The (Non)Separability of Air Quality: Evidence from Millions of Households Across the United States

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Abstract

The costs and benefits of environmental policy depend crucially on the assumed micro-elasticities between market and non-market goods. In their absence, general equilibrium models have assumed environmental amenities are perfect substitutes with market goods, such as consumption and leisure, producing qualitatively different welfare assessments of environmental policy under even a narrow range of micro-elasticities. First, I introduce a refinement upon a standard neoclassical model that allows for preferences over non-market goods (pollution). Second, I build a comprehensive dataset that combines micro-data from the Census Bureau, Consumption Expenditure Survey, American Time Use Survey, National Ocean and Atmospheric Administration, and Environmental Protection Agency between 2000-2014. Third, using the new database to exploit variation in individuals' housing and labor decisions, I jointly estimate two equilibrium conditions that emerge from the model in order to identify micro-elasticities between pollution and non-durables consumption, leisure, and housing services. To address endogeneity arising from omitted variables and non-random sorting, my identification strategy controls for time-invariant differences across metro areas, aggregate shocks, and a number of individual-level demographic and county-level economic factors. I also instrument for each of the endogenous variables. Fourth, using the estimated micro-elasticities, I simulate 2010 counterfactual distributions for consumption, leisure, and housing to compare how much households would be willing to pay in order to be indifferent between a decline in pollution comparable to those estimated by the Clean Air Act Amendments.

JEL: J23, Q51, Q53, Q5.

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1. Introduction

Pollution in the United States has been cut in half over the past forty years, concurrent with sustained rises in per capita consumption and leisure. These empirical regularities are driven by at least four factors: increasing tastes for environmental quality, biased technical change towards energy-savings technologies, more stringent regulation, and the composition of goods consumed (Shapiro and Walker, 2014; Makridis, 2014b). While the declines in pollution have unambiguously led to a higher quality of life (Costa and Kahn, 2003) and lower mortality (Chay and Greenstone, 2005, 2003; Currie and Neidell, 2005), the welfare effects of environmental regulation depend crucially on the extent to which households are able to substitute between market and non-market goods.

Unfortunately, all general equilibrium models used for evaluating environmental policies impose the restrictive assumption that non-market and market goods are perfect substitutes with each other. Mathematically, these models assume additive separability between market goods, such as consumption (c) and leisure (l), and the non-market good, like air quality (S): $u(c,l)+\Phi(S)$ where u and Φ are both increasing and weakly concave.[1] The assumption has the interpretation that changes in the demand for an externality occur independently of changes in the demand for private goods (Davis and Whinston, 1962). Although Diamond and Mirrlees (1973) initially adopted the assumption to rule out unstable equilibria, not only did Sandmo (1980) demonstrate that unstable equilibria can emerge even without income effects, but also subsequent literature cautioned against the assumption when evaluating candidate environmental policies.[2]

While an emerging body of empirical contributions have falsified the assumption of additive separability, current models (almost without exception) have deferred to it in the absence of quantitative estimates of behavioral elasticities between market and non-market goods.[3] Policy inter-

[1] Additive separability implies that there is an affine transformation of the non-market good. Since households take the non-market good as given in the competitive equilibrium, the externality drops out of the first-order conditions under additive separability; $u(c,l)$ does not depend on S. Additive separability differs from weak complementarity, i.e., $U(g(c,l),S)$, which would imply that S and c or l are average substitutes. The imposition of additive separability is less restrictive within a separate literature in environmental economics involving hedonic pricing, travel cost, and equilibrium sorting models (Kuminoff et al., 2013).

[2] For example Sandmo (1975) (p. 92-93) acknowledges that marginal damages are not independent of income and relative price effects under externality targeting in general equilibrium. Similarly, Kopczuk (2003) (p. 84) says "this conclusion [the generality of the principle of targeting] may break down when issues involving tax avoidance, evasion, and administrative cost are introduced. See Smith and Carbone (2008) for a more detailed discussion.

[3] There is an emerging body of empirical evidence, e.g., the effects of pollution on defensive investments (Greenstone et al., 2013), infant mortality (Chay and Greenstone, 2003; Currie and Neidell, 2005), labor productivity (Graff Zivin and Neidell, 2012; Hanna and Oliva, 2015), and health (Moretti and Neidell, 2009; Neidell, 2007; Schlenker and Walker, 2012) and human capital (Bharadwaj et al., 2014; Sanders, 2012; Neidell and Graff Zivin, 2013). See Currie et al. (2014) for a review of the literature on the link between health and pollution. See Guojun (2013) for a regression discontinuity approach from the 2008 Beijing Olympic games (their requirement to meet air quality standards) that found that a 10% decrease in mean PM10 concentrations decreased monthly cardiovascular mortality by 13.6% and Van Hee and Pope (2012) for a randomized medical experiment.

ventions that affect the provision of non-market goods will necessarily affect the demand for market goods since policy shifts the relationship between the marginal willingness to pay (MWTP) and marginal cost for other market goods. The quantity and quality of non-market goods (e.g., air quality) affects individuals' consumption of market goods by influencing their locational choice decisions (Banzhaf and Walsh, 2008). The fact that individuals cannot directly choose their consumption of non-market goods, but rather imperfectly substitute through their locational choices, is the source of the non-separability. The elasticities between market and non-market goods are precisely the parameters that pin down household's behavioral responses to changes in the provision of amenities. Ignoring the interaction between market and non-market goods can lead to gross underestimates of the excess burden of environmental policy in general equilibrium.[4] Therefore, establishing credible estimates of these parameters is crucial for properly valuing the costs and benefits of environmental regulation, as well as characterizing their quantitative effects, especially in the presence of the recent 2014 Clean Power Plan.[5]

The primary contributions of this paper are to develop an analytical framework for characterizing substitution between market and non-market goods, identify these structural elasticities, and conduct a welfare analysis to illustrate they can be introduced into general equilibrium models. This paper begins by establishing a stylized model in Section 2. that allows for non-separable interactions between non-market and market goods through constant elasticity of substitution functions in preferences. Whereas the competitive equilibrium would traditionally not contain an externality in the implied first-order conditions, pollution enters the intra-temporal Euler conditions here since it affects the quality of non-durables consumption, leisure, and housing. Using a log-linearization around the steady state, I derive two simple equations that jointly govern locational choice and labor supply decisions in equilibrium, reminiscent of the hedonic-wage models (Roback, 1982; Rosen, 1974) and equilibrium sorting models (Epple and Sieg, 1999).

In order to take these equilibrium conditions to the data, Section 3. introduces the most comprehensive database to date with millions of individual records on consumption, leisure, housing, and demographic attributes, together with county-level information on air quality, pollution, and

[4]Using Goulder and Williams III (2003) as a benchmark, Carbone and Smith (2008) found that even a small 5% environmental tax could understate the excess burden by nearly 100% when leisure and air quality are complements and overstate it by 50% when they are substitutes. The severity of the bias depends on how far away reality (the non-separable case) is from the assumption of additive separability. Berry et al. (2014) emphasizes that complementarities may easily arise between a non-market good and unobserved variables, which in this case are other rationed private goods/services.

[5]For example, \$1.7 of the \$2 trillion estimated net benefits in the Environmental Protection Agency's Second Prospective evaluation of the Clean Air Act Amendments are based on assumptions on the value of a statistical life and the relationship between air quality and mortality. These large benefits are based on statistical estimates that omit household cross-substitution between market and non-market goods.

weather between 2000-2014.[6] While the Census contains detailed demographic and geographic data, it does not contain measures of non-durables consumption, leisure, or housing services. To produce information on non-durables and leisure, I use auxiliary micro-data from the American Time Use Survey (ATUS) and Consumption Expenditure Survey (CES) in order to generate predicted measures of consumption and leisure in the Census data. My prediction algorithm builds on prior literature in labor economics that imputed consumption using the Panel Study of Income Dynamics (see Blundell et al. (2008) and Orazio and Pistaferri (2014)) by using a flexible sieve estimator (e.g., splines and polynomials). In order to examine the quality of the predicted values, I conduct two main tests. I begin by comparing the actual mean and standard deviation of non-durables and leisure from the predicted data with the actual data from the CES and ATUS, respectively. I subsequently compare the quantiles of data in the CES and ATUS with the predicted values in these same datasets. The prediction algorithm allows me to leverage the sample size, geographic content, and coverage of the Census without sacrificing key variables needed to estimate the preference elasticities.[7]

Before turning towards my main results, Section 4. uses the new dataset to characterize two additional identification problems associated with the traditional hedonic method, further motivating my semi-structural estimation of the model in Section 2.. First, failing to control for non-separabilities, such as consumption and leisure, produces omitted variables bias: changes in air quality affect the value of consumption and leisure, but both consumption and leisure are highly correlated with housing values/services. Second, using county-level, rather than household-level, data can produce bias if there is reallocation and/or compositional within-geographical changes over time. When households have preferences over non-market goods, changes in their levels will lead to changes in the underlying composition of the residents within a geographical unit.

Motivated by these new identification problems, Section 5. introduces an identification strategy for estimating the model in Section 2.. There are two sources of endogeneity that are important to confront. First, adverse local demand shocks increase households' allocation of time towards leisure (Aguiar et al., 2013), decrease their consumption (Mian et al., 2013), and decrease their housing wealth (Mian and Sufi, 2011). These quantities are all functions of the hourly wage and price of housing services, making them endogenous equilibrium objects. Second, household's locational sorting is driven by their preference for local amenities (e.g., air quality) (Banzhaf and Walsh, 2008;

[6] To put my sample selection in perspective, Chay and Greenstone (2005, 2003) exploit sharp changes in TSP between 1980-1982; Currie and Neidell (2005) use 1989-2000; Moretti and Neidell (2009) use 1993-2000 in Los Angeles; Neidell (2007) uses 1989-1997 in Los Angeles; Graff Zivin and Neidell (2012) use 2009 and 2010 in Central Valley of California (orange pickers).

[7] Heterogeneity and state-dependence are becoming increasingly important in macroeconomic (Guvenen, 2012; Guvenen and Smith, 2014; Heathcote et al., 2010, 2014) and health (Finkelstein et al., 2013) literatures.

Epple, 1987). Observing counties with high air quality levels and consumption, for example, might produce a spurious positive correlation that is driven instead by composition effects relating to income and other demographics. My identification strategy relies upon two central features. First, my estimates control for an array of time-varying (semi-parametric) measures of economic activity and demographics, as well as both year and metro fixed effects. These controls and fixed effects fixed effects help assuage concerns about the endogeneity of non-random sorting since there is little evidence that individuals respond to year-to-year *changes* in air quality, rather than the overall level. Second, I exploit quasi-natural variation in the tradition of Greenstone and Gayer (2009) by instrumenting air quality with wind speeds, non-durables consumption with interactions between the age of the house and the state electricity price, leisure with temperature and interactions with age brackets, and housing consumption with the housing supply elasticity (Saiz, 2010). Wind speeds provide exogenous variation in air quality since faster speeds blow dirty air out of a county; temperature and its interactions with age brackets provide exogenous variation for leisure since hotter temperatures reduce time allocated towards leisure with heterogeneous effects across the age range (Graff Zivin and Neidell, 2014); state electricity prices and their interaction with the age of a house provide exogenous variation in utility expenditures since newer homes tend to have higher energy efficiency; and, the housing supply elasticity provides exogenous variation in the cross-section of housing for counties within the same metro area.

