ABSTRACT

HAMILTON, TIMOTHY LAURENCE. A Multi-Level Residential Sorting Model with an Application to Cost of Living Indices. (Under the direction of Daniel Phaneuf.)

Sorting models to date have operated at the macro level or micro level. Regardless of the scale, all existing sorting models analyze a single choice from a single set of alternatives. Intuition suggests, however, that households choose a city and subsequently select a neighborhood within that city. This stylized reality is absent from conventional sorting models, which ignore information at one of these stages. In addition, due to the size of the full choice set, capturing this entire sorting process in a single model can be prohibitive in terms of computation and data collection. I use the theory of two-stage budgeting to develop an empirically feasible sorting model that more accurately replicates household behavior. Empirically, I focus on the cost of air pollution. Results point to an additional tradeoff between air pollution and neighborhood-level amenities that increases the marginal willingness to pay for clean air by a considerable amount. I also show that allowing for heterogeneity in preferences for local public goods has a considerable impact on the estimated value of clean air.

This dissertation also explores an application of the model in which I construct spatially explicit measures of the cost of living that can be used to adjust income and calculate a broad measure of welfare. The analysis focuses on the distribution of such welfare across the population, as well the change in this distribution followings simulated reductions pollution concentrations. Empirical results suggest that accounting for public goods leads to a distribution of adjusted income that has a wider spread than that of pure monetary income. This implies that households with less income tend to face higher costs of living, determined by an inferior set of public goods relative to housing prices paid to obtain such goods.
A Multi-Level Residential Sorting Model with an Application to Cost of Living Indices

by

Timothy Laurence Hamilton

A dissertation submitted to the Graduate Faculty of North Carolina State University in partial fulfillment of the requirements for the Degree of Doctor of Philosophy

Economics

Raleigh, North Carolina

2012

APPROVED BY:

__________________________  ____________________________
Laura Taylor               Walter Thurman

__________________________  ____________________________
Christopher Timmins        Daniel Phaneuf

Chair of Advisory Committee
DEDICATION

To my parents, who even through times of oblivion offered nothing short of unconditional love and support.
BIOGRAPHY

The author was born the second of three children to a modest family in the bucolic town of Hudson, MA. He was afforded the opportunity of a strong public education and eventually took his Bachelor’s degree from Bentley College. Following graduation, he immediately enrolled as a doctoral student at North Carolina State University to pursue a degree in economics. A rigorous approach to economic theory, modeling and econometric methods served him well, as he focused his attention on environmental economics, exploring technical approaches and empirical applications in the field. His studies have thus culminated in the following.
ACKNOWLEDGEMENTS

I extend my deepest gratitude to my parents, to whom this dissertation is dedicated, my brothers, my family, and my friends who have been there throughout and have contributed so heavily to preserving my sanity and motivation. I thank the faculty of North Carolina State University who have supplied me with the skills and techniques to finish this document. I thank my fellow graduate students who struggled alongside me, and those that continue to do so. I thank Chris Timmins and Wally Thurman, who have offered endless knowledge and expertise to get me to this point. I thank Laura Taylor, who has provided immeasurable support for this document and beyond. Finally, I thank my advisor, Dan Phaneuf, without whom this dissertation would not have been possible. His dedication, ingenuity, and perpetual guidance have sharpened, rounded, compiled, and shaped a young mind.
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Chapter 1

Introduction

Residential sorting models have become prevalent in urban and environmental economics as a tool for nonmarket valuation. Values for location-specific amenities are obtained by observing residential location decisions in which households make tradeoffs between wage earnings, home prices and environmental and other local public goods. The structural nature of these models makes them convenient and powerful for estimating household preference parameters and conducting counterfactual welfare analysis. This capability does not come for free, however, since numerous assumption are necessary for implementation. Among these are the spatial scale of analysis and the definition of choice alternatives. The first part of this dissertation focuses on overcoming the limitations of current residential sorting models, particularly as they relate to the choice set imposed on the consumer. In addition to contributions to the structure and estimation of sorting models, I examine the empirical implications for non-market valuation.

The second part explores an application of the model related to spatially explicit measures of the cost of living. The approach taken to develop such COL indices offers an alternative to the current quality of life literature and an arguably more pertinent characterization of access to public amenities. The analysis also focuses on the distribution of such welfare across the population. Income inequality has gained considerable attention in recent years and has amassed a significant voice in social and political advocacy. While this is a worthy issue,
the discussion may benefit from a better definition of the unequally distributed asset. Public policy may be less concerned with the distribution of income than with the distribution of a broader measure of the standard of living. Distributional issues relate to the fairness of the public provision of goods, such as whether public amenities disproportionately benefit particular income groups. This is an obvious policy concern that requires empirical evidence.

Sorting models to date have operated at the macro level (e.g. Bayer et al. (2009)) or micro level (e.g. Klaiber and Phaneuf (2010)). The former typically involves modeling the decision of which city to locate to from a collection of metropolitan areas across the country, while the latter focuses on which neighborhood a household selects within a city. Usually the scale of analysis is determined by the objectives of the study, in that amenity levels can vary at the local, regional, or national scale. Regardless of the scale, all sorting models in the current literature analyze a single choice from a single set of alternatives. Although this is computationally convenient, it ignores a stylized reality. In particular, household location choices tend to be two tiered. A large scale choice of which region or metropolitan area in which to reside is followed by a smaller scale neighborhood choice. The first of these may depend on labor market considerations and regionally varying amenities such as climate and certain types of air quality. The second may depend on local amenities such as proximity to open space and school quality. These choices can interact in a variety of ways, in that the macro level choice might depend on the portfolio of micro-level amenities provided by the area.

I develop a sorting model that formally reflects two levels of choice. I show how an assumption of two-stage budgeting, which is inherent in the structure typically used for empirical analysis, allows me to separately analyze the two choices and then link them in a single model. More specifically, the micro level choice sets and choice behavior are aggregated into a quality adjusted price index for the macro level decision. This provides a structurally consistent means of considering the role of both regional and local environmental variables in household decisions. I propose a feasible empirical version of this model at the macro level, which can be estimated with data on micro location decisions, as well as macro level housing prices and public goods.
Importantly, though the approach accounts for local public goods, I do not need to measure amenities at the local level across the macro landscape.

I demonstrate these ideas with a model that focuses on valuing air quality. If one considers variation in pollution across (but not within) metropolitan areas, valuation is possible through the macro sorting process. However, ignoring the impact of variation in micro-level amenities may confound identification of willingness to pay for macro-level amenities. To examine this I compare estimates of marginal willingness to pay for air quality obtained from the model with estimates obtained from a conventional macro sorting model. Empirical results show that this additional margin of sorting has considerable impacts on valuation of air pollution. Using a two-stage approach to residential sorting, the marginal willingness to pay for reductions in particulate matter ($PM_{10}$) increases upwards of 100%. In modeling the second stage of sorting, I identify an additional set of amenities over which individuals optimize and make tradeoffs with pollution. Note that the increase in willingness to pay is an empirical finding based on the relationship between air pollution and the set of local amenities, rather than a general theoretical result.

An application of the developed model examines a measure of welfare that reflects income, market prices, and the value of public goods. The structural approach allows for calculation of a true cost of living (COL) index that varies across space, which can then be used to construct a broad measure of standard of living. Development of true COL indices also allows for calculation of an adjusted income measure and precise characterization of the dispersion of welfare. With this, I measure the degree to which access to public amenities disproportionately benefits households based on their income.

Furthermore, I simulate federal policies in the form of exogenous changes in air pollution across different sets of locations to examine the distributional effects of federal public good provision. In response to policy that alters the level of some public good, individuals re-optimize and may move to new locations when one considers general equilibrium price effects. Therefore, the benefit of the policy is largely dependent on how individuals choose their location.
Partial equilibrium welfare analysis will fail to measure the gain or loss from any non-marginal changes in spatially delineated site attributes, as consumer optimization will result in individuals reallocating their housing and public good consumption. Thus, any examination of exogenous shocks must allow individuals to re-sort among residential locations. The residential sorting model offers a means of estimating the underlying process of the residential choice, rather than simply characterizing the equilibrium outcome. Knowledge of the sorting process allows for counterfactual analysis, in which a re-sorting due to public policy can be simulated. Then, one can ask, for example, whether individuals with already high levels of quality adjusted income are receiving a disproportionately high level of the welfare gain. This reveals the regressive or progressive effect of public good provision.

In general, explicitly accounting for public goods leads to a distribution of adjusted income that has a wider spread than that of pure monetary income. This implies that households with less income tend to face higher costs of living, determined by an inferior set of public goods relative to housing prices paid to obtain such goods. Such a widening of the distribution is a function of costly migration and the joint distribution of initial household locations and set of public goods. Simulations show that the distributional impacts of federal policy, in the form of pollution reductions, are highly dependent on the location in which they are targeted. Furthermore, general equilibrium re-sorting among locations has significant impacts on the distribution of benefits from policy, as households compete in the housing market to obtain access to public good improvements.

This dissertation proceeds as follows. Chapter 2 reviews the sorting model literature, including its development, empirical applications, and shortcomings. In Chapter 3, I discuss the theoretical foundation of residential sorting models and develop a theoretical and empirical model that incorporates the two-stage location choice introduced above. Data and estimation results are presented in Chapters 4 and 5 respectively. The final two chapters concentrate on cost of living indices and adjusted income. Chapter 6 includes a literature review related to cost of living indices and quality of life, as well as the empirical approach to calculating indices and
constructing a metric for comparing distributions. Chapter 7 then presents calculated indices, a discussion of adjusted income and results of policy simulations.
Chapter 2

Literature Review

2.1 Residential Sorting Models

Residential sorting models offer an approach to nonmarket valuation based on the implicit purchase of location specific amenities and public goods. When an individual chooses a location in which to live, she also chooses the amenities available at that site. The residential location choice is based on a utility maximizing framework in which individuals choose the location that offers their optimal bundle of market and nonmarket goods. The resulting equilibrium reveals information about the population’s preferences and willingness to pay for public goods.

The structural nature of empirical sorting models is a key advantage over hedonic estimation (Roback, 1982). While a hedonic price function uses the observed equilibrium to estimate the marginal price of a particular good, sorting models estimate the underlying preference structure that determines the observed equilibrium. Therefore, while some applications focus on the willingness to pay for particular goods such as air quality (Bayer et al., 2009) or open space (Klaiber and Phaneuf, 2010), some conduct counterfactual analyses for policy evaluation. These counterfactuals can be used to estimate welfare effects in a general equilibrium context in which individuals re-sort among locations. Given an underlying preference structure, sorting models can also contribute to the recent cost of living literature, which has been dominated by hedonic
approaches (Kahn (1995), Banzhaf (2005)). Furthermore, by matching equilibrium predictions to observed outcomes, one can empirically test models of spatial theory.

Sorting models typically fall into one of three general theoretical frameworks; 1) an equilibrium stratification framework (Epple and Platt (1998) and Epple and Sieg (1999)), 2) a random utility model (Bayer et al. (2005)), and 3) a general equilibrium model with an amenity production function (Ferreyra (2007)). Though the intuition behind the models is similar, they differ significantly in their analytical approaches. This leads to empirical applications that vary regarding the choice set, the structure of the housing market, the characterization of heterogeneous preferences, and geographic mobility costs.

2.1.1 Development of Literature

The foundation for residential sorting can be attributed to Tiebout (1956). The author argues that the level of public expenditures at the local level are efficiently allocated through the movement of individuals. An individual’s decision to move or remain in her current location “replaces the usual market test of willingness to buy a good.” Thus preferences for local public goods are reflected in the equilibrium location decision. Advances in computing power and data availability have led to numerous empirical studies of this mechanism.

The degree to which location decisions reveal demands identical to those of a market situation rests on the amount of information available to the consumer, the size and variation of the choice set, and the cost of mobility. Imperative in a model of geographic choice, mobility constraints hinder the efficient allocation of public goods. This problem is approached empirically in Bayer et al. (2009). Tiebout’s discussion also abstracts from the labor market, assuming that employment opportunities do not impact location decisions. Empirical analyses rely on a related literature that grew from a labor sorting model proposed in Roy (1951), which seeks to model potential income and characterize the relationship between the labor market and the residential location choice problem. Another assumption of Tiebout’s analysis is the lack of external economies or diseconomies. In other words, it is assumed that the attributes
of a particular community provide no utility for members of neighboring communities. Such external spillovers have been largely ignored in the literature. Finally, current sorting models have sought to address additional oversights of the original model, such as unobserved and endogenous attributes, estimation of location prices, and the existence of a spatial equilibrium.

Banzhaf and Walsh (2008) use a reduced form approach as a direct test of residential sorting. Given that individuals choose the location with the optimal allocation of goods and prices, an exogenous change in a location’s attributes should result in population changes. The authors use a difference-in-difference model to study the impact of the siting of polluting firms on a location’s population and population composition. Empirical results demonstrate population declines in response to increased toxic emissions. In addition, the authors note the existence of income effects in which exogenous increases in a normal public good attract higher income households to a neighborhood. In general, this study shows that migration patterns are consistent with the idea that individuals move in response to location attributes and prices, offering support for the type of sorting discussed in Tiebout (1956).

A similar type of sorting exists in the labor market, in which individuals choose an optimal job. Roy (1951) describes an economy with two occupations in which each individual is endowed with a certain skill level for each. The resulting distribution of wages is a general equilibrium outcome related to the distribution of skills. When labor markets are geographically defined, another dimension is added to the labor market choice. The relationship between skills and preferences for location attributes makes separate identification of them difficult. Empirically, the researcher must distinguish between an individual receiving lower wages due to her skill level versus receiving lower wages due to a compensating differential on location specific public goods.

As potential income levels are important location choice attributes, prediction of potential wages becomes a necessary component of sorting models. Self-selection in the labor market, however, confounds such prediction. Thus, significant research has been done to characterize the labor market decision and account for Roy sorting in location sorting models (Dahl 2002,
A related literature demonstrates how residential sorting can be used to identify potential wages in an economy with labor market sorting (Bayer et al., 2011).

Given a theoretical foundation and empirical evidence for location sorting, additional research explores the existence and uniqueness of an equilibrium. Epple and Platt (1998) describe the necessary conditions for a sorting equilibrium to exist in a model of consumers that differ in income and preferences and locations that differ in tax rates and the level of public goods. Equilibrium is defined as the allocation of each individual to a single location such that consumers maximize utility, the housing market clears, local government budgets balance, and taxes and government spending are decided through majority vote. Existence relies on a preference structure in which there are sets of income-preference combinations that make consumers indifferent between two neighborhoods and in which consumers smoothly trade off between consumption of housing and public goods so that higher income individuals substitute towards housing.

An alternative proof of a sorting equilibrium is given in Bayer et al. (2005). The authors prove the existence of a unique housing price vector that clears the market when utility is a decreasing, linear function of the price of housing. Furthermore, they also show the existence of an equilibrium in the presence of preferences for the endogenously determined sociodemographic composition of each neighborhood.

Under the assumption that individuals do optimally sort, many studies have taken a structural approach to examine individuals’ preferences for public goods. Epple and Platt (1998) develop a vertical model of residential sorting in which households are defined based on their level of income and a single preference parameter. Although variance in this preference parameter conveys heterogeneity in preferences for housing versus public goods, it does not allow for heterogeneity in preferences for individual public goods. Thus, all households agree on a ranking of communities by each location’s aggregate level of public goods. It is assumed that each household has a Cobb-Douglas utility function that includes housing and numeraire consumption, while public goods linearly enter the budget constraint. This class of models is based on identifying sets of income and preference parameters that make a household indiffer-
ent between two communities. Then, these conditions implicitly define the set of income and preference parameters for which a household would optimally choose any given community. A key aspect of such models is that they rely only on aggregate location data, rather than the choice and attributes of individual households.

A theoretical model shows that neighborhood sorting leads to an equilibrium in which stratification occurs based on income and preferences. This contrasts with previous results that predicted perfect income stratification. The authors also estimate income and preference distributions to calibrate and simulate a sorting model. Simulation of a two location model demonstrates the relationship between heterogeneous preferences and the lack of pure income sorting. In particular, when the variance of the preference parameter decreases, implying less preference heterogeneity, equilibrium approaches the case of perfect income stratification.

Epple and Sieg (1999) use an identical model to empirically estimate preferences for public goods. The model is estimated using aggregate community data from 92 municipalities in the Boston, MA metropolitan area. The cost of housing is estimated using structural assumptions of the model that define a relationship between income, observed housing expenditures, and the cost of housing that is necessary for the model. Income is ignored as part of the location choice. The authors use the observed income and population distributions across locations to estimate structural parameters of these distributions as well as parameters in the utility function. Following identification of these parameters, estimation of public good consumption is based on the role of public goods in the boundary indifference conditions implied by stratification. The boundary indifference conditions allow aggregate public good levels to be written as a function of location populations and housing prices. Due to the nature of preference heterogeneity aggregate public good levels can be decomposed into levels of individual public goods to obtain values for public goods. A simple linear specification includes the crime rate and per capita expenditures on education. However, the value of location amenities in this model must be interpreted as a monetary tradeoff between public goods, rather than a marginal price.

In an application that measures general equilibrium benefits, Sieg et al. (2004) use a vertical
sorting model to examine changes in ozone concentrations. The model follows that of Epple and Sieg (1999) but develops a new estimation procedure. More specifically, the study uses instrumental variables to increase the number of orthogonality conditions and estimate all parameters in a single stage. The model is estimated on school districts in the Los Angeles metropolitan area. Measuring the welfare impact of air quality improvement, empirical results show that general equilibrium benefits are substantially different from estimates obtained in partial equilibrium analysis.

The restriction on preferences in the previous papers is relaxed in Kuminoff (2008), which develops a horizontal sorting model that allows households to have heterogeneous preferences for individual public goods. Another important contribution here is the inclusion of the labor market. Each location offers an individual a wage that depends on the product of some average wage and an individual skill parameter. This skill parameter is estimated simultaneously with other model parameters. The analysis focuses on 268 neighborhood-labor market combinations in the San Francisco-Sacramento CMSA, using individual housing transaction data. Location amenities include air quality and school quality, proxied by ozone and a composite index of test scores, respectively. Estimates for the MWTP for air quality are significantly higher than those obtained from hedonic studies. In addition, preference heterogeneity and an endogenous labor market decision increase estimates on MWTP.

A second class of sorting models builds on a random utility model (RUM) framework, outlined in Bayer et al. (2005). The study specifies an indirect utility function that includes housing and neighborhood characteristics, housing prices, work commute distance, unobserved neighborhood characteristics, and neighborhood level sociodemographic variables that are determined in equilibrium. Heterogeneous preferences are easily modeled by interacting preference parameters with an individual’s income, education, race, employment status and household composition. This framework defines a horizontal model, in which preferences are defined over the attributes of a location, rather than over a location specific index. An important contribution is its discussion of equilibrium, as mentioned earlier.
The empirical analysis uses confidential census data that identifies a household in its census block within the San Francisco MSA. Given this definition of the choice set, utility maximization is restricted to choosing from a set of neighborhoods within the MSA. Neighborhood variables include school quality, elevation, population density, crime, and sociodemographics. Estimation follows the two step empirical strategy of Berry et al. (1995), in which the first stage estimates location fixed effects and the second stage decomposes fixed effects based on location attributes. This approach has become a common strategy in estimating sorting models. The authors then use the parameterized model to conduct a simulation in which the income distribution is altered. Simulation involves an iterative process that converges to a price vector and sociodemographic composition for each location. The results of the counterfactual analysis demonstrate general equilibrium price changes and partial stratification consistent with theoretical predictions of residential sorting.

Bayer and Timmins (2005) further explore equilibrium in the context of RUM-style sorting models. In particular, they outline the conditions under which a unique equilibrium is obtained in the presence of local spillovers. This is akin to the existence of population as an endogenously determined attribute. When individuals are averse to the endogenous share variable (congestion), the corresponding coefficient is negative and a unique equilibrium is guaranteed. However, in the case of preferences for endogenous shares (agglomeration), uniqueness is only guaranteed if the effect is less than some value. This value is analytically shown to depend on other components of the model, including site attributes and the distribution of preferences. Simulation demonstrates that the threshold value for uniqueness increases with the number of alternative choices, heterogeneity in preferences, and variation in the utility contribution of exogenous site attributes. Additional analytical results, however, show that multiple equilibrium may arise when local spillover effects are preference-specific (i.e. particular types of individuals have preferences for living with similar types).

A general theoretical result in sorting models is that utility is equalized across locations when there are no mobility costs. Intuitively, if utility were higher in any location, households...
would have incentive to relocate, driving up prices through increased demand for housing. Since utilities are equal, observed housing price and wage differentials reveal the aggregate impact of public goods. Kahn (1995) takes advantage of this property to rank the aggregate level of location amenities across cities using sorting equilibrium, rather than relying on hedonic methods in which it is necessary to observe amenity levels.

Bayer et al. (2009) use an application to air quality to empirically compare valuation in sorting models and hedonic estimation. The most important difference between the two approaches is that sorting models can incorporate the moving costs an individual faces in choosing a residential location. The hedonic model assumes free mobility, which causes all local amenity values to be reflected in wage and housing price differences. The authors use a structural framework to derive an indirect utility function similar to that of Bayer et al. (2005), but focus on MSA level attributes, with a choice set that includes only MSAs across the country rather than neighborhoods within any particular MSA. The extension here is that Bayer et al. (2009) include dummy variables that indicate an individual leaving his birth state, birth region, and birth macro-region, respectively, to capture money and non-money moving costs. For comparison, a conventional hedonic approach uses wage and housing regressions to obtain estimates of the marginal willingness to pay (MWTP) for air quality. Empirical results show significant differences in MWTP for air quality between the two approaches. These results emphasize the importance of mobility constraints in location decisions, particularly when modeling a macro level choice.

Focusing on open space as a location amenity, Klaiber and Phaneuf (2010) estimate a model of sorting among small neighborhoods in a single city. Using extremely fine location and attribute data, this paper obtains values for environmental amenities at a very disaggregated level. Similar to Bayer et al. (2005) an advantage of the model is its high spatial definition. Of course, such an analysis is difficult when one wants to consider multiple cities. In addition, a rich characterization of heterogeneous preferences demonstrates variance in MWTP estimates for local amenities.
While many empirical studies in the sorting literature are concerned primarily with estimating the marginal willingness to pay for some public good, sorting models offer a means of computing policy outcomes in a general equilibrium framework. This involves simulating some change in exogenous variables, followed by an iteration in which individuals maximize their utility function and housing prices and endogenous variables converge to equilibrium. Tra (2010) considers a non-marginal change in air quality. In particular, the paper first estimates a residential sorting model across 87 public use micro areas (PUMAs) in the Los Angeles metropolitan area. The analysis then uses these estimates to simulate a new location equilibrium in which the level of air pollution is consistent with improvements due to the 1990 Clean Air Act Amendments and all other attributes are unchanged. This approach offers a direct means of calculating welfare impacts of a specific policy. Empirical results display a substantial difference between partial and general equilibrium effects when public good adjustments are non-marginal. Timmins and Murdock (2007) analyze the effect of removing one site from the choice set, using a model with local spillovers. Their application focuses on recreational fishing areas in the state of Wisconsin. Rather than a welfare loss equal to the implicit value of that site’s amenities, individuals re-sort to other sites. Therefore, the model incorporates the added congestion effect into general equilibrium impacts.

2.1.2 Issues in Applications

A number of questions arise in specifying and estimating sorting models. Among these are definitions of the choice set, estimating location prices, predicting potential income, controlling for endogenous variables, and accounting for costly migration. A large body of research, as discussed above, has addressed many of these aspects, though significant issues remain.

Sorting models imply a location choice from a fixed set of alternatives. The choice set may include cities within a country (Kahn (1995), Bayer et al. (2009)), neighborhoods within a city (Bayer et al. (2005), Klaiber and Phaneuf (2010)), or one of many other designations. In some applications, the amenity of interest may determine the researcher’s specification of the
choice set, though the true choice behavior of households likely determines the set of amenities for which valuation using sorting models is valid. In addition, empirical applications so far have focused on a single location choice. For example, the model in Bayer et al. (2005) allows households to select from a number of neighborhoods within Los Angeles but restricts them to staying in Los Angeles rather than leaving the city. It also fails to distinguish those that came from another city from those that originated from within Los Angeles. Similarly, Bayer et al. (2009) specify a choice among cities but ignore the variance in neighborhood location choices among all of the households that chose to live in a particular city. For these reasons, development of sorting models may benefit from an integrated choice model that incorporates the location decision at different levels.

Another aspect of the choice set that deserves attention is the affordability of alternatives. Many of the RUM-style sorting models assume that all households can afford any home. Tra (2010), however, slightly adjusts the indirect utility function to force the choice probability to zero as the cost of housing in a location approaches an individual’s income. The stratification models based on Epple and Platt (1998) only assume that a household can purchase a subset of homes in their chosen neighborhood and in the next most expensive community.

Housing prices are typically estimated separate from the sorting model. Epple and Sieg (1999) estimate prices by combining observed income data and housing demand obtained from the model structure, though this is required due to data constraints. The conventional approach is to estimate housing prices in a hedonic framework that removes the impact of structural attributes, such as the number of rooms or age of the house. The results are comparable prices for a homogeneous housing good. However, this requires somewhat strict linear functional form assumptions and restricts the value of structural amenities to be constant across locations. Sieg et al. (2002) show that obtaining housing prices from hedonic regressions is consistent with sorting equilibrium when utility is separable in housing. The accuracy of housing price indices are tested against theoretical predictions of location sorting, though predictions are based on a simplified model with homogeneous households as described in Epple and Platt (1998).
Potential income is a necessary variable to describe the attributes of each location in the choice model. A related literature involves the role of income in residential sorting models. Roy (1951) discusses the means by which individuals self select into different occupations and examines the resulting observed distribution of earnings as it relates to the underlying distribution of skills in an economy. Given data on the distribution of wages in different markets, Heckman and Honore (1990) show that it is possible to identify the distribution of potential income across markets without any distributional assumptions.

Given the complexity of identifying potential wages, Dahl (2002) offers a simplified approach using nonparametric controls. The fundamental problem in identifying potential wages is that unobserved factors that contribute to an individual’s choice of a labor market may be correlated with individual attributes that determine wages. Therefore, coefficients in a linear wage regression are biased and generate problems for predicting wages. The strategy in Dahl (2002) is based on the notion that information related to labor market unobservables is contained in migration pattern choice probabilities. To simplify further, it is assumed that only optimal migration choice probabilities matter. Such probabilities then serve as controls for Roy sorting in a linear wage regression. Bayer et al. (2009) employ this approach in the context of a residential sorting model. Bayer et al. (2011) use location sorting as a means of estimating a model of Roy sorting. They exploit a non-pecuniary component of utility that varies across locations to identify potential wages in different labor markets. Though the objective of the paper is to estimate the wage distribution, no further research has sought to simultaneously estimate amenity prices.

Location price and sociodemographic attributes are naturally endogenous in a model of location choice. Properties of sorting equilibrium, however, offer possibilities for constructing instruments. Sieg et al. (2004) propose an instrument for the level of public goods based on community rank. The validity of this instrument follows from unobserved community attributes being small enough to affect only prices and equilibrium sorting, but not the rank of communities.
Klaiber and Phaneuf (2010) exploit the fact that demand for housing in a location is likely impacted by prices in other locations through general equilibrium effects. Therefore, an instrument is developed using neighborhood and housing attributes from surround communities. The general equilibrium argument to justify correlation is also used in Bayer and Timmins (2007), which discusses an approach to instrument for local spillover effects. Since location shares are endogenously determined, the authors predict shares using only exogenous attributes from surround alternatives. This approach is then applied to a model of recreation fishing decisions in Timmins and Murdock (2007). In these cases, the power of the instrument is derived from variation in different regions of the spatial landscape. An alternative means of dealing with endogenous prices is to appeal to the structure of the model. Bayer et al. (2009) derive an expression for the price coefficient that involves the demand for housing services. Housing expenditures are then calculated from observed data and the impact of price is simply a calculated value rather than a component to be estimated.

Second stage estimation in RUM sorting models is typically in the form of a linear regression on location attributes. Thus, in the case of endogeneity problems driven by unobserved attributes, estimation can follow a more conventional instrumental variable technique. Bayer et al. (2005) use a boundary discontinuity approach developed by Black (1999) to instrument for school quality, in which it is assumed that while school quality changes in a discrete manner across district lines, unobservables change in a continuously. Though it depends on finding appropriate instruments, a second stage instrumental variable regression can be applied to most sorting applications.

Finally, the integration of moving costs has proved to be a significant aspect of residential sorting models. As mentioned above, Bayer et al. (2009) control for moving costs, but in a very simplistic manner. Moving costs in their paper are constructed to control for the cost of being away from one’s birth place, but there is no control for the qualitatively, and likely quantitatively, different cost of moving from a second to a third location. In addition, no heterogeneity across preferences or income is allowed for in the moving cost specification. Models
that focus on smaller scale sorting, such as within cities, generally ignore moving costs based on the short distance of the move. However, it may be a bold assumption in imposing zero costs to reoptimize and purchase a new home, when one considers transaction cost as a type of moving cost.

Given the need for additional research to address limitations of residential sorting models, the next chapter will focus primarily on examining the role of the choice set and the geographic scale of the location decision. In particular, I develop a single horizontal sorting model that encompasses macro sorting across cities (Bayer et al., 2009) and micro sorting across neighborhoods (Klaiber and Phaneuf, 2010).
Chapter 3

Theoretical Model

This section outlines theory related to constructing a multi-level residential sorting model. The first subsection describes a sorting model in its most general form. The second subsection focuses on two-stage budgeting. In particular, I provide conditions under which a two-stage budgeting approach is consistent with utility maximization, and relate these conditions to the sorting context. Lastly, I examine a sorting model based specifically on a two-stage budgeting process.

3.1 Generalized Horizontal Sorting Model

Residential sorting models are based on random utility maximization (RUM) models in which individuals choose their location to maximize well-being. Utility is comprised of a deterministic portion that is observed by the analyst and a random portion that is known only to the decision maker. Sorting models rest on the notion that when an individual purchases a house, she simultaneously chooses all the attributes that accompany that house and its location. Therefore, the deterministic component of utility includes variables that describe structural characteristics of the house, location-specific public goods and amenities, and the household’s location-specific income potential. The random component is an idiosyncratic preference shock that is specific to each household for each alternative. In what follows, I first present a general model of
residential choice as a preface to the specific functional forms and structural assumptions to be discussed later.

