

Mobility Constraints and the Distributional Consequences of Particulate Matter

by

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Abstract

Wage-hedonic techniques are regularly used to determine willingness-to-pay to avoid environmental disamenities, like those associated with particulate matter and other forms of air pollution. A key assumption underlying these techniques is that individuals face an unconstrained choice over alternative locations. Evidence suggests that this is not the case and that, moreover, certain groups face disproportionate constraints on mobility. This has the potential to skew hedonic measurements toward finding smaller costs of pollution, especially for the immobile (typically disadvantaged) groups. We propose a model of residential sorting that recovers estimates of mobility costs and uses them to correct this source of bias. The model is applied to data from the micro samples of the 1990 and 2000 US Censuses, and the results are used to measure the welfare cost of a marginal increase in PM10. Results show a significant downward bias in WTP calculated with the wage-hedonic technique, particularly for those with less education.

Keywords: Particulate Matter, Mobility Costs, Willingness to Pay, Wage-Hedonics, Residential Sorting, Discrete Choice Models

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1. Introduction

Particulate matter (PM) refers to air pollution comprised of small particles, fine solids, and aerosols that form as a result of activities as diverse as the combustion of fossil fuels, mining, agriculture, construction and demolition, and driving on unpaved roads. While most of the particles resulting from these processes are relatively large in size (i.e., approximately 1/7th the diameter of a human hair), smaller particles result from chemical processes that occur when sulfur dioxide, nitrogen oxides, and volatile organics react with other compounds in the atmosphere. The result is an array of pollutants that carry with them serious health consequences. Beginning with the Harvard Six City Study [Dockery et al (1993)], thousands of analyses have come to the conclusion that atmospheric particulate matter can have serious health consequences. These are most severe for the young and the elderly – especially those suffering from asthma. [Lin et al (2002), Norris et al (1999), Slaughter et al (2003), and Tolbert et al (2000)] Fine particles have been shown to enter the bloodstream, increasing the risk of heart attacks and strokes. [Hong et al (2002), Tsai et al (2003), and D’Ippoliti et al (2003)] Numerous studies have found evidence of lung tissue inflammation [Ghio et al (2000)], reduced lung function in children [Gauderman et al (2002)], increased risk of lung cancer [Pope et al (2002)], and even the possibility of heritable diseases. [Samet et al (2004)]

The adverse health impacts of air pollution (primarily PM10 and ozone) have prompted a wide array of legislative responses at both the state and federal levels over the last thirty years. Evaluated according to simple criteria (i.e., emissions reductions and cost-effectiveness), these policies are generally considered to have been successful. Even so, studies find that over 81 million Americans face unhealthy short-term exposure to PM, while 66 million live with chronically high exposure. [American Lung Association (2004)] This is cause for concern, particularly in light of current legislative efforts that would reduce the capacity of the EPA to regulate certain pollution sources (i.e., old power plants). While most of these legislative efforts arise out of concern for the cost of compliance with EPA regulations, little is known about the size of the benefits. This complicates careful evaluation based on efficiency criteria. Even less is known about the how those benefits are distributed, precluding any discussion of equity. This paper uses a new technique to provide evidence on households’ willingnesses-to-pay (WTP) for reductions in PM pollution, and demonstrates how traditional wage-hedonic techniques are biased against finding benefits amongst the poor and uneducated members of society.

Techniques for Valuing Clean Air

As long as researchers have studied non-market valuation techniques, they have studied individuals’ WTP to avoid air pollution.¹ Most recently, the property value hedonic technique has been applied by Chay and Greenstone (2004) to measure the benefits of PM reductions associated with the Clean Air Act regulations of the 1970’s. A related literature has focused on the distribution of costs and benefits of air pollution

¹ See, for example, Harrison and Rubinfeld (1978), Palmquist (1984), and Ridker and Henning (1967). Smith and Huang (1995) summarize the results of these and other papers.

abatement. [Gianessi, Peskin, and Wolff (1979), Robison (1985)] The emphasis in these papers, however, is on how abatement costs are passed on to different types of households depending upon their consumption patterns, while the benefits of pollution reduction are assumed to be allocated in proportion to population density. More recently, the literature on environmental justice has examined the location decisions of pollution-generating firms relative to the geographic distribution of certain types of people (i.e., the poor and minorities), focusing either on their distribution at the time of siting [Wolverton (2002)], or after households have had time to react to those siting decisions. [US GAO (1983), UCC (1987)] While providing careful discussions of the determinants of facility location (i.e., *exposure* heterogeneity), these papers do not address the question of how WTP's to avoid pollution differ amongst different types of people (i.e., *benefit* heterogeneity).

Hedonic techniques (property value, wage-hedonic) take as a starting point the idea that individuals optimally sort over locations (e.g., houses in the context of property value hedonics, or cities in wage-hedonics). In equilibrium, the hedonic gradient – i.e., the derivative of the housing price (and wage) with respect to the amenity in question – reveals the decision-maker's marginal WTP for that amenity. PM concentrations vary significantly across cities, making wage-hedonics the appropriate technique for measuring value by looking at compensating differentials in both the labor and housing markets. Considering households' choices of cities, however, an important assumption underlying the wage-hedonic model becomes implausible. In particular, households face mobility costs. A cursory inspection of the data reveals that a significant fraction of individuals do not leave the state in which they were born, and even more do not leave the region.² Tables 1 (a) and (b) report regional long-run migration patterns based on 2000 US Census data. They show a significant fraction of household heads residing in the region of their birth (i.e., large entries on the diagonal of each panel). Moreover, this tendency is even stronger for those with less education, as is evidenced by comparing panel (a) (i.e., high school dropouts and graduates) with panel (b) (i.e., those with some college or college graduates). Table 2 re-emphasizes this point, reporting the results of a Probit estimation of a dummy variable for having stayed in one's birth state on individual attributes. Those with less education, Blacks, and female household heads are more likely to have done so.³

These data suggest that equally including all possible locations in a household's choice set is inappropriate, yet this assumption is an important part of the equilibrium underlying wage-hedonic valuation. How might this matter in the marginal valuation of particulate matter reductions? Suppose a disproportionate share of household heads were born in a region of the US where PM concentrations are high (e.g., the Northeast US), and that migration costs prevent many of them from leaving that region. The naïve wage-hedonic model, ignoring constraints on mobility, would interpret this as evidence that PM

² An alternative interpretation of this finding is that individuals simply have an idiosyncratic preference for the state and/or region in which they were born. This interpretation and that based on mobility costs (i.e., disutility of moving far from one's birth place) are both consistent with the model presented below.

