty \le p_h \le +\infty \\ > 0 & \text{for } h \ne m, \quad -\infty \le p_h \le +\infty \end{cases}$$

and $\lim_{p_h \to +\infty} \hat{d}_h = 0$ for each $h = 1,\ldots, H$. In other words, all residential locations are strict gross substitutes in the allowable range of market rents.

Proposition 4.1 is a well-known result in Walrasian equilibrium analysis. Mas-Colell et al. (1995, chapter 17) provide an extensive treatment of general equilibrium theory. It can be shown that the excess demand function $ed_h(p)$ satisfies the strict gross substitution property provided that the household location choice probabilities P_{ih} are strictly decreasing in the housing price p_h. This will occur when the estimate for the parameter α is positive.

5 Data Sources

This chapter describes the various datasets used in the estimation of household preferences. The focus of this study is on the four counties that make up the South Coast Air Quality Management District (AQMD): Los Angeles County, Orange County, Riverside County and San Bernardino County. The equilibrium model incorporates a discrete choice model of housing demand. Households choose their residential locations from a discrete set of housing alternatives. Households have heterogeneous preferences for the housing characteristics as well as the neighborhood amenities of residential locations. We estimate the parameters of households' preferences from a cross-section of 1990 microdata which includes household characteristics, housing characteristics, neighborhood air quality, neighborhood school quality, neighborhood crime rate, neighborhood racial composition, neighborhood housing density, neighborhood elevation, and proximity of the neighborhood to the Pacific coastline.

The chapter is organized in four sections. Section 5.1 describes the household and housing microdata. In section 5.2 we describe the procedure used to compute the rental price of housing across owner-occupied and renter-occupied housing units. Section 5.3 describes the neighborhood variables. In section 5.4 we characterize the housing alternatives. The STATA codes used to generate the data are provided in Appendix A.

5.1 Household and Housing Characteristics

Households and housing characteristics are obtained from the 1990 Census Public Use Microdata 5-percent Sample (PUMS).[10] These are records containing a 5-percent sample of all housing units in the United States. The records provide an extensive description of the housing stock and the households in the occupied dwelling units. The PUMS are extracts from the actual decennial Census long form questionnaire, which are taken in a way that protects the confidentiality of households. Unlike the confidential long form files, which identify each household's Census block (an area of approximately 100 people), the 5% PUMS sample only identifies the location of households in a PUMA (Public Use Microdata Area), which is a Census geographic area containing approximately 100,000 people. The PUMS also identify the employment location of household members by their workplace PUMA.

The 1990 PUMS 5-percent sample for the Los Angeles metropolitan area comprises 224,565 occupied housing units. The original household sample consists of the 224,565 households that occupy those housing units. Our analysis focuses on the households occupying single and multi-family dwelling units. Mobile homes and group quarters are excluded from the sample. In addition, we restrict our sample to households that have a monthly income of at least five hundred 1990 dollars. Finally, we dropped the observations where the household's reported monthly income was less than the imputed[11] monthly rental value of the housing unit. The final sample, which is used to represent the

[10] These data are publicly available from the U.S. Census bureau (www.Census.gov), or at www.ipums.umn.edu/usa/vars.html.

[11] We describe the method for imputing the rental value of housing, as well the various issues with the housing prices provided in the Census data, in the next section.

population of households and housing units in this study, consists of approximately 171,000 observations.

Sieg et al. (2004) estimate household preference parameters using housing transactions microdata from 1989 to 1991 in Los Angeles, Riverside, Orange and Ventura County. These data identify the Census tract in which a housing unit is located. Sieg et al. characterize residential communities using 1990 school district boundaries. Housing transactions data provide a more comprehensive set of housing characteristics than the Census long form. However, these data do not provide information on the households occupying the houses. As a result they do not allow one to estimate richer preference specifications, such as those used Bayer et al. (2005), where preferences for location amenities vary across household characteristics.

Table 5.1 provides mean values for selected household and housing characteristics in our 1990 PUMS sample. The microdata sample comprises 171,000 observations describing households and their occupied housing units. The vast majority (nearly 70 percent) of the households in the sample reside in Los Angeles County. Orange County has the second most households in the sample (17%), followed by San Bernardino County (10%) and Riverside County (3%).

The average number of bedrooms for houses in the sample is 2.25. We follow the approach of Bayer et al. (2005) to compute an imputed monthly rental housing price across tenure. A detailed description of the method is provided in the next section.[12] The mean monthly rental housing price is $749. Monthly housing prices are highest in Orange

[12] We construct a single price vector for owned and rental housing units by estimating a hedonic price regression for each of the 3 metropolitan statistical areas in the PUMS sample (Los Angeles-Long Beach, Orange County, and Riverside-San Bernardino). The regressions provide an estimate of the average ratio of housing values to monthly rents in each metropolitan statistical area. The average ratio for the study area is 316.1. The average ratios are then used to convert housing values to their corresponding rental rates.

County ($956) and lowest in San Bernardino County ($707). Half of the housing units in the sample are owner-occupied. Riverside and San Bernardino County have the largest owner-occupied housing shares (0.63). Overall the housing stock is quite young. Nineteen percent of the houses in the sample were built after 1980; 37 percent were built in the 1960s and 70s.

Table 5.1: Mean Household and Housing Characteristics in the 1990 PUMS

	Study Area	Los Angeles County	Orange County	Riverside County	San Bernardino County
Number of observations	170,955	119,726	28,209	5,642	17,378
Housing characteristics					
Monthly housing price ($)	749	709	956	725	707
1 if unit owned	0.51	0.47	0.58	0.63	0.63
Bedrooms	2.25	2.09	2.58	2.71	2.66
1 if built in 80s or 90s	0.19	0.15	0.24	0.43	0.32
1 if built in 60s or 70s	0.37	0.33	0.56	0.33	0.39
1 if single family dwelling	0.62	0.58	0.66	0.77	0.76
1 if unit is within householder’s employment zone	0.505	0.529	0.444	0.447	0.466
Household characteristics					
Monthly income ($)	4,098	3,943	4,945	3,860	3,926
1 if Asian and non-Hispanic	0.082	0.089	0.075	0.041	0.055
1 if Black and non-Hispanic	0.091	0.111	0.015	0.072	0.080
1 if Hispanic	0.237	0.262	0.147	0.189	0.224
1 if White and non-Hispanic	0.585	0.533	0.758	0.689	0.633
1 if children under 18	0.417	0.405	0.396	0.505	0.502
1 if married and has children under 18	0.015	0.014	0.015	0.014	0.017
1 if householder is 65 or older	0.16	0.17	0.13	0.12	0.13
1 if householder has college degree	0.35	0.33	0.44	0.29	0.32
Household size	2.99	2.97	2.95	3.14	3.16

A household’s preference for housing locations that are closer to its workplace is captured by a dummy variable which equals 1 if a residential location is within the household’s employment zone. The household’s employment zone is defined as the PUMA of the household head’s workplace. Other studies (see e.g. Bayer et. al, 2005 and Takeuchi et al., 2005) have instead used the distance to the householder’s employment location. However, in the PUMS data, the householder’s employment location is given by the workplace PUMA. Hence the distance to the householder’s employment location cannot be calculated. Because the workplace PUMA is a relatively large geographic area we prefer using a dummy variable for whether the residential location is within the workplace PUMA, instead of the distance from the residential location to the workplace PUMA. The later turns out to be a noisier measure. Roughly half of the households in the sample choose housing units which are located within their employment zone.

The lower half of Table 5.1 provides a summary of means for selected household characteristics. The average monthly household income in the sample is $4,098. Orange County has the highest average monthly income ($4,945) while Riverside County has the lowest average ($3,860). The racial profile of the household is given by the race of the household head. The sample comprises 8 percent non-Hispanic Asian and 9 percent non-Hispanic Black households. 58 percent of the households in the sample are non-Hispanic Whites. Households of Hispanic origin make up 23 percent of the sample. The share of Hispanic households is highest in Los Angeles County (26%) and lowest in Orange County (15%). Married couples with children under the age of 18 make up 1.5 percent of the households in the sample. In addition, 16 percent of the households in the sample are headed by a senior person, while 35 percent of households are headed by a college graduate.

5.2 Computing the Rental Price of Housing across Units

The housing price is a key characteristic which determines the sorting of households in our model. In the Census data the price of a house is reported as the owner's assessment of the market value, in the case of an owner-occupied unit, or the monthly rent in the case of a renter-occupied unit. To arrive at one price variable which will characterize both owner and renter-occupied units we follow the approach of Bayer et al. (2005) by converting the market value of owner-occupied units to a monthly rental rate. Before describing this procedure we address some potential issues with the reported market value and monthly rent. The procedures described in this section were performed in STATA. All the codes, as well as the regression results, are contained in the data appendix (Appendix A) provided at the end of the dissertation.

5.2.1 Value of Owner-Occupied Housing

A number of issues must be addressed when using the house value reported in the Census long form. The first issue relates to the fact that the housing price reported in the Census long form is based on the owner's own assessment of the market value. This assessment may not always reflect the true market value of the house, as most owners may either report the price of the house at the time of purchase or simply misrepresent the true market value of the house. The second issue regards the fact that the housing values reported in the 1990 Census are top-coded at $500,000. Because housing prices in California are generally higher than the remainder of the United States, we would expect to see a higher occurrence of binding top-codes. According to the 2000 Census 11.4 percent of houses in California where reported at a value of $500,000 or more compared to only 2 percent for the overall United States. In our 1990 sample approximately 8 percent of the houses have top-coded values.

To address these issues, we construct a predicted value for each house by making use of the property tax payment reported for each owner-occupied housing unit. The predicted value makes use of the fact that California law (Proposition 13) requires the property tax to equal either 1 percent of the transaction price of the house at the time the current owner bought the property or the value of the house in 1978. The predicted market value of each owner-occupied house is obtained by regressing the log of the reported house value on the estimated transaction price, i.e. 100 times the property tax, and a set of dummy variables for the year that the house was purchased. The regression specification is given by:

$$\log(p_h) = \alpha_1 \log(T_h) + \alpha_2 y_h + \varepsilon_h \,. \tag{5.1}$$

Where p_h represents the reported market value, T_h represents the estimated transaction price and y_h is a set of year dummies.

If the reported values were true, and all houses were identical except for the year of sale, then α_1 would equal 1 and α_2 would represent how much the house has appreciated in value. If, on the other hand, long time owners tend to underreport the value of their house then α_2 would underrepresent the appreciation of the house in the market. In this case, the predicted value of the house from equation (5.1) should be a conservative estimate of the true market value. We replace the reported value for each house with our computed estimate whenever the latter exceeds the former, which would represent a case of significant underreporting on the part of the owner. In the actual implementation we allow the parameters to vary across sub-regions of our study area by running the regression in (5.1) for each of the three metropolitan statistical areas (MSA) in the study area. These are, Los Angeles-Long Beach, Orange County and Riverside-San Bernardino.

To correct for the bias in the house values, resulting from top coding, we use the following procedure. First, we estimate equation (5.1) using only the sample of houses whose values do not equal the top-code. We then use the estimated parameters to predict the market value for the houses with reported top-coded values.

5.2.2 Reported Housing Rents

As in the case of reported owner-occupied house values one may expect that reported monthly rents of renter-occupied units may not represent a fair assessment of the true market rent. This is likely to be true when the resident has lived in the house for a long period of time. In this case, we may expect that the reported rent will be an understatement of the true market rent. This could be either a result of rent controls or implicit tenure discounts. To correct this issue we compute an adjusted market rent by regressing the log of the reported market rent on a set of dummies characterizing the tenure of the current owner as well as a vector of housing characteristics. The regression specification is given by:

$$\log(p_h) = \beta_1 y_h + \beta_2 X_h + \omega_h . \tag{5.2}$$

Where y_h is a dummy variable representing the year the current renter moved into the unit, and X_h is a set of housing and neighborhood characteristics for the house. As in the case of housing values we run this specification for each of the three MSAs in our sample. The parameter β_1 in equation (5.2) represents the tenure discount in a given PUMA. The corrected rent is then obtained as:

$$p_h^{corrected} = \exp[\log(p_h) - \beta_1 y_h] .$$

5.2.3 Imputing the Rental Value of Housing across Units

In order to arrive at a comparable measure of housing price for both owner and renter-occupied units, we convert owner-occupied house values into monthly rents using the approach described in Bayer et al. (2005). Poterba (1992) provides the theoretical foundation for this approach. Sieg et al. (2004) also use this approach to develop a price index for each housing unit in their sample. To convert housing values into monthly rents, we regress the log of the housing price (house value or monthly rent) on a dummy variable (O_h), indicating whether the unit is owner occupied, and a set of structural housing characteristics (X_h).

$$\log(p_h) = \gamma_1 O_h + \gamma_2 X_h + \upsilon_h \tag{5.3}$$

We run this specification for each of the three MSAs (Los Angeles-Long Beach, Orange County and Riverside-San Bernardino) in our sample. The parameter γ_1 represents the ratio of house values to rents for each MSA, controlling for structural characteristics of housing units. This is the user-cost of owner-occupied housing as defined by Poterba (1992). We use this ratio to convert owner-occupied house values to a corresponding monthly rent.

To summarize, there are three sets of adjustments that are used to characterize the price of housing across owner-occupied and renter-occupied units. The first adjustment accounts for the fact that the house values contained in the Census data are self reported and top coded. The second adjustment addresses the fact that housing rents contained in the Census data may misrepresent the true market rent. The final adjustment deals with converting owner-occupied housing values into monthly rents.

5.3 Neighborhood Variables

Table 5.2 reports average values for the neighborhood attributes used in the model. We use the 1990 Census PUMA boundaries to characterize neighborhood geography. This is because the PUMS identify the geographic location of a dwelling unit as the Census PUMA. A Census PUMA is a geographic area containing approximately 100,000 individuals. Sieg et al. (2004) characterize residential communities using 1990 school district boundaries. They were able to do so because housing transactions microdata identify the census tract as well as the school district for each housing unit. Because they had access to the 1990 Census long form files, Bayer et al. (2005) were able to use Census block boundaries to characterize neighborhoods. The census block is a geographic area of approximately 100 individuals.

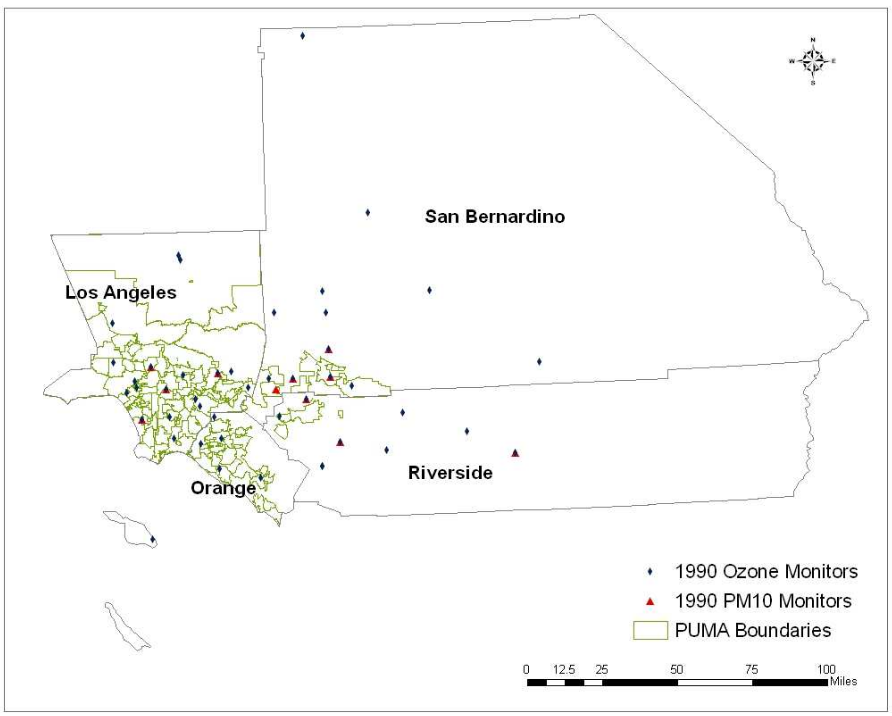
Table 5.2: Mean Neighborhood (PUMA) Characteristics In 1990

	Study Area	Los Angeles County	Orange County	Riverside County	San Bernardino County
Number of observations	79	55	11	3	10
8^{th} grade math score†	34.0	31.6	45.1	34.3	34.8
Crime (FBI index)	786.5	843.3	604.2	831.6	661.2
Elevation (meters)	200.7	172.9	63.2	345.6	461.8
PUMA is on pacific coastline	0.114	0.091	0.364	-	-
Housing density (sq. km)	1,061.7	1,116.2	1,056.9	2,022.2	479.4
Ozone‡ (ppm)	0.146	0.143	0.109	0.177	0.198
Exceedences national 1hr ozone standard	32.94	29.58	12.11	51.46	68.80
PM-10 annual average ($\mu g/m^3$)	55.51	51.87	60.45	68.72	66.12

† School district average for 1994 CLAS. Math test scores have been normalized so they fall between 0 and 100.
‡ Annual average of top 30 daily 1hr maximum readings. PUMA is assigned the 3-year centered average from the closest monitor.

The study area comprised a total of 87 PUMAs in 1990. This compares with approximately 150 school districts and 2400 Census tracts. The average PUMA in 1990 had approximately 3000 housing units. To reduce measurement errors in characterizing neighborhood attributes, the estimation only uses PUMAs whose boundaries are mutually exclusive. PUMAs that are enveloped by other PUMAs are excluded from the sample. This reduces the number of PUMAs to 79. A map of the study area with the PUMA boundaries is shown in Figure 5.1.

Figure 5.1: PUMA Boundaries with Ozone and PM10 Monitors



PUMAs are relatively large geographic units compared to Census tracts or school districts. However, for the main attributes used in the estimation, the variation within PUMAs is significantly small compared to the variation across PUMAs. Table 5.3 shows within and between PUMA standard deviations for selected characteristics. For math score, ozone and PM-10 values, the variation across PUMAs is nearly five times larger than the within PUMA variation. The difference is smaller though still significant for the crime measure. The standard deviation of crime values across PUMAs is 20 percent higher than the mean standard deviation within PUMAs. We therefore conclude that the PUMA boundaries provide a good characterization of neighborhood school quality, crime and air quality.

Table 5.3: Within and Between Variation for Selected PUMA Characteristics In 1990

	Mean of PUMA values	Std. of PUMA Means	Mean of within PUMA Std.
8^{th} grade math score	34.0	35.5	5.7
Crime (FBI index)	786.5	770.1	631.9
Ozone†	0.146	0.040	-
Ozone‡	0.148	0.031	0.006
PM-10†	55.5	11.0	-
PM-10‡	53.2	7.4	1.4

† Interpolation method: PUMA is assigned closest monitor reading.
‡ Interpolation method: PUMA is assigned distance-weighted average of readings from 3 closest monitor.

5.3.1 Air Quality Data

The air quality data used in this study was obtained from the California Air Resources Board (CARB). CARB provides California ambient air quality data for criteria and toxic pollutants from 1980 through 2002. The data include hourly and daily values as well as annual summaries collected from a large network of monitors dispersed throughout the state of California. Annual averages for 1990, 1995, and 2000, are obtained for two major primary criteria pollutants: ozone and particulate matter (PM-10). These pollutants have been shown to have a significant impact on housing prices (Sieg et al., 2004). Ozone is measured as the average of the top 30 daily maximum readings at a monitor, while particulate matter (PM-10) is measured by the annual geometric mean.

Tables 5.4 and 5.5 provide descriptive statistics of the monitor air quality data in the study area. Average ozone concentrations in 1990 were highest in Los Angeles County and lowest in Orange County. Ozone concentrations fell by nearly 40 percent between 1990 and 2000, with the largest reductions recorded in the worst areas. Monitor readings tend to be strongly correlated across pollutants. Table 5.6 shows the correlation between ozone, PM-10, nitrogen oxide (NOx) and sulfur dioxide (SO_2). The correlation coefficient for ozone and PM-10 at monitor locations measuring both pollutants is 0.44.

