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Does Air Quality Matter? Evidence from the Housing Market*

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Abstract

We use the declines in air pollution induced by the 1970 and 1977 Clean Air Acts to provide new evidence on the capitalization of air quality into housing values. County-level EPA regulations are used as instrumental variables for changes in total suspended particulates (TSPs) pollution. We find that TSPs fell substantially more in regulated than in unregulated counties during the 1970s and, at the same time, housing prices rose more in regulated counties. We estimate that a $1\text{-}\mu\text{g}/\text{m}^3$ decline in particulates levels results in a 0.4-0.5% increase in home values (a 0.3-0.4 elasticity). This appears to be a robust estimate of the average marginal willingness-to-pay for clean air across individuals. For example, the estimates from this design are remarkably stable across specifications, while the estimates based on 'conventional' designs are 6-7 times smaller and very sensitive to model specification. The Clean Air Act regulations seem to have provided substantial economic benefits to homeowners in regulated counties. Consistent with the Tiebout sorting hypothesis, the evidence also suggests that the marginal benefit of a pollution reduction is slightly lower in communities with high pollution levels.

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Introduction

Federal air pollution regulations have been among the most controversial interventions mandated by the U.S. government. Yet, there is an absence of convincing empirical evidence on the costs and benefits of these regulations. Thus, credibly estimating the economic value of clean air to individuals is an important topic to both policy makers and economists.

The hedonic approach to estimating the economic benefits of air quality uses the housing market to infer the implicit price function for this non-market amenity. Here, researchers estimate the association between property values and air pollution, measured by total suspended particulates (TSPs), regression-adjusted for differences across locations in observable characteristics. After over 30 years of research, the cross-sectional correlation between housing prices and particulates pollution appears weak. A meta-analysis of 37 cross-sectional studies suggests that a $1\text{-}\mu\text{g}/\text{m}^3$ decrease in TSPs results in a 0.05-0.10% increase in property values, which implies only a 0.04-0.07 elasticity (Smith and Huang 1995). As a result, many question whether the marginal willingness-to-pay (MWTP) for environmental amenities can be reliably inferred from market equilibrium.

Two econometric identification problems plague the hedonic method. First, the estimated housing price-air pollution gradient may be severely biased due to omitted variables. In cross-sectional analyses, there may be unobserved factors that covary with both air pollution and housing prices. This study uses a new research design to examine whether housing prices rise with air quality, all else equal. Second, if there is heterogeneity across individuals in tastes for clean air, then individuals may self-select into locations based on these unobserved differences. To address this, we use a random coefficients model to estimate the average MWTP across individuals while accounting for self-selection bias arising from negative assortive matching.

We use the regulations of the 1970 and 1977 Clean Air Act Amendments (CAAAAs) to provide new evidence on the capitalization of air quality into housing values. The CAAAs marked an unprecedented attempt by the federal government to mandate lower levels of air pollution. If pollution concentrations in a county exceeded the federal ceiling, then the Environmental Protection Agency (EPA) designated the county as 'nonattainment'. Polluters in nonattainment counties faced much greater

regulatory oversight than their counterparts in attainment counties.

We compare changes in particulates pollution and property values in counties that were and were not regulated during the 1970s. To do this, we compile the most detailed and comprehensive data available on pollution levels, EPA regulations, and housing values at the county-level. Although the attainment/nonattainment status of each county is central to federal environmental law, we are the first to collect and use this information for the entire U.S. during this key period. Further, through a Freedom of Information Act request, we obtained annual air pollution concentrations for each county based on the universe of state and national pollution monitors. All of this is merged to data on housing values and county characteristics from the County Data Books and five-percent Census files.

The county-level EPA regulations are used as instrumental variables for changes in TSPs pollution. We find strong evidence that the regulations are uncorrelated with virtually all other observable determinants of changes in housing prices, including economic shocks. In addition, the discrete relationship between regulatory status and the previous year's pollution levels provides a unique opportunity to gauge the credibility of the design. For example, due to the structure of the regulations, we can compare nonattainment and attainment counties with identical average TSPs levels in the regulation selection year. Finally, the analysis matches counties with similar TSPs levels, a plausible index for tastes, to estimate MWTP functions accounting for the confounding effect of 'Tiebout' sorting.

The analysis reveals two striking empirical regularities. TSPs declined substantially more in nonattainment than in attainment counties during the 1970s (by 8-9 $\mu\text{g}/\text{m}^3$), and, at the same time, housing prices rose more in regulated counties (by 4-5%). We estimate that a 1- $\mu\text{g}/\text{m}^3$ decline in particulates levels results in a 0.4-0.5% increase in home values (a 0.3-0.4 elasticity). This appears to be a robust estimate of the average marginal willingness-to-pay for clean air across individuals. For example, the estimates from this design are remarkably stable across specifications, while the estimates based on 'conventional' designs are 6-7 times smaller and very sensitive to model specification.

Exploiting the relationship between regulatory status and pollution levels, we find evidence consistent with the Tiebout sorting hypothesis. Under mild restrictions (e.g., non-increasing marginal utility), the results imply that individuals self-select across counties due to taste heterogeneity. While the

marginal benefit of a pollution reduction is lower in communities with relatively high pollution levels, the overall variation in MWTP is not large. The Clean Air Act regulations seem to have provided substantial economic benefits to homeowners in regulated counties during the 1970s. However, their design may not have accounted for taste heterogeneity and negative assortive matching based on these tastes. The results also indicate that the hedonic method can be successfully applied in certain contexts.

The Hedonic Method and Econometric Identification Problems

An explicit market for clean air does not exist. The hedonic price method is commonly used to estimate the economic value of this non-market amenity to individuals.¹ It is based on the insight that the utility associated with the consumption of a differentiated product, such as housing, is determined by the utility associated with the characteristics of the good. For example, hedonic theory predicts that an economic bad, such as air pollution, will be negatively correlated with housing prices, holding all other characteristics constant. Here, we review the method and the econometric identification problems associated with its implementation.

The Hedonic Method

Economists have estimated the association between housing prices and air pollution at least since Ridker (1967) and Ridker and Henning (1967). However, Rosen (1974) was the first to give this correlation an economic interpretation. In the Rosen model, a differentiated good can be described by a vector of its characteristics, $Q = (q_1, q_2, \dots, q_n)$. In the case of a house, these characteristics may include structural attributes (e.g., number of bedrooms), the provision of neighborhood public services (e.g., local school quality), and local amenities (e.g., air quality). Thus, the price of the i^{th} house can be written as:

$$(1) \quad P_i = P(q_1, q_2, \dots, q_n).$$

The partial derivative of $P(\bullet)$ with respect to the n^{th} characteristic, $\partial P / \partial q_n$, is referred to as the marginal implicit price. It is the marginal price of the n^{th} characteristic implicit in the overall price of the house.

¹ Other methods for non-market amenity valuation include contingent valuation, conjoint analysis, and discrete choice models. See Smith (1996) for a review and comparison of these methods.

In a competitive market the housing price-housing characteristic locus, or the hedonic price schedule (HPS), is determined by the equilibrium interactions of consumers and producers.² The HPS is the locus of tangencies between consumers' bid functions and suppliers' offer functions. The gradient of the implicit price function with respect to air pollution gives the equilibrium differential that allocates individuals across locations and compensates those who face higher pollution levels. Locations with poor air quality must have lower housing prices in order to attract potential homeowners. Thus, at each point on the HPS, the marginal price of a housing characteristic is equal to a consumer's marginal willingness to pay (MWTP) for that characteristic and a supplier's marginal cost of producing it. Since the HPS reveals the MWTP at a given point, it can be used to infer the welfare effects of a marginal change in a characteristic for a given individual.

In principle, the hedonic method can also be used to recover the entire demand or MWTP function. In this case, the welfare effects of nonmarginal changes can be calculated. Rosen proposed a 2-step approach for estimating the MWTP function, as well as the supply curve. In the first step, equation (1) is estimated and used to predict household-specific marginal implicit prices, $\partial P_i / \partial q_n$. In the second step, the following inverse demand and supply system of equations is estimated:

$$(2) \quad q_n^d = \partial P_i / \partial q_n = f(q_n, \mu), \text{ and}$$

$$(3) \quad q_n^s = \partial P_i / \partial q_n = g(q_n, \eta),$$

where the estimated implicit prices from equation (1) are used as observations on actual prices, and q_n^d and q_n^s are the demand and supply marginal prices of characteristic q_n .

Equation (2) is the MWTP function, which depends on the amenity level, q_n , and on consumer tastes and demand shifters, μ . Equation (3) is the inverse supply curve, which is a function of q_n and production technologies/cost shifters, η . Credible estimation of this system has tremendous practical importance. For example, one could estimate individuals' willingness-to-pay for the large improvements in air quality induced by the Clean Air Act Amendments of the 1970s.³

² See Rosen (1974), Freeman (1993), and Palmquist (1991) for details.

³ Two nontrivial assumptions are needed for equation (2) to produce an exact measure of willingness-to-pay in our context. First, consumers cannot move in response to an air quality change. Below, we find evidence that supports this assumption in our research design. Second, since equation (2) is an uncompensated demand curve, an implicit assumption is that the welfare benefits calculated from uncompensated and compensated bid functions are similar.

Econometric Identification Problems

There are two substantive statistical problems that plague the hedonic approach to estimating the willingness-to-pay for clean air. The first concerns credible estimation of the implicit price function embodied in equation (1). The second problem complicates estimation of equation (2) in the second stage. Solutions to both problems are required for reliable estimation of the increase in consumer welfare resulting from an air pollution reduction.

Consistent estimation of the HPS in equation (1) is extremely difficult since there may be unobserved factors that covary with both air pollution and housing prices.⁴ For example, areas with higher levels of TSPs tend to be more urbanized and have higher per-capita incomes, population densities, and crime rates. Consequently, cross-sectional estimates of the housing price-air quality gradient may be severely biased due to omitted variables. This is one explanation for the wide variability in HPS estimates from the cross-sectional studies of the last 30 years (Smith and Huang 1995).⁵ Hedonic theory predicts that housing prices rise with air quality, all else equal. Previous studies, on the other hand, may be relying on comparisons across locations in which several factors are not held constant.⁶

The seriousness of this problem cannot be overstated. The validity of any welfare calculation rests on the assumption that the HPS has been consistently estimated. First, the welfare effects of a marginal change in air quality are obtained directly from the HPS. Second, an inconsistent HPS will lead to an inconsistent MWTP function, invalidating any welfare analysis of non-marginal changes. While the importance of this issue was recognized shortly after Rosen (1974), it has received little attention since.⁷ Consequently, the first goal of this study is to credibly estimate the hedonic price function for clean air

⁴ See Halvorsen and Pollakowski (1981) and Cropper et al. (1988) for discussions of misspecification of the HPS due to incorrect functional form. Below, we estimate 'non-parametric' conditional mean functions in the analysis.

⁵ Smith and Huang find that a quarter of the reported estimates have perverse signs; that is, they indicate a positive correlation between housing prices and pollution levels.

⁶ Similar problems arise when estimating compensating wage differentials for job characteristics, such as the risk of injury or death. The regression-adjusted association between wages and many job amenities is weak and often has a counterintuitive sign (Smith 1979). Brown (1980) assumes that the biases are due to permanent differences across individuals and focuses on job 'changers'.

⁷ On the hedonic method, Small (1975) writes, "I have entirely avoided...the important question of whether the empirical difficulties, especially correlation between pollution and unmeasured neighborhood characteristics, are so overwhelming as to render the entire method useless. The degree of attention devoted to this [problem]...is what will really determine whether the method stands or falls..." (p. 107). We are aware of only one study that has seriously examined this issue (Graves et al. 1988).

and empirically assess whether housing prices rise with air quality.

Even if the HPS can be consistently estimated, there is a second serious impediment to estimating the MWTP function in equation (2). The estimated marginal implicit prices of the n^{th} characteristic, $\partial P_i / \partial q_n$, depend on q_n , and q_n is the explanatory variable of interest in the second stage system (Bartik 1987, Epple 1987). Therefore, estimation of the demand equation will be biased if there is an omitted variable in μ that is correlated with the individual's choice of q_n .⁸ Heterogeneity across individuals in tastes for environmental amenities could lead to this type of misspecification. The Tiebout hypothesis predicts that individuals will self-select to the locations that best satisfy their preferences for these amenities (Tiebout 1956).⁹ In the presence of taste sorting, the hedonic approach requires situations in which individuals with identical preferences for air quality (and similar levels of other demand factors, such as income) face different marginal prices. Our second goal is to estimate the MWTP function while accounting for self-selection and calculate the welfare effects of non-marginal changes in air quality.

Federal Air Quality Regulations and a New Research Design

In the ideal analysis, the researcher could randomly assign different levels of air pollution across locations and measure differences in the value of homes to their owners before taste sorting occurs. This experimental design would solve both econometric problems discussed above. In its absence, we use federally mandated environmental regulations imposed at the county level to isolate air quality changes that may be orthogonal to other determinants of housing price changes and unobserved 'tastes' for pollution. Here, we provide the background on the 1970 and 1977 Clean Air Act Amendments (CAAAAs) and describe how they provide a unique and compelling opportunity to recover the gradients of both the hedonic price and MWTP functions for clean air.

⁸ There is a consensus that this problem has never been circumvented, and that the second stage MWTP function for an environmental amenity has never been reliably estimated (Deacon et al. 1998).

⁹ Epple and Sieg (1999) develop a locational equilibrium model to value local public goods and test the Tiebout hypothesis. Sieg, Smith, Banzhaf, and Walsh (2000) apply this approach to value air quality changes in Southern California from 1990-1995. Below, we derive and implement a hedonic model that accounts and tests for nonrandom taste sorting.

The CAAAs and their Enforcement

Before 1970 the federal government did not play a significant role in the regulation of air pollution, a responsibility left primarily to state governments.¹⁰ In the absence of federal legislation, few states had an incentive to impose strict regulations on polluters within their jurisdictions. Concerned with the detrimental health effects of persistently high concentrations of suspended particulates pollution, and of other air pollutants, Congress passed the Clean Air Act Amendments of 1970.

The centerpiece of the CAAAs was the establishment of separate federal standards, known as the National Ambient Air Quality Standards (NAAQS), for six pollutants. Its stated goal is to reduce local air pollution concentrations until all U.S. counties are in compliance with the NAAQS. As directed by the CAAAs, the EPA annually determines the 'attainment-nonattainment' status of all U.S. counties for each of the regulated pollutants. If pollution concentrations in a county exceed the federal ceiling, then the EPA designates the county as being nonattainment for that pollutant in the following year.

For TSPs pollution, a county is nonattainment if either of two thresholds are exceeded in the previous year: 1) the annual geometric mean concentration exceeds $75 \mu\text{g}/\text{m}^3$, or 2) the second highest daily concentration exceeds $260 \mu\text{g}/\text{m}^3$ (see Appendix Table 1).¹¹ This standard prevailed from 1971 until 1987, when, instead of regulating all particulates, the EPA shifted its focus to finer particles. The regulations were changed to apply only to emitters of smaller PM-10s (particles with an aerodynamic diameter of at most 10 micrometers) in 1987 and to emitters of PM-2.5s in 1997.

To achieve these standards, the fifty states were required to form and enforce local pollution abatement programs. In its nonattainment counties, each state had to develop plant-specific regulations for every major source of pollution. These local rules ordered that any substantial investment by a new or existing plant must be accompanied by the installation of state-of-the-art pollution abatement equipment and strict emissions ceilings. The 1977 Amendment added the requirement that any increase in emissions from a new investment had to be offset by a reduction in emissions from another source within the same

¹⁰ Lave and Omenn (1981) and Liroff (1986) provide more details on the CAAAs. In addition, see Greenstone (1999) and Chay and Greenstone (1998).

¹¹ In addition to the TSPs standard, Appendix Table 1 lists the industrial and non-industrial sources, abatement techniques, and health effects of TSPs.

county.¹² The federally determined nonattainment designation also mandated that state authorities set emissions limits on existing plants.

In stark contrast, the restrictions on polluters in attainment counties were considerably less stringent. First, large-scale investments, such as new plants and large expansions at existing plants, required the installation of less expensive (and less effective) pollution abatement equipment. Moreover, it was not necessary to obtain offsets for increased emissions. Finally, both existing plants that were not expanding and smaller investments were essentially left unregulated.

Both the states and the federal EPA were given substantial enforcement powers to ensure that the goals of the CAAAs were met. To limit variation in the intensity of regulation across states, the federal EPA had to approve all state regulation programs. On the compliance side, states initiated their own inspection programs and frequently fined non-compliers. Also, the 1977 legislation made the plant-specific regulations both federal and state law. Thus, the EPA had legal standing to impose penalties on states that failed to aggressively enforce the regulations and on plants that failed to comply.

Several plant-level studies have documented the effectiveness of these regulatory actions (e.g., Nadeau 1997, Cohen 1998). Henderson (1996) provides direct evidence that the regulations were successfully enforced. He finds that ozone concentrations declined more in counties that were nonattainment for ozone than in attainment counties. We find striking evidence that TSPs levels fell substantially more in counties that were nonattainment for TSPs than in attainment counties after the passage of the 1970 Clean Air Act and throughout the 1970s.¹³

A New Research Design

In contrast to the previous literature, we estimate the HPS in first-differences and use the county-level EPA regulations as instruments for changes in TSPs. There are several reasons why this design may solve the problems of cross-sectional designs. First, TSPs regulation is strongly associated with large

¹² Offsets could be purchased from a different facility or could be generated by tighter controls on existing operations at the same site (Vesilind, Peirce, and Weiner 1988).

¹³ Greenstone (1999) provides further evidence on the effectiveness of the regulations. He finds that nonattainment status is associated with modest reductions in the employment, investment, and shipments of polluting manufacturers. Interestingly, the regulation of TSPs has little association with changes in employment. Instead, the overall employment declines are driven mostly by the regulation of other air pollutants.

differential reductions in particulates levels across counties. The timing and location of the changes provide convincing evidence that the estimated pollution impact is causal. Second, we find that the regulations are uncorrelated with the other observable determinants of housing price changes, including economic shocks. The instruments appear to purge the local demand and supply shocks that contaminate estimates based on ‘fixed-effects’ analyses. Third, since the regulations are federally mandated, their imposition is presumably orthogonal to underlying economic conditions and the local political process determining the supply of non-market amenities.¹⁴

Also, regulatory status is a discrete function of the annual geometric mean and second highest daily concentrations of TSPs in the previous year. Thus, the assignment of the regulations has the feature of a quasi-experimental regression-discontinuity design (Cook and Campbell 1979). If the unobservables are ‘smooth’ at the regulatory thresholds, then comparing outcome changes in nonattainment and attainment counties with similar pre-regulation TSPs levels will control for all omitted factors correlated with TSPs. Near the federal ceilings, discrete differences in mean outcome changes between regulated and unregulated counties are attributable to the regulations. We find evidence below that this ‘smoothness’ condition may hold in our context.¹⁵

The structure of the NAAQs allows for our most compelling test of causality. A county can be regulated due to having as few as 2 ‘bad’ days. The data indicate that a number of counties with low annual mean concentrations were designated nonattainment due to this rule. Thus, we can compare regulated and unregulated counties with identical average TSPs levels in the regulation selection year.

This design should solve the omitted variables problem that plagues estimation of the HPS in cross-sectional settings. However, the average gradient of the HPS may differ from the average MWTP

¹⁴ Scientific evidence provides additional support for the credibility of regulation instruments that depend on pollution levels. Cleveland et al. (1976) and Cleveland and Graedel (1979) document that wind patterns often transport air pollution hundreds of miles and that the ozone concentration of air entering into the New York region in the 1970s often exceeded the federal standards. A region’s topographical features can also affect pollution concentrations. Counties located in valleys (e.g., Los Angeles, Phoenix, Denver, the Utah Valley) are prone to weather inversions that lead to prolonged periods of high TSPs concentrations.

