SMELLY LOCAL POLLUTERS AND RESIDENTIAL PROPERTY VALUES: A HEDONIC ANALYSIS OF FOUR ORANGE COUNTY (CALIFORNIA) CITIES

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Resumen: Proponemos un enfoque que combina el uso de sistemas de información geográficos (GIS) y el método de regresión hedónica para evaluar el impacto de los malos olores producidos por la industria local en el precio de viviendas en cuatro ciudades del sur de California. Al utilizar GIS se identificaron las viviendas localizadas a diferentes distancias de talleres automotrices y plantas contaminantes. Resultados estadísticamente significativos indican que los precios de las casas se reducen hasta en un 3.4% debido a la contaminación del aire. Este resultado tiene importantes implicaciones para el diseño de políticas de control de emisiones industriales.

Abstract: We propose a simple framework combining GIS and hedonic pricing to evaluate the impacts of local industrial odors on surrounding residential houses for four Southern California cities. Using GIS, we flag houses located at various distances from car paint-shops and smelly polluters in the EPA's NET database. After accounting for heteroskedasticity through feasible GLS, we find a statistically significant reduction in house prices of up to 3.4%. These results have implications for the local control of industrial odors.

Clasificación JEL: C31, Q25, R52

Palabras clave: hedonic price model, air pollution, industrial odors

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1. Introduction

Many studies have been devoted to estimating the cost of various air pollutants, with mixed results (e.g., see Smith and Huang 1993, 1995, or Boyle and Kiel 2001). Anybody who has lived downwind from a paper mill, a trash dump, or a chemical plant, however, can attest to the nuisance of unpleasant odors. Industrial odors are not just an annoyance; they can also impact health, generating symptoms such as headaches, nausea, and shortness of breath (Shusterman, 1999). We thus expect, as predicted by economic theory, that unpleasant smells will decrease local property values. Unfortunately, odors are typically difficult to quantify and emissions data are often unavailable.

This paper contributes to the hedonic pricing literature by analyzing the micro level impacts of local smelly pollutant emissions on the price of single-family homes in four cities located in Orange County, California, based on a simple approach that circumvents the lack of emissions data. We rely instead on Geographic Information System (GIS) software to incorporate spatial information into a simple hedonic pricing model and assess the impact of polluters housing prices, using their proximity to various polluters, especially car paint and body shops. Our statistically significant results indicate that the presence of smelly pollutants decreases property values by up to 3.4% depending on distance and on model specification. Although this may also reflect the presence of other externalities such as noise or congestion, our results likely underestimate the true social costs from smelly pollutants because our approach imperfectly captures resulting health costs. Nevertheless, an approximate quantification of the losses related to bad smells provides local municipalities with a starting point for tackling this problem.

The point of departure of this study is a series of complaints by residents of the West Side neighborhood in Costa Mesa (California) concerning organic odors emanating from several businesses, including oil firms, boat building and repair, manufacturers, auto paint shops, and metal finishing companies. Several field trips confirmed the presence of strong, unpleasant odors caused partly by styrene, and more generally by organic volatile compounds (VOCs). Health consequences of these pollutants could be significant. For VOCs, they include eye, nose, and throat irritation, headache, drowsiness, mental fatigue, respiratory distress, and impaired neurobehavioral function (Koren, Graham, and Devlin, 1992).

Possible health consequences and drops in property values worry local residents and property owners (many residents are renters), but the impact of odors needs to be quantified in order for the City Council to take action. A similar situation exists in neighboring cities, and it is probably not uncommon in areas with mixed zoning.