Table 5.4: Active Monitors Measuring Ozone and PM-10 in the Los Angeles Area

		Study area	Los Angeles County	Orange County	Riverside County	San Bernardino County
Ozone	1989-1991	50	20	6	11	13
	1999-2001	43	18	6	6	13
PM10	1989-1991	18	6	2	5	5
	1999-2001	19	6	3	5	5

Table 5.5: Average Monitor Reading† for Ozone and PM-10[13]

		Study area	Los Angeles County	Orange County	Riverside County	San Bernardino County
Ozone*	1990	0.144	0.150	0.116	0.137	0.154
	2000	0.097	0.089	0.078	0.111	0.109
Ozone Exceedances**	1990	36	37	11	33	47
	2000	3	2	0	5	6
PM-10 ***	1990	55.4	51.5	42.3	61.1	59.5
	2000	44.1	41.6	34.5	44.8	52.2

* Average top 30 1-hour daily maximum readings at a monitor during a year (parts per million).
** Number of days with a recorded violation the one-hour national standard for ozone.
*** Annual geometric mean (ug/m^3).
† The yearly reading for each monitor is obtained by computing a 3-year centered average. For instance, the 1990 reading for monitor x is computed by averaging the readings for 1989, 1990 and 1991 at monitor x.

[13] Source: California Ambient Air Quality Data. 2004 Data CD

Ozone and PM-10 levels are also strongly correlated with secondary pollutants such as nitrogen oxide and sulfur dioxide. The correlation coefficient between ozone and NOx is 0.47; for ozone and SO_2 it is -0.56.

Table 5.6: Correlation between Primary and Secondary Pollutants In 1990

	Ozone	PM-10	Nitrogen Oxide (NOx)	Sulfur Dioxide (SO_2)
Ozone	-	0.44	0.47^{*}	-0.56^{**}
PM-10	0.44	-	0.52^{*}	-0.54

Note: * Significant at 5 percent level. ** Significant at 1 percent level.

The study area had a total of 50 active monitors measuring ozone between 1989 and 1991 (See Table 5.4). This compared with 18 monitors measuring PM-10 concentrations. We use two interpolation approaches to determine neighborhood air pollution levels. The first approach assigns to each PUMA the centered 3-year average of readings from the closest monitor. If more than one monitor falls within a PUMA, the PUMA is assigned the average from these monitors. Sieg et al. (2004) used a similar approach to assign air quality levels to each house in their sample. They then approximate the neighborhood air quality level using the averages for the houses sold in each school district. One potential issue with this approach is that it may assign the same monitor readings to a collection of neighborhoods, regardless of how far they are located from the monitor. Hence, it does not account for the fact that pollution concentrations are likely to dissipate with distance.

The second interpolation approach uses a distance-weighted method. We generate a pollution surface for the entire study area using 100 meter-by-100 meter grid cells. We then assign to each grid cell a distance-weighted average of the readings from the 3 closest monitors. The neighborhood air quality measure is then computed by averaging the grid values within each PUMA. The two interpolation approaches lead to similar neighborhood ozone and PM-10 concentrations. We follow Sieg et al. (2004) and use the pollution levels from the closest monitor interpolation approach in the estimation of household preferences and the computation of welfare benefits.

Figure 5.2 shows a map of the neighborhood air quality levels in 1990 across the study area. The coastal communities of Los Angeles and Orange counties had the highest air quality levels in the area. On the other hand, air quality was the worst in the inland areas of Los Angeles, Riverside and San Bernardino counties. It is interesting to note that the distribution of ozone levels does not appear at first glance to be correlated with the distribution of average household income across neighborhoods, shown in Figure 5.3. It is not clear that higher air quality areas are located in high income neighborhoods and vice versa. In fact, some of the lower income cities such as Inglewood and Long Beach are located in areas with very good air quality, while higher income cities such as Pasadena and Santa Clarita are in poor air quality areas.

The relationship between air quality and income levels implied by the raw data is merely reflecting the fact that households in the Los Angeles area might care more about other public goods (such as school and crime) than they do about air quality. It turns out that the distribution of income is highly correlated with the distribution of school quality. This also suggests that a more rigorous analysis is needed to disentangle the relationship between neighborhood air quality and household income.

Figure 5.2: 1990 Neighborhood Ozone Levels

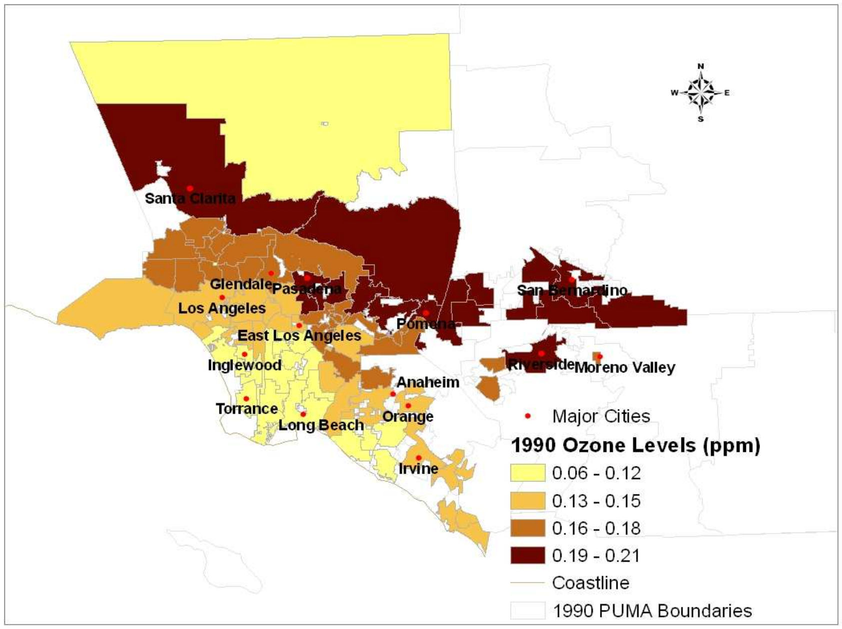
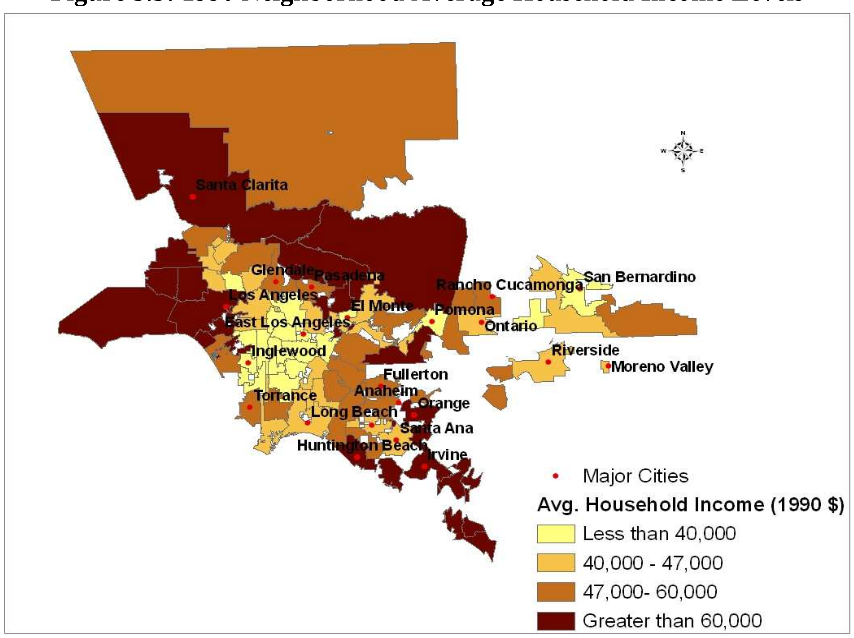


Figure 5.3: 1990 Neighborhood Average Household Income Levels



5.3.2 Other Neighborhood Data

In addition to air quality, we collect data on other neighborhood amenities that households may value. These include school quality, crime and racial composition. The racial composition of the PUMA is characterized by the proportion of Hispanics. Finally, three variables are used to control for unobserved factors that may affect the level of air pollution in a neighborhood. These are, mean elevation of the neighborhood, the proximity of the neighborhood to the Pacific coastline, and the housing density of the neighborhood.

School Quality

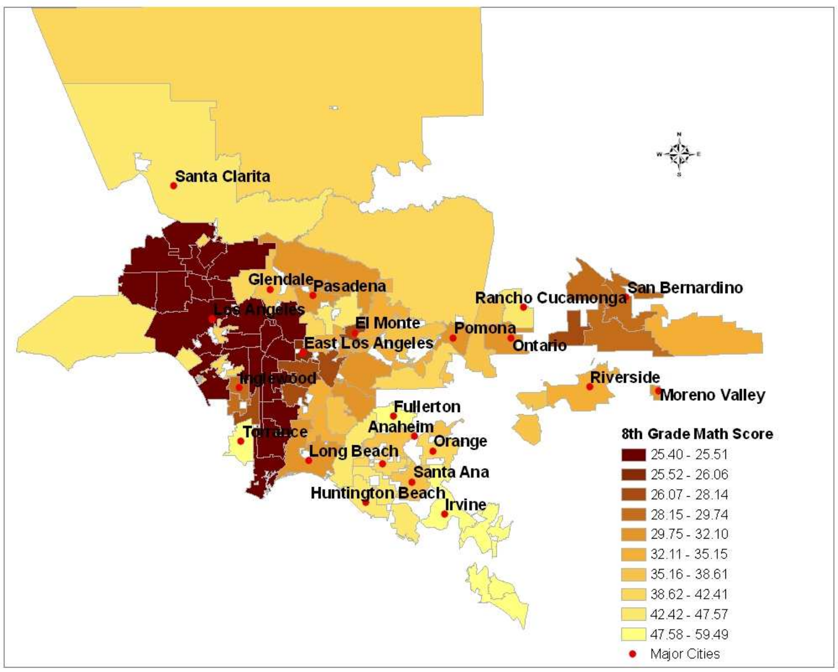
Because California State law limits expenditures of local school districts, a more reliable measure of school quality would be one that is based on academic performance outcomes rather than expenditures (Sieg et al. 2004). The California Department of Education (CDE) administers standardized tests that are used to monitor the academic performance of public schools. In the early 1990s the California Learning Assessment System (CLAS) was administered to public schools throughout the State of California. The 1994 CLAS provides a measure of students' academic performance in math, reading and writing. More recent academic performance test scores are the Academic Performance Index (API) and the STAR report.

We use the school district average 8th grade math score from the 1994 CLAS as our measures of school quality in 1990. Ideally one would want to use the 1989 CLAS data. Unfortunately this dataset is no longer available. The neighborhood school quality variable is computed by using a weighted average of the scores for all the school districts that intersect the PUMA. We use the area of the school district which intersects the

PUMA as weight. For instance, suppose PUMA *j* has total area A and overlaps area *a(x)* of school district *x* and area *a(y)* of school district *y*. Then the school quality level for PUMA *j* is computed as $a(x) \cdot score(x)/A + a(y) \cdot score(y)/A$.

Figure 5.4 provides a map of the neighborhood level school quality data. The large cluster of neighborhoods with the worst school quality levels is part of the Los Angeles unified school district (LAUSD). The LAUSD is one of the largest school districts in the United States and the largest in the State of California.

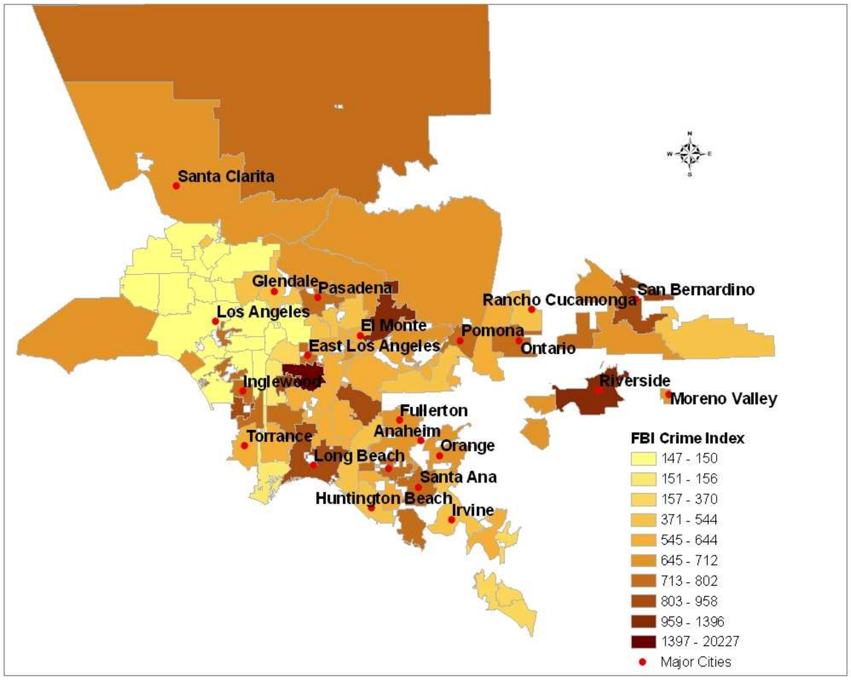
Figure 5.4: 1990 Neighborhood School Quality Levels



Crime Rate

Currently, the most disaggregated crime data for California is provided by the Criminal Justice Statistics Center (CJSC) from the Office of the California Attorney General. The CJSC compiles statewide, county and city crime statistics and publishes them every year in the Criminal Justice Profiles. The crime variable used in this study is the FBI crime index for each jurisdiction in 1990. The FBI crime index reports the number of crime occurrences per 10,000 populations. The neighborhood crime rate is computed using the same weighting average method used to compute the neighborhood school quality. The crime data is not as reliable as the school quality data since it is only provided at the jurisdiction level and not all of the study area is incorporated. A map of the neighborhood crime levels in 1990 is shown in Figure 5.5.

Figure 5.5: 1990 Neighborhood Crime Levels



Elevation, Proximity to Pacific Coastline, Housing Density

A number of factors may determine the level of air pollution in a neighborhood. For example all other things equals, air pollution will generally be less in coastal communities because of the prevailing west winds. In addition, local climate conditions are likely to have a significant impact on the concentration of air pollutants. Also, densely populated urban areas generally tend to have more air pollution because of higher road congestion. To account for these factors we add three neighborhood variables to the household preference specification. These are, the mean elevation of the neighborhood, the neighborhood's proximity to the Pacific coastline, and the housing density of the neighborhood.

The National Elevation Dataset (NED) is a product of the US Geological Survey. It was developed by merging the highest resolution and best quality elevation data across the United States into a seamless raster format. The data is provided at a resolution of 1 arc second with the unit of elevation in meters. We use the NED to calculate the average elevation of each PUMA. The neighborhood's proximity to the Pacific coastline is measured by a binary variable which equals one if a portion of the neighborhood's boundary is on the Pacific coastline. The housing density of the PUMA is given by the number of housing units per square kilometer.

5.4 Characterizing the Residential Location

We characterize the household's residential location choice alternatives in terms of 4037 discrete housing types. These are also referred as housing products. Each housing type is a collection of housing units that are located within the same neighborhood and have identical observed characteristics. Housing types are defined in terms of six variables: ownership status, number of bedrooms, dwelling type, built after 1980, built during the 1960s or 70s, and PUMA. The first five variables represent the housing characteristics for each housing type. We characterize the rental price of a given housing type h as the average of the rental prices for all units of type h. This is similar to the approach used by

Berry et al. (1995) to obtain average prices of car products. The neighborhood characteristics for each housing type are given by the characteristics of the PUMA (see Table 5.2).

The ownership status is defined as either renter-occupied or owner-occupied. The number of bedrooms ranges from 0 to 5, giving 6 types. The dwelling type is defined as either single-family or multi-family. The variables “built after 1980” and “built during 1960s or 70s” are binary variables that equal one if true and zero otherwise. Lastly, the study area contains 79 neighborhoods. These six categories provide a total of 7584 ($2 * 6 * 2 * 2 * 2 * 79$) possible housing types. The actual number of combinations that exist in the study area is much smaller. We obtain a total of 4037 distinct housing products. This is because some of the 7584 possible housing types do not exist in the data. For example, in a given neighborhood there are eight possible types of four-bedroom multi-family units. However, some neighborhoods contain no multi-family four-bedroom units. As a result these neighborhoods will have zero, instead of eight, types of four-bedroom multi-family units.

Using housing types rather than housing units to characterize residential locations significantly reduces the number of alternatives in the housing market while still providing a complete span of the product space. This has a direct implication for the identification of preference parameters in the first stage of the estimation. Indeed, a necessary requirement for the identification[14] of the first stage is that the number of observations be larger than the number of alternative-specific constants plus the number of interaction parameters. This requirement is not met when housing units are used to

[14] A discussion of identification issues is provided in section 6.3.

characterize residential locations, as the number of observations (i.e. households) will equal the number housing alternatives.

6 Estimation Strategy

This chapter describes the estimation of the parameters of the household's indirect utility in equations (4.3) and (4.4). In section 6.1 we characterize the sampling framework used to generate the household sample and the choice set of sampled households. Section 6.2 discusses the details of the estimation strategy. Section 6.3 discusses the properties of the estimated preference parameters. Section 6.4 presents the results of the estimation. The estimation is done in MATLAB. All the codes used in the estimation are contained in the estimation appendix (Appendix B) provided at the end of the dissertation.

6.1 Sampling Framework

Two issues arise in the empirical estimation of the household location choice model. The first issue regards how to draw the sample of households to be used in the estimation of the model. The sampling of households is necessary because it is not computationally feasible to estimate the model from the population of 171,000 households. The second issue pertains to the relevant choice set for the sampled households. This is a classical issue in the estimation of discrete choice models (See for example McFadden, 1978 and Quigley, 1985).

6.1.1 Drawing the Household Sample

We devise a sampling scheme that allows us to use a smaller yet representative sample of the households in the data. The sampling framework uses a stratified, choice-based[15] sampling design. In particular, we draw a 10 percent random sample of the households

[15] Ben-Akiva and Lerman (1985) provide a review of sampling theory and applications to the estimation of discrete choice models.

who choose each housing type. This produces the final sample of 17,894 households used to estimate the location choice model.

The choice-based sampling design does not produce a fully random sample of the household population. Indeed, it is easy to show that the average household characteristics from this sample will be biased estimates of the mean household characteristics in the population. An alternative to the choice-based sampling design would be to use a simple random sampling scheme. While a simple random sampling design produces independent observations, it does not guarantee that every housing type will be represented in the sample. This will likely be the case for housing alternatives that are chosen by very few households. In other words, the random sample may not produce households from those residential locations. In an attempt to provide a full characterization of the housing market, we opted to preserve the product space at the expense of the independence of household observations. We correct for the bias in the first stage estimation, resulting from the choice-based sampling design, using the approach of Manski and McFadden (1981). This correction is explained below in the details of the estimation.

6.1.2 Determining the Choice Set of Sampled Households

The household's relevant choice set or feasible set of alternatives is an essential component of the estimation. A sampling approach is also used to construct the choice set. Potentially, one could set the household's choice set as the 4037 housing types in the sample. However, this would render the estimation computationally intractable. The reason is that the computational burden of the estimation grows linearly with the size of the household's choice set (Ben-Akiva and Lerman, 1985). An alternative is to construct the choice set by sampling a few alternatives from the full set of available alternatives. In particular, the household's choice set includes (i) the household's chosen residential location and (ii) a random sample of 20 residential locations from the remaining non-chosen alternatives. McFadden (1978) has shown that such a scheme will yield consistent parameter estimates for the multinomial logit model. In section 6.4.2 we investigate the robustness of our estimates with respect to the size of the choice set.

6.2 Estimation of Household Preference Parameters

The parameters (α, γ, β_0, β_1) of the household indirect utility function defined by equations (4.3) and (4.4) are estimated from a multinomial logit model. The estimation follows the two-stage approach proposed by Bayer et al. (2005). In the first stage we estimate (H-1) alternative-specific constants[16] (δ_h) and the household-specific taste parameters (α, γ, β_1) in equation (4.3). The second stage estimates the vector of mean taste parameters (β_0) using the estimated vector of alternative constants as the dependent variable in the regression specification given by equation (4.4).

6.2.1 Recovering the Household-Specific Taste Parameters (First Stage)

The alternative-specific constants (δ_h) and the household-specific taste parameters (α, γ, β_1) are obtain via maximum likelihood estimation (MLE). The indirect utility in equation (4.3) defines the household-specific multinomial choice probabilities given by:

[16] Note: The H^{th} alternative constant is set to zero.

$$P_{ih}(p, z_i, x; \delta, \alpha, \gamma, \beta_1) = \frac{\exp[\delta_h + \alpha \log(y_i - p_h) + \gamma d_{ih} + \sum_{kr} x_{hk} z_{ir} \beta_{1kr}]}{\sum_{m \in C_i} \exp[\delta_m + \alpha \log(y_i - p_m) + \gamma d_{im} + \sum_{kr} x_{mk} z_{ir} \beta_{1kr}]}, \qquad (6.1)$$

where C_i represents the choice set of household i. Given the household choice probabilities, the log-likelihood for the household choices observed in the data is defined as:

$$L(\delta, \alpha, \gamma, \beta_1) = \sum_i \sum_{h \in C_i} I_{ih} \log P_{ih}(p, z_i, x; \delta, \alpha, \gamma, \beta_1), \qquad (6.2)$$

where I_{ih} is a dummy that equals 1 whenever household i chooses location h in the data. The estimates for the preference parameters (α, γ, β_1) and the choice-specific constants (δ) are then obtained via maximization of the log-likelihood $L(\delta, \alpha, \gamma, \beta_1)$.