To highlight the importance of these structural elasticities, Section 6. incorporates them into a simple partial equilibrium welfare analysis of the costs associated with the Clean Air Act Amendments (CAAA). I estimate counterfactual densities for consumption, leisure, and housing to compute a Lucas consumption-equivalent measure characterizing how much households would be willing to pay such that they are indifferent between the bundle of market and non-market goods in 2000 with those of 2010. To make it comparable with the CAAA, pollution is scaled appropriately. These results provide a clear and straightforward research agenda towards incorporating non-market goods in general equilibrium (Carbone and Smith, 2008, 2013; Klaiber and Smith, 2012).[8]

2. Modeling the Demand for Air Quality

The underlying framework is a modified neoclassical growth model with preferences over non-durables consumption, leisure, and housing services, denoted $B^j = (C, L, H, j)$, where $j = 1, 2, ..., J$ governs the location. The utility flow of these three market goods is also affected by the consumption

[8]Moreover, the elasticity of substitution between consumption and environmental amenities determines whether environmental degradation is decreasing or increasing in wealth (Shibayama and Fraser, 2014)—a literature on the Environmental Kuznets Curve dating back to Grossman and Krueger (1995).

of non-market goods (pollution), denoted P_j, which is chosen exogenously based on the location that the individual sorts into. In this sense, the individual chooses a bundle, $\tilde{B}^j$, which implies a pollution level of $\tilde{P}^j$ since the individual is unable to influence the quantity of the non-market good after having chosen B^j. Locational choice and labor supply decisions, therefore, reveal information about individual preferences for non-market goods along the lines of Rosen (1974), Roback (1982), and Epple and Sieg (1999).[9] Capital and labor markets are perfectly competitive and individuals are mobile, consistent with evidence from Blanchard and Katz (1992) that adjustment takes place.

2.1. Setup

Suppose that individuals have preferences over non-durables consumption (c), leisure (l), and housing services, (h), taking location-specific pollution, (P), as exogenous

$$\begin{aligned} u(c_{it}, l_{it}, h_{it}, j; P_t^j) &= e^{\eta_{it}^j}\Big[\alpha_C \ln\left(\mu c_{it}^{\phi} + (1-\mu)(P_t^j)^{-\phi}\right)^{\frac{1}{\phi}} \\ &+ \alpha_L \ln\left(\gamma l_{it}^{\psi} + (1-\gamma)(P_t^j)^{-\psi}\right)^{\frac{1}{\psi}} + \\ &+ \alpha_H \ln\left(\pi h_{it}^{\zeta} + (1-\pi)(P_t^j)^{-\zeta}\right)^{\frac{1}{\zeta}}\Big] \end{aligned} \tag{1}$$

subject to a budget constraint

$$c_{it} + q_t^j h_{it} + k_{it} + b_t^j(s_t - s_{t-1}) = w_t^j(1 - l_{it}) + R_t^j k_{i,t-1} \tag{2}$$

where η denotes individual-specific preferences over location j, α_C, α_L, α_H, μ, γ, and π are all share parameters, ϕ, ψ, and ζ are micro-elasticities between pollution and the market goods, s denotes housing structures, k denotes physical capital, and q, b, w, and R are the equilibrium factor prices on housing services, housing structures, labor, and capital, respectively. Each of the market goods are additively separable with one another.[10] The inclusion of pollution through the form $1/P$ captures the fact that higher levels of pollution affect the quality of consumption, leisure, and housing. Individual-specific heterogeneity is parameterized according to

$$\eta_{it}^j = \varrho(X_{it}) + \theta(Z_{jt}) + \overline{\eta}_i + \chi_j + u_{it}$$

where $\varrho(X)$ is a nonlinear function of individual and potentially time-varying characteristics,

[9] While pollution may vary between an individual's residence versus place of work, it will only generate measurement error. Robustness exercises restrict the sample to those commuting only short distances and produce similar elasticity estimates.

[10] While the parametric assumption is an abstraction, additive separability between consumption and leisure has been regularly applied in the labor economics (Altonji, 1986) and macroeconomic (Kydland and Prescott, 1982) literatures.

$\theta(Z)$ is a nonlinear function of local geographic time-varying conditions, $\overline{\eta}$ denotes the individual-specific component, χ_j the location-specific component, and u denotes measurement error. Under the assumption that u is distributed according to an extreme value type I distribution, then the conditional-choice probabilities associated with locational choice are characterized by

$$P(V_{it}^{j} \geq V_{it}^{j'}) = \frac{\exp\left[\varrho X_{it} + \theta Z_{jt} + \chi_j\right]}{\sum_j \exp\left[\varrho X_{it} + \theta Z_{jt} + \chi_j\right]}$$

Dahl (2002) provides a tractable approach to estimating models with many discrete choices, overcoming the dimensionality problens and data limitations that would arise by having to specify a likelihood function over the entire joint distribution of possible locations. While readers are referred to his paper for details, and the Appendix for an implementation of it here, the general idea involves estimating a single index that provides the probability that an individual will move to his most preferred location. Given the assumption of revealed preference methods, the location than an individual currently resides in is his preferred location. Since information on mobility is observed, a predicted probability can be computed to characterize the individual's propensity to move elsewhere.

2.2. Interpretation

The elasticity of substitution between the private good/service and air quality is given by, for example, $\varepsilon_c \in (0, \infty) = -\mathrm{d}\ln(c/S)/\mathrm{d}\ln(u_c/u_P)$ and where $\phi = (\varepsilon_c - 1)/\varepsilon_c$ such that the three extreme cases are given by $\varepsilon_c \equiv 1/(1-\phi) \to 0$ $(\omega \to -\infty)$, $\varepsilon_c \equiv 1/(1-\phi) \to \infty$ $(c \to 1)$, and $\varepsilon_c \equiv 1/(1-c) \to 1$ $(c \to 0)$, which imply perfect complementarity, perfect substitutability, and Cobb Douglas elasticities, respectively (equivalent for leisure). The private good/service and air quality are gross substitutes when $\varepsilon_c > 1$ $(c > 0)$ and gross complements when $\varepsilon_c < 1$ $(c < 0)$. These preferences are sufficiently parsimonious to capture the non-separability between consumption-leisure and air quality, but also tractable enough through additive separability between the consumption and leisure aggregates in order to obtain closed form expressions that map into the data.

While incorporating a richer production structure is an important avenue for future research, and is in fact the focus of companion work (Makridis, 2014a; Cai and Makridis, 2015), there is no need to add structure on the supply-side of the economy since the objective of the paper is identifying the three micro-elasticities, $\{\phi, \psi, \zeta\}$.[11] Households choose $\{c_t, l_t, h_t, k_t, s_t, j\}$ to maximize utility (Equation 1) subject to their budget constraint (Equation 2). After taking the first-order conditions,

[11] Conceptually, a perfectly competitive real estate company could transform housing structures into housing services and a perfectly competitive final goods firm could transform capital and labor into aggregate output. That is, suppose that $H = F(S)$ and $Y = G(1-L, K)$ and let the prices be given by their marginal products.

the two intra-temporal Euler conditions of interest are

$$w_t^j = \frac{u_l(c_{it}, l_{it}, h_{it}; P_t^j)}{u_c(c_{it}, l_{it}, h_{it}; P_t^j)} \tag{3}$$

$$q_t^j = \frac{u_h(c_{it}, l_{it}, h_{it}; P_t^j)}{u_c(c_{it}, l_{it}, h_{it}; P_t^j)} \tag{4}$$

These equations exploit within-geographic variation in pollution, consumption, leisure, and housing in order to identify the structural micro-elasticities linking the valuation of market and non-market goods. Specifically, the non-separabilities in these equations allow me to identify a virtual price on pollution—that is, a price associated with air quality as if households could purchase it directly; see Perroni (1992) and Amiran and Hagen (2014) for theoretical justification.

2.3. Comparison to the Literature

While the setup follows closely along the lines of the neoclassical growth model, the theoretical underpinnings are based on both hedonics (Roback, 1982; Rosen, 1974) and equilibrium sorting (Epple and Sieg, 1999). Aside from Kuminoff (2012)—who provides a unified model for households to sort across jobs and housing locations without assuming that every time a person changes houses, they change jobs, and vice versa—there are few equilibrium sorting models that incorporate both housing and labor decisions to value environmental amenities.[12] Given that housing and employment opportunities are fundamentally linked—for example, U.S. counties became less stratified by public goods provision and housing demographics as moving costs declined between 1850-1990 (Rhode and Strumpf, 2003)—obtaining unbiased estimates of preferences for local public goods hinges on how these decisions are jointly modeled. Specifically, Equation 4 captures the simultaneity of the labor-housing decision by equating their marginal utilities equal to the price ratio.

While the coefficients on pollution are analogous to traditional measures of willingness to pay—and, indeed, these elasticities are "inputs" to willingness to pay—there are three main differences. First, WTP estimates cannot be readily inserted into the current class of dynamic macroeconomic models. In addition to the fact that my companion work (Cai and Makridis, 2015) is, to my knowledge, the only example of a DSGE setup featuring both housing and environmental quality, there is no concept of spatially heterogeneous non-market goods in standard macroeconomics, making calibration exercises targeted to WTP estimates impossible. Second, Flores and Carson (1997) show

[12] There is, however, a large literature that uses wage rents to value risk in the workplace and the value of a statistical life (Viscusi and Aldy, 2003; Aldy and Viscusi, 2008; Viscusi, 1979), as well as literature linking jobs with their site characteristics (e.g., environmental amenities) (Cropper and Arriaga-Salinas, 1980; Cropper, 1988; Smith, 1983).

that there are at least three plausible reasons that the income elasticity (of environmental quality) provides insufficient information to evaluate the welfare impacts of a change in public goods. One condition, for example, is when the income elasticity depends on goods that might be rationed, which is always the case in the context of environmental policy interventions since they induce higher prices and declines in employment. Third, many previous studies make restrictive assumptions about the exogeneity of certain variables (e.g., labor/leisure; see Flores and Graves (2008)), which effectively behaves as an omitted variables bias problem. Although quasinatural experimental methods offer a solution, and they face separate identification challenges (see Kuminoff and Pope (2014)), the approach here provides a balance of structure and reduced-form identification.[13]

2.4. Empirical Implementation

The two intratemporal Euler equations (Equations 3 and 4) are non-linear equilibrium relationships. Estimating them via non-linear least squares runs into several problems. First, massive time-invariant differences exist across geographies, such as industry composition and household tastes, that are correlated with all of the variables of interest. For example, individuals with preferences for non-market goods tend to be wealthier, sorting into areas with lower pollution, healthier labor markets, and so on. Unfortunately, non-linear least squares with large vectors of fixed effects is still an open area of research, endeavoring to find resolutions to the incidental parameters problem. Second, non-linearities exacerbate any measurement error that might be present. Since neither consumption nor leisure are observed in the Census, but rather need to be predicted from supplementary datasets, measurement error is a non-trivial concern.

As an alternative to these non-linear expressions, the Appendix illustrates that the two intratemporal Eulers can be log-linearized and approimated using the following expressions[14]

$$\ln w_{ijt} = \beta_0 + (\psi - 2)\ln l_{ijt} + (2 - \phi)\ln c_{ijt} + (\psi - \phi)\ln P_{jt} + \varrho(X_{it}) + \epsilon_{ijt} \tag{5}$$

$$\ln q_{ijt} = \beta_1 + (\zeta - 2)\ln h_{ijt} + (2 - \phi)\ln c_{ijt} + (\zeta - \phi)\ln P_{jt} + \varrho(X_{it}) + \epsilon_{ijt} \tag{6}$$

Equation 3 builds upon this literature linking market and non-market goods via a new relationship between wages and pollution derived from a theoretically consistent structural general equilibrium model. The slope of the hedonic wage on pollution has the interpretation as a marginal

[13] To put this in perspective, the average household sacrifices over $5,000 per year to consume non-market amenities in their geographical location (Bieri et al., 2014), bigger cities tend to have differences in availability of consumption goods (Handbury and Weinstein, 2014) and higher wages (Glaeser and Resseger, 2009; Davis and Dingel, 2014).

[14] Furthermore, the Appendix provides a Kmenta (1967) approximation around the points $\omega = 0$ for $\omega \in \{C, L\}$, illustrating that the higher-order terms are not significant after controlling for the direct effects.

change in pollution for the individual found at the baseline level (Bockstael and McConnell, 2007). The traditional Roback (1982) model takes the sum of the estimated coefficient on pollution obtained from a regression of housing values on pollution and the coefficient from a regression of labor income on pollution. The value of a statistical life is the "population's aggregate willingness to pay for an increase in one expected life saved" (Bockstael and McConnell, 2007 p.219). Nevertheless, the interpretation of $\text{dlog}(p/w)/\text{dlog}S$ is: a 1% change in air quality induces a $(\psi+\zeta)\%$ decline in the ratio of the relative price of housing versus labor. For example, if a policy intervention increases air quality by 1% for N people, then the aggregate WTP would be $N \times (\psi+\zeta)\%$ and the value of a statistical life would be $(\psi+\zeta)\% \times$ risk of death. Getting the VSL right matters: of the \$2 trillion in estimated net benefits of the CAAA, a staggering \$1.7 trillion are attributed to reductions in mortality.