¹⁵ In some contexts, leveraging a discontinuity design could actually accentuate selection biases if economic agents know about the discontinuity point and change their behavior as a result (e.g., ‘avoidance’ behavior). Given the costly fixed investment required to reduce industrial emissions, it is unlikely that counties had fine enough control over pollution levels to engage in non-random sorting near the TSPs regulatory ceiling. Similarly, it is unlikely that individual homeowners were aware of the thresholds and would then move as a result.

in the population if there is sorting due to taste heterogeneity in the hedonic equilibrium. As a result, we use a random coefficients econometric model to estimate the average MWTP while controlling for bias arising from negative assortive matching. This model provides a simple and intuitive statistical test of the Tiebout hypothesis that is based on the weak restriction that marginal utilities are non-increasing.

Finally, the CAAs provide a unique opportunity to estimate MWTP functions purged of Tiebout sorting bias. Suppose that individuals with similar preferences for clean air choose to live in counties with comparable TSPs levels, all else equal. Then comparisons between regulated and unregulated counties with similar pre-regulation pollution levels will also be purged of selection bias arising from taste heterogeneity. This design matches on TSPs to eliminate the source of self-selection.

It is useful to compare this approach to estimating the MWTP function with the commonly used 'multiple markets' approach. In the multiple markets design, a separate HPS is estimated for a number of arbitrarily defined markets, and the differences in the estimated implicit prices across the markets are used to identify the demand parameters.¹⁶ Two assumptions are required for consistency: 1) tastes for the amenity are identical across the markets, and 2) individuals do not respond to the price differentials and remain in their respective markets. Both assumptions will fail to hold if individuals self-select into markets based on heterogeneous preferences.¹⁷

We also attempt to compare individuals with similar preferences and incomes who face different marginal prices. The static multiple markets approach uses price variation generated by an arbitrary stratification of spatial markets and assumes that tastes are identical across the markets. In contrast, our approach matches markets based on a plausible index for tastes (i.e., pollution levels) and uses the variation over time induced by the federal EPA regulations, which may be valid exclusion restrictions. While neither approach is nonparametric, the assumptions of our design may be more justifiable.¹⁸

¹⁶ Freeman (1974) first proposed this technique. See Palmquist (1984), Bartik (1987), and Blau and Hagy (1998) for applications. Michaels and Smith (1990) discuss the difficulties in correctly defining the markets.

¹⁷ Brown and Rosen (1982) point out that unless there are variables in equation (1) that are excluded from equation (2), the second stage estimation of the MWTP function may only reproduce the coefficients estimated in equation (1). In the multiple markets approach, the excluded variables are indicators for different locations. If these exclusion restrictions are not valid, then a correct specification of the second stage would simply identify the HPS parameters and the Brown and Rosen problem remains.

¹⁸ Rosen (1986) concludes "...it is difficult to obtain structural estimates from a single cross-section without using many detailed and often rather arbitrary assumptions...These difficulties arise because of the stratification of agents

Data and Overview of Changes in Air Pollution

To implement our design, we compile the most detailed and comprehensive data available on pollution levels, EPA regulations, and housing values for the 1970s at the county level. Here, we describe the data and give an overview of the dramatic changes in particulates concentrations induced by the CAAAs. More details on the data are provided in the Data Appendix.

TSPs Pollution Data and National Trends

Previous research has focused on the capitalization of TSPs pollution since it is the most visible and has the most pernicious health effects of all the regulated pollutants.¹⁹ The TSPs data were obtained by filing a Freedom of Information Act request with the EPA that yielded the *Quick Look Report* file, which comes from the EPA's *Air Quality Subsystem* (AQS) database. This file contains annual information on the location of and readings from every TSPs monitor in operation in the U.S. since 1967. Since the EPA regulations are applied at the county level, we calculated the annual geometric mean TSPs concentration for each county from the monitor-level data. For counties with more than one monitor, the county mean is a weighted average of the monitor-specific geometric means, with the number of observations per monitor used as weights. The file also has data on the number of daily monitor readings exceeding the federal standards in each year. This is used to determine which counties were regulated for exceeding the daily concentration ceiling only.

Figure 1 presents trends from 1969-1990 in average particulates levels across the counties with monitor readings in each year.²⁰ Air quality improved dramatically over the period, with TSPs levels falling from an average of 85 $\mu\text{g}/\text{m}^3$ in 1969 to 55 $\mu\text{g}/\text{m}^3$ in 1990. Most of the overall pollution reduction occurred in two punctuated periods. While the declines in the 1970s correspond with the implementation of the 1970 CAAA, the remaining improvements occurred during the 1981-82 recession. As heavily

inherent in these models. Pooled time series and cross-section data...appear to be necessary to overcome these difficulties." (p. 661)

¹⁹ See Dockery et al. (1993), Ransom and Pope (1995), and Chay and Greenstone (1999) for evidence on the effects of TSPs on adult and infant health. Chay and Greenstone (1998) find weak evidence that changes in ozone concentrations during the 1980s were capitalized into housing prices. For the 1970s, we found no association between housing values and levels of ozone, sulfur dioxide, and carbon monoxide.

²⁰ These are weighed averages of the county means, with the county's population in 1980 used as weights. The sample consists of 173 counties with a combined population of 85 million in 1980.

polluting manufacturing plants in the Rust Belt permanently closed due to the recession, air quality in these areas improved substantially (Kahn 1997, Chay and Greenstone 1999). This implies that local economic shocks could drive both declines in TSPs and declines in housing prices. Below, we find that fixed-effects estimates of the HPS may be seriously biased by these shocks.

Nonattainment Status and its Impact on Air Quality

The EPA uses the NAAQS to determine the attainment-nonattainment status of each county for TSPs on an annual basis. The Data Appendix details how the *Code of Federal Regulations* and the TSPs pollution data are used to determine the TSPs regulatory status for the 3,000+ U.S. counties in each year from 1971-1990. We now document the overall impact of the regulations on TSPs levels.

Figure 2A examines the initial impact of the 1970 CAAAs. Here, the counties with continuous monitor readings from 1967-1975 are stratified by their regulatory status in 1971.²¹ Before the CAAAs, TSPs concentrations were 40 $\mu\text{g}/\text{m}^3$ higher in the nonattainment counties. While the pre-regulation time-series patterns of the two groups are similar, attainment counties had a slightly larger pollution decline before 1971. These trends were dramatically reversed after the passage of the 1970 CAAAs. From 1971-75 newly regulated counties had a stunning 26- $\mu\text{g}/\text{m}^3$ reduction in TSPs, while TSPs fell by only 6 $\mu\text{g}/\text{m}^3$ in attainment counties, continuing the pre-1971 trend. This implies that virtually all of the national decline in TSPs from 1971-75 in Figure 1 is attributable to the regulations. Remarkably, this is the first direct evidence that has been established on the impact of the 1970 CAAAs on TSPs concentrations.

For reasons discussed below, our analysis focuses on the effects of TSPs regulation in the mid-1970s. Table 1 summarizes the TSPs data for the 1970s (1980s) by the county's nonattainment status in 1975-76 (1985-86). The sample is restricted to counties with TSPs monitor readings at the beginning and end of the decade and consists of 1,000 counties accounting for about 80 percent of the U.S. population.²² This is the primary sample used in the study and suggests that the analysis is comprehensive.

²¹ The sample consists of 231 counties with a total population of 88 million in 1970.

²² For the 1970s (1980s), the beginning and end of the decade are defined as 1969-72 (1977-80) and 1977-80 (1987-90), respectively. Since the EPA's monitoring network was still growing in the late 1960s, the 1969-72 definition increases the number of counties used in the analysis. The results are insensitive to these definitions.

Columns 1 and 2 of the table show that counties that were and were not regulated in 1975 or 1976 had nearly identical pre-regulation reductions in average TSPs of 13-14 $\mu\text{g}/\text{m}^3$ by 1974. This is not surprising since several counties that were attainment (nonattainment) in the mid-70s were nonattainment (attainment) at the start of the decade.²³ After 1975, however, TSPs fell over 7 $\mu\text{g}/\text{m}^3$ more in regulated counties than in unregulated counties. The patterns in the mean maximum daily concentration are similar.

Figure 2B plots annual TSPs levels by 1975-76 attainment status for the counties with monitor readings in every year from 1970-80. It confirms the conclusions from Table 1. While the pre-regulation trends of the two groups are identical, only regulated counties had a decline in TSPs after 1975. The post-regulation decline in mean TSPs is about 7 $\mu\text{g}/\text{m}^3$ greater in regulated than in unregulated counties.

Figure 3 provides more detailed evidence on the impact of TSPs nonattainment status in 1975. Panel A plots the 1974-77 post-regulation changes in mean TSPs for counties that were and were not regulated in 1975 by the geometric mean of TSPs in 1974, the regulation selection year. The smoothed mean TSPs changes are from locally weighted nonparametric regressions, estimated separately for unregulated and regulated counties. Counties that were nonattainment due to only exceeding the daily concentration threshold were dropped from this analysis. Thus, all counties with 1974 mean TSPs less than (greater than) 75 $\mu\text{g}/\text{m}^3$ are attainment (nonattainment) in 1975. Panel B plots the 1971-74 pre-regulation mean TSPs changes for the same sets of counties.²⁴

The patterns are striking. In Panel A, regulated counties had a 9.5 $\mu\text{g}/\text{m}^3$ greater decrease in mean TSPs from 1974-77 than unregulated counties right at the regulatory threshold (75 $\mu\text{g}/\text{m}^3$).²⁵ This discrete difference cannot be explained by the very small 'trend' in TSPs changes leading up to the threshold. Panel B shows that counties that were and were not regulated in 1975 had nearly identical pre-regulation changes in mean TSPs from 1971-74, including at the regulatory threshold. Thus, mean reversion and differential trends are not likely sources of bias. Mid-decade regulatory status appears to be

²³ 40-45% of the population in 1975-76 attainment counties lived in nonattainment counties in 1971-72. 15-18% of the population weighted 1975-76 nonattainment counties were attainment in 1971-72.

²⁴ The sample is restricted to counties with TSPs readings in 1971, 1974, and 1977. A total of 613 counties were used to construct Figure 3.

²⁵ This is the difference in the estimated 1974-77 TSPs change between the attainment and nonattainment counties with the highest (74.8 $\mu\text{g}/\text{m}^3$) and lowest (75.2 $\mu\text{g}/\text{m}^3$) geometric mean of TSPs in 1974, respectively. Both counties are in Ohio (Lawrence and Summit counties).

causally related to differential TSPs reductions in the second half of the 1970s. Taken together, Figures 2 and 3 contradict recent claims that clean air legislation had no effect on air quality (Goklany 1999).

Columns 3 and 4 of Table 1 show how the 1981-82 recession complicates an analysis of the 1980-1990 period. In contrast to the 1970s, TSPs fell more in nonattainment counties than in attainment counties in the pre-regulation period. In the post-regulation period, average TSPs actually declined more in unregulated counties. These findings are not surprising given the geographic variation in the effects of the 1981-82 recession (Chay and Greenstone 1999) and the termination of the TSPs regulatory program in 1987. When a figure similar to Figure 2B is constructed for the 1980s, the reduction in TSPs attributable to mid-decade regulations cannot be distinguished from differential responses to the 1981-82 recession. For this and many others reasons, this study focuses solely on the 1970s. Chay and Greenstone (1998) provide a fuller discussion of these issues and present the results from strategies that address the problems in estimating the HPS for the 1980s.

Figure 4 provides a geographic overview of the incidence of mid-1970s TSPs regulations in the U.S. A county's shading indicates its regulatory status in 1975-76: black for nonattainment, light gray for attainment, and white for counties without TSPs monitors in either the beginning or end of the 1970s. The figure reveals the pervasiveness of the TSPs regulatory program in the mid-1970s. In addition to the 'traditional' counties in the Rust Belt and South Coast Air Basin around Los Angeles, scores of other counties were regulated. Importantly, the unregulated counties containing pollution monitors are in close proximity to the regulated counties. That is, the 'treatment' and 'control' counties are predominantly from the same parts of the U.S.

Housing Values and County Characteristics

The property value and county characteristics data come from the 1972 and 1983 County and City Data Books (CCDB). The CCDBs are comprehensive, reliable, and contain a wealth of information for every U.S. county. Much of the data come from the 1970 and 1980 Censuses of Population and Housing. The outcome variable is the log-median value of owner-occupied housing units in the county. The control variables include demographic and socioeconomic characteristics (population density, race, education, age, per-capita income, poverty and unemployment rates, fraction in urban area),

neighborhood characteristics (crime rates, doctors and hospital beds per-capita), fiscal/tax variables (per-capita taxes, government revenue, expenditures, fraction spent on education, welfare, health, and police), and housing characteristics (e.g., year structure was built).²⁶ The Data Appendix provides more details on the CCDBs and the variables used in the analysis

The use of these data raises a few issues. First, consider how individuals may respond to the housing value question in the Census. The household head provides his/her assessment of the monetary value of the owner-occupied housing unit. Although the response may partially reflect his perceptions of the market price, it may also reflect the value of the house to him. Thus, it may be more correlated with the owner's WTP than sales price data, which reflect the market hedonic by definition. In this case, Census housing values provide a better measure of the preferences of the average homeowner in the county. Still, our estimates of the average MWTP should provide a lower bound on the 'true' average.

Next, consider the reasons for focusing on the mid-1970s regulations. County-level housing value data are only available in 1970 and 1980. Also, Figures 2A and B suggest that there is at least a 2-3 year lag before the full effects of TSPs regulation on pollution reductions are realized. If local housing markets are integrated over a long time horizon, then it is not valid to use 1970-80 housing price changes to measure the capitalization of early 1970s TSPs reductions.²⁷

Suppose, however, that demand-side Tiebout sorting adjusts slowly in response to a pollution shock due to moving costs, etc., and/or the supply-side of the housing market is not perfectly elastic in the short-run. In this case, TSPs reductions at the end of the 70s would be capitalized into 1980 housing values without substantial contamination by general equilibrium adjustments in demand and supply. We find evidence consistent with this. We also find that counties that were and were not regulated in 1975-76 had nearly identical changes in economic conditions during the 1970s. This is not true when comparing counties that were and were not regulated earlier in the decade.

²⁶ In Chay and Greenstone (1998), we also examined data from the 1980 and 1990 5-percent Census PUMS microdata, which can be matched to the county-level pollution and regulation data at the PUMA level. The PUMS contain housing characteristics not available in the CCDBs, such as numbers of rooms and bedrooms and acreage. We found that the PUMS results were identical to the CCDB results for the 1980s.

²⁷ For example, Blanchard and Katz (1992) find that local housing prices fall in the first five years following a negative local employment shock but rebound fully within about a decade of the shock.

Before proceeding, we note that a few studies have used census tract level data (e.g., Ridker and Henning 1967, Harrison and Rubinfeld 1978). We use county-level data for two reasons: TSPs regulations are enforced at the county-level, and census tracts are difficult to match between the 1970 and 1980 Censuses. However, this aggregation may not be an important source of bias. Using the fact that most counties contain several pollution monitors, we find that only 25% of the total variation in 1970-80 TSPs changes is attributable to within-county variation, with the rest due to between-county variation. Also, regulated and unregulated counties had almost identical changes in urbanization rates during the 70s, suggesting that ‘urban sprawl’ within counties is not a source of bias. Finally, our cross-sectional estimates are very similar to those summarized in Smith and Huang (1995).²⁸ However, it should be noted that our analysis does not address within-county taste heterogeneity and sorting.

Econometric Models for the HPS and Average MWTP

Here, we discuss the econometric models used to estimate the hedonic price locus. First, we focus on the constant coefficients version of these models. We then discuss a random coefficients model that allows for self-selection bias arising from taste sorting. We show how this model identifies the average MWTP in the population while providing a simple statistical test of the Tiebout hypothesis.

Estimation of the HPS Gradient

The cross-sectional model predominantly used in the literature is:

$$(4) \quad y_{c70} = X_{c70}'\beta + \theta T_{c70} + \varepsilon_{c70}, \quad \varepsilon_{c70} = \alpha_c + u_{c70}$$

$$(5) \quad T_{c70} = X_{c70}'\Pi + \eta_{c70}, \quad \eta_{c70} = \lambda_c + v_{c70},$$

where y_{c70} is the log of the median property value in county c in 1970, X_{c70} is a vector of observed characteristics, T_{c70} is the geometric mean of TSPs across all monitors in the county, and ε_{c70} and η_{c70} are the unobservable determinants of housing prices and TSPs levels, respectively.²⁹ The coefficient θ is the ‘true’ effect of TSPs on property values and is interpreted as the average gradient of the HPS. For

²⁸ Since there are few air pollution monitors in a given area, using census tract data has its own set of issues. For example, Harrison and Rubinfeld’s analysis of 506 census tracts relies on only 18 TSPs monitors. As noted by Moulton (1986), treating these correlated observations as being independent can lead to misleading inference.

²⁹ See Table 1 for the definitions of T_{c70} and T_{c80} . Averaging over more than one year reduces the impact of temporary perturbations on our measures of pollution.

consistent estimation, the least squares estimator of θ requires $E[\varepsilon_{c70}\eta_{c70}]=0$. If there are omitted permanent (α_c and λ_c) or transitory (u_{c70} and v_{c70}) factors that covary with both TSPs and housing prices, then the cross-sectional estimator will be biased.

Table 2 presents the association of TSPs levels in 1970 and 1980 with other potential correlates of housing prices. The Small and Big categories correspond to the counties in the lowest and highest quartiles of pollution, while the Middle category consists of the counties in the middle two quartiles. The variable means and the F-statistics testing for significant differences across the groups are presented. If TSPs levels were randomly assigned across counties, one would expect very few significant differences. However, the differences across the groups are significant for almost every variable. Counties with higher TSPs levels tend to be more urbanized and have higher per-capita incomes, population densities, and crime rates. This suggests that ‘conventional’ cross-sectional estimates will be biased due to omitted variables, which is what we find below.

With repeated observations over time, a ‘fixed-effects’ model implies that first-differencing the data will absorb the county permanent effects, α_c and λ_c . This leads to:

$$(6) \quad y_{c80} - y_{c70} = (X_{c80} - X_{c70})'\beta + \theta(T_{c80} - T_{c70}) + (u_{c80} - u_{c70})$$

$$(7) \quad T_{c80} - T_{c70} = (X_{c80} - X_{c70})'\Pi + (v_{c80} - v_{c70}).$$

For identification, the least squares estimator of θ requires $E[(u_{c80} - u_{c70})(v_{c80} - v_{c70})]=0$. That is, there are no unobserved shocks to pollution levels that covary with unobserved shocks to housing prices.

The first 4 columns of Table 3 perform an analysis similar to Table 2 for 1970-80 TSPs changes. The Small and Big categories correspond to the counties in the lowest and highest change quartiles, while the Middle category consists of the counties in the middle two quartiles. Column 4 gives the F-statistic testing the equality of the sample means across the groups. Reductions in TSPs are highly correlated with economic shocks. The counties with large pollution declines experienced substantially less growth in per-capita income, a bigger increase in unemployment rates, and a larger decline in manufacturing employment. To the extent that local economic shocks cause reductions in both pollution and housing prices, the fixed-effects estimator of the HPS will have a positive bias. For example, the first row of the table shows that housing values grew more in the counties that had an increase in TSPs levels.