³ College graduate, Asian, male household heads are the excluded group in this regression. All parameter estimates can be evaluated relative to that group.

is less disagreeable than it is in reality. This source of bias, moreover, will be more severe for the household heads who face greater mobility costs. In practice, wage-hedonic estimates of marginal WTP would understate the benefits of pollution reductions, especially for these groups.

The wage-hedonic technique uses only the information in the observed equilibrium of the residential sorting process of households over locations. In order to overcome this source of bias, the modeling strategy needs to be extended back to the location decisions themselves. Only then can mobility costs be recovered and accounted for in measuring WTP. The model outlined in this paper does just that, recovering estimates of a long-run measure of migration costs based on the disutility of settling far from one's birthplace.

This paper proceeds as follows. The next section derives a simple model of household sorting across US metropolitan statistical areas. Section 3 derives the traditional wage-hedonic model from the same underlying utility maximization problem (but ignoring mobility costs). Section 4 describes the data sources we use to identify both models, and reports parameter estimates for each. That section goes on to use those estimates to derive the value of a marginal change in particulate matter according to each model, and demonstrates the bias inherent in ignoring mobility constraints. Section 5 concludes and discusses some extensions to this preliminary research.

2. Model: Household Residential Sorting

We outline here a model of residential sorting of households across locations (e.g., US Metropolitan Statistical Areas). The model begins with the specification of the utility a household i of type k receives from living in location j :

$$(1) \quad U_{i,j,k} = C_{i,k}^{b_{C,k}} H_{i,k}^{b_{H,k}} e^{f(M_{i,j,k}; b_{M,k}) + b_{X,k} X_j + \mathbf{x}_{j,k}}$$

where

- $C_{i,k}$ = household i 's consumption of numeraire composite commodity
- $H_{i,k}$ = household i 's consumption of housing services
- $M_{i,j,k}$ = household i 's long-run migration distance associated with location j
- X_j = observable attributes of location j (including PM pollution)
- $\mathbf{x}_{j,k}$ = unobserved attributes of location j (varies with household type k)

Type may refer to household attributes like race, sex, and education of the household head, number of children, and the presence of an elderly adult. In the current application, we define type according to two levels of education – (i) high school dropouts and graduates, and (ii) those with some college training and college graduates. Extending this model to a richer specification of types is the first extension to be considered.

Utility maximization in sorting models of this sort proceeds in two stages: (i) optimal location choice, and (ii) optimal disposition of income over $H_{i,k}$ and $C_{i,k}$ conditional upon that choice. Working backwards, we begin with the optimal allocation of income subject to a budget constraint.

$$(2) \quad \max_{\{C_{i,k}, H_{i,k}\}} U_{i,j,k} = C_{i,k}^{\mathbf{b}_{C,k}} H_{i,k}^{\mathbf{b}_{H,k}} e^{f(M_{i,j,k}; \mathbf{b}_{M,k}) + \mathbf{b}_{X,k} X_j + \mathbf{x}_{j,k}} \quad s.t. \quad C_{i,k} + \mathbf{r}_j H_{i,k} = I_{i,j,k}$$

\mathbf{r}_j represents the price of a unit of housing services in location j . Housing services (and their prices) are not readily observed magnitudes, but can be imputed from data on observed rents or house values and housing attributes, given a suitable functional form assumption. Given a vector of characteristics of the dwelling inhabited by household i ($h_{i,k}$), a dummy variable $\mathbf{W}_{i,k} = 1$ if that home is owned ($= 0$ if it is rented), and a house price variable $P_{i,j,k}$ that represents either house value (if $\mathbf{W}_{i,k} = 1$) or monthly rent (if $\mathbf{W}_{i,k} = 0$), we recover the price of housing services in each location, \mathbf{r}_j , from the following regression:

$$(3) \quad \ln P_{i,j,k} = \ln \mathbf{r}_j + \mathbf{I} \mathbf{W}_{i,k} + h'_{i,k} \mathbf{j} + \mathbf{e}_{i,j,k}^H$$

where \mathbf{I} measures the premium on owned housing (i.e., making monthly rents comparable to housing values), $H_{i,k} = \text{EXP}[h'_{i,k} \mathbf{j}]$ serves as our housing services index, and location specific intercepts provide us with estimates of $\ln \mathbf{r}_j$.

Incorporating the budget constraint into the utility function:

$$(4) \quad \ln U_{i,j,k} = \mathbf{b}_{C,k} \ln(I_{i,j,k} - \mathbf{r}_j H_{i,k}) + \mathbf{b}_{H,k} \ln H_{i,k} + f(M_{i,j,k}; \mathbf{b}_{M,k}) + \mathbf{b}_{X,k} X_j + \mathbf{x}_{j,k}$$

and differentiating with respect to $H_{i,k}$ yields the following first-order condition:

$$(5) \quad -\frac{\mathbf{b}_{C,k} \mathbf{r}_j}{I_{i,j,k} - \mathbf{r}_j H_{i,k}} + \frac{\mathbf{b}_{H,k}}{H_{i,k}} = 0$$

After some manipulation, we recover an expression for household i 's optimal consumption of housing services conditional upon choosing to live in location j :

$$(6) \quad H_{i,j,k}^* = \frac{\mathbf{b}_{H,k}}{\mathbf{b}_{H,k} + \mathbf{b}_{C,k}} \frac{I_{i,j,k}}{\mathbf{r}_j}$$

Incorporating (6) back into (4) provides an indirect utility function that can be taken directly to household i 's location choice decision:

$$(7) \quad \ln V_{i,j,k} = \mathbf{b}_{I,k} \ln I_{i,j,k} + f(M_{i,j,k}; \mathbf{b}_{M,k}) + \mathbf{q}_{j,k}$$

where

$$(8) \quad \mathbf{q}_{j,k} = B_{0,k} + \mathbf{b}_{H,k} \ln \mathbf{r}_j + \mathbf{b}_{X,k} X_j + \mathbf{x}_{j,k}$$

is a composite of the utility effects of all local attributes that are common to households of a particular type, and

$$(9) \quad B_{0,k} = \ln \mathbf{b}_{0,k} + \mathbf{b}_{C,k} \ln \mathbf{b}_{C,k} + \mathbf{b}_{H,k} \ln \mathbf{b}_{H,k} - (\mathbf{b}_{C,k} + \mathbf{b}_{H,k}) \ln(\mathbf{b}_{C,k} + \mathbf{b}_{H,k})$$

$$(10) \quad \mathbf{b}_{I,k} = \mathbf{b}_{C,k} + \mathbf{b}_{H,k}$$

Modeling Household Location Choice

We now use equation (7) to model the household's choice of location. In making this decision, households trade-off income earning opportunities ($I_{i,j,k}$) versus the price of housing services (\mathbf{r}_j) and other local attributes ($\mathbf{q}_{j,k}$) in each location. Additionally, $f(M_{i,j,k}; \mathbf{b}_{M,k})$, the (dis)utility of migration distance, plays a critical role in their decisions and in our analysis. Our goal is to demonstrate how hedonic valuation of marginal improvements in air quality may be biased if one assumes that households treat every MSA as an equally viable alternative in their location choice set. Based on the tables shown above, this looks to be a particularly poor assumption – households tend to settle closer to where the household head was born. We capture this feature of the data with two dummy variables, $d_{i,j,k}^{M1} = 1$ if location j is outside the state in which the household head was born, and $d_{i,j,k}^{M2} = 1$ if location j is outside the birth region.^{4,5}

$$(11) \quad f(M_{i,j,k}; \mathbf{b}_{M,k}) = -\mathbf{b}_{M1,k} d_{i,j,k}^{M1} - \mathbf{b}_{M2,k} d_{i,j,k}^{M2}$$