The closing conditions of the equilibrium model are implicitly enforced via maximization of the log-likelihood. As pointed out by Bayer et al (2005), this can be observed from the first order condition of the maximization problem. Differentiating the log-likelihood in (6.2) with respect to $\hat{\delta}_h$ yields:

$$\frac{\partial L}{\partial \hat{\delta}_h} = \sum_{i \in h} (1 - \hat{P}_{ih}) + \sum_{i \notin h} (-\hat{P}_{ih}) = \sum_{i \in h} 1 - \sum_{i \in h} \hat{P}_{ih} - \sum_{i \notin h} \hat{P}_{ih} = s_h - \sum_i \hat{P}_{ih} = 0, \qquad (6.3)$$

where $\hat{P}_{ih}$ is the estimated choice probability, s_h represents the sample housing supply for alternative h, and $i \in h$ indicates that household i chooses housing type h. Notice that equation (6.3) closely resembles the equilibrium condition in equation (4.10). It is indeed the sample equivalent of equation (4.10). Hence, the vector of alternative-specific constants which maximizes the log-likelihood also insures that the equilibrium condition in equation (4.8) holds for the sample.

The maximization of the log-likelihood in equation (6.2) with respect to the full set of parameters ($\delta, \alpha, \gamma, \beta_1$) is computationally demanding. This is because the dimension of δ (the vector of location-specific constants) is generally large. In this study, the housing market comprises a total of 4037 housing alternatives. This requires estimating 4036 alternative-specific constants in the first stage. As a result, maximizing the log-likelihood using standard search algorithms (i.e. Newton-Raphson, quasi-Newton or direct search) can be extremely slow and inefficient. A contraction mapping proposed by Berry et al. (1995) allows one to circumvent this computational burden by solving for the alternative-specific constants separately using the first order condition in equation (6.3).

Equation (6.3) implicitly defines the vector of alternative-specific constants (δ) as a function of the household-specific taste parameters (α, γ, β_1) and the vector of housing-type supplies (s). This allows one to derive a concentrated version of the log-likelihood as a function of (α, γ, β_1). The concentrated log-likelihood is given by:

$$L_c(\alpha,\gamma,\beta_1) = \sum_i \sum_{h \in C_i} I_{ih} \log P_{ih}(\delta(\alpha,\gamma,\beta_1),\alpha,\gamma,\beta_1)\,. \tag{6.4}$$

For given values of (α, γ, β_1) that maximize the concentrated log-likelihood L_c, we can obtain estimates of the alternative constants by solving the system in equation (6.3). The contraction mapping of Berry et al. (1995) provides a quick numerical solution to this system. It suggests solving iteratively for the location constants using the following recursive algorithm:

$$\delta_h^{t+1} = \delta_h^t - \log\left[\sum_i \hat{P}_{ih}(\delta_h^t, \alpha, \gamma, \beta_1) \Big/ s_h\right]. \tag{6.5}$$

Berry et al. (1995) prove that the algorithm in equation (6.5) is a contraction mapping, which means that it is guaranteed to converge for any starting value of δ. Convergence generally occurs quickly. In our estimation, convergence of the contraction mapping usually occurs after 20 to 30 iterations. The computing time is usually between 5 and 10 seconds on Pentium 4 2Ghz PC stations.

The first stage estimation can be summarized as follows:

i. Set an initial guess for δ.

ii. Given δ, maximize the constrained log-likelihood in (6.4) with respect to (α, γ, β_1).

iii. Given the estimates of (α, γ, β_1), solve for δ using the contraction mapping in (6.5).

iv. Repeat (ii) and (iii) until the estimates converge.

It is easy to see that the above steps solve the system of first order conditions for the unconstrained log-likelihood in equation (6.2). This implies that the estimates produced by this sequential estimation are indeed the MLE estimates of (δ, α, γ, β_1), which are unique given the global concavity of the multinomial logit log-likelihood.

6.2.2 Correcting for the Sampling Design

As discussed previously, the choice-based sampling approach does not produce a random sample from the household population. As a result, additional steps need to be taken to ensure that the first stage MLE estimates are consistent. It turns out that the log-likelihood in equation (6.2) represents a special case which requires only a minor correction to achieve consistency. In fact, it has been shown (McFadden and Manski, 1981) that the MLE estimates of (α, γ, β_1) are consistent as long as (i) the choice model is a multinomial logit and (ii) the model contains a full set of alternative-specific constants. (Ben-Akiva and Lerman, 1985) Both of these conditions are satisfied by the log-likelihood in equation (6.2). In addition, a minor correction will ensure the consistency of the alternative constants when the sampling design is such that each choice alternative is a stratum and the population share of each stratum is known. The consistent estimate of δ_h is obtained as:

$$\hat{\delta}_h = \hat{\delta}_h^{mle} - \ln\left({w_h}/{W_h} \right), \tag{6.6}$$

where w_h is the fraction of the sample drawn from stratum h, and W_h represents the population share of stratum h. For the sampling design described in the previous section, each housing type represents a stratum. w_h is therefore the ratio of the number of households drawn from housing type h to the total number of households in the sample. W_h is the proportion of the household population choosing each housing type h.

6.2.3 Estimating the Mean Taste Parameters (Second Stage)

In the second stage, the mean taste parameters (β_0) are estimated via ordinary least-squares (OLS). We regress the vector of alternative-specific constants estimated in the first stage on the housing and neighborhood attributes. The regression specification is given by:

$$\hat{\delta}_h = \sum_k x_{hk}\beta_{0k} + \xi_h \,. \tag{6.7}$$

The underlying assumption of the second stage regression is that the housing and neighborhood attributes in x_h are uncorrelated with the unobserved attributes of the residential location. That is, they must be exogenous or at least determined prior to the revelation of the household's valuation for the unobserved attribute (Nevo, 2000). A potential endogeneity problem may be due to the fact that unobservable neighborhood attributes may be correlated with neighborhood air quality. Bayer, Keohane and Timmins (2007) address this issue by constructing an instrument for neighborhood PM-10 air pollution that uses panel data. In particular, they compute the PM-10 measure, for a location *j*, using changes in PM-10 levels originating from sources outside location *j*. Though we recognize the potential endogeneity of the neighborhood ozone measure, the fact that we have a small number of neighborhoods (79) limits our ability to construct reliable instruments. However, robustness checks suggest that the endogeneity of the PUMA-level ozone measure is not a severe problem. We return to this issue below in the estimation results.

Differentiated product models (see e.g. Berry et al., 1995 and Bayer et al., 2005) have used an instrumental variable (IV) approach to deal with the potential endogeneity problem that arises when the housing price enters the second stage. This endogeneity is caused by the fact that housing prices are likely to be correlated with unobserved characteristics of residential locations. However, we do not instrument for housing prices as they do not enter the second stage regression. Our model does not treat housing prices as attributes of residential locations. Rather, housing prices enter the first stage estimation as part of the household's budget constraint. The first stage maximum likelihood estimation does, however, assume that the household's expenditure on non-housing goods, i.e. the term $(y\text{-}p)$, is uncorrelated with the household-specific random error term (ε_{ih}).

6.3 Properties of Parameter Estimates

6.3.1 Identification

We briefly discuss the identification of the parameters of the household's indirect utility function. Specifically, we ask what features of the data allow for the identification of the estimated parameters. A separate, though not unrelated, identification argument can be given for the each of the stages of the estimation.

A necessary data requirement for identification of the first stage parameters is that the number of observations be larger than the number of alternative-specific constants (H-1) plus the number of interaction parameters (k) to be estimated. In particular let N be the number of households in the sample. Then we must have that $N \geq H + k - 1$. Note that this condition has a direct implication for the characterization of residential locations and the household sample. First, it implies that the household sample used in the estimation must be at least of size $H + k - 1$. Second, characterizing the residential locations as individual housing units would imply that $N < H + k - 1$. As a result, the alternative constants may not be identified. Hence the need to characterize residential locations using housing products rather than individual houses.

Given that the data satisfies the necessary requirement for identification, the heterogeneous taste (i.e. interaction) parameters will be identified, provided that there are sufficient differences in the attributes of households' location choices across each dimension of the household characteristics. For instance, suppose we hypothesize that college educated households have a higher willingness to pay for school quality relative the remainder of the population. Then, for the interaction parameter between school quality and college education to be identified, we need to observe a sufficient difference (in this case positive) in the school quality levels of residential locations chosen by college educated households compared to the remainder of households.

The alternative-specific constants, which will characterize the mean utility from each residential location, are identified by the variation in the market shares[17] of residential locations. Simply put, if residential location A is on average preferred to residential location B (i.e. $\delta_A > \delta_B$) then, all other things equal, we should observe more households choosing A over B in the data.

The mean taste parameters in the second stage regression are identified from the variation in the market shares of residential locations across housing and neighborhood attributes. Notice that a necessary condition is that the alternative-specific constants are

[17] The market share of a housing product is defined as the proportion of households choosing the housing product in the 1990 PUMS data.

identified in the first stage estimation. This should obviously be the case, since the second stage regression cannot be defined without the alternative-specific constants. We can illustrate the second stage identification argument as follows. Suppose, for example, that we hypothesize that households place, on average, a negative value on air pollution. Then in order to identify the negative mean taste parameter for air pollution we must observe that, holding all other attributes equal, residential locations in highly polluted areas have a lower market share compared to residential location in the least polluted areas.

6.3.2 Consistency and Asymptotic Normality

Similar to the identification argument, the asymptotic properties of the estimates can be discussed in terms of the first and second stage estimation. An in-depth discussion of the asymptotic properties of the two-stage estimator can be found in Bayer et al. (2005). The consistency and asymptotic normality of the first stage estimates follow in the same spirit as in the traditional multinomial logit estimation. Given identification of the first stage, the estimated alternative-specific constants and heterogeneous taste parameters will be consistent and asymptotically normal as long as the number of households (N) in the sample grows large (Bayer et al., 2005).

The argument for consistency of the second stage is, however, less straightforward. The complication arises because the dependent variable in the second stage regression is the estimated vector of alternative-specific constants from the first stage. Hence a large number of housing products is not sufficient to guarantee consistency and asymptotic normality. A formal proof is given in Berry, Linton and Pakes (2004). They show that the second stage estimates will be consistent as long as (i) the number of housing alternatives, H, grows large and (ii) $H \log H/N$ goes to zero. That is, not only must H

grow large but the number of households in the sample must also grow faster than H. In addition, asymptotic normality at a rate $\sqrt{H}$ requires that H^2/N be bounded. In other words, N must grow at a rate faster than H^2.

6.4 Estimation Results

We estimate the specification of the household's indirect utility function in equations (4.3) and (4.4). The study area had a total of 50 active monitors measuring ozone between 1989 and 1991 (see Table 5.4). This is compared with only 18 monitors measuring PM-10 concentrations. We use ozone concentrations to characterize air pollution in 1990. Due to the high correlation among the household characteristics we only estimate a limited set of interaction parameters in the first stage.

6.4.1 Parameter Estimates

Table 6.1 summarizes the results of the estimation. Model 1 estimates the benchmark specification which is used in the welfare estimation. The other models provide robustness checks which are described below. The household-specific taste parameters estimated in first stage are all significant. The interaction parameters also have the expected signs except for the interaction parameter between crime and household income. We find that households with higher income levels have a higher willingness to pay for air quality, which is in accordance with the hypothesis that air quality is a normal good. We also find that larger households are willing to pay more for additional bedrooms. Households with college educated heads tend to have a stronger preference for school quality. This is in accordance with the hypothesis that educated people place a higher value on the quality of their children's education. Households also prefer residential locations that are within their employment zone. This supports the hypothesis that households dislike commuting.

Table 6.1: Estimation Results

	Model 1‡	Model 1a	Model 2	Model 3	Model 4
First Stage					
Log(y-p)	1.475**	-	1.499**	1.649**	2.052**
Ozone * Log(y-p)	-0.019**	-	-0.020**	-0.028**	0.01**
Bedrooms * Household size	0.066**	-	0.066**	0.066**	0.064**
Single family * Children under 18	0.227**	-	0.227**	0.227**	0.165**
Math * college	0.309**	-	0.31**	0.244**	0.337**
Log crime * Log(y-p)	0.004**	-	-	-0.013**	0.026**
Within household's employment zone	1.989**	-	1.989**	-	2.194**
Log-Likelihood	-37,072	-	-37,072	-40,719	-47,733
Likelihood Ratio statistic (H_0: δ =0)	25,996	-	26,009	26,857	5,541
Likelihood Ratio p-value (H_0: δ =0)	0.000	-	0.000	0.000	0.999
McFadden pseudo-R^2	0.319	-	0.319	0.252	0.124
Observations	17,894	-	17,894	17,894	17,894
Second Stage OLS †					
Bedrooms	0.04*	0.041*	0.04*	0.044*	0.155**
Built after 1980	-0.594**	-0.594**	-0.594**	-0.596**	0.267**
Built in 60s or 70s	-0.172*	-0.171*	-0.173**	-0.169**	0.131**
Single family dwelling	0.352**	0.346**	0.353**	0.349**	0.185**
Owned	0.054	0.057	0.053	0.04	0.044**
Math test score	0.139**	0.172**	0.153**	0.086*	0.092**
Log FBI crime index	0.0005	-0.0005	-	0.003**	-0.044**
Log Elevation	0.016	0.035	0.007	-0.018	0.066**
PUMA is on Pacific coastline	0.342**	0.378**	0.327**	0.315**	0.167**
Log Density	0.079	0.075	0.068	0.001	0.188**
Prop. of population Hispanic	-0.380*	-	-0.32*	-0.498**	-0.611**
Ozone	0.161	0.120	0.17	0.211	-0.095**
R^2	0.054	0.053	0.054	0.052	0.302
Observations	4,037	4,037	4,037	4,037	17,894

Notes:
** Significant at 1% level. * Significant at 5% level. † Standard errors are computed using White's robust covariance matrix.
‡ Model 1 : Benchmark specification used in the simulation and welfare analysis.
Model 1a: Estimates the second stage OLS **without** the variable "proportion of Hispanics". This is intended to check the endogeneity of neighborhood ozone.
Model 2: Estimates the first and second stage **without** the "crime" variable.
Model 3: Estimates the first stage **without** the "employment" variable.
Model 4: Characterizes residential locations using individual houses instead of discrete housing types.

The positive and significant interaction between the log of crime and household income is contrary to our intuition. We would tend to expect that public safety is a normal good. This means that households with a higher income would want to have more public safety and hence be willing to pay more. This would imply a negative sign for the interaction of crime with income. As described in chapter 5, the crime variable is quite noisy as crime rates are only available at the city level. Also, as Table 5.3 shows, there is not enough variation in the crime variable across neighborhoods. These factors may contribute to the counterintuitive interaction effect between crime and income.

The mean taste parameters estimated in the second stage also generally have the expected signs. On average, households are found to prefer more bedrooms, owner-occupied dwellings, single family dwellings, better school quality and coastal communities. The second-stage ozone coefficient is not statistically different from zero at either the one, five or ten percent level. The mean taste for ozone can be obtain by multiplying the ozone-income interaction coefficient, -0.02, by the mean of Log(y-p) in our sample, 8. The fact that the average taste for owner-occupied dwellings is not significant may be due to the positive correlation between single-family and owner-occupied dwelling. The sample correlation coefficient between the two variables is 0.68 for the housing units in the study area.

6.4.2 Robustness Checks

Endogeneity of Neighborhood Air Pollution

As discussed in the previous section, the estimate of ozone pollution in the second stage regression is likely to be endogenous as a neighborhood's ozone level may be correlated with unobserved neighborhood socioeconomic variables that enter the error term (ξ_h). As a result the estimated mean taste parameter for air pollution may be biased and inconsistent. The direction of this bias is to make the coefficient less negative, as air pollution will generally be positively correlated with neighborhood characteristics, such share of low-income households and share of ethnic minorities, which are generally disliked by households. This could explain the positive estimate of ozone pollution in the second stage regression.

As explained previously, the small number of neighborhoods in our data limits our ability to construct reliable instruments. However, we do a simple robustness check for the endogeneity problem that would result from the correlation between neighborhood ozone level and unobserved neighborhood characteristics. This involves estimating the second stage OLS regression without the proportion of Hispanics. The assumption is that the unobserved neighborhood socioeconomic variables are correlated with the proportion of Hispanics in the neighborhood. Hence, if the ozone level is correlated with unobserved socioeconomic characteristics, removing the neighborhood proportion of Hispanics from the second stage regression should significantly lessen the bias in the estimated ozone mean taste parameter. Model 1a of Table 6.1 reports the results from the alternate regression specification. We find that the estimated ozone coefficient remains positive and insignificant. The magnitude of the coefficient is also roughly the same in Model 1 and Model 1a. We should again note that the mean taste for ozone remains negative, as the ozone-income interaction coefficient is the same across models 1 and 1a.

Robustness Checks with Respect to the Crime and Employment Variables

As mentioned previously, the crime variable is quite noisy as crime rates are only available at the city level. One may wonder whether the noisiness in the crime variable may significantly affect the estimates of the taste parameters for the other neighborhood variables. Model 2 of Table 6.1 runs the estimation without the crime variable in both first and second stages. The estimated parameters from this model are very similar to the estimates in Model 1.

The estimated taste parameter for the household's preference for locations that are within its employment zone is significantly large in absolute value compared to the other taste parameters. It is possible that the employment dummy may also be capturing household-specific preferences for other neighborhood characteristics that are not observed in the data. To the extent that this is the case, one may wonder if the presence of the employment dummy significantly distorts the estimated coefficient for ozone in both the first and second stages. As a robustness check, we run the estimation without the employment dummy in the first stage. The results are reported in Model 3 of Table 6.1. Except for the coefficients involving the crime variable, the remaining of the estimated parameters are similar to those in Model 1.

Alternative Characterization of Residential Locations

We explained in section 5.4 that the residential locations are characterized in terms of housing types, rather individual housing units. This not only reduces the computational burden of the estimation, but also plays a key role in the identification and asymptotic properties of the estimates (see section 6.3). When residential locations are characterized in terms of individual housing units, the alternative constants may not be identified since $N < H + k - 1$.[18] One would essentially be trying to recover more parameters than the number of observations in the first stage estimation.

[18] Here H is the number of housing alternatives and k represents the number of interaction parameters to be estimated in the first stage.

Model 4 of Table 6.1 estimates the household preference parameters by characterizing residential locations using housing units. This is the approach used by Bayer et al. (2005). The sample of housing alternatives is formed by taking a random sub-sample of H (= 17,894) housing units from the 171,000 houses in the 1990 PUMS data for the study area. The household sample is given by the households choosing the H sampled housing units (i.e. $N = H$). This means that the first stage will involve estimating N-1 alternative-specific constants plus k interaction parameters from the location choices of N households. Hence there are not enough observations to explain all the parameters in the first stage estimation. This is reflected by the likelihood ratio test result for the first stage estimation. The joint null hypothesis that the estimated alternative constants are all zero cannot be rejected.

Alternative Sampling Strategies

We also check the robustness of the estimated preference parameters with respect to the size of the household's sampled choice set. In section 6.1.1 we explained that the household's relevant choice set includes (i) the chosen alternative and (ii) a random sample of 20 non-chosen alternatives. Model 5a in Table 6.2 re-estimates the preference parameters using a choice set that includes (i) the chosen alternative and (ii) a random sample of 10 non-chosen alternatives. Model 5b uses a random sample of 50 non-chosen alternatives to form the household choice set. The estimated parameters from both specifications have the same signs with the coefficients in Model 1. The magnitudes of the estimated parameters are also very similar across the specifications.