Suppose there is an instrumental variable, Z_c , that causes changes in TSPs without having a direct effect on housing price changes. One plausible instrument is mid-1970s TSPs regulation, measured by the attainment-nonattainment status of a county. Here, equation (7) becomes:

$$(8) \quad T_{c80} - T_{c70} = (X_{c80} - X_{c70})'\Pi_{TX} + Z_{c75}\Pi_{TZ} + (v_{c80} - v_{c70})^o, \text{ and}$$

$$(9) \quad Z_{c75} = 1(T_{c75} > \bar{T}) = 1(v_{c75} > \bar{T} - X_{c75}'\Pi - \lambda_c),$$

where Z_{c75} is the regulatory status of county c in the middle of the decade, $1(\bullet)$ is an indicator function equal to one if the enclosed statement is true, and \bar{T} is the maximum concentration of TSPs allowed by the federal regulations.³⁰ Regulatory status is a discrete function of mid-decade pollution levels. Further, if T_{c75}^{avg} and T_{c75}^{max} are the annual geometric mean and 2nd highest daily TSPs concentrations, respectively, then the actual regulatory instrument used is $1(T_{c75}^{avg} > 75 \mu\text{g}/\text{m}^3 \text{ or } T_{c75}^{max} > 260 \mu\text{g}/\text{m}^3)$.

Two sufficient conditions for the IV estimator (θ_{IV}) to provide a consistent estimate of the HPS gradient are $\Pi_{TZ} \neq 0$ and $E[v_{c75}(u_{c80} - u_{c70})] = 0$. The first condition clearly holds. The second condition requires that unobserved price shocks from 1970-80 are orthogonal to transitory shocks to 1975 TSPs levels. In the simplest case, the IV estimator is consistent if $E[Z_{c75}(u_{c80} - u_{c70})] = 0$.

The final 3 columns of Table 3 suggest that even this stronger condition may hold. The mean 1970-80 changes in the variables are shown by 1975-76 regulatory status, with the final column giving the F-statistics testing for differences between the two groups. Remarkably, the regulation instrument purges the non-neutral economic shocks that contaminate the fixed-effects analysis. The changes in per-capita income, unemployment rates, and manufacturing employment in regulated and unregulated counties are statistically identical. In this respect, the 1975-76 regulation instrument is unique.³¹ Also, regulated counties had both a greater reduction in TSPs and a greater increase in housing values from 1970-80, foreshadowing the IV results.

Even if $E[v_{c75}(u_{c80} - u_{c70})] \neq 0$, causal inferences on θ can be made by leveraging the regression discontinuity design implicit in the $1(\bullet)$ function determining regulatory status. If the relationship

³⁰ The notation used for the instrumental variable is for ease of exposition. According to the law, the regulatory status of a county in 1975 is determined by TSPs levels in 1974.

³¹ Counties that were regulated in 1971-72, and in 1973-74, had significantly less per-capita income growth and a greater decline in manufacturing employment from 1970-80 than their unregulated counterparts. This may be due to non-neutral impacts of the 1974-75 recession and/or the economic effects of the regulations themselves.

between v_{c75} and $(u_{c80} - u_{c70})$ is sufficiently smooth at the regulatory ceilings, then comparing regulated and unregulated counties at the thresholds will control for all omitted variables. Further, utilizing the $T_{c75}^{\max} > 260 \mu\text{g}/\text{m}^3$ regulation selection rule, we can compare regulated and unregulated counties with identical T_{c75}^{avg} , which we do below.

Finally, since nonattainment status is a function of T_{c75} , we also use TSPs levels in the regulation selection year as an instrumental variable. An advantage of this instrument is that it is more informative and has broader support than the crude 0-1 regulation indicator. In particular, this continuous instrument can be used to estimate the entire hedonic price schedule. We return to this below.

Random Coefficients, Self-Selection, and the Average MWTP

Each point on the HPS provides the marginal consumer's MWTP for a marginal change in TSPs. If individual tastes for clean air are identical, then the average gradient of the HPS, θ , gives the average marginal rate of substitution for all consumers. However, if there is Tiebout sorting arising from taste dispersion, then θ may differ from the average MWTP in the population. We use a random coefficients model to illustrate this and derive a test for a negative assortive matching equilibrium.

Suppose preferences for air quality can be summarized at the county level (e.g., individual tastes vary more between than within counties). Simplifying notation, define $y_i \equiv y_{c70}$, $\Delta y_{it} \equiv (y_{c80} - y_{c70})$, $\Delta T_{it} \equiv (T_{c80} - T_{c70})$, and $Z_i \equiv Z_{c75}$. Ignoring the observables, the random coefficients version of equation (4) is:

$$y_i = \theta_i T_i + \varepsilon_i,$$

where θ_i represents heterogeneity in the MWTP across individuals/counties, and $E(\theta_i) = \bar{\theta}$ is the average MWTP in the population. Here, the least squares estimator of $\bar{\theta}$ will be biased if either $E(\varepsilon_i T_i) \neq 0$ due to omitted variables or $E(\theta_i T_i) \neq 0$ due to self-selection. The Tiebout model predicts that $E(\theta_i T_i) > 0$, i.e., individuals with a high valuation for clean air select to counties with low TSPs levels.

If θ_i is stationary over time, then the random coefficients analogs of equations (6) and (8) are:

$$(10) \quad \Delta y_{it} = \bar{\theta} \Delta T_{it} + (\theta_i - \bar{\theta}) \Delta T_{it} + \Delta u_{it},$$

$$(11) \quad \Delta T_{it} = \Pi Z_i + \Delta v_{it},$$

Suppose that ΔT_{it} is monotonically related to T_i , in that the size of 1970-80 TSPs reductions is (weakly) increasing in 1970 TSPs levels. Then θ_i and ΔT_{it} may be correlated through either a nonconstant marginal

between v_{c75} and $(u_{c80} - u_{c70})$ is sufficiently smooth at the regulatory ceilings, then comparing regulated and unregulated counties at the thresholds will control for all omitted variables. Further, utilizing the $T_{c75}^{\max} > 260 \mu\text{g}/\text{m}^3$ regulation selection rule, we can compare regulated and unregulated counties with identical T_{c75}^{avg} , which we do below.

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Suppose that ΔT_{it} is monotonically related to T_i , in that the size of 1970-80 TSPs reductions is (weakly) increasing in 1970 TSPs levels. Then θ_i and ΔT_{it} may be correlated through either a nonconstant marginal

utility or self-selection due to taste heterogeneity.

In the presence of correlated random coefficients, identification of $\bar{\theta}$ requires stronger assumptions than the orthogonality conditions above. First, consider the conditions under which the two-stage least squares estimator of the HPS gradient, θ_{2sls} , consistently estimates $\bar{\theta}$. Wooldridge (1997) shows that $E(\theta_{2sls}) = \bar{\theta}$ only if:³²

A1: $E(\Delta u_{it}|Z_i) = 0, \Pi \neq 0$

A2: $E(\Delta v_{it}|Z_i) = 0, E(\Delta v_{it}^2|Z_i) = \sigma_{\Delta v}^2$

A3: $E(\theta_i|Z_i, \Delta v_{it}) = E(\theta_i|\Delta v_{it}) = \rho \Delta v_{it}$.

θ_{2sls} is consistent since A1-A3 imply that $E(\theta_i \Delta T_{it})$ does not depend on Z_i . A1 is a slightly strengthened IV condition, and A2 requires that TSPs shocks are homoskedastic with respect to Z_i . In general, A3 is the key condition. It requires that θ_i is conditionally mean independent of Z_i and linear in Δv_{it} .

If A3 holds, then including the first-stage residuals, Δv_{it} , as a control variable in the outcome equation will purge both the omitted variables and selection biases. Since this is numerically identical to 2SLS, θ_{2sls} will be consistent. However, if A3 does not hold, then both sources of bias cannot be summarized by a single linear index. In this case, $E(\theta_{2sls}) \neq \bar{\theta}$ and 2SLS may identify the average MWTP for a nonrandom subpopulation.

There is an alternative two-step approach to estimating $\bar{\theta}$ that allows for separate ‘control functions’ for the omitted variables and self-selection biases (Garen 1984). This procedure also provides a simple statistical test of the Tiebout hypothesis. Consider the following assumptions:

B1: $E(\Delta u_{it}|Z_i) = E(\theta_i|Z_i) = 0$

B2: $E(\Delta u_{it}|\Delta T_{it}, Z_i) = \lambda_T \Delta T_{it} + \lambda_Z Z_i$

B3: $E(\theta_i|\Delta T_{it}, Z_i) = \psi_T \Delta T_{it} + \psi_Z Z_i$

B2 and B3 allow the conditional expectations of both Δu_{it} and θ_i to depend linearly on ΔT_{it} and Z_i . B1-B3 imply $E(\Delta u_{it}|\Delta T_{it}, Z_i) = \lambda_T \Delta v_{it}$ and $E(\theta_i|\Delta T_{it}, Z_i) = \psi_T \Delta v_{it}$, resulting in the regression model:

$$(12) \quad \Delta y_{it} = \bar{\theta} \Delta T_{it} + \lambda_T \Delta \hat{v}_{it} + \psi_T \Delta T_{it} \Delta \hat{v}_{it} + \Delta \epsilon_{it},$$

³² Wooldridge derives an alternative set of assumptions that places more restrictions on the stochastic relationship between θ_i and Z_i . Also, see Heckman and Vytlacil (1998).

where $\Delta \hat{v}_{it}$, the estimated residuals from the 1st-stage equation, is the potentially endogenous component of TSPs changes. Under B1-B3, least squares estimation of (12) provides a consistent estimate of the average MWTP in the population.³³

2SLS only allows for the $\lambda_T \Delta \hat{v}_{it}$ control function and assumes that it absorbs both sources of bias. Equation (12) relaxes this single-index restriction and uses separate control functions for the two sources of bias. Here,

$$\lambda_T = \frac{\text{Cov}(\Delta u_{it}, \Delta v_{it})}{\text{Var}(\Delta v_{it})} \text{ and } \psi_T = \frac{\text{Cov}(\theta_i, \Delta v_{it})}{\text{Var}(\Delta v_{it})}.$$

Thus, the λ_T coefficient measures the importance of omitted variables bias in the conventional estimate. The results in Table 3 imply that the estimated λ_T will be positive. The ψ_T coefficient, on the other hand, measures the importance of heterogeneity in the MWTP.

The sign and significance of the estimated ψ_T provides a test of the Tiebout hypothesis. First, note that homogeneous preferences and marginal utilities that do not increase in air quality imply $\psi_T \leq 0$. Only if there is taste heterogeneity and individuals Tiebout sort can ψ_T be greater than 0 (i.e., individuals who prefer clean air sort into low pollution counties). As a result, an estimated $\psi_T > 0$ is consistent with negative assortive matching under the weak restriction of non-increasing marginal utilities.

This test has important implications for the optimal design of regulatory policy. If tastes are homogeneous, then a diminishing marginal utility implies that the marginal benefit of a pollution reduction is greater in communities with higher pre-regulation TSPs levels. This is consistent with the maximum allowable concentration design of the CAAAs. However, if there is taste heterogeneity and Tiebout sorting, then those with greater distaste for pollution will sort to areas with lower TSPs levels. Here, the welfare gain from a TSPs reduction may be greater in communities with lower pollution levels, a possibility that the NAAQS design of the CAAAs effectively ignores.

³³ In contrast to the typical 0-1 treatment model, identification of a model with a continuous endogenous variable does not require functional form assumptions on the joint distribution of the unobservables. Below, we also use the fact that one of the instruments is continuous to facilitate identification. See Blundell and Powell (2000), Heckman and Vytlačil (1999), Vytlačil (1999), and Manski and Pepper (2000) for a discussion of these issues.

Empirical Estimates of the HPS Gradient and the Average MWTP

Here, we present the estimates of the HPS gradient and the average MWTP from the econometric models discussed above. There are three main findings. First, conventional regression analysis produces unreliable estimates of the HPS gradient. Second, the instrumental variables research design yields robust estimates that imply individuals place greater value on clean air than previously recognized. Finally, while the random coefficients results provide evidence of Tiebout taste sorting in equilibrium, the overall variation in the MWTP is not large.

'Conventional' Estimates of the HPS Gradient

Table 4 presents the 'conventional' estimates of the capitalization of TSPs pollution into property values for the 1970 and 1980 cross-sections and the 1970-80 first differences. These estimates provide a useful benchmark since they are based on the regression specifications typically used in the literature. For the 1970 and 1980 cross-sections, Column 1 gives the unadjusted correlation; Column 2 allows the observables to enter linearly; Column 3 adds unrestricted state effects; and Column 4 adds cubic polynomials and interactions of the control variables.

For 1970 the unadjusted correlation between housing prices and TSPs has a counterintuitive sign. However, the correlation adjusted for a linear combination of the observables suggests that a 1-unit decline in TSPs leads to a 0.07% increase in housing values. While the implied elasticity is only 0.05-0.06, the estimate is statistically significant. Also, it is in the middle of the range of estimates summarized in the Smith and Huang (1995) meta-analysis. This is particularly noteworthy since it is based on a time period and regression specification similar to those used in the bulk of previous research.

The estimate implies that if Allegheny county, which is in Pittsburgh, reduced its 1970 TSP levels by 50% (a 65- $\mu\text{g}/\text{m}^3$ reduction), housing prices would increase by only \$2,000 (\$1982-84), all else equal. Further, the estimate is greatly reduced and insignificant when the analysis adjusts for state effects and a flexible functional form for the covariates. Note that the fit of the regressions is quite good.

The 1980 results also bring into question the reliability of cross-sectional analysis. Here, a linear covariate adjustment leads to the perverse result that a 1-unit TSPs reduction is associated with a 0.12% decrease in housing prices. This is particularly disturbing given the estimate's precision and the excellent

fit of the regression equation ($R^2=0.84$). Controlling for state effects and nonlinearities in the covariate effects results in estimates that are very similar to the 1970 estimates. Overall, the cross-sectional correlation between TSPs and property values is weak and very sensitive to the choice of specification. Thus, we have replicated the previous literature's results with our more comprehensive data.

The final 2 columns of the table contain the 1970-80 fixed effects results. First-differencing the data eliminates the bias in the cross-sectional estimates attributable to permanent differences across counties. However, this approach will be biased if there are shocks that drive both pollution and price changes. In the first column, the unadjusted correlation between housing price and TSPs changes has the perverse positive sign and is highly significant. This finding was foreshadowed by the results in Table 3. Although greatly reduced, the estimate remains positive even after adjusting for changes in the economic variables and other covariates. We conclude that conventional estimates of the HPS gradient may be plagued by very large omitted variables bias.

Instrumental Variables Estimates of the HPS Gradient

The instrumental variables estimate of the HPS gradient is a simple function of two reduced-form relations, the effects of TSPs regulation on TSPs changes and on log-housing price changes:

$$(13) \quad T_{c80} - T_{c70} = (X_{c80} - X_{c70})'\Pi_{TX} + Z_{c75}\Pi_{TZ} + (v_{c80} - v_{c70})^\circ, \text{ and}$$

$$(14) \quad y_{c80} - y_{c70} = (X_{c80} - X_{c70})'\Pi_{yX} + Z_{c75}\Pi_{yZ} + (u_{c80} - u_{c70})^\circ,$$

where $\theta_{IV} = \Pi_{yZ}/\Pi_{TZ}$. First, we present evidence that our design plausibly identifies the causal effects of the regulations, Z_{c75} , and provides credible estimates of both Π_{yZ} and Π_{TZ} . Then we present the IV estimates of the HPS Gradient

Reduced Form Relations

Table 5 contains the regression results from estimating equations (13) and (14). In the first set of columns, the regulation variable is an indicator equal to one if the county was nonattainment in either 1975 or 1976. In the second set of columns, the instrument is the geometric mean of TSPs in 1974, a variable used to determine 1975 regulatory status (see equation (9)). Both the unadjusted and regression adjusted effects of the regulation variables are presented.

In the first two columns, the regulation indicator is associated with an 8-9 $\mu\text{g}/\text{m}^3$ (10-12%)

reduction in TSPs. This estimate is highly significant with an F-statistic around 50, suggesting that it is the most important (observable) determinant of 1970-80 TSPs changes. The second column shows that the estimate is insensitive to the inclusion of the full set of control variables. Thus, the first-stage impact of regulation is very powerful and appears valid.

The next two columns reveal another striking empirical regularity. The TSPs nonattainment variable is associated with a 4-5% relative increase in housing values from 1970-80. These estimates are also highly significant. Taken literally, this implies that federal EPA regulations resulted in substantial monetary benefits for homeowners in regulated counties. The estimate changes only slightly when the controls are included, even as there is a large improvement in the regression fit ($R^2=0.60$).

The results are very similar when 1974 TSPs levels are used as the regulation variable in the next four columns. First, greater TSPs levels in the regulation selection year are strongly associated with larger pollution declines over the 1970s. Again, the estimated pollution impact is highly significant and insensitive to regression adjustment. Second, this regulation variable is also strongly correlated with greater increases in housing values. The adjusted and unadjusted estimates of the price effects are identical, suggesting that the regulation instrument is orthogonal to the observable covariates. Overall, Table 5 shows that regulated counties had both larger declines in TSPs pollution and greater increases in housing values during the 1970s.

Figure 5 provides more detailed evidence on the validity of using the TSPs regulation variables as instruments. Each panel graphs the bivariate relation between an outcome of interest and TSPs levels in the regulation selection year. We estimated 'nonparametric' regressions as a function of the geometric mean of TSPs in 1974 using a locally weighted regression smoother (see Cleveland 1979).³⁴ Thus, the panels plot the impact of the regulation variables from the raw data without regression adjustment.

Panel A presents the probability of a county being nonattainment in 1975 and the 1970-80 change in mean TSPs by the level of mean TSPs in 1974.³⁵ The correspondence between the two series is

³⁴ The smoothed scatterplots are not very sensitive to the bandwidth choice.

³⁵ The figure uses 1978 attainment status, since it is based on the published Code of Federal Regulations. The graph that uses 1975 attainment status determined by the actual monitor readings in 1974 is qualitatively identical, with regulation probabilities equal to 1 at high 1974 mean TSPs levels.

remarkable. The upward ‘jumps’ in the probability of regulation are closely mirrored by downward ‘jumps’ in the decline in TSPs. For counties with low TSPs levels in 1974 ($<40 \mu\text{g}/\text{m}^3$), the regulation probabilities are small and constant as mean TSPs increase, as are the 1970-80 reductions in pollution. However, for counties with 1974 mean TSPs between 50 and $80 \mu\text{g}/\text{m}^3$, the 1970-80 pollution reductions increase sharply as the probability of regulation rises.³⁶ For counties with concentrations above $80 \mu\text{g}/\text{m}^3$, both the regulation probabilities and the pollution declines are constant in pre-regulation TSPs levels. Overall, the figure strongly supports a causal relationship between mid-decade TSPs regulation and reductions in TSPs pollution during the 1970s. The monotonic relation between TSPs reductions and TSPs levels in the regulation selection year is also worth noting.

Panel B plots the conditional change in log-housing values from 1970-80 along with the conditional change in mean TSPs from Panel A. The figure reveals a striking association between larger reductions in mean TSPs and greater increases in housing prices. This suggests that our research design identifies the casual relationship between pollution and property values through the mechanism of regulation. In addition, there does not appear to be a systematic relation between 1974 TSPs levels and housing price changes, except where there are increases in pollution reductions ($50 \mu\text{g}/\text{m}^3 < 1974 \text{ TSPs} < 80 \mu\text{g}/\text{m}^3$). Thus, mean TSPs in 1974 may be a valid continuous instrumental variable.