Suppose an individual or household $i$ chooses a location $j$ to maximize utility, where each location $j = 1, ..., J$ offers a bundle of location specific amenities and defines a distinct labor market. At the intensive margin the household optimizes over consumption of a numeraire good $C$ and continuous housing services $H$, subject to a budget constraint. Specifically, individuals solve a maximization problem of the form

$$\max_{j=1,\ldots,J} \left\{ \max_{C,H} U_{ij} = U(C, H, X_j, \xi_j, \eta_{ij}; \beta^i) \quad \text{s.t.} \quad C + \rho_j H = I_{ij} \right\}, \quad (3.1)$$

where $U_{ij}$ is the location $j$ specific utility level, and $X_j$ is a vector of observable location attributes that contains public goods such as air quality, school quality, and cultural amenities. Unobserved variables are decomposed into $\xi_j$, which is constant for all people in a location, and $\eta_{ij}$, which is an individual-level random idiosyncrasy. Income for household $i$ in location $j$ is denoted by $I_{ij}$ where the location subscript implies earnings can depend on the labor market the household selects. A vector of preference parameters is denoted by $\beta^i$, where the superscript indicates that preferences can vary across individuals.

In equation (3.1) the price of all non-housing market goods is normalized to one for all locations. The amount $\rho_j H$ is expenditures on housing. By writing expenditures in this form, I assume there is a continuous housing services index, where the choice of the bundle of structural characteristics of a property is reflected in the level of $H$. Thus $H$ can be viewed as the output from a production function that maps a multiple dimension vector of property characteristics to a continuous, ordinal index. I assume this production function is constant for all locations. Under this assumption $\rho_j$ is the price of a single unit of housing services in location $j$.

The inner optimization of (3.1) results in conditional Marshallian demands for consumption and housing services $C(I_{ij}, X_j, \rho_j, \xi_j, \eta_{ij}; \beta^i)$ and $H(I_{ij}, X_j, \rho_j, \xi_j, \eta_{ij}; \beta^i)$, respectively. Substituting these demand functions back into the utility function gives the location specific condi-
tional indirect utility function

\[ W_{ij} = W(I_{ij}, X_j, \rho_j, \xi_j, \eta_{ij}; \beta^i), j = 1, ..., J \] (3.2)

To make estimation feasible additional assumptions are necessary concerning the idiosyncratic utility component, \( \eta_{ij} \). Following convention, we assume the indirect utility function is multiplicative in \( \eta_{ij} \), so that the natural log of utility can be written

\[ \ln W(I_{ij}, X_j, \rho_j, \xi_j, \eta_{ij}; \beta^i) = \ln V(I_{ij}, X_j, \rho_j, \xi_j; \beta^i) + \eta_{ij}, j = 1, ..., J \] (3.3)

The standard choice rule implies that households are observed in a location only if that location generates higher utility than all others. This choice is deterministic from the household’s perspective, but stochastic from an observer’s perspective due to the random variable \( \eta_{ij} \). By knowing the distribution of \( \eta_{ij} \) we can derive the probability of observing household \( i \) in location \( j \) as

\[ Pr_{ij} = Pr(\ln V_{ij} + \eta_{ij} \geq \ln V_{iq} + \eta_{iq} \ \forall q \neq j). \] (3.4)

Following Bayer et al. (2005), a sorting equilibrium exists when the housing market clears and each household chooses its optimal location, given the decisions of all other households. If \( V_{ij} \) is a decreasing, linear function of price and \( \eta \) is drawn from a continuous distribution, Bayer et al. (2005) show that there exists a vector of housing prices that leads to a sorting equilibrium. Such an equilibrium implies that all households are in their optimal location, given the decision of all other households.

The assumed distribution of \( \eta \) determines the form of the right hand side of equation (3.4) and thus, the class of discrete choice model. Issues concerning endogenous attributes, unobserved variables, and estimation will be discussed later in the context of specific functional forms.
3.2 Two-Stage Budgeting

A defining characteristic of the model described above is that the choice is limited to a single element from a given set of alternatives. In the context of a sorting model, this implies households select a particular city (in macro level models), a neighborhood within a city (in micro level models), or from a large choice set consisting of all possible combinations of cities and neighborhoods. The latter tends to be empirically infeasible due to the large choice set and substantial data needed. Furthermore, individual macro and micro sorting models ignore the stylized reality that household location choices tend to be two tiered. First a particular labor market is selected, which tends to correspond to a metropolitan area; conditional on this a neighborhood is selected based on local housing prices and local public goods. In what follows, I examine how an assumption of two-stage budgeting can be used to specify an empirically tractable model that is consistent with this two tiered intuition.

In consumer choice theory, two-stage budgeting postulates a budget allocation process in which expenditures are assigned to broad groups of consumption categories and then allocated to individual goods within each group, conditional on group-level expenditures. The practical benefit of such a framework is that it allows the researcher to separately analyze the two stages, where group level expenditures depend on group price indices rather than individual prices, and within group allocations depend on individual prices and group (rather than total) expenditures.

Of course, this pattern of consumption behavior does not always hold. Two-stage budgeting depends on assumptions regarding functional forms of the underlying optimization problem. As described by Blackorby and Russell (1997), two-stage budgeting is consistent with utility maximization when both price aggregation and decentralisability are satisfied, corresponding to optimal behavior in two stages. In the first stage, price aggregation implies an optimization problem that depends on group-level price indices rather than individual product prices. Consumers optimally allocate expenditures to broad commodity groups based on price aggregates and total income. In the second stage, decentralisability implies an optimization problem in which commodity levels are determined based only on within-group prices and the previously
determined expenditures on the group. When price aggregation and decentralisability are satisfied, the consumer’s two-stage optimization problem is identical to optimizing over all goods. The following subsections define conditions under which these concepts hold.

3.2.1 Price Aggregation

Partition the set of all $N$ goods into $G$ groups, $G \leq N$, with the vector of prices of goods in group $g$ denoted as $p^g$. Define price indices $\Lambda^g$ that aggregate prices of the individual commodities of each group to a single group index. Also, define allocation functions $\Theta^g$ that map all prices and income into optimal group expenditures. Strong price aggregation is defined as the existence of linearly homogeneous index functions for each group,

$$\Lambda^g(p^g), \quad g = 1, \ldots, G$$

(3.5)

and linearly homogeneous expenditure allocation functions of the form,

$$E_g = \Theta^g(I, \Lambda^1(p^1), \ldots, \Lambda^G(p^G)) \quad g = 1, \ldots, G,$$

(3.6)

where $I$ is total expenditure and $E_g$ is optimal expenditure on group $g$. The above makes clear that group $g$ expenditures can be determined with knowledge of only income and group indices.

Conditions under which price aggregation holds are most evident from the expenditure function. If the expenditure function can be written as

$$E(p, u) = E(k(p, u), \Lambda^1(p^1), \ldots, \Lambda^G(p^G)),$$

(3.7)

where $k(\cdot)$ is homogeneous of degree zero in $p$ and $\Lambda^g(p^g)$ are homothetic for all $g$, then price aggregation is satisfied (Blackorby and Russell, 1997). Here, the expenditure function depends on price indices and a homogeneous function of all prices and utility. This ensures optimality in the first stage of the budgeting problem.
3.2.2 Decentralisability

Corresponding to the second stage of budgeting, strong decentralisability (for the remainder of this chapter, strong decentralisability is implied when decentralisability is discussed) requires that goods within a single group can be properly allocated based only on group expenditures and prices of the commodities within the group. Denote the vector of demand for goods in group \( g \) as \( d_g(I, p) \). Then, define the function \( \Phi^g \) that maps income and prices within a particular group into a vector of demand. Decentralisability holds if demands can be expressed as

\[
d_g(I, p) = \Phi^g(E_g, p^g) \quad \forall g = 1, \ldots, G. \tag{3.8}
\]

Thus, demand for commodities within a particular group can be determined from group expenditures and prices of goods in that group. Prices of goods in other groups will affect demand for goods in \( g \) only through their impact on expenditure allocated to group \( g \).

Denote \( q^g \) as the consumption bundle of goods in group \( g \). Decentralisability is satisfied (Blackorby and Russell, 1997) when there exist subutility functions, \( U^g \), and a continuous, positive monotonic, and strictly quasi-concave separable utility function of the form

\[
U(q) = (U^1(q^1), \ldots, U^G(q^G)). \tag{3.9}
\]

When utility is separable in in some partition of commodities, maximization can proceed over subutility functions for different commodity groups. Together, equations (3.7) and (3.9) define necessary and sufficient conditions for two-stage budgeting analysis (see Appendix A and B for further discussion). Later, it will be shown that functional forms commonly used in sorting literature satisfy these conditions.
3.3 Two-Stage Residential Sorting Model

When two-stage budgeting holds for the underlying preference structure of the sorting model, the residential choice can be modeled in two stages. These stages are defined based on the geographic level at which the separable commodity groups vary. The conventional residential sorting model links each house to one specific geographic entity. In the current study each house corresponds to two locations, where one location encompasses the other. In the empirical application, I use census tracts and metropolitan statistical areas (MSA), which are comprised of multiple tracts, as the two levels, though other divisions are possible. In general this type of differential spatial resolution implies that some public amenities vary at a micro level (across census tracts) and others vary only at a macro level (across MSAs). In this case, the two-stage budgeting process is analogous to a sequential location choice that proceeds at two geographic levels. One aggregate commodity group is MSA level spending on housing, which is then divided between housing services and local location amenities in the second stage.

To examine this formally I rewrite the utility maximization problem for individual $i$ in neighborhood (census tract) $j$ of MSA $m$ as

$$\max_{C,H} U_{ijm} = U(C,H,X_{jm},Y_m,\xi_{jm},\zeta_m,\eta_{ijm};\beta^i) \quad (3.10)$$

$$s.t. \quad C + p_{jm}H \leq I_{im}. \quad (3.11)$$

The additional notation in (3.10) and (3.11) is defined as follows. There are now two types of location specific attributes entering preferences. The vector $X_{jm}$ refers to observed characteristics specific to tract $j$ in MSA $m$, while the vector $Y_m$ refers to observed characteristics that vary only over MSAs. The difference between MSA and tract characteristics is based on the extent of variability in location amenities. Any amenity that is constant across tracts in an MSA is considered an MSA amenity that is captured by $Y_m$, and the vector $X_{jm}$ captures tract-level deviations from MSA levels. Likewise the scalars $\xi_{jm}$ and $\zeta_m$ refer to tract-varying and MSA-varying unobserved characteristics, respectively. Individual idiosyncratic shocks are
given by $\eta_{ijm}$. The scalar $p_{jm}$ is the price of housing services in a particular tract, conditional on a particular MSA, and it varies across the entire micro and macro landscape based on local spatial characteristics. This price can be further decomposed into an MSA and a tract component

$$p_{jm} = \rho_{m}^{X} \rho_{jm}^{Y},$$

(3.12)

where $\rho_{m}^{Y}$ varies only across MSAs and $\rho_{jm}^{X}$ varies with tracts in each MSA. The component that varies at the MSA level can be interpreted as a base MSA price, while the component that varies at the tract level can be interpreted as a price adjustment arising from the variation in tract-level amenities. Finally, based on the notion that an MSA is a single labor market, income varies only across MSAs. These assumptions give rise to a conditional indirect utility function of the form

$$V_{ijm} = V(I_{im}, p_{jm}, Y_{m}, X_{jm}, \xi_{jm}, \zeta_{m}, \eta_{ijm}; \beta^{i}), j = 1, \ldots, J_{m}, \ m = 1, \ldots, M,$$

(3.13)

where $J_{m}$ is the number of census tracts in MSA $m$.

A specific function form for equation (3.10) will ensure that two-stage budgeting holds. A sufficient condition for two-stage budgeting is that the conditional indirect utility function can be expressed as a function of price indices that correspond to consumption groups. I define three consumption groups as general consumption $C$, the MSA-level public goods $Y$, and a composite good $Q$. The latter group is an aggregate of tract-level public goods $X$ and housing services $H$. If two-stage budgeting holds we can rewrite (3.13) as

$$V_{ijm} = V(I_{im}, Y_{m}, \Gamma_{jm}^{i}(p_{jm}, X_{jm}, \xi_{jm}, \eta_{ijm}), \zeta_{m}, \eta_{im}; \beta^{i}), j = 1, \ldots, J_{m}, \ m = 1, \ldots, M.$$

(3.14)
where the idiosyncratic error term is divided into two components so that $\eta_{ijm} = \eta_{ij} + \eta_{im}$, and $\Gamma_{jm}^i(\cdot)$ is a price index for individual $i$ in tract $j$ of MSA $m$. The index reflects the aggregation of tract-level public goods, tract-level unobservables and housing services. Due to the fixed quantity nature and implicit pricing of public goods, the index $\Gamma_{jm}^i(\cdot)$ includes levels of the commodity $X$ rather than the explicit price of $X$. While the price index here corresponds to the index $\Lambda^g$ discussed earlier, notation has been changed for two reasons to avoid direct comparison. First, more conventional price indices include the price of a good rather than the level, as is the case for $\Gamma_{jm}^i(\cdot)$. Second, the subscript $j$ on each $\Gamma_{jm}^i(\cdot)$ illustrates that the index summarizing tract level public goods and prices corresponds to an optimal decision regarding tract choice; likewise the superscript $i$ highlights the role of preferences in the structure of the price index.

Under certain conditions, the two-stage sorting model discussed above collapses to a single-stage MSA sorting model. When all neighborhoods in an MSA are identical, the second stage of sorting becomes irrelevant since all variation occurs at the MSA level. In such a situation, there should be no variation in price across tracts. Thus, $\rho^X_{jm} = 1$ for all tracts in the MSA so that each tract has a price described only by the MSA portion $\rho^Y_m$. Given this special case for $\rho^X_{jm}$, it is evident that the price function in equation (3.12) becomes identical to that of the more conventional model in equation (3.1).

To summarize, an individual chooses from among a set of MSAs that each offer a fixed bundle of income, MSA-level public goods, and a composite good. The composite good consists of housing services and tract-level public goods, where each tract offers a different bundle of public goods and housing prices. The choice of an MSA is analogous to choosing optimal expenditures on the broad groups of commodities, including housing, without choosing the exact consumption of housing services and local public goods. In other words, an individual decides on an MSA without yet determining a particular tract. The choice of a tract is then analogous to choosing the bundle that optimally distributes expenditures between housing services and tract-level public goods. Equation 3.14 serves as the basis of a micro-consistent,
macro-level sorting model. With this structure it is possible to model the MSA choice while still accounting for the further division of metropolitan areas into neighborhoods and households’ sorting behavior among those neighborhoods.

### 3.4 Empirical Basis

To derive an empirical model, it is necessary to specify relationships for the utility and other functions identified in the previous section. Similar to previous sorting studies, the household’s conditional optimization problem is

$$\max_{C,H} U_{ijm} = C^{\beta_C} Y^{\beta_Y} H^{\beta_H} X^{\beta_X} \exp(\xi_{jm} + \zeta_m + \eta_{ijm})$$  \hspace{1cm} (3.15)

subject to

$$C + p_{jm} H = I_{im}$$  \hspace{1cm} (3.16)

where the superscript $k$ on each preference parameter denotes a type $k$ individual. An individual’s type is defined by a unique set of personal characteristics. Since $Y_m$ and $X_{jm}$ are vectors, the preference parameters associated with them are also vectors; correspondingly the preference parameters associated with $C$ and $H$ are scalars. For ease of exposition in what follows, however, we refer to all four of these terms as scalars. To account for heterogeneity in preferences, some specifications allow for preference parameters to be composed of a mean component and a type-specific deviation, so that

$$\beta^k_r = \beta^0_r + \gamma^k_r \quad r = C,Y,H,X$$  \hspace{1cm} (3.17)

In the application that follows we distinguish types based on four levels of education and the presence of children. Given this our model includes eight unique household types, which are described in 3.1.

Maximizing (3.15) with respect to $C$ and $H$ subject to the budget constraint results in the familiar conditional indirect utility function,
\[ \ln V_{ijm} = \beta^k_I \ln I_{im} + \beta^k_Y \ln Y_m + \beta^k_X \ln X_{jm} - \beta^k_H \ln \rho^Y_m - \beta^k_H \ln \rho^X_{jm} + \xi_{jm} + \zeta_m + \eta_{ijm}, \quad (3.18) \]

where a fixed (and therefore irrelevant) constant term is dropped, and \( \beta^k_I = \beta^k_C + \beta^k_H \).

### 3.4.1 Conditions for Two-Stage Budgeting

Before discussing the explicit equations of the two-stage budgeting model, I now show that the optimization framework satisfies the conditions for such an approach. In particular, the common functional form shown in (3.15) and (3.16) satisfies the conditions for two-stage budgeting, and therefore provides an opportunity to use additional structure in characterizing the problem. Once again partition the set of all goods into the three groups consumption \( C \), MSA-level amenities \( Y \) and the composite housing good \( Q \), consisting of housing services \( H \) and local amenities \( X \).\(^1\) The primary concern in proving the existence of two-stage budgeting here is to show that dividing the entire set of commodities into these groups is consistent with utility maximization. In particular, as discussed earlier, I will show that this grouping satisfies price aggregation and decentralisability, the necessary and sufficient conditions for two-stage budgeting. For the following discussion, it is assumed that the discrete choice space is large enough to treat location specific amenities \( X \) and \( Y \) as continuous goods. This allows for the use of derivatives for optimization over these goods.

Focusing first on price aggregation, equations (3.6) and (3.7) offer two alternative ways of characterizing the optimization problem to show that two-stage budgeting holds. The maximization problem defined in (3.15) and (3.16) results in the following expenditures for \( C \) and \( H \),

\( ^1\)Reverting back to the original definition of \( Y \) as a vector of public goods, the model actually has several groups, one for each macro-level good. The group \( Y \) should not be interpreted as a group of macro-level public goods
For expenditures on $Y$, consider a hedonic framework and define a marginal implicit price for $Y$ as $E^r_{im} = \beta^k_r \frac{I_{im}}{\beta^k_C + \beta^k_H}, r = C, H$. (3.19)

so that expenditures on MSA amenities are also a fixed share of income. Thus commodity group expenditures do not depend on the prices for individual goods, suggesting price aggregation is satisfied. In equation (3.19), $E^H_{im}$ refers to expenditures on housing, which implicitly includes expenditures on $X$. Therefore, equation (3.6) is clearly satisfied.

Alternatively, the expenditure function that results from utility maximization (excluding unobservables) is

$$E(p, u) = \left[ \frac{u}{\beta_0} (\rho^Y)^{\frac{\beta^k_Y}{\beta^k_H}} \left( \frac{\partial pH}{\partial Y} \right)^{\frac{\beta^k_Y}{\beta^k_C}} \left( \frac{\partial ph}{\partial X} \right)^{\frac{\beta^k_X}{\beta^k_C}} \right] \frac{1}{\sigma_{Y} + \sigma_{X} + \sigma_{Y}}$$ (3.21)

The components $\frac{\partial pH}{\partial X}$ and $\frac{\partial pH}{\partial Y}$ comes from differentiating the budget constraint with respect to $X$ and $Y$, respectively, in the optimization problem. They are left in this form since there is no explicit price for either of the public goods, though $p$ can be interpreted as a hedonic price that depends on $X$ and $Y$. To see that this equation satisfies price aggregation, equation (3.21) must be rearranged to correspond with equation (3.7). Rewrite (3.21) so that

$$E(p, u) = \left[ \frac{u}{\beta_0} (\rho^Y)(\rho^X)^{\frac{\beta^k_Y}{\beta^k_X}} \left( \frac{\partial pH}{\partial Y} \right)^{\frac{\beta^k_Y}{\beta^k_C}} \left( \frac{\partial (pH)}{\partial X} \right)^{\frac{\beta^k_X}{\beta^k_C}} \right] \frac{1}{\sigma_{Y} + \sigma_{X} + \sigma_{Y}}$$ (3.22)

It is obvious now that $\frac{1}{\beta_0} \frac{1}{\beta^k_X}$ is homogeneous of degree zero in prices and $\frac{\partial pH}{\partial Y} \frac{\beta^k_Y}{\beta^k_C} \frac{1}{\sigma_{Y}}$ is a homothetic function. The final condition is that the remaining portion be a homothetic func-
tion in prices of $H$ and $X$. Recall that a homothetic function is a function that can be expressed as $F(G(\cdot))$, in which $F(\cdot)$ is a monotonically increasing function and $G(\cdot)$ is homogeneous of degree one. Rewrite the remaining elements of the expenditure function in the form $F\left(G\left(\rho^X, \rho^Y, \frac{\partial p H}{\partial X}\right)\right)$ where

\[
F\left(G\left(\rho^X, \rho^Y, \frac{\partial p H}{\partial X}\right)\right) = \left[\rho^Y \rho^X$$^\beta_k$$^X \frac{\partial p H}{\partial X}\right]^\frac{\beta_k^y}{\beta_k^x} F(G(\cdot)) = G(\cdot)$$^\frac{\beta_h + \beta_k}{\beta_k}$$^X \frac{\rho^Y}{\rho^X} G\left(\rho^Y, \rho^X, \frac{\partial p H}{\partial X}\right) = \left[p^{B_h^k}\left(\frac{\partial p H}{\partial X}\right)^\frac{\beta_k^y}{\beta_k^x} \frac{1}{\rho^Y \rho^X}$$^\frac{\beta_h + \beta_k}{\beta_k}$$

in which

\[
F(G) = G(\cdot)$$^\frac{\beta_h + \beta_k}{\beta_k}$$^X \frac{\rho^Y}{\rho^X} G\left(\rho^Y, \rho^X, \frac{\partial p H}{\partial X}\right) = \left[p^{B_h^k}\left(\frac{\partial p H}{\partial X}\right)^\frac{\beta_k^y}{\beta_k^x} \frac{1}{\rho^Y \rho^X}$$^\frac{\beta_h + \beta_k}{\beta_k}$$

Given the assumption that the price of $X$ is equal to $\frac{\partial p H}{\partial X}$ and independent of $p$, this equation conforms to the homotheticity restrictions and thus the expenditure function satisfies the conditions in equation (3.7). Equations (3.19), (3.20) and (3.22) establish that price aggregation holds.

Turning to decentralisability, it is necessary to show that within group expenditures are independent of prices of goods in other commodity groups. Sufficient conditions come from the direct utility function and commodity demands, equations (3.9) and (3.8). In the current model, this implies

\[
U = (U^C(C), U^Y(Y), U^Q(H, X))
\] (3.23)
and

\[ d_g(I, p) = \Phi^g(E_g, p^g) \quad g = C, Y, Q \tag{3.24} \]

The separability highlighted by equation (3.23) is obvious in equation (3.15) with subutility functions

\[
\begin{align*}
U^C &= C^{\beta_C}_{im} \\
U^Y &= Y^{\beta_Y}_{im} \\
U^Q &= \left( H^{\beta_X}_{ijm} X^{\beta_H}_{jm} \right)^{\beta_H}
\end{align*}
\]

First order conditions from utility maximization result in demand relationships \( C(\cdot) = E^C_{im} \) for the consumption group and \( H(\cdot) = E^H_{im} / p_{jm} \) for housing services. From (3.20), it is clear that the demand for \( Y \) is similar to that of \( C \) and \( H \), in that it depends only on preference parameters and total \( Y \) expenditures. The demand for \( X \), like \( Y \), is based on an implicit marginal price derived from a hedonic interpretation,

\[ X_{jm} = I_{im} \left( \frac{\partial E^H_{im}}{\partial X} \right)^{-1}, \tag{3.25} \]

so that the demand for \( X \) depends on total expenditures on \( H \) and the implicit price of \( X \). Decentralisability is therefore satisfied as the demand for each commodity depends only on group expenditures and own-group prices. In general, the model assumes that any tradeoffs between \( Y \) and \( H \) or \( Y \) and \( X \) are captured in the tradeoff between \( Y \) and total expenditures devoted to \( H \) and \( X \). Having shown that the optimization problem satisfies price aggregation and decentralisability, two-stage budgeting can be applied to the choice problem.
### 3.4.2 A Two-Stage Model

Equation (3.18) is written to reflect a choice between all neighborhoods in all MSAs. However, as shown above, the form of the optimization problem allows the location choice to be modeled in two stages. The first stage determines expenditures for three broad groups and is equivalent to a choice among MSAs. Such a correspondence is evident from equations (3.19) and (3.20), where we see that expenditures on the three groups vary only at the MSA level. Therefore, the optimization problem can be modeled first as a choice among MSAs. To see this rewrite the conditional indirect utility function as

\[
\ln V_{im} = \beta^i_k I_{im} + \beta^v_k Y_m - \beta^h_k \ln \rho^Y_m + \tilde{\Gamma}^i_m + \zeta_m + \eta^i_{jm},
\]

(3.26)

where once again \(\eta_{ijm} = \eta_{im} + \eta_{ij|m}\) and

\[
\tilde{\Gamma}^i_m = \max_{j \in J_m} \left( -\beta^k_H \ln \rho^X_{jm} + \beta^k_X \ln X_{jm} + \xi_{jm} + \eta^i_{jm} \right)
\]

(3.27)

reflects the optimal allocation of housing services based on tract variation and tract level public goods, which corresponds to the second stage of the two-stage budgeting process.

It is theoretically consistent to write equations (3.26) and (3.27) with the full price of housing services included as part of the index. Due to the linear nature of (3.26) and (3.27) combined with a two-stage budgeting framework in which \(\rho^Y_m\) does vary across tracts, however, \(-\beta^k_H \ln \rho^Y_m\) can simply be removed from the index so that it directly enters the MSA-level function. We do this for two reasons. First, \(\rho^Y_m\) is estimable in a hedonic framework and leads to a feasible strategy for identifying behavior in the second stage of budgeting. This will be addressed further when calculation of the index is discussed. Second, having it explicitly enter the choice function allows for a direct comparison to conventional sorting models that ignore tract variation and offers an intuitively consistent interpretation for \(X_{jm}\).

The two indirect utility functions in (3.18) and (3.26) represent identical preferences and choice behavior. When interest centers only on the macro choice, the term \(\tilde{\Gamma}^i_m\) becomes an
MSA-level price index for the first stage of the individual’s location choice, reflecting the cost of housing services and local amenities (the quantity of $X$) throughout the MSA. Though it is labeled a price index, $\hat{\Gamma}_m^i$ is more appropriately thought of as a utility or quality adjusted price index, in that it contains preference parameters as well as fixed attributes of neighborhood $j$.

In the following subsection, I show that equation (3.26) allows for estimation of a macro scale sorting model that is consistent with micro sorting behavior. A full sorting model that defines a choice set made up of all census tracts in all MSAs is prohibitively large, both computationally and concerning data needs. The above model is applicable to sorting on a large geographic scale, but also takes advantage of information obtained from households’ micro decision. To complete the model, the next subsection derives the price index from the second stage of the consumer’s choice problem.

### 3.4.3 Construction of Index

Given optimal expenditures on the three broad groups, the second stage involves choosing the allocation of goods within each group conditional on group expenditures. In terms of second stage optimization, groups $C$ and $Y$ have no goods to be allocated once expenditures are determined. For group $Q$, individuals allocate expenditures on the composite housing good between housing services and neighborhood-level amenities. This implies a tradeoff between the attributes of the property and the quality of the surrounding area. Within the context of the original utility function in (3.15) the second stage problem can be written as

$$\max_{j \in J_m} \max_{H} U_{ijm} = \alpha_{im} H^{\beta_h} X^{\beta_X} \exp(\xi_{jm} + \zeta_m + \eta_{hj|m}) \quad \text{s.t.} \quad \bar{E}_{im}^H = \rho_{jm}^X,$$

where $\alpha_{im}$ holds the $m$-specific terms in the utility function and $\bar{E}_{im}^H = E_{im}^H / \rho_{m}^Y$. This gives the conditional indirect utility function for individual $i$ in neighborhood $j$ of MSA $m$. 

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\[ \ln V_{ijm}^2 = \bar{\omega}_{im} - \beta^k_H \ln \rho_{jm}^X + \beta^k_X \ln X_{jm} + \xi_{jm} + \eta_{ijm}, \]  

where \( \bar{\omega}_{im} \) is a person-specific parameter that is constant across neighborhoods in the same MSA. Since \( F_{im}^H \) is constant within an MSA, it is absorbed by \( \bar{\omega}_{im} \). Note that the component of utility separate from \( \bar{\omega}_{im} \) in (3.29) is equal to the term \( \tilde{\Gamma}^i_m \) in (3.27), the desired price index. This result suggests a strategy that uses the micro sorting problem to obtain values for \( \tilde{\Gamma}^i_m \).

**The Error Distribution and Index Construction**

Returning to the full maximization problem, I assume that the idiosyncratic preference shock \( \eta_{ijm} \) follows a generalized extreme value (GEV) distribution, resulting in a nested logit structure. The vector of unobserved utility, \( \eta_i = [\eta_{i11}, ..., \eta_{i1J1}, \eta_{i12}, ..., \eta_{iJM}] \) has cumulative distribution (cdf)

\[
\exp \left[ - \sum_{m=1}^{M} \left( \sum_{j=1}^{J_m} e^{-\eta_{ijm}/\tau_m} \right)^{\tau_m} \right].
\]

(3.30)

This distribution is a generalization of the distribution that gives rise to the conditional logit, in that draws are not restricted to be independent within MSAs. Rather, \( \tau_m \) defines some degree of dependence between \( \eta_{ijm} \) and \( \eta_{iqm} \), while \( \eta_{ijm} \) and \( \eta_{iqn} \) for \( m \neq n \) are still independently distributed. Note that if \( \tau_m = 1 \forall \ m \), then (3.30) reduces to the same assumption of the multinomial logit model. A value of \( \tau_m = 1 \) signifies complete independence, while lower values of \( \tau_m \) denote higher degrees of correlation. The intuition for this distribution is that for an individual, there can be correlation between idiosyncratic shocks in tracts within the same MSA. The distribution in (3.30) implies a choice probability of the form

\[
P_{rijm} = \frac{\exp(V_{ijm}/\tau_m) \left( \sum_{q=1}^{J_m} \exp(V_{iqm}/\tau_m) \right)^{\tau_m-1}}{\sum_{n=1}^{M} \left( \sum_{q=1}^{J_m} \exp(V_{iqm}/\tau_n) \right)^{\tau_n}}
\]

(3.31)

A familiar property of the nested logit model is that its choice probability reduces to the
product of two multinomial logit models,

\[ Pr_{ijm} = (Pr_{ij|m})(Pr_{im}), \]  

(3.32)

where \( Pr_{ij|m} \) is the conditional probability that individual \( i \) chooses tract \( j \) given the choice of MSA \( m \) and \( Pr_{im} \) is the marginal probability that individual \( i \) chooses MSA \( m \). I make an additional assumption on the distribution of \( \eta_i \) to restrict \( \tau_m = \tau \) for \( m = 1, \ldots, M \). This assumption implies an identical level of correlation among idiosyncratic shocks in each MSA.