It is not possible to observe the income that each individual would earn in every location, but rather only that which he earns in the location where he actually resides. In the micro-data used for estimation, however, many other observationally similar household heads are found living in other locations, and we are able to observe their

⁴ We use the same regional definitions employed in Table 1.

⁵ Aside from helping to describe a salient feature of the data, including migration costs plays an important role in econometrically identifying this class of sorting models. In particular, they cause decision-makers to have different perceptions of alternatives in a choice set that are otherwise identical. Identifying discrete choice models of the sort used here without relying exclusively on functional form assumptions depends upon seeing similar decision-makers being confronted with different choice sets. Observing how similar individuals respond in different market situations tells us something about their substitution patterns – i.e., their willingness to trade-off different local attributes for one another. It is from these substitution patterns that a discrete choice model infers preference parameters. In many applications (e.g., individuals sorting across all the counties in a country) it is difficult to achieve explicit cross-market variation – one would need to use data from many different countries in the same regression. Local attributes that differ with the individual (like proximity to one's birth location), however, provide the same effective source of variation in the choice set (for the purposes of identification) and can do so in a single cross-section of data.

incomes. From these data, we can impute the income each individual would earn in every location with a series of location-specific regressions of incomes on a set of individual attributes s that contain k as a subset:

$$(12) \quad \ln I_{i,j,k} = \mathbf{a}_{0,j} + \mathbf{a}_{\text{WHITE},j} \text{WHITE}_{i,k} + \mathbf{a}_{\text{MALE},j} \text{MALE}_{i,k} + \\ \mathbf{a}_{\text{AGE} > 60,j} \text{AGE} > 60_{i,k} + \mathbf{a}_{\text{HSDROP},j} \text{HSDROP}_{i,k} + \mathbf{a}_{\text{HSGRAD},j} \text{HSGRAD}_{i,k} \\ + \mathbf{a}_{\text{SOMECOLL},j} \text{SOMECOLL}_{i,k} + \mathbf{a}_{\text{COLLGRAD},j} \text{COLLGRAD}_{i,k} + \mathbf{e}_{i,j,k}^I$$

We can then split $I_{i,j,k}$ into a type-specific component fitted with the output of these regressions ($\hat{I}_{j,s}$) and an idiosyncratic error ($\mathbf{e}_{i,j,k}^I$). The resulting indirect utility function for individual i (type $k \subset s$) in location j can be written as:

$$(13) \quad \ln V_{i,j,k} = \mathbf{b}_{l,k} \ln \hat{I}_{j,s} - \mathbf{b}_{M1,k} d_{i,j,k}^{M1} - \mathbf{b}_{M2,k} d_{i,j,k}^{M2} + \mathbf{q}_{j,k} + \mathbf{b}_{l,k} \mathbf{e}_{i,j,k}^I$$

Owing to its computational tractability, the conditional logit model conveniently describes the household's indirect utility maximizing choice of location. $\mathbf{e}_{i,j,k}^I$ is therefore assumed to be distributed i.i.d. Type-I Extreme Value. The familiar Independence of Irrelevant Alternatives property associated with this distributional assumption holds within types, but not in the aggregate, further motivating a richer type specification in model extensions. The parameters of the conditional logit model are only identified relative to the variance of $\mathbf{e}_{i,j,k}^I$. We therefore divide through the log indirect utility function by $\mathbf{b}_{l,k}$ (i.e., a monotonic transformation that does not affect marginal rates of substitution), yielding:

$$(14) \quad \ln \tilde{V}_{i,j,k} = \ln \hat{I}_{j,s} - \tilde{\mathbf{b}}_{M1,k} d_{i,j,k}^{M1} - \tilde{\mathbf{b}}_{M2,k} d_{i,j,k}^{M2} + \tilde{\mathbf{q}}_{j,k} + \mathbf{e}_{i,j,k}^I$$

where, for example, $\tilde{\mathbf{b}}_{M1,k} = \mathbf{b}_{M1,k} / \mathbf{b}_{l,k}$. This implies the following probability that a type- k individual will choose to reside in location j :

$$(15) \quad P(\ln \tilde{V}_{i,j,k} \geq \ln \tilde{V}_{i,l,k} \quad \forall l \neq j) = \frac{e^{\ln \hat{I}_{j,s} - \tilde{\mathbf{b}}_{M1,k} d_{i,j,k}^{M1} - \tilde{\mathbf{b}}_{M2,k} d_{i,j,k}^{M2} + \tilde{\mathbf{q}}_{j,k}}}{\sum_{q=1}^J e^{\ln \hat{I}_{q,s} - \tilde{\mathbf{b}}_{M1,k} d_{i,q,k}^{M1} - \tilde{\mathbf{b}}_{M2,k} d_{i,q,k}^{M2} + \tilde{\mathbf{q}}_{q,k}}}$$

With the number of type- k individuals (N_k) sufficiently large to rule-out integer problems, their equilibrium population in location j will be given by:

$$(16) \quad \text{pop}_{j,k} = N_k P(\ln \tilde{V}_{i,j,k} \geq \ln \tilde{V}_{i,l,k} \quad \forall l \neq j)$$

and the share of the type- k population in location j is:

$$(17) \quad s_{j,k} = \frac{POP_{j,k}}{\sum_{q=1}^J POP_{q,k}}$$

The parameter vector $\{\tilde{\mathbf{b}}_{M1,k}, \tilde{\mathbf{b}}_{M2,k}, \tilde{\mathbf{Q}}_k\}$ can then be recovered by maximizing the type-specific likelihood function:

$$(18) \quad L_k(\tilde{\mathbf{b}}_{M1,k}, \tilde{\mathbf{b}}_{M2,k}, \tilde{\mathbf{Q}}_k) = \prod_{i \in k} [P(\ln \tilde{V}_{i,j,k} \geq \ln \tilde{V}_{i,l,k} \quad \forall l \neq j)]^{c_{i,j,k}}$$

where $c_{i,j,k} = 1$ if household i chooses location j ($= 0$ otherwise). In practice, when the choice-set is large (as in the application we consider here), estimating the full vector $\tilde{\mathbf{Q}}_k$ by maximum likelihood can be computationally prohibitive. Berry (1994) provides a computational algorithm whereby these values are imputed indirectly.⁶