Panel C empirically examines the validity of the ‘smoothness’ condition discussed above. It plots the housing price changes predicted by the observable covariates excluding TSPs changes, $E(\Delta y_{it} | \Delta X_{it})$, along with the actual price changes from Panel B. The predicted changes are from a linear regression. The figure implies that the non-pollution determinants of price changes are smooth at the points where prices grow more due to greater TSPs reductions. In fact, for counties with 1974 TSPs greater than $45 \mu\text{g}/\text{m}^3$, there is virtually no association between predicted price changes and pre-regulation TSPs levels. Thus, all else may be held fixed when comparing counties over this range.

Panel D plots 1970 per-capita incomes and 1970-80 income changes by pre-regulation TSPs levels. Income is a particularly important demand shifter if clean air is a normal good. The graph shows

³⁶ Below the annual mean regulatory ceiling of $75 \mu\text{g}/\text{m}^3$, the probability of regulation rises as more counties exceed the daily concentration threshold.

that income levels and changes are very stable across counties with 1974 TSPs greater than 45-50 $\mu\text{g}/\text{m}^3$. These are the same counties for which the probability of regulation increases with pre-regulation TSPs levels (Panel A). Counties with 1974 concentrations less than 45 $\mu\text{g}/\text{m}^3$ have lower per-capita incomes in 1970. They also have much smaller populations and lower urbanization rates. Therefore, these small rural counties may not be comparable to the other monitored counties.³⁷

Finally, our most compelling test of causality utilizes the daily concentration regulatory ceiling and compares regulated and unregulated counties with identical pre-regulation annual TSPs levels. These are valid comparisons if the number of 'bad' days in a county does not independently affect price changes holding constant the annual mean of TSPs, which seems likely. Figure 6 presents the results from this design. It plots 1970-80 mean TSPs changes (Panel A) and housing price changes (Panel B) for regulated and unregulated counties with annual emissions below the geometric mean regulatory threshold.

The patterns are striking. At every point, regulated counties have both larger pollution reductions and greater housing price increases than unregulated counties. Also, there is an exact correspondence between the divergence in the pollution series and the divergence in the price series at pre-regulation mean TSPs greater than 61-62 $\mu\text{g}/\text{m}^3$. Finally, there is a strong association between the 'trend breaks' in the group-specific pollution and price series of both groups. Taken together, the results in Table 5 and the plots of the raw data in Figures 5 and 6 provide convincing evidence of a causal link between EPA regulations and changes in air pollution and housing values.

Instrumental Variables Estimates

Table 6 contains the instrumental variables estimates of the HPS gradient derived from two-stage least squares (2SLS). The first and second sets of columns, respectively, use the 1975-76 nonattainment indicators and 1974-75 mean TSPs levels as instruments, while the final two columns use both instrument sets. The estimates imply that a 1- $\mu\text{g}/\text{m}^3$ reduction in mean TSPs results in a 0.4-0.5% property value increase, which is a 0.3-0.4 elasticity. This is 6-7 times larger than the largest cross-sectional estimate in Column 2 of Table 4. Further, the 2SLS estimates are highly significant and remarkably stable across the

³⁷ These counties get little weight in the analysis since all regressions use the population of each county as weights.

different specifications and choice of instruments. The similarity between the estimates based on the full set of instruments and the other 2SLS estimates implies that the overidentifying orthogonality conditions are not rejected by the data. Also, the estimated HPS gradient is insensitive to regression adjustment, which is not surprising given the patterns in Panels C and D of Figure 5.³⁸

Panel A of Figure 5 reveals that the relation between 1970-80 TSPs changes and 1974 TSPs levels is not linear. As a result, we also estimated the HPS gradient using ‘nonparametric’ indirect least squares. Suppose the first-stage equation is $\Delta T_{it} = f(T_{i74}) + \Delta v_{it}$ instead of $\Delta T_{it} = \Pi T_{i74} + \Delta v_{it}$, and the reduced-form equation is $\Delta y_{it} = \theta \cdot f(T_{i74}) + \Delta u_{it}$ instead of $\Delta y_{it} = \theta \cdot (\Pi T_{i74}) + \Delta u_{it}$. Then θ can be estimated by two-stage least squares using the estimated conditional mean function graphed in Panel A, $f(T_{i74}) = E(\Delta T_{it}|T_{i74})$, as an instrument. The resulting estimates are nearly identical to those in Table 6, suggesting that a (strong) conditional expectations restriction, $E(\Delta u_{it}|T_{i74}) = 0$, may be valid.

Random Coefficients Estimates of the Average MWTP and Evidence on Tiebout Sorting

If tastes for clean air are homogeneous, then the 2SLS estimates of the HPS gradient in Table 6 are consistent estimates of the average MWTP in the population. However, if individuals self-select across counties due to taste heterogeneity, these estimates may represent the average MWTP for a nonrandom subpopulation. To examine this issue more formally, we estimate the random coefficients regression model specified in equation (12). The model relaxes the single-index restriction of 2SLS and includes separate control functions for the omitted variables and self-selection biases. As long as the linear conditional expectations restrictions B2 and B3 hold, the model will consistently identify the population average MWTP and provide a simple test of Tiebout sorting.

Table 7 presents the results from estimating this model using the same sets of instruments as in Table 6.³⁹ There are several important findings. First, the estimates of the average MWTP are only slightly higher than the 2SLS estimates in Table 6. Thus, the single control function underlying 2SLS appears to do a reasonable job of absorbing both sources of bias. Second, the estimated coefficient of the

³⁸ The IV estimates are also insensitive to adjusting for the levels of the variables in 1970. For the 1975-76 TSPs nonattainment instrument, for example, the IV estimates are $-0.397(0.114)$ and $-0.406(0.123)$ when the analysis adjusts for the 1970 levels of the controls and 1970 housing prices, respectively.

³⁹ Some of the regressors in equation (12) are generated from 1st-stage estimation. As a result, we calculated the standard errors of this sequential estimator using the bootstrap with 1,000 replications.

first control function, λ_T , is positive and highly significant. This implies that the omitted variables bias in the conventional first-differences estimate is substantial, even after regression adjustment. Third, the selection bias control function also has a positive and significant coefficient estimate ($\psi_T > 0$). Under the assumptions of the model, it provides direct statistical evidence of nonrandom taste sorting. The fact that the estimated ψ_T is reduced substantially by regression adjustment implies that much of the unobservable Tiebout behavior can be explained by observable differences across counties.

It appears that negative assortive matching is a relevant phenomenon in the housing market. However, Table 7 suggests that the overall heterogeneity in the MWTP across the population is not large.⁴⁰ Further, the relative magnitudes of the λ_T and ψ_T estimates imply that omitted variables bias is a much bigger issue than selectivity bias in estimating the HPS and MWTP. This interpretation relies on assumptions B2 and B3 in which both sources of bias have linear conditional expectations. We also estimated a model that allows polynomials of both control functions to enter the outcome equation. This led to average MWTP estimates that are identical to those in Table 7, suggesting that the linear ‘approximations’ in B2 and B3 may be robust.

Empirical Estimates of MWTP Functions

The real promise of hedonic theory is that it provides a method for estimating MWTP functions, as in equation (2). These functions allow one to calculate the welfare effects of non-marginal changes in air quality and forecast the likely impact of proposed policies. If there are an uncountable number of consumer ‘types’ sorting across counties, then MWTP functions cannot be estimated without strong parametric assumptions that may be neither plausible nor verifiable. However, individual bid functions can be estimated over limited ranges if there are a finite number of consumer types. Here, we use the assumption of non-increasing marginal utility to interpret the HPS and derive estimates of MWTP functions for two types of consumers.

⁴⁰ It is possible that taste heterogeneity and sorting may be greater within counties than between counties. In this case, our results understate the individual-level dispersion in the MWTP and the overall role of Tiebout.

The continuous instrumental variable, T_{174} , can be used to estimate the entire hedonic price locus. Suppose $\Delta y_{it} = h(\Delta T_{it}) + \Delta u_{it}$, where $h(\Delta T_{it}) = E(\Delta y_{it} | \Delta T_{it})$ is the conditional expectations function relating changes in housing prices and mean TSPs. Define $E(\Delta y_{it} | T_{174}) = g_y(T_{174})$ and $E(\Delta T_{it} | T_{174}) = g_T(T_{174})$ to be the conditional expectations of the reduced-form and first-stage equations, respectively. Then under suitable regularity conditions, the hedonic price function, $h(\Delta T_{it})$, can be recovered from $E[g_y(T_{174}) | g_T(T_{174})]$.⁴¹

Figure 7 presents the results from correlating the estimated $g_y(T_{174})$ and $g_T(T_{174})$ functions plotted in Figure 5B using the Cleveland (1979) regression smoother.⁴² The figure shows that the gradient of the estimated HPS is always negative but its 2nd-derivative appears positive, on average. This finding corresponds with the positive estimate of ψ_T in Table 7. Since there is a monotonic relation between T_{174} and ΔT_{it} , the concavity in the estimated HPS implies that the marginal benefit of a pollution reduction is lower in areas with higher pre-regulation TSPs levels. Under the assumption of non-increasing marginal utility, the figure is consistent with self-selection arising from taste heterogeneity, since homogeneous preferences would imply a weakly convex HPS.

The estimated HPS in Figure 7 appears to have two gradients. Thus, it is consistent with a world with two consumer types; those with high and low average marginal rates of substitution. Although a purely inductive conjecture, this assumption fits the data and seems more plausible than the assumptions typically needed to identify structural demand primitives. If individuals in counties before (and after) the ‘inflection’ point in Figure 7 have similar tastes for clean air, then one can put meaningful structure on the hedonic price function.

To implement the assumption of two consumer types, the estimated regression functions $g_y(T_{174})$ and $g_T(T_{174})$ are used to estimate HPS gradients over ranges of 1974 TSPs levels. Local gradients are calculated by regressing $g_y(T_{174})$ on $g_T(T_{174})$ over each range. These are used to determine the TSPs concentration at which there is a switch from the 1st to 2nd type of consumer in the hedonic sorting equilibrium. They also provide separate MWTP functions for the 2 types. This approach effectively

⁴¹ The regularity conditions include: 1) ΔT_{it} and T_{174} are continuous, 2) $E(\Delta u_{it} | T_{174}) = 0$, and 3) $h(\Delta T_{it})$ is sufficiently ‘smooth’. See Blundell and Powell (2000) for more details. Heckman and Vytlačil (1999) and Vytlačil (1999) examine the case in which the endogenous variable is a 0-1 treatment.

⁴² This is analogous to ‘nonparametric’ local Wald estimation applied over fixed bandwidths using the Cleveland weighted smoother. The Appendix Figure shows both the ‘actual’ and smoothed price changes.

matches counties with similar pre-regulation TSPs levels, which is the source of self-selection.

Table 8 presents the local gradients. It shows that the price gradient increases as the 1974 mean TSPs range grows from 40-50 to 40-65 $\mu\text{g}/\text{m}^3$. This is consistent with a declining marginal utility for individuals with identical tastes over this range. The price gradient decreases as the 65-70 and 70-75 $\mu\text{g}/\text{m}^3$ increments are added, suggesting a mixing of different consumer types in these regions. As a result, starting at the 70-75 $\mu\text{g}/\text{m}^3$ range, we estimate a new set of price gradients for a 2nd consumer type, who may have a lower average marginal rate of substitution. The local gradients again increase as the range moves from 70-75 to 70-120 $\mu\text{g}/\text{m}^3$, implying a declining marginal utility for the 2nd type as well.

Overall, the average gradient from 40-65 $\mu\text{g}/\text{m}^3$ is greater than the average gradient from 70-120 $\mu\text{g}/\text{m}^3$, mirroring the results in Figure 7. These findings are not very sensitive to using mean TSPs in 1975 or choosing different TSPs ranges (results available from the authors). It is important to note, however, that the data underlying these local gradients are constructed by smoothing the raw data. It is quite possible that if sampling errors were calculated, one would conclude that several of the local gradients are statistically indistinguishable from each other.

Figure 8 presents the bid functions implied by the estimated gradients in Table 8. Panel A graphs the estimated indifference curves under the assumption of 2 consumer types; Type I and Type II with higher and lower distaste for air pollution, respectively. Note that while we can estimate marginal rates of substitution, the ‘intercepts’ of the bid functions are not identified. Thus, an arbitrary base for housing prices is set.

For Type I’s indifference curve, the first point has a x-value of 40 $\mu\text{g}/\text{m}^3$ and a y-value equal to the arbitrary base. The 2nd point has a x-value of 50 $\mu\text{g}/\text{m}^3$ and a y-value equal to the base plus $[-.00127 \times 10 \times \$101,642]$, where the numbers are the gradient in the 40-50 $\mu\text{g}/\text{m}^3$ range, the length of the range, and the average value of a house in this range, respectively. The 3rd, 4th, and 5th points are similarly calculated using the gradients in the 40-55, 40-60, and 40-65 $\mu\text{g}/\text{m}^3$ ranges, respectively. Type II’s indifference curve is graphed using the gradients in the 70-75, 70-80, 70-85, 70-90, and 70-100 $\mu\text{g}/\text{m}^3$ ranges. Under the stated assumptions, these curves reveal the willingness to trade-off wealth for air quality for Type I and II consumers.

Panel B shows the negative MWTP functions for both consumer types. Each segment of the 2 functions is calculated by multiplying the slope of the indifference curve between consecutive points by the (negative) average housing value in that range. For example, the first segment of Type I's MWTP function (x-values from 40-50 $\mu\text{g}/\text{m}^3$) has a y-value of \$129 ($-.00127 \times -\$101,642$). It implies that Type I consumers are willing to pay \$129 for a 1- $\mu\text{g}/\text{m}^3$ reduction in TSPs over this range. Similar calculations reveal that Type I's MWTP for a unit reduction in pollution is \$412, \$1991, and \$1428 over the ranges of 50-55, 55-60, and 60-65 $\mu\text{g}/\text{m}^3$, respectively. For Type II consumers, the MWTP is \$67, \$211, \$580, \$896, and \$455 over the relevant ranges. Note that the lower estimated MWTP in the last segment of Type II's bid function suggests the possibility of a Type III consumer with a lower average MRS.

Taken literally, these functions allow for the types of welfare calculations necessary for policy analysis. For example, they can be used to estimate WTP for non-marginal reductions in air pollution from different possible regulatory thresholds for TSPs concentrations. We return to this issue in the next section. Also, with the exception of the last segment of each function, both MTWP functions are consistent with a declining marginal utility of clean air. Finally, although individuals in low pollution counties have a higher average MWTP for clean air, the differences in the MWTP for a TSPs reduction are not large due to the convexity of the utility functions.

The analysis above relies on the assumption that the hedonic locus has not shifted between 1975 and 1980 due to demand/supply responses to the late 70s TSPs reductions.⁴³ Although this may be a reasonable assumption, we provide indirect evidence on its validity using the 1980 5% Census files. The Census provides information on the household head's location of residence in both 1980 and 1975. Thus, we can examine whether there were differential changes in the numbers and types of households in regulated and unregulated counties after 1975. The Data Appendix explains how the 1980 Census microdata are merged to the TSPs pollution and regulation data.

Table 9 presents the number and composition of households in counties that were and were not regulated in 1975-76 for both 1975 and 1980. The first 2 columns show that the 1975-80 changes in the

⁴³ If the hedonic shifted between 1975 and 1980, it likely shifted down as the overall supply of clean air increased. In this case, our estimates are understatements (overstatements) relative to the 1975 (1980) hedonic.

number of households are small and identical in regulated and unregulated counties. The remaining columns show that the changes in the socioeconomic characteristics of households are also identical in the two county groups. Although not a direct proof, it suggests that the analysis is not contaminated by general equilibrium responses to the regulation-induced pollution shocks of the late 70s. Further, in 1980, the fraction of all houses built during the 1970s was the same in counties that were (24%) and were not (26%) regulated in 1975-76 (from the 1983 CCDB). Again, the 1975-76 regulations are unique in this respect. Appendix Table 2 shows that 1970-80 changes in per-capita incomes are also not systematically related to regulation-induced TSPs changes (final four columns).

Welfare Calculations and Implications

It appears that mid-decade TSPs regulation is causally related to both air pollution reductions and housing price increases during the 1970s. Here, we use the findings above to develop measures of the economic benefits of the regulations, and, more generally, the WTP for air quality. We also discuss the implications of the results for the design of optimal regulatory policy.

The estimated gradient of the hedonic price function provides the average MWTP for a 1-unit decline in air pollution. Thus, welfare analysis of the non-marginal TSPs reductions induced by the mid-decade regulations requires identification of a MWTP function, as in equation (2). An ad hoc approach to obtaining this function is to make strong assumptions on its shape.

A popular assumption, proposed by Freeman (1974), presumes a constant MWTP for clean air.⁴⁴ The dashed horizontal line in Figure 8B depicts this assumption. It is straightforward to calculate WTP from this function.⁴⁵ Nonattainment counties had about an 8-unit reduction in mean TSPs attributable to the 1975-76 regulations. This decline was capitalized into property values at a rate of about 0.45% per

⁴⁴ This is equivalent to assuming that preferences are homogeneous and linear with respect to air quality.

⁴⁵ Setting aside the validity of the constant MWTP assumption, there are some important differences between this measure and the ideal measure of the welfare change. First, this measure will tend to overstate the welfare gain relative to one derived from a compensated MWTP function that holds utility constant. Second, we assume that consumers and suppliers have not had time to respond to the TSPs change by moving or changing the supply or quality of the housing stock. However, at the existing HPS, some individuals are likely to be made better off by making these changes. Our measure of the welfare change does not account for this type of compensatory behavior and will thus tend to understate the true welfare gain. See Bartik (1988) for a clear discussion of these issues.

unit. Since the average value of a house in regulated counties was approximately \$93,400 (in \$1997), the regulation-induced air quality improvement caused about a \$3,400 value increase per house. Based on the Census PUMS data, there were about 19 million houses in nonattainment counties. Altogether, this implies that the WTP for the late 1970s TSPs reductions was approximately \$65 billion.⁴⁶

The \$65 billion figure is also an estimate of the increase in local property values attributable to mid-1970s TSPs regulation. This is very useful information for county governments, since it provides a monetary measure of the local benefits of regulation (e.g., the increase in the tax base). By this metric, the mid-decade regulation of TSPs provided substantial benefits.

These calculations do not allow for heterogeneity in the MWTP for air quality. Figure 8B shows the potential problems with this by graphing the MWTP functions of Type I and Type II consumers along with the constant MWTP function. First, compare the Type I and constant MWTP functions. The two functions are nearly identical in the 50-55 $\mu\text{g}/\text{m}^3$ range. However, at higher and lower pre-regulation TSPs levels, the constant MWTP assumption leads to an understatement and overstatement of Type I's WTP, respectively. Also, the population-weighted average of Type I's MWTP for a unit-reduction is substantially greater than the constant MWTP (\$807 versus \$424). For Type II consumers, the population-weighted average MWTP is close to the constant MWTP (\$375 versus \$424). However, as with Type I consumers, the constant MWTP assumption does not account for the declining marginal utility of air quality within Type.

The CAAAs have operated under the implicit assumption that the value of a TSPs reduction is highest in the dirtiest counties.⁴⁷ Our findings suggest that this may not be the case in the presence of Tiebout self-selection arising from taste heterogeneity. However, determining the optimal set of counties to regulate requires a great deal of information. For example, it is necessary to know the distribution of consumer types across counties and each of their MWTP functions. The last 30 years of research has

⁴⁶ This measure ignores the benefits accruing to renters. Appendix Table 2 presents the IV estimates of the effect of changes in TSPs on changes in rental prices for the 1970s. These estimates are smaller than the housing estimates, which is to be expected since rent only reflects the change in utility over a single year.