As tract-level utility is measured as a tract-type fixed effect, idiosyncratic shocks are entirely the result of household preferences for tract-level amenities. It is thus reasonable to assume that these shocks have a similar structure in each MSA. However, since \( \tau \) characterizes the distribution of idiosyncratic preference shocks, it may vary with preferences. Therefore, a separate \( \tau^k \) is defined for each individual type \( k \) in the model. Based on the level of geographic variation in the utility function components in equation (3.26), the marginal and conditional probabilities can be written as

\[
Pr_{im} = \frac{\exp \left( \beta_k^I \ln I_m + \beta_k^Y \ln Y_m - \beta_k^H \ln \rho_m + \zeta_m + \tau^k IV^k_m \right)}{\sum_{n=1}^N \exp \left( \beta_k^I \ln I_n + \beta_k^Y \ln Y_n - \beta_k^H \ln \rho_n + \zeta_n + \tau^k IV^k_n \right)},
\]

(3.33)

and

\[
Pr_{ij|m} = \frac{\exp \left( -\beta_k^H \ln \rho_{jm}^X + \beta_k^X \ln X_{jm} + \xi_{jm} \right) / \tau^k}{\sum_{l=1}^J \exp \left( -\beta_k^H \ln \rho_{lm}^X + \beta_k^X \ln X_{lm} + \xi_{lm} \right) / \tau^k} = \frac{\exp(\delta_{jm}^k)}{\sum_{l=1}^J \exp(\delta_{lm}^k)},
\]

(3.34)

respectively, where \( IV^k_m \) is type specific and given by

\[ IV^k_m = \ln \sum_{j=1}^J \exp(\delta_{jm}^k). \]

(3.35)

Expressions (3.33), (3.34), and (3.35) are useful for both the theoretical and empirical aspects of the model. Note that the terms entering (3.34) nearly match those in equation
(3.27), with the difference being the scale term $\tau^k$ and the absence of the error term $\eta_{ijm}$ in (3.34). More specifically, we see that the expected value of $\Gamma^i_m$ is given by equation (3.35), where the dependence on $\tau^k$, local prices, and local public goods are subsumed into the fixed effects. That is, we define $\Gamma^k_m = E[\tilde{\Gamma}^i_m]$ and note that $\Gamma^k_m$ is equivalent to $IV^k_m$. With this, equation (3.33) is equivalent to a macro-level sorting model in which MSA probabilities are given by

$$Pr_{im} = \frac{\exp \left[ \beta^k_I \ln I_{im} + \beta^k_Y \ln Y_{m} - \beta^k_H \ln \rho_{m} + \zeta_{m} + \tau^k \Gamma^k_m \right]}{\sum_{n=1}^{N} \exp \left[ \beta^k_I \ln I_{in} + \beta^k_Y \ln Y_{n} - \beta^k_H \ln \rho_{n} + \zeta_{n} + \tau^k \Gamma^k_n \right]}.$$  

(3.36)

This suggests an empirical strategy for estimating a micro-consistent, macro sorting model that first uses data on micro sorting to recover the $\delta^k_{jm}$ terms and $\Gamma^k_m$, and then uses the macro information to estimate a version of 3.26. Econometrically, this is equivalent to sequentially estimating a nested logit model in which the top level choice involves selecting an MSA and the bottom level choice involves selecting a neighborhood within an MSA. Therefore, when individuals behavior conforms to two-stage budgeting, a nested logit model becomes a convenient means of estimating the first budgeting stage, and one can interpret the inclusive value as a quality adjusted price index over the goods or attributes that vary within a nest. It should be emphasized that two-stage budgeting is not driven by the nested logit structure; indeed for $\tau^k = 1$ the model collapses to a multinomial logit. The budgeting process arises entirely from household preferences and, with certain distributional assumptions on the idiosyncratic shocks, can be modeled using any type of discrete choice model.

There are three points to add to this discussion. First, we are assuming that the analysis is not concerned with separating the effects of price and $X_{jm}$ on local sorting, but rather seeks to account for their combined effect on behavior. For a purely macro level model it is in any case usually infeasible to observe $X_{jm}$ for every neighborhood in the landscape. Second, a common concern with sequential nested logit models is that the scale of utility in the constructed $IV$ covariates can be different across nests, making values of the expected utilities non-comparable in the upper level analysis. However, since the neighborhood utility function is estimated as
a fixed effect that does not contain cross-nest restrictions, the usual normalization via $\tau^k$ is absorbed in the parameter value. Finally, there is an issue of normalization that needs to be discussed. Due to the ordinal nature of utility, $\delta^k_{jm}$ can only be identified up to a normalization in each $m$ and for each $k$. Therefore the estimated vectors $\delta$ for different MSAs $m$ and $n$ are not in general comparable. To deal with this issue, we employ an effects coding strategy, rather than the dummy coding approach that is often used in discrete choice models.

### 3.4.4 Normalization of Tract-Level Fixed Effects

Given a set of $M$ MSAs, it is possible to estimate a separate tract allocation model based on (3.29) for $m = 1, ..., M$. This gives $M$ vectors of tract-specific fixed effects (Appendix C shows equilibrium conditions in micro sorting). Since the discrete choice model is invariant to the scale of utility, fixed effects in each MSA must follow some normalization. Typically, this is done by setting a single tract fixed effect to zero. However, the estimates are not directly comparable across MSAs since the fixed effects are measured relative to different normalized values. Therefore, we take an effects coding approach to normalization, rather than the typical dummy coding approach.

With effects coding the sum of all fixed effects in a particular MSA is zero. Parameters are then interpreted relative to a grand mean, which in this case is the mean utility from an MSA. Thus, tract fixed effects convey variability in tract-level amenities within an MSA. For example, if all tracts are identical the entire utility effect in those locations is captured as an MSA level amenity.

The micro-level utility function in (3.29) depends on public attributes $X$ and the price of housing services $\rho^X$, but is estimated as a single fixed effect. For individual of type $k$ in tract $j$ in MSA $m$, 

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\[
\ln V_{jm}^2 = -(\beta^k_H \ln \rho_{jm}^X + \beta^k_X \ln X_{jm} + \xi_{jm})/\tau^k
\]
\[= \delta_{jm}^k. \tag{3.37} \]

The value \(\delta_{jm}^k\) is the true fixed effect, a function of public goods and prices that is comparable across multiple MSAs. Estimation using dummy coding, however, only gives a fixed effect normalized on a different tract in each MSA. The problem is highlighted by the fact that adding some constant to the entire set of true fixed effects will have no effect on choice probabilities. Effects coding imposes the restriction that

\[
\sum_{j=1}^{J_m} \delta_{jm}^k = 0, \tag{3.39} \]

where \(J_m\) is the number of tracts in MSA \(m\). The normalization in equation (3.39) implies that each tract fixed effect can be calculated as

\[
\delta_{jm}^k = \frac{1}{J_m} \sum_{q \neq j} \ln \left(\frac{s_{jm}}{s_{qm}}\right), \tag{3.40} \]

where \(s_{jm}\) is the share of type \(k\) individuals in MSA \(m\) that chooses tract \(j\) (the derivation of this calculation is shown in Appendix D).

Consider an MSA in which all tracts are identical. As discussed earlier, the model collapses to a conventional model of MSA sorting. In terms of tract-level fixed effects, all shares should be equal and amenity impacts will be identified in an MSA fixed effect. If all shares are equal, the effects coding normalization forces all of them to be zero, as they are simply all equal to the summation of the natural log of 1. The intuition and econometrics correspond perfectly given the interpretation that the second stage is capturing tract deviations from the MSA amenity levels.

If we look at the decomposition of the tract-level fixed effects in (3.37) (assuming that all
unobservable amenities are in $X$), they are equal to zero when $\ln X_{jm}$ and $\ln \rho_{jm}X$ are both equal to zero. When these logged values are both zero, $X_{jm}$ is a vector of 1s, having no impact on utility, and $\rho_{jm}X$ is a vector of 1s, having no impact on the price of a house so that price is determined solely by the MSA price. In the general theoretical model, it is evident that such a situation is identical to a conventional model that accounts only for macro sorting, since the second stage impact is simply 0. In addition, the price of housing services exactly matches that of the conventional macro sorting model. Intuitively, when there is no tract variation on which households can sort, the macro sorting model captures all relevant information.

However, it is important to recognize that since we calculate the index based on the expectation of tract fixed effects across the MSA, as in (3.35), the index is positive for a set of fixed effects equal to zero. Furthermore, the index is increasing in the number of tracts. Intuitively, the expectation of idiosyncratic shocks, as well as the increased number of possible shocks, generates positive utility.

### 3.4.5 Macro Stage Sorting

From equations (3.26) and (3.27), the price index is a reflection of the optimal allocation of within-group goods $X$ and $H$ at the micro level. While this is derived from the observed optimal location, the index value for cities in which the individual is not observed to be living (i.e. the remainder of the choice set) is based on the choice of individuals with identical preferences. Though random preference shocks create variation in the observed tract choice, the index is equal to the deterministic portion of utility at the tract level. The empirical index is defined as the log-sum of the properly normalized fixed effects for each type-MSA combination.

A final aspect of residential sorting to consider is the cost of migration. I assume that costly migration exists for moves between MSAs, but not between tracts in the same MSA. Denote these costs as $MC_{im}$. While the exact form of these costs will be defined later, note that they may involve the cost of moving from one MSA to another, as well as the cost of being away from one’s birth location. Assume that $MC_{im}$ enters the direct utility function exponentially,
and thus enters the log indirect utility function linearly so that

\[ \ln V_{im}^1 = \beta_I^k \ln I_m + \beta_Y^k \ln Y_m + MC_{im} - \beta_H^k Y_m + \tau^k \Gamma^k_m + \zeta_m \]  

(3.41)

As shown earlier, this first stage of the budgeting process can be estimated in a logit framework.

The macro sorting model defined in (3.41) can be estimated as three different models, depending on the characterization of the term \( \tau^k \Gamma^k_m \). Recall that when the index is equal to 0, two-stage sorting simplifies to a traditional single stage sorting model driven by MSA prices. When \( \tau^k \) is equal to 1, the error distribution discussed earlier reduces to that of a logit model characterization of sorting among tracts. Finally, the most general case is that in which \( \tau^k \) is type specific and varies between 0 and 1, leading to a nested logit model, in which MSAs denote nests. All three models are consistent with two-stage budgeting theory.
Table 3.1: Type Definitions

<table>
<thead>
<tr>
<th>Type</th>
<th>Definition (presence of children and education)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type 1</td>
<td>No children in household, No high school degree</td>
</tr>
<tr>
<td>Type 2</td>
<td>No children in household, High school degree or some college</td>
</tr>
<tr>
<td>Type 3</td>
<td>No children in household, Bachelor’s degree</td>
</tr>
<tr>
<td>Type 4</td>
<td>No children in household, Graduate or professional degree</td>
</tr>
<tr>
<td>Type 5</td>
<td>Children in household, No high school degree</td>
</tr>
<tr>
<td>Type 6</td>
<td>Children in household, High school degree or some college</td>
</tr>
<tr>
<td>Type 7</td>
<td>Children in household, Bachelor’s degree</td>
</tr>
<tr>
<td>Type 8</td>
<td>Children in household, Graduate or professional degree</td>
</tr>
</tbody>
</table>
Chapter 4

Data and Preliminary Estimation

4.1 Data

The micro-level portion of the model requires information regarding tract location decisions for households across the country. The U.S. Census long form, a decennial census distributed to approximately 1 in 6 households, serves as the basis for information used to construct MSA indices in the micro-level sorting model. Though the long form is confidential, access is permitted for research purposes through the Triangle Census Data Research Center. This allows for observations of individuals and their census tract location. Pertinent information includes an individual’s age, education, and household composition. The subsamples for my analysis in 1990 and 2000 include household heads between the ages of 23 and 40, living in one of 226 MSAs.

Census tracts make up the finest definition of location used in my model. Since tracts are not constant across years, reported locations in the 2000 census are geographically matched to 1990 tracts. A household’s 2000 census block group geographically identifies the corresponding tract for 1990. There are no cases in which year 2000 block groups cross 1990 tract borders, implying perfect identification of 1990 tracts. This approach implies that 1990 tracts serve as the geographic basis for the full model. Mean tract population for 1990 is 3,791 with a
standard deviation of 1,778. For 2000, the mean is 4,387 with a standard deviation of 2,209. Thus, micro sorting is analyzed on a sample of 8,587,816 individuals for 1990 and 7,619,164 individuals for 2000, across 40,416 tracts.

The macro-level model requires income predictions, migration data, and observations of individuals living in MSAs. These data are obtained from the Integrated Public Use Microdata Series (IPUMS), managed by the University of Minnesota. Data sets for 1990 and 2000 include a 5% sample of census long form observations, identifying households in their current MSAs as well as their birth and previous location. Variables also include individual attributes for wage predictions and type identification. Based on the availability of data and consistency across years, a subset of 226 MSAs in the continental United States is chosen out of the full set of 290 defined MSAs in 1990 and 301 MSAs in 2000. This subset covers 71% (171,413,984) of the U.S. population in 1990 and 70% (190,474,896) in 2000. Furthermore, the sample accounts for 91% and 86% of the nation’s urban population in 1990 and 2000, respectively. As in the micro-level analysis, I restrict the sample to only household heads between the ages of 23 and 40. After random sampling, the final sample includes 37,165 individuals for the year 2000 and 39,058 individuals for the year 1990, spanning the 226 MSAs.

In addition to household data the macro-level analysis requires data for attributes of locations. These attributes include environmental, social, and demographic variables. Among the environmental variables, I use concentrations of particulate matter smaller than 10 micrometers ($PM_{10}$) as a measure of air quality. Emissions data from the 1990 and 2000 EPA National Emissions Inventory are transformed into concentrations using a source-receptor (input-output) matrix. The source-receptor matrix is based on a pollution dispersion model developed by EPA (Latimer, 1996), in which there is a unique transfer coefficient for each source-receptor combination for both $PM_{10}$ and sulfur dioxide ($SO_2$) sources. Emissions of $PM_{10}$ and $SO_2$ are observed at the 5903 sources, measured separately as ground level county emissions (3,080 locations), emissions from stacks below 250 meters (1885 locations), emissions from stacks 250–500 meters high (373 locations), and emissions from stacks higher than 500 meters (565 locations). The
3080 receptors of the matrix corresponds to county PM10 concentrations, which are then averaged to obtain MSA concentrations. Concentrations of $PM_{10}$ are measured as micrograms per cubic meter ($\mu g/m^3$). Concentrations in 1990 range from 2.87 $\mu g/m^3$ in Tucson, AZ to 108.5 $\mu g/m^3$ in Longview-Marshall, TX. However, the data are somewhat concentrated around the median of 33.88 $\mu g/m^3$, with the 20% quantile at 17.74 $\mu g/m^3$ and the 80% quantile at 48.92 $\mu g/m^3$. Similarly, $PM_{10}$ concentrations for 2000 span 2.35 $\mu g/m^3$ to 85.31 $\mu g/m^3$, representing Tucson, AZ and Jackson, TN. Median concentrations are 29.05 $\mu g/m^3$ with the 20% and 80% quantiles at 15.49 $\mu g/m^3$ and 41.86 $\mu g/m^3$, respectively. Table 4.1 suggests that while there is considerable variation in concentrations across MSAs, there is also significant change in pollution concentrations over time. Finally, Figures 4.1 and 4.2 show the distribution of pollutant concentrations in 1990 and 2000, respectively.

Other location variables in the macro-level model are crime, economic activity, and culture and recreation. I use MSA-level gross domestic product (GDP) per capita as a measure of the level of economic activity, along with percent of the population employed. Note that this employment variable does not correspond to the unemployment rate. Per capital real GDP is reported by the Bureau of Economic Analysis and employment data comes from the Bureau of Labor Statistics. Other economic data include government expenditures and percent of revenue from property taxes, both obtained from the County and City Data Books for 1988 and 2000, maintained by the University of Virginia Library. Crime data is also taken from this source. Public transportation infrastructure, healthcare, and cultural amenities are measured based on MSA rankings developed in Boyer and Savageau (1993) and D’Agostino and Savageau (2000). Finally, the U.S. Census Bureau provides MSA demographic composition data related to age, race, education and family structure, variables that may be used as attributes of each location. These aggregate estimates are taken from the 1990 Summary File 3 and 2000 Summary File 3, respectively. Table 4.1 reports summary statistics for these attributes.
4.2 Estimation Approach

The following section describes the empirical approach to estimating a set of housing prices as well as calculating price indices. There also remains the task of characterizing moving costs and predicting income for individuals in locations other than their observed MSA.

4.2.1 Housing Prices

The empirical model requires the price of a homogeneous unit of housing services, rather than the price of a house. From the budget constraint, the market price for house $i$ in tract $j$ of MSA $m$ can be expressed as

$$P_{ijm} = \rho_m \rho_j^X H_i \exp(\nu_{ijm}),$$

(4.1)

where $\nu_{ijm}$ is a house-specific idiosyncratic shock.

Define the index of housing services as a function that maps the vector of discrete structural variables of a property $h_i$ into a continuous index defined by $H_i = \exp(\phi h_i)$. With this equation (4.1) can be rewritten as

$$P_{ijm} = \rho_m^Y \rho_j^X \exp(\phi h_i) \exp(\nu_{ijm}),$$

(4.2)

Empirically, I am interested in an estimate of $\ln \rho_m^Y$ for macro sorting stage. Taking logs,

$$\ln P_{ijm} = \ln \rho_m^Y + \phi h_i + \ln \rho_j^X + \nu_{ijm}$$

(4.3)

For the housing hedonic, I only observe households in MSAs but not their tract location. Since the MSA base price captures an average price in each MSA, I expect average tract deviations around this base to be zero. Therefore, I can define a tract-specific deviation from the MSA base prices as $\nu_{im} = \ln \rho_j^X + \nu_{ijm}$ and treat it as a mean-zero unobservable to estimate

$$\ln P_{im} = \ln \rho_m^Y + \phi h_i + \nu_{im}$$

(4.4)
treating $\ln \rho_m^{Y}$ as an MSA constant. To allay any concerns regarding the properties of $\nu_{im}$ and the consistency of $\ln \rho_m^{Y}$, note that equation (4.4) is exactly the housing hedonic used in conventional macro sorting models. Since I have already shown that the two-stage model is a generalization of the conventional model, it follows that the parameter should be identical in both models. Therefore, equation (4.4) is a valid means of obtaining housing services prices for the two-stage sorting model.

Variable definitions for the vector of housing services can be found in Table 4.2. The price that serves as the dependent variable in (4.4) is the annual cost of housing. For units that are rented, this value is simply the annual rent plus utilities and fees. For owned units, however, an annual rent must be imputed from the housing value. Rents are calculated in a manner similar to Albouy (2009) and Blomquist et al. (1988), following methods described in Poterba (1992). In equilibrium, the ratio of the rental value to the house price is the user cost of owner-occupied housing. This ratio is equal to the sum of the nominal interest rate, property tax rate, risk premium, maintenance costs and depreciation, less the inflation rate. Since property taxes are observed and treated as an additional cost, the property tax rate is omitted from calculation of the user cost of owner-occupied housing. Following Poterba (1992), I assign maintenance costs and depreciation each to be 2% and the risk premium on home ownership at 4%. The nominal interest rate is the average commitment rate on new fixed mortgages and the inflation rate is calculated as a five year average of the CPI inflation rate. The respective values for the interest rate and inflation are 10.13 and 4.12 for 1990 and 8.05 and 2.54 for 2000. The resulting rent to value ratio is 11.48 for 1990 and 11.50 for 2000. Given a rent to value ratio of 11.5, a $100,000 house takes on an annual housing cost of $8,695, equivalent to an apartment with monthly rent of $725.

This hedonic is estimated on a sample of 262,735 households for 1990 and 233,095 households for 2000 across the 226 MSAs, obtained from the IPUMS dataset. Note that the set of households used for the MSA hedonic estimation is not the same as the set of households used for the macro sorting model. Both data sets are subsets of the same set of household
observations, but different selection criteria lead to different sets of observations.

4.2.2 Hedonic Results

Equation (4.4) estimates an MSA-specific price for each year. Coefficients on housing services parameters are reported in Table 4.4. The hedonic regression gives highly significant and expected results. Price increases for homes that have larger living quarters, are more recently built, and on larger plots of land. In addition, single family detached homes and apartment units are more expensive than attached single family homes. The mean and standard deviation for MSA prices in each year are reported in Table 4.5.

4.2.3 Price Indices

Recall from (3.35) that the price index $\Gamma^k_m$ is defined by

$$\Gamma^k_m = \ln \sum_{j=1}^{J_m} \exp(\delta^k_{jm}) \quad k = 1, \ldots, K; \quad m = 1, \ldots, M,$$

(4.5)

where $\delta^k_{jm}$ are properly normalized fixed effects that arise from the micro level sorting model in which the probability that a person $i$ in MSA $m$ selects neighborhood $j$ is

$$\Pr_{i,j|m} = \frac{\exp(\delta^k_{jm})}{\sum_{l=1}^{J_m} \exp(\delta^k_{lm})}.$$

(4.6)

Table 4.5 shows summary statistics for the calculated index using normalized tract fixed effects. Rows 2-8 display means and standard deviations of the index separately for each of the 8 individual types. Since tract fixed effects are normalized across years, these indices are comparable across years. The last two columns display statistics based on the change in the index, which becomes an independent variable in the macro sorting model. A positive change indicates an increase in the utility obtained from tract-level amenities. The average size of the index means is fairly small, but high standard deviations imply a significant amount of variation in the change in tract-level amenities. It is also interesting to note that while index means are
of a similar magnitude as the log price of housing services, the explanatory variable in a typical macro sorting model, standard deviations are much higher.

4.2.4 Income

The final piece of information required to estimate a discrete choice model is the potential earnings of all individuals in all locations. Recall that each MSA is assumed to be a single labor market. Estimates from a regression of observed income on individual characteristics are used to predict income across locations based on location specific coefficients and an individual’s characteristics. The dependent variable in such a regression, an individual’s income, is observed only for the optimally chosen location. Since this is an optimal choice, observed income likely includes some unobserved factor that is not mean zero, as individuals self select into labor markets based on location specific attributes. Furthermore, since individual characteristics determine self selection through the sorting process, unobservables in the wage hedonic are likely correlated with these individual characteristics. A simple regression of income on individual characteristics, therefore, will result in biased coefficients that arise from correlation between the unobservables and the regressors. A semi-parametric correction for this problem is proposed by Dahl (2002) and implemented in a residential sorting model in Bayer et al. (2009). This method rests on the intuition that while unobserved location attributes induce moves to labor markets, information regarding such sorting is captured by the probability of an identical type individual making the observed move.

An income regression is estimated in which the dependent variable is the log of weekly income, as reported on the U.S. Census long form. The sample includes 874,809 total observations for 1990 and 749,618 total observations for 2000, with a range of MSA populations of 465−45,921 (mean of 3,976) and 390−34,476 (mean of 3,637) for each year, respectively. Regressors include gender, marital status, race/ethnicity, age, part-time employment, citizenship, education, and industry, as well as type-specific migration probabilities to account for nonrandom sorting. These variables are located in Table 4.3. Observations include employed
household heads not in the military and not disabled. A separate wage hedonic is run for each MSA using 4.7, controlling for effects related to labor demand and allowing the income effect of individual traits to vary across locations. The equation for estimation is

\[
\ln I_{im} = \alpha_1 X_{i}^{Inc} + \alpha P_{k,R1:R2} + \alpha P_{k,R1:R2}^2.
\] (4.7)

Individual attributes are included in \( X_{i}^{Inc} \), while \( P_{k,R1:R2} \) is the observed probability that an individual of type \( k \) migrated from region \( R1 \) to region \( R2 \). Data constraints limit the probabilities to migration between regions, rather than between MSAs.

Income is predicted for each individual in each MSA for 1990 and 2000. Note that the migration probabilities act only as controls for consistent estimates, and so are not included when predicting income. The weekly wage prediction is multiplied by the individual’s number of weeks worked to obtain the final income prediction, \( \hat{I}_{im} \).

Regression results can be found in Table 4.6. Since the empirical analysis involves 226 sets of coefficients representing each MSA/labor market, only summary measures are reported. Elements of the table refer to summary statistics across the 226 regressions. Coefficient means all have expected signs, with positive wage premiums for individuals who are male, married, white, older, educated, U.S. citizens, full time workers, and are in management positions. In some cases, the minimum coefficient estimate may be negative for a variable that has a positive (and expected positive) mean coefficient estimate. Similarly, the maximum coefficient estimate may be positive for a variable that has a negative (and expected negative) mean coefficient estimate. The fact that such results show up for some MSAs is likely a function of supply and demand idiosyncrasies in local labor markets. The last two rows report coefficients on type specific migration probabilities and migration probabilities squared. There is very little interpretation that follows these parameters, but their significance suggests that the approach is valid.

These regression coefficients are then used to predict annual incomes for each individual.
in each MSA. Empirically, log income is predicted and used in the model, avoiding any issue related to predicting values from a regression in which log values serve as dependent variables. Given different labor market forces in each MSA and compensating differentials for non-market goods, variation is expected across locations. One way to demonstrate the amount of variation in income predictions, and thus the degree to which they may influence the macro model, is to look at the average wage variation across locations. For year 1990, the standard deviation for an individual’s wage predictions across the set of MSAs has 10%, 50% and 90% quantiles of $2,695, $4,415 and $6,720, respectively. Without making a direct comparison to values at particular quantiles, these standard deviations should be considered relative to mean income prediction 10%, 50% and 90% quantiles of $13,226, $24,857, and $38,210, respectively. To be clear, the preceding means and standard deviations are summaries of individuals’ summary statistics. Significant variation is also evident for year 2000. Mean predicted income has 10%, 50% and 90% quantiles of $17,164, $34,522 and $54,167, respectively, with standard deviation 10%, 50% and 90% quantiles of $3,833, $7,233 and $13,458, respectively.

4.2.5 Moving Costs

Moving costs are characterized in a reduced form manner, similar to Bayer et al. (2009). For individual \( i \) in MSA \( m \)

\[
MC_{im} = \mu_{bs} D_{bs}^{i} + \mu_{br} D_{br}^{i},
\]

(4.8)

where \( D_{bs}^{i} = 1 \) if MSA \( m \) is outside of individual \( i \)'s birth state and \( D_{br}^{i} = 1 \) if MSA \( m \) is outside of individual \( i \)'s birth region.