Table 6.2: Alternative Sampling Strategies

	Model 1‡	Model 5a	Model 5b	Model 6a	Model 6b
First Stage					
Log(y-p)	1.475**	1.394**	1.536**	1.6**	1.56**
Ozone * Log(y-p)	-0.019**	-0.023**	-0.019**	-0.022**	-0.021**
Bedrooms * Household size	0.066**	0.07**	0.066**	0.062**	0.053**
Single family * Children under 18	0.227**	0.271**	0.225**	0.21**	0.253**
Math * college	0.309**	0.32**	0.3**	0.295**	0.297**
Log crime * Log(y-p)	0.004**	0.001	0.006**	0.006**	0.009**
Within household's employment zone	1.989**	1.986**	2.006**	1.971**	1.961**
Log-Likelihood	-37,072	-27,104	-51,690	-67,241	-130,056
Likelihood Ratio p-value (H_0: δ =0)	0.000	0.000	0.000	0.000	0.000
McFadden pseudo-R^2	0.319	0.368	0.265	0.353	0.365
Observations	17,894	17,894	17,894	34,132	67,304
Second Stage OLS †					
Bedrooms	0.04*	0.03	0.045*	0.048*	0.05**
Built after 1980	-0.594**	-0.602**	-0.588**	-0.596**	-0.59**
Built in 60s or 70s	-0.172*	-0.18**	-0.168*	-0.18**	-0.175**
Single family dwelling	0.352**	0.359**	0.356**	0.351**	0.355**
Owned	0.054	0.06	0.041	0.045	0.047
Math test score	0.139**	0.13**	0.143**	0.147**	0.138**
Log FBI crime index	0.0005	0.001	0.0001	0.000	0.000
Log Elevation	0.016	0.009	0.025	0.028	0.028
PUMA is on pacific coastline	0.342**	0.341**	0.334**	0.341**	0.349**
Log Density	0.079	0.07	0.089*	0.09*	0.094*
Prop. of population Hispanic	-0.38*	-0.401*	-0.387*	-0.376*	-0.41**
Ozone	0.161	0.19	0.148	0.151	0.141
R^2	0.054	0.052	0.055	0.056	0.057
Observations	4,037	4,037	4,037	4,037	4,037

Notes:
** Significant at 1% level. * Significant at 5% level. † Standard errors are computed using White's robust covariance matrix.
‡ Model 1 : Benchmark specification used in the simulation and welfare analysis.
Model 2a: Characterizes the household's relevant choice set using 10, instead of 20, randomly sampled non-chosen alternatives.
Model 2b: Characterizes the household's relevant choice set using 50, instead of 20, randomly sampled non-chosen alternatives.
Model 3a: household sample is form by drawing 20, instead of 10, percent of the households choosing each alternative in the 1990 PUMS.
Model 3b: household sample is form by drawing 40, instead of 10, percent of the households choosing each alternative in the 1990 PUMS.

We do a final robustness check of the estimated parameters with respect to the sampling of the households. In section 6.1 we explained that the household sample is formed by drawing a 10 percent random sample of the households choosing each housing type. We re-estimate the household parameters using a different sample size for the random draws. The results are reported in Models 6a and 6b of Table 6.2. Model 5a reports the estimates from a household sample obtained by drawing 20 percent of the households choosing each housing type. Model 5b reports the estimates from a household sample obtained by drawing 40 percent of the households choosing each housing type. The estimated coefficients are very similar to those in Model 1.

6.4.3 Implications of the Estimated Preference Parameters

The predictive power of the model can be seen by mapping the neighborhood mean valuations. Figure 6.1 maps the neighborhood (PUMA) averages of the mean utilities (δ_h) estimated in the first stage. This provides a spatial representation of the model's prediction of the relative rankings of neighborhoods in 1990. The predicted rankings generally concur with the distribution of other neighborhood attributes across the study area. The least preferred neighborhoods in 1990 are located in the south-central and south-eastern portions of Los Angeles County, and the western portions of Riverside and San Bernardino County. This encompasses areas such as East Los Angeles and Inglewood. Those are areas which also possess some of the highest neighborhood crime rates (see Figure 5.5) and lowest school performance results (see Figure 5.4). On the other hand, the most preferred places are generally found in Orange County, as well as the central and north western neighborhoods of Los Angeles. This includes cities such as Beverly Hills, Glendale, Pasadena, Anaheim and Irvine. These are also areas with the lowest neighborhood crime rates and best school performance results.

Figure 6.1: Neighborhood Average of Estimated Mean Utilities (1990)

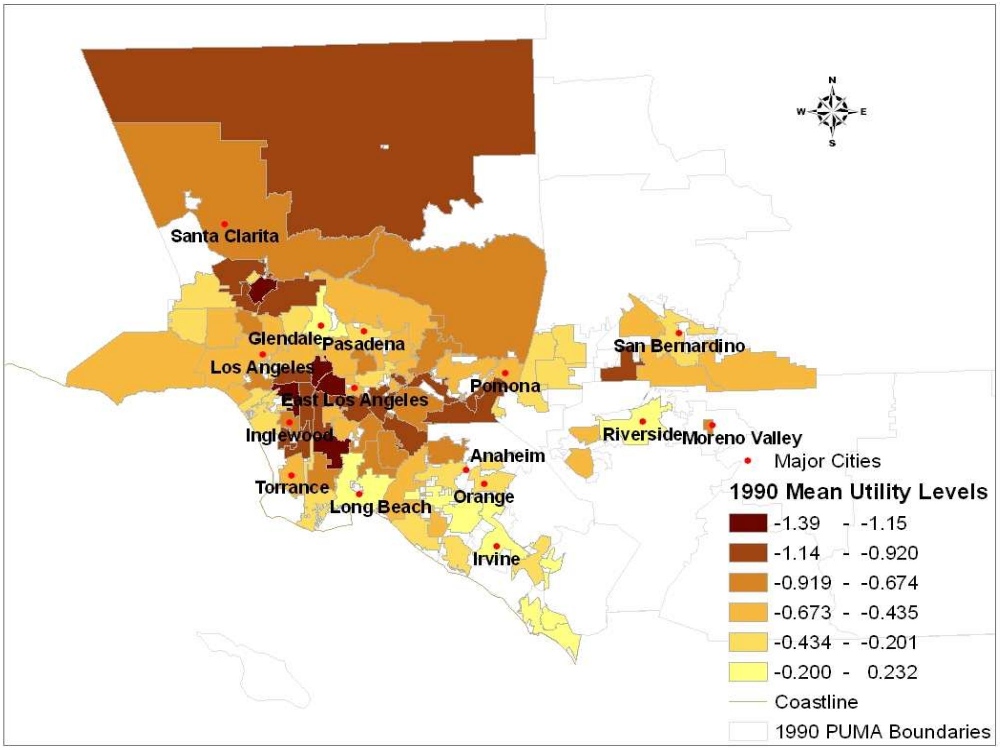


Table 6.3 summarizes the marginal willingness to pay (MWTP) estimates, in annual dollar terms, for selected housing and neighborhood characteristics. The mean MWTP, in annual dollar terms, for a housing attribute x_k is defined as:

$$MWTP_k = \frac{\overline{(\partial \hat{V}_{ih} / \partial x_k)} \cdot 12}{\hat{\alpha} / \overline{(y-p)}} . \tag{6.8}$$

Where, $\hat{V}_{ih}$ is the estimated household indirect utility function, and $\overline{\partial \hat{V}_{ih} / \partial x_k}$ represents the marginal utility of x_k evaluated at the mean of the household sample. The multiplication by 12 converts the MWTP to an annual rental rate. The term in the denominator represents the marginal utility of income evaluated at the mean of the household sample. The mean MWTP for a specific group of the household population (i.e. college graduates, households with annual income below $19,000) is obtained by evaluating the marginal value and the marginal utility of income at the group mean.

Table 6.3: MWTP for Selected Housing and Neighborhood Attributes (1990 Annual Dollars)

	Mean MWTP	College grads	Income < $19,600	Income > $60,400
Bedrooms (+1 bedroom)	1,143	-	150	2,426
Single-family dwelling (vs. Multi-family)	10,104	-	1,326	21,450
Math test score* (+1 standard deviation)	3,550	11,474	466	7,538
PUMA is within household's employment zone (vs. outside)	57,119	-	7,494	121,262
PUMA is on pacific coastline (vs. inland)	9,821	-	1,289	20,850
Share Hispanics (+0.01)	-109	-	-14	-232
Ozone† (-1%)	62	-	8	131

Note: All values are in annual rental rates. For example, the average household is willing to pay $1,143 annually for an additional bedroom while households with income below 19,000 are only willing to $150. The annual mean rental housing price in the study area is $9,000.
†MWTP for a one percent change in 1990 average.
* Math test score: mean = 34, standard deviation = 8.9, range: 25 to 60.

All things equal, we find that households are willing to pay an additional $1,100 in annual housing rent for an extra bedroom in their house. Households are willing to pay an additional $10,000 annually or nearly twice the average annual rent to reside in a single-family housing unit. Households are also willing to pay an additional $9,800 annually for a one standard deviation increase in neighborhood school quality. The model also predicts that households will pay nearly twice the average rent to live in coastal communities. The estimated mean MWTP for locations that are within the household's employment zone is very large. Households are on average willing to pay roughly seven times the average annual rent for locations that are within their employment zone. As explained earlier, this may be due to the fact that the employment zone dummy may be capturing unobserved neighborhood characteristics that are valued by households. MWTP estimates also vary across household characteristics. For instance, compared to the average household, college graduates will pay an extra $500 per year for a one-point increase in the neighborhood schools' average math score. Math scores range from 25 to 60 in the study area.

The estimated ozone coefficient implies a mean MWTP of $62 for a one-percent reduction in the 1990 average ozone concentration. We follow Sieg et al. (2004) by reporting the MWTP for a one-percent reduction in the 1990 ozone levels. This allows comparing the MWTP estimates with estimates from previous studies. We also find a significant variation in MWTP across households. For example, the MWTP for a one-percent reduction in ozone for households in the highest income quartile (top 25 percent) is $130 compared to only $8 for households in the lowest income quartile.

Our estimate of the MWTP for a one-percent ozone reduction compares well with MWTP estimates for other air pollutants in the literature. Sieg et al. (2004) report a marginal willingness to pay of $61 for a one-percent reduction in the 1990 average ozone concentration. Sieg et al. also report that MWTP estimates for other air pollutants in the literature range from $18 to $181, for a one-percent reduction. The Estimates of the MWTP for bedrooms also vary in the literature. Bayer et al. (2005) find a mean MWTP of $1,312, in annual 1990 dollars, for an additional bedroom. Quigley (1985) estimates a nested logit model of household choice in the Pittsburgh metropolitan area, and finds that households are on average willing to pay $618 in annual 1990 dollars for an additional bedroom.[19] Chattopadhyay (2000) estimates a similar model, as Quigley (1985), for the Chicago area using four alternative nesting structures. He finds that the willingness to pay for an additional bedroom ranges from $82 to $533, in 1990 annual dollars.

Our estimate of the mean MWTP for a one standard deviation increase in school quality is very large compared to the estimate obtained by Bayer et al. (2005). Our mean MWTP estimate for a one standard deviation increase in the school quality level is $3,550 in annual terms. This compares with the Bayer et al.'s estimate of $21.5. It should be noted, however, that the two school quality measures are reported using different scales. The mean school quality in the Bayer et al sample is 527, while our school quality measure has a mean of 34. As a result it makes sense to also compare the mean MWTP for a one percent change in the annual 1990 mean school quality, as suggested by Sieg et al. (2004) in the case of air quality. Our estimate of the mean MWTP for a one percent increase in the mean school quality level is $136, which is closer to the Bayer et al. estimate of $18, but still quite high.

We would expect our MWTP estimate of school quality to be relatively higher than the estimate from Bayer et al. (2005). This is because, in our model, school quality may be correlated with unobserved neighborhood characteristics captured by the error term ξ_h. As result, the second stage OLS regression may tend to overestimate the mean taste for school quality. Bayer et al. control for this problem using school district boundary fixed effects. It is not possible to apply this approach to our data because the neighborhoods, ie. PUMAs, are too large compared to school districts. The neighborhoods in Bayer et al. are

[19] The estimate reported in the paper is $13.18 per month in 1967 dollars. This estimate is converted into annual 1990 dollars.

Census blocks, which are much smaller geographic units compared to school districts. This facilitates the use of school district boundary fixed effects because most census blocks fall within the boundary of a school district, while most PUMAs do not.

7 The Benefits of the 1990 Clean Air Act Amendments

This chapter evaluates the equilibrium welfare impacts of the air quality changes brought about by the implementation of the 1990 Clean Air Act Amendments (CAAA) in the Los Angeles area. Section 7.1 discusses the simulation of the equilibrium price changes that emerge from the re-sorting of households as a result of the large changes in air quality. Section 7.2 defines the welfare measures and Section 7.3 discusses their computation. We conclude with a discussion of the welfare results in Section 7.4.

7.1 Simulation of the counterfactual locational equilibrium

Induced price changes that result from the re-sorting of households are obtained by simulating the counterfactual equilibrium which would have emerged in 1990 if air quality levels were identical to those observed in 2000 while all other housing attributes and household characteristics remained at their 1990 levels. Our estimation of the household preference parameters ensures that the housing market is in equilibrium in 1990 (see section 6.2.1). The counterfactual equilibrium is given by the new set of housing prices and the resulting household location choice probabilities which solve the market equilibrium condition in equation (4.10). Residential location demands are calibrated using the estimates of the preference parameters entering the household indirect utility function. The counterfactual equilibrium only reflects the changes in the air quality that occurred in the Los Angeles area between 1990 and 2000. Other factors characterizing the Los Angeles area housing market, such as population, household income and housing supply, are not allowed to change in this simulation.

7.1.1 Calibrating the housing demand

The economic agents in this model are households. We consider the housing choices of N_s (=17,894) households sampled from the overall population of N_p (=171,000) households obtained from the 1990 Census PUMS. The sampling framework used to generate the household sample is described in section 6.1. The housing market is characterized by 4037 distinct housing types. The choice set of each sampled household is characterized by the sampling framework in section 6.1.

We could have each household facing the full set of 4037 housing types. However, this would not be consistent with the estimation of household preference parameters. Recall that the maximum likelihood estimation, which uses choice set sampling, ensures that the market is in equilibrium in the 1990 benchmark (see section 6.2.1). This benchmark equilibrium, which is enforced via the first order conditions of the maximum likelihood estimation (see equation 6.3), will no longer hold when households face the full set of alternatives.[20] As a result significant errors arise in the computation of the predicted housing-type demands, and the counterfactual equilibrium housing-type prices may have undesirable[21] properties. Hence we prefer to maintain the choice set sampling framework, used during the estimation, in the calibration of housing-type demands. We next discuss strategies for obtaining consistent estimates of housing-type demands under choice set sampling.

Obtaining an Appropriate Forecast of the Demand for Housing Types

The computation of the counterfactual equilibrium begins with forecasting the predicted demand for each housing type in the household population under the new air quality

[20] In order for the benchmark equilibrium to hold we will need to re-estimate the preference parameters using the full choice set, which is not computationally feasible.
[21] Notably, some housing types may have negative prices in the counterfactual equilibrium.

levels. Ben-Akiva and Lerman (1985) provide a detailed overview of various techniques for obtaining appropriate forecasts of aggregate demands for choice alternatives in discrete choice models. Our prediction of the aggregate demand for a residential location *h* uses the method of sample enumeration. This technique is especially appropriate in cases when (i) the household sample is drawn nonrandomly[22] from the population and (ii) the choice set of the household is formed by taking a random subsample of the full set of alternatives. In both of these cases sample enumeration allows the researcher to obtain a consistent[23] estimate of the share of the household population choosing a residential location *h*. For a stratified sample with $g = 1,\dots, G$ strata, Ben-Akiva and Lerman (1985) define the sample enumeration estimate of the share of the household population choosing an alternative *h* as:

$$\hat{\sigma}_h = \sum_{g=1}^{G} \left(\frac{N_g}{N_p} \right) \frac{1}{N_{sg}} \sum_{i=1}^{N_{sg}} \hat{P}_{ih}(\hat{\delta}^{mle}, \hat{\alpha}, \hat{\gamma}, \hat{\beta}_1), \tag{7.1}$$

where, N_p is the household population, N_g is the population size of strata *g*, N_{sg} is the sample size of strata *g*, and $\hat{P}_{ih}$ is the estimated household choice probability. For the sampling design used in this study (see section 6.1.1), each housing type *h* represents a stratum. As a result $N_g = N_h$, $N_{sg} = N_{sh}$, the first summation term drops out and the expression for the estimated population share become:

[22] Our household sample is formed by drawing a 10 percent random sample of the households choosing each housing type.
[23] Consistency of the estimated population share holds as long as the estimated preference parameters are consistent, which is the case in our estimation.

$$\hat{\sigma}_h = \left(\frac{N_h}{N_p}\right)\frac{1}{N_{sh}}\sum_{i=1}^{N_{sh}}\hat{P}_{ih}(\hat{\delta},\hat{\alpha},\hat{\gamma},\hat{\beta}_1)\,, \tag{7.2}$$

Where, N_h is the number of households choosing location h in the population and N_{sh} the number of households choosing location h in the household sample. The population share is then converted into the predicted population demand for a housing location h by multiplying the estimated share by the household population (N_p). For a given housing type h the predicted population demand is given by:

$$\hat{d}_h(p) = \frac{N_h}{N_{sh}}\sum_{i=1}^{N_{sh}}\hat{P}_{ih}(\hat{\delta},\hat{\alpha},\hat{\gamma},\hat{\beta}_1)\,. \tag{7.3}$$

The main limitation of the sample enumeration estimate, of the predicted population demand, is that it is subject to sampling error. The sampling error is due to the sampling of households and the sampling of the household choice sets. However, in our application, the sampling error is relatively small given the large size of our sample. The sampling error in the predicted population share for housing type h can be computed using the weighted root mean square formula provided by Ben-Akiva and Lerman (1985), which is due to Koppelman (1975). For our sampling framework, the sampling error in estimating the population shares for the 1990 benchmark is given by:

$$rms = \left\{\sum_{h=1}^{H}\frac{N_h}{N_p}\hat{\sigma}_h\left[\frac{\sigma_h - \hat{\sigma}_h}{\sigma_h}\right]^2\right\}^{1/2}, \tag{7.4}$$

where σ_h represents the actual share of the household population choosing housing type h, which in our sampling framework turns out to equal N_h / N_p. The weighted root mean square in our application is approximately 10^{-10} which is fairly small. An alternative way of assessing the sampling error is to compute the square root of the sum of squares of the excess demands across housing types in the benchmark. This is because, by virtue of the maximum likelihood estimation, the benchmark excess demands[24] must equal zero if there is no sampling error in the predicted population demand. The sampling error in the predicted population demand can then be obtained as $\left\{\sum_{h=1}^{H}\left(\hat{d}_h - s_h\right)^2\right\}^{1/2}$. In our application the sampling error in the predicted population demand is roughly 10^{-6} which is also small.

Computing the Predicted Population Demand under the New Air Quality Levels

Using equation (7.3) we can now characterize the predicted population demand for each housing type under the new air quality levels. It is given by:

$$\hat{d}_h^1(p) = \frac{N_h}{N_{sh}} \sum_{i=1}^{N_{sh}} \frac{\exp[\hat{\delta}_h + \hat{\alpha}\log(y_i - p_h) + \hat{\gamma} d_{ih} + \sum_k x_{hk}^1 z_{ir} \hat{\beta}_{1kr}]}{\sum_{m \in C_i} \exp[\hat{\delta}_m^1 + \hat{\alpha}\log(y_i - p_m) + \hat{\gamma} d_{ih} + \sum_k x_{mk}^1 z_{ir} \hat{\beta}_{1kr}]}, \tag{7.5}$$

where, $\hat{P}_{ih}$ has been defined explicitly. C_i represents the choice set of household i. The superscript 1 is used to indicate market conditions after the air quality changes have occurred. x_{kh}^1 is the vector of attributes for housing type h which includes the new air

[24] The excess demands are given by $\hat{d}_h - s_h$, where s_h is the supply of housing units of type h.

quality level. $\hat{\delta}_h^1$ represents the predicted mean utility for housing type h under the new air quality levels. It is given by:

$$\hat{\delta}_h^1 = \sum_k x_{hk}^1 \hat{\beta}_{0k} + \hat{\xi}_h ,$$

where $\hat{\xi}_h$ is the vector of residuals obtained in the second stage OLS estimation (Equation 6.7). $\hat{\xi}_h$ characterizes the estimate of the mean valuation from the unobserved location attributes. The vector of residuals must be added because the alternative constants which characterize the benchmark 1990 equilibrium are given by:

$$\delta_h^0 = \sum_k x_{hk}^0 \beta_{0k} + \xi_h .$$

The reader can note that this is the same equation characterizing the mean utility in equation (5.4). Hence ξ_h is an key component of the functional form of δ_h .