⁴⁷ This discussion presumes that the government has decided to reduce pollution in some counties and asks what is the welfare-maximizing way to do this. It does not address the broader question of whether such policies are, on net, beneficial. This would require precise information on the costs of regulation.

shown that this information may not be obtainable.

In principle, a market-based approach to regulation could provide a solution to this information problem. Suppose that the government decides to impose clean air regulations on an arbitrary number of counties. Rather than deciding on its own to regulate the dirtiest counties, the government could auction the rights to be regulated, which come with the implied benefit of a reduction in air pollution. In a well functioning auction market, the counties with the greatest WTP for a pollution reduction would purchase these rights. Given the likely heterogeneity in pollution abatement costs, the WTP of polluters to avoid regulation could be accommodated in a similar fashion.

The advantage of a market-based system is that it obviates the need for government to determine the counties in which pollution reductions are valued the most and/or abatement costs are the smallest. However, the implementation of such a program could be extremely complex. Also, a market-based system may not account for the non-economic reasons why government may prefer to regulate the dirtiest counties. In particular, the CAAs were specifically established to achieve air quality standards that 'protect public health' with an 'adequate margin of safety'. As a result, regulators were legally precluded from considering heterogeneity in the economic costs and benefits of reaching this goal.

Conclusion

This study has used the air pollution reductions induced by the 1970 and 1977 Clean Air Act Amendments to provide new evidence on the capitalization of air quality into housing values. The evidence strongly suggests that TSPs regulation is causally related to both air pollution declines and housing price increases during the 1970s. Using the county-level regulations as instruments, we estimate that a $1\text{-}\mu\text{g}/\text{m}^3$ reduction in TSPs results in a 0.4-0.5% increase in housing prices, which is a 0.3-0.4 elasticity. Importantly, this estimate is remarkably stable across a variety of specifications. By contrast, cross-sectional and fixed-effects designs result in estimates that are very sensitive to specification and sometimes have the perverse sign.

Using a random coefficients econometric model, we find that the IV design provides robust estimates of the average MWTP for clean air. The evidence also suggests that the marginal benefit of a

TSPs reduction may be lower in communities with higher pollution levels. This finding is consistent with self-selection across locations due to taste heterogeneity. However, the overall variation in the MWTP is not large, and the results imply that omitted variables bias is a much bigger issue than selectivity bias in estimating the HPS and MWTP. Welfare calculations suggest that the mid-1970s TSPs regulations provided a \$65 billion aggregate gain for homeowners in regulated counties. On the other hand, the federal ceiling design of the CAAAs may not have accounted for the heterogeneity in benefits arising from negative assortive matching across counties.

It appears that markets can be used to value environmental amenities and that the hedonic method can be successfully applied in certain contexts.⁴⁸ However, it is important to cross-validate our findings in other situations in which the hedonic method is an appropriate tool for analysis. Also, future research on the potential channels through which clean air is valued, health related and otherwise, would be very useful (e.g., Chay and Greenstone 1999).

⁴⁸ Our research design addresses 2 major points made in Rosen (1986). First, “It is clear that nothing can be learned about the structure of preferences in a single cross-section...” (p. 658). Second, “On the empirical side of these questions, the greatest potential for further progress rests in developing more suitable sources of data on the nature of selection and matching...” (p. 688).

DATA APPENDIX

Determining Attainment/Nonattainment Status at the County Level

The ability to accurately determine the EPA's assignment of counties to attainment/nonattainment status for TSPs is crucial for implementing our research design. In the 1972-1977 period, the EPA did not publicly release the names of the counties that were designated nonattainment. To learn the identity of these counties, we contacted the EPA but were informed that records from that period "no longer exist." However, the readings from the air pollution monitoring system were used by the EPA and the states to determine which counties were in violation of the federal air quality standards. Consequently, for the years 1972-77, we use our pollution data to replicate the EPA's selection rule. Counties with monitor readings exceeding the NAAQS for TSPs were assigned nonattainment status; all other counties were designated attainment.

Beginning in 1978, the *Code of Federal Regulations* (Title 40, Part 80) published annually the names of counties whose pollution levels exceeded the federal standards. For each of the regulated pollutants, the CFR lists every county as, "does not meet primary standards," "does not meet secondary standards," "cannot be classified," "better than national standards," or "cannot be classified or better than national standards." In addition, the CFR occasionally indicates that only part of a county did not meet the primary standards. For the years 1978 through 1990, we assigned a county to the TSP nonattainment category if all or part of it failed to meet the "primary standards" for TSPs in that year; otherwise, it was assigned to TSP attainment. These annual county-level designations were collected for each of the 3,063 U.S. counties. Comparing the 1978 published attainment status to the attainment status generated from the EPA's selection rule using the 1977 pollution data suggests that our regulation data for 1972-77 is accurate. The results in Figure 5A confirm this interpretation.

The Siting of TSPs Monitors and the "Reliability" of the TSPs Pollution Data

Central to the credibility of the analysis is that the pollution concentration readings used accurately reflect the "true" air quality faced by individuals. Since readings from the TSPs monitors are used to determine nonattainment status, it is possible that states or counties strategically placed the monitors to fabricate the appearance of low (or improving) pollution concentrations. To explore the likelihood of this, we examined the CFR and found that the Amendments contain very precise criteria that govern the siting of a monitor.⁴⁹ In particular, the legislation forbids states from siting a monitor in a location that does not meet one of the scientific criteria outlined for monitors.⁵⁰

Moreover, the Amendments provided the EPA with a number of enforcement tools to ensure that the states complied with the criteria for siting a monitor. First, the part of the CFR that lists the criteria for monitor placements is incorporated into the SIPs. Since the SIPs are both federal and state law, the EPA can sue states for violating federal law. Second, the usual process for siting is that the states propose a monitor network, and the EPA's district office either approves it or suggests alterations. The federal EPA can also review and reject the siting program, resulting in two layers of oversight. Third, the district offices often require photographs of sites to verify a monitor's placement. Fourth, it is illegal to move many of the monitors. For the monitors that can be moved, the relocation can only be done to better meet the scientific criteria outlined in the CFR. Finally, the district offices are cognizant of which states do not

⁴⁹ The substance of this discussion results from the Code of Federal Regulations (CFR) 1995, title 40, part 58 and a conversation with Manny Aquilania and Bob Palorino of the EPA's District 9 Regional Office. Using a recent CFR is not a problem, because the hierarchical control over monitor placement specified in the 1995 CFRs is consistent with previous monitor siting guidelines.

⁵⁰ These criteria require that the monitors be placed so that they determine: the highest concentration expected in the area, the representative concentrations in areas of high population density, the impact on ambient pollution levels of significant fixed and mobile categories, and the general background concentration level due to geographic factors. Moreover, the CFR specifically requires that the monitors be a minimum distance from stationary sources of pollution. Using the Landview CD-ROM to examine maps of counties giving the location of pollution monitors, the location of stationary pollution sources, and the location and demographics of the population confirmed the above.

put resources into their siting programs. One district officer said that in these situations they are willing to “play dictator.”⁵¹

Matching the 1980 Census PUMS to the TSPs Pollution and Regulation Data

From the 5-percent PUMS sample of the 1980 Census, we extracted all heads of households who resided in the United States in 1980. This results in a micro data set containing 4.023 million household heads; 2.91 million men and 1.12 million women. The household heads locations of residence in 1980 and 1975 are derived from questions on the state and county group (PUMA) of residence in 1980 and 1975. About 31 thousand of the over 4 million household heads living in the U.S. in 1980 resided outside of the 50 states in 1975.

We merged this Census extract to the TSPs pollution and regulation data. Based on the 1980 County Group Equivalency File for the 1980 Census, we wrote code for three different schemes for matching the PUMA/County Group identifier provided in the PUMS to the FIPS county codes. The schemes matched PUMAs to counties which accounted for 100%, at least 75%, and at least 50% of the populations in the PUMAs.⁵² We then matched the Census data to the TSPs regulation data by the FIPS county identifiers. The results in Table 8 are insensitive to the choice of matching algorithms and to the mid-decade regulation variable used to stratify the sample.

Variables from the 1972 and 1983 County and City Data Books

The following are the list of variables taken from the 1972 and 1983 County and City Data Books (CCDB) and used in the housing value regressions. Most of the information comes from the 1970 and 1980 Censuses of Population and Housing. The crime data comes from the U.S. Federal Bureau of Investigation; the medical data comes from the American Hospital Association and the American Medical Association; the spending and tax variables come from the Census of Governments. See “Source Notes and Explanations” in the CCDB for more detailed explanations of the variables and their sources. We start with the variables used in the 1980 analysis from the 1983 CCDB.

outcome variable

log-median value of owner occupied housing units in 1980

(deflated to \$1982-84 by the total shelter component of the CPI)

economic conditions variables

per-capita money income in 1979

civilian labor force (aged 16 or older) unemployment rate

% of employment in manufacturing in 1980

demographic and socioeconomic variables

population per square mile in 1980

% of population white in 1980

% of population female in 1980

% of population aged 65 and over in 1980

% of population over 25 with at least a high school degree in 1980

⁵¹ The county-level measures of mean TSP pollution levels used in the analysis are based on averaging the annual geometric mean reading of every monitor in the county over 4 years. Consequently, any idiosyncratic shocks to pollution levels in a county in a short time span will not pose any problems.

⁵² The matches are comprehensive. The total U.S. population in 1980 was 226,545,805. For the match requiring that a county account for 100% of the PUMA population, 603 PUMAs accounting for 369 counties with a population of 143,462,851 could be matched. For the match in which the county accounts for at least 50% of the PUMA population, the numbers were 831 PUMAs, 561 counties, and 178,872,025 people. It appears that the PUMAs/counties that can be matched are relatively large.

% of population over 25 with at least a college degree in 1980
% of population in urban area
% of families below the poverty level in 1979

housing variables

% of year round housing built in last 10 years
% of year round housing built 10-20 years ago
% of year round housing built before 1939
% of occupied housing units lacking complete plumbing in 1980
% of housing units vacant in 1980
% of housing units owner occupied in 1980

neighborhood variables

crime rate per 100,000 in 1981
all serious crimes known to police per 100,000 in 1981
property crimes per 100,000 in 1981
physicians per 100,000 in 1980
hospital beds per 100,000 in 1980

spending and tax variables

per-capita government revenue in 1977
per-capita total taxes in 1977
per-capita property taxes in 1977
per-capita general expenditures in 1977
% of spending on education in 1977
% of spending for police protection in 1977
% of spending on public welfare in 1977
% of spending on health in 1977
% of spending on highways in 1977

For 1970 the following variables were unavailable:

% of year round housing built in last 10 years
% of year round housing built 10-20 years ago
% of year round housing built before 1939
crime rate per 100,000
all serious crimes known to police per 100,000
property crimes per 100,000
physicians per 100,000
hospital beds per 100,000
per-capita total taxes
% of spending for police protection

For the 1970-80 First-Differences and Instrumental Variables Regressions

“First differences” in all of the variables that are in both the 1972 and 1983 CCDB’s are included as control variables.

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Table 1: Summary Statistics for TSPs Pollution Data, by Mid-Decade Regulation Status

	<u>1970-1980</u>		<u>1980-1990</u>	
	Attainment (1)	Nonattainment (2)	Attainment (3)	Nonattainment (4)
Number of Counties Monitored	709	277	810	126
1970 (1980) Population	84,540,131	76,535,797	117,291,804	57,005,694
<u>Mean (Standard Deviation) of County-Level Average Daily Concentrations</u>				
1969-1972 (1977-1980)	65.6 (22.3)	92.6 (22.3)	55.2 (11.5)	77.9 (14.2)
1974 (1984)	52.6 (11.6)	78.0 (18.0)	47.3 (9.9)	65.7 (16.6)
1977-1980 (1987-1990)	53.2 (10.6)	71.4 (15.3)	46.5 (9.5)	66.7 (17.9)
<u>Mean (Standard Deviation) of County-Level Maximum Daily Concentrations</u>				
1969-1972 (1977-1980)	290.6 (275.8)	544.9 (290.0)	237.7 (147.6)	473.1 (227.4)
1974 (1984)	221.1 (119.9)	506.4 (397.3)	168.4 (119.2)	276.8 (107.8)
1977-1980 (1987-1990)	212.7 (139.3)	419.6 (236.9)	150.9 (59.1)	305.7 (148.2)

Notes: Calculations are based on data from the EPA's TSPs monitoring network and the Code of Federal Regulations. The 1970-80 and 1980-90 samples are restricted to counties with TSPs monitors in both the 1969-72 and 1977-80 periods and in both the 1977-80 and 1987-90 periods, respectively. Nonattainment refers to counties that were nonattainment for TSPs pollution in the middle of the decade; that is, in either 1975 or 1976 (1985 or 1986). Attainment corresponds to the remaining counties. TSPs are measured in micrograms per cubic meter. The average daily pollution concentration for each county-year is the weighted average of the geometric mean concentrations of each monitor in the county, using the number of observations per monitor as weights. The county-level mean across multiple years (e.g., 1969-1972) is the average of the annual means. The attainment/nonattainment mean TSPs readings are the weighted average of these means, using county populations as weights. The annual county-level maximum daily reading is the maximum recorded concentration across all monitors within a county. The county-level maximum across multiple years (e.g., 1969-1972) is the average of the annual maximums. The mean attainment/nonattainment maximum TSPs concentrations are the weighed average of the maximums, using the county populations as weights.

Table 2: Sample Means by TSPs Pollution Groups in 1970 and 1980 Cross-Sections

	1970 TSPs Groups			Test of Equality	1980 TSPs Groups			Test of Equality
	Small (1)	Middle (2)	Big (3)	F-Statistic (4)	Small (5)	Middle (6)	Big (7)	F-Statistic (8)
Housing Value (\$82-84)	50,797	52,929	55,636	4.07	61,699	63,063	69,814	13.8*
Mean TSPs Concentration	37.8	62.5	99.4	1426*	36.6	53.7	77.2	1610*
<u>Economic Conditions</u>								
Income per Capita (\$82-84)	7,859	8,429	8,649	12.1*	8,517	9,145	9,270	13.6*
Unemployment Rate	0.048	0.041	0.045	12.6*	0.067	0.061	0.072	32.5*
% Employment in Manufacturing	0.23	0.25	0.27	11.1*	0.20	0.23	0.22	4.2
<u>Demographic and Socioeconomic Characteristics</u>								
Population Size	65,393	120,352	295,881	31.6*	61,576	135,231	210,487	18.0*
Population Density	487	1,067	5,790	44.3*	373	2,467	3,071	9.3*
% >= High School Graduate	0.558	0.554	0.533	7.1*	0.685	0.677	0.680	0.6
% >= College Graduate	0.119	0.124	0.109	13.5*	0.163	0.176	0.169	3.7
% White	0.90	0.90	0.85	20.2*	0.89	0.84	0.79	34.5*
% Urban	0.65	0.77	0.90	95.8*	0.61	0.79	0.88	99.4*
% Senior Citizens	0.095	0.092	0.096	2.7	0.123	0.110	0.106	18.5*
<u>Housing Variables</u>								
% Vacant	0.071	0.055	0.047	41.1*	0.134	0.071	0.071	135*
% Owner Occupied	0.67	0.65	0.57	61.2*	0.61	0.59	0.56	13.0*
% of Houses Built in Last 10 Years	---	---	---	---	0.304	0.253	0.247	14.5*
% of Houses Built 10-20 Years Ago	---	---	---	---	0.204	0.203	0.200	0.6
% of Houses Built Before 1939	---	---	---	---	0.263	0.253	0.244	1.1
<u>Tax and Expenditure Variables</u>								
Per Capita Government Revenue	259	271	355	11.8*	772	840	833	0.6
Per Capita Total Taxes	---	---	---	---	328	360	353	0.7
Per Capita Property Taxes	115	134	143	14.1*	299	270	282	14.1*
Per Capita General Expenditures	234	241	260	10.0*	810	727	806	3.0
% of Spending on Education	0.532	0.527	0.473	37.3*	0.476	0.472	0.450	8.5*
% of Spending on Highways	0.085	0.073	0.067	13.8*	0.069	0.052	0.050	31.4*
% of Spending on Welfare	0.052	0.048	0.061	6.9*	0.063	0.043	0.051	10.1*
% of Spending on Health	0.045	0.045	0.049	1.2	0.055	0.066	0.065	2.0
% of Spending on Police	---	---	---	---	0.045	0.050	0.058	47.3*
<u>Neighborhood Variables</u>								
Crime Rate per 100,000	---	---	---	---	4,814	6,286	6,469	12.5*
Physicians per 100,000	---	---	---	---	133	185	213	27.5*
Hospital Beds per 100,000	---	---	---	---	639	618	636	0.3

Notes: See notes to Table 1 for a description of the TSPs pollution and regulation data. The other entries are derived from the 1972 and 1983 County and City Data Books. The CPI and total shelter component of the CPI are used to deflate income per capita and housing values to \$1982-84, respectively. All other variables are in nominal dollars. The 1090 counties with TSPs data in 1970 were divided into three categories based on their level of mean TSPs in that year. The "Small" category, col. (1), contains the 25% of the counties with concentrations less than 46.1 units, and the "Large" category, col. (2), contains the 25% of the counties with concentrations greater than 77.1 units. The "Middle" category, col. (3), contains the remaining 50% of the counties. Column (4) presents the F-statistics testing the equality of the means across cols. (1) - (3). The entries in columns (5) through (8) are for the 1441 counties with pollution monitors in 1980 and were calculated using the same method. * indicates significance at the 1% level

Table 3: 1970 to 1980 Changes in Sample Means by TSPs Pollution Change Groups and 1975-76 Attainment Status

	1970-1980 TSPs Change Groups			Test of Equality		1975-1976 Attainment Status		Test of Equality
	Small (1)	Middle (2)	Big (3)	F-Statistic (4)	Attainment (5)	Nonattainment (6)	F-Statistic (7)	
Change in Housing Value (\$82-84)	19,628	15,105	8,093	35.8*	10,526	14,753	16.4*	
Change in TSPs Concentration	13.5	-8.7	-31.4	1007*	-11.9	-20.7	54.1*	
<u>Change in Economic Conditions</u>								
Income per Capita (\$82-84)	1,268	948	466	113*	810	729	3.4	
Unemployment Rate	0.012	0.020	0.027	36.7*	0.021	0.023	1.9	
% Employment in Manufacturing	-0.017	-0.027	-0.041	40.6*	-0.030	-0.034	3.4	
<u>Change in Demographic/Socioeconomic Characteristics</u>								
Population Size	0.182	0.202	0.115	11.1*	0.178	0.168	0.3	
Population Density	85	19	-541	40.1*	-294	-152	4.5	
% >= High School Graduate	0.141	0.138	0.131	10.5*	0.139	0.131	24.6*	
% >= College Graduate	0.062	0.058	0.057	3.5	0.060	0.056	5.5	
% White	-0.052	-0.043	-0.075	35.7*	-0.049	-0.070	34.7*	
% Urban	0.019	0.019	0.010	4.8	0.018	0.011	5.0	
% Senior Citizens	0.013	0.015	0.016	5.2	0.015	0.015	0.7	
<u>Change in Housing Variables</u>								
% Vacant	0.021	0.021	0.017	2.5	0.021	0.017	5.6	
% Owner Occupied	-0.057	-0.052	-0.036	25.5*	-0.049	-0.041	10.1*	
<u>Change in Tax and Expenditure Variables</u>								
Per Capita Government Revenue	441	474	512	2	425	554	26.4*	
Per Capita Property Taxes	133	148	172	11.8*	154	160	0.9	
Per Capita General Expenditures	487	508	576	18.3*	502	571	32.0*	
% of Spending on Education	-0.055	-0.046	-0.041	2.1	-0.048	-0.042	2.3	
% of Spending on Highways	-0.021	-0.020	-0.022	0.3	-0.022	-0.020	2.4	
% of Spending on Welfare	-0.006	-0.011	0.001	8.4*	-0.004	-0.006	0.3	
% of Spending on Health	0.017	0.015	0.016	0.2	0.016	0.016	0.1	