A number of papers in the now voluminous empirical hedonic pricing literature deal with smelly pollutants (mostly sulfur dioxide), but most studies rely on census tract averages or interpolations between pollution measuring stations (see Boyle and Kiel, 2001). One way to circumvent the difficulty of measuring odors is to use distance as a proxy. This approach was adopted, for example, by Nelson, Genereux, and Genereux (1992) or Reichert, Small, and Mohanty (1992) for landfills; by Flower and Ragas (1994) for oil refineries; by Kiel (1995) for smelly superfund sites; and by Batalhone, Nogueira, and Mueller (2002), who investigate how the rental price of apartments in Brasilia is affected by smells from a nearby sewage treatment plant. Measures of proximity have also been used to investigate property value losses from agricultural smells. Palmquist, Roka, and Vukina (1997) estimate the impact of large-scale hog-operations on surrounding rural houses in North Carolina. Le Goffe (2000) relies instead on the presence of specific activities to quantify some external effects of agriculture and sylviculture (e.g., noxious odors from cows, pigs, or poultry) on the renting price of rural self-catering cottages in Western France. However, little seems to have been done so far for urban industrial polluters at the micro level, which is the focus of our study.

This paper is organized as follows. In the next section, we outline our methodology. Section 3 provides information about our data. In section 4, we present our models and some of the econometric difficulties encountered. Section 5 discusses our results. Finally, section 6 summarizes our conclusions and makes suggestions for future work.

2. Methodology

The application of the hedonic method (Rosen, 1974) to the housing market for measuring environmental impacts is well established (e.g., see Palmquist, 1999 or Freeman, 1993, chapter 11). It is popular because the housing market is one of the few places where environmental quality is traded. The hedonic pricing approach posits that the price of a differentiated product can be explained by its characteristics. For a house, relevant characteristics include structural features (such as number of rooms, bathrooms, square footage), neighborhood characteristics (crime, distance to supermarkets, etc), location (e.g., distance to the ocean), and environmental quality. By explaining the sale price of a house by its characteristics, a hedonic regression can reveal whether or not an environmental characteristic has a significant impact on housing values and how much residents value a marginal change in environmental quality.

However, implementing the hedonic pricing approach is not without difficulties. First, hedonic-price theory does not provide a comprehensive list of explanatory variables. Selection of these variables is guided by experience but also by data availability.

Second, the functional relationship between the price of a house and its attributes is not known a priori. As pointed out by Rosen (1974), a nonlinear specification is usually preferred because consumers can rarely arbitrage by choosing bundles of housing attributes. Different functional forms are thus typically investigated. Using simulation, Cropper, Deck, and McConnell (1988) find that simpler models (such as semilog, log-log, or even linear) outperform more complex ones (such as quadratic) when some relevant explanatory variables are omitted or represented by proxies, as is often the case in practice.

Third, in order to interpret the marginal implicit price as an estimate of the marginal willingness to pay for a characteristic, each household must be in equilibrium and the housing market must offer a full spectrum of housing characteristics. This assumption may be contested for the housing market in the four communities considered in our study, given the strong demand for housing in southern California during the last few years. However, Maclennan (1977) argues that equilibrium may be satisfactorily assumed if the housing market does not undergo severe shocks and if the period of study is reasonable short. In addition, Meese and Wallace (1997) find that the speed of adjustment to a shock may be quite fast in some markets, in which case the equilibrium assumption is reasonable.

Finally, the hedonic pricing method assumes that buyers and sellers have access to the same information; otherwise the implicit price of an environmental characteristic may be biased. We also suppose that this assumption is reasonable verified, although many families who rent houses located in areas affected by smelly pollutants are immigrants with limited English proficiency and only a basic education. However, they are unlikely to buy houses in these areas and most of the property owners appear to be absentee landlords.

Measuring and modeling the diffusion of odors are challenging and costly tasks, so many studies rely instead on distance to a polluter (see above). To compensate for a lack of emissions data for part of the polluters (see below) we adopt a simple approach to investigate statistically the following questions: Are house prices negatively affected by the proximity of smelly polluters? How do these impacts decrease with distance? Can we obtain a preliminary quantification of these impacts?

Our simple approach allows us to answer these questions by implementing the first stage of the hedonic pricing approach. Moreover, if we can argue that local odors do not fundamentally affect the equilibrium of the housing markets, then this approach gives us an estimate of the marginal price of local odors pollution. However, our approach does not enable us to perform the second stage of the approach (estimating the marginal willingness to pay) because it requires a continuous relationship between the level of pollution and house values. Unfortunately, there are no available data on pollutant emission in the cities we studied. Much more extensive data, including detailed emissions data combined with a spatial dispersion model or actual measurement of odors would be necessary to reliably estimate such a relationship.