An alternative specification accounts for variation in moving costs based on the presence of children in a household, an obvious constraint to migration. Therefore, additional components of moving costs interact the above dummy variables with dummy variables indicating a household with children,

\[
MC_{im} = \mu_{bs} D_{bs}^{i} + \mu_{br} D_{br}^{i} + \nu_{bs}(D_{bs}^{i} \times D_{C}^{i}) + \nu_{br}(D_{br}^{i} \times D_{C}^{i}),
\]

(4.9)
where $D_i^C = 1$ if there are children under the age of 18 living in household $i$. 
Table 4.1: MSA Attribute Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>PM10</td>
<td>PM10 Concentrations (µg/m³)</td>
<td>34.562</td>
<td>18.082</td>
<td>29.746</td>
<td>15.344</td>
<td>-4.816</td>
<td>5.807</td>
</tr>
<tr>
<td>Crime</td>
<td>Crime rate (per 1000 people)</td>
<td>0.590</td>
<td>0.189</td>
<td>0.464</td>
<td>0.155</td>
<td>-0.126</td>
<td>0.144</td>
</tr>
<tr>
<td>Prop_Tax</td>
<td>% of tax revenue from property taxes</td>
<td>75.443</td>
<td>16.510</td>
<td>74.034</td>
<td>16.107</td>
<td>-1.409</td>
<td>5.606</td>
</tr>
<tr>
<td>Gov_Exp</td>
<td>Local government expenditures per capita (thousands of dollars)</td>
<td>1.291</td>
<td>.314</td>
<td>1.506</td>
<td>.369</td>
<td>.214</td>
<td>.244</td>
</tr>
<tr>
<td>White</td>
<td>% of population that is white</td>
<td>0.836</td>
<td>0.104</td>
<td>0.792</td>
<td>0.114</td>
<td>-0.045</td>
<td>0.029</td>
</tr>
<tr>
<td>Health</td>
<td>Health Ranking</td>
<td>152.916</td>
<td>91.345</td>
<td>147.674</td>
<td>89.682</td>
<td>-5.243</td>
<td>43.216</td>
</tr>
<tr>
<td>Art</td>
<td>Arts Ranking</td>
<td>149.456</td>
<td>89.821</td>
<td>146.385</td>
<td>90.355</td>
<td>-3.071</td>
<td>52.914</td>
</tr>
<tr>
<td>Trans</td>
<td>Transportation Ranking</td>
<td>147.172</td>
<td>88.095</td>
<td>141.682</td>
<td>88.743</td>
<td>-5.490</td>
<td>69.882</td>
</tr>
<tr>
<td>Employment</td>
<td>% of population employed</td>
<td>0.460</td>
<td>0.047</td>
<td>0.473</td>
<td>0.114</td>
<td>0.013</td>
<td>0.112</td>
</tr>
<tr>
<td>Manuf_Est</td>
<td># of manufacturing establishments</td>
<td>1136.594</td>
<td>2200.280</td>
<td>1123.741</td>
<td>1972.251</td>
<td>0.051</td>
<td>0.144</td>
</tr>
<tr>
<td>Population</td>
<td>Population (millions of people)</td>
<td>0.731</td>
<td>1.147</td>
<td>0.813</td>
<td>1.227</td>
<td>0.113</td>
<td>0.098</td>
</tr>
</tbody>
</table>
Figure 4.1: Histogram of $PM_{10}$ Concentrations: 1990

Figure 4.2: Histogram of $PM_{10}$ Concentrations: 2000
<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>room2</td>
<td>.0439</td>
<td>2 rooms in dwelling</td>
</tr>
<tr>
<td>room3</td>
<td>.0973</td>
<td>3 rooms in dwelling</td>
</tr>
<tr>
<td>room4</td>
<td>.1476</td>
<td>4 rooms in dwelling</td>
</tr>
<tr>
<td>room5</td>
<td>.1986</td>
<td>5 rooms in dwelling</td>
</tr>
<tr>
<td>room6</td>
<td>.1954</td>
<td>6 rooms in dwelling</td>
</tr>
<tr>
<td>room7</td>
<td>.1298</td>
<td>7 rooms in dwelling</td>
</tr>
<tr>
<td>room8</td>
<td>.0848</td>
<td>8 rooms in dwelling</td>
</tr>
<tr>
<td>room9</td>
<td>.0822</td>
<td>9+ rooms in dwelling</td>
</tr>
<tr>
<td>bedroom2</td>
<td>.1347</td>
<td>2 bedrooms in dwelling</td>
</tr>
<tr>
<td>bedroom3</td>
<td>.2658</td>
<td>3 bedrooms in dwelling</td>
</tr>
<tr>
<td>bedroom4</td>
<td>.3904</td>
<td>4 bedrooms in dwelling</td>
</tr>
<tr>
<td>bedroom5</td>
<td>.1488</td>
<td>5 bedrooms in dwelling</td>
</tr>
<tr>
<td>bedroom6</td>
<td>.0327</td>
<td>6+ bedrooms in dwelling</td>
</tr>
<tr>
<td>yr1</td>
<td>.0186</td>
<td>Dwelling built 0-1 yrs ago</td>
</tr>
<tr>
<td>yr2</td>
<td>.0764</td>
<td>Dwelling built 2-5 yrs ago</td>
</tr>
<tr>
<td>yr3</td>
<td>.0784</td>
<td>Dwelling built 6-10 yrs ago</td>
</tr>
<tr>
<td>yr4</td>
<td>.1748</td>
<td>Dwelling built 11-20 yrs ago</td>
</tr>
<tr>
<td>yr5</td>
<td>.1701</td>
<td>Dwelling built 21-30 yrs ago</td>
</tr>
<tr>
<td>yr6</td>
<td>.1548</td>
<td>Dwelling built 31-40 yrs ago</td>
</tr>
<tr>
<td>yr7</td>
<td>.1166</td>
<td>Dwelling built 41-50 yrs ago</td>
</tr>
<tr>
<td>yr8</td>
<td>.1372</td>
<td>Dwelling built 51-60 (51+ for 1990) yrs ago</td>
</tr>
<tr>
<td>yr9</td>
<td>.1551</td>
<td>Dwelling built 61+ yrs ago</td>
</tr>
<tr>
<td>acre1</td>
<td>.8744</td>
<td>Dwelling on 0-1 acre lot</td>
</tr>
<tr>
<td>acre2</td>
<td>.0980</td>
<td>Dwelling on 1-3 acre lot</td>
</tr>
<tr>
<td>acre3</td>
<td>.0276</td>
<td>Dwelling on 3+ acre lot</td>
</tr>
<tr>
<td>own</td>
<td>.6430</td>
<td>Dwelling is owned by resident</td>
</tr>
<tr>
<td>bld1</td>
<td>.6354</td>
<td>1 family house, detached</td>
</tr>
<tr>
<td>bld2</td>
<td>.1156</td>
<td>1 family house, attached</td>
</tr>
<tr>
<td>bld3</td>
<td>.2490</td>
<td>Multiple family building</td>
</tr>
</tbody>
</table>
Table 4.3: Wage Hedonic: Variable Definitions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>male</td>
<td>.7422</td>
<td>Sex (Male = 1, Female = 0)</td>
</tr>
<tr>
<td>married</td>
<td>.6004</td>
<td>Marital status (Married = 1, Single = 0)</td>
</tr>
<tr>
<td>nonwhite</td>
<td>.1605</td>
<td>Race (Nonwhite = 1, White = 0)</td>
</tr>
<tr>
<td>age</td>
<td>32.06</td>
<td>Age</td>
</tr>
<tr>
<td>nohs</td>
<td>.0786</td>
<td>No high school degree</td>
</tr>
<tr>
<td>hs</td>
<td>.6298</td>
<td>High school degree/Some College</td>
</tr>
<tr>
<td>bach</td>
<td>.2058</td>
<td>Bachelor’s Degree</td>
</tr>
<tr>
<td>grad</td>
<td>.0858</td>
<td>Graduate or Professional Degree</td>
</tr>
<tr>
<td>cit1</td>
<td>.9122</td>
<td>Born as U.S. Citizen</td>
</tr>
<tr>
<td>cit2</td>
<td>.0314</td>
<td>Naturalized U.S. Citizen</td>
</tr>
<tr>
<td>cit3</td>
<td>.0564</td>
<td>Not a U.S. Citizen</td>
</tr>
<tr>
<td>ptime</td>
<td>.0791</td>
<td>Part time worker (Part time = 1, Full time = 0)</td>
</tr>
<tr>
<td>occ1</td>
<td>.4305</td>
<td>Management occupation</td>
</tr>
<tr>
<td>occ2</td>
<td>.2984</td>
<td>Service or Sales occupation</td>
</tr>
<tr>
<td>occ3</td>
<td>.2711</td>
<td>Farming/Production/Other occupation</td>
</tr>
</tbody>
</table>
Table 4.4: MSA Housing Hedonic

<table>
<thead>
<tr>
<th>Dependent Variable: ln(price)</th>
<th>1990 Coefficient</th>
<th>t-statistic</th>
<th>2000 Coefficient</th>
<th>t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>room2</td>
<td>0.0585 ***</td>
<td>3.33</td>
<td>0.0597 ***</td>
<td>4.49</td>
</tr>
<tr>
<td>room3</td>
<td>0.0855 ***</td>
<td>4.47</td>
<td>0.0551 ***</td>
<td>4.01</td>
</tr>
<tr>
<td>room4</td>
<td>0.1490 ***</td>
<td>7.54</td>
<td>0.0809 ***</td>
<td>5.60</td>
</tr>
<tr>
<td>room5</td>
<td>0.2305 ***</td>
<td>11.46</td>
<td>0.1415 ***</td>
<td>9.59</td>
</tr>
<tr>
<td>room6</td>
<td>0.3531 ***</td>
<td>17.36</td>
<td>0.2394 ***</td>
<td>15.94</td>
</tr>
<tr>
<td>room7</td>
<td>0.4982 ***</td>
<td>24.20</td>
<td>0.3686 ***</td>
<td>24.20</td>
</tr>
<tr>
<td>room8</td>
<td>0.6392 ***</td>
<td>30.64</td>
<td>0.4868 ***</td>
<td>31.40</td>
</tr>
<tr>
<td>room9</td>
<td>0.8346 ***</td>
<td>39.63</td>
<td>0.6858 ***</td>
<td>43.58</td>
</tr>
<tr>
<td>bedroom2</td>
<td>0.0950 ***</td>
<td>5.80</td>
<td>0.0759 ***</td>
<td>6.42</td>
</tr>
<tr>
<td>bedroom3</td>
<td>0.2050 ***</td>
<td>11.65</td>
<td>0.1909 ***</td>
<td>15.08</td>
</tr>
<tr>
<td>bedroom4</td>
<td>0.2024 ***</td>
<td>11.19</td>
<td>0.2101 ***</td>
<td>16.01</td>
</tr>
<tr>
<td>bedroom5</td>
<td>0.2246 ***</td>
<td>12.10</td>
<td>0.2798 ***</td>
<td>20.60</td>
</tr>
<tr>
<td>bedroom6</td>
<td>0.2622 ***</td>
<td>13.33</td>
<td>0.3614 ***</td>
<td>24.36</td>
</tr>
<tr>
<td>yr2</td>
<td>-0.0047</td>
<td>-0.49</td>
<td>-0.0202 ***</td>
<td>-2.32</td>
</tr>
<tr>
<td>yr3</td>
<td>-0.1285 ***</td>
<td>-13.50</td>
<td>-0.0803 ***</td>
<td>-9.23</td>
</tr>
<tr>
<td>yr4</td>
<td>-0.2036 ***</td>
<td>-22.50</td>
<td>-0.1814 ***</td>
<td>-22.11</td>
</tr>
<tr>
<td>yr5</td>
<td>-0.2771 ***</td>
<td>-30.37</td>
<td>-0.2838 ***</td>
<td>-34.89</td>
</tr>
<tr>
<td>yr6</td>
<td>-0.3488 ***</td>
<td>-38.03</td>
<td>-0.3264 ***</td>
<td>-39.59</td>
</tr>
<tr>
<td>yr7</td>
<td>-0.4021 ***</td>
<td>-42.22</td>
<td>-0.3537 ***</td>
<td>-42.66</td>
</tr>
<tr>
<td>yr8</td>
<td>-0.4276 ***</td>
<td>-46.63</td>
<td>-0.4134 ***</td>
<td>-47.56</td>
</tr>
<tr>
<td>yr9</td>
<td>-</td>
<td>-</td>
<td>-0.3952 ***</td>
<td>-47.64</td>
</tr>
<tr>
<td>acre1</td>
<td>-0.0526 ***</td>
<td>-12.97</td>
<td>-0.1214 ***</td>
<td>-32.12</td>
</tr>
<tr>
<td>acre3</td>
<td>0.0808 ***</td>
<td>11.13</td>
<td>0.0846 ***</td>
<td>9.86</td>
</tr>
<tr>
<td>bld1</td>
<td>0.0925 ***</td>
<td>21.98</td>
<td>0.0687 ***</td>
<td>17.60</td>
</tr>
<tr>
<td>bld3</td>
<td>0.0533 ***</td>
<td>11.56</td>
<td>0.0224 ***</td>
<td>5.31</td>
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</table>

R-Squared: 0.54, 0.60
Observations: 262,735, 233,095

*** p<0.01, ** p<0.05, * p<0.1
Table 4.5: Price and Index Summary Statistics

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>ln ρ</td>
<td>log price of housing services</td>
<td>8.146</td>
<td>0.304</td>
<td>8.448</td>
<td>0.258</td>
<td>0.302</td>
<td>0.139</td>
</tr>
<tr>
<td>Γ¹</td>
<td>MSA Index: Type 1</td>
<td>5.730</td>
<td>1.099</td>
<td>5.974</td>
<td>1.165</td>
<td>0.244</td>
<td>0.409</td>
</tr>
<tr>
<td>Γ²</td>
<td>MSA Index: Type 2</td>
<td>5.583</td>
<td>1.266</td>
<td>5.443</td>
<td>1.315</td>
<td>-0.139</td>
<td>0.681</td>
</tr>
<tr>
<td>Γ³</td>
<td>MSA Index: Type 3</td>
<td>5.911</td>
<td>1.067</td>
<td>5.925</td>
<td>1.101</td>
<td>0.014</td>
<td>0.364</td>
</tr>
<tr>
<td>Γ⁴</td>
<td>MSA Index: Type 4</td>
<td>5.522</td>
<td>1.045</td>
<td>5.747</td>
<td>1.066</td>
<td>0.225</td>
<td>0.270</td>
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<tr>
<td>Γ⁵</td>
<td>MSA Index: Type 5</td>
<td>5.390</td>
<td>1.014</td>
<td>5.743</td>
<td>1.037</td>
<td>0.353</td>
<td>0.298</td>
</tr>
<tr>
<td>Γ⁶</td>
<td>MSA Index: Type 6</td>
<td>5.476</td>
<td>1.169</td>
<td>5.312</td>
<td>1.260</td>
<td>-0.164</td>
<td>0.585</td>
</tr>
<tr>
<td>Γ⁷</td>
<td>MSA Index: Type 7</td>
<td>5.658</td>
<td>1.116</td>
<td>5.892</td>
<td>1.229</td>
<td>0.234</td>
<td>0.440</td>
</tr>
<tr>
<td>Γ⁸</td>
<td>MSA Index: Type 8</td>
<td>5.278</td>
<td>1.091</td>
<td>5.738</td>
<td>1.135</td>
<td>0.460</td>
<td>0.310</td>
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</table>
Table 4.6: Income Regression: Summary of Coefficients for 229 MSAs

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>1990</th>
<th>2000</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
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Chapter 5

Results

5.1 Macro Sorting Results

Following Berry et al. (1995), the model in (3.41) is estimated using MSA-level alternative specific constants that control for any endogenous variables in the indirect utility function. A second estimation step then decomposes fixed effects into components that include MSA-level public goods. In particular,

\[ \ln V_{im}^1 = \theta_m + \beta^0_1 \ln I_{im} + \lambda^k_m + MC_{im} + \tau^k \Gamma^k_m + \eta^1_{im}, \]  
(5.1)

\[ \theta_m = \beta^0_Y \ln Y_m - \beta^0_H \ln \rho^Y_m + \zeta_m, \]  
(5.2)

\[ \lambda^k_m = \gamma^k_Y \ln Y_m - \gamma^k_H \ln \rho^Y_m \]  
(5.3)

and \( \gamma^k_Y \) is a type specific parameter. The full above is written with \( \lambda^k_m \) in its most general form, though estimation focuses on the case of no preference heterogeneity and preference heterogeneity only for \( PM_{10} \). Note that \( \theta_m \) is estimated as a fixed effect while the component parameters of \( \lambda^k_m \) are estimated in the logit model. An important component of the macro-level model is the MSA index \( \Gamma^k_m \), estimated from the micro sorting process.

A macro-level sorting model is estimated jointly for 1990 and 2000. Parameters include
an alternative specific constant for each MSA/year and parameters on moving cost variables. The model is estimated following the two-stage budgeting framework with index \( \Gamma \), as well in a more conventional framework using only an MSA price and setting \( \Gamma^k_m = 0 \) for all \( m \) and \( k \). The index model includes type-specific parameters on the index, which follows from a nested logit specification. However, when all of these parameters are equal to 1, the nested logit model simplifies to a conditional logit model. Therefore, I estimate three models: i) the price model, also referred to as the baseline model, in which \( \Gamma^k_m \) for all \( m \) and \( k \), ii) the restricted index model, in which \( \tau^k = 1 \) for all \( k \), and iii) the unrestricted index model, in which \( \tau^k \) is estimated as a value between 0 and 1.

To control for endogenous prices in the decomposition of \( \theta_m \), I follow Bayer et al. (2009) in moving the term to the left-hand side of the equation and setting it to \( .25 \). This value is an empirical calculation implied by the structure of the model, equal to the average share of income devoted to expenditures on housing services. In addition, I take first differences from 2000 to 1990 to remove the MSA unobservable.

Finally, all specifications include an instrumental variable (IV) approach to control for correlation between unobservable MSA changes and changes in \( PM_{10} \) concentrations. Following Bayer et al. (2009), I use the source-receptor matrix discussed earlier to construct an instrument for \( PM_{10} \). \( PM_{10} \) concentrations are calculated using only emissions from sources greater than 50 km from a particular receptor. Since MSA concentrations are aggregated from county concentrations, if a source is within 50 km from any county in an MSA, then that source is dropped in calculating concentrations for all counties in that MSA. The validity of this instrument rests on the notion that the spatial aspect of air pollution creates correlation between distant sources and local receptors, but local unobservables such as economic activity are uncorrelated with distant pollution sources.

Table 5.1 shows coefficient estimates from maximum likelihood estimation of the price model. Nearly all coefficients are highly significant. Results suggest a nonlinear effect of migration from one’s birthplace, with a large negative impact from leaving one’s birthstate and a smaller neg-
ative impact when an individual moves to a different region of the country. In other words, migration costs increase at a decreasing rate with distance. Specification 2 accounts for heterogeneous migration costs related to the presence of children in a household. As expected, having children increases the cost of migration in a similarly nonlinear fashion. Results for the unrestricted and restricted index models, Table 5.2 and Table 5.3, show nearly identical coefficients for migration costs. This is not unexpected, as migration costs refer only to the cost of macro sorting.

The coefficient on income tends to increase in the cases of heterogeneous moving costs. Results related to moving costs imply an additional tradeoff in sorting behavior. In particular, once the model accounts for higher costs of relocating, an additional monetary benefit from greater income is identified. The opposite effect holds for the index models, in which the income coefficient decreases as we move from the price model to the restricted index model to the unrestricted index model. This suggests an additional tradeoff between income and tract amenities. Given the heterogeneous impacts of tract-level public goods, the index model shows a lower benefit of income. This last result is lost in the price model as the implicit tradeoff is only between income and an MSA constant.

The remaining sorting parameters for the macro model in Table 5.3 refer to the coefficients on the MSA index, \( \Gamma \). This index should theoretically generate positive utility. Recall from earlier that macro stage sorting is estimated in a nested logit framework that captures two-stage budgeting. Therefore, parameters on \( \Gamma \) can also be interpreted as inclusive value parameters from a nested logit model. In such a context, the parameters show the degree of correlation between tract-level amenities within an MSA. In the nested logit structure, inclusive value coefficients are restricted to be between 0 and 1. We use an empirical restriction that estimates an underlying parameter, rather than the actual coefficient on \( \Gamma \). Table 5.3 displays both the estimated parameter and the corresponding \( \Gamma \) coefficients (\( \tau \) column), which range from .44 to .87 for specification 1 and, similarly, from .45 to .88 for specification 2.

Second stage results include a decomposition of alternative specific constants using pollu-
tion and other MSA attributes, as described in Table 4.1 in Chapter 4. All results include
dummy variables for the 9 census regions. Coefficients are interpreted as marginal utilities, and
and can be converted to marginal willingness to pay (MWTP) with a simple calculation. Before
that, however, it is of interest to discuss variation in coefficient estimates across specifications
and across models. Table 5.4 summarizes these alternative specific constants for each model
specification.

Table 5.5 reports results for the baseline price model. Recall that all coefficients should be
interpreted relative to the coefficient on ln I. For the two prices models, the income coefficient
is 1.77 and 1.91, respectively. In column 1, ln PM10 is the only MSA attribute considered and
the regression gives a negative, though statistically insignificant, sign. When other attributes
are controlled for, the magnitude of the ln PM10 coefficient decreases. Therefore, the impact
of pollution found in column 1 could be due to a confounding effect. I find positive and
significant effects of an MSA’s cultural amenities and white population. Columns 3 and 4
employ an instrumental variables strategy to control for possible correlation between MSA
unobservables and the change in pollution. The coefficient on ln PM10 is negative and significant
and much larger than the OLS specification. Also, controlling for other MSA amenities has
very little impact on the pollution coefficient. Results for other attributes are close to their
OLS counterparts.

A second price model includes a moving cost specification that allows for heterogeneity
due to the presence of children. These results can be found in Table 5.6. Results are very
similar to the baseline OLS specification when considering the impact of controlling for all
MSA amenities and instrumenting for ln PM10. However, there is a marked decrease in
the magnitude of pollution costs. Columns 3 and 4 show negative but insignificant coefficients on
ln PM10 that are less than in the case of homogeneous moving costs. Thus, in the homogeneous
moving costs specification, the higher cost of migration faced by households with children tends
to show up as an averseness to pollution. Intuitively, the sorting model captures households
with children remaining in relatively clean MSAs (not moving to more polluted MSAs) as being

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due to the cost of pollution, when some of this cost is actually due to the cost of moving with children. The results on pollution concentrations are not significant in the heterogeneous moving costs specification, as the point estimate decreases, but standard errors remain relatively unchanged.

Second stage estimates from the restricted index model are reported in Tables 5.7 and 5.8. Results show similar results for the alternative moving cost specification and our IV approach. More importantly, the coefficient on $\ln PM_{10}$, relative to the income coefficient, increases considerably compared to the price model. Therefore, the disutility of pollution is greater in the index model.

Tables 5.9 and 5.10 show estimates for the unrestricted index model for specifications corresponding to those in previous models. Columns 1 and 2 of Table 5.9 report OLS estimates for the case of homogeneous moving costs. The coefficient on $\ln PM_{10}$ is larger than that of the unrestricted index model, and we find a smaller $\beta_I$ of 1.56. When the IV strategy is used, columns 3 and 4, pollution coefficients become significant, with a much stronger negative impact. In addition, the negative effect of pollution increases when other MSA attributes are controlled for. A similar outcome to the other models occurs when heterogeneous moving costs are incorporated, as shown in Table 5.10. The magnitude of negative coefficients on $\ln PM_{10}$ decreases and the specification has a slightly larger $\beta_I$ of 1.67. Estimates remain significant in the IV regression.

Compared to the results of the baseline model, controlling for tract sorting using the $\Gamma$ index results in a higher disutility of pollution. This can be seen by comparing Tables 5.5 and 5.7 and considering income coefficients of 1.77 and 1.75, respectively, or by comparing Tables 5.5 and 5.9 and considering income coefficients of 1.77 and 1.55, respectively. While the baseline model estimates a cost of $PM_{10}$ based on the tradeoff between pollution and MSA prices, both index models estimate the cost of $PM_{10}$ based on the tradeoff between pollution, MSA prices and an MSA index that includes both tract prices and tract amenities. It is these amenities that escape analysis in the price model. By controlling for tract amenities, the model shows an
additional tradeoff that increases the cost of pollution.

Finally, note that \( \ln PM_{10} \) impacts from the restricted index model with heterogenous moving costs in Table 5.8 are very close to the price model with homogeneous moving costs. Second stage results suggest a decrease in the size of the negative coefficient when heterogeneous moving costs are allowed for, but an increase when the index model is considered. These effects are combined in a comparison of the restricted index model with heterogeneous moving costs to the price model with homogeneous moving costs.

In comparing the restricted and the unrestricted index models, it is clear that the restriction has a significant impact on estimation of macro stage sorting, as the heterogeneous effect of second stage sorting is swept up as an average in the MSA fixed effect. In the homogeneous moving cost model, Table 5.9, the coefficient on \( \ln PM_{10} \) increases relative to its counterpart in the general model in Table 5.7. A similar results holds for the heterogeneous moving costs specifications. A higher disutility of pollution is a result of the cost of pollution being confounded in an overly restricted model. Setting the index parameter to 1 overemphasizes the utility impact of tract-level amenities. Given a positive correlation between \( PM_{10} \) and \( \Gamma \), the restricted model may observe an individual choosing an MSA with low pollution concentrations but overly attribute that choice to the MSAs tract-level amenities due to the larger index parameter. Thus, the model does not account for the full tradeoff between \( PM_{10} \) and tract amenities.

Regarding other MSA amenities, the impact of government expenditures becomes positive and significant in the unrestricted index model. In addition, the coefficient on percent white goes from being positive and significant to much smaller and insignificant. It is interesting to note that these two amenities tend to have highly localized benefits. Therefore, the index model that accounts for 33 heterogeneous tract sorting may offer a better characterization of their impacts.
5.1.1 Willingness to Pay for Clean Air

Regression coefficients take on more economic meaning when converted to MWTP measures, using the marginal utility of income. Since both income and $PM_{10}$ are measured in log form, the MWTP for a reduction in $PM_{10}$ concentrations by 1 unit ($\mu g/m^3$) is calculated as $\frac{\delta_{PM}}{\delta I} \left( \frac{Inc}{PM_{10}} \right)$, using mean observed income ($\$25,683$) and mean $PM_{10}$ concentrations ($33.87$) from the sample. Also note that using annual income implies an annual MWTP. These estimates suggest how much the median household is willing to pay per year to reduce $PM_{10}$ concentrations. Table 5.11 reports MWTP in 1990 dollars across models and specifications. Comparing rows 1 and 2 with 3 and 4, respectively in each panel, highlights the importance of instrumenting for $PM_{10}$, as the MWTP more than doubles in the price and restricted index models and more than triples in the unrestricted index model. The importance of allowing for heterogeneous moving costs is also evident. The MWTP decreases substantially in all three models when one considers the additional moving costs for households with children, falling from 20% to 30%. Finally, given the discussion in the preceding section, the impact of accounting for tract sorting can be seen by comparing IV estimates in columns across the three panels. The amenity tradeoff of $PM_{10}$ with tract level amenities, rather than with an average MSA price, results in a significantly higher cost of pollution, as can be seen by comparing values in Panel B with those in Panel A. An additional increase in the cost of air pollution is evident in the unrestricted index model that allows for a higher degree of heterogeneity in tract-level sorting. Though this result does not hold for the OLS estimates, these coefficients are not significant. Finally, estimates show that MWTP more than doubles in some cases, when we consider moving from a conventional price model to the unrestricted index model. Across the three models, our best estimates for the annual MWTP for a reduction in $PM_{10}$ concentrations by 1 $\mu g/m^3$ are $\$161$, $\$221$, and $\$371$, respectively.

To gain a more intuitive understanding of MWTP estimates, consider an approximate calculation using the MSAs of Raleigh-Durham-Chapel Hill, NC, which has $PM_{10}$ concentrations of 57.09 $\mu g/m^3$, and Charlottesville, VA, which has $PM_{10}$ concentrations of 45.39 $\mu g/m^3$. These
PM$_{10}$ concentrations roughly correspond to the 75% and 50% quantile, respectively, in the sample of MSAs. The pollution change from Charlottesville to Raleigh-Durham-Chapel Hill offers a 26% reduction in PM$_{10}$ concentrations ($11.8 \mu g/m^3$). Using the coefficient estimate from the unrestricted index model with heterogeneous moving costs, $-0.82$, and a marginal utility of income of 1.67, this difference corresponds to a 19% increase in a household’s willingness to pay for clean air. Therefore, based on a median income of $31,397 in Charlottesville, VA, the move offers $2,919 in benefits derived from less pollution.

5.1.2 Normalized Index

One property of the second-stage index $\Gamma_m^k$ is that it is increasing in $J_m$, the number of tracts in the MSA. Econometrically, this results directly from the definition of the expectation of the maximum in a logit context. Recall that the expectation is taken over the idiosyncratic unobservable to obtain the highest expected utility. Intuitively, an increase in the number of tracts is analogous to an increase in the size of the choice set for the individual in the second stage. It is obvious that increasing the choice set should certainly make an individual no worse off. Furthermore, holding all else constant, a larger choice set increases the expected maximum draw from the distribution of unobservables by simply increasing the number of draws. Consider the case in which all tract fixed effects are identical. This implies that the location choice rests entirely on the set of idiosyncratic unobservables. Incrementally increasing the number of tracts leads to an additional draw of the unobservable. If the incremental draw is less than the current maximum draw, the individual is unaffected. However, if the incremental draw is greater than the current maximum draw, the individual is better off as a tract with higher utility has appeared. Therefore, it is reasonable to have an MSA index that is increasing in the number of tracts in that MSA.

While it is not derived directly from the model, it is worth controlling for the number of tracts in an MSA to test whether empirical results are driven by a combination of tract amenities and individual idiosyncrasies, or entirely by only one of these effects. To accomplish
this, I normalize the price index $\Gamma^k_m$ by the number of tracts in MSA $m$. Specifically, the normalized index $\bar{\Gamma}^k_m$ is calculated as

$$\bar{\Gamma}^k_m = \ln \left( \frac{\sum_{j \in J_m} \delta_j}{J_m} \right) = \Gamma^k_m - \ln J_m$$

(5.4)

Note that the denominator is $\ln J_m$, rather than simply $J_m$. To see why this done, consider an MSA in which all tracts are identical, so that $\delta_{j|m} = 1\forall j \in J_m$. The non-normalized index $\Gamma^k_m$ is simply equal to $\ln J_m$. Thus, normalizing by $\ln J_m$ sets the index equal to 0.

Before discussing specific estimation results, it is worth looking at correlations between the original index and the number of tracts to determine to what degree $J_m$ influences the index. Correlation between $\Gamma^k_m$ and $J_m$ is very high, ranging from .73 to .78 across the 8 types and two years in the sample. However, identification in this model rests considerably on first-differences across years. Correlation between $J_m$ and the change in $\Gamma^k_m$ from 1990 to 2000 is quite small, ranging from .06 to .15.

A specification is run using the normalized index in the restricted (logit) and unrestricted (nested logit) index models with heterogeneous moving costs. Maximum likelihood and second stage fixed effect decomposition results show similar magnitudes and significance levels on parameter estimates, as is evident in Tables 5.12 and 5.13. To analyze the role that the number of tracts plays in the model, the best comparison is the implied MWTP. Table 5.14 shows the MWTP for a 1 unit reduction in $PM_{10}$ concentrations for specifications with the normalized index. For the restricted index model in which the coefficient on the index is set to 1, there is essentially no change. Estimates are within a few dollars between the the non-normalized and normalized index models. For the unrestricted index model, estimates decrease. However, the MWTP is still substantially higher than the baseline model in which second-stage sorting is ignored. Such a result would imply that the impact of the index is due to a combination of both the number of available tracts and the level of variation across those tracts, with both effects contributing to a considerable degree. Given the result of nearly identical estimates in
the restricted model, however, it may be the case that a poorly estimated coefficient on the index is driving the results in the unrestricted model.

5.1.3 Preference Heterogeneity

An additional specification estimates type-specific parameters on $PM_{10}$ to capture heterogeneous preferences based on observed attributes of the individual. Results from the second-stage regression in which MSA fixed effects are decomposed are reported in Table 5.15. The set of coefficients is quite close to and exhibits similar patterns across specifications as the model with homogeneous preferences. However, Table 5.16 shows the type-specific deviations from the mean parameter, displaying variation in the cost of $PM_{10}$ across individuals. Aside from the insignificant parameter estimate for Type 1 individuals, there is a positive monotonic relationship between education and preferences for clean air. This is evident from increasingly negative coefficients as education level increases, regardless of the presence of children. Results are less conclusive when looking at the impact of having children present in the household. Though they indicate very slight differences, estimates hint at the counterintuitive idea that there are lower costs associated with pollution concentrations for households that do not have children. The final column of Table 5.16 displays the MWTP for a 1 unit reduction in $PM_{10}$ concentrations. The MWTP fluctuates considerably, upwards of 14% above and 32% below the mean. These numbers are directly comparable to those reported earlier for other model specifications.