3. Micro-data on Consumption, Leisure, and the Environment

3.1. Descriptive Statistics

Using a combination of the American Community Survey and Decennial Census, Consumption Expenditure Survey, American Time Use Survey, and Environmental Protection Agency Annual Summary / AirData files, this paper builds the most comprehensive micro-dataset to date containing measures of individual-level demographics, consumption, leisure, housing, labor market participation, as well as county-level measures of weather and air quality. Unfortunately, the Census contains neither consumption nor leisure, so these two variables are imputed using a sieve estimator discussed in the following subsection. The purpose of this subsection is to provide a broad overview of the produced dataset.

There are several standard empirical challenges in the existing data. The first is selection bias arising from individuals who are unemployed, and thus do not have an hourly wage. While some methods are traditionally used to impute hourly wages (as if the individual were employed, e.g., Heckman (1979)), I restrict the sample to full-time workers and those earning over \$20,000 in labor earnings. The second is a truncation bias arising from the fact that not all households explicitly pay for utilities. Electricity, water, gasoline, and fuel consumption expenditures are imputed using a Heckman selection model for those observations that have them included in the rent.[15] The third is that housing services and the prices of these are not explicitly measured. Housing services are

[15]The predictors include an indicator for marital status, male, white/black/asian races, family size, educational attainment, age, number of bedrooms, and the age the house was built. The selection terms are the housing value (rental payments for renters), age the house was built, and family size. The exclusion restriction is that the housing value affects utilities expenditures only through its effect on the probability that the residence has utilities included in the rent.

measured based on a strategy recommended by Deaton and Zaidi (2002) that takes the predicted rental rate implied by a regression of the rental rate among the subset of the sample that are renters (not home owners) on a full set of housing characteristics, such as number of bedrooms and housing age, together with geographic fixed effects.[16] The predicted housing consumption has a statistically significant 0.58 correlation with self-reported property values among this set of home owners with a mean of $3,414. The price of these housing services is obtained by taking the residual of a regression of log owner housing costs on the aforementioned measure of housing services.

Finally, the sample is also trimmed based on individuals with outlier values of hourly wages, and winsorized based on individuals with outlier values of utilities, leisure, and housing prices.[17] All nominal variables are deflated according to the 2010 price of consumption expenditure index (similar to the consumer price index).

Table 1 summarizes the main properties of the data over the 2000-2014 time horizon. There are several novel facts to point out. The first is that the imputed non-durables consumption, housing, and utilities expenditures are surprisingly close to Bureau of Economic Analysis' national income and product accounts (NIPA). For example, the 2000 per capita consumption was $24,105 according to NIPA, whereas it is $24,526 in the imputed Census sample. As the next subsection will illustrate, imputed leisure is also very close to the actual mean derived from the American Time Use Survey. The second is that there is a great deal of cross-sectional and intertemporal variation in the pollution variables. Air quality is generally improving over the 2000-2014 period—evident in the rise of the air quality index and decline in PM10 (although ozone stays relatively constant on average). The third is that there is also cross-sectional and intertemporal variation in the weather variables. There are a few minor differences between the weather variables for 2000 and 2013-2014 versus 2005-2012 since they combine two different data sources that differ in slight fashions. Nonetheless, the standard deviations of temperature and wind is about a sixth the magnitude of their means and the standard deviation of pollution criteria is about a third the magnitude of their means.

All of the traditional anecdotal facts about the Great Recession are evident in the established data set: consumption declined by 10%, both the mean and standard deviation of leisure rose by about 3%, housing prices declined by 10%, unemployment doubled, and pollution—whether measured as total suspended particulates or PM10—declined by about 20%. While the rise in

[16]The predictors include: number of bedrooms, year the house was built, housing tenure, whether the house occupies less than 10 acres of land, the cost of electricity, and fixed effects on both the type of fuel used and county.

[17]I also experimented with a selection model to impute hourly wages for those who are unemployed (predictors includeed gender, race indicators, educational attainment, age, and the selected variables included marital status, family size, educational attainment, age), but the quality of the imputation was not very strong given the violation of the exclusion restriction (that family size and marital status affect the hourly wage only through their effects on the probability someone is unemployed).

Table 1: Summary statistics, 2000-2014

	2000		2005-2007		2008-2010		2011-2014	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Individual								
Non-durables Consumption	24526	8935	24551	10283	24185	9899	23382	9556
Housing consumption	12533	3863	13599	4095	13967	4455	13926	4585
Utilities	9987	2526	9392	2382	9064	2260	8605	2035
Hours worked	2204	505	2193	497	2172	490	2174	487
Leisure	2906	505	2917	497	2938	490	2936	487
Labor earnings	48628	39335	51304	38712	51096	37900	50336	36780
Family income	96157	73614	98415	72046	98289	71689	96267	71426
Education	13.49	2.46	13.77	2.48	13.84	2.53	13.92	2.58
White	0.76	0.42	0.77	0.42	0.77	0.42	0.75	0.43
Black	0.11	0.31	0.10	0.29	0.10	0.30	0.10	0.30
Age	40.14	11.07	42.17	11.53	42.63	11.77	43.56	11.67
Male	0.54	0.50	0.53	0.50	0.52	0.50	0.52	0.50
Bedroom	3.78	1.07	3.97	1.00	4.02	1.16	4.00	1.17
Married	0.59	0.49	0.60	0.49	0.59	0.49	0.59	0.49
Housing/Economy								
Housing Tenure	1.99	2.41	2.03	2.15	2.06	2.18	2.13	2.23
Selected owner costs	8193	3257	20123	14082	20244	14194	17824	12408
Housing Value	157872	181010	258870	260140	229802	307237	197220	280034
Year home built	4.45	2.15	4.93	2.47	5.21	2.81	5.27	3.09
Unemployment Rate	0.04	0.01	0.05	0.01	0.08	0.02	0.08	0.02
No. Employed, 000s	1812	2447	1820	2375	1788	2347	1944	2525
Payroll Exp., 000s	69644	100293	82292	117251	87169	125095	101119	141258
No. Establishments, 000s	106	137	116	148	116	150	127	166
Population, 000s	1346	2031	1378	2023	1401	2057	1595	2242
Environment								
Air Quality (Index)	239.83	14.86	244.13	12.14	249.05	10.74	249.86	11.08
Ozone, parts per million	0.04	0.01	0.04	0.01	0.04	0.01	0.04	0.01
Ozone, s.d.	0.02	0.00	0.01	0.00	0.01	0.00	0.01	0.00
PM10, micrograms/cubic meter	25.72	7.42	25.04	7.50	21.86	6.03	20.82	6.77
PM10, s.d.	12.35	4.37	12.87	5.91	10.81	4.06	10.68	4.78
Maximum temperature	56.58	8.58	68.78	8.79	68.04	9.17	57.45	8.33
Minimum temperature	38.91	7.44	47.88	7.91	47.14	8.36	39.65	7.23
Mean Resultant Wind	9.54	5.56	6.24	1.91	6.30	1.88	5.63	3.58
Observations	352163		1180712		1125199		1170495	

Notes.–Sources: Environmental Protection Agency AirData's air quality index (AQI), the Census Bureau's American Community Survey (ACS), Consumption Expenditure Survey (CEX), and American Time Use Survey (ATUS). The table contains the means and standard deviations of the most relevant variables contained in the econometric specifications. Using the definition of non-durables from Attanasio and Weber (1995), it is the sum of food (home and away), alcoholic beverages, tobacco, services (e.g., repairs), heating, gasoline, transportation, electricity, water, fuel, personal care, clothing, footware, and rents. Using the definition of leisure from Aguiar and Hurst (2007), specifically their "Measure 1", it is the sum of socializing, passive and active leisure, volunteering, pet care, gardening. Housing values are self-reported from the ACS and are upwards biased to the extent homeowners are overly optimistic about the sale price of their property. Air quality, call it S, is transformed from the Environmental Protection Agency's (EPA) "AirNow" air quality index, call it $\tilde{S}$, by taking $S = 300 - \tilde{S}$, where 300 is a hazardous measure of air quality. With the transformation, higher values enter positively into utility. Ozone pollution and particulate matter of 10 microns or less are measured in parts per million and micrograms per cubic meter, respectively.

consumption inequality (Aguiar and Bils, 2009) and time use (Aguiar et al., 2013) over the Great Recession are not new, the decline in pollution is stark. However, what remains unknown is how counties with higher air quality differ from those with lower air quality. Figure 1 plots the residualized (conditional) correlations in the data between county-level air quality and market "goods", such as consumption, leisure, wages, and selected owner costs. Counties with higher air quality tend to have more of each of thse respective quantities, consistent with the hypothesis that air quality is a normal good.

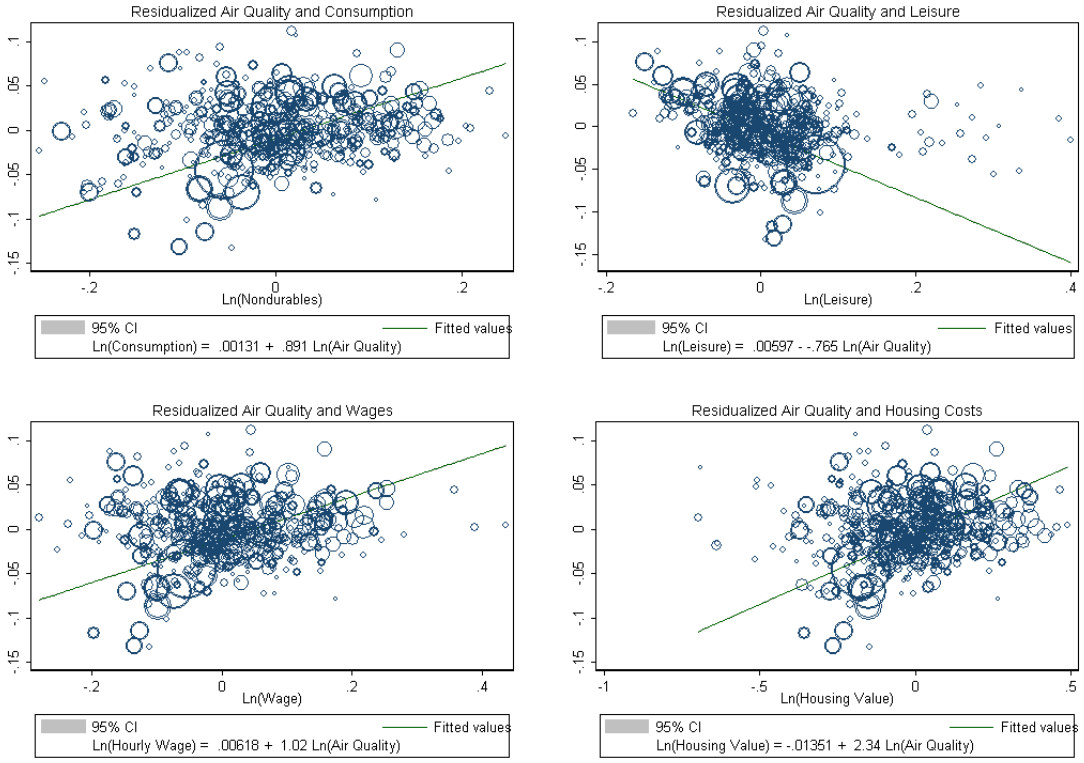


Figure 1: The Relationship between Air Quality and Market Goods

Notes.–Sources: CEX, ATUS, ACS, EPA. The figure plots the residualized log variable consumption, leisure, wages, and selected owner costs) with residualized log air quality (normalized index) and subsequently averaged across counties. Each observation is a county-level average between 2000-2014 and the circles are weights based on the population of the county. Controls include: age, age group fixed effects (30-39, 40-49, 50+), educational attainment, number of bedrooms in the house, number of vehicles for the household, family size, race fixed effects (white, black, asian), household tenure, male, marital status, fixed effects on the decade the home was built (1940-1949,...,2000+), log county-level establishments and employment, log state-level non-durables, energy, durables, and housing consumption, log electricity sales revenue, and the state unemployment. All standard errors are clustered at a county-level and weighted by the product of the county-to-PUMA (from the Missouri Population Center) and person/household weights (from the Census).