Having estimated the vector of parameters $\{\tilde{\mathbf{b}}_{M1,k}, \tilde{\mathbf{b}}_{M2,k}, \tilde{\mathbf{Q}}_k\}$, the remaining preference parameters can be recovered by decomposing the local fixed effects $\tilde{\mathbf{Q}}_k$ into their component parts.

$$(19) \quad \begin{aligned} \tilde{\mathbf{q}}_{j,1} &= \tilde{B}_{0,1} - \tilde{\mathbf{b}}_{H,1} \ln \mathbf{r}_j + \tilde{\mathbf{b}}_{X,1} X_j + \tilde{\mathbf{x}}_{j,1} \\ \tilde{\mathbf{q}}_{j,2} &= \tilde{B}_{0,2} - \tilde{\mathbf{b}}_{H,2} \ln \mathbf{r}_j + \tilde{\mathbf{b}}_{X,2} X_j + \tilde{\mathbf{x}}_{j,2} \\ &\vdots \\ \tilde{\mathbf{q}}_{j,K} &= \tilde{B}_{0,K} - \tilde{\mathbf{b}}_{H,K} \ln \mathbf{r}_j + \tilde{\mathbf{b}}_{X,K} X_j + \tilde{\mathbf{x}}_{j,K} \end{aligned}$$

In practice, (19) represents a K -dimensional system of regression equations, where the unobserved local attributes $\tilde{\mathbf{x}}_{j,k}$ serve as regression errors. A pervasive problem in hedonic analyses is that these unobservable local attributes are likely correlated with the observable attributes X_j , leading to omitted variables bias in the estimation of this system. This is a difficult problem to correct, and we resort to panel data for the solution. In particular, we can recover different sets of $\tilde{\mathbf{Q}}_k$ using micro-data from the 1990 and 2000

⁶ A contraction mapping based on equations (16) and (17) can be used to generate values of $\tilde{\mathbf{Q}}_k$ that match observed to predicted population shares given a vector of values for the remaining parameters $\{\tilde{\mathbf{b}}_{M1,k}, \tilde{\mathbf{b}}_{M2,k}\}$. The algorithm (i) guesses at a value of these two parameters, (ii) calculates the corresponding vector $\tilde{\mathbf{Q}}_k$, (iii) calculates the likelihood for the full vector of parameters, and (iv) selects new values of $\{\tilde{\mathbf{b}}_{M1,k}, \tilde{\mathbf{b}}_{M2,k}\}$ that increase the likelihood function. The procedure repeats until the likelihood function is maximized.

US population censuses. We can then estimate the effect of PM on utility from a system of differenced regressions.⁷

$$(20) \quad \begin{aligned} \tilde{\mathbf{D}}\mathbf{q}_{j,1} &= \tilde{\mathbf{b}}_{q,1} - \tilde{\mathbf{b}}_{H,1}\mathbf{D}\ln \mathbf{r}_j + \tilde{\mathbf{b}}_{PM,1}\mathbf{D}PM_j + u_{j,1} \\ \tilde{\mathbf{D}}\mathbf{q}_{j,2} &= \tilde{\mathbf{b}}_{q,2} - \tilde{\mathbf{b}}_{H,2}\mathbf{D}\ln \mathbf{r}_j + \tilde{\mathbf{b}}_{PM,2}\mathbf{D}PM_j + u_{j,2} \\ &\vdots \\ \tilde{\mathbf{D}}\mathbf{q}_{j,K} &= \tilde{\mathbf{b}}_{q,K} - \tilde{\mathbf{b}}_{H,K}\mathbf{D}\ln \mathbf{r}_j + \tilde{\mathbf{b}}_{PM,K}\mathbf{D}PM_j + u_{j,K} \end{aligned}$$

where $\tilde{\mathbf{b}}_{q,k}$ is included to account for differences in the arbitrary normalizations undertaken in recovering the vector of fixed effects in each year (as well as the average of any other factors that change over the course of the 1990's), and $u_{j,k}$ is the time varying component of the unobservables $\tilde{\mathbf{x}}_{j,k}$. Because one might still be concerned about the potential for correlation between $u_{j,k}$ and ΔPM_j ,⁸ we are currently working on approaches to instrument for the latter with the average change in particulate matter in nearby locations over the same time period ($\Delta PM_{.j}$). Scientific evidence suggests that a great deal of the air pollution (both PM and ozone) in a city is the result of polluting activities hundreds of miles away, meaning that pollution concentrations in other cities $-j$ should be good predictors of pollution in city j , while not being caused by $u_{j,k}$.⁹ Similar concerns, also requiring instrumental variables solutions, might be raised regarding $\Delta \ln \mathbf{r}_j$.

With these estimates, we are now in a position to calculate the individual's marginal willingness to pay for a marginal reduction in PM pollution. Typically, this takes the form of a marginal rate of substitution – i.e., the amount of numeraire commodity the household would be willing to forego in exchange for a one-unit increase in PM while remaining at the same level of utility:

$$(21) \quad \frac{\mathcal{M}V_{i,j,k} / \mathcal{M}PM_j}{\mathcal{M}V_{i,j,k} / \mathcal{M}I_{i,j,k}} = \tilde{\mathbf{b}}_{PM,k} I_{i,j,k}$$

Because we expect $\tilde{\mathbf{b}}_{PM,k} < 0$, this expression should take on a negative value (i.e., a marginal willingness to pay to avoid a marginal increase in PM). We now derive the

⁷ Note that, while we assume that other local attributes X_j are held constant, we have accounted for changes over the decade of the 1990's in the spatial distribution of both incomes and prices of housing. This should control for many of the most important non-pollution changes in each location over the time period.

⁸ Suppose, for example, that $u_{j,k}$ includes the effects of an economic recession that hits location j . While these are generally undesirable, they may also be correlated with reductions in PM pollution from reduced economic activity, biasing down the estimate of $\tilde{\mathbf{b}}_{PM,k}$.

⁹ In work currently underway, we are exploring alternative instrumenting strategies for PM concentrations. These are further described in the conclusion.

comparable expression associated with the traditional wage-hedonic technique, which is based on the underlying assumption of perfect mobility.