Notes: See notes to Tables 1 and 2. The entries in columns (1)-(3) and (5)-(6) are the mean changes in the variables from 1970-1980. The 989 counties with TSPs data in both the 1969-1972 and 1977-1980 periods were divided into three categories based on the change in mean TSPs between these periods. The "Small" category, col. (1), contains the 25% of the counties with changes greater than 4.5 units, and the "Large" category, col. (2), contains the 25% of the counties with changes less than -19.9 units. The "Middle" category, col. (3), contains the 25-75 interquartile range of counties. Column (4) presents the F-statistics testing the equality of the means across cols. (1) - (3). In columns (5) and (6), these same counties are divided into two groups: 1) counties that were nonattainment for TSPs in either 1975 or 1976; and 2) counties that were attainment for TSPs in both 1975 and 1976. Column (7) presents the F-statistics testing the equality of the means in columns (5) and (6).
* indicates significance at the 1% level

Table 4: Cross-Sectional and Fixed-Effects Estimates of the Effect of Pollution on Log-Housing Values
 1970 and 1980 County Data Books
 (estimated standard errors in parentheses)

	1970 County Data Book				1980 County Data Book				1970-1980	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	First Differences	
Mean TSPs (1/100)	0.106 (0.039)	-0.069 (0.018)	-0.024 (0.016)	-0.020 (0.014)	0.244 (0.056)	0.119 (0.027)	-0.029 (0.022)	-0.022 (0.020)	0.299 (0.032)	0.029 (0.023)
Pop. Density	N	Y	Y	Y	N	Y	Y	Y	N	Y
Unemp. Rate	N	Y	Y	Y	N	Y	Y	Y	N	Y
Income Per-Capita	N	Y	Y	Y	N	Y	Y	Y	N	Y
Pct. Employ Manf.	N	Y	Y	Y	N	Y	Y	Y	N	Y
Demog./Socio-Econ.	N	Y	Y	Y	N	Y	Y	Y	N	Y
Housing Vars.	N	Y	Y	Y	N	Y	Y	Y	N	Y
Fiscal and Tax Vars.	N	Y	Y	Y	N	Y	Y	Y	N	Y
Crime Vars.	N	N	N	N	N	Y	Y	Y	N	N
Medical Vars.	N	N	N	N	N	Y	Y	Y	N	N
State Effects	N	N	Y	Y	N	N	Y	Y	N	N
Flexible Form	N	N	N	Y	N	N	N	Y	N	N
County Effects	N	N	N	N	N	N	N	N	Y	Y
R-Squared	0.01	0.84	0.91	0.95	0.01	0.84	0.94	0.96	0.08	0.59
Sample Size	1090	1083	1083	1083	1441	1411	1411	1411	1001	993

Notes: See notes to Tables 1-3. See the Data Appendix for the definitions of the pollution and control variables used. The 1970 and 1980 cross-sectional regressions are weighted by the 1970 and 1980 county populations sizes, respectively; while the 1970-80 first-differences regressions are weighted by the sum of the 1970 and 1980 county population sizes. For 1970 and 1980, the Mean TSPs variable is the 1969-72 and 1977-80 average of the annual geometric mean concentrations, respectively. The Demographic and Socioeconomic variables include fractions white, female, aged 65 and over, with at least a high school degree, with at least a college degree, in urban areas, and below the poverty level. The Housing variables include fractions of housing units vacant, owner-occupied, built in the last 10 years, built 10-20 years ago, built before 1939, and fraction of occupied housing units without complete plumbing. The Fiscal and Tax variables include per-capita measures of government revenue, total taxes, property taxes, and general expenditures; and percentages of spending on education, police protection, public welfare, health, and highways. The Crime variables are the rates of crime, serious crimes, and property crimes per 100,000. The Medical variables are physician and hospital bed rates per 100,000. State Effects and County Effects are separate indicator variables for each state and county, respectively. The flexible functional form includes quadratics, cubics, and interactions of the variables as controls.

Table 6: Instrumental Variables Estimates of the Effect of 1970-80 Changes in Pollution on Changes in Log-Housing Values
(estimated standard errors in parentheses)

	<u>Nonattainment for TSPs in</u> 1975		<u>Nonattainment for TSPs in</u> 1975 or 1976		<u>Geometric Mean of TSPs in</u> 1974			<u>Geometric Mean of TSPs in</u> 1974 and 1975		<u>Nonattain '75 or '76</u> <u>and Mean TSPs in</u> <u>'74 and '75</u>	
Mean TSPs (1/100)	-0.566 (0.186)	-0.553 (0.184)	-0.426 (0.125)		-0.399 (0.140)	-0.487 (0.120)	-0.398 (0.143)	-0.475 (0.121)	-0.431 (0.142)	-0.458 (0.111)	
Pop. Density	N	N	Y		N	Y	N	Y	N	Y	
Unemp. Rate	N	N	Y		N	Y	N	Y	N	Y	
Income Per-Capita	N	N	Y		N	Y	N	Y	N	Y	
Pct. Employ Manf.	N	N	Y		N	Y	N	Y	N	Y	
Demog/Socio-Econ	N	N	Y		N	Y	N	Y	N	Y	
Housing Vars	N	N	Y		N	Y	N	Y	N	Y	
Fiscal and Tax Vars	N	N	Y		N	Y	N	Y	N	Y	
County Effects	Y	Y	Y		Y	Y	Y	Y	Y	Y	
Sample Size	976	1001	993		974	966	968	960	968	960	

Notes: See notes to previous tables. The coefficients are estimated using two-stage least squares. The sum of the 1970 and 1980 county populations are used as weights in all of the regressions. In the first 3 columns, the instrumental variable is an indicator equal to one if the county was nonattainment for TSPs in 1975 and in either 1975 or 1976. In the next set of columns, the instrumental variable(s) is the county-level geometric mean TSPs concentrations in 1974 and in 1974 and 1975. In the final two columns, the instruments are the indicator for nonattainment in 1975 or 1976 and geometric mean TSPs in 1974 and 1975.

Table 7: Control Function Estimates of the Capitalization of 1970-80 Changes in Pollution,
With Correction for Selectivity Bias Due to Random Coefficients
(estimated standard errors in parentheses)

	TSPs Nonattainment in 1975 or 1976		Geometric Mean of TSPs in 1974 and 1975				Nonattain '75 or '76 and Mean TSPs in '74 and '75	
Mean TSPs (1/100)	-0.585 (0.182)	-0.431 (0.125)	-0.421 (0.139)	-0.492 (0.119)	-0.421 (0.141)	-0.483 (0.120)	-0.456 (0.138)	-0.464 (0.111)
v_i (1 st -stage residual) (1/100)	1.050 (0.185)	0.527 (0.124)	0.912 (0.141)	0.603 (0.117)	0.919 (0.142)	0.594 (0.119)	0.962 (0.139)	0.580 (0.111)
v_i * Mean TSPs (1/10,000)	0.274 (0.064)	0.086 (0.029)	0.280 (0.065)	0.092 (0.029)	0.284 (0.066)	0.094 (0.030)	0.288 (0.066)	0.095 (0.030)
Pop. Density	N	Y	N	Y	N	Y	N	Y
Unemp. Rate	N	Y	N	Y	N	Y	N	Y
Income Per-Capita	N	Y	N	Y	N	Y	N	Y
Pct. Employ Manf.	N	Y	N	Y	N	Y	N	Y
Demog/Socio-Econ	N	Y	N	Y	N	Y	N	Y
Housing Vars	N	Y	N	Y	N	Y	N	Y
Fiscal and Tax Vars	N	Y	N	Y	N	Y	N	Y
County Effects	Y	Y	Y	Y	Y	Y	Y	Y
Sample Size	1001	993	974	966	968	960	968	960

Notes: The standard errors are calculated based on 1,000 bootstrap replications of the sequential estimator. See text for details on the selectivity bias correction when the endogenous variable is continuous. Estimates are insensitive to including polynomials of the arguments of the two control functions.

Table 8: Estimates of the Value of Air Quality by TSPs Pollution Levels in the Regulation Selection Year,
Based on the Conditional Mean Functions of Changes in Pollution and Housing Prices
(estimated standard errors in parentheses)

Value of Air Quality by Geometric Mean of TSPs in 1974	Categories of Geometric Mean of 1974 TSPs Pollution ($\mu\text{g}/\text{m}^3$)											
	40-50	40-55	40-60	40-65	40-70	40-75	70-75	70-80	70-85	70-90	70-100	70-120
Price Gradient	-0.127	-0.222	-0.711	-0.888	-0.654	-0.509	-0.055	-0.135	-0.328	-0.451	-0.487	-0.505
Incremental												
# of Counties	217	91	117	92	57	61	61	46	30	21	27	25
1980 Population (in millions)	30.81	16.68	23.10	14.43	13.52	16.91	16.91	13.07	9.64	10.28	5.59	5.32
1970 TSPs Level	60.6	61.7	70.7	75.5	79.0	86.4	86.4	93.1	100.7	109.0	111.0	114.6
1980 TSPs Level	49.3	55.8	55.3	58.8	65.2	65.6	65.6	70.5	73.1	80.2	84.0	95.3
1970 House Price	57,751	56,837	51,964	50,774	52,788	64,046	64,046	55,657	46,120	62,104	46,219	43,563
1980 House Price	70,486	70,717	63,922	62,417	63,887	68,339	68,339	65,286	62,500	94,317	52,819	60,958

Notes: The estimates are derived from regressing the estimated conditional mean of 1970-80 housing price changes on the conditional mean of 1970-80 TSPs changes (1/100), both predicted by the 1974 county-level geometric means of TSPs. The conditional mean functions are estimated by locally weighted regressions and are graphed in Figure 4B. The analysis is weighted by the sum of the 1970 and 1980 county populations. The "incremental" statistics are based on the additional counties not included in the previous category. The 1970 and 1980 TSPs levels are the 1969-72 and 1977-80 averages, respectively. There are 206 counties, containing 15.5 million people in 1980, with 1974 TSPs levels less than or equal to $40 \mu\text{g}/\text{m}^3$, and 13 counties, containing 3.27 million people in 1980, with 1974 TSPs levels greater than or equal to $120 \mu\text{g}/\text{m}^3$.

Table 9: Characteristics of Household Heads in Counties in 1975 and 1980 by Attainment Status in 1975-1976,
Based on the 5-Percent PUMS Sample of the 1980 Census

	# of HH Heads (millions)		Black (percent)		White (percent)		HS Dropout (percent)		College Grad. (percent)		Poverty Rate (percent)	
	1975	1980	1975	1980	1975	1980	1975	1980	1975	1980	1975	1980
<u>100% Match</u>												
Attainment '75-'76	1.134	1.140	11.40	11.52	84.16	83.80	30.00	29.87	21.17	21.33	11.49	11.60
Nonattain. '75-'76	1.333	1.334	12.97	13.01	82.42	82.03	30.41	30.37	19.47	19.63	11.46	11.59
<u>50% Match</u>												
Attainment '75-'76	1.495	1.505	10.72	10.81	85.41	85.12	31.04	30.91	20.43	20.54	11.68	11.77
Nonattain. '75-'76	1.451	1.455	12.39	12.41	83.04	82.69	30.65	30.59	19.16	19.33	11.52	11.64

Notes: The entries are based on the 5-percent PUMS sample of the 1980 Census and are derived from the questions on state and county group of residence in 1980 and in 1975. The sample is restricted to the 4.023 million household heads in the 5-Percent PUMS; 1.116 million females and 2.907 million males. About 31 thousand of the over 4 million household heads living in the U.S. in 1980 resided outside of the 50 states in 1975. See the Data Appendix for a description of how the Census PUMS extracts are matched to the TSPs regulation data. The '100% Match' consists of all counties which account for 100-percent of the populations in the Census PUMAs. The '50% Match' consists of all counties which account for at least 50-percent of the populations in the Census PUMAs. Nonattainment '75-'76 consists of those counties that were nonattainment for TSPs in either 1975 or 1976. Attainment '75-'76 consists of those counties that were attainment for TSPs in both 1975 and 1976.

Appendix Table 1: Regulation, Sources, Control Technologies, and Health Effects of Total Suspended Particulates (TSPs) Pollution

National Ambient Air Quality Standards

Maximum Allowable Concentration (Primary Standard):

Annual Geometric Mean (never to be exceeded)	75 Micrograms per Cubic Meter
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Maximum 24 Hour Concentration (not to be exceeded more than once a year)	260 Micrograms per Cubic Meter
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Sources

Industrial Processes (e.g., Pulp and Paper; Stone, Clay, Glass, and Concrete Products; Iron and Steel), Smelters, Automobiles, Burning Industrial Fuels, Woodsmoke, Dust from Paved and Unpaved Roads, Construction, and Agricultural Ground Breaking.

Techniques to Control Emissions

The control of TSPs is frequently accomplished by directing the polluted air through a “bag” filter, which captures the pollutants, or a wet “scrubber” that increases the mass of the particulates, causing their separation from the “clean” air (Vesilind, et al. 1988).

Health Effects

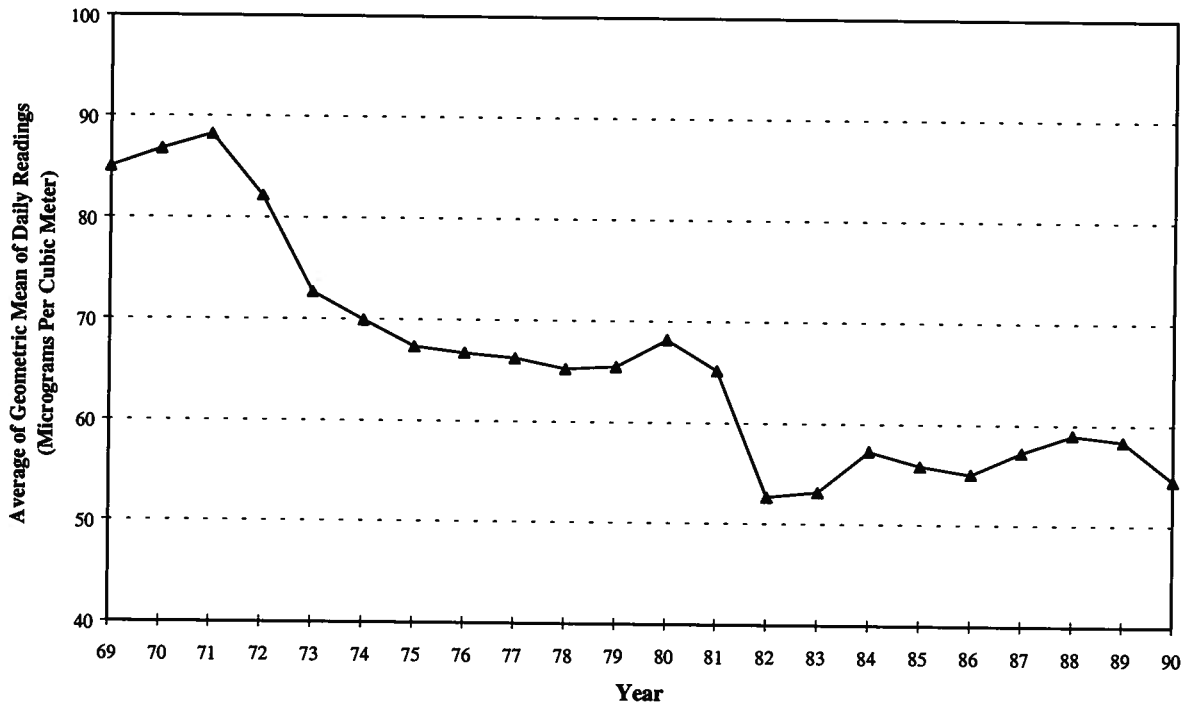
TSPs can affect breathing and respiratory systems, causing increased respiratory disease and lung damage. Children, the elderly and people suffering from heart or lung disease (e.g., asthma) are especially at risk. Recent research has linked particulates pollution to increased mortality rates (Dockery, et al. 1993; Ransom and Pope 1995; Chay and Greenstone 1999).

Appendix Table 2: Instrumental Variables Estimates of the Association Between 1970-80 Changes in TSPs
 And Changes in Log-Rents and Log-Incomes Per-Capita
 (estimated standard errors in parentheses)

	1970-80 Log-Rent Changes		1970-80 Log-Income Changes	
	Nonattain. in 1975, 1976 (1)	Mean TSPs in 1974, 1975 (2)	Nonattain. in 1975, 1976 (1)	Mean TSPs in 1974, 1975 (2)
Mean TSPs (1/100)	0.144 (0.078)	-0.187 (0.070)	0.150 (0.056)	-0.045 (0.045)
Population Density	N	Y	N	Y
Unemployment Rate	N	Y	N	Y
Income Per-Capita	N	Y	N	N
Pct. Employ Manuf.	N	Y	N	Y
Demog./Socio-Econ. Housing Vars.	N	Y	N	Y
Fiscal and Tax Vars.	N	Y	N	Y
County Effects	Y	Y	Y	Y
Sample Size	1001	993	1001	993
		968		968
		960		960
				960

Notes: The coefficients are estimated using two-stage least squares. The sum of the 1970 and 1980 county populations are used as weights in all of the regressions. The dependent variables are the 1970-80 changes in log-rents and in log-income per capita. The first instrumental variable is an indicator equal to one if the county was nonattainment for TSPs in either 1975 or 1976. The second pair of instrumental variables are the county-level geometric mean TSPs concentrations in 1974 and 1975. In the log-income regressions, per-capita income and poverty rates are dropped from the analysis.