5.1.4 The Marginal Cost of Pollution

The empirical specification up to this point implies particular second order impacts of pollution. In particular, if $PM_{10}$ is an undesirable amenity, and thus has a negative coefficient, the MWTP for a 1 unit reduction in $PM_{10}$ is restricted to decrease in concentration levels. All else constant, higher concentrations of $PM_{10}$ result in a MWTP that approaches 0 as concentrations approach infinity. This suggests that the negative impact of pollution becomes less severe at very high...
levels. This can be seen from the first derivative of the MWTP with respect to $PM_{10}$,

$$\frac{\partial MWTP}{\partial PM_{10}} = \frac{\partial}{\partial PM_{10}} \left( -\frac{\beta_{PM}}{\beta_{I}} \frac{Inc}{PM_{10}} \right) = \left( \frac{\beta_{PM}}{\beta_{I}} \frac{Inc}{PM_{10}^2} \right). \quad (5.5)$$

There is no a priori reason to assume a diminishing negative impact of pollution. In fact, intuition might lead one to think that the MWTP to reduce $PM_{10}$ would be higher at higher concentrations. Therefore, alternative specifications for the utility impact of $PM_{10}$ are tested. One alternative involves the inclusion of clean air in utility, rather than pollution. Given a maximum $PM_{10}$ concentration of 110 in the sample, define $(110 - PM)$ as the level of clean air. Then, $U_{ij|m} = \Theta (110 - PM)^{\beta_{PM}}$ and

$$MWTP = \frac{\beta_{PM}}{\beta_{I}} \frac{Inc}{(110 - PM_{10})} \quad (5.6)$$

and

$$\frac{\partial MWTP}{\partial PM_{10}} = \frac{\beta_{PM}}{\beta_{I}} \frac{Inc}{(110 - PM_{10})^2}. \quad (5.7)$$

Given this specification, the coefficient $\beta_{PM}$ is expected to be positive. This gives a positive MWTP and a positive first derivative, implying that the MWTP for a reduction in $PM_{10}$ increases with pollution concentrations.

A second alternative specifies a quadratic utility impact of pollution, so that the utility function may be written as $U_{ij|m} = \Theta \exp (\beta_{1} PM + \beta_{2} (PM)^{2})$, with

$$MWTP = -\frac{\beta_{1} - 2\beta_{2} \ln PM_{10}}{\beta_{I}} \frac{Inc}{PM_{10}} \quad (5.8)$$

and

$$\frac{\partial MWTP}{\partial PM_{10}} = \frac{1}{PM_{10}^2} \frac{Inc}{\beta_{I}} \left( 2\beta_{2} (\ln PM_{10} - 1) + \beta_{1} \right) \quad (5.9)$$

Here, it is evident that specific values for $\beta_{1}$, $\beta_{2}$ and $PM_{10}$ determine whether the MWTP for pollution reduction is positive or negative and whether this value increases or decreases with $PM_{10}$ levels. This specification is sufficiently flexible to accommodate different dynamics.
Rather than examine analytical solutions that sign the MWTP and its derivative, I will discuss this point further in the context of empirical results.

Tables 5.17 and 5.18 report results from the two alternative specifications. In focusing on clean air as an environmental good, Table 5.17 shows positive and significant coefficients on $\ln(110 - PM_{10})$. For the quadratic specification, Table 5.18 shows a positive coefficient on the linear term and a negative coefficient on the squared term. Technically, this implies a negative MWTP for pollution reduction at very low concentration levels, and a positive MWTP for pollution reduction at higher levels at which the magnitude of the squared term dominates. Again, the instrumental variable approach leads to significant estimates for both new specifications.

Table 5.19 reports point estimates for the MWTP for reduction in pollution concentrations, calculated at mean income and pollution levels identical to those in earlier calculations. For the clean air good specification, MWTP is considerably higher than the baseline $PM_{10}$ specification, while the quadratic specification has a slightly lower value. These results highlight the sensitivity of the point estimates to this modeling choice. However, rather than estimates at mean values, the motivation for these alternative specifications is the change in MWTP as concentration levels change. As discussed earlier, results from the baseline specification imply a MWTP that decreases at higher levels of $PM_{10}$. It may be more intuitive to imagine that households would be willing to pay a higher price to reduce pollution at a point of very high concentrations, as opposed to a point of lower concentrations. The positive coefficient on $\ln(110 - PM_{10})$ implies a MWTP that increases with pollution levels in the clean air good specification. Note that there is a significant amount of overlap between this and the baseline specification, in terms of the range of the MWTP. In the quadratic specification there is an odd dynamic. At very low levels, there is a positive willingness to pay for pollution. However, this is likely due to the still restrictive nature of the quadratic specification, rather than the existence of preferences for higher concentration levels. MWTP for pollution reduction becomes positive at a $PM_{10}$ concentration level of 20.88, corresponding approximately to the first quartile of the
pollution distribution. While the quadratic specification is driving the positive MWTP at low levels, such low levels of $PM_{10}$ may go relatively unnoticed to households and not command a significant willingness to pay for improvement.
Table 5.1: Macro Sorting Parameters: Baseline Model

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Observations: 1990 = 39058, 2000 = 37165

All parameters are significant at the 1% level
Table 5.2: Macro Sorting Parameters: Restricted Index Model

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Observations: 1990 = 39058, 2000 = 37165

All parameters are significant at the 1% level
Table 5.3: Macro Sorting Parameters: Unrestricted Index Model

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</tr>
<tr>
<td>MSA Index: $\Gamma_7$</td>
<td>$\tau^7$</td>
<td>0.238</td>
</tr>
<tr>
<td>MSA Index: $\Gamma_8$</td>
<td>$\tau^8$</td>
<td>0.707</td>
</tr>
</tbody>
</table>

Observations: 1990 = 39058, 2000 = 37165
All parameters are significant at the 1% level
Table 5.4: Macro Sorting Alternative Specific Constants

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>1990</th>
<th>2000</th>
<th>Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta_{Price}$</td>
<td>$\theta$: baseline</td>
<td>0.268</td>
<td>1.071</td>
<td>0.952</td>
</tr>
<tr>
<td>$\theta_{MC,Price}$</td>
<td>$\theta$: baseline, MC interaction</td>
<td>-0.023</td>
<td>0.963</td>
<td>0.775</td>
</tr>
<tr>
<td>$\theta_{Index,Res}$</td>
<td>$\theta$: restricted</td>
<td>0.622</td>
<td>0.818</td>
<td>2.059</td>
</tr>
<tr>
<td>$\theta_{MC,Index,Res}$</td>
<td>$\theta$: restricted, MC interaction</td>
<td>0.327</td>
<td>0.689</td>
<td>1.872</td>
</tr>
<tr>
<td>$\theta_{Index,Unres}$</td>
<td>$\theta$: unrestricted</td>
<td>0.455</td>
<td>0.779</td>
<td>1.306</td>
</tr>
<tr>
<td>$\theta_{MC,Index,Unres}$</td>
<td>$\theta$: unrestricted, MC interaction</td>
<td>0.164</td>
<td>0.630</td>
<td>1.133</td>
</tr>
</tbody>
</table>
Table 5.5: Second Stage Regression: Fixed Effects From Baseline Model

<table>
<thead>
<tr>
<th>Dependent Variable: $\Delta \theta + .25 \Delta \ln(\rho)$</th>
<th>OLS</th>
<th>IV for PM10</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>$\Delta \ln PM_{10}$</td>
<td>-0.2965</td>
<td>-0.1551</td>
</tr>
<tr>
<td></td>
<td>(.2187)</td>
<td>(0.2184)</td>
</tr>
<tr>
<td>$\Delta$ Crime</td>
<td>-0.0014</td>
<td>(0.2037)</td>
</tr>
<tr>
<td></td>
<td>(0.0058)</td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Prop_Tax</td>
<td>0.0002</td>
<td>(0.0001)</td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
<td></td>
</tr>
<tr>
<td>$\Delta$ White</td>
<td>3.6238 ***</td>
<td>(1.2295)</td>
</tr>
<tr>
<td></td>
<td>(0.0005)</td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Health</td>
<td>-0.0002</td>
<td>(0.0007)</td>
</tr>
<tr>
<td></td>
<td>(0.0004)</td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Art</td>
<td>-0.0021 ***</td>
<td>(0.0005)</td>
</tr>
<tr>
<td></td>
<td>(0.0004)</td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Trans</td>
<td>-0.0001</td>
<td>(0.0004)</td>
</tr>
<tr>
<td></td>
<td>(0.0004)</td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Employment</td>
<td>-0.0047</td>
<td>(0.2532)</td>
</tr>
<tr>
<td></td>
<td>(0.2813)</td>
<td></td>
</tr>
<tr>
<td>$\Delta \ln$ (Manuf_Est)</td>
<td>0.1678</td>
<td>(0.2813)</td>
</tr>
<tr>
<td></td>
<td>(0.4653)</td>
<td></td>
</tr>
<tr>
<td>$\Delta \ln$ (Population)</td>
<td>0.4076</td>
<td>(0.4653)</td>
</tr>
</tbody>
</table>

Regional Dummies | yes | yes | yes | yes |
R-Squared         | 0.77 | 0.80 | 0.07 | 0.19 |
Observations      | 226 | 226 | 226 | 226 |

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
**Table 5.6: Second Stage Regression: Fixed Effects From Baseline Model With MC Interaction**

<table>
<thead>
<tr>
<th>Dependent Variable: $\Delta \theta + .25 \Delta \ln(\rho)$</th>
<th>OLS</th>
<th>IV for PM10</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>$\Delta \ln PM_{10}$</td>
<td>-0.2110</td>
<td>-0.0658</td>
</tr>
<tr>
<td>(0.2208)</td>
<td>(0.2207)</td>
<td>(0.2650)</td>
</tr>
<tr>
<td>$\Delta$ Crime</td>
<td>-0.0828</td>
<td>-0.0732</td>
</tr>
<tr>
<td>(0.2059)</td>
<td>(0.1978)</td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Prop_Tax</td>
<td>-0.0028</td>
<td>-0.0040</td>
</tr>
<tr>
<td>(0.0059)</td>
<td>(0.0057)</td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Gov_Exp</td>
<td>0.0002</td>
<td>0.0002</td>
</tr>
<tr>
<td>(0.0001)</td>
<td>(0.0001)</td>
<td></td>
</tr>
<tr>
<td>$\Delta$ White</td>
<td>3.6683 ***</td>
<td>3.2833 ***</td>
</tr>
<tr>
<td>(1.2428)</td>
<td>(1.2054)</td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Health</td>
<td>-0.0002</td>
<td>-0.0003</td>
</tr>
<tr>
<td>(0.0007)</td>
<td>(0.0007)</td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Art</td>
<td>-0.0021 ***</td>
<td>-0.0020 ***</td>
</tr>
<tr>
<td>(0.0005)</td>
<td>(0.0005)</td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Trans</td>
<td>-0.0002</td>
<td>-0.0002</td>
</tr>
<tr>
<td>(0.0004)</td>
<td>(0.0004)</td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Employment</td>
<td>-0.0265</td>
<td>0.0246</td>
</tr>
<tr>
<td>(0.2560)</td>
<td>(0.2468)</td>
<td></td>
</tr>
<tr>
<td>$\Delta \ln$ (Manuf_Est)</td>
<td>0.1706</td>
<td>0.1533</td>
</tr>
<tr>
<td>(0.2843)</td>
<td>(0.2731)</td>
<td></td>
</tr>
<tr>
<td>$\Delta \ln$ (Population)</td>
<td>0.3481</td>
<td>0.4183</td>
</tr>
<tr>
<td>(0.4704)</td>
<td>(0.4527)</td>
<td></td>
</tr>
<tr>
<td>Regional Dummies</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.81</td>
<td>0.84</td>
</tr>
<tr>
<td>Observations</td>
<td>226</td>
<td>226</td>
</tr>
</tbody>
</table>

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Table 5.7: Second Stage Regression: Fixed Effects From Restricted Model

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>OLS</th>
<th>IV for PM10</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>$\Delta \theta + 0.25 \Delta \ln(\rho)$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta \ln PM_{10}$</td>
<td>-0.58640 **</td>
<td>-0.35760</td>
</tr>
<tr>
<td></td>
<td>(0.2880)</td>
<td>(0.2874)</td>
</tr>
<tr>
<td>$\Delta \text{Crime}$</td>
<td>-0.15290</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.2681)</td>
<td></td>
</tr>
<tr>
<td>$\Delta \text{Prop.Tax}$</td>
<td>-0.00470</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0077)</td>
<td></td>
</tr>
<tr>
<td>$\Delta \text{Gov.Exp}$</td>
<td>0.00020</td>
<td>0.00020</td>
</tr>
<tr>
<td></td>
<td>(0.0002)</td>
<td>(0.0002)</td>
</tr>
<tr>
<td>$\Delta \text{White}$</td>
<td>5.48520 ***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.6182)</td>
<td></td>
</tr>
<tr>
<td>$\Delta \text{Health}$</td>
<td>0.00040</td>
<td>0.00030</td>
</tr>
<tr>
<td></td>
<td>(0.0010)</td>
<td>(0.0009)</td>
</tr>
<tr>
<td>$\Delta \text{Art}$</td>
<td>-0.00230 ***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0007)</td>
<td></td>
</tr>
<tr>
<td>$\Delta \text{Trans}$</td>
<td>0.00050</td>
<td>0.00050</td>
</tr>
<tr>
<td></td>
<td>(0.0005)</td>
<td>(0.0005)</td>
</tr>
<tr>
<td>$\Delta \text{Employment}$</td>
<td>0.10730</td>
<td>0.15510</td>
</tr>
<tr>
<td></td>
<td>(0.3333)</td>
<td>(0.3205)</td>
</tr>
<tr>
<td>$\Delta \ln (\text{Manuf.Est})$</td>
<td>0.62290 *</td>
<td>0.60680 *</td>
</tr>
<tr>
<td></td>
<td>(0.3702)</td>
<td>(0.3546)</td>
</tr>
<tr>
<td>$\Delta \ln (\text{Population})$</td>
<td>-0.52300</td>
<td>-0.45740</td>
</tr>
<tr>
<td></td>
<td>(0.6125)</td>
<td>(0.5878)</td>
</tr>
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</table>

Regional Dummies yes yes yes yes
R-Squared 0.88 0.90 0.11 0.22
Observations 226 226 226 226

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Table 5.8: Second Stage Regression: Fixed Effects From Restricted Model and MC Interaction

<table>
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<tr>
<th>Dependent Variable:</th>
<th>OLS</th>
<th>IV for PM10</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \theta + 0.25 \Delta \ln(\rho)$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>$\Delta \ln PM_{10}$</td>
<td>-0.5083</td>
<td>-0.2752</td>
</tr>
<tr>
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<td>(0.2911)</td>
<td>(0.2908)</td>
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<tr>
<td>$\Delta$ Crime</td>
<td>-0.2150</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.2713)</td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Prop_Tax</td>
<td>-0.0056</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0078)</td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Gov_Exp</td>
<td>0.0002</td>
<td>0.0002</td>
</tr>
<tr>
<td></td>
<td>(0.0002)</td>
<td>(0.0002)</td>
</tr>
<tr>
<td>$\Delta$ White</td>
<td>5.5444</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>(1.6375)</td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Health</td>
<td>0.0005</td>
<td>0.0004</td>
</tr>
<tr>
<td></td>
<td>(0.0010)</td>
<td>(0.0006)</td>
</tr>
<tr>
<td>$\Delta$ Art</td>
<td>-0.0023</td>
<td>***</td>
</tr>
<tr>
<td></td>
<td>(0.0007)</td>
<td>(0.0007)</td>
</tr>
<tr>
<td>$\Delta$ Trans</td>
<td>0.0004</td>
<td>0.0004</td>
</tr>
<tr>
<td></td>
<td>(0.0006)</td>
<td>(0.0006)</td>
</tr>
<tr>
<td>$\Delta$ Employment</td>
<td>0.0830</td>
<td>0.1246</td>
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<tr>
<td></td>
<td>(0.3373)</td>
<td>(0.3241)</td>
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<tr>
<td>$\Delta \ln (\text{Manuf_Est})$</td>
<td>0.6396</td>
<td>*</td>
</tr>
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<td>(0.3746)</td>
<td>(0.3586)</td>
</tr>
<tr>
<td>$\Delta \ln (\text{Population})$</td>
<td>-0.5795</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.6198)</td>
<td></td>
</tr>
</tbody>
</table>

Regional Dummies: yes, yes, yes, yes
R-Squared: 0.89, 0.91, 0.08, 0.20
Observations: 226, 226, 226, 226

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Table 5.9: Second Stage Regression: Fixed Effects From Unrestricted Index Model

<table>
<thead>
<tr>
<th>Dependent Variable: $\Delta \theta + .25 \Delta \ln(\rho)$</th>
<th>OLS 1</th>
<th>OLS 2</th>
<th>IV for PM10 3</th>
<th>IV for PM10 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \ln PM_{10}$</td>
<td>-0.3726</td>
<td>-0.3262</td>
<td>-1.0229 ***</td>
<td>-1.1079 ***</td>
</tr>
<tr>
<td></td>
<td>(0.3274)</td>
<td>(0.3318)</td>
<td>(0.3953)</td>
<td>(0.3935)</td>
</tr>
<tr>
<td>$\Delta$ Crime</td>
<td>0.2151</td>
<td></td>
<td>0.2372</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.3095)</td>
<td></td>
<td>(0.2996)</td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Prop.Tax</td>
<td>-0.0105</td>
<td></td>
<td>-0.0131</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0088)</td>
<td></td>
<td>(0.0086)</td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Gov.Exp</td>
<td>0.0005 **</td>
<td></td>
<td>0.0005 ***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0002)</td>
<td></td>
<td>(0.0002)</td>
<td></td>
</tr>
<tr>
<td>$\Delta$ White</td>
<td>0.8887</td>
<td></td>
<td>0.0050</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.8684)</td>
<td></td>
<td>(1.8259)</td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Health</td>
<td>0.0000</td>
<td></td>
<td>-0.0002</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0011)</td>
<td></td>
<td>(0.0011)</td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Art</td>
<td>-0.0028 ***</td>
<td></td>
<td>-0.0026 ***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0008)</td>
<td></td>
<td>(0.0008)</td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Trans</td>
<td>-0.0002</td>
<td></td>
<td>-0.0001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0006)</td>
<td></td>
<td>(0.0006)</td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Employment</td>
<td>0.2335</td>
<td></td>
<td>0.3509</td>
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</tr>
<tr>
<td></td>
<td>(0.3848)</td>
<td></td>
<td>(0.3739)</td>
<td></td>
</tr>
<tr>
<td>$\Delta \ln (\text{Manuf_Est})$</td>
<td>0.2292</td>
<td></td>
<td>0.1895</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.4274)</td>
<td></td>
<td>(0.4137)</td>
<td></td>
</tr>
<tr>
<td>$\Delta \ln (\text{Population})$</td>
<td>0.2348</td>
<td></td>
<td>0.3959</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.7071)</td>
<td></td>
<td>(0.6858)</td>
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</tr>
</tbody>
</table>

Regional Dummies: yes, R-Squared: 0.75, Observations: 226

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Table 5.10: Second Stage Regression: Fixed Effects From Unrestricted Model and MC Interaction

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>OLS</th>
<th>IV for PM10</th>
</tr>
</thead>
<tbody>
<tr>
<td>\Delta \theta + 0.25 \Delta \ln(\rho)</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>\Delta \ln PM_{10}</td>
<td>-0.2477</td>
<td>-0.1949</td>
</tr>
<tr>
<td></td>
<td>(0.2964)</td>
<td>(0.2988)</td>
</tr>
<tr>
<td>\Delta \text{Crime}</td>
<td>0.2370</td>
<td>0.2546</td>
</tr>
<tr>
<td></td>
<td>(0.2787)</td>
<td>(0.2987)</td>
</tr>
<tr>
<td>\Delta \text{Prop}_\text{Tax}</td>
<td>-0.0116</td>
<td>-0.0137 *</td>
</tr>
<tr>
<td></td>
<td>(0.0080)</td>
<td>(0.0077)</td>
</tr>
<tr>
<td>\Delta \text{Gov}_\text{Exp}</td>
<td>0.0004 **</td>
<td>0.0004 ***</td>
</tr>
<tr>
<td></td>
<td>(0.0002)</td>
<td>(0.0002)</td>
</tr>
<tr>
<td>\Delta \text{White}</td>
<td>1.7718</td>
<td>1.0668</td>
</tr>
<tr>
<td></td>
<td>(1.6823)</td>
<td>(1.6823)</td>
</tr>
<tr>
<td>\Delta \text{Health}</td>
<td>0.0000</td>
<td>-0.0002</td>
</tr>
<tr>
<td></td>
<td>(0.0010)</td>
<td>(0.0010)</td>
</tr>
<tr>
<td>\Delta \text{Art}</td>
<td>-0.0025 ***</td>
<td>-0.0023 ***</td>
</tr>
<tr>
<td></td>
<td>(0.0007)</td>
<td>(0.0007)</td>
</tr>
<tr>
<td>\Delta \text{Trans}</td>
<td>-0.0001</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>(0.0006)</td>
<td>(0.0006)</td>
</tr>
<tr>
<td>\Delta \text{Employment}</td>
<td>0.2497</td>
<td>0.3434</td>
</tr>
<tr>
<td></td>
<td>(0.3465)</td>
<td>(0.3465)</td>
</tr>
<tr>
<td>\Delta \ln (\text{Manuf}_\text{Est})</td>
<td>0.2208</td>
<td>0.1890</td>
</tr>
<tr>
<td></td>
<td>(0.3849)</td>
<td>(0.3849)</td>
</tr>
<tr>
<td>\Delta \ln (\text{Population})</td>
<td>0.2599</td>
<td>0.3885</td>
</tr>
<tr>
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<td>(0.6367)</td>
<td>(0.6367)</td>
</tr>
<tr>
<td>Regional Dummies</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.81</td>
<td>0.83</td>
</tr>
<tr>
<td>Observations</td>
<td>226</td>
<td>226</td>
</tr>
</tbody>
</table>

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Table 5.11: MWTP for Reduction in PM10 Concentrations

A. Baseline Model

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>IV for $PM_{10}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No MC Interaction</td>
<td>With MC Interaction</td>
</tr>
<tr>
<td>No MSA Attributes</td>
<td>127.04</td>
<td>255.75</td>
</tr>
<tr>
<td>With MSA Attributes</td>
<td>66.45</td>
<td>232.22</td>
</tr>
<tr>
<td></td>
<td>83.69</td>
<td>187.12</td>
</tr>
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</table>

B. Restricted Index Model

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>IV for $PM_{10}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No MC Interaction</td>
<td>With MC Interaction</td>
</tr>
<tr>
<td>No MSA Attributes</td>
<td>253.08</td>
<td>358.94</td>
</tr>
<tr>
<td>With MSA Attributes</td>
<td>154.33</td>
<td>291.62</td>
</tr>
<tr>
<td></td>
<td>203.40</td>
<td>287.43</td>
</tr>
</tbody>
</table>

C. Unrestricted Index Model

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>IV for $PM_{10}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No MC Interaction</td>
<td>With MC Interaction</td>
</tr>
<tr>
<td>No MSA Attributes</td>
<td>181.64</td>
<td>498.65</td>
</tr>
<tr>
<td>With MSA Attributes</td>
<td>159.02</td>
<td>540.08</td>
</tr>
<tr>
<td></td>
<td>112.29</td>
<td>345.21</td>
</tr>
<tr>
<td></td>
<td>88.35</td>
<td>371.05</td>
</tr>
</tbody>
</table>
Table 5.12: Second Stage Regression: Fixed Effects From Restricted Model with Normalized Index and MC Interaction

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>OLS</th>
<th>IV for PM10</th>
</tr>
</thead>
<tbody>
<tr>
<td>∆θ + .25∆ ln(ρ)</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>∆ ln PM10</td>
<td>-0.5077 *</td>
<td>-0.2743</td>
</tr>
<tr>
<td></td>
<td>(0.2917)</td>
<td>(0.2913)</td>
</tr>
<tr>
<td>∆ Crime</td>
<td>-0.2136</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.2718)</td>
<td></td>
</tr>
<tr>
<td>∆ Prop_tax</td>
<td>-0.0057</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0078)</td>
<td></td>
</tr>
<tr>
<td>∆ Gov_exp</td>
<td>0.0002</td>
<td>0.0002</td>
</tr>
<tr>
<td></td>
<td>(0.0002)</td>
<td>(0.0002)</td>
</tr>
<tr>
<td>∆ White</td>
<td>5.5462 ***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.6404)</td>
<td></td>
</tr>
<tr>
<td>∆ Health</td>
<td>0.0005</td>
<td>0.0004</td>
</tr>
<tr>
<td></td>
<td>(0.0010)</td>
<td>(0.0009)</td>
</tr>
<tr>
<td>∆ Art</td>
<td>-0.0023 ***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0007)</td>
<td></td>
</tr>
<tr>
<td>∆ Trans</td>
<td>0.0004</td>
<td>0.0004</td>
</tr>
<tr>
<td></td>
<td>(0.0006)</td>
<td>(0.0005)</td>
</tr>
<tr>
<td>∆ Employment</td>
<td>0.0841</td>
<td>0.1259</td>
</tr>
<tr>
<td></td>
<td>(0.3379)</td>
<td>(0.3247)</td>
</tr>
<tr>
<td>∆ ln(Manuf_Est)</td>
<td>0.6429 *</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.3753)</td>
<td></td>
</tr>
<tr>
<td>∆ ln(Population)</td>
<td>-0.5848</td>
<td>-0.5275</td>
</tr>
<tr>
<td></td>
<td>(0.6209)</td>
<td></td>
</tr>
<tr>
<td>Regional Dummies</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.78</td>
<td>0.81</td>
</tr>
<tr>
<td>Observations</td>
<td>226</td>
<td>226</td>
</tr>
</tbody>
</table>

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Table 5.13: Second Stage Regression: Fixed Effects From Unrestricted Model with Normalized Index and MC Interaction

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>OLS</th>
<th>IV for PM10</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \theta + .25 \Delta \ln(\rho)$</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>$\Delta \ln PM_{10}$</td>
<td>-0.3168 (0.2194)</td>
<td>-0.1707 (0.2188)</td>
</tr>
<tr>
<td>$\Delta$ Crime</td>
<td>-0.0189 (0.2041)</td>
<td>-0.0079 (0.1964)</td>
</tr>
<tr>
<td>$\Delta$ Prop_Tax</td>
<td>-0.0021 (0.0058)</td>
<td>-0.0033 (0.0056)</td>
</tr>
<tr>
<td>$\Delta$ Gov_Exp</td>
<td>0.0002 (0.0001)</td>
<td>0.0002 (0.0001)</td>
</tr>
<tr>
<td>$\Delta$ White</td>
<td>3.7450 *** (1.2321)</td>
<td>3.3057 *** (1.1972)</td>
</tr>
<tr>
<td>$\Delta$ Health</td>
<td>-0.0002 (0.0007)</td>
<td>-0.0003 (0.0007)</td>
</tr>
<tr>
<td>$\Delta$ Art</td>
<td>-0.0021 *** (0.0005)</td>
<td>-0.0020 *** (0.0005)</td>
</tr>
<tr>
<td>$\Delta$ Trans</td>
<td>-0.0001 (0.0004)</td>
<td>0.0000 (0.0004)</td>
</tr>
<tr>
<td>$\Delta$ Employment</td>
<td>-0.0048 (0.2538)</td>
<td>0.0535 (0.2452)</td>
</tr>
<tr>
<td>$\Delta \ln(\text{Manuf.Est})$</td>
<td>0.1887 (0.2819)</td>
<td>0.1690 (0.2713)</td>
</tr>
<tr>
<td>$\Delta \ln(\text{Population})$</td>
<td>0.3816 (0.4663)</td>
<td>0.4617 (0.4497)</td>
</tr>
<tr>
<td>Regional Dummies</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.76</td>
<td>0.79</td>
</tr>
<tr>
<td>Observations</td>
<td>226</td>
<td>226</td>
</tr>
</tbody>
</table>

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
### A. Restricted Index Model

<table>
<thead>
<tr>
<th></th>
<th>Original Index</th>
<th>Normalized Index</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>OLS</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No MSA Attributes</td>
<td>203.40</td>
<td>202.09</td>
</tr>
<tr>
<td>With MSA Attributes</td>
<td>110.12</td>
<td>109.18</td>
</tr>
<tr>
<td><strong>IV for PM$_{10}$</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No MSA Attributes</td>
<td>287.43</td>
<td>285.80</td>
</tr>
<tr>
<td>With MSA Attributes</td>
<td>221.16</td>
<td>219.72</td>
</tr>
</tbody>
</table>

### B. Unrestricted Index Model

<table>
<thead>
<tr>
<th></th>
<th>Original Index</th>
<th>Normalized Index</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>OLS</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No MSA Attributes</td>
<td>112.29</td>
<td>137.66</td>
</tr>
<tr>
<td>With MSA Attributes</td>
<td>88.35</td>
<td>74.18</td>
</tr>
<tr>
<td><strong>IV for PM$_{10}$</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No MSA Attributes</td>
<td>345.21</td>
<td>268.29</td>
</tr>
<tr>
<td>With MSA Attributes</td>
<td>371.05</td>
<td>243.00</td>
</tr>
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</table>
Table 5.15: Second Stage Regression: Fixed Effects From Unrestricted Model with Heterogeneous Parameters on $PM_{10}$