3. Model: Wage-Hedonics

The typical wage-hedonic approach to valuing amenities like clean air can be summarized in the context of the same behavioral equations described in the previous section. We begin by writing down a more general form of the household's constrained utility maximization problem:

$$(22) \quad \max_{\{C_{i,k}, H_{i,k}, X_j\}} U(C_{i,k}, H_{i,k}, X_j) \quad s.t. \quad C_{i,k} + \mathbf{r}_j(X_j)H_{i,k} = I_{i,j,k}(X_j)$$

We denote \mathbf{r}_j and $I_{i,j,k}$ as functions of local attributes X_j , because prices and incomes vary spatially, and because the household's spatial location decision is equivalent to choosing a value of X_j . In contrast to the discrete choice model used above to describe residential sorting, the hedonic model assumes that the choice set is dense in X_j . Constrained maximization then yields the following first-order conditions:

$$(23) \quad \begin{aligned} \frac{\mathcal{U}_{i,j,k}}{\mathcal{X}_j} + \mathbf{d}_{i,k} \left(\frac{\mathcal{U}_{i,j,k}}{\mathcal{X}_j} - H_{i,k} \frac{\mathcal{r}_j}{\mathcal{X}_j} \right) &= 0 \\ \frac{\mathcal{U}_{i,j,k}}{\mathcal{C}_{i,k}} - \mathbf{d}_{i,k} &= 0 \\ \frac{\mathcal{U}_{i,j,k}}{\mathcal{H}_{i,k}} - \mathbf{d}_{i,k} \mathbf{r}_j(X_j) &= 0 \end{aligned}$$

where $\mathbf{d}_{i,k}$ represents household i 's Lagrange multiplier on its income constraint. The first and second first-order conditions together imply a function for the MRS between a local attribute (X_j) and numeraire consumption:

$$(24) \quad \frac{\mathcal{U}_{i,j,k} / \mathcal{X}_j}{\mathcal{U}_{i,j,k} / \mathcal{C}_{i,k}} = H_{i,k} \frac{\mathcal{r}_j}{\mathcal{X}_j} - \frac{\mathcal{U}_{i,j,k}}{\mathcal{X}_j}$$

This is the traditional wage-hedonic measure of the marginal WTP for X_j .

Equation (3), which was used in the previous section to impute the price of housing services (\mathbf{r}_j) and the housing services index (H_i), can be employed along with the set of income equations described in (12) to calculate (24). First, we regress changes in estimates of $\ln \mathbf{r}_j$ on changes in $\ln PM$ over the course of the 1990's (i.e., controlling for all other determinants that do not vary over time, but which might be correlated with PM in the cross-section):

$$(25) \quad \mathbf{Dln} \mathbf{r}_j = \mathbf{g}_r \mathbf{Dln} PM_j + \mathbf{e}_j^r$$

We use the estimated housing index parameters to impute values of $H_{i,k}$ for each household according to $H_{i,k} = EXP[h'_{i,k} \mathbf{j}]$. We similarly carry out a differenced regression on the natural log of the intercept parameter from the MSA-specific income regressions described in (12) using both 1990 and 2000 data:

$$(26) \quad \mathbf{Dln} \mathbf{a}_{0,j} = \mathbf{g}_{a,0} + \mathbf{g}_{a,PM} \mathbf{Dln} PM_j + \mathbf{e}_{i,j,k}^{a,0}$$

The fit of this estimation was greatly improved by including a constant ($\mathbf{g}_{a,0}$) to control for the average shift in log incomes (over and above that caused by changing PM) over the course of the 1990's.

With the parameter estimates from equations (25) and (26), we are in a position to calculate all of the derivatives in equation (24) and to report the WTP to avoid a marginal increase in PM pollution for each individual in the sample. We do so in the following section after briefly describing the data.

4. Data and Results

Data

The data used for this analysis come from two sources: (i) the 1% and 5% micro data samples of the 1990 and 2000 US Population Censuses, respectively, and (ii) EPA pollution monitoring data. The census data are publicly available at <http://www.ipums.org>, and describe attributes of the household head along with the household's composition. We treat the household head as the decision-maker, and focus on his/her attributes, along with those of the dwelling in which the household resides. Table 3 describes the key census variables used in the analysis. Households are included if residing in one of 276 MSA's that we use as our choice set. We calculate migration variables from data describing the household's current state of residence (STATE) and its state of birth (BPL). Regional definitions are the same as those used in Table 1.

The EPA's pollution monitoring data were taken from the 1999 National Air Quality and Emissions Trends Report. [US EPA (2001)] These data describe concentrations of PM10, SO₂, O₃, NO₂, CO, and Pb for each MSA for the years 1990 – 1999. Many pollutants are missing for many cities, but PM10 has by far the broadest coverage – i.e., 169 of the census MSA's for the full time-period. Moreover PM10 concentrations are reported both in average annual concentrations and 90th percentiles of the distribution of highest second maximum 24-hour concentration. We use the latter. This set of 169 cities acts as our sample for all of the second-stage regressions in which differences in $\ln PM$ concentrations are used as the explanatory variable. Figure 1

describes the minimum, maximum, 25th and 75th percentiles, and median concentration each year for this sample of cities between 1990 and 1999.

Estimation Results

We first carry-out the income and housing price regressions described in equations (3) and (12) for each year of census data (using the full 1% and 5% samples, respectively). Table 4 summarizes the results of 276 separate income regressions. Table 5 reports the results of the housing index regressions (i.e., ownership premium and housing index parameters), and Table 6 lists the top and bottom five MSA's in each year in terms of their prices of housing services. Results are as expected, with an income premium evident for Whites, males, those under the age of 60 (i.e., not retired), and for those with more education. Bigger, newer houses yield more housing services, as do houses on larger plots and with complete kitchen and plumbing facilities. An inspection of the five most and least expensive cities in the US, in terms of the price of housing services, corresponds to conventional wisdom.

We now come the estimation of the mobility cost parameters underlying the residential sorting model described in Section 2. If preferences are stable over time, we should estimate a single set of behavioral parameters $\{\tilde{\mathbf{b}}_{M1,k}, \tilde{\mathbf{b}}_{M2,k}\}$ for both years 1990 and 2000. Ideally, this would be done by pooling the data and imposing parameter restrictions across years. In the current application, we use only data from the 2000 census to estimate these parameters, and then impose their values on the 1990 data in recovering estimates of $\tilde{\mathbf{Q}}_k$ for that year. Table 7 reports the results of the first stage maximum likelihood estimation of the utility function parameters based on the 2000 data. Estimates are statistically significant and have the expected sign – i.e., increasing migration distance is increasingly undesirable (although at a decreasing rate).