7.1.2 Defining the Locational Equilibrium

The 171,000 housing units occupied by the population of households in the 1990 Census PUMS are classified into 4037 residential locations. The housing supply s_h is given by the number of housing units at each residential location h. We assume that the housing supply is exogenous with respect to the changes in air quality. Given the housing supply (s_h) and the predicted housing demand ($\hat{d}_h^1$), the counterfactual equilibrium price vector is defined by:

$$ed_h(p^*) = \hat{d}_h^1(p^*) - s_h = 0 \qquad\qquad h = 1,\ldots, H. \qquad (7.6)$$

The counterfactual locational equilibrium defined by equation (7.6) is unique and locally stable. This follows from the fact that the parameter estimate $\hat{\alpha}$ is positive and hence the excess demand $ed_h(p)$ satisfies the strict gross substitution property. (See Proposition 4.1)

7.1.3 Implementation

A numerical solution to the system of H equations in H variables, which defines the counterfactual locational equilibrium, is obtained via an efficiently convergent algorithm suggested by Anas (1982). The equilibrium price vector is found iteratively via a price adjustment process that starts with the benchmark 1990 price vector p^0 and adjusts the location prices until the adjusted price vector is arbitrarily close to the equilibrium price vector p^*.

Let $t = 1, \ldots, T$ define a sequence of T iterations such that $p^T \approx p^*$. The price vector at iteration $t + 1$ is given by the Newton step:

$$p^{t+1} = p^t - [\partial ed(p^t)/\partial p]^{-1}[ed(p^t)]. \qquad (7.7)$$

$ed(p)$ represents the system of excess demands for all H residential locations, and $[\partial ed(p^t)/\partial p]$ is the Jacobian matrix of $ed(p)$ evaluated at p^t. Computation of the Newton step defined in (7.7) requires evaluating and inverting the Jacobian which has dimension $H = 4037$. The computational cost of this algorithm is considerably large. The evaluation of the Jacobian alone takes approximately 30 minutes on a Pentium 4 2Ghz PC station.

Anas (1982) suggests a less costly iteration step which is obtained by ignoring the off diagonal element of the Jacobian matrix. In this case the iteration step $t + 1$ is defined independently for each residential location h as:

$$p_h^{t+1} = p_h^t - ed_h(p^t)/[\partial ed_h(p^t)/\partial p], \qquad h = 1,\ldots, H. \tag{7.7a}$$

The computational cost of the iteration step in (7.7a) is significantly less than that of (7.7) since it only requires computing the diagonal vector of the Jacobian matrix and its element inverse. This alternate Newton step will converge to the equilibrium price vector p^* as long as the off-diagonal elements of the Jacobian are significantly small in absolute value compared to the diagonal elements. Convergence is achieved when the price vector p^T at iteration T is "sufficiently" close to p^*. In our counterfactual simulation p^T is considered "sufficiently" close to p^* if

$$ed_h(p^T)/s_h \leq 10^{-5} \qquad h = 1,\ldots, H. \tag{7.8}$$

In other words, the absolute absolute value of the excess demand for each location is less than 0.001% of the housing supply.

A computational issue arises from the fact that knowledge of H-1 housing-type excess demands is sufficient to characterize the system of H excess demands. This is because we assume that the housing market is a closed economy, which implies that no household relocates outside the study area. A direct implication of the closedness assumption is that the housing-type demands always sum to the total population (*N*) of households. This means that the system of *H* housing-type excess demands has only *H-1* degrees of freedom. As a result, we fix one of the prices when solving for the numerical solution. This normalization guarantees that any starting value will lead to the same market clearing prices. The normalization also guarantees that the counterfactual equilibrium prices are within the same *H*-dimensional simplex as the benchmark price vector and hence lies in the positive quadrant $\Re^{H+}$.

7.1.4 Simulation Results: Impact of Air Quality Changes on Housing Rents

We discuss the extent of the equilibrium price effects that result from the air quality improvements brought about by the 1990 CAAA. These equilibrium price effects are the result of the re-sorting of households across housing locations. Figure 7.1 maps the changes in ozone levels for the neighborhoods in the study area. The lowest improvements in air quality occurred in the coastal neighborhoods of Los Angeles and Orange counties. These were also areas that had the best air quality levels in 1990. On the other hand, air quality improvements were highest in the inland areas of Los Angeles, Riverside and San Bernardino counties. Those were the areas with the worst air quality levels in 1990.

Figure 7.2 shows the PUMA-level average housing price changes in the counterfactual 2000 equilibrium. We find that housing prices are lower, in the counterfactual equilibrium, in the areas with below average air quality improvements. These were also areas with the highest air quality levels in 1990 (see Figure 4.2). Average housing prices fell by as much as 13 percent in those areas. On the other hand

Figure 7.1: Percent Change in Ozone Levels (1990-2000)

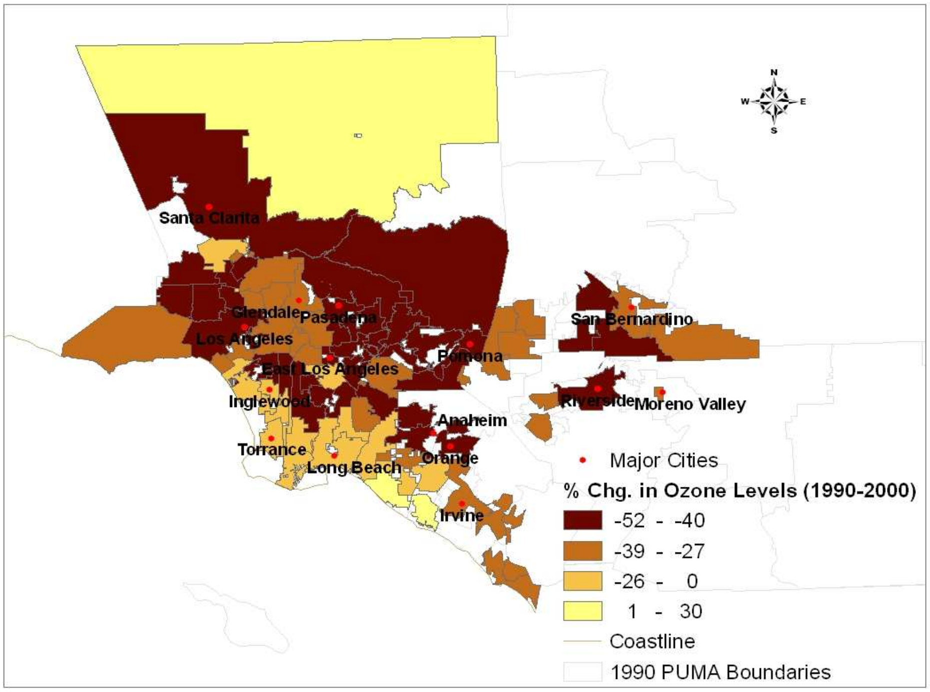
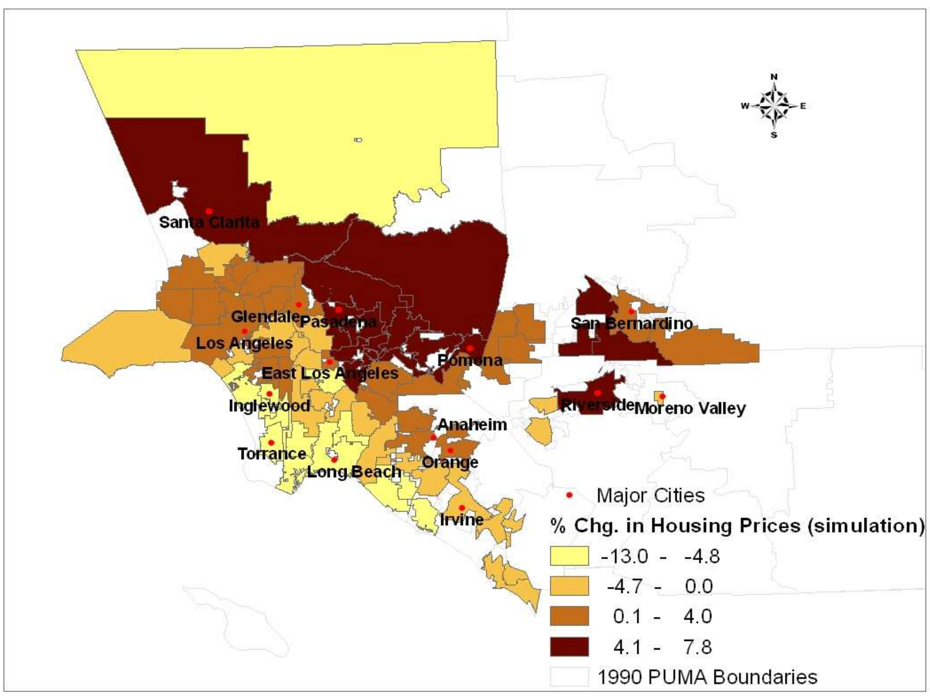


Figure 7.2: Percent Housing Price Changes in Counterfactual Simulation (PUMA average)



housing prices, in the counterfactual equilibrium, are higher in the areas that experienced above average air quality improvements. These were areas with the highest ozone levels in 1990. Housing prices rose by as much as 8 percent in those areas.

The equilibrium price effects observed across neighborhoods were conceptually predicted by Bartik (1988). The intuition is as follows. The large air quality improvements are likely to have two effects on the hedonic equilibrium. First, the fact that a larger proportion of residential locations now have good air quality implies that the hedonic housing rent differentials between high and low air quality areas would be significantly reduced. Table 7.1 shows the proportion of locations with ozone levels below the federal one-hour ozone standard (0.12 ppm) in 1990 and 2000.

Table 7.1: Proportion of Residential Locations below the Federal 1-Hr Ozone Standard (0.12 Ppm)

	Study area (mean)	Los Angeles County	Orange County	Riverside County	San Bernardino County
1990	29.5	32.3	48.7	0.0	0.0
2000	92.7	98.1	100.0	100.0	51.3

The second effect is that, because the supply of air quality has gone up, rents are likely to fall for any given amenity level but relatively more for high air quality areas since the air quality price premium is now lower. This effect is characterized by a shift in the hedonic function. The result of these two effects is that high air quality locations that experience relatively little improvement are likely to experience rent declines. This is because the rent increase from the air quality improvement at these locations is not enough to offset the rent decline from the second effect. On the other hand, low air quality areas that experience large improvements in air quality would likely have higher rents. This is due to the fact that the rent premium from the air quality improvement at each location is large enough to offset the shift in the hedonic function.

7.2 Welfare Measurement in Locational Equilibrium Models

The measurement of welfare in the Epple and Sieg (1999) equilibrium framework was first implemented by Sieg et al. (2005). The study also provides the first empirical analysis of the welfare impacts of non-marginal amenity changes in the context of the Epple-Sieg equilibrium approach. Because the household utility is deterministic in this framework, the derivation of Hicksian welfare measures is straightforward. Given the estimated household preference parameters, one can define the Hicksian compensating variation (*CV*) for an amenity change as the reduction in income such that the household's maximized utility after the change equals the maximized utility before the change.

The earliest empirical evidence on the welfare impacts of non-marginal amenity changes in the context of the discrete choice locational equilibrium framework can be traced back to Anas (1982). The study does not however derive a Hicksian welfare measure that is consistent with the random utility model. An approximation of the Hicksian *CV* measure for an amenity change is obtained as the expected change in the household's maximized utility. This is the approach suggested by Small and Rosen (1977). Timmins (2007) adopts a similar approximation of the Hicksian welfare measure when evaluating the welfare cost of rainfall changes in Brazil using a discrete choice locational equilibrium model of the labor market. Bayer et al. (2005) do not conduct a welfare analysis. Instead, they investigate the impact of changes in income inequality on equilibrium housing prices.

Defining the Welfare Measure

We characterize and estimate Hicksian welfare measures which are derived from a random utility function with non-linear income effects. The household-level Hicksian welfare measure for an air quality change is defined as the reduction in the household's income which is such that the household's maximum utility after the change equals the maximum utility before the change. Hence, by definition, the compensating variation will be negative for an air quality improvement and positive for a reduction in air quality.

For the utility function (v_{ih}) defined by equation (4.1), the household compensating variation for the air quality improvements that occurred in the Angeles area is implicitly defined by:

$$V_{ih}(y_i - p_h^0, x_{1h}^0, x_{2h}^0, \varepsilon_{ih}) = V_{ij}\,(y_i - p_j^1 - CV_i, x_{1j}^1, x_{2j}^0, \varepsilon_{ij})\,, \tag{7.9}$$

where $V_{ih} = \underset{h}{Max}\{v_{ih}\}$. The superscript zero indicates the 1990 market conditions, and the superscript one indicates the market conditions after the air quality changes. For ease of exposition, the attribute vector is broken into two components. x_{1h} represents the air quality level at location h, and x_{2h} is a vector capturing all other attributes of the residential location.

Direct vs. Equilibrium Welfare Measures

For the purpose of evaluating the benefits of the changes in air quality across the Los Angeles area two welfare measures are of interest. The first measure asks what households are willing to pay for the change in air quality at their residence, holding housing prices and all other attributes fixed. This is the “pure” WTP measure defined in chapter 3. We will refer to this welfare measure as the direct WTP measure (CV^d) since it can be recovered directly from the indirect utility function. For our random utility model, CV^d is implicitly defined by:

$$V_{ih}(y_i - p_h^0, x_{1h}^0, x_{2h}^0, \varepsilon_{ih}) = V_{ih}(y_i - p_h^0 - CV_i^d, x_{1h}^1, x_{2h}^0, \varepsilon_{ih}), \tag{7.10}$$

where the notation is similar to that used in equation (7.9).

The direct willingness to pay measure does not, however, provide a complete picture of the welfare impact of the changes in air quality across the Los Angeles area. Bartik (1988) shows that CV^d provides a lower bound to the full, i.e. equilibrium, welfare impact of the air quality changes. We define the equilibrium welfare measure (CV^e) as the WTP measure which takes into account the induced changes in housing prices that occur as households change their residential location choice. It is given by:

$$V_{ih}(y_i - p_h^0, x_{1h}^0, x_{2h}^0, \varepsilon_{ih}) = V_{ij}(y_i - p_j^1 - CV_i^e, x_{1j}^1, x_{2j}^0, \varepsilon_{ij}). \tag{7.11}$$

The household’s residential location choice j in the *ex-post* equilibrium differs from the location h in the benchmark equilibrium. This indicates that the household might change its residential location choice as a result of the change in air quality.

Assumptions about the Equilibrium Welfare Measure

The characterization of the equilibrium welfare impacts of the 1990 CAAA only accounts for air quality changes and induced price changes resulting from the re-sorting of households across locations. In reality, however, one could expect other changes to take place. First, in addition to induced price changes, induced changes in the housing supply may occur as developers respond to the price changes. Moreover, exogenous changes in the model's primitives may occur between 1990 and 2000. These would include changes in household income, population, and economic conditions. Our equilibrium model cannot account for either induced changes in the housing supply or other exogenous changes in market conditions. As a result we do not attempt to replicate the real market conditions that prevail after the air quality changes. Rather, we simulate a counterfactual market equilibrium in which induced price changes occur while all other factors are held to their 1990 levels.

One might wonder about how accounting for these other factors would affect the equilibrium welfare measure. Using the higher household income levels in 2000 would likely lead to higher benefit estimates as high-income households would have a higher marginal willingness to pay for air quality. If the supply of housing is elastic with respect to price, accounting for housing supply adjustments would likely increase equilibrium benefits as the influx of new housing units would provide more choices to households. An increase in population is likely to reduce equilibrium welfare gains to the extent that the increased demand for housing results in higher prices. This effect is however likely to vanish in the long run as the supply of housing adjusts. Hence, it is likely that accounting for the other exogenous changes in the housing market will result in higher equilibrium benefit estimates.

7.3 Computing Compensating Variation in a Random Utility Model

The household level *CV* measure defined by equation (7.9) is a random variable as it is a function of the unobserved taste error ε. Hence the welfare measure that is of interest to policy analysis is the expected value of the household level compensating variation over the distribution of the unobserved taste error ε. We define this expectation as:

$$ECV = E[CV \mid (y, p^0, p^1, x^0, x^1, \varepsilon)] \tag{7.12}$$

The expectation *ECV* will characterize the household's expected willingness to pay (*WTP*) for the air quality changes across the Los Angeles area.

A general closed form expression for *ECV* does not exist for the indirect utility function in equation (4.3). This is because in certain cases the *CV* measure may be a nonlinear function of the stochastic error term ε. As a result its expectation, which requires integrating out the nonlinear error term, cannot be characterized explicitly. Two empirical approaches have been suggested for recovering *ECV*. Morey et al. (1993) suggested approximating *ECV* as the income reduction which equates the expected maximum utility after the change with the expected maximum utility before the change. This approach gets around the computational problem of integrating out the nonlinear error term by defining CV as the income compensation to a representative household. Hence it is known as the representative consumer approximation of *ECV*. McFadden (1999) suggested a general simulation approach for recovering the exact *ECV*. We adopt the simulation approach of McFadden to obtain the average and income distributional welfare impacts of the 1990 CAAA.

We compare the mean and income distributional welfare impacts from the simulation and representative consumer approach. McFadden (1999) argues that the representative consumer approximation to *ECV* is biased when large changes are considered. However, in a study of fishing mode choices by California anglers, Herriges and Kling (1999) find that the two approaches do not lead to substantially different welfare results. We attempt to provide additional empirical evidence on the relative performance of these two approaches in the context of measuring equilibrium welfare impacts.

7.3.1 A Representative Consumer Approximation of *ECV*

Morey et al. (1993) suggested approximating *ECV* by computing the income compensation that equates the expected maximum utility of a representative consumer before and after the air quality and price change. This approximation to *ECV*, denoted $\overline{CV}$, is defined implicitly as:

$$E[V_{ih}(y_i - p_h^1 - \overline{CV}_i, x_{1h}^1, \varepsilon_{ih})] = E[V_{ih}(y_i - p_h^0, x_{1h}^0, \varepsilon_{ih})]. \tag{7.13}$$

A closed for expression for the expected maximum utility $E[V_{ih}]$ can be obtained when the unobserved household taste error ε enters the utility additively and is drawn from an extreme value (EV) distribution. Both of these assumptions are satisfied by the indirect utility function in equation (5.3). The expected maximum utility is given by:

$$E[V_{ih}(y_i - p_h, x_h, z_i, \varepsilon_{ij})] = \log \sum_h Exp\left[\delta_h + \alpha \log(y^i - p_h) + \gamma d_{ih} + \sum_{kr} x_{hk} z_{ir} \beta_{1kr}\right] + c, \tag{7.14}$$

where c is Euler's constant. This constant term cancels out of the computation of *ECV* as it appears on both sides of equation (7.13). The computation of $\overline{CV}$ is achieved via a simple one dimensional search algorithm. Our computations use the Fzero function in MATLAB. The direct and equilibrium WTP measures are obtained for a random sample of 1,674 households from the household population in the study area.

The advantage of the representative consumer approach is that it is simple and relatively easy to implement. In addition, the computational burden of the one-dimensional search is minimal. The search will generally converge in a fraction of a second on most standard personal computers. The main limitation of the representative consumer approximation approach is that, for large quality improvements, $\overline{CV}$ may provide a biased measure of the true expectation of the household's CV measure defined by equation (7.9). McFadden (1999) showed evidence of this bias using an analytical example which compares the exact measure of *ECV* with the approximation $\overline{CV}$.

7.3.2 A Simulation Approach to Recovering the Exact *ECV*

For each household, a random sample of size T is drawn from the distribution of the unobserved taste error ε. For every draw t the household level *CV* measure defined in equation (7.9) is computed. The household's *ECV*, denoted $\overline{CV^t}$, is obtained as the average of the *CV* measures across the draws:

$$\overline{CV^t} = \frac{1}{T}\sum_{t=1}^{T} CV^t . \qquad (7.15)$$

This is the simulation estimator suggested by McFadden (1999). It has been shown that $\overline{CV^t}$ is a consistent estimate of *ECV*. McFadden (1997) has shown that $\overline{CV^t}$ almost surely converges to *ECV*, and $\sqrt{T}\left(\overline{CV^t} - ECV\right)$ is asymptotically distributed as a normal with mean zero and variance σ^2. A consistent estimate of σ^2 can be obtained given *r* = *1,…, R* independent replications of the random sample of unobserved taste errors. It is defined by:

$$\hat{\sigma}^2 = \frac{1}{R}\sum_{r=1}^{R}\left[\frac{1}{T}\sum_{t=1}^{T} CV^t - \frac{1}{TR}\sum_{r=1}^{R}\sum_{t=1}^{T} CV^{tr}\right], \tag{7.16}$$

where CV^t is the household level *CV* measure computed for each random draw *t* using equation (7.9).