While not exogenous variation, the Great Recession is a suitable natural experiment for recovering preferences over environmental amenities because of the vast amount of reallocation and migration dynamics. As counties experienced different magnitudes and durations of labor and housing market shocks, individuals moved locations. For example, many households moved from one county to another for new employment opportunities and/or housing decisions (i.e., to move

into a less expensive house). The demographic reallocation and resorting coincides with a massive decline in pollution (rise in air quality) that affected household's locational choices. To the extent that households value environmental amenities, holding all else constant, a homeowner with tastes for non-market goods would choose to locate in an area with better amenities. The density and time series properties of air quality are illustrated below in Figure 2. All additional data details are located in the Appendix.

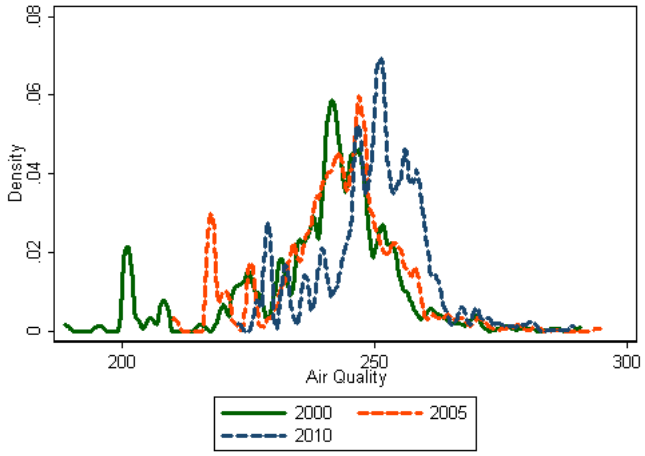


Figure 2: Distribution of Air Quality, 2000-2010

Notes.–Source: Environmental Protection Agency AirData's air quality index (AQI). The figure plots the distribution of air quality (normalized such that a higher air quality index implies better air quality) across counties in the United States.

3.2. Imputing Nondurables Consumption and Leisure

While the Census data contains rich household-level demographic details and comprehensive coverage, it lacks measures of consumption and leisure. A naive way—that fails to provide sufficient variation to identify the parameters of interest—would involve proxying non-durables consumption with electricity expenditures and leisure with non-work hours (e.g., 5100 minus hours worked in a year).[18] There is a detailed theoretical literature on corrections for measurement error and imputation, but a sparse empirical literature.[19] Using a sieve estimator and auxiliary data from the

[18] Just as food expenditures were used to proxy for non-durables in the early literature on estimating the intertemporal elasticity of substitution (Hall and Mishkin, 1982), and later found to be weak proxies because of their relative low covariance with the overall consumption bundle (Attanasio and Weber, 1995), electricity expenditures fall into the same trap. Similarly, taking leisure as the difference of total hours and hours worked would attenuate the variation since many allocations of leisure time (e.g., sleeping) are unresponsive to environmental amenities. An entirely separate strategy would involve creating grids of representative households (e.g., households in a certain income bracket, education level, race, etc) and match among the datasets; this approach is guaranteed to provide strictly worse and more inaccurate results since the household-level behavioral responses to county-level air quality is vital for identification—and preferences for environmental amenities differ immensely across the population.

[19] One vein of the literature (e.g., Robins et al. (1994)) focuses on consistent estimation when some of the variables are missing for a subset of the sample series, but not all; these methods have tended to involve inverse probability

Consumption Expenditure Survey (CEX) and the American Time Use Survey (ATUS), I predict the distributions of non-durables and leisure. The semi-parametric estimator is able to capture the rich nonlinearities of the demand for non-durables and leisure based on data observed in all of the datasets and follows thematically in line with Blundell et al. (2008) who estimate a demand system to impute non-durables in the Panel Study of Income Dynamics using data from the CEX.[20] Aside from some flexible semi-parametric restrictions, the only limitation is the requirement that the variables used in the imputation are common across all datasets such that only the to-be-imputed variable is missing in the using (primary) data set. To further enhance the quality of the imputation, I estimate a propensity score associated with the probability of an individual being in the American Community Survey and consider scores within the range of 0.1 and 0.9. Crump et al. (2009a) show that this helps ensure overlap in the distributions.

Sieve estimators are relatively easy to implement and have desirable properties when the approximating functions are unknown (Chen, 2007). Its accuracy depends on the extent to which the target (to-be-imputed) variable is a smooth function of its explanatory variables. The sieve estimator achieves asymptotic consistency by allowing these explanatory variables to enter nonlinearly and with many higher order terms. An alternative approach would be to specify a structural model; see the footnote for details.[21] However, because it relies on the assumption that the model is properly specified, mis-specification in the imputation can give rise to unknown forms of non-classical measurement error in the actual estimation of air quality elasticities. Robustness checks indicate that my sieve estimator yields the most accurate estimates.

I now turn to estimating the demand for non-durables consumption and leisure in order to predict their unobserved quantities in the ACS. Denote $Y_{1i} = (Y_{1i}1, ..., Y_{1iM})' \in \mathcal{R}^M$ as the target M variables (e.g., non-durables and leisure), Y_{2i} as the proxy for Y_{1im}, $X_{1i}^{'} \in \mathcal{X}$ as the "equivalence scale" common across households, with $\dim(X_1) \geq 1$, $\dim(X_2) \geq 1$, and $Z_i = (Y_{1i}^{'}, Y_{2i}, X_i)'$. Denote

weights associated with the missing variables. Another vein of the literature (e.g., Chen et al. (2008)) focuses on consistent estimation when variable(s) might be missing for a large subset of the sample series or all of it; these methods have tended to emphasize auxiliary datasets and semi-parametric method of moments and propensity score estimators for out-of-sample estimation. See Chen et al. (2011) for a detailed survey.

[20] Although the approach suggested by Blundell et al. (2008) was attempted here, it did not produce successful predicted values. One possibility arises from an argument in Campos and Reggio (2014) that instrumenting does not address the asymptotic bias resulting from the covariance between their control variables and the error, which is non-zero especially if demographic and other household-level variables are reported with error differentially in the two datasets. For example, Gibson (2002) finds that household size is correlated with measurement error since a single respondent asked to remember expenditures for an entire household is likely to make more mistakes the greater the number of people he must remember for.

[21] For example, let $u(c, l) = [ac^{\alpha} + (1-a)l^{\alpha}]^{1/\alpha}$ denote a constant elasticity of substitution function between consumption and labor. If households maximize utility subject to a budget constraint with no savings (just equal to the wage times labor services), then the intratemporal Euler implies that $(1-a)l^{\alpha-1}/(aw) = c^{\alpha-1}$. Taking the log of both sides yields $\log c = \log l - (\alpha - 1)^{-1} \log w + \epsilon$, where $\epsilon = (1-a)/a$. Running some version of least squares with instruments could yield an unbiased measure of $\hat{\alpha}$. Using this estimate, and letting a be the corresponding value share taken from the data, then consumption could be imputed as $\tilde{c} = \left[(1-a)l^{\hat{\alpha}-1}/(aw)\right]^{1/(\hat{\alpha}-1)}$.

$\alpha = (\theta, h_1, ..., h_M)$ as all the unknown parameters of interest and $\mathcal{A} \equiv \Theta \times \mathcal{H}_1 \times \cdots \times \mathcal{H}_M$ as the parameter space where $\theta \equiv (\theta_1', \theta_{2,1}', ..., \theta_{2,M}')'$ denotes the vector of finite dimensional parameters given by $\theta \in \Theta$, a compact subset of $\mathcal{R}^{d_\theta}$ with $d_\theta \equiv (1 + M)\dim(X_1)$. The terms $h_m \in \mathcal{H}_m$ will denote the unknown demand curves associated with subsets of the target good m, $m = 1, ..., M$, where $\mathcal{H}_m$ is a subset of a space of functions that are square integrable against the probability measure of Y_{2i}. Letting $\rho \equiv (\rho_1, ..., \rho_M)' \in \mathcal{H}^M$ represent

$$\rho_m(Z_i, \alpha) \equiv Y_{1im} - h_m(Y_{2i} - \chi(X_{1i}', \theta_1)) - X_{1i}'\theta_{2,m} \tag{7}$$

for a specified functional form $\chi(\cdot)$, then individual i facing the same prices for goods $m = 1, ..., M$ will have a demand curve that satisfies $E[\rho(Z_i, \alpha_o)|X_i] = 0$ where $\alpha_o \equiv (\theta_o, h_{o1}, ..., h_{oM}) \in \mathcal{A}$ is the true (unknown) parameter. The objective is to estimate θ_o and the demand functions h_{om} in order to recover parameters that fully characterize the mapping between the target and input variables of interest. Under very general regularity conditions, Blundell et al. (2007) show that these demand restrictions will be satisfied. Following Ai and Chen (2003) who establish a framework for estimating moment conditions of unknown functional forms, consider approximating functions $h_m \in \mathcal{H}_m$ by $h_{m,n} \in \mathcal{H}_{m,n}$ for $m = 1, ..., M$ where $\mathcal{H}_{m,n}$ is a sieve space for $\mathcal{H}_m$ (e.g., Fourier series, splines, and so on) so that $\mathcal{H}_{m,n}$ becomes dense in $\mathcal{H}_m$ as $n \to \infty$. Arbitrarily fixing a value of $\alpha = (\theta, h_{1,n}, ..., h_{M,n})$ in the sieve parameter space, then the population conditional moment function, characterized by $g(x, \alpha) \equiv (g_1(x, \alpha), ..., g_M(x, \alpha))'$, can be estimated using sieve generalized least squares

$$\min_{\alpha \in \mathcal{A}_n} \frac{1}{n} \sum_{i=1}^{N} \rho(Z_i, \alpha) \left[\hat{W}(X_i)\right]^{-1} \rho(Z_i, \alpha)$$

where $\hat{W}$ is a consistent estimator of a positive definite weighting matrix.[22],[23] In addition to using standard demographics, I use separate flexible semi-parametric functions for consumption and leisure. Specifically, I use information on electricity expenditures, property taxes, and mortgage payments to generate accurate predictions for consumption. Housing and non-durables consumption are closely related (Campbell and Cocco, 2007), and utilities are an important component of overall non-durables expenditures. I use information on hours not working and wage income to generate accurate predictions for leisure. Since leisure is a subset of hours not working, and the hourly wage is an important summary statistic on the individual's opportunity cost of time, these two variables provide important information for predicting leisure. Using these flexible functional forms, I estimate Equation 7 to obtain parameters that can be used to extrapolate and impute

[22] Blundell et al. (2007) provides an excellent methodology for implementing this procedure when the target variables are endogenous and an instrument is needed for Y_2; here, it is taken as exogenous.

[23] Hellerstein and Imbens (1999) show that orthogonality conditions can be created by using moments from axillary data (e.g., Census and ATUS).

consumption and leisure in the Census.[24] While I consider a variety of specifications (see the Appendix), the annual means/variances are plotted below in Figures 3 and 4 for imputed consumption and leisure.