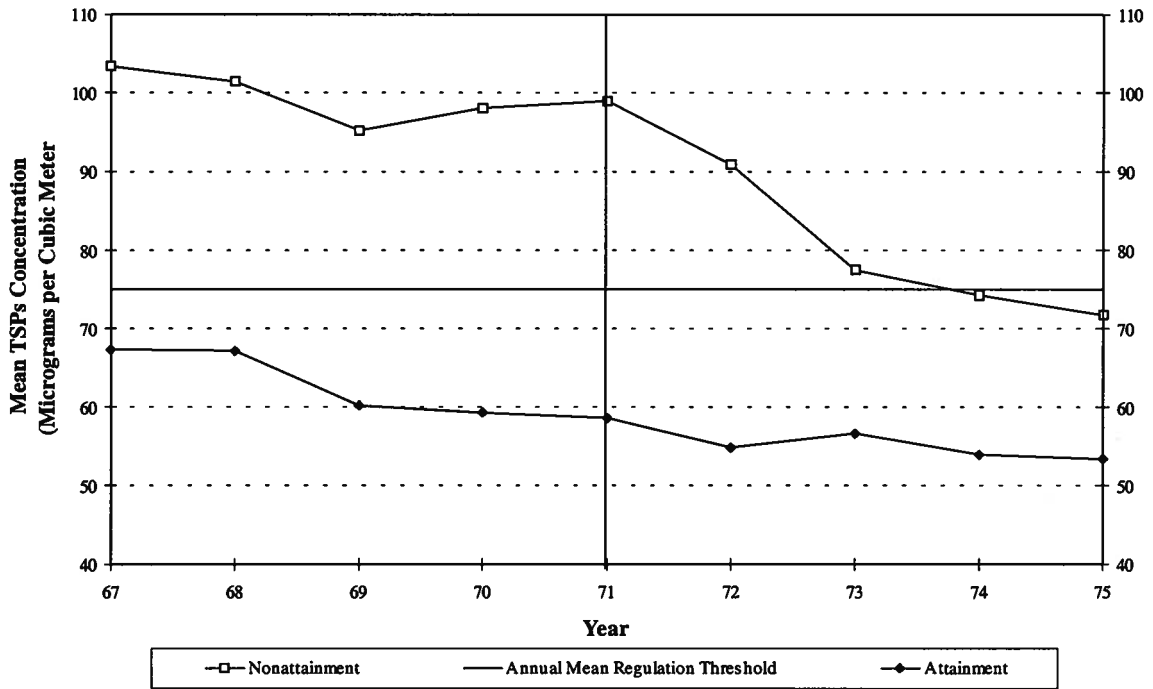
Figure 1: National Trends in Total Suspended Particulates Pollution, 1969-1990



Note: Calculations are based on the 173 counties that were monitored in every year from 1969-90. These counties contained approximately 85 million people in 1980. The county-level pollution concentrations are the weighted average of the geometric mean concentrations of each monitor in the county, using the number of observations per monitor as weights. The year-specific mean concentration is the weighted average of the county-specific means, using county populations in 1980 as weights.

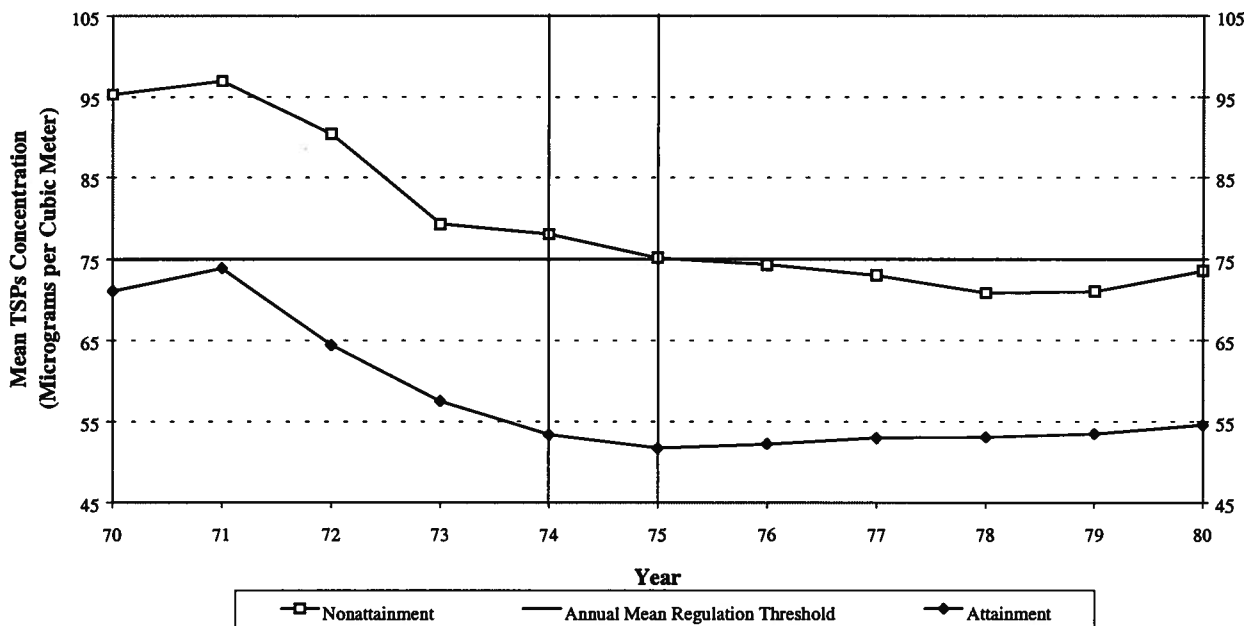
Figure 2: Trends in Total Suspended Particulates Pollution by Regulatory Status

A. TSPs Concentrations by 1971 Attainment Status, 1967-1975



Note: Calculations are based on the 231 counties that were monitored in every year from 1967-75. The 105 attainment counties contained about 24 million people in 1970, while the 126 nonattainment counties contained about 64 million people in 1970. See note to Figure 1 for a description of the method used to calculate mean TSPs concentrations.

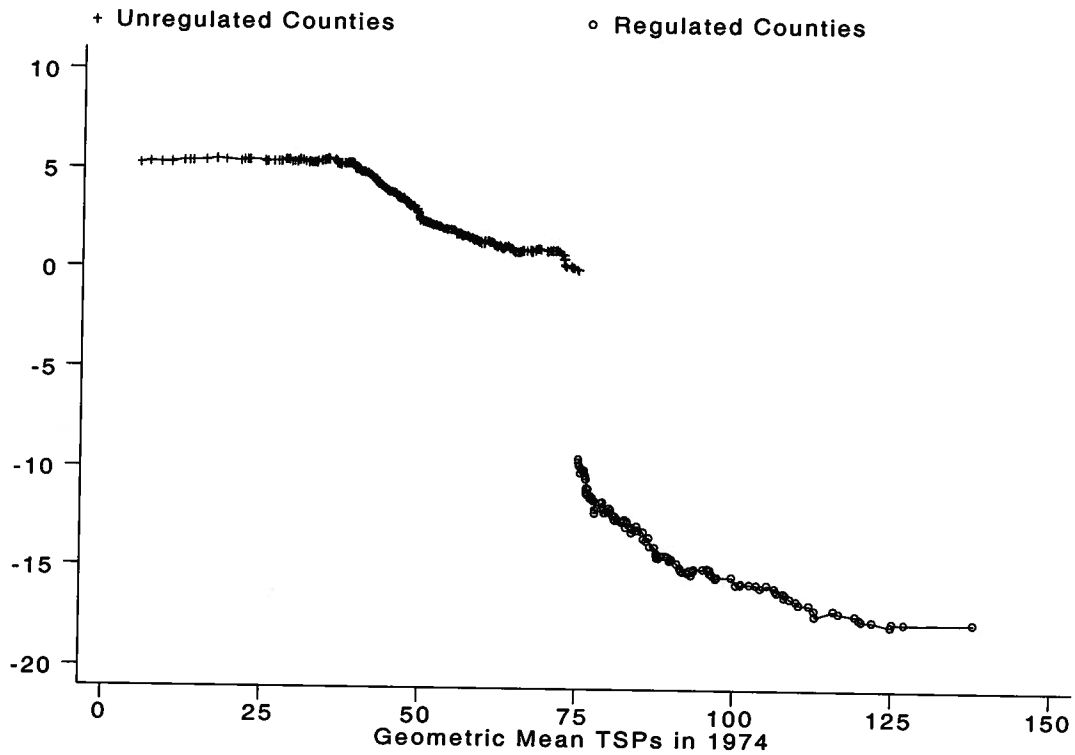
B. TSPs Concentrations by 1975-76 Attainment Status, 1970-80



Note: Calculations are based on the 420 counties that were monitored in every year from 1970-80. The 266 attainment counties contained about 56 million people in 1970, while the 154 nonattainment counties contained about 67 million people in 1970. See note to Figure 1 for a description of the method used to calculate mean TSPs concentrations.

Figure 3: Pre- and Post-Regulation Changes in Mean TSPs by 1975 Regulatory Status

A. 1974-77 (Post-Regulation) Change in Mean TSPs by 1975 Attainment Status



B. 1971-74 (Pre-Regulation) Change in Mean TSPs by 1975 Attainment Status

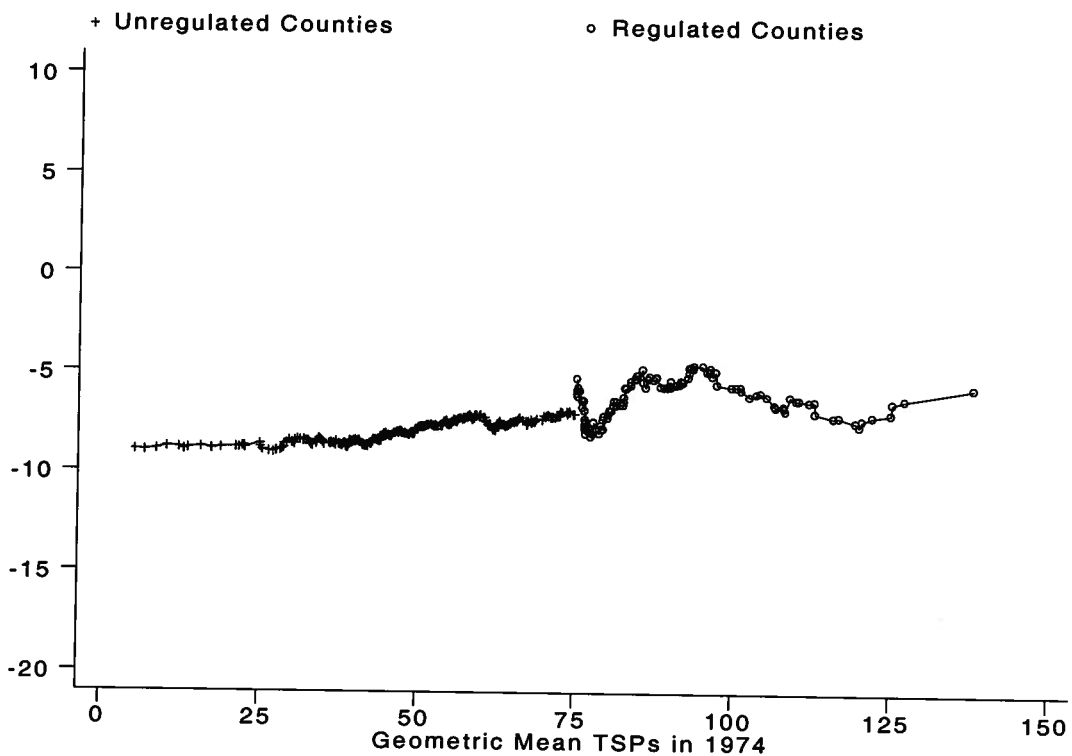
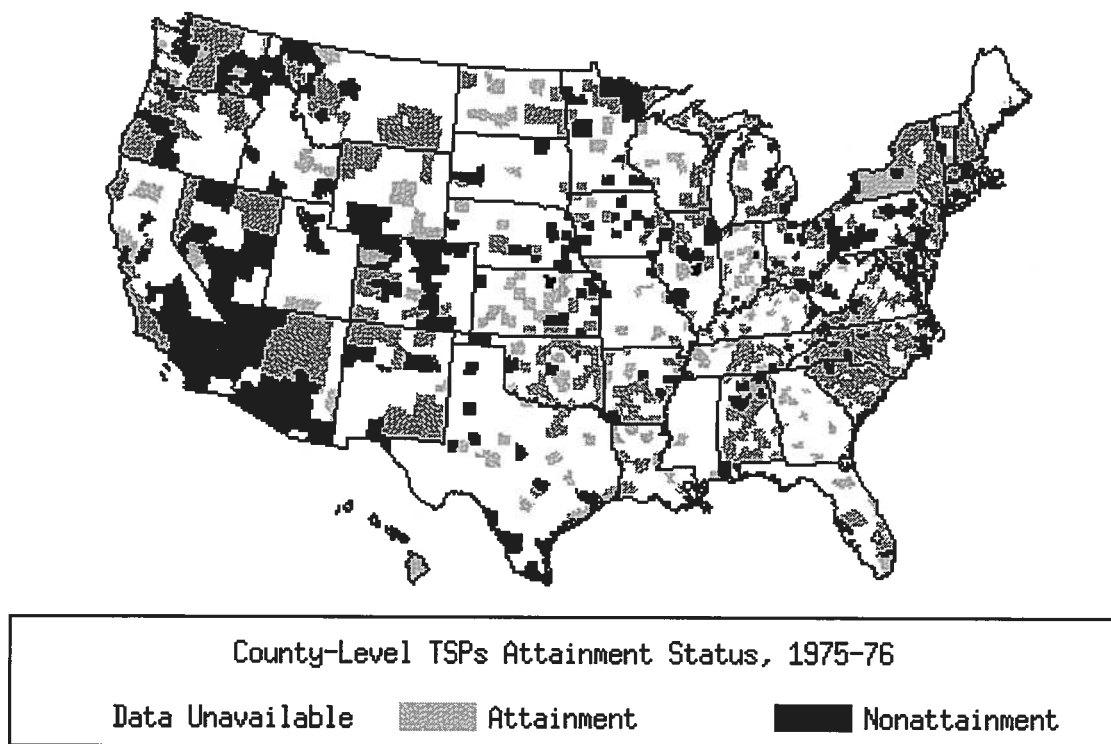


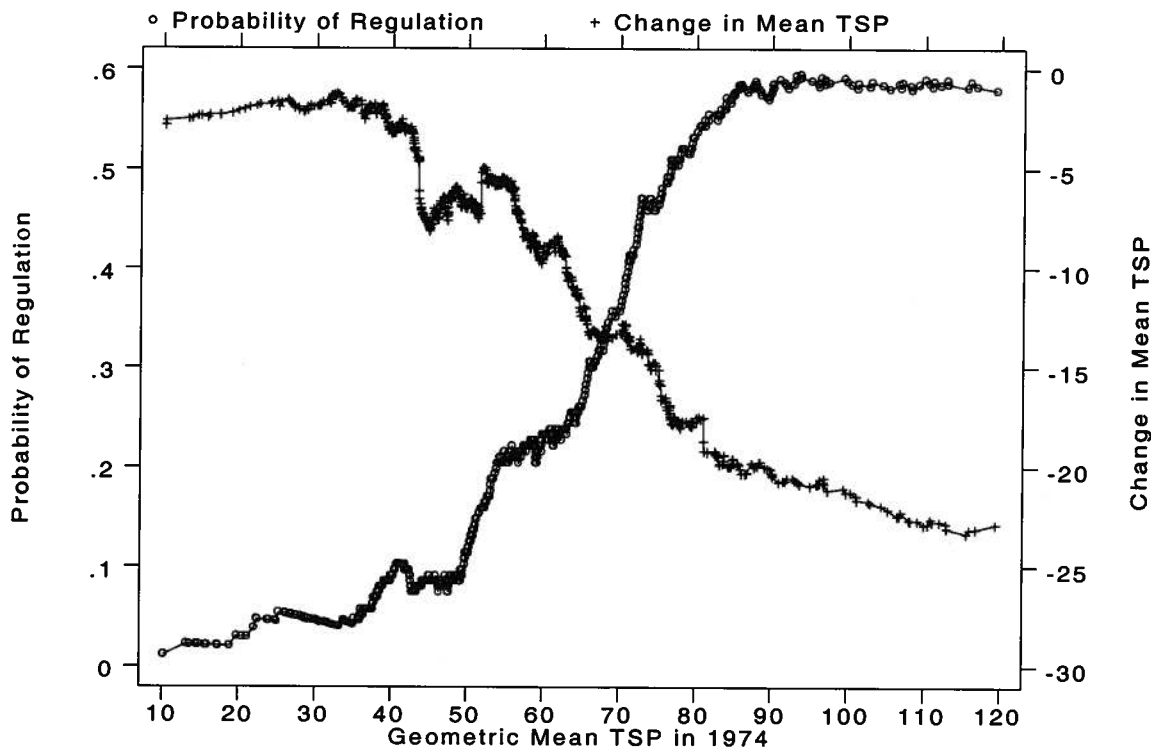
Figure 4: Incidence of Nonattainment for TSPs by County, 1975-76



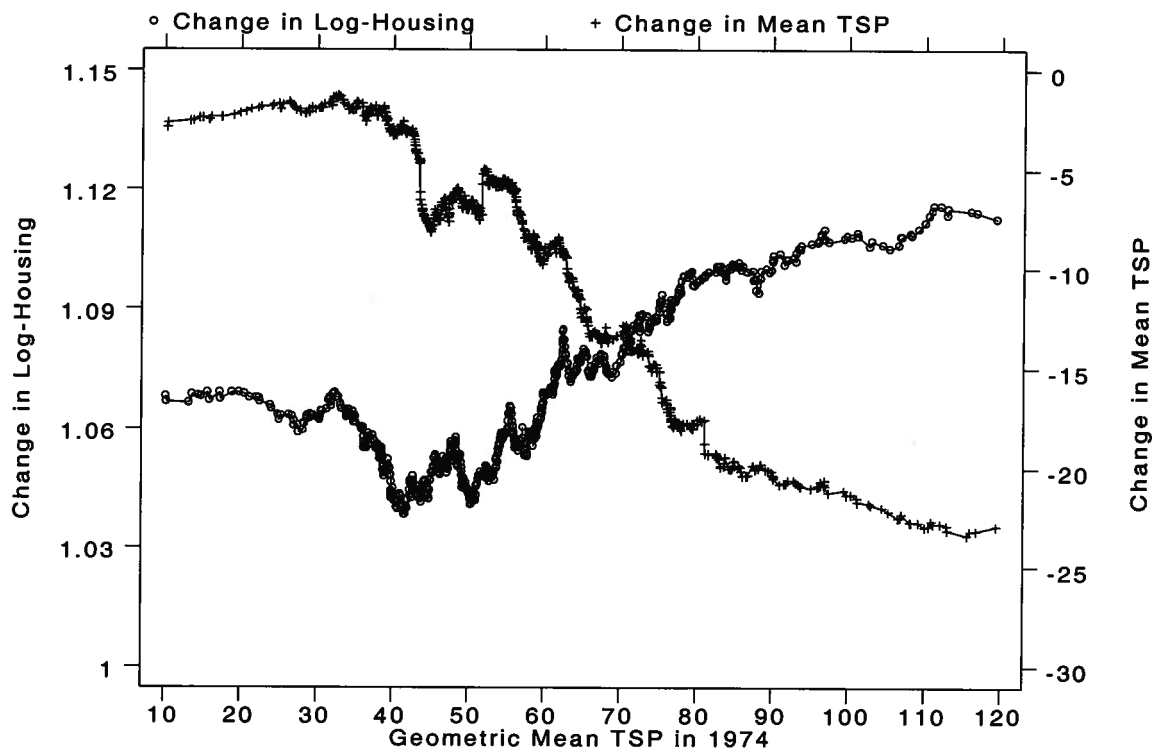
Notes: The 2,166 counties without a TSPs monitor in either the 1969-1972 or 1977-1980 periods are in white. In the counties with TSPs monitors in both periods, nonattainment refers to the 277 counties that exceeded federal TSPs standards in either 1974 or 1975, and attainment corresponds to the 709 counties below the federal ceiling in both years.