The complete simulation procedure was outlined by McFadden (1999) for the general case of an unobserved taste error term with a generalized extreme value (GEV) distribution. The following simulation steps are outlined by Herriges and Kling (1999):

Simulation algorithm:

Step 1: At iteration t (t = 1,…, T) a pseudorandom number generator is used to draw the vector $\hat{\varepsilon}_i^t$ *from the hypothesized GEV distribution of* ε_i.

Step 2: For each draw $\hat{\varepsilon}_i^t$, *a numerical algorithm is then used to search iteratively for the* CV^t *defined by:*

$$\underset{h}{Max}\ \ v_{ih}(y_i - p_h^0, x_{1h}^0, x_{2h}^0, \varepsilon_{ih}^t) = \underset{h}{Max}\ \ v_{ih}(y_i - p_h^1 - CV^t, x_{1h}^1, x_{2h}^0, \varepsilon_{ih}^t).$$

Step 3: A consistent estimate of $E[CV \mid (y, p^0, p^1, x^0, x^1, \varepsilon)]$ *is obtained as:*

$$\overline{CV^t} = \frac{1}{T}\sum_{t=1}^{T} CV^t .$$

Steps 2 and 3 of the simulation algorithm are relatively easy to evaluate. The numerical search in Step 2 is achieved via a simple one dimensional search algorithm. The main computational task of the simulation algorithm regards the evaluation of Step 1. Generating the random sample from the GEV distribution can be a fairly complex exercise. McFadden (1999) outlines a Markov Chain Monte Carlo (MCMC) algorithm for generating draws from a GEV distribution. The MCMC algorithm uses an independence Metropolis-Hasting sampler. The algorithm, which McFadden termed a GEV sampler, is as follows:

GEV sampler: At step t draw J+1 independent variables ζ_j^t *(t= 1,…, J) and* η^t *from a uniform (0, 1) distribution. Form J extreme value random variables using the transformation:* $\tilde{\varepsilon}_j^t = -\log(-\log(\zeta_j^t))$. *The GEV draw* $\hat{\varepsilon}^t$ *is obtained from the following Markov chain:*

$$\hat{\varepsilon}^t = \begin{cases} \tilde{\varepsilon}^t & \text{if } \eta^t \le \dfrac{f(\tilde{\varepsilon}^t)/g(\tilde{\varepsilon}^t)}{f(\tilde{\varepsilon}^{t-1})/g(\tilde{\varepsilon}^{t-1})}, \\ \varepsilon^{t-1} & \text{otherwise} \end{cases}$$

where f and g are the GEV and EV density function, respectively.

In their empirical applications, McFadden (1999) and Herriges and Kling (1999) find that the computational burden of the GEV sampler increases significantly as *f* departs from the EV distribution. When the unobserved tastes are distributed as EV, i.e. the choice model is multinomial logit, the GEV sampler is unbiased and Step 1 can be evaluating using a EV pseudorandom generator from standard statistical packages. In our application we used the EV pseudorandom generator from MATLAB's Statistical Toolbox.

The direct and equilibrium WTP measures are obtained for a random sample of 1,674 households from the household population in the study area. Step 1 of the simulation algorithm is implemented by generating $T = 100$ independent vectors of 4,037 pseudorandom EV variables. The numerical search in Step 2 is achieved via MATLAB's Fzero function. The computation of the *ECV* simulation estimate takes an average of 4.5 hours on a Pentium 4 2Ghz PC station. This compares to an average time of about 5 minutes for the computation of the representative consumer ECV estimate.

The size of T was selected on the basis of a Monte Carlo experiment suggested by Herriges and Kling (1999). The estimation of *ECV* using T iterations was repeated 100 times. We found that after $T = 50$, the estimated mean compensating variations were very similar over the 100 trials. The standard deviation was roughly 4 percent of the mean value across the 100 trials for $T = 50$. By $T = 100$ the standard deviation was reduced to roughly 1 percent of the mean compensating variation across the 100 trials.

7.4 Welfare Impacts of the 1990 CAAA

Our analysis of the benefits of the 1990 CAAA focuses on the changes in neighborhood ozone levels between 1990 and 2000. The neighborhoods of the Los Angeles area experienced significant reductions in ozone levels during the years that followed the 1990 CAAA. Table 7.2 summarizes the changes in ozone levels for the neighborhoods in our sample. The neighborhood average ozone concentration fell by nearly 21 percent between 1990 and 1995. By the year 2000, the average reduction in ozone levels was close to 40 percent. The changes in ozone levels also varied across the area. The neighborhoods of

Los Angeles and San Bernardino counties experienced the greatest ozone reductions between 1990 and 2000, while Orange and Riverside counties had the smallest average fall in ozone levels.

Table 7.2: Changes in Neighborhood Ozone Levels across the Los Angeles Area

	1990	1995	2000	% Δ 1990-95	% Δ 1990-95 (Sieg et al.)	% Δ 1990-2000
Study area	0.146	0.116	0.089	-20.8	-19.3	-38.9
Los Angeles County	0.143	0.110	0.086	-22.6	-20.8	-39.8
Orange County	0.109	0.094	0.076	-13.8	-18	-29.8
Riverside County	0.177	0.140	0.115	-20.6	-20.7	-35.2
San Bernardino County	0.198	0.162	0.115	-18.1	-16.3	-41.9

The neighborhood ozone changes for our sample differ slightly from the changes in ozone levels used by Sieg et al. (2002). In Orange County, for instance, our neighborhood ozone reductions between 1990 and 1995 were 4 percent lower than the reductions observed by Sieg et al. The slight divergence in ozone changes can be attributed to the differences in neighborhood geography. This study characterizes neighborhoods with PUMA boundaries while Sieg et al. use school district boundaries to characterize neighborhoods.

7.4.1 Results

The direct and equilibrium WTP measures, defined by equations (7.10) and (7.11), are computed for a random sample of 1,674 households from the household population in the study area. This sample represents one-percent of the household population in our study area. The random sampling allows us to derive unbiased means for the distribution of WTP.

Unlike in the simulation model, households face the full set of housing alternatives in the housing market. While there are strategies for obtaining consistent[25] estimates of preference parameters and housing-type demands under choice set sampling (see Ben-Akiva and Lerman, 1985), we do not know of any strategies for obtaining consistent estimates of the Hicksian welfare measure under the sampling of choice sets. Hence we allow households to face the full set of alternatives in the welfare estimation.

Mean Welfare Impacts

Table 7.3 presents the mean welfare impacts of the CAAA from 1990 to 2000. These are the exact welfare measures obtained via McFadden's simulation approach. The first row provides the overall results for the study area. The second group of rows provides the county-level results. The last two groups of rows provide results for selected neighborhoods. In the third set of rows, neighborhoods are ranked by their average 1990 income level and we present the mean welfare results for the 1st, 50th and 99th percentile. In the last set of rows we rank neighborhoods by their 1990 ozone level and present the mean welfare results for the 1st, 50th and 99th percentile.

The welfare results suggest that, on average, the air quality improvements provided significant benefits to the households of the Los Angeles metropolitan area. We estimate that the reductions in ozone levels between 1990 and 2000 provided an average equilibrium welfare benefit of $1,829 to the households of the Los Angeles Area. This benefit represents 4 percent of the annual average household income in 1990. As conceptually predicted by Bartik (1988) and demonstrated by Sieg et al. (2004), direct welfare benefits, which do not account for induced changes in housing prices,

[25] Here consistent estimate implies an estimate that is asymptotically equivalent to the estimate which is computed using the full set of housing alternatives.

underestimate the benefits of the air quality improvements. On average, equilibrium benefits were 32 percent higher than the direct benefit estimates.

Table 7.3: Mean Direct (D) and Equilibrium (E) WTP* for the CAAA (1990-2000)

	Avg. 1990 Income	1990 Ozone	% Δ Ozone	1990 Avg. Price	% Δ Price	WTP_D	WTP_E	$WTP_{E/D}$
Study area (mean)	49,197	0.146	-36.1	748	0.14	1,386	1,829	1.32
Counties								
Los Angeles County	47,152	0.143	-37.6	728	0.17	1,325	1,757	1.33
Orange County	60,924	0.109	-23.8	926	-4.10	1,659	2,134	1.29
Riverside County	47,374	0.177	-34.4	687	1.02	1,299	1,764	1.36
San Bernardino County	48,096	0.198	-41.9	682	4.35	1,384	1,836	1.33
Neighborhoods by income levels								
1st percentile (lowest)	24,657	0.103	-46.8	455	-1.14	382	704	1.84
50th percentile	47,331	0.119	-40.4	805	-1.33	1,157	1,665	1.44
99th percentile (highest)	92,708	0.148	-48.7	982	2.57	2,378	2,837	1.19
Neighborhoods by ozone levels								
1st percentile (lowest)	65,135	0.058	30.0	1,000	-12.93	2,018	2,434	1.21
50th percentile	54,568	0.148	-43.7	822	1.41	1,462	1,832	1.25
99th percentile (highest)	39,979	0.212	-43.9	580	5.22	1,109	1,492	1.35

* Note: WTP is computed as the expected compensating variation (*ECV*). All WTP estimates are computed using McFadden's simulation approach. WTP estimates are in annual 1990 dollars.

The estimated mean welfare gains vary across the counties in the sample. Average benefits are highest in Orange County and lowest in Los Angeles County. The mean equilibrium WTP for the ozone changes between 1990 and 2000 was $2,134 in Orange County. This compares with an average equilibrium benefit of $1,757 in Los Angeles County. The distribution of welfare gains across counties tends to reflect equilibrium price effects across the counties. Orange County, which experienced a fall in housing prices, has a significantly larger average equilibrium WTP.

We find a significant variation in welfare gains across neighborhoods. The mean equilibrium benefit in the neighborhoods with the highest average income is nearly four times the mean equilibrium benefit in the poorest neighborhoods. This variation can be attributed to the fact that richer households have a significantly higher MWTP for air quality compared to low-income households in our model. However, relative equilibrium gains are higher in the low-income neighborhoods as evidenced by the ratio of equilibrium to direct benefits. Indeed, equilibrium benefits are 84 percent higher than direct benefits in the poorest neighborhoods, as compared to only 19 percent in the richest neighborhoods.

We also find that households originally located in the most polluted neighborhoods have on average lower equilibrium benefits than households originally located in the least polluted neighborhoods. This variation can be attributed to the fact that the most polluted neighborhoods, which had above average ozone reductions, experienced an increase in housing prices. On the other hand, housing prices decreased in the least polluted neighborhoods as they generally had below average ozone reduction (an ozone increase in the case of the cleanest neighborhood).

Income Distributional Welfare Impacts of the 1990 CAAA

Table 7.4 presents the distribution of equilibrium welfare estimates across household income quartiles. The lowest income quartile is comprised of households with 1990 annual 1990 income below $20,000 dollars, while the highest income quartile includes households with annual income above $60,000. Income distributional benefits are provided for the study area as well as counties and neighborhoods. The WTP estimates are obtained using McFadden’s simulation approach.

Equilibrium benefits vary significantly across household income groups. Specifically we find that richer households generally have significantly higher benefits compared to households in the lower income groups. This is true for the overall study area as well as within counties and neighborhoods. The variation in welfare gains across income groups is to be expected as the higher income households have a significantly higher MWTP for air quality in our model.

Table 7.4: Distribution of Equilibrium WTP* for the CAAA (1990-2000)

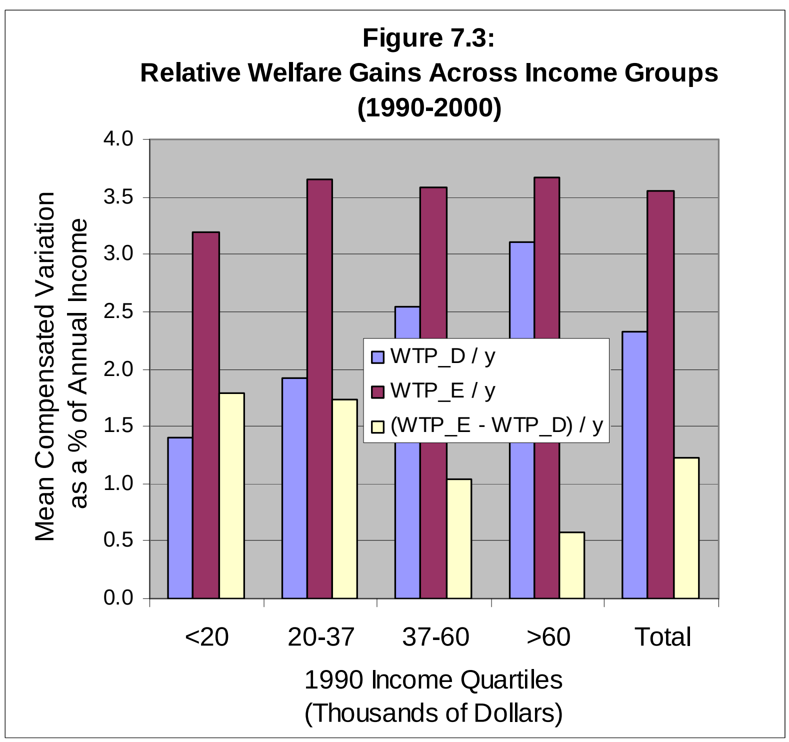
	Avg. 1990 Income	% Δ Ozone	% Δ Price	Income < 20k	Income 20k - 37k	Income 37k - 60k	Income > 60k
Study area (mean)	49,197	-36.1	0.14	441	1,019	1,706	3,634
Counties							
Los Angeles County	47,152	-37.6	0.17	433	1,009	1,682	3,638
Orange County	60,924	-23.8	-4.10	518	1,058	1,707	3,774
Riverside County	47,374	-34.4	1.02	384	1,053	1,796	3,133
San Bernardino County	48,096	-41.9	4.35	433	1,017	1,812	3,510
Neighborhoods by income levels							
1st percentile (lowest)	24,657	-46.8	-1.14	409	850	1,439	2,325
50th percentile	47,331	-40.4	-1.33	392	1,075	1,695	2,566
99th percentile (highest)	92,708	-48.7	2.57	479	909	1,590	4,505
Neighborhoods by ozone levels							
1st percentile (lowest)	65,135	30.0	-12.93	577	1,090	1,759	4,015
50th percentile	54,568	-43.7	1.41	388	964	1,790	4,341
99th percentile (highest)	39,979	-43.9	5.22	541	845	1,527	2,761

* Note: WTP is computed as the *ECV*. All WTP estimates are computed using McFadden's simulation approach. WTP estimates are in annual 1990 dollars.

We also find a somewhat significant variation in welfare gains across neighborhoods within each income group. For instance, high-income households who were located in neighborhoods with low and median air quality levels in 1990 have significantly higher benefits than the average high-income household. On the other hand, high-income households who resided in the dirtiest neighborhoods experience significantly lower benefits than the average high-income household in the study area. This disparity can be attributed to the fact that housing prices increased in the neighborhoods with the highest ozone levels in 1990 as a result of the above average air quality improvements in those neighborhoods.

Comparing Relative Welfare Gains across Income Groups

Figure 7.3 shows the mean WTP as a proportion of the household's income in 1990. The bar graphs characterize the distribution of relative welfare gains across income groups. The WTP estimates are obtained using McFadden's simulation approach. The distributional findings seem to differ between the direct and equilibrium welfare measures. While the direct welfare measure suggests that the richer households experienced higher relative welfare gains, the equilibrium welfare measure suggests that the distribution of relative benefits is fairly even across income groups. This implies that ignoring equilibrium price effects can significantly alter the distribution of relative welfare gains.



The divergence between the distribution of relative welfare gains in the direct and equilibrium approach can be explained from the difference between the two welfare measures which is also show in Figure 7.3. This difference can be interpreted as the household's relative welfare gain from adjusting to a new location after the air quality changes. Figure 7.3 shows that the welfare gains from the equilibrium adjustments are regressive in the sense that the gains represent a larger share of income for low-income household. On the other hand, the direct welfare gains are progressive since high-income households are willing to pay more for a marginal improvement in air quality. Hence the direct benefit measure will tend misrepresent the distribution of the equilibrium welfare impacts from large air quality changes.

7.4.2 Alternative Welfare Estimations

The welfare results presented in the previous section use McFadden's (1998) simulation approach (see section 7.3). We compare these exact welfare estimates with the approximations obtained from the representative consumer approach suggested by Morey et al. (1993). McFadden (1999) argues that the representative consumer approach leads to biased estimates of *ECV* when improvements are large. Herriges and Kling (1999) revisit this issue in a study of fishing mode choices by California anglers. The study estimates the WTP of the fishermen for a policy regime that leads to a doubling of the catch rate. They find that the two approaches lead to quite similar estimates of the *ECV*. The exercise in this section is intended to shed further light on this issue. That is, whether welfare estimates from the complex simulation approach are substantially different from the simpler representative consumer approximations so as to justify the significantly higher computational cost.

Comparing the ECV Estimates

Table 7.5 presents the direct and equilibrium welfare measures for the two estimation procedures. As suggested by McFadden, we find that the estimate of the overall mean WTP from the representative consumer approximation differs significantly from the exact welfare estimate obtained from the simulation approach. The representative consumer approach severely overestimates the mean welfare impact of the air quality changes that occurred in the Los Angeles area between 1990 and 2000. The direct and equilibrium benefits from the representative consumer approach are almost twice the size of the exact welfare estimate obtained from the simulation approach.

Table 7.5: Comparing Alternative Welfare Estimates (1990-2000)

	WTP_D (Exact)	WTP_E (Exact)	$WTP_{E/D}$ (Exact)	WTP_D (Approximation)	WTP_E (Approximation)	$WTP_{E/D}$ (Approximation)
Study area (mean)	1,386	1,829	1.32	2,152	2,289	1.06
Household Income†						
< 20,000	196	441	2.25	223	300	1.35
20,000 - 37,000	546	1,019	1.87	853	1,000	1.17
37,000 - 60,000	1,216	1,706	1.40	1,918	2,067	1.08
> 60,000	3,137	3,634	1.16	4,889	5,041	1.03

Note: †1990 $. WTP is computed as the *ECV*. Exact welfare measure is computed via the simulation approach of McFadden (1999). Approximation of ECV uses the approach suggested by Morey et al. (1993)

The results also suggest that the representative consumer approximation severely underestimates households' welfare gains from the equilibrium adjustments that take place as a result of the large air quality changes. The mean equilibrium benefit estimate from the representative consumer approximation is only 6 percent larger that the direct benefit estimate, which would suggest that the equilibrium adjustments that result from the air quality changes do not have a significant impact on households' benefits. On the other hand, the exact welfare estimate of the mean equilibrium benefit is 32 percent larger than the direct benefit measure, implying that the equilibrium adjustments do provide significant additional benefits to households.

7.4.3 Comparing with previous studies

To provide a comparison of our results with those of Sieg et al. (2004) we simulate the counterfactual equilibrium that would have resulted from the changes in ozone levels between 1990 and 1995. This is because, in their empirical analysis, Sieg et al. use the changes in ozone levels that occurred between 1990 and 1995. Table 7.6 reports the welfare results for the changes in ozone levels between 1990 and 1995. We find that the reductions in ozone pollution between 1990 and 1995 provided an average equilibrium benefit of $896 to the households of the Los Angeles Area. Similar to the welfare benefits from 1990 to 2000, there is a significant variation in the equilibrium benefits for 1995 across counties.

Table 7.6: Direct and Equilibrium WTP for the CAAA (1990-1995)

	Discrete Choice equilibrium approach			Epple-Sieg equilibrium approach (Sieg et al, 2004)		
	WTP_D	WTP_E	$WTP_{E/D}$	WTP_D	WTP_E	$WTP_{E/D}$
Study area	589	896	1.52	1,210	1,371	1.13
Counties						
Los Angeles County	568	866	1.52	1,472	1,556	1.06
Orange County	698	1,029	1.47	901	1,391	1.54
Riverside County	526	858	1.63	834	372	0.45
San Bernardino County	576	891	1.55	738	367	0.50

The last three columns of Table 7.6 report the overall and county-level mean benefit estimates from Sieg et al. (2004). Our overall direct and equilibrium benefit estimates are substantially lower than the Sieg et al. estimates. The county-level benefit estimates also differ significantly. The county-level direct WTP estimates are consistently lower than the Sieg et al. estimates. The relationship between the equilibrium benefit estimates is, however, more complex. The equilibrium welfare estimates from this study are higher than the Sieg et al. benefit measures in Los Angeles and Orange counties. The relationship between the welfare measures is reversed in Riverside and San Bernardino counties. Sieg et al. also find that equilibrium adjustments in the 1995 counterfactual equilibrium resulted in average welfare losses for households in Riverside and San Bernardino counties. Our results, on the other hand, suggest that on average the equilibrium adjustments resulted in welfare gains for households in all four counties.