For the current application, we are primarily interested in the remaining first-stage parameter estimates – the vector of local fixed effects $\tilde{\mathbf{Q}}_k$, separately recovered for each year. For the sake of brevity, we do not report all of these estimates, but instead go straight to the regression of the change in $\tilde{\mathbf{Q}}_k$ on the change in PM concentration and $\ln \mathbf{r}_j$. Results are reported in the first six rows of Table 8, and show evidence of disutility from increasing PM concentrations for both the group of high school dropouts and graduates ($\tilde{\mathbf{b}}_{PM,HS}$) and those with some college training and college graduates ($\tilde{\mathbf{b}}_{PM,COLL}$). The remaining three rows of Table 8 report the results of regressions describing the effect of changing PM concentrations on the price of housing services ($\ln \mathbf{r}_j$) and on the intercept of the location-specific income equations ($\mathbf{a}_{0,j}$). Corresponding to the predictions of wage-hedonic theory, the price of housing services falls with increasing PM concentrations, while the effect of PM on income is positive. Several of the estimation results are, however, not overwhelmingly statistically significant. The two least significant parameters, $\tilde{\mathbf{b}}_{PM,COLL}$ and \mathbf{g}_{PM} , have p-values of

0.238 and 0.216 respectively. The most direct solution to this problem would be to expand the coverage of the PM data beyond the relatively small set of 169 cities that we are currently using, to incorporate pollution data for more years (i.e., 1980-2000), or to switch to a completely different pollutant with broader coverage. These estimates may also improve, however, with instruments for ΔPM and $\Delta \ln r$; as the likely direction of the bias from failing to instrument for these variables is towards zero.

For the sake of comparison, we also include in Table 8 the second-stage parameter estimates based on 2000 cross-sectional data (i.e., not controlling for time invariant unobservable local attributes that may be correlated with PM). Because PM generally accompanies economic activity, which people find valuable but for which we do not have good descriptive data, the usual bias in this sort of regression is to understate the costs of pollution. Indeed, using cross-sectional data, the sorting model yields positive values for PM and the costs implied by the wage-hedonic model are much smaller. Using data from 1990 and 2000 to control for time invariant unobservables therefore appears to handle for much of this source of bias, but continued efforts towards instruments for $\Delta \ln PM$ are merited.

Marginal Willingness to Pay

We now consider the aggregation of wage and housing price effects in Table 9, where we report average WTP for a marginal increase in PM for a sample of 7580 households drawn randomly from the 2000 Census. WTP's are calculated both according to the wage-hedonic model as well as according to the residential sorting model. We have tried to minimize the differences in the underlying structures of the two models, so that differences in valuations can be attributed primarily to the fact that the wage-hedonic model fails to account for the disutility of migration. Note, however, that the wage hedonic estimates might also be biased if the choice set is sparse – i.e., households are not able to zero the derivative of their utility with respect to local attributes X_j . The sorting model, using discrete-choice apparatus, relaxes this assumption and assumes only that households choose the best location from the set of available options

Results suggest that the wage-hedonic technique consistently understates households' WTP to avoid a marginal increase in PM (treating the household sorting model as correct). Across all household types, the wage-hedonic model predicts that households would be willing to pay 0.25% of their income to avoid a 1-unit increase in PM (elasticity = 0.10), while the sorting model predicts a WTP of 0.38% (elasticity = 0.16). Table 10 reports the results of three regressions that describe how the tendency for the wage-hedonic technique to understate WTP varies according to type. If the hypothesized role of mobility costs is correct, we should expect to see this difference be greater for more mobility-constrained groups. The regressions in Table 10 use $\ln(WTP_{\text{wage-hedonic}}) - \ln(WTP_{\text{residential-sorting}})$ as the dependent variable. Results imply that $WTP_{\text{wage-hedonic}}$ is, on average, 94% of $WTP_{\text{residential-sorting}}$ for those with college degrees or some college training, while it is only 45% for high school graduates and dropouts. This difference is, moreover, highly statistically significant. Similarly, for races other than

Blacks, $WTP_{\text{wage-hedonics}}$ is, on average, 70% of $WTP_{\text{household-sorting}}$, while for Whites, it is 65%. Differences for female household heads are much smaller, but still statistically significant. These results cast doubt on the ability of traditional wage-hedonic estimates to provide adequate measurements of benefits for use in determining the efficiency of environmental policies, and raise even greater concerns about their ability to adequately describe the distributional consequences of pollution abatement.

5. Conclusions and Extensions

Uninhibited mobility is a crucial assumption underlying hedonic non-market valuation techniques. These techniques may therefore be subject to biases when decision-makers face constraints in their choice of location, housing unit, etc.... Moreover, when those constraints differ with socio-economic status, the biases they induce will vary along those lines as well. This paper demonstrates that there is a strong tendency for certain groups (especially the less educated and minorities) to exhibit less geographic mobility over the course of their lives. With a simple model of residential sorting that incorporates mobility costs, the paper then shows that traditional wage-hedonic models have a tendency to understate willingness-to-pay, particularly for those immobile groups, and that this problem can be corrected by modeling the full sorting process, including mobility constraints. This has important implications for the way in which we evaluate the efficiency and distributional consequences of pollution abatement policies.

The most obvious ways to extend the analysis in this paper are to allow for a greater degree of heterogeneity in the utility function specification, and to efficiently use data from both the 1990 and 2000 censuses in recovering first-stage utility function parameters in the sorting model. Particularly important for the former would be differentiating households based on factors that put them more or less at risk from PM pollution (e.g., the presence of young children or elderly adults). US Census data readily allow for the inclusion of young children in the specification of household type. We also plan to explore a number of alternative strategies for instrumenting for changes in particulate matter concentration and in the price of housing services.¹⁰ The choice of instrument can have important implications for estimated parameter values, and subsequently, imputed WTP, so it should be made with care.

¹⁰ In addition to the approach proposed in the paper, another strategy currently being explored is to use data on power plants' inputs in conjunction with atmospheric circulation models to derive an exogenous determinant of each MSA's PM concentration. This work is joint with Nat Keohane of the Yale School of Management.