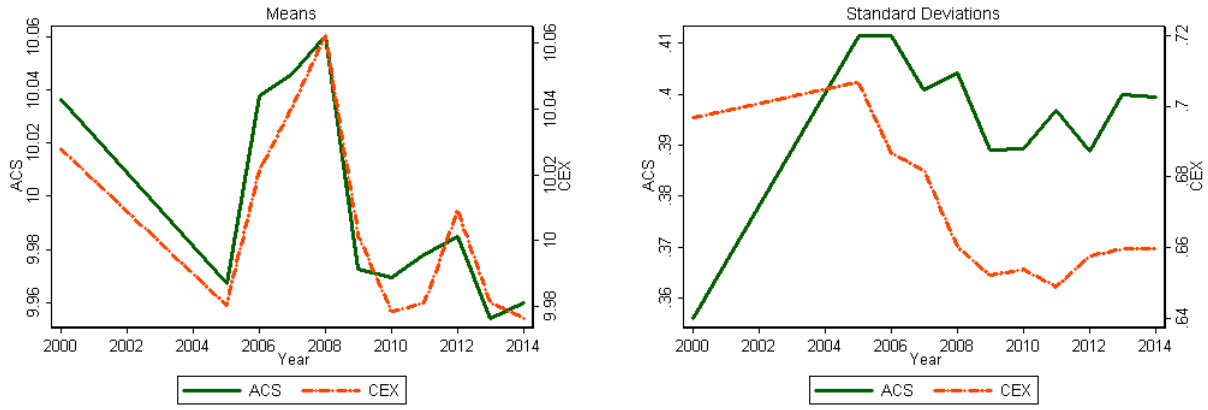


Figure 3: Non-durables Mean and Variance, Actual (CEX) and Imputed (ACS)

Notes.–Source: CEX and ACS. These plot the mean and variance of consumption from the CEX with the mean and variance of the ACS-imputed consumption measure. Using the definition of non-durables from Attanasio and Weber (1995), non-durables is the sum of food (home and away), alcoholic beverages, tobacco, services (e.g., repairs), heating, gasoline, transportation, electricity, water, fuel, personal care, clothing, footware, and rents.

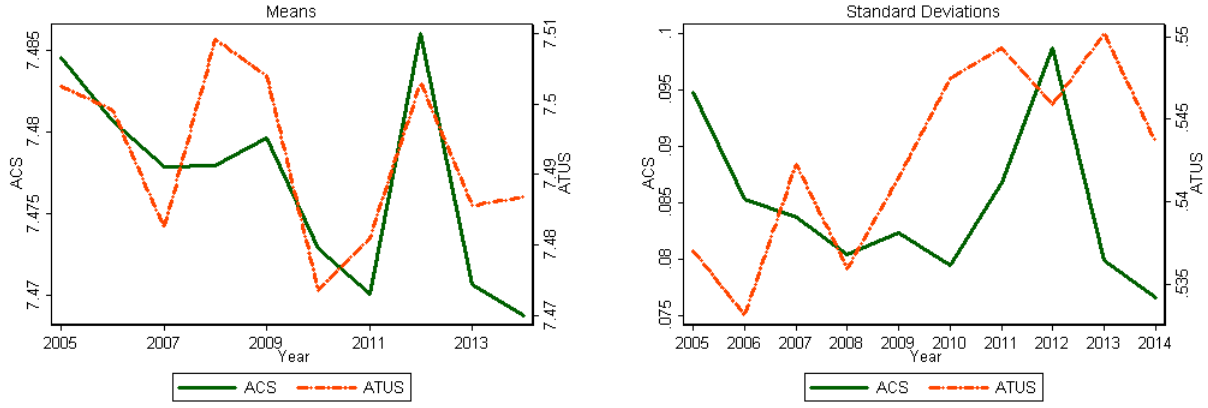


Figure 4: Leisure Mean and Variance, Actual (ATUS) and Imputed (ACS)

Notes.–Source: CEX and ACS. These plot the mean and variance of leisure from the ATUS with the mean and variance of the ACS-imputed leisure measure. Using the definition of leisure from Aguiar and Hurst (2007), their "Measure 1" definition includes: socializing, passive and active leisure, volunteering, pet care, gardening.

Figures 3 and 4 both characterize the mean log non-durables and leisure in the actual (CEX and ATUS) datasets and the imputed values (in the CEX and ATUS) datasets. An important assumption that is necessary for validity is that there is overlap in the distribution of covariates between the "using" and "imputed" dataset. In the Appendix, I provide summary tables that com-

[24] Splines provide a better fit of the data within local regions of the space of points and are well behaved on the endpoints, whereas polynomials can experience unexpected fluctuations ("Runge's phenomenon").

pare each of the datasets, showing that they are not statistically different from each other based on observables. Differences in the levels between the actual and predicted values are resolved through the inclusion of year fixed effects that remove trends. The fact that the R-squared is lower for the predicted values arises from the fact that perfectly explaining variation in consumption and leisure is not feasible, meaning that the predicted values will mechanically have lower standard deviations. While the Appendix documents several other pieces of evidence pointing towards high accuracy, any measurement error in the imputation is likely to be cleaned out through my instrumental variables.

4. Identification Problems in the Hedonic Method

Before turning towards the main results of the sorting model established in Section 2, it is useful to provide some background. Hedonic methods are used to infer prices on environmental amenities by exploiting individuals' observed choices. The canonical framework that followed from Rosen (1974) considers an environment where households have different tastes and will choose a location that maximizes their utility based on the amenities of the location, including both market and non-market goods. Suppose that housing can be decomposed into its various components, differentiating between air quality and all other taste shifters or housing attributes

$$\log PROPERTYVAL_{ict} = X_{it}\beta + POLL_{ct}\zeta + \pi_c + \lambda_t + \epsilon_{ict} \tag{8}$$

where the dependent variable is the self-reported property value (or rental payment for non-homeowners), X are controlling covariates, $POLL$ is the county pollution level, and π and λ are fixed effects on county and year. As Chay and Greenstone (2005) point out, there exists endogeneity arising from locational sorting based on air quality and omitted variables that co-vary with air quality. While panel data can be used to remove time-invariant unobservables, first-differencing and/or policy-based quasi-natural variation identifies the marginal willingness to pay interpretation only under restrictive assumptions about the movement of the hedonic price function (Kuminoff and Pope, 2014). My model provides a tractable framework for estimating structural parameters in light of possible omitted variables (e.g., consumption and leisure) and their endogeneity.[25]

While these concerns are not new, the model in Section 2. illustrates additional identification problems. First, depending on the strength of non-separabilities, determining the willingness to pay and/or conducting welfare analysis requires knowledge of the income elasticities of demand for all other rationed goods (Flores and Carson, 1997). Given that there is now clear evidence that

[25]See Bajari et al. (2012) for an alternative solution that exploits assumptions about expectations and unobservables in the hedonic price function. However, during the Great Recession and/or environmental policy interventions, these assumptions may be fragile.

housing price fluctuations affect both consumption (Mian and Sufi, 2011) and employment (Mian and Sufi, 2014), omitting measures of non-durables consumption and leisure from Equation 8 will generate bias in the presence of non-separabilities. Using attainment status as an instrument may also generate bias if the regulation affects the optimal choice of consumption and/or leisure among households.[26] Second, the variance of these unobserved *household-level* shocks is time varying and orders of magnitude larger than those in the *county-level* data. In this sense, using county-level data, rather than the underlying micro-data, may produce bias in at least two ways: (a) the potential for heterogeneous treatment effects under selection effects (Imbens and Angrist, 1994), and (b) reallocation and composition effects (Lemieux, 2006). A third, but smaller point relegated to the Appendix, is that hedonic studies must use the price of housing and/or labor services, rather than the aggregate expenditure (e.g., housing values or labor earnings). When using the aggregate expenditure, bias can emerge due to unobserved shocks that affect the quantity (e.g., housing consumption or hours worked) and are correlated with changes in air quality.

4.1. Non-separabilities and Omitted Variables

Applying least squares on Equation 8 produces consistent estimates on ζ if unobserved shocks to property values are uncorrelated with air quality, after controlling for observables and fixed effects. Frequent applications contain county fixed effects in order to remove time-invariant differences across counties that are not captured using simple demographic controls. While fixed effects are an important improvement upon purely cross-sectional analyses, they may still fail to identify the marginal willingness to pay for air quality if there are non-separabilities between air quality and other unobserved determinants of housing prices.

To examine whether the above concern for omitted variables produces any bias on the coefficient associated with air quality, I estimate Equation 8 with and without consumption and leisure as controls. Importantly, Equation 8 is augmented with fixed effects on county and year in order to remove time-invariant differences in county unobservables. I also instrument for air quality using county-level attainment status, which has been used in a number of related contributions. The coefficient on $POLL$, therefore, can be mapped one-to-one into the results from Chay and Greenstone (2005) who find that a one cubic micrograms ($\mu g/m^3$) decline in TSP is associated with a 0.2-0.4% increase in property values (e.g., a -0.2 to -0.35 elasticity).

Table 2 documents these results. The first fascinating result is that, while statistically significant and reasonably "signed" when county fixed effects are omitted (and state fixed effects are

[26] Since prior work has already shown that attainment status affected employment (Greenstone, 2002; Walker, 2013), the presence of non-separabilities implies that these changes in leisure and/or consumption are correlated with air quality.

included), the correlation vanishes with the inclusion of county fixed effects (e.g., columns 1 versus 2-4 and 5 versus 6-8). These regressions contain detailed demographic and economic state/county -level controls, as well as county and year fixed effects. Their statistical insignificance is also robust to using alternative measures of pollution, such as the air quality index or ozone pollution. The second result is that instrumenting pollution with attainment status does not produce a statistically significant coefficient in the housing regression, nor does it produce a statistically significant coefficient with the correct sign in the earnings regression. The fact that the data spans between 2000-2014 suggests that a lack of variation in attainment status is an unlikely culprit, but rather a potential for omitted variables bias. The third key result is that the inclusion of consumption and leisure as controls helps raise both the economic and statistical significance of the coefficient on pollution. The fact that they are so precisely estimated also indicates that omitting them constitutes a form of omitted variables bias.

Table 2: Non-separabilities and Omitted Variables in Hedonic Regressions

	Dep. var. = Ln(Housing Value)				Dep. var. = Ln(Labor Earnings)			
	OLS	OLS	IV	OLS	OLS	OLS	IV	OLS
Ln(Pollution)	-.157***	.006	-25.005	.067**	-.060***	.002	.192	.042***
	[.039]	[.028]	[188.795]	[.032]	[.014]	[.008]	[.389]	[.015]
Ln(Leisure)				.382***				-.755***
				[.020]				[.019]
Ln(Nondurables)				1.928***				1.480***
				[.039]				[.020]
R-squared	.44	.45	-2.20	.55	.22	.22	.23	.60
Sample Size	2143307	2143307	1582047	2014161	2143381	2143381	1569661	2014234
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	No	No	Yes	No	No	No
County FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Notes.–Sources: Census, EPA, NOAA. The table reports the coefficients associated with regressions of log housing values and labor earnings on log PM10 pollution (cubic micrograms); columns 4 and 8 add log non-durables consumption and leisure as additional controls. The IV specification uses attainment status (for PM10) as an instrument for pollution. Controls include age, bedrooms, number of vehicles, family size, race indicators, household tenure, marital status, age of the house, state consumption on energy, non-durables, durables, housing, and electricity prices, as well as county-level log employment, establishments, and payroll expenditures. Standard errors are clustered at the county-level and observations are weighted by the product of the Census household/individual weights and the Missouri Population Center PUMA-to-county share.

4.2. Time Varying Standard Deviations, Counties versus Households

The variance of unobserved shocks to households might change over time and differ from the variance of unobserved shocks at the county-level. Within-county reallocation correlated with air quality will bias the elasticity between air quality and housing prices. Such reallocation is likely

given that the Great Recession—and any period featuring a large-scale intervention—had such heterogeneous impacts across the United States. Individuals, rather than counties, should be the unit of analysis.[27] The exercise that follows builds on a comparison of different measures of housing price indices in Banzhaf and Farooque (2013) who also find that relying on county-level averages or medians "substantially changes the patterns of cross-sectional prices regardless of the actual source of those prices."

Undertaking a similar decomposition exercise as Lemieux (2006) and Chay and Lee (2000), suppose the error in Equation 3 (and analogously for Equation 4) consists of two components, $\epsilon_{it} = q_t e_{it} + v_{it}$, where q denotes the price of unobserved heterogeneity and v denotes idiosyncratic noise. Since $Var(\epsilon_{it}) = q_t^2 Var(e_{it}) + Var(v_{it})$, then it becomes possible to decompose the residual by the level of aggregation. If the extent of unobserved variation at the county versus household level is varying over time, then merely conditioning on demographics with year fixed effects will not provide consistent estimates of marginal willingness to pay when relying on county-level aggregations.