The disparity between our welfare estimates and those found by Sieg et al. can be due to a number of factors. First, the differences could emerge as a result of differences in the data. The fact that the two studies use a different characterization of neighborhoods (PUMA vs. school district) is likely to affect the welfare results. In addition, Sieg et al.'s average welfare benefit for the Los Angeles area includes Ventura County while ours does not. We excluded Ventura County from our sample because the 1990 PUMA boundaries for that county were not mutually exclusive and hence did not meet our selection criteria (See section 5.3).

Second, our welfare results are likely to diverge from the Sieg et al. results because of the differences in the specification of households' location choices. The discrete choice characterization of households' location choices allows us to estimate household preferences for that vary across income groups and educational levels. Our preference estimates suggest that high-income households have stronger preferences for air quality relative to the average population. We also find that the average household population has a lower preference for school quality compared to college educated households. This contrasts with the Sieg et al. framework in which households are restricted to have the same preference ordering of neighborhoods with respect to neighborhood amenities. This is due to the fact that the marginal rate of substitution between community amenities is independent of the household's income and taste (see equation 3.14 in Chapter 3). In addition, the preference specification in this study naturally captures the geography of the housing market by allowing household preferences for locations to depend on the proximity to their employment location. We find that households have stronger preferences for housing alternatives that are located within their employment zone.

8 Conclusions

This dissertation has developed a discrete choice equilibrium model to evaluate the benefits of the air quality improvements that occurred in the Los Angeles area between 1990 and 2000 as a result of the implementation of the 1990 Clean Air Act Amendments. The study has two main objectives. The first is to apply the discrete choice equilibrium framework (Anas, 1980, Bayer et al., 2005) to the valuation of large environmental changes. The second objective is to evaluate the distributional welfare impacts of the 1990 CAAA in the Los Angeles area.

Main Findings

The empirical analysis suggests that the reductions in ozone concentrations across Los Angeles, Orange, Riverside and San Bernardino counties, provided an average equilibrium benefit of $1,800 to households. In contrast, average benefits are $1,400 when equilibrium price effects are not accounted, demonstrating that ignoring equilibrium effects will likely underestimate the benefits of large environmental changes. We find that the equilibrium welfare impacts of the 1990 CAAA, in the Los Angeles area, varied significantly across income groups. Households in the highest income quartile experienced equilibrium benefits of approximately $3,600 as compared to only $400 for households in the lowest income quartile. We also find that ignoring equilibrium adjustments in housing prices can significantly alter the distribution of relative welfare gains (i.e. welfare gains as a proportion of household income). Indeed, welfare impacts that do not account for equilibrium adjustments suggest that high-income households have larger relative welfare gains compared to low-income households. However, when accounting for equilibrium adjustments, we find that the distribution of relative welfare gains from the 1990 CAAA is fairly even across income groups.

Potential Limitations

We now discuss some limitations of the equilibrium welfare measures developed in this dissertation. The equilibrium welfare estimates in this study are based on the simulation of a counterfactual equilibrium which only accounts for air quality changes and induced housing price changes that result from the resorting of households. The actual welfare impacts of the 1990 CAAA would also account for changes in the housing supply, household income, and household population. These changes will likely affect the welfare benefits of the 1990 CAAA.

Using the higher household income levels in 2000 would likely lead to higher benefit estimates as high-income households have a higher marginal willingness to pay for air quality. If the supply of housing is elastic with respect to price, accounting for housing supply adjustments would likely increase equilibrium benefits as the influx of new housing units would provide more choices to households. An increase in population is likely to reduce equilibrium welfare gains to the extent that the increased demand for housing result in higher prices. This effect is however likely to vanish in the long run as the supply of housing adjusts.

The estimated equilibrium welfare measures could be sensitive to the geographic definition of the housing market. We assume in this work that the Los Angeles area housing market comprises four counties: Los Angeles County, Orange County, Riverside County and San Bernardino County. One could argue, as in Sieg et al. (2004), that the Los Angeles area housing market also includes Ventura County. All else equal a larger geographic area is likely to lead to higher welfare benefits as it would provide more choices to households.

The equilibrium welfare measures could also be sensitive to the geographic characterization of neighborhoods. This study uses the 1990 Census Public Use Microdata Areas (PUMA) to characterize neighborhoods. On the other hand, Sieg et al. (2004) use the 1990 school district boundaries to define neighborhoods. One could also characterize neighborhoods using smaller geographic units such Census tracts, Census blocks groups or Census blocks. Altering the geographic definition of neighborhoods is less likely to significantly affect the air quality measures as they generally do not vary much across small areas. As a result welfare impacts of air quality changes are likely to be less sensitive to the characterization of neighborhoods.

The random utility model defined by equation (4.3) assumes that the household-specific unobserved tastes are independently distributed as Type I Extreme Value. This assumption gives rise to the multinomial logit (MNL) model. A major limitation of the MNL model is the IIA assumption, which generates individual household demands with limited substitution patterns. In Section 4.2 we discussed that the use of household interactions will produce residential location demands that possess rich substitution patterns. However, it is still the case that relaxing the IIA assumption would provide much richer substitution patterns across residential locations. The extent to which these richer substitution patterns affect the equilibrium welfare results is an empirical issue that will be addressed in future extensions of this research.

The random utility specification in equation (4.3) also assumes away endogenous social interaction effects. Social interaction effects emerge from the fact that households may care about the average socioeconomic characteristics of their neighborhoods. These social interaction effects are likely to be endogenously determined in the sorting equilibrium when households have heterogeneous preferences. This is because the average socioeconomic makeup of neighborhoods changes each time households resort.

Our utility function incorporates an exogenous social interaction effect. The social interaction effect is a result of households' homogeneous tastes for the proportion of Hispanics in the neighborhood. Incorporating endogenous social interactions in the household's utility could affect the equilibrium welfare estimates. For example, low-income renters could suffer welfare losses as increases in housing prices in their original neighborhoods force them to relocate to neighborhoods with less desirable attributes. An avenue for future research would be to explore empirically the extent to which the overall and distributional impacts of the 1990 CAAA are affected when endogenous social interactions are incorporated in the household's random utility function.

Future Research

We discuss two extensions of this work to be explored in future research. One extension involves relaxing the assumption about the housing supply. The current framework assumes an exogenously determined housing supply. However, in the long run, the housing supply is likely to respond to large changes in air quality and housing prices. The question from a policy perspective is whether these changes substantially change the overall and distributional welfare impacts of the 1990 CAAA.

Sieg et al. (2004) try to address this question by using different predetermined supply elasticities in the counterfactual simulation. They find that the changes in housing supply elasticities do not lead to significant changes in welfare predictions. However, the Sieg et al. conclusions rely on ad-hoc, instead of endogenous, changes in the housing supply. Walsh (2003) evaluates the equilibrium welfare impacts of open space policies, in the Epple-Sieg equilibrium framework, by incorporating an endogenous housing supply. To our knowledge, no one has yet investigated the equilibrium welfare impacts of policy changes using a discrete choice equilibrium model which incorporates endogenous housing supply adjustments.

Another extension of this work would consider a detailed investigation of the implications of alternative specifications of household preferences on equilibrium welfare impacts. The question of policy interest here is whether the estimates of the equilibrium welfare impacts of the 1990 CAAA differ substantially across alternative specifications of the household utility function. Our welfare results suggest that the specification of household preferences could play a rather significant role in equilibrium welfare predictions. This is evidenced by the significant divergence between the county-level equilibrium benefit estimates from this study and the estimates from Sieg et al. (2004) (see Table 7.6). A clean comparison of the two approaches would, however, require estimating the Sieg et al. (2004) model using our data. This investigation would compare the benefit estimates from the Epple-Sieg and discrete choice equilibrium approaches using the same data. The analysis would also compare the equilibrium welfare impacts from two alternative specifications of the household's random utility, which relax the IIA assumption. These are the nested logit model and the random coefficient logit model. The nested logit allows a partial relaxation of the IIA assumption, whereas the random coefficient logit fully relaxes the IIA assumption. This type of investigation has been tried in the empirical industrial organization literature by Berry, Levinsohn and Pakes

(1995, 2004), and Petrin (2002). However, these studies were only interested in the implications for estimates of price elasticities, not welfare predictions.

Appendix A: Generating the Data

A1. Regression output from computation of the rental housing price

Table A1. Regression Used for Correcting House Values

	Los Angeles – Long Beach MSA	Orange County MSA	Riverside – San Bernardino MSA
Log Transaction price (10 times property tax)	.335**	.349**	.440**
Moved in 1985 to 1988 (compared to 1989-90)	-0.013**	0.017**	-0.060**
Moved in 1980 to 1984	0.037**	0.075**	-0.071**
Moved in 1970 to 1979	0.192**	0.309**	0.040**
Moved in 1960 to 1969	0.253**	0.395**	0.097**
Moved in 1959 or earlier	0.201**	0.307**	0.088**
R^2	0.325	0.263	0.431
Observations	138,181	39,550	33,891

Note: * Significant at the 5 percent level. ** Significant at the 1 percent level. Dependent variable is log of house value. Regression includes a full set of PUMA dummies.

Table A2. Regression Used for Correcting Monthly Rents

	Los Angeles – Long Beach MSA	Orange County MSA	Riverside – San Bernardino MSA
Moved in 1985 to 1988 (compared to 1989-90)	-0.082**	-0.062**	-0.081**
Moved in 1980 to 1984	-0.207**	-0.193**	-0.234**
Moved in 1970 to 1979	-0.329**	-0.298**	-0.328**
Moved in 1960 to 1969	-0.410**	-0.439**	-0.295**
Moved in 1959 or earlier	-0.421**	-0.310**	-0.459**
Rooms	0.027**	0.014**	0.043**
Bedrooms	0.154**	0.144**	0.121**
One-family house attached (compared One-family attached)	-0.056**	-0.029**	-0.080**
2 Apartments complex (compared One-family attached)	-0.098**	-0.128**	-0.182**
3-4 Apartments complex	-0.128**	-0.132**	-0.168**
5-9 Apartments complex	-0.144**	-0.168**	-0.174**
10-19 Apartments complex	-0.142**	-0.166**	-0.133**
20-49 Apartments complex	-0.113**	-0.138**	-0.143**
50 or more apartments complex	-0.145**	-0.170**	-0.148**
Built in 1985 to 1988 (compared to 1989-90)	-0.001**	0.011**	-0.053**
Built in 1980 to 1984	-0.089**	-0.073**	-0.139**
Built in 1970 to 1979	-0.078**	-0.045**	-0.158**
Built in 1960 to 1969	-0.068**	-0.072**	-0.211**
Built in 1950 to 1959	-0.105**	-0.103**	-0.257**
Built in 1940 to 1949	-0.122**	-0.149**	-0.291**
Built in 1939 or earlier	-0.146**	-0.161**	-0.322**
R^2	0.368	0.410	0.395
Observations	138,181	39,550	33,891

Note: * Significant at the 5 percent level. ** Significant at the 1 percent level. Dependent variable is monthly rent. Regression includes a full set of PUMA dummies.

Table A3. Regression Used for Converting House Values to Rental Rates

	Los Angeles – Long Beach MSA	Orange County MSA	Rverside – San Bernardino MSA
Owner-occupied	5.654**	5.830**	5.474**
Rooms	0.049**	0.042**	0.090**
Bedrooms	0.052**	0.080**	0.036**
One-family house attached (compared One-family attached)	-0.126**	-0.080**	-0.015**
2 Apartments complex (compared One-family attached)	-0.217**	-0.143**	-0.160**
3-4 Apartments complex	-0.210**	-0.179**	-0.130**
5-9 Apartments complex	-0.232**	-0.207**	-0.138**
10-19 Apartments complex	-0.229**	-0.204**	-0.108**
20-49 Apartments complex	-0.201**	-0.166**	-0.111**
50 or more apartments complex	-0.234**	-0.188**	-0.119**
Built in 1985 to 1988 (compared to 1989-90)	-0.014**	-0.063**	-0.049**
Built in 1980 to 1984	-0.083**	-0.158**	-0.142**
Built in 1970 to 1979	-0.105**	-0.191**	-0.200**
Built in 1960 to 1969	-0.182**	-0.239**	-0.303**
Built in 1950 to 1959	-0.247**	-0.293**	-0.382**
Built in 1940 to 1949	-0.255**	-0.316**	-0.402**
Built in 1939 or earlier	-0.257**	-0.319**	-0.409**
R^2	0.992	0.987	0.986
Observations	138,181	39,550	33,891

Note: * Significant at the 5 percent level. ** Significant at the 1 percent level. Dependent variable is log of corrected house value if owned, otherwise, log of corrected monthly rent. Regression includes a full set of PUMA dummies.

A2. STATA Codes Used to Generate the Data

Main Code

```
/* generates household sample from original CA pums*/

capture log close

cd "H:\dissert_files\datasets\sata_data\pums"
*cd "E:\research\data\"
log using gen_pumsdata90.log, replace
set more off

/* preliminaries:
1. generate unit and person record from pums original files (pumsah90)
2. generate puma pollution data
3. generate puma distance data
4. generate puma elevation data
5. generate puma crime and school data
(2-5: pums90_attr.dta)
*/

* housing unit record
use pumsah90, clear
keep rectype serialno sample state puma msapmsa houswgt persons gqtype units1 rooms tenure acreage value rent1 yrmoved
///
          bedrooms yrbuilt condo oneacre proptax rgrent rrentunt rvalunt rhhinc rhhfamtp r18undr r65over
*keep if  msapmsa=="6000" | msapmsa=="4480" | msapmsa=="6780" | msapmsa=="0360"
keep if  msapmsa=="4480" | msapmsa=="6780" | msapmsa=="0360"
gen pmsaname="."
replace pmsaname="Orange County" if  msapmsa=="0360"
replace pmsaname="Los Angeles - Long Beach" if  msapmsa=="4480"
*replace pmsaname="Ventura" if  msapmsa=="6000"
replace pmsaname="Riverside - San Bernardino" if  msapmsa=="6780"
drop if  msapmsa=="6000" /*drop ventura cnty*/
 * cleanup
drop if units1=="00" | units1=="01" | units1=="10"
drop if tenure=="0" | tenure=="4"
sort serialno
save pumsah90_socal, replace

* person record
clear
set mem 500m
use pumsap90.dta, clear
keep serialno relat1 sex race age marital ragechld hispanic poverty pob school yearsch mobility migrstat migpuma ///
          disabl1 disabl2 powstate powpuma travtime

 * racial characteristics
destring hispanic, replace
gen hispanic1=(hispanic!=0 & hispanic!=199)
gen mexic_org=(hispanic==1 | (hispanic>=210 & hispanic<=220))
drop hispanic
ren hispanic1 hispanic
destring race, replace
gen black=(hispanic==0 & race==2)
gen white=(hispanic==0 & race==1)
gen asianpi=(hispanic==0 & (race>=6 & race <=36))
 * keep household headers
keep if relat1=="00" /*NOTE: this implies that only */

* merge person and unit record
sort serialno
merge serialno using pumsah90_socal
tab _merge
keep if _merge==3
drop _merge
sort serialno

save pumsah90_socal, replace
clear
set mem 250m

* generate price variable
do generate_price

* merge price variable with master dataset
use pumsah90_socal, clear
merge serialno using pums90price
tab _merge
keep if _merge==3
drop _merge
sort serialno

* drop non-contiguous pumas (see file puma_list.xls)
drop if puma=="04808" | puma=="06420" | puma=="06424" | puma=="06901" | puma=="06904" | puma=="06905" | puma=="07201" |
puma=="07207"
save pumsah90_socal, replace

* generate hsld and location data for estimation
do gen_hsld_hsg90
```

```
log close
```

Sub-Code for Generating the Housing Price Variable

```
/* do-file to generate adjusted home value and rent. Also converts home
values to rental rates.*/


******************************************************************************
/*Part1: 1990 Pums housing sample*/

/*
use value1990pums, clear
gen value2=value
tostring value, replace format(%02.0f)
sort value
save value1990pums, replace

* add tax amounts
use proptax1990pums, clear
gen proptax2=proptax
tostring proptax, replace format(%02.0f)
sort proptax
save proptax1990pums, replace
*/

/* cleanup housing values in pums using tax data*/


use pumsah90_socal, clear
* evaluate how many values or rents are top coded
gen topcoded=(value=="25" | rgrent>=1500)
sum topcoded
tab topcoded

* add value amounts
sort value
merge value using value1990pums, keep(value1)
tab _merge
drop if _merge==2
drop _merge
* add tax amounts
sort proptax
merge proptax using proptax1990pums, keep(taxamt1)
tab _merge
drop if _merge==2
drop _merge

* begin cleanup
tab msapmsa, gen(msa_dum)

gen ln_val=log( value1)
gen ln_tax=log( taxamt1)
drop if value1!=. & ln_tax==. /* drop owner occupied units with no reported property tax*/
destring value, replace

 * compute predicted value
xi: regress ln_val ln_tax i.puma i.yrmoved if  value>0 & value<25 & msa_dum1==1 [fw= houswgt]
predict pred_lnval1
xi: regress ln_val ln_tax i.puma i.yrmoved if  value>0 & value<25 & msa_dum2==1  [fw= houswgt]
predict pred_lnval2
xi: regress ln_val ln_tax i.puma i.yrmoved if  value>0 & value<25 & msa_dum3==1  [fw= houswgt]
predict pred_lnval3

gen  pred_lnval= pred_lnval1 if msa_dum1==1
replace  pred_lnval= pred_lnval2 if msa_dum2==1
replace  pred_lnval= pred_lnval3 if msa_dum3==1

 * replace reported value with predicted value if predicted value greater than reported value
gen val_low=.
replace val_low=1 if  pred_lnval!=. & ln_val!=. & pred_lnval> ln_val
replace val_low=0 if  pred_lnval!=. & ln_val!=. & pred_lnval< ln_val
tab val_low,m
tab val_low if value==25,m
tab val_low if value==25 & pred_lnval==.,m
gen val_adj= value1 if val_low==0
replace val_adj= exp(pred_lnval) if val_low==1

 * regress adjust rents to market values
gen ln_rent=log(rgrent)
*replace ln_rent=. if tenure=="4"
destring rooms bedrooms condo oneacre units1, replace

 * adjust reported rents based on year moved
xi: regress ln_rent i.yrmoved rooms bedrooms i.units1 i.yrbuilt i.puma if msa_dum1==1 [fw= houswgt]
gen ln_rent_a= ln_rent + _b[_Iyrmoved_2]*_Iyrmoved_2 + _b[_Iyrmoved_3]*_Iyrmoved_3 + _b[_Iyrmoved_4]*_Iyrmoved_4 +
_b[_Iyrmoved_5]*_Iyrmoved_5 + _b[_Iyrmoved_6]*_Iyrmoved_6  if msa_dum1==1
xi: regress ln_rent i.yrmoved rooms bedrooms i.units1 i.yrbuilt i.puma if msa_dum2==1 [fw= houswgt]
replace ln_rent_a= ln_rent + _b[_Iyrmoved_2]*_Iyrmoved_2 + _b[_Iyrmoved_3]*_Iyrmoved_3 + _b[_Iyrmoved_4]*_Iyrmoved_4 +
_b[_Iyrmoved_5]*_Iyrmoved_5 + _b[_Iyrmoved_6]*_Iyrmoved_6  if msa_dum2==1
xi: regress ln_rent i.yrmoved rooms bedrooms i.units1 i.yrbuilt i.puma if msa_dum3==1 [fw= houswgt]
```

```
replace ln_rent_a= ln_rent + _b[_Iyrmoved_2]*_Iyrmoved_2 + _b[_Iyrmoved_3]*_Iyrmoved_3 + _b[_Iyrmoved_4]*_Iyrmoved_4 +
_b[_Iyrmoved_5]*_Iyrmoved_5 + _b[_Iyrmoved_6]*_Iyrmoved_6  if msa_dum3==1
gen rent_adj=exp(ln_rent_a)

 * generate price variable using values and rents
gen price1=.
replace price1=val_adj if tenure=="1"|tenure=="2"
replace price1 =rent_adj if tenure=="3"
tab tenure if price1==.,m
gen ln_price1=log(price1)
drop if price1==.

 * regress log prices on owner dummy to get coefficient for conversion of values  to gross rents
gen owned=(tenure=="1"|tenure=="2")
*xi: regress ln_price1 owned rooms bedrooms oneacre i.units1 i.yrbuilt i.puma [fw= houswgt]
xi: regress ln_price1 owned rooms bedrooms i.units1 i.yrbuilt i.puma if msa_dum1==1 [fw= houswgt]
gen coef901=exp(_b[owned])                                                    /* use value from previous
regressions*/
xi: regress ln_price1 owned rooms bedrooms i.units1 i.yrbuilt i.puma if msa_dum2==1 [fw= houswgt]
gen coef902=exp(_b[owned])
xi: regress ln_price1 owned rooms bedrooms i.units1 i.yrbuilt i.puma if msa_dum3==1 [fw= houswgt]
gen coef903=exp(_b[owned])

gen coef90=.
replace coef90=coef901  if owned==1 & msa_dum1==1
replace coef90=coef902  if owned==1 & msa_dum2==1
replace coef90=coef903  if owned==1 & msa_dum3==1
tab coef90,m
tab tenure if coef90 ==.

 * convert values to rental rates
gen rt_price1=price1/coef90  if owned==1
replace rt_price1=price1  if owned==0
replace ln_price1=log(rt_price1)

*keep serialno price1 rt_price1 ln_price1
*ren price1 price
keep serialno rt_price1 ln_price1 coef90 topcoded
ren rt_price1 rt_price90
ren ln_price1 ln_price
sort serialno
save pums90price, replace
```