Figure 5: Probability of Regulation and 1970-80 Changes in Mean TSPs and Log-Housing Values By the Geometric Mean of TSPs Concentrations in 1974

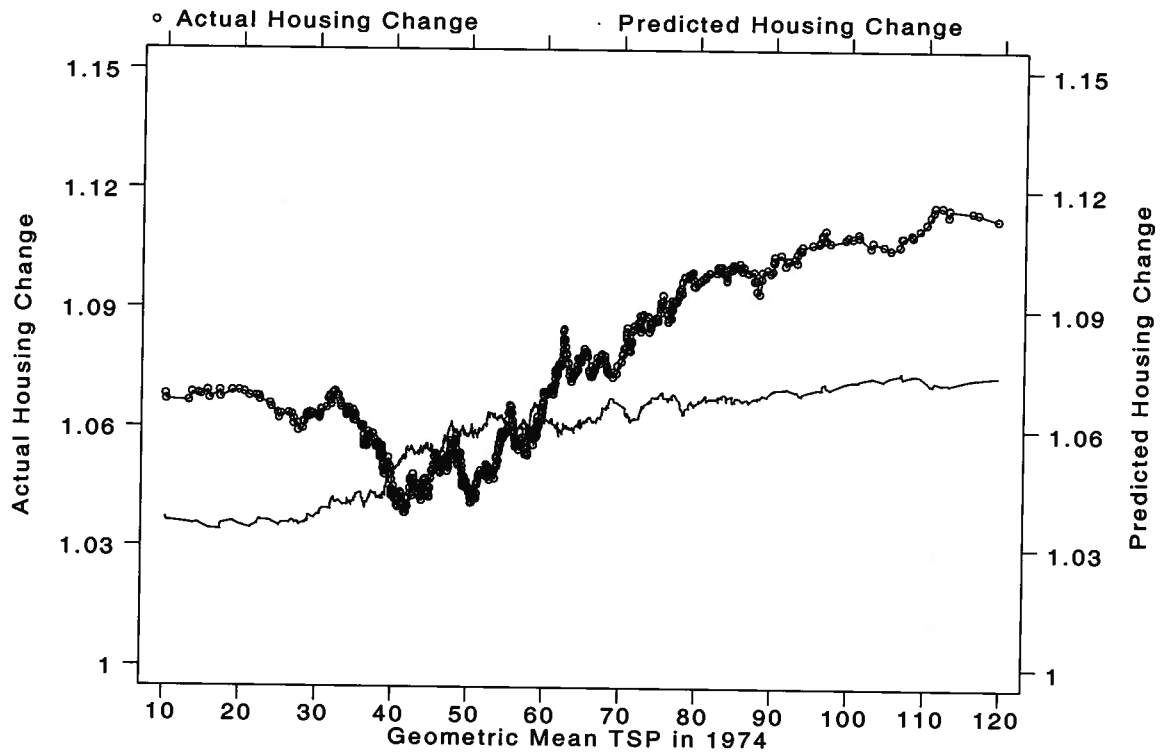
A. Probability of Nonattainment and 1970-80 Changes in Mean TSPs



B. Changes in Log-Housing Values and Mean TSPs, 1970-1980



C. Changes in Actual and Predicted Log-Housing Values, 1970-80



D. 1970 Per-Capita Income and 1970-80 Changes in Income

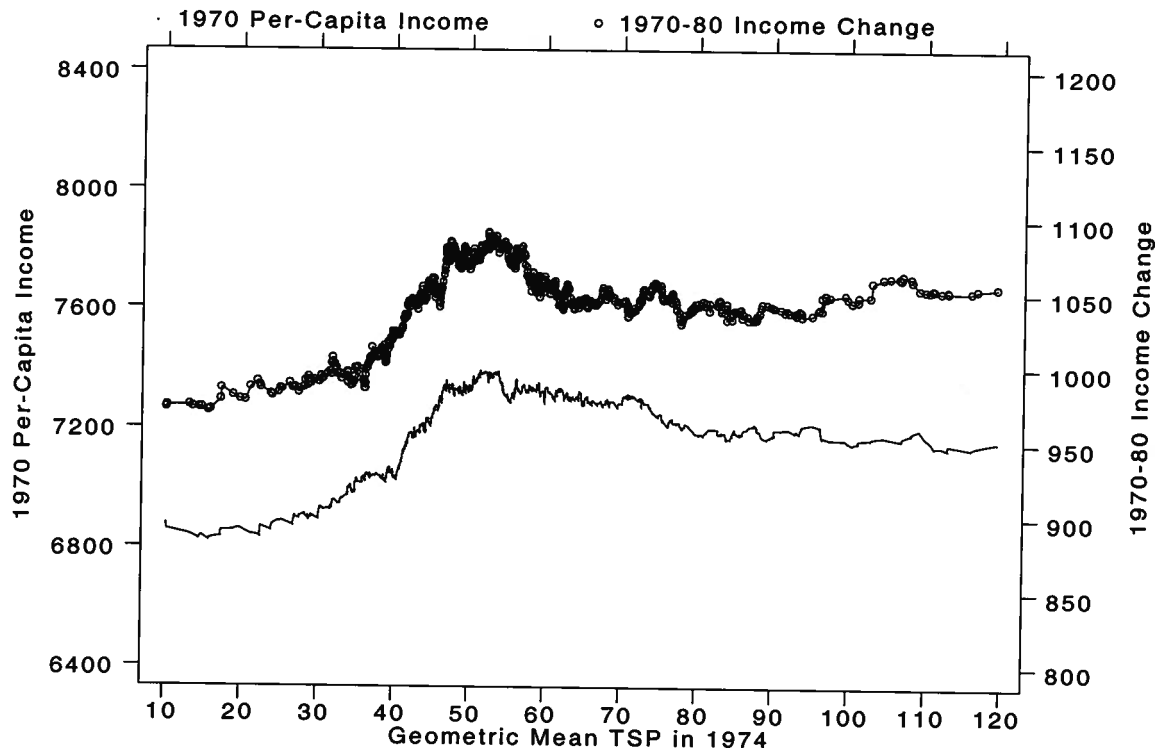
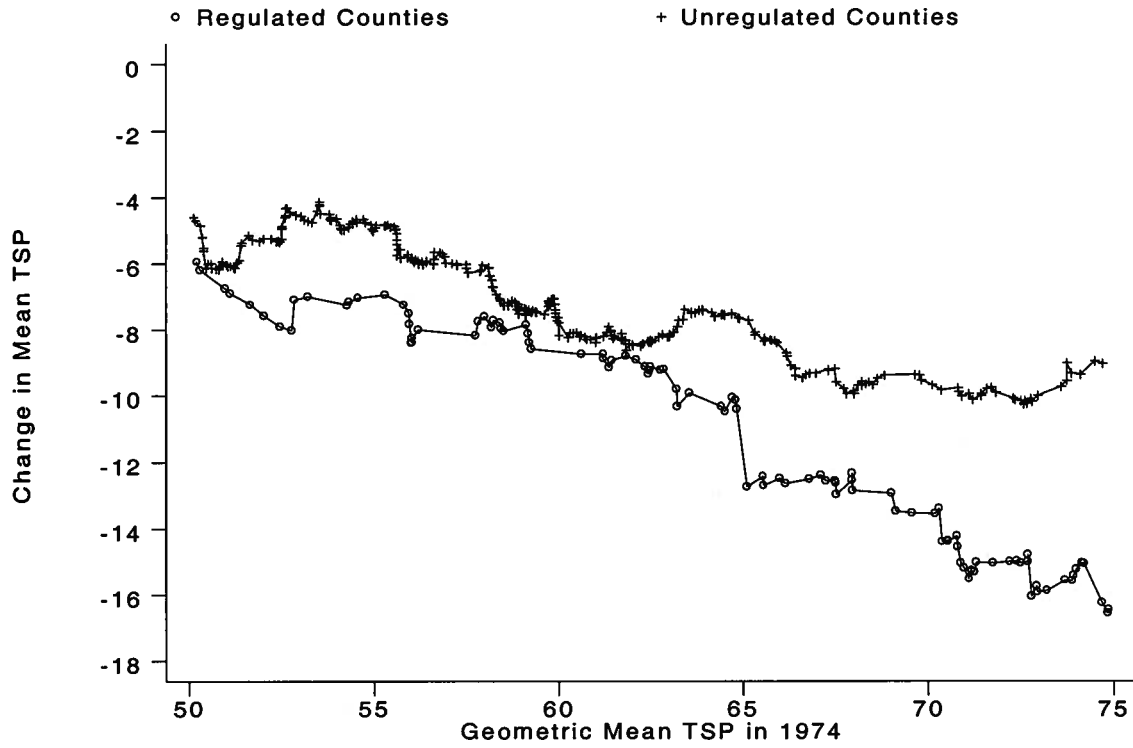


Figure 6: Changes in Mean TSPs and Log-Housing Values by Regulatory Status For Counties with 1974 Mean TSPs Concentrations <math> < 75 \mu\text{g}/\text{m}^3 </math>

A. 1970-80 Changes in Mean TSPs by Regulatory Status



B. 1970-80 Changes in Log-Housing Values by Regulatory Status

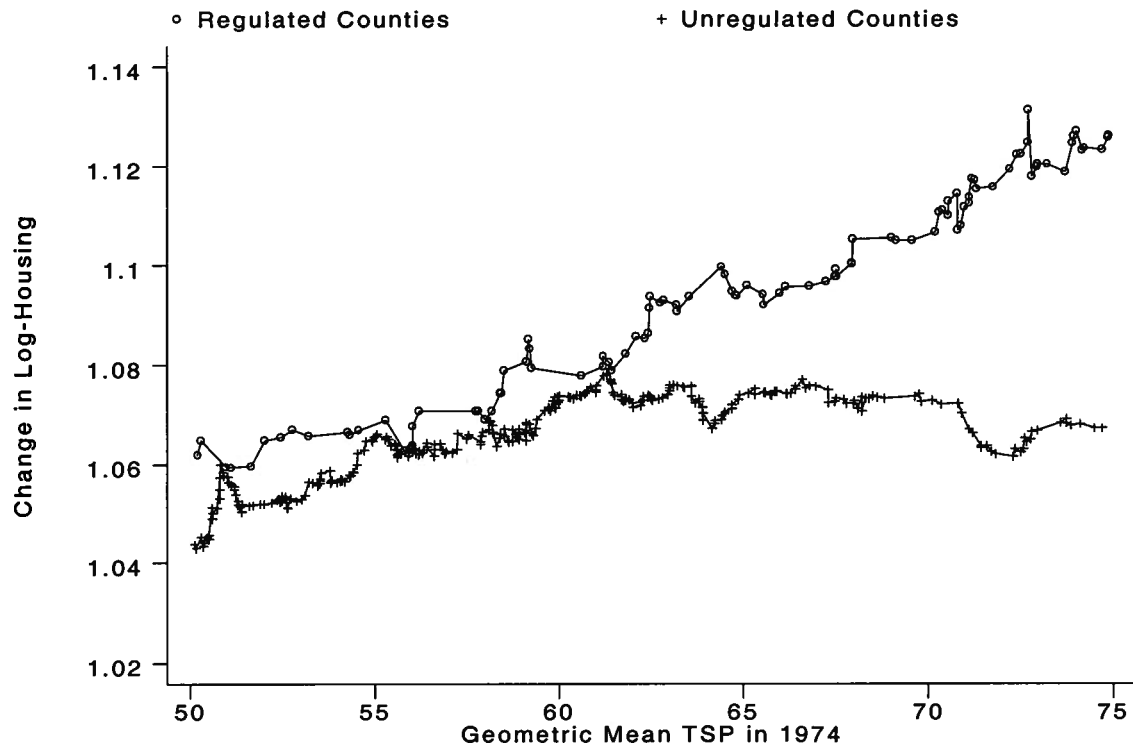


Figure 7: Nonparametric Relation between Changes in Housing Prices and Mean TSPs Conditional on the Geometric Mean of TSPs in 1974

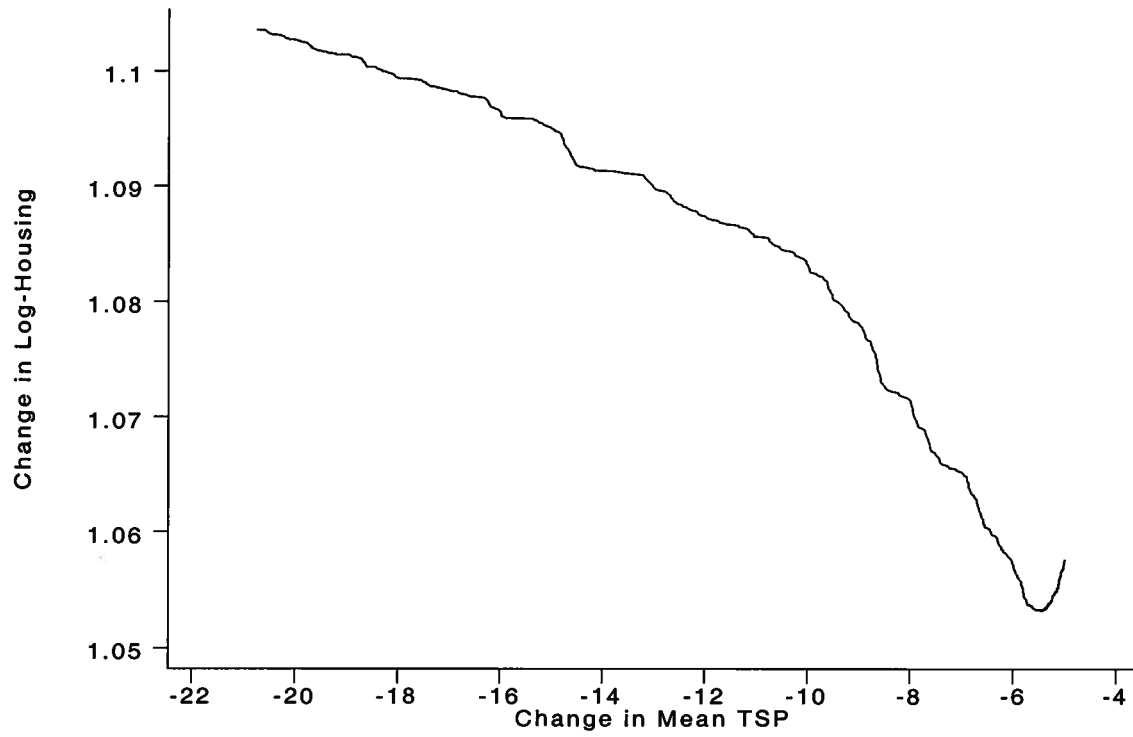
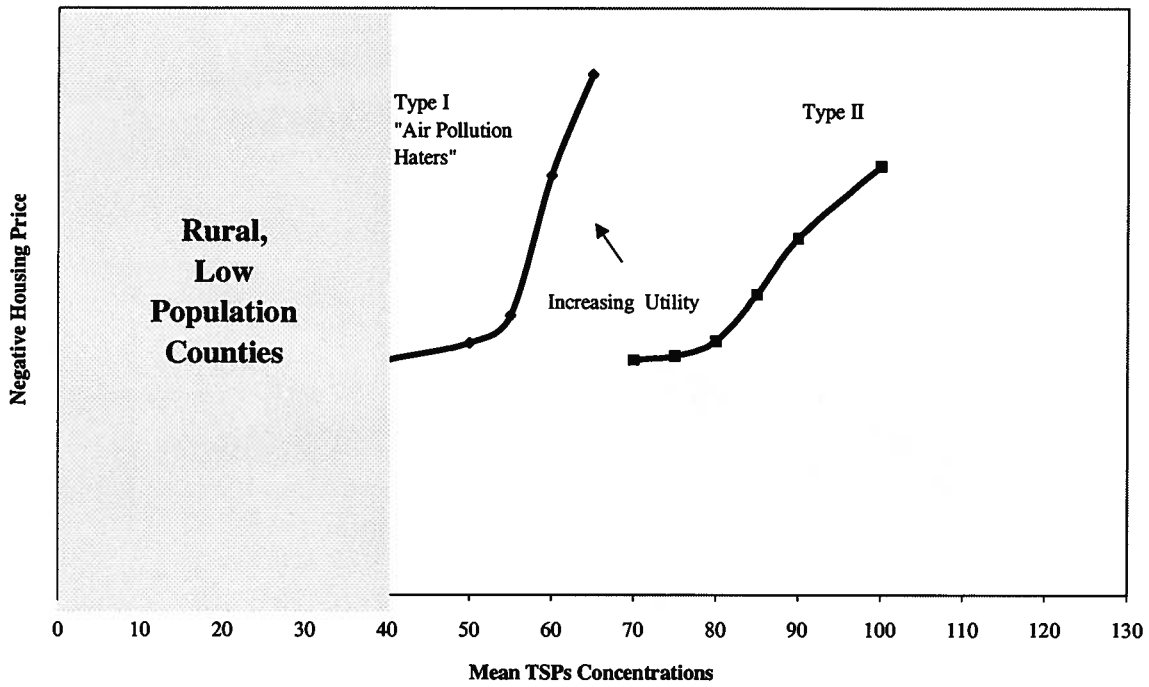
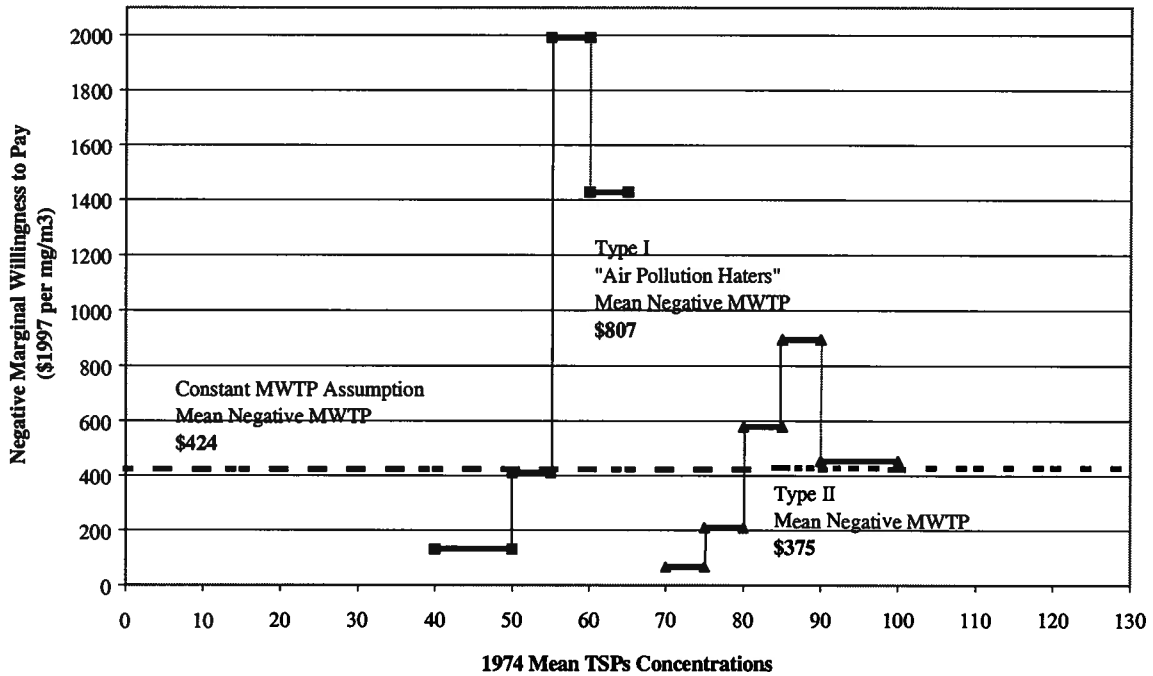


Figure 8: Willingness-To-Pay Functions under the Assumption of 2-Types of Consumers

A. Indifference/Bid Curves for Two Types



B. Negative Marginal Willingness to Pay for TSPs



Notes: See text for a description of the data underlying these figures.

**Appendix Figure: Relation between Changes in Housing Prices and Mean TSPs
Conditional on the Geometric Mean of TSPs in 1974**