Figure 5 examines whether reallocation and composition effects are a serious issue by plotting the county and individual average log consumption, leisure, housing, and earnings over the relevant sample period with correlations displayed at the bottom of the figures. In every case, the correlation between unobserved prices at the county versus individual levels are weakly or even negatively correlated. On top of the different trends, it is useful to point out that the magnitude of the standard deviations are also dramatically different. For example, the standard deviation of unobserved heterogeneity in non-durables at the county-level is on average 0.115, but 0.335 at the individual-level. Instrumental variables may address these sources of bias only if they are truly exogenous to the changes in within-geographic reallocation, which is a difficult assumption to test.

5. Using Intratemporal Variation to Estimate the Demand for Environmental Quality

5.1. Identification Problems

Empirically identifying the micro-elasticities between air quality and consumption, leisure, and housing using an equilibrium sorting model is especially challenging because of the endogeneity of not only air quality (e.g., due to locational sorting), but also consumption, leisure, and housing. There are two main identification concerns associated with a naive OLS estimate of Equations 5

[27] For example, Yagan (2014) documents that there were large spatial adjustment frictions in the U.S. labor market during the Great Recession. The importance of examining dynamics at sufficiently disaggregated levels has been articulated by Davis and Haltiwanger (1992) in the context of firm dynamics, Auffhammer et al. (2009) in the context of the Clean Air Acts, and Banzhaf and Walsh (2008) in the context of Tiebout sorting.

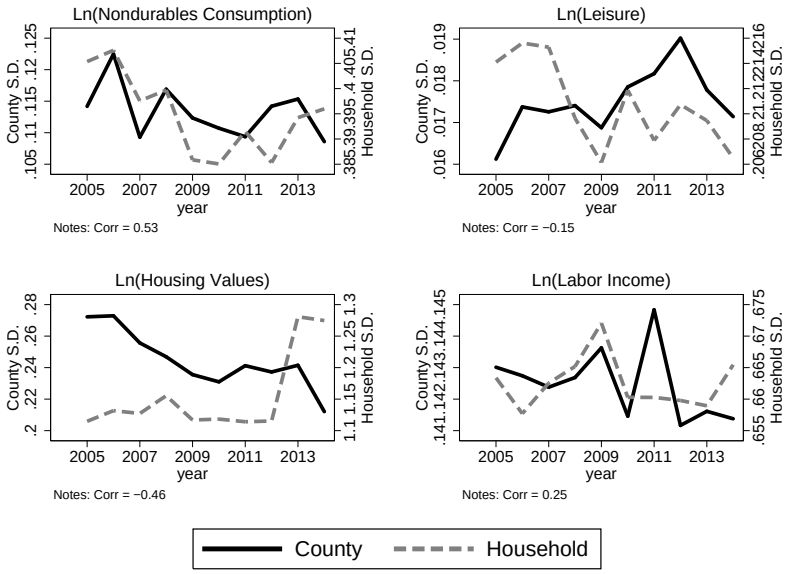


Figure 5: County versus Household Trends, 2005-2010

Notes.–Source: Census. The plots consist of the standard deviation of the ratio of log residual property values and earnings at the county to household level. After regressing log property values (and separately, log labor earnings) on controls, then the county measure is generated by averaging across individuals, and finally averaging across all individuals and county averages. Controls include: age, educational attainment, family size, number of children, age of the house, household tenure, state employment, establishments, and population. The aggregated statistics are weighted by Census county population weights.

and 6.

First, both the hourly wage and relative price between housing and labor are linked with consumption, leisure, and housing. For example, Campbell and Cocco (2007) find that housing price fluctuations affect consumption, especially for older homeowners, and Mian and Sufi (2011) find that the expansion of credit fueled by the sub-prime mortgage crisis led to a large drop in consumption. Mian and Sufi (2014) also show that the mortgage crisis led to a large decline in employment among jobs in the non-tradables sector during the Great Recession. These unobserved shocks have an ambiguous effect on the coefficients of interest. Even if there were sufficient controls to deal with all the time-varying shocks, there is still the potential for reverse causality: changes in the hourly wage and/or price of housing services lead to a change in consumption, leisure, and/or housing consumption. Reverse causality will tend to produce upwards bias.

Second, households are not randomly assigned to locations with different levels of market and non-market goods. Rather, individuals with preferences for air quality will sort into areas with higher environmental amenities. Unobserved heterogeneity in workers' productivity can create a downward bias since more productive workers will receive systematically different wage offers and be correlated with leisure and risk preferences (Epple, 1987). Similarly, since people sort into residential communities and local labor markets based on their preferences for public goods (Rhode

and Strumpf, 2003), including air quality (Banzhaf and Walsh, 2008), naive applications of least squares will attribute variation in wages to preferences for air quality when it is really driven by unobserved heterogeneity in tastes.

5.2. Identification Solutions

The Census micro-data contains rich demographic and geographic details, as well as a large sample size. The array of cross-sectional and intertemporal variation enables me to exploit within-metro variation through the inclusion of metropolitan area and year fixed effects, as well as industry and/or occupation fixed effects in later robustness exercises. The inclusion of various state-level measures of consumption (energy, non-durables, durables, and housing) and county-level measures of economic activity (semiparametric controls for establishment closures and employment) also helps control for time-varying shocks to the underlying economic state. These fixed effects also behave as a proxy for removing time-invariant sources of heterogeneity in individuals' tastes for air quality due to locational sorting of individuals into counties that have their optimal provision of public goods (Banzhaf and Walsh, 2008).

Despite the granularity of the controls, they do not fully address the bulk of the endogeneity problems. Instead, I instrument for each of the endogenous variables. Pollution is instrumented with a quadratic of various measures of wind speeds (average, resultant, maximum 5 seconds, maximum 2 minutes). Wind speeds affect both the direction and rate of air diffusion patterns, which carries pollution from one area to another. The identifying variation arises from the fact that random fluctuations in wind blow pollutants from one geographical area to another. In this sense, areas experiencing higher-than average win speeds will simultaneously experience a positive shock to air quality. Non-durables consumption is instrumented with the log state electricity price (kWh/cent) and its interactions with six bins denoting the age of an individual's home (normalizing relative to those individuals with a home built in 1930-1939). Electricity prices affect individuals' electricity and utility expenditures, which is an important determinant of non-durables consumption. The identifying variation arises from the fact that exogenous movements in the state electricity prices affect consumption expenditures differently based on the age of the home. Those homes built more recently tend to have better insulation and energy technology, helping to save on electricity expenditures.

Leisure is instrumented with a quadratic in temperature and its interactions with different age groups (normalized to individuals between ages 20-29). The identifying variation arises from the fact that random temperature fluctuations affect the quality of time spent outdoors and the work-versus-leisure trade-off. In this sense, hotter years will tend to exert downward pressure on

leisure (Graff Zivin and Neidell, 2014), increasing the returns to work. Housing consumption is instrumented with the housing supply elasticity form Saiz (2010). Since my baseline specifications contain metro fixed effects, and the instrument is time-invariant, the identifying variation arises from cross-sectional differences in the response of more versus less housing elastic *counties* within the same metro area. Mian and Sufi (2011) show that areas with more elastic housing supply elasticities experienced much larger drops in housing prices, meaning that these same areas experienced a large decline in the flow of housing services. Figure 6 provides a graphical representation of the first-stage results by comparing the residualized endogenous variable with one of the residualized instruments; see the Appendix for a more parsimonious test in a regression format.

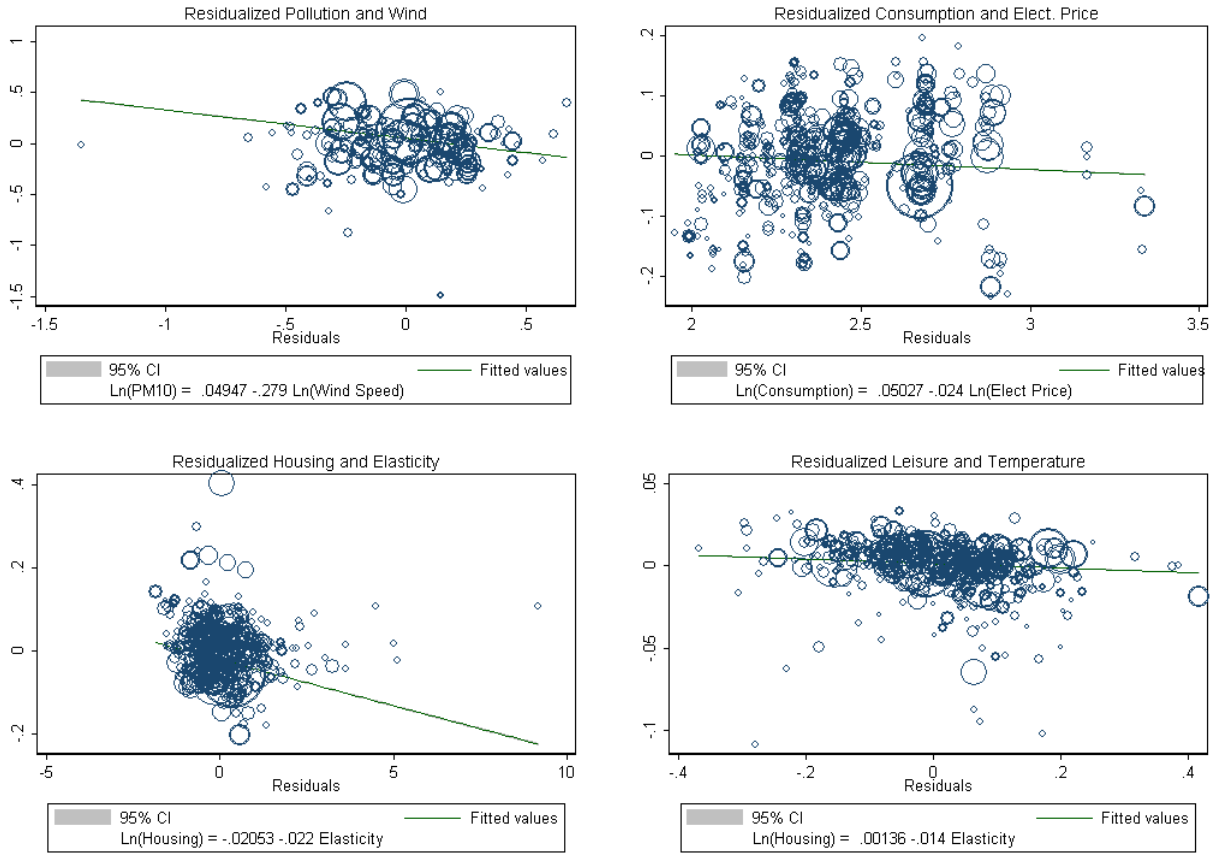


Figure 6: Instrumental Variables First-stage Correlations

Notes.–Sources: Census, EPA, NOAA. The figure plots the residualized endogenous variables (log PM10, non-durables, housing, and leisure) with one of the residualized instruments (log resultant wind speeds, log state electricity price, the housing elasticity, and log maximum temperature). Controls used for the residualizing include: age, age group fixed effects (30-39, 40-49, 50+), educational attainment, number of bedrooms in the house, number of vehicles for the household, family size, race fixed effects (white, black, asian), household tenure, male, marital status, fixed effects on the decade the home was built (1940-1949,...,2000+), log county-level establishments and employment, log state-level non-durables, energy, durables, and housing consumption, log electricity sales revenue, and the state unemployment. Counties are weighted in the plots by their population.

The more challenging requirement for valid instrumental variables is their exclusion restric-

tions. The challenge is compounded by the fact that there are four endogenous variables, requiring greater scrutiny towards the interactions among each of the identifying sources of variation. Table 3 documents the main test for randomization by including instruments as controls in the least squares versions of the model. While the randomization test is not perfect, if these instruments are statistically insignificant, then it suggests that the only way they affect the relevant dependent variables is through the variables that they are instrumenting.