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Figure 1
Median, IQ Range, and Min/Max
PM Concentrations

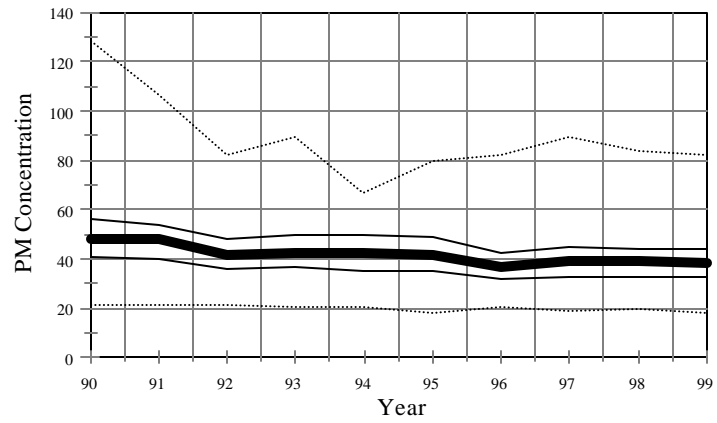


Table 1 – Regional Mobility Patterns¹¹¹²
 % Birth Region by Residence Region, 2000 US Census Data

(a) High-School Graduates and Dropouts

	New England	Mid-Atlantic	East N. Central	West N. Central	South Atlantic	East S. Central	West S. Central	Mountain	Pacific
New England	69.19	4.65	1.47	1.22	14.91	0.49	0.24	1.47	6.36
Mid-Atlantic	1.39	76.19	2.51	0.32	13.27	0.32	0.96	1.66	3.37
East N. Central	0.13	1.24	78.07	1.37	8.26	0.72	2.28	3.12	4.81
West N. Central	0.55	0.74	6.84	56.01	5.18	0.55	5.36	8.87	15.90
South Atlantic	1.22	7.55	4.46	0.72	80.01	1.87	1.87	0.58	1.73
East S. Central	0.48	2.57	21.19	1.77	11.88	52.97	4.33	1.61	3.21
West S. Central	0.11	0.89	4.58	2.46	3.13	1.68	72.74	3.58	10.84
Mountain	0.38	0.76	3.05	1.91	1.91	0.76	4.20	66.79	20.23
Pacific	0.13	0.42	1.39	0.97	3.32	0.83	3.32	7.34	82.27

(b) Some College and College Graduates

	New England	Mid-Atlantic	East N. Central	West N. Central	South Atlantic	East S. Central	West S. Central	Mountain	Pacific
New England	51.19	6.32	3.36	0.99	18.77	0.59	1.78	3.16	13.83
Mid-Atlantic	3.09	59.14	4.87	0.89	18.81	0.63	1.83	3.20	7.54
East N. Central	1.59	2.52	60.45	3.06	11.21	1.86	3.61	5.25	10.45
West N. Central	0.55	1.37	8.79	44.64	9.07	1.10	6.18	10.71	17.58
South Atlantic	1.25	6.36	4.48	0.81	73.14	2.51	3.49	2.24	5.73
East S. Central	0.21	2.53	14.32	1.89	15.58	52.21	5.47	2.11	5.68
West S. Central	0.46	0.93	2.78	2.20	7.77	1.51	68.10	4.29	11.95
Mountain	1.10	2.19	3.29	2.19	2.47	2.19	6.85	58.08	21.64
Pacific	0.71	1.69	2.31	0.80	5.33	0.71	3.11	6.93	78.42

¹¹ Rows indicate birth regions while columns denote regions of current residence. The first element of panel (a) indicates that 69.19% of high school dropout and graduate household heads born in New England are found living in New England in 2000.

¹² Regional Definitions: (1) *New England* (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont), (2) *Middle Atlantic* (New Jersey, New York, Pennsylvania), (3) *East North Central* (Illinois, Indiana, Michigan, Ohio, Wisconsin), (4) *West North Central* (Iowa, Kansas, Minnesota, Missouri, Nebraska, South Dakota, North Dakota), (5) *South Atlantic* (Delaware, DC, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia), (6) *East South Central* (Alabama, Kentucky, Mississippi, Tennessee), (7) *West South Central* (Arkansas, Louisiana, Oklahoma, Texas), (8) *Mountain* (Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah), and (9) *Pacific* (Alaska, California, Hawaii, Oregon, Washington).

Table 2 – Determinants of Mobility, Probit Estimation¹³
 N = 10000, R² = 0.109

Variable	Estimate	t-statistic
Constant	-1.332	-15.36
Northeast	0.654	16.75
South	0.183	5.19
Mid-West	0.720	18.06
High School Dropout	0.206	5.01
High School Graduate	0.453	12.55
Some College	0.309	8.96
White	0.964	12.33
Black	0.983	11.48
Other	0.308	3.26
Female	0.076	2.75
Age	-0.005	-5.89

¹³ Dependent variable = 1 if household is found in state of household head's birth

Table 3 – Data Summary

Variable	Mean	Description
HSDROP	0.175	High school dropout
HS	0.249	High school graduate
SOMECOLL	0.291	Completed some college (not four year degree)
COLL	0.286	College graduate
WHITE	0.770	Race = White
BLACK	0.125	Race = Black
ASIAN	0.038	Race = Asian (Chinese, Japanese, other Asian or Pacific Islander)
OTHER	0.063	American Indian and other racial categories
AGE	49.36	Age of the household head
MALE	0.651	Sex of the household head (1 = MALE, 0 = FEMALE)
INCTOT	42305	Total income from employment
ROOM2	0.047	2 rooms in dwelling
ROOM3	0.096	3 rooms in dwelling
ROOM4	0.148	4 rooms in dwelling
ROOM5	0.192	5 rooms in dwelling
ROOM6	0.194	6 rooms in dwelling
ROOM7	0.128	7 rooms in dwelling
ROOM8	0.088	8 rooms in dwelling
ROOM9	0.086	9+ rooms in dwelling
BED2	0.130	1 bedroom dwelling
BED3	0.268	2 bedroom dwelling
BED4	0.385	3 bedroom dwelling
BED5	0.151	4 bedroom dwelling
BED6	0.035	5+ bedroom dwelling
YR1	0.018	0-1 year-old dwelling
YR2	0.070	2-5 year-old dwelling
YR3	0.070	6-10 year-old dwelling
YR4	0.157	11-20 year-old dwelling
YR5	0.176	21-30 year-old dwelling
YR6	0.147	31-40 year-old dwelling
YR7	0.138	41-50 year-old dwelling
UNITS2	0.001	Boat, tent, van, other
UNITS3	0.590	1 family house, detached
UNITS4	0.066	1 family house, attached
UNITS5	0.046	2 family building
UNITS6	0.048	3-4 family building
UNITS7	0.045	5-9 family building
UNITS8	0.043	10-19 family building
UNITS9	0.035	20-49 family building
UNITS10	0.058	50+ family building
ACRE1_9	0.104	Acreage of property 1-9 acres
ACRE10	0.024	Acreage of property 10+ acres
NOKITCH	0.007	Dwelling does not contain complete kitchen facilities
NOPLUMB	0.005	Dwelling does not contain complete plumbing facilities
OWNER	0.661	Dwelling owned
RENTER	0.339	Dwelling Rented
MSA_ID		Metropolitan Statistical Area identification number
BLP		Birth state
STATE		Current state of residence