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>OLS</th>
<th>IV for PM10</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \theta + .25 \Delta \ln(\rho)$</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>$\Delta \ln PM_{10}$</td>
<td>-0.3538</td>
<td>-0.2008</td>
</tr>
<tr>
<td></td>
<td>(0.2173)</td>
<td>(0.2192)</td>
</tr>
<tr>
<td>$\Delta$ Crime</td>
<td>-0.1887</td>
<td>-0.2045</td>
</tr>
<tr>
<td></td>
<td>(0.2045)</td>
<td>(0.2045)</td>
</tr>
<tr>
<td>$\Delta$ Prop.Tax</td>
<td>-0.0032</td>
<td>-0.0058</td>
</tr>
<tr>
<td></td>
<td>(0.0058)</td>
<td>(0.0058)</td>
</tr>
<tr>
<td>$\Delta$ Gov.Exp</td>
<td>0.0002</td>
<td>0.0001</td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
<td>(0.0001)</td>
</tr>
<tr>
<td>$\Delta$ White</td>
<td>3.3215 ***</td>
<td>2.9047 **</td>
</tr>
<tr>
<td></td>
<td>(1.2344)</td>
<td>(1.1985)</td>
</tr>
<tr>
<td>$\Delta$ Health</td>
<td>0.0002</td>
<td>0.0001</td>
</tr>
<tr>
<td></td>
<td>(0.0007)</td>
<td>(0.0007)</td>
</tr>
<tr>
<td>$\Delta$ Art</td>
<td>-0.0020 ***</td>
<td>-0.0019 ***</td>
</tr>
<tr>
<td></td>
<td>(0.0005)</td>
<td>(0.0005)</td>
</tr>
<tr>
<td>$\Delta$ Trans</td>
<td>0.0002</td>
<td>0.0002</td>
</tr>
<tr>
<td></td>
<td>(0.0004)</td>
<td>(0.0004)</td>
</tr>
<tr>
<td>$\Delta$ Employment</td>
<td>-0.0189</td>
<td>0.0365</td>
</tr>
<tr>
<td></td>
<td>(0.2542)</td>
<td>(0.2454)</td>
</tr>
<tr>
<td>$\Delta \ln$ (Manuf.Est)</td>
<td>0.2934</td>
<td>0.2747</td>
</tr>
<tr>
<td></td>
<td>(0.2824)</td>
<td>(0.2715)</td>
</tr>
<tr>
<td>$\Delta \ln$ (Population)</td>
<td>-0.0615</td>
<td>0.0145</td>
</tr>
<tr>
<td></td>
<td>(0.4672)</td>
<td>(0.4501)</td>
</tr>
<tr>
<td>Regional Dummies</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.82</td>
<td>0.84</td>
</tr>
<tr>
<td>Observations</td>
<td>226</td>
<td>226</td>
</tr>
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</table>

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Table 5.16: MWTP for Reduction in PM10 Concentrations: Unrestricted Model with Heterogeneous Parameters on $PM_{10}$

<table>
<thead>
<tr>
<th>Individual Type</th>
<th>Mean $\beta$ Deviation</th>
<th>MWTP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type 1</td>
<td>No H.S. Degree</td>
<td>0.0222 (0.0295)</td>
</tr>
<tr>
<td>Type 2</td>
<td>H.S. Degree</td>
<td>-0.0412 (0.0113)</td>
</tr>
<tr>
<td>Type 3</td>
<td>Bachelor’s Degree</td>
<td>0.0354 (0.0141)</td>
</tr>
<tr>
<td>Type 4</td>
<td>Grad./Prof. Degree</td>
<td>0.0823 (0.0214)</td>
</tr>
<tr>
<td>Type 5</td>
<td>No H.S. Degree</td>
<td>-0.1823 (0.0197)</td>
</tr>
<tr>
<td>Type 6</td>
<td>H.S. Degree</td>
<td>-0.0255 (0.0094)</td>
</tr>
<tr>
<td>Type 7</td>
<td>Bachelor’s Degree</td>
<td>0.0268 (0.0177)</td>
</tr>
<tr>
<td>Type 8</td>
<td>Grad./Prof. Degree</td>
<td>0.0803 (0.0243)</td>
</tr>
</tbody>
</table>

Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Table 5.17: Second Stage Regression: IV Regression, Pollution Variable = ln(110 - PM10)

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>OLS</th>
<th>IV for PM10</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \theta + .25\Delta \ln(\rho)$</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>$\Delta \ln(110 - PM_{10})$</td>
<td>0.7458</td>
<td>0.8799 *</td>
</tr>
<tr>
<td></td>
<td>(0.4891)</td>
<td>(0.4898)</td>
</tr>
<tr>
<td>$\Delta$ Crime</td>
<td>0.2331</td>
<td>0.2339</td>
</tr>
<tr>
<td></td>
<td>(0.2767)</td>
<td>(0.2647)</td>
</tr>
<tr>
<td>$\Delta$ Prob_Tax</td>
<td>-0.0128</td>
<td>0.0079</td>
</tr>
<tr>
<td></td>
<td>(0.0079)</td>
<td>(0.0076)</td>
</tr>
<tr>
<td>$\Delta$ Gov_Exp</td>
<td>0.0004 **</td>
<td>0.0004 ***</td>
</tr>
<tr>
<td></td>
<td>(0.0002)</td>
<td>(0.0002)</td>
</tr>
<tr>
<td>$\Delta$ White</td>
<td>1.7042</td>
<td>1.5569</td>
</tr>
<tr>
<td></td>
<td>(1.6448)</td>
<td>(1.5770)</td>
</tr>
<tr>
<td>$\Delta$ Health</td>
<td>0.0001</td>
<td>0.0001</td>
</tr>
<tr>
<td></td>
<td>(0.0010)</td>
<td>(0.0009)</td>
</tr>
<tr>
<td>$\Delta$ Art</td>
<td>-0.0025 ***</td>
<td>-0.0025 ***</td>
</tr>
<tr>
<td></td>
<td>(0.0007)</td>
<td>(0.0007)</td>
</tr>
<tr>
<td>$\Delta$ Trans</td>
<td>-0.0001</td>
<td>-0.0001</td>
</tr>
<tr>
<td></td>
<td>(0.0006)</td>
<td>(0.0005)</td>
</tr>
<tr>
<td>$\Delta$ Employment</td>
<td>0.3352</td>
<td>0.3939</td>
</tr>
<tr>
<td></td>
<td>(0.3472)</td>
<td>(0.3347)</td>
</tr>
<tr>
<td>$\Delta \ln(\text{Manuf}_{\text{Est}})$</td>
<td>0.2421</td>
<td>0.2480</td>
</tr>
<tr>
<td></td>
<td>(0.3820)</td>
<td>(0.3655)</td>
</tr>
<tr>
<td>$\Delta \ln(\text{Population})$</td>
<td>0.3518</td>
<td>0.4193</td>
</tr>
<tr>
<td></td>
<td>(0.6338)</td>
<td>(0.6082)</td>
</tr>
</tbody>
</table>

Regional Dummies: yes  yes  yes  yes  
R-Squared: 0.81  0.83  0.14  0.24  
Observations: 226  226  226  226  

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
<table>
<thead>
<tr>
<th>Dependent Variable: $\Delta \theta + .25 \Delta \ln(\rho)$</th>
<th>OLS</th>
<th></th>
<th>IV for PM10</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>$\Delta \ln PM_{10}$</td>
<td>1.6390 (1.2645)</td>
<td>2.0082 (1.2677)</td>
<td>3.3649 (2.2340)</td>
<td>4.6211 (2.2214) **</td>
</tr>
<tr>
<td>$\Delta (\ln PM_{10})^2$</td>
<td>-0.2957 (0.1927)</td>
<td>-0.3458 * (0.1935)</td>
<td>-0.5763 * (0.3307)</td>
<td>-0.7616 ** (0.3295)</td>
</tr>
<tr>
<td>$\Delta$ Crime</td>
<td>0.1876 (0.2786)</td>
<td>0.1292 (0.2717)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Prob_Tax</td>
<td>-0.0118 (0.0079)</td>
<td>-0.0122 (0.0076)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Gov_Exp</td>
<td>0.0004 ** (0.0002)</td>
<td>0.0004 *** (0.0002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta$ White</td>
<td>1.9144 (1.6753)</td>
<td>2.0450 (1.6375)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Health</td>
<td>0.0002 (0.0010)</td>
<td>0.0005 (0.0010)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Art</td>
<td>-0.0025 *** (0.0007)</td>
<td>-0.0024 *** (0.0007)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Trans</td>
<td>-0.0002 (0.0006)</td>
<td>-0.0003 (0.0006)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Employment</td>
<td>0.2993 (0.3458)</td>
<td>0.3643 (0.3341)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta \ln(\text{Manuf_Est})$</td>
<td>0.2479 (0.3831)</td>
<td>0.2786 (0.3701)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta \ln(\text{Population})$</td>
<td>0.4125 (0.6391)</td>
<td>0.6034 (0.6232)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Regional Dummies</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.81</td>
<td>0.83</td>
<td>0.13</td>
<td>0.23</td>
</tr>
<tr>
<td>Observations</td>
<td>226</td>
<td>226</td>
<td>226</td>
<td>226</td>
</tr>
</tbody>
</table>

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Table 5.19: Alternative $PM_{10}$ Specifications: MWTP for Reduction in PM10 Concentrations

<table>
<thead>
<tr>
<th>Model</th>
<th>Clean Air</th>
<th>Quadratic</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Unrestricted Index Model</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>No MSA Attributes</td>
<td>340.55</td>
</tr>
<tr>
<td>OLS</td>
<td>With MSA Attributes</td>
<td>399.53</td>
</tr>
<tr>
<td>IV for $PM_{10}$</td>
<td>No MSA Attributes</td>
<td>558.49</td>
</tr>
<tr>
<td></td>
<td>With MSA Attributes</td>
<td>603.90</td>
</tr>
</tbody>
</table>
Chapter 6

Cost of Living and Adjusted Income

6.1 Quality Adjusted Cost of Living Indices

A cost of living (COL) index defines the relative cost of reaching a particular level of well-being. The presence of different prices makes it more or less expensive to achieve some level of utility at different times or in different locations. A theoretically consistent means of deriving a true COL index is to take the ratio of two expenditure functions, in which the expenditure function gives the amount of income necessary to reach a base level of utility. Given accurate measures of the cost of living, it is possible to move beyond simple income measures and conduct a more complete examination of a population’s well-being. Applications of COL indices may include analysis of welfare effects over time as income changes at a rate different than that of the cost of living or across locations as the cost of living may vary spatially. Conventional COL indices focus on measures that use market prices and market expenditures. However, public goods may contribute a significant amount to an individual’s utility. Of course, the non-market nature of public goods makes it difficult to observe prices and quantities of goods or even total expenditures. In the following, I briefly review traditional COL indices and discuss attempts to create COL indices and well-being measures that incorporate public goods.

Two common approximations of the true COL index are the Laspeyres index and the
Paasche index. Both of these measures calculate the ratio of price times quantity across a number of goods in two regions with different prices, and assume that the same fixed basket of goods is purchased in both regions. A fixed basket of goods is necessary to make a valid comparison. Summing total expenditures is similar to calculating an expenditure function, but the requirement of a fixed basket of goods does not capture optimal behavior on the part of the consumer. The indices differ in the region that defines the fixed basket of consumption, and thus the region that defines base utility. This assumption creates the problem of no substitution of goods in the presence of different prices, and gives a biased estimate of the true cost of living. Since the reference level of utility differs, the bias moves in opposite directions between the two indices. To correct for the bias, Fisher (1922) introduced the Fisher ideal index, which takes the geometric mean of the Laspeyres and Paasche index. Konus (1939) shows that under a homogeneous quadratic utility function the Fisher index is the exact true COL. However, rather than imposing this restriction, directly estimating an expenditure function allows for calculation of the true COL index. Kakwani and Hill (2002) estimate a variety of functional forms for an expenditure function and use parameterized functions to calculate COL indices.

Nordhaus (1999) develops an augmented cost of living index (ACOLI) that includes "augmented consumption", and captures the price and consumption effect of public goods. He puts forth the example of a government funded project. Higher taxes will raise prices on the item being taxed, leading to an increase in a traditional price index. At the same time, the benefit of the project will increase well being and counteract the effect of higher prices. Thus, an individual may be able to achieve the same (or greater) level of well being after the project is completed, while a traditional price index will reflect an increase in the cost of living. The ACOLI is formally defined as the ratio of expenditure functions of different price/public good regimes, holding the value of a social welfare function constant. In other words, it measures the relative cost of achieving some level of utility under different prices and public goods. The use of the ACOLI may be preferable in a number of situations; government programs that raise taxes to improve the environment or public safety, employer provided benefits that may
translate into higher output prices, or taxes for social security and welfare programs.

To illustrate the effect of ignoring public goods, Nordhaus develops a "narrow" ACOLI. The narrow ACOLI measures the true price of private consumption once the augmented aspect has been removed. This is in contrast to a "broad" ACOLI that would measure a price index for private and public consumption combined. An important point is that the two measures converge as the benefit-cost ratio of public goods approaches one. The author’s choice is based on data constraints. In comparing the ACOLI to a more conventional index, it is shown that the ACOLI can be derived from a conventional index with a correction based on the level of public good spending relative to total consumption spending. In the empirical application, public good consumption is calculated as the sum of social insurance taxes, employer provided goods, indirect business taxes, and mandated social regulations. This calculation is then used to measure the inflation rate once public good consumption is accounted for. Results show an upward bias in the traditional measure of 19% from 1960 to 1997, an average of 0.47 percentage points per year. Essentially, Nordhaus’s method creates a means of deflating market expenditures. Given accurate price and consumption indices for each location this technique could be used to construct spatial COL indices.

Banzhaf (2005) also examines the issue of including public goods in a cost of living index, providing two approaches to do so. The first approach involves the use of virtual prices, prices at which individuals would choose to consume some fixed quantity of a good once income is adjusted. These prices, along with changes in public good levels, can be used to include public goods in a conventional price index. In addition, expenditure must be adjusted to account for hypothetical purchases of public goods. Banzhaf refers to this as the "augmented cost of living index". In the sense that virtual prices can be interpreted as values for marginal willingness to pay, they can be estimated using revealed preference techniques. It is then necessary to evaluate virtual prices at a comparison level, creating the need for a willingness to pay function, rather than simply a point estimate. This problem could be solved by using spatial variation in the level of public goods to recover virtual price estimates at different levels.
Banzhaf’s second technique is based on the assumption that public goods are weak complements to some market goods (housing in this case). Such an assumption implies that public goods only generate utility if some market good is consumed. Conventional indices can be adjusted by substituting a new price for the price of the market good (the good to which public goods are weak complements). This substituted price is a price index that compensates consumers for forgoing changes in public goods so that they obtain the reference level of utility. Again, prices are obtained from hedonic regressions. The COL indices derived from this method are referred to as adjusted cost of living indices.

Public goods of interest include air quality, teacher-student ratio, and public safety in Los Angeles from 1989 to 1994. Results show that incorporating public goods into the Bureau of Labor Statistics Los Angeles Consumer Price Index reduces the index by 0.4 and 0.3 percentage points, respectively, in the first two years where LA saw improving air quality and education. The adjusted index suggest similar effects, with a reduction of 0.3 and 0.2 percentage points in the first two years, and a total reduction of 0.1 percentage points over the final three years. This study, though focused only a few public goods, further indicates the significant impact of including public goods in COL indices.

A related literature attempts to directly calculate a measure deemed as “quality of life” that reflects public good provision. The empirical approach uses wage and housing price differentials. The intuition is similar, as individuals trade off income and housing expenditures to gain access to public goods in a particular location. Blomquist et al. (1988) estimate wage and housing hedonic equations to attain implicit prices for public goods. Quality of life is then calculated as the sum of the value of all public goods, in which value is simply marginal price times quantity. This study assumes that all individuals have identical preferences and earning potential. Empirical estimates show significant impacts of public goods on housing prices and wages. This framework is also used for quality of life calculations in Albouy (2009), which measures differences across U.S. cities. Kahn (1995) employs a similar hedonic analysis, but only defines quality of life in terms of its rank order, rather than a cardinal measure. Lower
wages and higher housing prices imply that a location has a higher quality of life as individuals arbitrage away money for public goods. The assumption of identical preferences holds, but individual characteristics will affect wages.

Several problems are inherent in the previous papers in determining quality of life. First, wages and income are fully arbitrated. However, in a geographic choice set that includes MSAs across the United States, there are likely to be significant moving costs. Therefore, the value of a location’s public goods may not be fully reflected in wages and housing prices. Second, in deriving equilibrium conditions, studies also assume that each individual achieves the same level of utility. With exogenously determined origin locations and significant individual heterogeneity, this is likely an unrealistic assumption. Finally, the notion of quality of life seems to measure something a bit different than what the name implies, as it reflects only the level of public goods. Since individuals have the same level of utility, one could argue that quality of life is identical across individuals. A true quality of life should indicate the combined effect of wages, market prices, and public goods.

Following an expenditure function approach, Timmins (2006) estimates a residential sorting model to estimate the parameters of a utility function that depends on consumption, housing, location attributes and moving costs. Preferences for such variables vary with individual characteristics. An expenditure function is then derived from the indirect utility function. The ratio of a location and individual type specific expenditure function to an area weighted average expenditure function gives the true COL index for each of the 495 locations. When these indices are applied to the observed income distribution of Brazil, results suggest a higher degree of inequality. In what follows, I adopt this method of deriving COL indices.
6.2 Cost of Living Indices

6.2.1 Introduction

While parameters of the model described in Chapter 3 convey marginal values for public amenities, a more thorough welfare analysis is possible due to the structure of the model. In particular, the model implies cost of living (COL) indices that reflect the welfare that arises from market prices and public goods in various locations. In deflating an individual’s income by the cost of living, we can observe a more accurate measure of the true standard of living. Furthermore, the following analysis examines the distribution of such welfare across the population. Thus concerns related to income inequality are extended to inequality related to fairness in the provision of public goods.

Beyond characterizing the distribution of adjusted income, an additional question pertains to the distributional impact of public policy. In response to policy that alters the level of some public good, general equilibrium effects result in individuals reoptimizing and possibly moving to new locations. Therefore, the benefit of the policy is largely dependent on how individuals choose their location. Partial equilibrium welfare analysis will fail to measure the gain or loss from any non-marginal changes in spatially delineated site attributes when people are at least partially mobile. Therefore, any examination of exogenous shocks must allow individuals to re-sort among residential locations. The residential sorting model offers a means of estimating the underlying process of the residential choice, rather than simply characterizing the equilibrium outcome. Knowledge of the sorting process allows for counterfactual analysis, in which a re-sorting due to public policy can be simulated. Then, one can ask, for example, whether individuals with already high levels of quality adjusted income are receiving a disproportionately high level of the welfare gain. This reveals the regressive or progressive nature of public good provision.
6.2.2 Cost of Living Indices

Given a fully parameterized model, the indirect utility function implicitly defines an expenditure function specific to each location. For conventional goods, cost of living (COL) indices are defined as a ratio with numerator equal to the minimum income required for purchase of a particular bundle of goods that will leave utility unchanged and denominator equal to a base income. In the context of a location choice model, spatial COL indices make this comparison across geographic locations and include publicly provided goods as elements of the consumption bundle. Therefore, indices measure the necessary income to reach some utility level in a location relative to the necessary income to reach that same utility level in a base location.

The expenditure function for individual \( i \) in MSA \( m \) is easily derived from the indirect utility function in (3.41) by fixing utility at level \( \bar{V}^1 \) and solving for income, \( I_{im} \),

\[
E^k_m = \exp \left[ \frac{1}{\beta^1} \left( \ln \bar{V}^1 - \theta_m - MC_{im} - \tau^k \Gamma^k_m - \eta^1_{im} \right) \right]
\] (6.1)

6.2.3 Moving Costs and Cost of Living

An important advantage of sorting models relative to housing and wage hedonics is their ability to account for the large spatial dimension of the choice set. The present model includes a variable that indicates the geographic distance between each choice alternative and the individual’s starting location. Such a specification allows for a cost of moving, rather than assuming a simple choice based only on the attributes of an alternative. Bayer et al. (2009) demonstrate the implications for calculating the utility value derived from different site attributes using a hedonic framework that ignores any cost to moving. In a hedonic model, the value of site amenities is fully capitalized into housing costs and wages, and the amenity value is equal to the sum of the compensating differentials from housing and income. However, if positive moving costs exist, there is a third component contributing to the amenity value that captures the variation in the cost of moving to each location. The effect of housing and wages alone will undervalue site amenities as they ignore the additional cost of moving to a location to obtain the amenity.
In calculating adjusted income, the importance of accounting for moving costs to obtain proper values for non-market goods is obvious. However, the existence of moving costs between alternatives raises another issue in determining the cost of living. In particular, while moving costs are imperative for accurately calculating amenity values, such costs should not be included in calculating an individual’s baseline cost of living. This assumption implies that two identical individuals in the same location face the same baseline cost of living index, regardless of their original locations. Still, a third identical individual may face a higher cost of living index in another location since positive moving costs prevent her from choosing the location with a lower net-of-moving-costs cost of living. Such a scenario underscores the impact that the spatial nature of public good provision has on the distribution of benefits.

Consider the case in which there are no moving costs. Then, individuals simply choose the location with the optimal bundle of income, housing prices, and amenities. If any location offers higher income, lower prices, and/or better amenities (i.e. lower cost of living), more individuals will move to that location, driving down wages and increasing prices. The equilibrium result is that all locations offer the same cost of living for identical individuals. The existence of moving costs and the previous assumption, however, preclude such a result. An alternative location may offer higher income, lower prices, and/or better amenities, but positive moving costs prevent an individual from obtaining the bundle. Therefore, the individual is worse off in her current location due to the inferior bundle of income, prices, and amenities.

As a thought experiment, assume two locations, A and B, where individual 1 begins in location A and individual 2 begins in location B. An individual chooses A if $U_{iA} > U_{iB}$ and chooses B if $U_{iA} < U_{iB}$. Assume that both locations offer the same income and price level, but B has better amenities and that both individuals have identical preferences. Further assume that equilibrium sorting results in individual 1 staying in A and individual 2 staying in B. Intuitively, it is easy to see that individual 2 is better off than individual 1 due to higher amenity value of B. Individual 1 cannot move to the location with a lower cost of living due to constraints arising from moving costs. From the structure of utility, individual 1’s decision allows us to
assign a lower bound to the cost of moving from A to B. However, to capture the idea that individual 1 is worse off, moving costs are left out of the COL calculation. While moving costs serve as a necessary factor in explaining the observed equilibrium, they are not a reasonable component in calculating the cost of living in a particular location. Therefore, the derivation of the expenditure function is modified to omit moving costs in the cost of living.

6.2.4 Cost of Living Calculation

Unobservable idiosyncratic shocks, $\eta_{im}^1$, make equation (6.1) individual specific. To calculate a type-location expenditure function, I simulate draws of $\eta_{im}^1$ from a Type-I Extreme Value distribution for every individual in each location and calculate the income required to reach $\bar{V}^1$ in each location. Note that $\bar{V}^1$ is chosen to be the average calculated utility in the data set in 1990. I use the parameters of the indirect utility function, presented in Chapter 5, along with each individual’s observed income level to calculate their utility in their optimal location. I then average this utility across all individuals to get $\bar{V}^1$. For the index model in which expenditure functions are type-specific, average utility $\bar{V}_k^1$ is calculated separately for each type. The income required to reach $\bar{V}^1$ is averaged over the random idiosyncratic draws for each type of individual in a location to get the value of the type-location expenditure function.

Regarding simulation of the idiosyncratic term $\eta_{im}^1$, random draws are taken conditional on observed behavior. The optimal location choice reveals some information about the distribution of the random term, namely that draws are values such that maximum utility is achieved in the observed location,

$$V_{im}^1 + \eta_{im}^1 \geq V_{in}^1 + \eta_{in}^1 \quad \forall n \neq m,$$

(6.2)

where individual $i$ lives in MSA $m$. I follow von Haefen (2003) for the conditional simulation of $\eta^1$. The required expenditure to reach $\bar{V}^1$ in each location is calculated as the average across individuals and across 100 simulations.

After integrating over idiosyncratic shocks and removing moving costs, the expenditure
function for a type $k$ individual in MSA $m$ becomes

$$E^k_m = \exp \left[ \frac{1}{\beta I} \left( \ln \bar{V}^1 - \theta_m - \tau^k \Gamma^k_m \right) \right].$$

(6.3)

A type-location COL index is defined as the ratio of the value of the expenditure function relative to that of the same individual type in a base location,

$$COL^k_m = \frac{E^k_m}{E^k_0}.$$  \hspace{1cm} (6.4)

The COL index reflects whether the attributes of a location make it more or less expensive to achieve some level of utility relative to the base location. The result is an $M \times 1$ vector of COL indices for each year in the price model for both moving cost specifications. For the index models that include preference heterogeneity, there exists an $M \times 1$ vector of COL indices for each year and each type.

In addition, I try an alternative approach to calculating expenditure functions. I follow the same simulation technique to draw idiosyncratic shocks. Then, for each individual, I calculate the income required to reach their observed (calculated from model parameters and observed income) level of utility in each location, averaged over 100 simulations. A COL index can be calculated for each individual in each location using equation (6.4). This index is then averaged across all individuals in an MSA to get the MSA (or MSA-type) COL index. The difference between the two approaches is that the former relies on a COL index calculated from average expenditures, while the latter relies on an average COL index. Results from the second approach are omitted since they are nearly identical. There is, however, a slightly larger spread in COL indices in the second approach that arises from a nonlinear specification. Still, reported results and additional calculations are all based on the first approach.

Beyond calculating such an index for each MSA, interest lies in the impact of particular amenities, such as air pollution, on the cost of living. This impact can be characterized by the correlation between a location’s COL index and the utility impact of air pollution. Define
$PM_m$ as the level of particulate matter in MSA $m$. Then, the relevant measure is the correlation between $COL^k_m$ and $PM_m$. Since air pollution is a disamenity, a negative correlation implies that a higher cost of living is driven by high concentrations of PM10. A positive correlation implies locations with a high cost of living tend to have low PM10 concentrations, and thus the high cost of achieving welfare is a result of other attributes.

**6.2.5 Adjusted Income**

The COL indices derived above are used to deflate observed income. This works to adjust income according to market prices and public goods. The resulting measure reflects an individual’s income in the context of the price of housing, as in traditional COL indices, as well as the level of public amenities available at a location:

$$I_{im} = \frac{I_{im}}{COL^k_m} \quad (6.5)$$

Adjusted income can inform us about two important features of the economy. The first is the evolution in the standard of living over time. Standard economic analysis examines standards of living by considering nominal income and prices to calculate real income. Such an approach focuses on households’ ability to consume in private markets but does not account for their consumption of public goods. Across two periods it is possible that real income declines but the actual well-being of households may increase if public good consumption increases by a sufficient amount. This latter notion of well-being may be a better measure. The current model allows us to look at the consumption value of both market and non-market goods to calculate a standard of living and assess its progress over time.

The second question surrounds the distribution of adjusted income, particularly as it compares to the distribution of observed income. The distribution of observed income is of interest insomuch as it conveys information about the distribution of standard of living throughout the population. However, the general equilibrium theory that underlies residential sorting models implies that differences in income, to some degree, reflect compensation for public goods and
prices in private markets. It is therefore necessary to control for differences in location amenities and housing prices to obtain what is arguably a better measure of the standard of living. This statistic is estimated as the adjusted income measure explained above. An examination of the distribution of adjusted income relative to the distribution of observed income reveals the degree to which public good provision alleviates or exacerbates inequalities in the standard of living. If empirical results show a more equal distribution of adjusted income, then public goods serve to make up for variation in nominal income across the population. Thus a portion of the inequality in income exists as compensation for public amenities across locations, rather than differences in the overall standard of living. For example, in an economy in which all individuals received the same compensation for their production, income differences would be entirely due to compensation for public goods and the distribution of adjusted income would reduce to a degenerate distribution. However, if empirical results show higher inequality in the distribution of adjusted income, relative to nominal income, we can take this as evidence that access to public goods increases inequalities in the standard of living. In considering only nominal income in such a situation, the level of inequality in the standard of living would be underestimated since higher income households also have access to a superior set of public goods.

A final matter related to adjusted income that deserves attention is the impact of moving costs. In the absence of moving costs, public amenities should be fully capitalized into labor and housing markets, and any differences in the quality of locations will be arbitraged away. Of course in the context of the earlier discussion surrounding the removal of moving costs from expenditure functions, when costly migration is present individuals may be prevented from obtaining a lower cost of living in a distant location. This feature of the sorting process drives a wedge between expenditure functions for identical individuals so that location amenities are not entirely capitalized into labor and housing markets. While moving costs may prevent some households from moving to locations with a lower cost of living, moving costs will also shield particular households from an influx of people that could drive up housing prices and drive down
wages. To test this effect, I use a comparison of adjusted income calculated with and without moving costs in the expenditure function. A more unequal distribution of adjusted income calculated without moving costs indicates that the state of the geographic landscape results in disproportionately greater moving costs for households that already have a lower standard of living. While this is an intuitive result that is expected to arise after sorting over a number of time periods, it is an important consideration in focusing the provision of public goods. Such an outcome is the result of public policy that has increased the set of public goods in already desirable locations and thus disproportionately benefits those households at the higher end of the standard of living distribution. Moving costs can be interpreted as transaction costs in obtaining welfare increasing consumption bundles, and thus their impact may be of concern to policy.

Given the empirical focus on the inequality of particular distributions, the primary criterion used to evaluate the equity of different distributions is the Gini coefficient, $G$, a measure of inequality based on the cumulative distribution of some variable. Normalize income so that $\tilde{I}_i = \frac{I_i}{I_{\max}}$, which suggests an individual’s relative income. Assuming some parametric distribution, a fitted cdf $F(\tilde{I}) = S$ represents the share of the population with relative income less than $\tilde{I}$. The inverse cdf, $F^{-1}(S)$, represents the level of relative income below which $S$ percent of the population receive. This is known as the Lorenz curve. Figure 6.1 shows the Lorenz of an arbitrary distribution, as well as a Lorenz curve for a perfectly equal distribution, in which the cdf is simply a straight line. The Gini coefficient can be calculated as $A/(A + B)$. As the income distribution approaches a perfectly equal distribution, $A$ approaches 0 and the coefficient also approaches 0. In the extreme case in which a single individual receives all income, the cdf essentially follows the bottom and right axes. Therefore, $A$ approaches 1, $B$ approaches 0, and the coefficient approaches 1, the highest level of inequality.