Table 3: Examining Randomization with Instrumental Variables

	Dep. var. = Ln(Housing Price / Hourly Wage)		
Panel B			
Ln(Housing)	.95***	1.01***	1.00***
	[.01]	[.01]	[.01]
Ln(Leisure)	-1.04***	-1.07***	-1.08***
	[.01]	[.01]	[.01]
Ln(Pollution)	-.02***	.01	.01
	[.00]	[.01]	[.01]
Wind, 2 min	-.09***	-.04*	-.04*
	[.01]	[.02]	[.02]
Wind, 5 sec	.07***	.02	.02
	[.01]	[.01]	[.01]
Wind, resultant	-.06***	-.01	-.02
	[.01]	[.02]	[.02]
Wind, mean	.08***	.02	.04
	[.01]	[.02]	[.02]
Max temp	.02***	-.02***	-.02***
	[.00]	[.00]	[.00]
Max temp × Ages 30-40	.02***	.01***	.01***
	[.00]	[.00]	[.00]
Max temp × Ages 40-50	.03***	.02***	.02***
	[.00]	[.00]	[.00]
Max temp × Ages 50+	.04***	.03***	.03***
	[.00]	[.00]	[.00]
Housing supply elasticity	-.05***	-.03	-.01
	[.00]	[.03]	[.03]
R-squared	.21	.22	.24
Sample Size	589562	589562	589562
Controls	Yes	Yes	Yes
Year FE	No	Yes	Yes
State FE	No	No	No
MSA FE	No	Yes	Yes
Industry FE	No	No	Yes

Notes.–Sources: Census, EPA, NOAA.

An important, and more nuanced, assumption is that the treatment effect is monotone in each of the instruments. If, for example, a rise in electricity expenditures raises overall consumption

for some individuals, but decreases it for others, then the condition would be violated. However, it is hard to think of a plausible scenario where overall consumption expenditures would fall due to competing income and substitution effects if one of the sub-categories rose. The more plausible concern is that a rise in wind speeds has a heterogeneous effect on air quality for some counties, but not others. To partially test this assumption, the Online Appendix estimates the association between air quality and wind speeds separately for each geographic region to examine whether the direction of the effect holds even in spatially distinct regions of the United States. A similar exercise is implemented to test for monotonicity in the temperature instruments by separately estimating the coefficient for individuals with and without a college degree across each of the age brackets.

Do these instruments contain the right sources of identifying variation? While omitted variables has been highlighted as a serious threat to identification of consistent measures of marginal willingness to pay (Chay and Greenstone, 2005), leveraging quasi-natural policy-induced variation may only identify a "capitalization effect", rather than the public's willingness to pay for the non-market good for two inter-related reasons (Kuminoff and Pope, 2014). First, policy variation may conflate willingness to pay for improvements in a public good with the changes in its shadow price and other housing attributes following the policy change. That is, even if an environmental regulation is unanticipated, it may have other equilibrium effects that impact the value of various housing attributes and/or equilibrium prices. Second, since the Rosen (1974) model focuses on the equilibrium, difference-in-difference and/or other quasi-experimental estimators may only have access to variation in the adjustment process following a plausibly exogenous shock.

Instead, the identifying source of variation in my equilibrium sorting model arises from two different exogenous sources: (i) shocks to state electricity prices that affect the cross-section of households within a metro area, and (ii) weather fluctuations (e.g., wind or temperature) that are orthogonal to the initial level of the public good and both levels & changes of the control variables.[28] My setup also has the advantage of identifying an average treatment effect (ATE), rather than just a local average treatment effects (LATE) (see Deaton (2009) and Heckman and Urzua (2010) for some critiques and Imbens (2010) for a defense). I also study the presence of heterogeneous treatment effects by income bracket, age, educational attainment, and exposure.

[28] Kuminoff and Pope (2014) point to two sufficient conditions for the capitalization effects to identify MWTP. The first is that the hedonic gradient is time-constant. This is clearly violated over the 2000-2014 time horizon. The second is that the instrument is orthogonal to the initial level of the public good and to the initial levels & changes of the control variables. The weather fluctuations in my model satisfy the second sufficient condition. My companion work in Makridis (2016) show that temperature shocks have no statistically significant effect on wages or earnings after controlling for metro fixed effects and other demographic shifters.

5.3. Main Results

To identify the elasticities on consumption and leisure, I estimate a system of simultaneous equations following from the first-order equilibrium conditions (Equations 3 and 4).[29] These equations allow me to estimate preference parameters with structural interpretations and avoid the aforementioned identification problems.

[UPDATE IN LATER VERSION]

To my knowledge, the only other paper that has estimated a potentially comparable elasticity is West and Williams III (2007) between gasoline and leisure, finding evidence of complementarity between the two, although they do not advocate a particular mechanism behind the results. Since gasoline produces emissions, and thus negatively correlated with air quality, the result is evidence of substitutability between air quality and leisure. There are a variety of reasons that motivate the contrasting result. First, they exploit cross-sectional variation in labor supply and cross-state variation in gasoline prices. Because unobserved shocks to gasoline prices are time varying, and they have heterogeneous effects on workers' transitory incomes and local labor demands, they introduce endogeneity. The negative correlation with both consumption and labor supply/earnings induces upwards bias and makes the elasticity between air quality and leisure appear more substitutable. Second, they instrument for earnings using occupation, state, and gender -specific means, real income using an alternative price index, and gasoline prices using national-average gas prices and gasoline refinery outages. However, the variation in these instruments does not match the variation needed to identify household-level valuations of environmental amenities (or gasoline).[30]

These conclusions remain relatively robust to additional checks. First, non-parametrically controlling for county-level time varying economic shocks through the inclusion of different bins indicating the number of establishment closures of a particular size (e.g., 1-10 employees, 10-20, and so on) should imply similar estimates. Second, I test for a pre-trend across counties using a flexible estimator operationalized by Mora and Reggio (Forthcoming).[31] After conditioning on county-level measures of economic activity and county fixed effects, there is no significant pre-trend. Third, and very interestingly, to the extent that employment at the county-level is a broad indicator of a

[29] Although the division bias (Borjas, 1980) is a common problem in labor studies, and is best addressed using another measurement of wages as an instrument, there are no alternative measurements of hourly wages available in the Census. Fortunately, given the sample size, any attenuation resulting from division bias does not have a quantitatively strong effect on my estimates given the sample size and quality of variation. Furthermore, measurement error in the dependent variable (wages are typically an independent variable) will just raise the standard error at worst.

[30] They also use a shorter time series (1996-1998) with much lower sample size and fewer controls.

[31] Mora and Reggio (2012) show that recovering causal effects in difference in difference estimators actually requires more than just a parallel path condition, but also similar time trends. They introduce a flexible form for allowing for various types of trends—not just linear—and show that results in many prior papers are not robust to this threat to identifying assumptions.

county's economic trajectory, regressing it on the number of establishments and payroll expenditures yields an R^2 of .9927. Evidently, the R^2 cannot rise much further. Adding in county-specific year trends only raises the R^2 to .9999, meaning that these proxies are successfully absorbing the relevant county-specific time varying economic shocks.

5.4. Validity of the Exclusion Restriction

Many economic forces were present during the Great Recession. While it is highly unlikely that counties with different climate variabilities in wind speeds and temperature were on differential trends, such a threat to identification would induce bias. Earlier evidence in Table 3 provides evidence that the instruments are exogenous since they have no statistically significant effect on the variables of interest after controlling for the direct effects. Nonetheless, the Appendix contains several additional checks. First, I show that proxies for economic shocks (establishment closures, employment, pay, and hours at the county-level) are uncorrelated with each of the instruments. Since the only threatening violation to the identifying assumptions of the model is that time varying economic shocks to economic activity are in some way correlated with time varying unobservables. Each of the four proxies of economic factors are uncorrelated with the instruments. Second, the distributions of hourly wages and housing prices are very similar above and below the median level of the given instrument of interest, meaning that the distribution of unobservables is likely to be uncorrelated with the instruments. Taken even further, conditioning on controls and plotting the distribution of residuals implies a nearly identical overlap. Third, there is no correlation between two proxies for locational sorting (housing values and commuting time from home to work) with the instruments. To the extent that time-varying unobservables, these results imply that they are unlikely to be endogenous time-varying unobservables since they are uncorrelated after conditioning on fixed effects and observable controls.

5.5. Interpretation of Treatment Effects

There are two important advantages of the empirical strategy here to alternative methods that are commonly employed in the literature. First, whereas quasi-natural variation often identifies only a local average treatment effect (Deaton, 2009), especially in the context of valuation of non-market goods where cross-sectional variation is needed to identify the hedonic price function. Second, while many approaches have used exogenous temporal variation in the level of pollution to identify how quality changes are capitalized into housing prices, these estimates are not necessarily informative of the marginal willingness to pay (Kuminoff and Pope, 2014). Since the source of the exogenous variation is typically a policy experiment, the hedonic price function necessarily adjusts in order to

clear the housing market, confounding the adjustment in the pricing function with the change in non-market amenities. Both of these challenges are exacerbated by the use of linear approximations to the hedonic price function (Ekeland et al., 2004; Heckman et al., 2010).[32]

Depending on the instrument, whether the "never takers" and "always takers" differ may be a controversial issue. In these cases, obtaining an average treatment effect requires the assumption that treatment effects are constant across sub-populations ("identification at infinity"). In the Appendix, I provide evidence that the "never takers" and "always takers" sub-populations (with respect to the instrument) do not differ with respect to the outcome variables. For example, the distribution of wages and price of housing services are similar in housing elastic and inelastic geographies. Furthermore, my instruments exploit cross-sectional variation within metropolitan areas (e.g., across housing markets within the same metro area), which is important for identification (Ekeland et al., 2004). The granularity of my data also enables me to explore the potential for heterogeneous treatment effects both by estimating my baseline model separately by bracket and by using a procedure developed by Xie et al. (2012).[33]

5.6. Robustness without Structural Assumptions

While the exclusion restrictions of the instruments withstand various robustness exercises, I now turn to reduced-form estimates of the micro-elasticities. These regressions follow more closely with the quasi-natural experimental research in the literature that exploits exogenous variation in natural or policy phenomena to identify quality changes in a non-market good (Chay and Greenstone, 2003, 2005; Greenstone, 2002; Greenstone et al., 2013). The two-staged least squares estimating equation is as follows

$$\begin{aligned} \log P_{jt} &= \alpha_1 + \theta f(Z_{jt}) + \beta_1 X_{ijt} + \nu_{ijt} \\ \log y_{ijt} &= \alpha_2 + \varepsilon_X \widehat{\log P_{jt}} + \beta_2 X_{ijt} + \epsilon_{ijt}, \quad \forall y \in \{C, L, H\} \end{aligned} \tag{9}$$

where X denotes the usual vector of controls and $f(Z)$ denotes a quadratic vector of instruments consisting of wind speed measurements. The elasticities, ε_X, can be transformed to map into the model parameters as follows by letting $\omega = 1 - (1/\varepsilon_X)$ $(\varepsilon = 1/(1-\omega))$ where $\omega \in \{\phi, \psi, \zeta\}$ under the assumption that the error now includes unobserved variation in leisure, consumption, and/or housing depending on the outcome variable in Equation 9 and the coefficient on air quality is scaled by a constant. The identifying assumption is that changes in unobserved shocks to the outcome

[32] Kuminoff et al. (2010) performs a series of Monte Carlo analyses over different functional forms of hedonic estimators, illustrating that linear approximations do not do a good job capturing movements to a new market equilibrium.

[33] Crump et al. (2009b) develop a fully nonparametric test for treatment effects of heterogeneity.

variable are uncorrelated with wind speeds after controlling for differences across counties and industries.

The reduced-form regressions that follow are estimated in a way that confronts endogeneity problems arising from non-random sorting and time-varying shocks to consumption, leisure, and housing over the Great Recession. Since consumption, leisure, and housing are all normal goods, the potential identification problem runs in the same direction for each estimated elasticity. In particular, unobserved preferences (e.g., income) for non-market goods tend to be positively correlated with consumption, thereby generating a downwards bias since these individuals sort into less polluted areas. Three specifications are considered for each dependent variable: least squares conditional on controls, least squares conditional on controls and fixed effects, and instrumental variables conditional on controls and fixed effects. These specifications span the spectrum of plausible identification problems, ranging from non-random sorting to time-varying unobserved shocks to the outcome variable, allowing me to characterize the direction of the bias.