Table 4 – Summary of Income Regressions

Variable	1990			2000		
	Average Parameter Estimate	Standard Deviation of Estimates	Average t-statistic	Average Parameter Estimate	Standard Deviation of Estimates	Average t-statistic
Constant	8.688	0.300	107.09	9.081	0.172	275.68
MALE	0.594	0.095	13.24	0.521	0.060	25.91
AGE>60	-0.135	0.117	-3.17	-0.099	0.112	-5.72
WHITE	0.328	0.221	4.82	0.297	0.090	11.43
HS	0.377	0.108	6.51	0.361	0.069	12.20
SOMECOLL	0.517	0.160	8.91	0.533	0.126	18.83
COLLGRAD	0.935	0.167	14.80	0.986	0.126	32.76

Table 5 – Housing Services Index Parameters

	1990 (N=638159)		2000 (N=3674433)	
	Estimate	t-statistic	Estimate	t-statistic
CONSTANT	4.035	477.04	4.982	1504.54
OWNER	5.506	2201.95	5.328	4547.26
ROOM2	0.033	2.50	0.096	19.17
ROOM3	0.058	4.04	0.115	22.18
ROOM4	0.123	8.32	0.126	23.28
ROOM5	0.217	14.51	0.208	37.57
ROOM6	0.362	23.85	0.347	61.66
ROOM7	0.524	34.16	0.495	86.81
ROOM8	0.665	42.73	0.634	109.32
ROOM9	0.857	54.55	0.855	145.26
BED2	0.056	4.54	0.029	6.56
BED3	0.124	9.41	0.107	22.67
BED4	0.135	10.01	0.155	31.90
BED5	0.162	11.68	0.221	43.95
BED6	0.168	11.42	0.281	51.12
YR1	0.534	79.52	0.479	161.47
YR2	0.514	139.19	0.428	238.24
YR3	0.384	104.74	0.363	206.21
YR4	0.287	97.37	0.250	179.26
YR5	0.209	69.61	0.129	97.76
YR6	0.138	45.88	0.092	67.54
YR7	0.056	15.93	0.064	47.10
UNITS2	1.018	103.35	-0.449	-34.18
UNITS3	1.154	261.36	0.748	460.14
UNITS4	1.027	186.73	0.628	281.46
UNITS5	1.283	217.15	0.873	344.37
UNITS6	1.310	220.37	0.891	356.72
UNITS7	1.297	217.80	0.886	351.96
UNITS8	1.347	224.03	0.917	348.26
UNITS9	1.304	204.79	0.842	302.06
UNITS10	1.267	203.63	0.873	351.96
ACRE1_9	0.086	28.99	0.164	120.88
ACRE10	0.124	24.75	0.252	88.90
NOKITCH	-0.091	-7.53	-0.041	-7.38
NOPLUMB	-0.448	-36.09	-0.258	-44.53
R ²	0.942		0.926	

Table 6 – Prices of Housing Services

(a) 1990			
Most Expensive		Least Expensive	
MSA Name	r_i	MSA Name	r_i
Ventura, CA	2.14	Johnstown, PA	0.43
Santa Barbara-Santa Maria, CA	2.23	McAllen-Mission, TX	0.45
Stamford-Norwalk, CT	2.34	Anniston, AL	0.45
San Jose, CA	2.46	Terre Haute, IN	0.46
San Francisco, CA	2.64	Florence, AL	0.47

(b) 2000			
Most Expensive		Least Expensive	
MSA Name	r_i	MSA Name	r_i
Los Angeles-Long Beach, CA	1.86	McAllen-Mission, TX	0.44
Santa Barbara-Santa Maria, CA	2.31	Johnstown, PA	0.46
Stamford-Norwalk, CT	2.35	Dothan, AL	0.47
San Francisco, CA	2.77	Brownsville-San Benito, TX	0.47
San Jose, CA	2.80	Gadsden, AL	0.49

Table 7 – First-Stage Maximum Likelihood Estimates

	High School Dropouts and Graduates		Some College and College Graduates	
	Estimate	Standard Error	Estimate	Standard Error
$\tilde{b}_{M1,k}$	3.250	0.040	2.624	0.036
$\tilde{b}_{M2,k}$	1.358	0.042	1.329	0.035

Table 8 – Results of Difference Regressions for the Impact of ΔPM and $\Delta \ln r$ on Change in Parameter Estimates

Parameter	Difference Regressions		2000 Cross-Section	
	Estimate	Standard Error ¹⁴	Estimate	Standard Error
$b_{i,HS}$	0.0247	0.041	-0.9573	0.268
$b_{i,HS}$	0.2227	0.197	1.2571	0.261
$b_{PM,HS}$	-5.364×10^{-3}	2.51×10^{-3}	0.0245	6.39×10^{-3}
$b_{i,COLL}$	0.3350	0.033	-0.4059	0.278
$b_{i,COLL}$	0.1483	0.184	1.6747	0.263
$b_{PM,COLL}$	-2.621×10^{-3}	2.22×10^{-3}	0.0173	6.63×10^{-3}
g	-0.1370	0.048	-0.0431	6.46×10^{-3}
$g_{,0}$	0.3871	0.024	8.9946	0.147
$g_{,PM}$	0.1017	0.082	0.0268	0.040

¹⁴ All standard errors are White heteroskedastic-consistent.

Table 9 – Average Willingness-to-Pay for Marginal Increase in PM¹⁵

	Wage-Hedonic Model			Residential Sorting Model		
	WTP	% Income	Elasticity	WTP	% Income	Elasticity
Full Sample	109.02	0.25	0.10	145.51	0.38	0.16
HSDROP	54.09	0.25	0.10	117.58	0.54	0.23
HSGRAD	78.75	0.25	0.10	169.46	0.54	0.23
SOMECOLL	100.04	0.25	0.10	106.22	0.26	0.11
COLLGRAD	174.39	0.26	0.10	179.46	0.26	0.11
WHITE	119.69	0.25	0.10	156.86	0.37	0.16
BLACK	68.50	0.25	0.10	100.71	0.40	0.17
FEMALE	73.23	0.26	0.10	99.82	0.39	0.16

Table 10 – Differences in WTP by Type
 Dependent Variable = $\ln(\text{WTP}_{\text{wage-hedonic}}) - \ln(\text{WTP}_{\text{residential-sorting}})$, N=7580

Specification	Variable	Estimate	Standard Error	Wage-Hedonic WTP as a % of Residential Sorting WTP
1	Constant	-0.061	3.74×10^{-3}	94.1
	HSDROP, HS	-0.730	5.78×10^{-3}	45.3
2	Constant	-0.359	5.37×10^{-3}	69.8
	BLACK	-0.066	0.015	65.4
3	Constant	-0.362	6.21×10^{-3}	69.6
	FEMALE	-0.014	-0.011	68.7

¹⁵ Based on a random sample of 7580 households taken from the 5% sample of the 2000 US Population Census.