Sub-Code for Generating Household and Housing-Type Data used in MATLAB Estimation

```
/* This do-file generates (1) housing types dataset and (2) household population dataset*/

cd "H:\dissert_files\datasets\sata_data\pums"
set more off


/************ generate 1990 housing types and their attributes for matlab **************/
use pumsah90_socal, clear

* drop hslds with monthly inc less than 500 or rental hsg price
gen hincm90=rhhinc/12
drop if hincm90<500
drop if  hincm90<=rt_price90 /*drop hslds who cannot affort their hsg unit*/

* merge 3-digit puma coordinates
generate str puma1 = substr(puma,1,3)
gen a="00"
egen puma3dg = concat(puma1 a)
drop puma1 a
sort puma3dg
merge puma3dg using work_puma, keep(pow_x pow_y)
tab _merge
keep if _merge==3
drop _merge
ren pow_x puma3dg_x
ren pow_y puma3dg_y
* merge place of work puma coordinates
ren puma3dg puma3dg_a
gen puma3dg=powpuma
sort puma3dg
merge puma3dg using work_puma, keep(pow_x pow_y)
tab _merge
keep if _merge==3
drop _merge
ren pow_x powrk_x
ren pow_y powrk_y
replace powrk_x=0 if powrk_x==.
replace powrk_y=0 if powrk_y==.

gen workplace=(powrk_x!=0)

save      pumsah90_socal1, replace

* generate puma indices
gen a=1
rename a numhses
destring msapmsa, gen(pmsa)
```

```
destring puma3dg_a, replace
collapse (mean) pmsa hispanic mexic_org black white asianpi rhhinc puma3dg_a puma3dg_x puma3dg_y (count)
numhses,by(puma)
ren puma3dg_a puma3dg
egen int pumaind1  = seq()
*tostring pumaind1, generate(pumaind2) format(%03.0f)
*gen year="1990"
*egen pumaind = concat(year pumaind2)
tostring pumaind1, generate(pumaind) format(%02.0f)
ren hispanic shrhisp
ren black shrblack
ren white shrwhite
ren asianpi shrasian
ren rhhinc avginc
sort puma
save puma90ind, replace

* merge puma indices and average demographics to master dataset
use pumsah90_socal1, clear
sort puma
merge puma using puma90ind , keep(pumaind pumaind1)
tab _merge
keep if _merge==3
drop _merge

* generate new variables
tab yrbuilt
gen blt80s90s=(yrbuilt=="1" | yrbuilt=="2" | yrbuilt=="3")
gen blt60s70s=(yrbuilt=="4" | yrbuilt=="5")
tab  units1
gen singlefam=( units=="02" | units=="03")
gen owned=(tenure=="1"|tenure=="2")
destring bedrooms, replace
replace bedrooms=bedrooms-1 /*number of bedrooms in census starts at 1 instead of 0*/
egen hsid = concat(pumaind owned bedrooms blt80s90s blt60s70s singlefam)
sort hsid
egen pricetype=mean(rt_price90), by(hsid)
drop if  hincm90<=pricetype /*drop hslds who cannot affort their hsg type*/
save      pumsah90_socal1, replace

* generate location types
gen a=1
collapse (mean) pricetype owned bedrooms blt80s90s blt60s70s singlefam ///
          pumaind1 (count) a [fw= houswgt], by( hsid)
gen rt_price90=pricetype
* generate housing units by location type
ren a agrgdem_w
egen totmkt=sum( agrgdem_w)
gen mktsh= agrgdem_w / totmkt

* generate indices for location types
sort hsid
egen int altid = seq()
sort hsid
*save pums90_discr, replace

* merge puma demographics
save pums90alt1b, replace
use puma90ind, clear
sort pumaind1
save puma90ind , replace
use pums90alt1b, clear
sort pumaind1
merge pumaind1 using puma90ind , keep(pmsa shrblack shrhisp shrasian shrwhite avginc puma puma3dg puma3dg_x puma3dg_y)
tab _merge
keep if _merge==3
drop _merge


* merge puma attributes
sort puma
*merge puma using puma90_attr, keep(math crime elev ozmean ozexmean pm10 hdens_km  dist_coast coast5km)
merge puma using puma90_attr, keep(math crime elev hdens_km dist_coast coast5km)
tab _merge
keep if _merge==3
drop _merge
sort puma
merge puma using pollution, keep(cntyid ozo89_91 ozo94_96 ozo99_01 oz8991mean oz9496mean oz9901mean pm89_91 pm94_96
pm99_01 pm8991mean pm9496mean pm9901mean)
tab _merge
keep if _merge==3
drop _merge


/* merge ozone 3-yr centered averages
destring puma, gen(puma1)
sort puma1
merge puma1 using ozone89t01p5, keep(ozo99_01 ozo94_96 ozo89_91 cntyname)
tab _merge
keep if _merge==3
drop _merge
*/
/*
* merge 3-digit puma coordinates
generate str puma1 = substr(puma,1,3)
```

```
gen a="00"
egen puma3dg = concat(puma1 a)
drop puma1 a
sort puma3dg
merge puma3dg using work_puma, keep(pow_x pow_y)
tab _merge
keep if _merge==3
drop _merge
ren pow_x puma3dg_x
ren pow_y puma3dg_y
* merge place of work puma coordinates
drop puma3dg
gen puma3dg=powpuma
sort puma3dg
merge puma3dg using work_puma, keep(powrk_x powrk_y)
tab _merge
keep if _merge==3
drop _merge
gen workplace=(powrk_x!=.)
*/

drop hsid puma
sort altid
save pums90alt1c, replace


/************ generate 1990 household data for matlab **************/

* add location indices to household data
use pumsah90_socal1, clear
sort hsid
merge hsid using pums90alt1b, keep( altid)
tab _merge
drop _merge
ren altid altind
ren serialno hhid
destring msapmsa, gen(pmsahh)

/*
* merge puma coordinates for place of work
egen puma1=concat(powstate powpuma)
destring puma1, replace
sort puma1
merge puma1 using pums90dist_cor, keep( point_x point_y)
tab _merge
keep if _merge==3
drop _merge
ren point_x powpuma_x
ren point_y powpuma_y
*/



* create cnty and pmsa dummies
destring puma, gen(puma1)
sort puma1
merge puma1 using ozone89t01p5, keep(cntyname)
tab _merge
keep if _merge==3
drop _merge
gen cntyhh=37
replace cntyhh=59 if cntyname=="Orange"
replace cntyhh=65 if cntyname=="Riverside"
replace cntyhh=71 if cntyname=="San Bernardino"
*tab cntyname, gen(cntyid)
*tab pmsaname, gen(pmsaid)

gen age65=(age>=65)

ren persons  hsld_size
gen female=(sex=="1")
gen mwkids=(rhhfamtp=="01" & (ragechld=="1" | ragechld=="2"))
gen mwkids6=(rhhfamtp=="01" & ragechld=="1")
gen kids=(r18undr=="1")
destring yearsch, replace
gen college=(yearsch>=12)
gen hincm_price=hincm90 - rt_price90
*keep hincm90 houswgt year hsld_size female age mwkids mwkids6 white black ///
          hispanic asianpi college pumaind hsid ///
          age65 cntyid1-cntyid4 pmsaid1-pmsaid3 hhid altind
keep hincm90 houswgt year hsld_size female age kids mwkids mwkids6 white black ///
          hispanic asianpi college pumaind hsid puma3dg_a powpuma workplace powrk_x powrk_y ///
          age65 cntyhh pmsahh hhid altind
destring pumaind hhid puma3dg_a powpuma , replace
ren puma3dg_a puma3dg_hh
drop hsid
sort altind

save pumshh1990c, replace

* cleanup temporary files
erase pumsah90_socal1.dta
erase puma90ind.dta
erase value1990pums.dta
```

Appendix B: Matlab Codes for Estimation

B1. Main Code for Maximum Likelihood Estimation

```
% PURPOSE: 2-step ML estimation of residential location model for Los
% Angeles area

% Constant Tra, March 2006.
% University of Maryland, College Park
% ctra@arec.umd.edu

clear all

global zbi n k y prob12 meanvalue ii nj nprod wg iter xtol

% get data
load zbi8901oz_wkd_k20aa2 % sample affordable alternatives, k=50, translog utility

zbi=zbi8991;

nprod=size(wg,1);

%-----------------------------------------------------------------%
% FIRST STAGE: MAXIMUM LIKELIHOOD ESTIMATION OF MULTINOMIAL LOGIT %
%-----------------------------------------------------------------%

theta2=.001*ones(size(zbi,2),1);

xtol=5e-3; dtol=1e-1; ftol=1e-5; maxiter=100;
coefs=zeros(size(theta2,1),100);
iter=1;
totfuneval=0;
tot_iter=0;
convcrit=[1;1;1];
df=1;

% initialize delta_h

mvalold=full(sparse(ii,jj,1,nprod,1));
oldt2=1;
save mvalold_a mvalold oldt2

delta=log(mvalold);
delta = delta(prob12(:,2)); % this assigns the deltas to the n*(k+1)-by-1 individual probabilities choices
meanvalue=delta;

tic; like=mlogit_likedh1a(theta2); toc

tic   % Initialize computing time
while any(convcrit > 0) && (maxiter > iter)
    options=optimset('Display','iter','Diagnostics','off','LargeScale',...
    'off','GradObj','on','MaxIter', 5000);
    disp(' ')
    disp('**************************************************************************')
    disp(['            OUTER ITERATION #   ' num2str(iter)])
    oldtheta2=theta2;
    olddelta=delta;
    oldlike=mlogit_likedh1a(theta2);
    oldfuneval=totfuneval;
    olditer=tot_iter;

    disp(' ')
        disp('Starting optimization ...')
        disp(' ')
        [theta2, like, exitflag, output] = fminunc('mlogit_likedh1a',theta2,options);
        coefs(:,iter)=theta2;
        disp(' ')
        disp(['....Optimization  Completed.  Exitflag=  ' num2str(exitflag)  '  Obj.  Fun.=  ' num2str(like)  '   1st  oder
condition=: ' num2str(output.firstorderopt)])
        disp(' ')
        delta=meanval_a(theta2);
        meanvalue=delta;
    if max(isnan(delta)) == 1
        disp('error: mean value not a number')
        break
    else
        dtheta2= theta2 - oldtheta2;
        dxcrit=max(abs(dtheta2) - xtol);
        ddelta= delta - olddelta;
        ddcrit=max(abs(ddelta) - dtol);
        df=(oldlike - like)/oldlike;
        convcrit=[(ddcrit);(dxcrit);(abs(df)-ftol)];
        disp(' ')

        disp([ 'Relative Chg. in Obj. Func.= ' num2str(df) '.  Infinity Norm of dX= ' num2str(max(abs(dtheta2)))])
        disp(' ')
        disp(['.... End of Outer Iteration # ' num2str(iter)])
        tot_iter=output.iterations + olditer;
```

```
        totfuneval=output.funcCount + oldfuneval;
        iter=iter+1;
    end
end

comp_t = toc/60;  % Get Computing time in minutes

disp(' ')
disp('***************************************************************************')
disp('FINAL RUN')
[theta2, like, exitflag, output] = fminunc('mlogit_likedh1a',theta2,options);
delta=meanval_a(theta2);
meanvalue=delta;
coefs(:,iter)=theta2;
clear coefs
disp(' ')
% Write a message about why it stopped
  if all(convcrit <= 0)
    critmsg ='Convergence Tolerance Achieved';
  else
    critmsg =  'Maximum Iterations Reached';
  end


% COMPUTE COVARIANCE MATRICES FOR HOUSEHOLD INTERACTION PARAMETERS
clear zbi8991 zbi9496 zbi9901 dinc3q dinc4q pmsahh olddelta hhind hhid cntyhh ddelta hhinc

load delta
hg1=hg./sum(hg);
wg1=wg./sum(wg);
delta1=delta11-log(hg1./wg1);
delta = delta1(prob12(:,2));
mval=exp(delta);

% compute cov of theta2
m=k+1; K=size(theta2,1); T=size(hg,1); grad=zeros(K,1);
covbeta=zeros(K,K);
% covdelta=zeros(T,T);
for j=1:n
    xi=zbi(m*(j-1)+1:m*j,:);
    yi=y(m*(j-1)+1:m*j);
    prob3i=prob3(m*(j-1)+1:m*j);
    gradi=xi'*(yi - prob3i);
    grad=grad + gradi;
    covbeta=covbeta + gradi*gradi';
%     covdelta=covdelta + (yi - prob3i)'*(yi - prob3i);
end
% save covbeta covbeta
setheta=sqrt(diag(inv(covbeta)));
tstats=theta2./setheta;
% clear covdelta


fprintf('OPTIMIZATION TERMINATED: %s\n',critmsg);
disp('***************************************************************************')
disp(' ')

% basic specification testing;
theta0=zeros(size(theta2));
lik=-like;
lr1 = -mlogit_likedh1a(theta0); % restricted log-likelihood: intercepts only
meanvalue=zeros(size(delta));
lr = -mlogit_likedh1a(theta0); % restricted log-likelihood: all estimates
lr2 =  -mlogit_likedh1a(theta2); % restricted log-likelihood: constants only
lratio = -2*(lr - lik);
lratio1 = -2*(lr1 - lik);
lratio2 = -2*(lr2 - lik);
% lratio_p=; % likelihood ratio p-value
rsqr = 1 - (lik / lr); % McFadden pseudo-R^2

disp('MULTINOMIAL LOGIT MAXIMUM LIKELIHOOD ESTIMATES: 1990 OZONE AVG. Model')
fprintf('Nobs, Nprods, Nvars                    : %6d,%6d,%6d \n',n,nprod,size(theta2,1));
  disp(['Log-Likelihood                         :  ' num2str(lik)])
  disp(['# of func. iterations                  :  ' num2str(tot_iter)])
  disp(['# of obj. func. evaluations            :  ' num2str(totfuneval)])
  disp(['run time (minutes)                     :  ' num2str(comp_t)])
  disp(['Likelihood ratio  statistic (all=0)    :  ' num2str(lratio)])
fprintf('LR p-value (all=0)              : %9.4f \n',1-chi2cdf(lratio,size(theta2,1)+ nprod - 1));
fprintf('LR p-value (deltas=0)           : %9.4f \n',1-chi2cdf(lratio2,nprod - 1));
fprintf('LR p-value (slopes=0)           : %9.4f \n',1-chi2cdf(lratio1,size(theta2,1)));
  disp(['McFadden pseudo-R^2              :  ' num2str(rsqr)])
disp(' ')

disp('FIRST STAGE ESTIMATES')
out=[theta2 tstats]


%----------------------------%
% SECOND STAGE OLS ESTIMATION %
%----------------------------%

vnames_a=strvcat('delta','const','bedrooms','built80a','built60s70s', 'Singlefam',...
    'math','logcrime','logelev','coast5km','logdensk', ...
    'shrhisp','owned', 'ozone');
vnames_b=strvcat('delta','const','bedrooms','built80a','built60s70s', 'Singlefam',...
```

```
    'math','logcrime','logelev','coast5km','logdensk', ...
    'owned', 'ozone');

disp(' ')
disp('SECOND STAGE ESTIMATES (OLS)')
disp(' ')

delta1a=delta1 - min(delta1)+1;
delta1a=log(delta1a);

z1 = [ones(size(zmat,1),1) zmat(:,2:end)];
results=hwhite(delta1,z1); % control for heteroskedasticity using White's Robust covariance estimate
prt_reg(results,vnames_a)


disp(' ')
disp('SECOND STAGE ESTIMATES (OLS w/o prop. hispanics)')
z1(:,end-2)=[];
results=hwhite(delta1,z1); % control for heteroskedasticity using White's Robust covariance estimate
prt_reg(results,vnames_b)
```

B2. Code for Computation of Log-Likelihood Function

```
function [like,grad] = mlogit_likedh1a(beta)
% PURPOSE: Computes value of log likelihood function for multinomial logit
% estimation of Los Angeles area residential location model.

% Constant Tra, March 2006.
% University of Maryland, College Park
% ctra@arec.umd.edu

global zbi n k y meanvalue prob12

    % compute choice vector of choice probabilities for household
    ezb=exp(meanvalue + zbi*beta); % n*(k+1)-by-1
    ezb1=reshape(ezb,k+1,n); % (k+1) by n
    sumezb1=sum(ezb1)';  % n by 1

    probi=ezb./(sumezb1(prob12(:,1)));

    % compute likelihood of household and update population likelihood
    if all(probi)<1
        like=-1e10;
    else
        like=y'*log(probi);
    end

    like=-like;

    if nargout>1    % compute gradient
        grad=zbi'*(y - probi);
        grad=-grad;
    end
```

B3. Code for Computation of Alternative Constants via Contraction Mapping

```
function delta = meanval_a(theta2)
% This function computes the mean utility level given estimates of the
% household interaction parameters

% Constant Tra, March 2006.
% University of Maryland, College Park
% ctra@arec.umd.edu

% Based on code by:
% Aviv Nevo, May 1998.Source: "A Research Assistant's Guide to Discrete
% Choice Models of Demand," NBER technical paper #221, and "Measuring
% Market Power in the Ready-to-Eat Cereal Industry," NBER WP #6387.

global  prob12 nj iter xtol

load mvalold_a

if max(abs(theta2-oldt2)) < xtol;
          tol = 1e-9;
          flag = 0;
else
          tol = 1e-1;
          flag = 1;
end

norm = 1;
avgnorm = 1;
i = 1;

while norm > max(tol*10^(-flag*floor(iter/2)),1e-9) && avgnorm > max(1e-1*tol*10^(-flag*floor(iter/2)),1e-11)

    alpha=sumiprobi_a(theta2,mvalold); % this returns the vector housing-type demands (see B4)
          mval= mvalold.*nj./alpha;

    t = abs(log(mvalold) - log(mval));
```

```
      norm = max(t);
      avgnorm = mean(t);
      disp(['iteration #  ' num2str(i) ' mval(4): ' num2str(mval(4)) ' aplha(4): ' num2str(alpha(2)) ' max chg mval: '
num2str(min(norm,avgnorm))])
            mvalold = mval;
      i = i + 1;
end
disp(['     # of iterations for delta convergence:  ' num2str(i)])

oldt2=theta2;
save mvalold_a mvalold oldt2

delta11=log(mvalold);
delta11=delta11-delta11(1); % normalize delta: first element is set to zero

delta = delta11(prob12(:,2)); % this assigns the deltas to the n*(k+1)-by-1 individual probabilities choices
save delta delta11 alpha
```

B4. Code for Computation of the sample Housing-Type Demands

```
function [f,prob3] = sumiprobi_a(beta,mvalold)
% PURPOSE: Computes sample housing-type demands used in computation of
% alternative constants

% Constant Tra, March 2006.
% University of Maryland, College Park
% ctra@arec.umd.edu

global zbi n k prob12

delta11=log(mvalold);
delta = delta11(prob12(:,2)); % this assigns the deltas to the n*(k+1)-by-1 individual probabilities choices

    % compute choice vector of choice probabilities for household
    ezb=exp(delta + zbi*beta); % n*(k+1)-by-1
    ezb1=reshape(ezb,k+1,n); % (k+1) by n
    sumezb1=sum(ezb1)';  % n by 1

    prob3=ezb./(sumezb1(prob12(:,1))); % vector of choice probabilities
    f=full(sum(sparse(prob12(:,1),prob12(:,2),prob3))');
```

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