Analytically, the Gini coefficient can be calculated as

$$G = 1 - 2 \int_0^1 F^{-1}(t)dt$$

(6.6)
If income is distributed equally among a population, the cdf is a straight line whose integral over $t \in [0, 1]$ is equal to $\frac{1}{2}$. Therefore, the Gini coefficient equals 0, indicating perfect equality. Conversely, if all income is received by a single individual and $\tilde{I}_i = 0$ for the remainder of the population, the integral of the inverse cdf approaches 0. The resulting Gini coefficient is 1, suggesting the highest degree of inequality.

For each type of individual in each year, I use observed incomes and adjusted incomes and create an empirical cdf for each as an approximation to the integral in (6.6) to calculate the Gini coefficient. Due to the arbitrary scale of utility in the model, the Gini coefficient is calculated for a sample of the entire population, as well as separately for each individual type.

Alternatively, I use a discrete approximation to (6.6) to calculate the Gini coefficient. For the distribution of income described by the vector $I$,

$$G = \frac{\sum_i^n \sum_j^n |I_i - I_j|}{2n^2 \bar{I}}$$  \hspace{1cm} (6.7)

where $n$ is the number of individuals and $\bar{I}$ is mean income.

While the Gini coefficient may be of interest in itself, a more useful analysis focuses on its change over time. The progressive or regressive nature of public policy, in general, will be reflected in the evolution of the Gini coefficient. One approach is to consider the change from 1990 to 2000, the two available years in the data. However, a simulation exercise can
also illustrate the distributional impacts. The parameterized model describes the behavior of individuals as it pertains to choosing where to live. Thus, given a hypothetical exogenous change in the level of some attribute, say PM10, the model allows for prediction of a new sorting equilibrium. Several simulations will include variation in the degree and location of any attribute change. A comparison of the Gini coefficient in the new equilibrium to Gini coefficient before any change in attributes offers insight into whether public policy disproportionately benefits different income groups and the extent to which this depends on the specifics of the policy.
Chapter 7

Cost of Living Results

7.1 COL Indices

Cost of living calculations measure the relative cost of achieving some level of utility. All reported indices are measured relative to the national average cost of living in 1990 so they can be compared across years. In other words, expenditures required to reach $V^1$ are averaged across all MSAs in 1990 to calculate the denominator in equation (6.4). This choice of denominator impacts the magnitude of COL indices, but is irrelevant in making comparisons across locations. Given previous model specifications, I focus exclusively on the unrestricted index model that contains the second stage index $\Gamma_k^m$ with a type-specific parameter.

First, I present results for COL indices in which expenditure functions include moving costs. For 1990, across the 8 individual types, the minimum COL index for an MSA is between 0.28 and 0.51 and the maximum is between 1.61 and 2.27. Again, these indices are measured relative to the 1990 average. These extrema have interpretations that are difficult to accept intuitively. For example, a COL index of 0.28 implies that while it takes $100,000 to reach base utility in the “average” location, it only takes $28,000 to reach base utility in this particular location. However, these truly are extreme values. The 10% quantile across the 8 types ranges from 0.51 to 0.76 and the 90% quantile ranges from 1.23 to 1.57. Therefore, the majority of the calculated
COL indices do fall within a more reasonable range. Similar results hold for year 2000 COL indices. Considering only variation in the cost of living within the year 2000 by normalizing out the 1990 comparison, the minimum COL index is between 0.27 and 0.52 and the maximum is between 2.16 and 2.69, across the 8 types. Again, however, the 10% and 90% quantiles range from 0.51 to 0.74 and 1.19 to 1.49, respectively. Based on these bounds and standard deviations of the COL indices, the magnitude of spatial variation in the cost of living appears to be quite similar for each year.

Looking across years, it is possible to analyze the degree to which the cost of living has increased or decreased. For 1,832 type-MSA combinations, only 17 of these show an increase in the COL index. This includes 11 MSAs for individuals that have no children and a high school degree and 6 MSAs for individuals that have children and a high school degree. The average decrease in the COL index is between $-0.34$ and $-0.52$ across individual types. If the COL index decreases by 0.52, for example from 1.56 to 1.04, it implies that only two thirds of one’s 1990 (real) income is necessary to reach the same utility in the year 2000 in that location. Empirical results suggest that there has been a considerable decrease in the cost of living. These results contrast with those from a more conventional approach that does not consider location amenities. If one analyzed the cost of living based only on (inflation adjusted) market prices, specifically housing prices, results suggest an increase in the cost of living as households face higher real prices. Only 3 MSAs saw a decrease in the price of housing services from 1990 to 2000 and the average change was an increase of 30%. In addition, the average increase in income from these calculations indicates that the decrease in the cost of living found in the current analysis is driven primarily by public amenities. Further discussion will examine the driving forces behind changes in COL indices. It is interesting to note, as mentioned above, that the only COL index increases from 1990 to 2000 were those that impacted less educated households. Given that these households tend to be at the lower end of the income distribution, these COL index changes hint at the widening distribution of adjusted income that will be explicitly addressed in the next section.
As discussed earlier, there is a logical reason to leave moving costs out of the expenditure function and thus, out of COL index calculations, even when they are part of the estimated model. This reasoning rests on the notion that this part of the analysis is interested in COL indices based on spatial variation exclusively in prices and local amenities. When moving costs are not removed from expenditure function calculations, the minimum and maximum COL indices across individual types for 1990 range from 0.57 to 0.59 and 1.44 to 1.57, respectively. For 2000, measured against the 2000 average, these ranges are 0.45 to 0.47 and 1.88 to 2.09. There are two empirical observations here relative to the indices that include moving costs in their calculation. First, the range of COL indices across MSAs is much smaller when moving costs are dropped. Dropping moving costs removes a cost from an individual’s expenditure function and allows her to reach some base utility with less income. This acts to reduce the cost of living in general. The fact that there is also a force that increases the indices, as extremely low COL indices no longer exist, suggests that higher moving costs are concentrated in those MSAs that had very low COL indices in the original calculations. Such a phenomenon is not surprising, at it simply implies more migration towards MSAs with a lower cost of living. Second, variation across types is significantly smaller. The average cross-type standard deviation is 0.04 for 1990 and 0.05 for 2000. Compare this to 0.09 for 1990 and 0.11 for 2000 when moving costs enter the calculation. This suggests that the degree to which variation in the landscape offers alternative residential locations for individuals may differ based on an individual’s education and family structure, and thus different proportions of different types may be observed to have incurred moving costs.

A comparison across years shows similar results when moving costs are dropped from the indices. The average change in the COL index from 1990 to 2000 is a decrease of between 0.37 and 0.49, depending on the individual type. These numbers are very similar to those derived with moving costs included, but with slightly less variability. In addition, only a single type-MSA combination experienced an increase in the cost of living over time. These results, combined with the changes in housing prices discussed earlier, demonstrate a significant decrease
in the cost of living across the country between 1990 and 2000 that is due to the provision of public goods.

Tables 7.1 - 7.8 show the highest and lowest ranked MSAs, in terms of their COL index, across types, specifications, and years. Recall that a high cost of living implies a relatively undesirable location due to a lack of amenities or high housing prices. Results show considerable differences in rankings depending on whether or not moving costs are included in the calculation. Tables 7.1 and 7.3 suggest that the set of MSAs that have the lowest COL is dominated by the larger MSAs in the nation. While many of these cities are known to have relatively higher housing prices, their location amenities have the effect of decreasing the cost of living enough to rank them as the top cities. Similarly, as evidenced in Tables 7.2 and 7.4, MSAs with high COL indices tend to be smaller cities that have lower housing prices. These results conform to points discussed earlier, in which location amenities have an opposite and more substantial impact than the price of housing services. Tables 7.5 - 7.8 show MSA rankings based on indices calculated without moving costs in the expenditure function. Note that these are significantly different from rankings determined by calculations that include moving costs. The MSAs with the lowest COL index are no longer comprised of the largest cities in the nation. This is likely a result of moving costs having more of an impact in smaller cities. Since moving costs are measured relative to birth location, a greater number of people being born in larger cities relative to smaller ones leads to fewer individuals incurring moving costs to reach larger cities. Therefore, when moving costs are removed from expenditure functions, the decrease in costs is less drastic in larger cities. The remainder of this analysis will focus on the specification in which moving costs are left out of the expenditure function.

To further analyze what is driving the cost of living in different MSAs, I run two regressions with the COL index as the dependent variable and $\ln \rho_Y$ (the price of housings services) and $\ln PM_{10}$ concentrations as independent variables, respectively. Regressions are estimated separately for each individual type and include observations for all 229 MSAs across both years with year fixed effects. Table 7.9 displays regression coefficients and 95% confidence intervals.
from the regression of COL indices on the price of housing services. For all individual types, parameter estimates are negative, though they are significant at the 5% level for only three types. These results support the idea that while higher housing prices tend to increase the cost of living, there are a number of other factors, namely public goods, that contribute to true measures of the cost of living. Furthermore, COL indices that include only market prices and omit public goods will give qualitatively different results. Table 7.10 shows results from the regression of COL indices on pollution concentrations. Coefficients are positive but insignificant for all types. Still positive point estimates suggest a role for air pollution in the cost of living in an MSA. Results are extremely similar when COL indices are regressed on both air pollution and housing prices together.

7.2 Adjusted Income

Given COL indices for each type, MSA, and year, it is now possible to calculate adjusted income. Recall that adjusted income is nominal income normalized to reflect the location specific cost of achieving a particular level of well being. For example, if the COL index is 1.5 and an individual earns $90,000, adjusted income is calculated as $90,000/1.5 = $60,000. Intuitively, the individual’s income in the high cost of living location is the equivalent of $60,000 in the base location. Consistent comparisons of well-being are based on such an approach, which accounts for market prices and local amenities.

Conventional economic analysis relies on real income (inflation adjusted) to proxy for the standard of living. In the context of this analysis, the mean (inflation-adjusted) income increased in 143 of 229 MSAs from 1990 to 2000. Of these MSAs, 106 experienced an increase in mean income adjusted for the value of location amenities. This leaves 37 MSAs in which real income may have increased, but the standard of living fell due to changes in the set of public goods. In addition, there are 38 MSAs in which the standard of living, as described by adjusted income, increased but real income actually declined. These results point to the imperfect nature of real income as a proxy for the standard of living. Even while households’
purchasing power may be rising or falling in private markets, changes in access to public goods can sometimes more than compensate for changes in real income. In addition to considering MSAs that experienced increases or decreases in real income versus adjusted income, the role of public goods is further emphasized when considering the magnitude of these changes. Across all locations the mean increase in real income from 1990 to 2000 was 5.8%, while the mean increase in adjusted income was 7.4%. Given a mean real income in 2000 of $32,488, these percentages translate to $1,900 and $2,400, respectively. In general, the inclusion of public good values suggests that living standards increased by a greater magnitude than revealed by an income analysis alone.

Adjustments to income for access to public goods reveal higher increases in the standard of living. In addition, it is obvious that any positive level of public good consumption generates some benefits and increases an individual’s welfare. However, the distribution of these benefits across the population may be of greater interest. As discussed earlier, this question is approached using the Gini coefficient for the adjusted income distribution relative to that of the real income distribution. Before discussing these results, consider the Gini coefficient for income by full-time workers in the U.S. to put the numbers in context. In the last 40 years, the lowest value of the Gini coefficient was .326 in 1969, 1970, and 1974. The highest value was .409 in 2001 and 2005. Notice that fluctuations in the value of the coefficient are extremely small but still indicate considerable variation in distributions over time.

Table 7.11 shows Gini coefficients in 1990 and 2000 for the distributions of income and of adjusted income. Calculations are done for the population as a whole as well as for each individual type. The top panel reports results for the distribution of all individuals in a sample of 920,208 individuals for 1990 and 782,323 individuals for 2000. For both years, a higher Gini coefficient for adjusted income, relative to real income, defines a more unequal distribution. This indicates a higher degree of inequality in living standards across households when both income and public goods are considered. Higher income individuals, therefore, tend to live in locations that offer a better set of location amenities. An increase in the Gini coefficient holds
for all individual types, though the adjustments for public goods are less drastic since a portion of the inequality in adjusted income is due to cross-type differences. Note that this result goes beyond the idea that households with higher income simply consume more public goods. This result also accounts for housing price variation that reflects different levels of public goods. In other words, the adjustment is made for the aggregate impact of the benefit of public goods net of the cost of housing price adjustments for such goods. The larger Gini coefficient on adjusted income demonstrates more inequality that is driven by unequal access to high-quality locations.

These results are also evident from the Lorenz curves displayed in Figure 7.1, in which the underlying distributions used to calculate the Gini coefficients are plotted along with the forty-five degree line that signifies a perfectly equal distribution. Recall that higher inequality is denoted by curves that are bowed further from this forty-five degree line. The graph in Panel A shows changes in the real income distribution from 1990 to 2000 to demonstrate some magnitude. Panels B and C both indicate a higher degree of inequality in adjusted income, as discussed above. While these changes look small graphically, they are fairly substantial in the context of changes in real income.

As an additional means of giving context to differences in the distribution of adjusted income relative to real income, consider scenarios that would alter the real income distribution so that it reaches a level of inequality identical to that of the adjusted income distribution. While there are an infinite number of ways to redistribute income to achieve any particular Gini coefficient, I describe two here that demonstrate the increase in inequality. The first way involves taking all of the income from the bottom $p\%$ and giving it to the top $p\%$. For the 1990 distribution, reducing the income of the bottom 31% to 0 and giving it to the top 31% leads to a Gini coefficient equal to that of the adjusted income distribution in 1990. For 2000, the corresponding $p$ is 26%. Alternatively, consider redistributing income from the bottom half of the distribution to the top half. For 1990, the adjusted income Gini coefficient is replicated in the real income distribution by reducing all incomes below the median by $20,189, and evenly distributing that money to all individuals above the median income level. For 2000, the
Figure 7.1: Lorenz Curves for Real and Adjusted Income
required individual reduction in income is $19,380. While differences in the distributions of real and adjusted incomes may appear small when looking at the Gini coefficient or the Lorenz curve, these differences become quite substantial when put in the more intuitive context of a monetary redistribution.

To further analyze the variation across income groups, consider the initial position of households in the income distribution and their position in the adjusted income distribution. Type 8, indicating a graduate degree and children in the household, is at the upper end of the real income distribution as well as the upper end of the adjusted income distribution. Similarly, Types 2 and 6, those with a high school degree are at the lower end of both the real and adjusted income distributions. This trend is consistent across all types. These results do not offer much in explaining rising inequality. However, the real and adjusted income distributions do convey information regarding the means by which the Gini coefficient increases. For all types, probability density functions for adjusted income shift dramatically upwards at the lower tail, relative to the income distribution. This suggests an increasing portion of individuals at the lower end of the adjusted income distribution. This could be a significant portion of the increase in the Gini coefficient when adjusted income is analyzed. Such an effect implies that households with very low incomes have very little access to public goods. While it may be the case that benefits are disproportionately enjoyed by extremely wealthy households, the more important driver here is likely the adjustment at the lower end of the income distribution.

The final portion of the analysis looking at the current state of the distribution of adjusted income focuses on the impact of moving costs. Recall that the above calculations are based on expenditure functions that do not include moving costs in a household’s expenditure function for reasons discussed earlier. In particular, the omission of moving costs in COL calculation makes for a better interpretation of the standard of living. However, a comparison of results obtained when omitting versus including moving costs highlights whether moving costs disproportionately impact those with an already lower standard of living. Gini coefficients for both sets of results are shown in Table 7.12. The top row and the first row for each type are
simply repeats of numbers reported in Table 7.11. The second rows, respectively, show Gini coefficients when moving costs are included in expenditure functions used to calculate COL indices. In all cases, there is a substantial increase in the level of inequality when moving costs are included. The increase in inequality suggests that households with lower standards of living are currently facing higher costs of migrating away from their birthplace. Put another way, households with lower standards of living, relative to the rest of the population, were forced to disproportionately incur high moving costs to reach a better location. This may be the result of public good provision that has been concentrated in locations with already high standards of living. Whether such a situation is driven by federal policy with a skewed focus or MSA-level policy driven by higher incomes in better locations is unknown in this analysis. Still, these results, combined with the more general results concerning inequalities, suggest the importance of distributional considerations in federal public good provision.

7.3 Policy Simulations

To analyze the welfare effects and distributional impacts associated with non-marginal changes in air quality, I simulate 8 different policy changes in a general equilibrium framework. The spatial equilibrium of the year 2000 serves as the pre-policy baseline. In the context of residential sorting, general equilibrium simulations allow households to re-optimize and choose different locations following changes to location amenities. Each policy involves an exogenous decrease in $PM_{10}$ concentrations, though the location of these concentration reductions varies across each simulation. This exercise suggests the importance of location in targeting federal policy when there is a large amount of variation in current public good levels and when there exist significant costs to re-optimization, i.e. moving costs. The eight policies are as follows:

1. Reduce concentrations by 10% across all locations
2. Reduce concentrations by 20% across all locations
3. Reduce concentrations by 20% in top half of $PM_{10}$ distribution
4. Reduce concentrations by 20% in bottom half of $PM_{10}$ distribution
5. Reduce concentrations by 20% in top half of COL distribution
6. Reduce concentrations by 20% in bottom half of COL distribution

7. Reduce concentrations by 20% in top quartile of COL distribution

8. Reduce concentrations by 20% in bottom quartile of COL distribution

Note that the bottom half of the $PM_{10}$ distribution refers to locations with the lowest concentrations. The bottom half of the COL distribution, however, refers to the most desirable locations that have a numerically low COL index.

In simulating a new equilibrium following a change to the amenity vector it is assumed that the supply of housing is fixed. General equilibrium simulations allow for price and demand changes in the housing market but no changes on the supply side. The fixed supply of housing is proxied for by using the pre-simulation (2000) shares. Following the change in $PM_{10}$ concentrations, a new equilibrium is reached through an iterative process. First, a new vector of shares is calculated based on the new set of location amenities and the original price vector. For those locations in which demand for housing (defined by location shares) exceeds the fixed supply of housing, the price of housing services is marginally increased. Then a new vector of shares is calculated with the new price vector. This process continues until housing demand is equal to housing supply in all locations and prices converge. The final vector of MSA-specific prices, population shares, and updated location amenities describes the new equilibrium.

Total welfare effects are measured by the Willingness to Pay (WTP) for the change in $PM_{10}$, using the Compensating Surplus (CS) as an approximation. Compensating Surplus is implicitly defined as the amount of money an individual would pay post-policy to have no change in utility from the baseline. To account for individual idiosyncracies, it is defined as the level of income reduction following the policy that makes expected utility in the post-policy equilibrium equal to expected utility pre-policy. CS satisfies the following equation,

$$
\ln \left[ \sum_{j=1}^{M} \exp \left( V(I_{ij} - CS_i, \rho_{m,1}^Y, Y_{m,1}, \Gamma_{m}^k, MC_{im}; \beta) \right) \right] - \left[ \ln \sum_{j=1}^{M} \exp \left( V(I_{ij}, \rho_{m,0}^Y, Y_{m,0}, \Gamma_{m}^k, MC_{im}; \beta) \right) \right] = 0,
$$

(7.1)
where \( \rho^Y_{m,1} \) and \( Y_{m,1} \) denote, respectively, the price of housing services and the vector of location attributes after the policy shock and \( \rho^Y_{m,0} \) and \( Y_{m,0} \) denote, respectively, the price of housing services and the vector of location attributes before the policy shock. Note that the re-sorting process is type-specific so that general equilibrium CS varies across individual types. As a comparison, consider the partial equilibrium welfare impacts from these policy scenarios. Partial equilibrium analysis restricts households to remain in their location and consume the exogenously changed amenity vector at original prices. Therefore, welfare benefits are still calculated using equation (7.1), though \( \rho^Y_{m,1} \) is fixed at \( \rho^Y_{m,0} \) for all MSAs.

### 7.3.1 Welfare

An important factor that determines welfare benefits and their distribution is the existence of costly migration. Mobility constraints may even lead to some household being made worse off following a decrease in pollution. As pollution concentrations fall, housing prices increase in that MSA. The new bundle of pollution and housing prices may be suboptimal, but if moving costs are greater than the welfare loss associated with pollution and price changes in the location, households will simply accept the welfare loss and remain in that MSA. Much of the impact of moving costs depends on the initial locations of households (i.e. the distribution of birth places) relative to the distribution of location amenities across space. The process of residential sorting over decades of policy and the subsequent origin locations that this process creates lead to an initial spatial distribution of households that factors into the general equilibrium re-sorting. Furthermore, the distribution of income across households within this spatial composition will also play a significant role. Similarly, the discreteness of the choice set may lead to solutions in which households experience decreases in welfare following changes in location attributes and prices, yet do not have the ability to re-optimize due to a lack of choice opportunities.

Table 7.13 reports CS estimates for general equilibrium simulations across the 8 different policy scenarios for each individual type. Numbers should be interpreted as annual welfare gains. Across policies, welfare gains are as expected. Policies 3 and 4 target MSAs with high
and low $PM_{10}$ concentrations, respectively. Differences here, greater gains from targeting highly polluted areas, are driven primarily by the fact that 20% reductions are larger in absolute terms for locations with higher concentrations. However, in a policy context, the costs of these reductions may be more comparable than costs from identical absolute reductions. More interesting results are evident from Policies 5-8. There are larger welfare gains in Policy 6 relative to Policy 5 and in Policy 8 relative to Policy 7. Both of these comparisons show that improvements to locations with a lower COL generate greater benefits. Among other aspects of the model, this is a result of non-linear preferences over housing prices and positive correlation between prices and the COL. Larger benefits are obtained when locations with a low COL and low price of housing services experience a price increase. Price decreases take place in the relatively high priced locations that do not see a reduction in concentrations. This pattern of price changes translates to greater overall benefits.

Focusing on variation across individual types, recall that types 5-8 are those with children in the household and thus have higher moving costs. These types tend to have slightly smaller welfare gains as they are hindered by costly migration. Still, several type-policy combinations have nearly identical benefits since the heterogeneity in moving costs is small relative to the total moving cost. Welfare gains are highest for types 4 and 8, households with the highest level of education. Types 1 and 5, households with the lowest level of education, consistently have the second highest welfare gains. Aside from moving costs, this variation in benefits arises from variation in the value of $PM_{10}$ improvements relative to the micro-sorting index developed in Chapter 3, since this is the only other source of heterogeneity in the model. Therefore, particular household types obtain larger welfare gains due to their preferences for air quality and local public goods. However, differences are extremely small, particularly given the magnitude of welfare gains.
7.3.2 Post-Shock Gini Coefficient

While there are considerable welfare gains from these policies, any notion of the distribution of gains is absent from a discussion of compensating surplus. Returning to the use of the Gini coefficient as the preferred indicator of inequality, the focus now turns to the distribution of benefits following the previously discussed policies. Note that this framework does not account for capital gains that may arise when a household can sell their property at a higher price following the policy shock.

Across all of the policies some general empirical results hold. First, I obtain the intuitive result that prices increase in locations that experience pollution reductions. The correlation coefficient between changes in $\text{PM}_{10}$ and changes in $\ln \rho^Y$ ranges from $-0.22$ to $-0.55$ for the eight policies. In addition, correlation coefficients are positive for all but 7 policy-type combinations when looking at changes in $\ln \rho^Y$ and changes in COL indices. Finally, correlations are consistently positive between changes in pollution and changes in the cost of living. Pollution reductions, though they lead to higher prices, tend to decrease the overall cost of living in an MSA.

Similar to the discussion above related to the baseline scenario, moving costs have a substantial role in general equilibrium re-sorting. The distribution of benefits of any policy will be highly dependent on the location of amenity improvements relative to the set of household’s origin locations. Another aspect of the model that is important for understanding why amenity improvements may offer disproportional benefits to households is the within-MSA distribution of income. The response to simulated policies only affects differences in the cost of living across MSAs. However, the Gini coefficient measures a distribution that is a pooling of distributions across MSAs. Therefore, the impact of policies on the overall distribution of adjusted income across MSAs depends on the within-MSA distributions of those locations that experienced amenity improvements.

Finally, functional form will be a factor in the measured impacts of simulations. Given the form of utility, and thus of expenditure functions, the decrease in required expenditures
following a decrease in $PM_{10}$ concentrations is larger at low levels of pollution concentrations. Conversely, the increase in required expenditures following an increase in $\ln \rho^Y$ is smaller at high levels of the price of housing services. This preference structure implies that locations with low $PM_{10}$ concentrations and high prices will experience relatively greater decreases in the cost of living than locations with high $PM_{10}$ concentrations and low prices.

Predictions of the distributional impacts of policies can be made by looking at the post-policy set of COL indices. Locations with higher COL indices to begin with experienced a smaller decrease in the cost of living after the decrease in pollution concentrations. Though there were larger price decreases in MSAs with initially high COL indices, the amenity effect of pollution reductions had a more substantial impact on COL indices. Relatively smaller decreases in the cost of living for locations with higher COL indices and similarly, relatively larger decreases in the cost of living for locations with lower COL indices, suggest a growing disparity in the cost of living across the country. Households that previously incurred low costs of living benefited to a greater degree from reductions in $PM_{10}$.

Growing inequality is most evident from the Gini coefficient. Table 7.14 shows the calculated Gini coefficient in the new equilibrium that results from each policy. The first row displays the baseline case before any reduction in pollution concentrations. Columns refer to general equilibrium and partial equilibrium, in which households do not re-optimize. Again, the eight alternative policies result in very small differences in the Gini coefficient, though even such small differences translate into significant monetary disparities. For example, in the context of the earlier thought exercise in which income was taken from the bottom half of the income distribution and given to the top half of the distribution, a change in the third decimal place of the Gini coefficient is equivalent to a redistribution from the bottom half of over $1,000.

Policies 1 and 2, in which $PM_{10}$ reductions take effect in every MSA, show very little changes in the distribution of adjusted income. There is only a slight increase as households facing a very low COL receive similar benefits to those in high COL locations. Since amenities are improved in uniform fashion, much of this result in the Gini coefficient is due to the functional form of
expenditure functions, as discussed above. The direction of the change supports the intuitive notion that wealthier households live in locations with high prices and better amenities, while lower income households live in locations that offer less amenity value but have lower housing prices. In addition, the magnitude of the change in the Gini coefficient establishes an extremely small baseline size of the functional form effect. Thus, it is reasonable to assume that subsequent results are not dominated by the functional form of the preferences.

Policies 3 and 4 specifically target the MSAs with $PM_{10}$ concentrations above and below the median, respectively. When reductions occur in the most polluted areas there is a widening of the adjusted income distribution and the Gini coefficient increases from .5363 to .5379. The opposite effect results from targeting the least polluted areas, in which case the Gini coefficient decreases to .5360. In addition, the resulting Gini coefficients stand on either side of those from the baseline and the uniform policies. This is somewhat counterintuitive in that focusing on the worst locations, in terms of pollution, does not have a narrowing effect on the adjusted income distribution. However, as $PM_{10}$ concentrations are only a small portion of an individual’s well-being, the relationship between the initial set of prices, pollution, and other amenities has a dominating impact. Locations with the highest pollution concentrations are not necessarily those with the highest COL indices. As a result, the targeting of these locations does not transfer benefits to those households at the lower end of the adjusted income distribution.

Policies 5-8 use the initial set of COL indices to focus policy. In Policy 5, pollution reductions take place in the top half of the COL distribution. As mentioned before, the top half refers to those with the highest COL index, and thus are the more undesirable locations. In this case, the Gini coefficient falls to .5320. Similarly, when policy targets the top quartile, as in Policy 7, there is a decrease in the Gini coefficient to .5338. These decreases in inequality arise when policy is directly focused on those locations that are initially the worst off. However, in considering only partial equilibrium, there are considerable differences in empirical results as households are not allowed to re-sort among MSAs. Policies 5 and 7 result in Gini coefficients of .5316 and .5335, respectively, in partial equilibrium. A re-sorting of individuals allows
households outside of the targeted MSA to drive up housing prices and take advantage of $PM_{10}$ reductions. When reductions take place in high COL locations, partial equilibrium results show a larger decrease in inequality due to a lack of price increases.

Policies that target the low COL locations, as expected, increase inequality in adjusted income. In Policy 6, the Gini coefficient increases from .5363 to .5414. In Policy 8, the Gini coefficient increases to .5443. The impact of partial versus general equilibrium continues to hold, though it has the opposite effect here. The partial equilibrium Gini coefficient for Policy 6 is .5420. For Policy 8, the effect is too small to alter the Gini coefficient. Since policy targets the lowest COL MSAs, partial equilibrium benefits those that are already well-off, widening the adjusted income distribution. A re-sorting of households drives up prices in the high COL locations and allows households outside of the high COL MSAs to take advantage of the improved locations. It is important to note that increases in inequality do not guarantee that some set households is made worse off. Increases in the Gini coefficient only convey relative welfare gains across the population.

To determine the driving force of this increase in inequality, I again examine the probability density functions before and after the policy shock. The result is similar to that discussed earlier related to accounting for public goods. Following a policy change, the most significant change in the distribution of adjusted income takes place at the lower tail for each type. While earlier results suggested that a lack of access to public goods for very low income households was a driving force in a higher Gini coefficient for adjusted income, an identical process occurs following each of the policies. The increase in inequality arises as households at the very low end of the adjusted income (and also the real income) distribution benefit disproportionately less than the majority of the population.

To put some of these Gini coefficient changes in context, they can be converted into percent changes and translated to monetary transfers. For example, Policy 6 generates a .95% increase in inequality. In a similar manner, Policy 8 generates a 1.49% increase in inequality. In terms of monetary compensation, a 1% increase in the Gini coefficient beginning with a value of .5363, is
equivalent to evenly transferring $1,022 from the all households below the median income level to all households above the median income level. The distributional impact of these policies, therefore, is quite substantial.