Table **??** documents these results. Columns 1, 4, and 7 are conditional correlations of the association between PM10 pollution and consumption, leisure, and housing. Columns 2, 5, and 8 introduce fixed effects on metro area and year in order to remove the time-invariant differences across locations that may be correlated with unobserved preferences, which Chay and Greenstone (2005) is an important source of bias. Columns 3, 6, and 9 now instrument for pollution using wind speeds on the basis that there are many time-varying unobservables that could be simultaneously correlated with both pollution and consumption, leisure, and housing. Given evidence of the large decline in consumption, employment, and housing (Mian et al., 2013; Mian and Sufi, 2011, 2014), it is reasonable to suspect that these same areas experienced a decline in pollution.[34] Using plausibly exogenous variation in county-level wind diffusion patterns as instruments for pollution produces estimates that are broadly in line with the conditional correlations and fixed effects estimates, but contain some substantive differences.

5.6.1. Other Issues

A. Measurement of Pollution: The benchmark model has used particulate matter of 10 microns or less (PM10), but the results are qualitatively robust to various other measures of air quality, including an air quality index and ozone pollution.

B. Willingness to Pay v. Willingness to Accept: Amiran and Hagen (2014) caution

[34] For example, running a panel regression of the change in log consumption and leisure on the change in log PM10 produces coefficients of 0.15 and -0.13 with p-values equal to 0.00. However, the change in log housing values appears to lack any association with a decline in PM10, although it is associated with a decline in the log air quality index (correlation of 0.15 with a p-value of 0.00).

Table 4: Reduced-Form Elasticity Results

	Dep. var. = Ln(Consumption)			Dep. var. = Ln(Leisure)			Dep. var. = Ln(Housing)		
	OLS	OLS	IV	OLS	OLS	IV	OLS	OLS	IV
Ln(Pollution)	-.02	-.03**	-.09*	.01	.00	-.01	-.04**	-.04**	.07*
	[.02]	[.01]	[.05]	[.00]	[.00]	[.01]	[.02]	[.02]	[.04]
R-squared	.53	.55	.53	.07	.08	.06	.60	.63	.60
Sample Size	2635789	2635789	1372631	2768691	2768691	1433573	2569626	2569597	1323889
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
County FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Notes.–Sources: Census, EPA, NOAA, CEX, ATUS. The table reports the coefficients associated with reduced-form regressions of log non-durables consumption, leisure, and housing (separately) on log air quality and a vector of controls. The IV regressions instrument for air quality using a quadratic in wind speeds. The controls specifications contain a quadratic in employment, payroll expenditures, wage income, and a five-way bin of establishment closures (1-10, 10-49, 50-249, 500-999, 1000+). All standard errors are clustered at the county level and observations are weighted by the ACS person and household weights for consumption & leisure and housing, respectively.

that willingness to pay and willingness to accept—which are crucial for identifying the value of a non-market good—may differ, especially when exploiting cross-sectional variation since aggregation problems may arise. Determining the empirical relevance of the concern is likely to vary with the quality of the data (e.g., variation and richness of controls) and is the topic of a companion paper. Nonetheless, this approach provides serious advantages to the traditional hedonic approach. First, since matching site-specific amenities with housing unit and demographic records often occurs at different levels of aggregation, my approach avoids an errors-in-variables problem that would traditionally introduce noise and/or bias depending on the correlation of the errors with other independent variables. Second, while a standard challenge is addressing omitted variables concerns arising from unobserved heterogeneity in housing prices that are correlated with the amenity, my household level data is able to provide a much finer set of controls on local labor market outcomes and housing values.[35]

F. Long versus Short Run Elasticities: A recurring tension in macroeconomics is the identification of Frisch versus Hicksian elasticities (e.g. see Chetty (2012) for the former and Keane and Rogerson (2012) and Keane (2011) for the latter). There are two reasons to suspect that my results are informative about long-run elasticities between market and non-market goods. First, there is tremendous cross-sectional variation in the Census, especially over the 2000-2014 era. Housing prices and wages—the factor prices that pin down sorting behavior—vary significantly both within and across counties. Second, my baseline model exploits equilibrium sorting behavior, meaning that my estimated coefficients are representative of equilibrium (Hicksian) behavior. To further investigate the extent to which my elasticities are more informative for short-run behavior,

[35]See Bajari et al. (2012) for an alternative approach that exploits rational expectations over the unobserved error.

the next sub-section conducts a heterogeneity analysis, in particular heterogeneity based on the level of air quality in order to determine the potential for state dependence. While there is evidence of state dependence, the coefficients are not substantially different, indicating that elasticities between air quality and consumption, leisure, and housing may not have substantially differed in the 1970s, relative to today.

6. Macroeconomic Implications

Using these estimated elasticities and willingness to pay for air quality, my results allow me to implement a welfare evaluation of changes in air quality, offering a point of comparison with the EPA results on the Clean Air Act Amendments. Higher levels of air quality are valued, but come at the cost of lower household real incomes since firms pass-through the cost of emissions in the form of higher prices (Fabra and Reguant, 2014). A common approach is to assume that preferences are homogeneous and linear with respect to air quality, making the marginal willingness to pay for air quality constant (Freeman, 1974). Unfortunately, the gradient of the hedonic price function provides only an average *marginal* willingness to pay for a one-unit change in air quality or pollution, rather than (total) willingness to pay through the identification of the entire hedonic price function. The hedonic price function may shift over time based on unobserved shocks, undermining the mapping of MWTP estimates into WTP estimates both due to bias (mis-specification) and lack of identification of the new (shifted) hedonic price function (Kuminoff et al., 2010; Kuminoff and Pope, 2014).

6.1. Estimating Counterfactual Densities

Given the estimated micro-elasticities, I now compute how much households would be willing to pay to keep air quality at its 2000 level in 2010, e.g., solving for the Δ such that $u(C(1+\Delta), L, H, S)$ equals $u(\tilde{C}, \tilde{L}, \tilde{H}, S)$ where $\tilde{D}$ denotes the counterfactual distribution of variable $D \in \{C, L, H\}$ in 2010. While all these variables are observed in the 2000 and 2010 data, the problem with computing Δ directly (without computing counterfactuals) is that Δ will be driven by changes in C, L, and H, rather than just S. Following Dinardo et al. (1996), I compute the 2010 counterfactual densities and weighting the observed 2010 values appropriately.[36] These counterfactuals have the interpretation of the density that would have prevailed if attributes (X) stayed the same at their 2000 level and

[36] Dinardo et al. (1996) developed an initial approach for computing these counterfactuals when separating between two groups (e.g., union status). Bound et al. (2010) has recently applied a version of their counterfactual simulation in the context of the economics of education. Heckman and Vytlacil (2005) studies it in the context of estimating treatment effects. The counterfactual density is given by $f^{2010}_{2005}(\ln D) =$

$$\int f^{2010}(\ln D|X)h(X|t=2000)dx = \int \left(\rho^{2005}(X)/(1-\rho^{2005}(X))\right)\left(P^{2010}/P^{2005}\right) f^{2010}(\ln D|X)h(X|t=2010)dx$$

the relationship between the outcome variable of interest, $D \in \{C, L, H\}$, and economic returns are as observed in 2010.

7. Conclusion

Current general equilibrium models overwhelmingly assume that non-market goods are additive substitutes with market goods. Because individuals cannot choose the externality, instead they take it as given, non-market goods necessarily drop out of the first-order conditions in the competitive equilibrium. Given the mounting evidence of non-separable interactions between market and non-market goods, and the fact that allowing for non-separable interactions produces qualitatively different welfare implications depending on the assumed micro-elasticities (Carbone and Smith, 2008, 2013), obtaining credible estimates of these micro-elasticities is an important research objective to discipline cost-benefit and macroeconomic analyses.

This paper began by introducing a refinement upon an otherwise standard neoclassical model with preferences over consumption, leisure, and housing services by including non-separable interactions between each of the market goods and a non-market good: pollution. Since pollution is created on the production-side of the economy, individuals take it as given when choosing their optimal bundle of consumption, leisure, and housing. However, by choosing where to live and where to work, individuals are able to imperfectly substitute since pollution varies across space, which is conceptually grounded in both hedonic (Rosen, 1974; Roback, 1982) and equilibrium sorting (Epple and Sieg, 1999) models. The intra-temporal Euler equilibrium conditions of this model provide structural relationships that can be taken directly to the data.

In order to estimate these micro-elasticity parameters in preferences, I build the most comprehensive database to date, containing individual-level consumption, leisure, housing, and demographic outcomes matched with weather and pollution outcomes at a county-level in order to structurally estimate elasticities between air quality and market goods and services (consumption, leisure, housing) between 2000-2014. Since the American Community Survey does not contain aggregate measures of non-durables consumption or leisure, I use a sieve estimator consisting largely

where P denotes the proportion of observations in the corresponding years, ρ denotes the predicted probability of a county being a 2005 observation, given the observed distribution of characteristics X. ρ^{2005} can be estimated by running a probit model with X controls on the distribution of attributes within a county, including both household-level attributes and business patterns (e.g., employment and establishments). Controls include an individual's property value, labor earnings, bins for the number of closures of plants within a particular size (1-10, 10-49, 50-249, 250-499, 500-999, and 1000 or more employees), establishments, payroll, and employment. The counterfactual density is weighted using

$$\Phi(X) = \left(\rho^{2005}(X)/(1-\rho^{2005}(X))\right)\left(P^{2010}/P^{2005}\right)$$

of splines in order to predict consumption and leisure in the Census data by extrapolating statistically estimated coefficients on micro-data from the Consumption Expenditure Survey and the American Time Use Survey. These predicted values have the same year-to-year average as the actual values and, moreover, the same trends in the standard deviations, and quantiles that match closely.

My identification strategy primarily exploits variation in individuals' locational choices over both their residence and job. To address time-varying omitted variables and non-random sorting, I control for a number of proxies for economic activity at the county-level, remove time-invariant differences across metro areas and time, and instrument for each of the endogenous variables. Consumption in instrumented using the log state electricity prices and its interactions with the year the individual's house was built to capture the impact of exogenous changes in the price of electricity consumption on the individual's purchases of non-durables; leisure is instrumented using interactions between mean / median maximum temperatures and age brackets to capture the impact of exogenous changes in the disutility of time spent outside on the allocation of time; housing services is instrumented using the housing supply elasticity to capture the impact of shocks on housing prices; and, pollution is instrumented using wind speeds to capture the impact of exogenous changes in air diffusion patterns on a geography's temporal air quality. The estimated elasticities imply that consumption, leisure, and housing are complements with air quality. These results are robust to various exercises, including a series of reduced-form regressions with different identifying assumptions.

To assess the macroeconomic implications, I simulate counterfactual 2010 distributions for consumption, leisure, and housing according based on their 2000 covariates. By scaling 2010 air quality to make the rise in air quality between 2000-2010 comparable to the decline in TSPs between 1990-2010 (the time span of the Clean Air Act Amendment evaluation), I examine how much households would be willing to pay to keep pollution levels as high as they were in 2000, holding constant their bundle of market goods. These estimates imply larger costs associated with the CAAA than previously found in the literature primarily because of the additional channel for substitution that individuals face.

This paper provides many avenues for future research. First and foremost, disentangling heterogeneity in preferences over private goods/services and amenities matters and cannot be captured purely by examining county-level data. Refinements should incorporate Roy sorting in a more structured way (e.g., as suggested by DeLeire et al. (2013)) in order to confront the inherent endogeneity in standard hedonic wage-risk regressions.[37] Second, there are a variety of distributional

[37]Kniesner et al. (2012) take an alternate route with panel data and using first-differences to remove time invariant

issues that can be investigated using accessible software routines (e.g., Frolich and Melly (2010)). For example, the comprehensive database can be used to understand how the spatial distribution of air quality inequality has changed over time—that is, differential access to non-market and market goods. Third, and most importantly, these elasticities can be used in macroeconomic models used to understand the welfare and general equilibrium effects of environmental policy intervention (see my companion work (Makridis, 2014b; Cai and Makridis, 2015)).

heterogeneity. However, as many have documented (Bound et al., 2001, 1994; Bound and Krueger, 1991), there are massive measurement error problems in the PSID and researchers need to weigh the costs and benefits of using panel data over small samples with cross-sectional data over large samples.

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