Table 7.15 displays type-specific Gini coefficients. General results discussed above apply to adjusted income distributions isolated by type. Note that these numbers are slightly smaller than those in Table 7.14, as some of the disparities in adjusted income are due to variation across different types.
Table 7.1: Lowest COL Index (w/ MC), 1990

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Table 7.2: Highest COL Index (w/ MC), 1990

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<td>3</td>
<td>Fargo-Moorhead, ND/MN</td>
<td>Fort Smith, AR/OK</td>
<td>Columbus, GA/AL</td>
<td>Fargo-Moorhead, ND/MN</td>
</tr>
<tr>
<td>4</td>
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<td>Fargo-Moorhead, ND/MN</td>
<td>Fargo-Moorhead, ND/MN</td>
<td>Columbus, GA/AL</td>
</tr>
<tr>
<td>5</td>
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<td>Columbus, GA/AL</td>
<td>Tallahassee, FL</td>
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<tr>
<td>6</td>
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<td>Portland, ME</td>
<td>Athens, GA</td>
<td>Columbus, GA/AL</td>
</tr>
<tr>
<td>7</td>
<td>Jacksonville, NC</td>
<td>Sioux City, IA/NE</td>
<td>Athens, GA</td>
<td>Jacksonville, NC</td>
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<tr>
<td>8</td>
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<td>Lynchburg, VA</td>
<td>Albany, GA</td>
<td>Jacksonville, NC</td>
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<td>Lynchburg, VA</td>
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<tr>
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Table 7.8: Highest COL Index, 2000

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<td>Bridgeport, CT</td>
<td>Binghamton, NY</td>
</tr>
<tr>
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<td>Flint, MI</td>
<td>Reading, PA</td>
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<td>Flint, MI</td>
<td>Atlantic City, NJ</td>
<td>Santa Rosa-Petaluma, CA</td>
</tr>
<tr>
<td>4</td>
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<td>Santa Rosa-Petaluma, CA</td>
<td>Peoria, IL</td>
<td>San Francisco-Oakland, CA</td>
</tr>
<tr>
<td>5</td>
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<td>Peoria, IL</td>
<td>Santa Rosa-Petaluma, CA</td>
<td>Atlantic City, NJ</td>
</tr>
<tr>
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<td>San Francisco-Oakland, CA</td>
<td>Bridgeport, CT</td>
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<td>San Jose, CA</td>
<td>Peoria, IL</td>
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<td>Flint, MI</td>
<td>Flint, MI</td>
<td>Reading, PA</td>
</tr>
<tr>
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<tr>
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### Table 7.9: Regression of COL Index on Price of Housing Services, $\ln \rho^Y$

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>95% C.I.</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type 1</td>
<td>-.1876</td>
<td>(-.3556, -.0195)</td>
<td>.1960</td>
</tr>
<tr>
<td>Type 2</td>
<td>-.0869</td>
<td>(-.2557, .0818)</td>
<td>.1434</td>
</tr>
<tr>
<td>Type 3</td>
<td>-.1516</td>
<td>(-.3331, .0299)</td>
<td>.1421</td>
</tr>
<tr>
<td>Type 4</td>
<td>-.2796</td>
<td>(-.4613, -.0979)</td>
<td>.1879</td>
</tr>
<tr>
<td>Type 5</td>
<td>-.1418</td>
<td>(-.3077, .0242)</td>
<td>.2119</td>
</tr>
<tr>
<td>Type 6</td>
<td>-.0983</td>
<td>(-.2481, .0515)</td>
<td>.1748</td>
</tr>
<tr>
<td>Type 7</td>
<td>-.1076</td>
<td>(-.2731, .0578)</td>
<td>.1880</td>
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<tr>
<td>Type 8</td>
<td>-.2802</td>
<td>(-.4436, -.1168)</td>
<td>.2381</td>
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</table>

### Table 7.10: Regression of COL Index on $\ln PM_{10}$

<table>
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<th>95% C.I.</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type 1</td>
<td>.0493</td>
<td>(-.0221, .1207)</td>
<td>.1908</td>
</tr>
<tr>
<td>Type 2</td>
<td>.0471</td>
<td>(-.0244, .1185)</td>
<td>.1446</td>
</tr>
<tr>
<td>Type 3</td>
<td>.0337</td>
<td>(-.0433, .1107)</td>
<td>.1384</td>
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<tr>
<td>Type 4</td>
<td>.0152</td>
<td>(-.0625, .0929)</td>
<td>.1719</td>
</tr>
<tr>
<td>Type 5</td>
<td>.0665</td>
<td>(-.0037, .1367)</td>
<td>.2130</td>
</tr>
<tr>
<td>Type 6</td>
<td>.0600</td>
<td>(-.0033, .1233)</td>
<td>.1781</td>
</tr>
<tr>
<td>Type 7</td>
<td>.0496</td>
<td>(-.0204, .1197)</td>
<td>.1885</td>
</tr>
<tr>
<td>Type 8</td>
<td>.0420</td>
<td>(-.0279, .1120)</td>
<td>.2215</td>
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</table>
Table 7.11: Inequality as Measured by the Gini Coefficient

<table>
<thead>
<tr>
<th>Type-Specific</th>
<th>Real Income</th>
<th>Adjusted Income</th>
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<tbody>
<tr>
<td>Type 1</td>
<td>0.3189</td>
<td>0.5174</td>
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<tr>
<td>Type 2</td>
<td>0.2912</td>
<td>0.4449</td>
</tr>
<tr>
<td>Type 3</td>
<td>0.3022</td>
<td>0.4954</td>
</tr>
<tr>
<td>Type 4</td>
<td>0.3472</td>
<td>0.5402</td>
</tr>
<tr>
<td>Type 5</td>
<td>0.3240</td>
<td>0.5110</td>
</tr>
<tr>
<td>Type 6</td>
<td>0.2985</td>
<td>0.4405</td>
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<tr>
<td>Type 7</td>
<td>0.3126</td>
<td>0.4812</td>
</tr>
<tr>
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<td>0.3841</td>
<td>0.5277</td>
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Table 7.12: Inequality as Measured by the Gini Coefficient (Include MC in Expenditure Functions)

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<th></th>
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<th>1990</th>
<th>2000</th>
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<td><strong>All Individuals</strong></td>
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<tr>
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<td>.5266</td>
<td>.5363</td>
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</tr>
<tr>
<td>With MC</td>
<td>.5756</td>
<td>.5855</td>
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</tr>
<tr>
<td><strong>Type-Specific</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td><strong>Type 1</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Without MC</td>
<td>.5147</td>
<td>.4758</td>
<td></td>
</tr>
<tr>
<td>With MC</td>
<td>.5995</td>
<td>.5423</td>
<td></td>
</tr>
<tr>
<td><strong>Type 2</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Without MC</td>
<td>.4449</td>
<td>.4405</td>
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</tr>
<tr>
<td>With MC</td>
<td>.5573</td>
<td>.5436</td>
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</tr>
<tr>
<td><strong>Type 3</strong></td>
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</tr>
<tr>
<td>Without MC</td>
<td>.4954</td>
<td>.4857</td>
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</tr>
<tr>
<td>With MC</td>
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<td>.5265</td>
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</tr>
<tr>
<td><strong>Type 4</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Without MC</td>
<td>.5402</td>
<td>.5151</td>
<td></td>
</tr>
<tr>
<td>With MC</td>
<td>.5658</td>
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</tr>
<tr>
<td><strong>Type 5</strong></td>
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</tr>
<tr>
<td>Without MC</td>
<td>.5110</td>
<td>.4692</td>
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<td>With MC</td>
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<tr>
<td><strong>Type 6</strong></td>
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</tr>
<tr>
<td>Without MC</td>
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<td>With MC</td>
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<td>.5564</td>
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<td><strong>Type 7</strong></td>
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<tr>
<td>Without MC</td>
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<td>.4883</td>
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<tr>
<td>With MC</td>
<td>.5771</td>
<td>.5623</td>
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<td><strong>Type 8</strong></td>
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<tr>
<td>Without MC</td>
<td>.5277</td>
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<td>With MC</td>
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### Table 7.13: General Equilibrium Compensating Surplus

<table>
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<th>Type 4</th>
<th>Type 5</th>
<th>Type 6</th>
<th>Type 7</th>
<th>Type 8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Policy 1</td>
<td>2,120.03</td>
<td>1,936.48</td>
<td>2,009.69</td>
<td>2,230.91</td>
<td>1,973.06</td>
<td>1,899.92</td>
<td>2,009.76</td>
<td>2,156.84</td>
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<tr>
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<td>3,578.05</td>
<td>3,367.04</td>
<td>3,492.72</td>
<td>3,748.71</td>
<td>3,450.97</td>
<td>3,323.78</td>
<td>3,493.13</td>
<td>3,661.40</td>
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<tr>
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<td>2,380.40</td>
<td>2,417.91</td>
<td>2,685.26</td>
<td>2,380.01</td>
<td>2,342.88</td>
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<td>1,419.72</td>
<td>1,532.86</td>
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<td>Partial Equilibrium</td>
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<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
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<tr>
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<td>0.5363</td>
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</tr>
<tr>
<td>20% across all locations</td>
<td>.5365</td>
<td>0.5365</td>
<td></td>
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<tr>
<td>20% in top half of PM10 distribution</td>
<td>.5379</td>
<td>0.5382</td>
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<tr>
<td>20% in bottom half of PM10 distribution</td>
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<td>0.5363</td>
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<td>20% in bottom half of COL distribution</td>
<td>.5414</td>
<td>0.5420</td>
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<tr>
<td>20% in top quartile of COL distribution</td>
<td>.5338</td>
<td>0.5335</td>
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<td>20% in bottom quartile of COL distribution</td>
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### Table 7.15: Gini Coefficient (type-specific): Post-Simulation Equilibrium

<table>
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<th>Type 1</th>
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<th>Type 3</th>
<th>Type 4</th>
<th>Type 5</th>
<th>Type 6</th>
<th>Type 7</th>
<th>Type 8</th>
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<tbody>
<tr>
<td>(Pre-Policy Baseline)</td>
<td>.4758</td>
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<td>.4687</td>
<td>.4387</td>
<td>.4883</td>
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<td>.4405</td>
<td>.4853</td>
<td>.5149</td>
<td>.4687</td>
<td>.4387</td>
<td>.4883</td>
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<td>.4414</td>
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<td>.4674</td>
<td>.4392</td>
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<td>.5359</td>
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<td>.4626</td>
<td>.4311</td>
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<td>.4752</td>
<td>.4467</td>
<td>.4942</td>
<td>.5389</td>
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<td>.4368</td>
<td>.4825</td>
<td>.5122</td>
<td>.4660</td>
<td>.4348</td>
<td>.4852</td>
<td>.5319</td>
</tr>
<tr>
<td>Policy 8</td>
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<td>.4508</td>
<td>.4949</td>
<td>.5223</td>
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<td>.4488</td>
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Chapter 8

Conclusion

This dissertation has developed a two stage residential sorting model that is consistent with individual utility maximization and operates within the constraints of data and computation. The model allows for a city choice followed by a neighborhood choice within that city. By incorporating this micro-sorting stage, the framework enhances conventional sorting models that consider only a macro-level location choice. The model relies on constructing quality adjusted price indices at the MSA level that reflect the availability of tract-level amenities and tract specific prices. This approach is in contrast to using only MSA average prices.

Empirical results show considerable differences in the MWTP for reductions in $PM_{10}$ across the three approaches, as we see increased values when tract amenities are considered and further increases when more flexible preference heterogeneity is considered. The index models allows individuals to substitute between air pollution, MSA and tract housing prices, and tract-level amenities, while the price model allows only for substitution between air pollution and MSA housing prices. This additional dimension of substitution offers another source of utility in each MSA. Therefore, the lower cost of pollution in the price model is driven by ignoring tract-level benefits that identify an additional tradeoff. In other words, while marginal values are identified by observing tradeoffs between clean air and housing prices, more accurate values must also account for tract-level amenities. The result of higher MWTP in the index models arises due
to the relationship between pollution and tract-level amenities, but is not a general qualitative result for all macro-level public goods. This result can also be interpreted as an omitted variable problem, in which tract-level variations are not included in the choice model.

A further contribution comes in the characterization of moving costs. Previous research has shown the importance of including moving costs in choice models that have a spatial dimension. In this study, I allow for heterogeneity in moving costs. Results suggest a higher cost of moving for households with children. This specification significantly reduces the MWTP for clean air. In a framework with homogeneous moving costs, a portion of these costs are attributed to poor air quality, increasing the MWTP for clean air. Heterogeneity in costs, as well as costly migration in general, further plays a role in the empirical application and simulations that follow.

I use the fully parameterized model to calculate cost of living indices that convey the overall quality of an MSA, characterized by the cost of housing and the set of location-specific public goods. Results suggest significant variation in the cost of living across space. Such findings arise as the spatial nature of the choice set across cities prevents perfect arbitration of public goods. This creates disparities in access to public goods and quality of life. A simple regression analysis offers some support for the expected result that both higher housing prices and higher pollution concentrations increase the cost of living.

COL indices then allow for direct calculation of adjusted income, a broad measure of an individual’s standard of living that incorporates market and non-market goods. While public goods obviously generate some level of benefits for all households, the analysis here is concerned with how such benefits are distributed across the population. A comparison of the adjusted income distribution to the real income distribution demonstrates that the benefits from public goods are disproportionately enjoyed by households at different points in the income distribution. Households at the low end of the income distribution tend to receive fewer benefits from public amenities, creating a larger spread in the distribution of adjusted income.

Simulations analyze the distributional impacts of policy that may reduce pollution con-
centrations. General equilibrium re-sorting ensures that though benefits may be targeted at particular segments of the population, those segments are not the sole beneficiaries of public good improvements. Therefore, in the case of uniform pollution reductions across all cities, there is still an increase in inequality. This phenomenon is also evident from the difference between partial and general equilibrium results. When distributional impacts are a concern to public policy, the geographic targeting of policy becomes an important consideration. Focusing public amenity improvements on locations with higher costs of living tends to decrease inequality in adjusted income. However, this does not necessarily hold for targeting the most polluted areas. Empirical results show that reducing concentrations in the most polluted areas will actually increase inequality. Of course, this is an empirical result that will vary based on the public good of interest and its relationship with COL indices. In general, policies that reduce pollution concentrations provide welfare gains, but distributional impacts are equivalent to considerable monetary transfers from low-income to high-income households.

The work in this dissertation establishes a broad research agenda related to the functional structure of sorting models and the importance of the geographic nature of public amenities. The primary contribution comes in the form of a multi-stage sorting process that can be applied to many other non-market valuation problems. The model discussed here, as well as the empirical application, focus on the macro sorting process and the impact of controlling for micro sorting. However, a great deal of information exists in the developed sorting indices that has yet to be examined. Given a link between micro and macro sorting, future research will explore these indices to further analyze micro sorting and micro-level amenities.

There is also potential for research concerning construction of second stage price indices. Two-stage budgeting theory provides additional ways of developing indices that may offer alternative approaches to modeling two-stage residential sorting. These alternative approaches may depend on the structure of the underlying model or on ideal properties of price indices. Similarly, much of the empirical application in this work relies on the assumption of a nested logit specification. While this does not drive the two-stage nature of the model, considering
other econometric specifications could provide further empirical results.

A final aspect of this dissertation that deserve further attention is the role of moving costs. Moving costs prove to be a considerable part of residential sorting and have significant impacts on empirical results, particularly for questions that consider the means by which public amenities are consumed in equilibrium and following exogenous shocks. Here, they are simply a function of a household’s birth place and coarse measure of family structure. However, true moving costs are likely determined by a complicated function of a number of household attributes. For example, income may be an important determinant of a household’s ability to relocate. This possibility could have sizable impacts on questions related to the distribution of benefits given the spatial variation in public goods.
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A.  Price Aggregation

To prove that the form of the expenditure function in equation (3.7) is necessary and sufficient for price aggregation to hold, I follow Gorman (1965). The proof proceeds in two steps: I first show that a particular utility function satisfies price aggregation and then show that the aforementioned form of the expenditure function is consistent with that utility function.

Recall that price aggregation is defined by the existence of expenditure aggregation function that depend only on total income and price aggregates, as in equation (3.6),

\[ E_g = \Theta^g (I, \Lambda(p)) \quad g = 1, \ldots, G, \]  

where

\[ \Lambda(p) = (\Lambda^1(p), \Lambda^2(p), \ldots, \Lambda^G(p)) . \]  

In addition, \( \Lambda^g(p^g) \) is homogeneous of degree one \( \forall \ g \in G \) (note that the assumption of homogeneity can be generalized to one of homotheticity, in which each \( \Lambda(\cdot) \) can be normalized to be homogeneous of degree one).

Define the indirect utility function corresponding to equation (A-1) as \( u = \phi(I, p) \), where \( I \) is income and \( p \) is the full vector of individual commodity prices. I make the conventional assumption that \( u(\cdot) \) is homogeneous of degree one in \( (I, p) \). Next, define a smooth bijection \( Q : p^g \to (\Lambda^g, q^g) \) where the elements of vector \( q^g \) are homogeneous of degree zero in \( p^g \). Then,

\[ u = \phi(I, p) = \psi(I, \Lambda(p), q(p)). \]  

By Roy’s identity, the demand for good \( i \) is

\[ x_i = -\left( \frac{\partial \psi}{\partial \Lambda^i} \frac{\partial \Lambda^g}{\partial p^g_i} + \sum_{j \in g} \frac{\partial \psi}{\partial q^g_j} \frac{\partial q^g_j}{\partial p^g_i} \right) \frac{\partial \psi}{\partial I} \]  

In addition, since \( u \) (and thus \( \psi \)) is homogeneous of degree one in \( (I, p) \) and \( q^g \) is homoge-
neous of degree zero in $p^g_i$, Euler’s theorem makes clear that

$$E_g = \sum_{j \in g} = -\frac{\partial \psi}{\partial \Lambda^g}$$

(A-5)

In applying Roy’s identity, it is apparent that the ratio of partial derivatives of $\psi$ with respect to $p^g_i$ and $I$ is independent of $q(p)$, implying separability. Therefore, $\psi(\cdot)$ can be written as

$$u = \psi(M, \Lambda(p), q(p)) = \theta(h(I, \Lambda), q(p)) = H(h, p),$$

(A-6)

Since $q^g$ is homogeneous of degree zero in $p^g \forall g$, it follows that $H(\cdot)$ is homogeneous of degree zero in each $p^g$. From (A-6),

$$u = H(h(I, \Lambda(p)), p).$$

(A-7)

Roy’s identity now demonstrates that the demand for good $i$ is

$$x_i = \frac{-\frac{\partial \psi}{\partial h} \frac{\partial \Lambda^g}{\partial p_i^g} + \frac{\partial H}{\partial p_i^g}}{\frac{\partial H}{\partial h} \frac{\partial \Lambda^g}{\partial I}}.$$  

(A-8)

Again, homogeneity restrictions allow for the application of Euler’s theorem, which shows that

$$E_g = \sum_{j \in g} = -\frac{\partial h}{\partial \Lambda^g} = X^g \Lambda^g.$$  

(A-9)

The preceding equation demonstrates that expenditures on group $g$ depend on some price index $\Lambda^g$ and the function $X^g$, which can be interpreted as composite commodity made up of all goods in group $g$. Note that $X^g$ are the composite commodity demands that are obtained from applying Roy’s identity to utility function $u = h(I, \Lambda)$. Therefore, given an indirect utility function $h(\cdot)$ that includes only price aggregates and income, optimal group expenditures are identical to those that arise from indirect utility function $u = \psi(I, \Lambda(p), q(p))$ in equation (A-3).

This proves that $u = \psi(\cdot)$ satisfies price aggregation. Next, I derive the expenditure function
that corresponds to $\psi(\cdot)$, and thus allows for price aggregation.

The utility function in equation (A-7) can be inverted to find a new function $k(\cdot)$,

$$h(I, \Lambda(p)) = k(p, u),$$

(A-10)

where $k$ is homogeneous of degree zero in each $p^g$. Solving for $I$ gives expenditure function

$$E(k(p, u), \Lambda(p)) = M.$$  (A-11)

This is the required form of the expenditure function to satisfy price aggregation. As shown above, $k(p, u) = h(I, \Lambda(p))$ results in demands for composite commodities with prices $\Lambda$. Expenditure function $E(k(p, u), \Lambda(p))$ is equivalent to $E(U, \Lambda)$, the expenditure function from utility maximization in a hypothetical aggregate commodity problem, $\max X U = U(X) \quad s.t. \Lambda X \leq I$.

When $k(u, p) = u$ so that utilities are equal in the full and aggregate utility maximization problems, Gorman (1965) shows that $E(u, \Lambda(p))$ is an admissible cost function in that it is positively homogeneous of degree one and closed concave in $p$.

It has been shown that specific restrictions on the utility function are necessary and sufficient to ensure that the notion of expenditure allocation functions for commodity groups is consistent with utility maximization. Furthermore, the corresponding expenditure function is of a specific form and therefore defines necessary and sufficient conditions under which price aggregation holds.

**B. Decentralisability**

I follow Blackorby et al. (1978) to prove that equation (3.9) is necessary and sufficient for decentralisability. It is first necessary to define a conditional indirect utility function, $V^C(I, P)$. Note that for the following proof, the conditional indirect utility function is defined differently than in previous sections. For the set of goods, $x$, that can be partitioned into $G$ groups,
\[ V^C(E, p) = \max_x (U(x) \mid p^g x^g \leq E_g, \ g = 1, ..., G), \]  

where \( I \) denotes income and \( p \) is the full vector of prices. \( p^g \) and \( x^g \) are the group \( g \) vector of prices and vector of demands, respectively. \( E \) is the vector of optimal group expenditures, \( E_g \) for \( g = 1, ..., G \). The conditional indirect utility function is extremely close to the indirect utility function, except that the former expresses the budget constraint in terms of group expenditures. Note that if only one group exists, \( (G = 1) \), (B-12) becomes the indirect utility function.

Now, consider the problem,

\[ \max_E V^C(E, p) \quad s.t. \sum_{g=1}^{G} E_g < E. \]  

Maximizing over group expenditures results in expenditure allocation functions, \( \Theta^g(I, p) \), that give optimal expenditures as a function of total expenditure (income) and prices, respectively. Of course, \( \Theta^g(I, p) = E_g, \ g = 1, ..., m \). Substituting \( \Theta \) back into the conditional indirect utility function,

\[ V^C(\Theta^1(I, p), ..., \Theta^G(I, p), p) = \max_x (U(x) \mid px \leq I), \]  

produces the indirect utility function that corresponds to the full maximization problem.

To prove that a (continuous, positive monotonic, and strictly quasi-concave) separable utility function is sufficient for decentralizability to hold, I show the existence of group-level demand functions that depend only on intragroup prices and group expenditures and are consistent with utility maximization.

If \( U(X) \) is separable, the conditional indirect utility function becomes

\[ V^C(E, P) = \max_x \left( U(U^1(x^1), ..., U^G(x^G)) \mid p^g x^g \leq E_g, \ g = 1, ..., G \right) \]  

\[ = U \left( \max_{x^1} (U^1(x^1) \mid p^1 x^1 \leq E_1), ..., \max_{x^G} (U^G(x^G) \mid p^G x^G \leq E_G) \right). \]
The full utility maximization problem is now expressed as a function of $G$ different maximization problems, where each sub-maximization requires prices and expenditures only for that particular commodity group. The $G$ solutions are denoted as vector-valued functions $\phi^g(E_g, p^g)$. Then, maximized utility in the above equation can be written as

$$U(\phi^1(E_1, p^1), ..., U^G(\phi^G(E_G, p^G))) .$$

From (B-13) and (B-14), maximization of the conditional indirect utility function yields optimal expenditures, which can be substituted in to give the solution to the full maximization problem. Therefore, using the solution from maximizing (B-17),

$$U(\phi^1(\Theta^1(I, p), p^1), ..., U^G(\phi^G(\Theta^G(I, p), p^G))) = \max_x (U(x) \mid px \leq I) .$$

This final equation establishes the utility maximizing consistency of the group-level demand functions, $\phi^g(E_g, p^g)$, which follow from a separable utility function.

### C. Equilibrium Conditions in Micro Sorting Process

Tract-level fixed effects are obtained from a type-specific sorting model within each MSA. Here, I show that this is consistent with a sorting equilibrium for each MSA in which the sum of the probabilities that each observed individual chooses each location is equal to the supply of housing occupied by that household type. This is evident from first order conditions in maximum likelihood estimation of tract fixed effects. Recall that the probability of a type-$k$ household choosing tract $j$ in MSA $m$ is

$$p_{jm} = \frac{\exp(\delta_j^k)}{\sum_{q \in J_m} \exp(\delta_q^k)} .$$

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where \( J_m \) is the set of tracts in MSA \( m \). Define \( i^k \) as the set of all type-\( k \) individuals. Then, setting the derivative of the log likelihood function with respect to \( \delta^k_j \) equal to 0 gives

\[
\sum_{i^k \in j} \frac{\partial \ln P^k_j}{\partial \delta^k_j} + \sum_{i^k \ni j} \frac{\partial \ln P^k_j}{\partial \delta^k_j} = \sum_{i^k \in j} (1 - P^k_j) + \sum_{i^k \ni j} (-P^k_j) = -\sum_{i^k \in m} P^k_j + \sum_{i^k \in j} 1 = 0.
\]

The supply of housing in the model is proxied for by the number of households in each location, so that \( \sum_{i^k \in j} 1 = S^k_j \) is the supply of housing in tract \( j \) for type-\( k \) households. The second to last line in (C-20) can be interpreted as setting the tract-type supply of housing equal to the sum of probabilities of choosing tract \( j \) across all type-\( k \) households in MSA \( m \). This result holds for all \( j \) tracts in \( m \) and for all MSAs.

### D. Solution for Normalized Fixed Effects

The following demonstrates the closed-form solution for calculating tract fixed effects derived from an effects coding normalization.

Define the share of type \( k \) individuals in tract \( i \) relative to tract \( j \) as

\[
S_{i,j} = \frac{Share^k_i}{Share^k_j},
\]

where \( Share^k_i \) is the population of type \( k \) individuals in tract \( i \) divided by the population of type \( k \) individuals in msa \( m \). These shares need only be defined for tracts in the same MSA. Also note that fixed effects are type specific but an \( k \) notation will be dropped in the subsequent discussion. As discussed in the text, a logit framework allows for tract fixed effects
to be calculated directly from relative shares. Given the connection between observed shares and choice probabilities,

\[ S_{i,j} = \frac{\exp(\delta_i)}{\sum_{q=1}^{J} \exp(\delta_q)} \left( \frac{\exp(\delta_i)}{\sum_{q=1}^{J} \exp(\delta_q)} \right)^{-1} = \frac{\exp(\delta_i)}{\exp(\delta_q)}. \]  

(D-25)

where \( J \) denotes the number of tracts in the MSA. Two important results fall out of equation (D-25):

\[
\begin{align*}
\ln (S_{i,j}) &= \ln (S_{i,x}) + \ln (S_{x,j}) \quad \forall \ x \\
\ln \left( \frac{1}{S_{i,j}} \right) &= \ln (S_{j,i}) = -\ln (S_{i,j}).
\end{align*}
\]

Order all tracts in an MSA from \( j = 1, \ldots, J \) and assume that tract \( J + 1 \) denotes tract 1. From (D-25),

\[
\begin{align*}
\ln (S_{1,2}) &= \delta_1 - \delta_2 \\
\ln (S_{2,3}) &= \delta_2 - \delta_3 \\
\ldots & \ldots \\
\ldots & \ldots \\
\ln (S_{J-1,J}) &= \delta_{J-1} - \delta_J \\
\ln (S_{J,1}) &= \delta_J - \delta_1
\end{align*}
\]

In general, therefore, \( \delta_j = \ln(S_{j,j+1}) + \delta_{j+1} \).
Effects coding restricts the summation of all fixed effects to be zero,

\[ 0 = \sum_{j=1}^{J} \delta_j. \]  \hspace{1cm} (D-26)

Using the above ways of writing the tract fixed effects, iteratively substitute \( \delta_J \) into \( \delta_{J-1} \) and then into \( \delta_{J-2} \) and so on, so that each \( \delta \) is a function of \( \delta_1 \). The respective results for \( \delta_J \) and \( \delta_2 \) are

\[ \delta_J = \ln (S_{J,1}) + \delta_1 \]  \hspace{1cm} (D-27)

\[ \delta_2 = \ln (S_{2,3}) + \ln (S_{3,4}) + ... + \ln (S_{J,1}) + \delta_1. \]  \hspace{1cm} (D-28)

Then, use this result with the effects coding restriction to get

\[ \delta_1 = -\sum_{q \neq 1}^{J-1} \delta_j = -\sum_{q=1}^{J-1} q \ln (S_{q+1,q+2}) - (J - 1)\delta_1 \]  \hspace{1cm} (D-29)

\[ J \ast \delta_1 = -\sum_{q \neq 1}^{J-1} \delta_j = -\sum_{q=1}^{J-1} q \ln (S_{q+1,q+2}). \]  \hspace{1cm} (D-30)

(D-31)

Using \( a \) above,

\[ J \ast \delta_1 = -\sum_{q \neq 1}^{J-1} \delta_j = -\sum_{q=1}^{J-1} q \ast [\ln (S_{q+1,q}) + \ln (S_{1,q+2})]. \]  \hspace{1cm} (D-32)

Distributing the negative sign and using \( b \) above,

\[ J \ast \delta_1 = \sum_{q \neq 1}^{J-1} \delta_j = -\sum_{q=1}^{J-1} q \ast [\ln (S_{1,q+1}) - \ln (S_{1,q+2})]. \]  \hspace{1cm} (D-33)

Noting the repetition of relative shares in the above equation as the summation cycles through \( k \),

\[ J \ast \delta_1 = \sum_{q=1}^{J-1} \ln (S_{1,q+1}) - (J - 1) \ln (S_{1,1}). \]  \hspace{1cm} (D-34)
The final term $S_{1,1}$ is simply 1 so its log is 0 and the final result is,

$$\delta_1 = \frac{1}{J} \sum_{q=1}^{J-1} \ln (S_{1,q+1}).$$  \hspace{1cm} (D-35)

Since tracts were arbitrarily ordered, this holds for every tract. Normalized fixed effects simplify to an average of a tract’s log relative shares.