3. Data

The study area includes four cities located in Orange County, California: Costa Mesa, Newport Beach, Huntington Beach, and Seal Beach. We manage our data using the GIS package ArcView. Our explanatory variables can be grouped in three categories: physical characteristics of houses, neighborhood variables, and data on polluters.

3.1. *Physical characteristics of house*

For information about physical characteristics of houses, we rely on a dataset of single-family home sales between 1997 and the first quarter of 2000 for the four cities considered. This dataset is a subset of the database used by Boarnet and Chalermpong (2001), who analyze the link between urban highways and urban development. Available information includes sale price; age (number of years since the house was built); lot size; as well as number of bedrooms and bathrooms.[1] Home sale prices were deflated to constant dollars using the Bureau

[1] The availability of sales prices for individual houses allows us to avoid measurement error problems resulting from using owner evaluations or aggregated prices.

of Labor Statistics housing price index for the Los Angeles-Riverside-Orange County metropolitan statistical area.

3.2. *Neighborhood variables*

We employ five neighborhood characteristics: straight distance to the ocean; straight-line distance to the nearest supermarket; total number of violent and property crimes per 1,000 residents; a weighted Academic Performance Index (API) for elementary, middle, and high schools; and 3 dummy variables for capturing other, city specific attributes.[2] Straight-line distances were calculated using ArcView. The crime information comes from the California Department of Justice's Statistics Center and the California Department of Finance Demographic Research Unit Reports. We collected information about supermarkets in our four cities from the Yellow Pages, entered their location in a GIS map of our study area containing the location of houses sold, and calculated the straight distance between each house and the nearest store.

To capture school quality, we create a compound API index. Many hedonic studies rely only on SAT scores for high schools. We expect, however, that the quality of other types of schools is important. In order to calculate our API index, we first geocode boundaries of school attendance areas for elementary, middle and high schools. We then assign an API score per school type to each houses based on its location within each attendance areas. The third stage is to calculate an average of 1999 API scores weighted by the proportion by city of students attending each school type.

We also include dummy variables for three of the four cities considered (Newport Beach, Huntington Beach, and Seal Beach) to reflect specificities not captured by our other explanatory variables. This includes, for example, different local taxes, better services (libraries), or simply the prestige of living in a specific city (this could be the case for Newport Beach where a number of well-known artists, sport stars or other celebrities reside).

Finally, we include dummy variables for 1997, 1998, and 1999 to account for possible yearly price effects in our sample data, which covers 1997 to the first quarter of 2000.

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[2] The API is a key measure of the Public Schools Accountability Act (PSAA-Senate Bill 1X), a California bill signed into law in April 1999. The API tracks the academic performance and progress of schools. It is a numeric index that ranges from a low of 200 to a high of 1000. For more information, see www.cde.ca.gov/-news/releases2002/rel03.asp

3.3. *Polluters' data*

Our polluters' data come from the 1999 Industrial Air Releases by company in Orange County, from EPA's National Emission Trends (NET) database for 1999.[3] We find 81 different polluters who emitted either volatile organic compounds (VOCs) or sulfur dioxide (SO2), but we are able to geocode the addresses of only 76 of them on our GIS map. Based on the standard industrial classification (SIC), this group of polluters is fairly diverse: it includes 8 companies in the crude petroleum and natural gas business (oil extraction takes place in Huntington Beach and Seal Beach), 7 firms in automobile body repair/painting and 2 car dealers, 6 companies dealing with refuse or waste management, 4 firms involved with plastic products, and 3 with boat building and repairing. Other firms are in commercial printing, metal coating or finishing, valve and pipe-fittings, printed circuit boards, but also defense and government.

This list does not seem, however, to capture all of the emitters of foul smells. A review of the complaints received by the city of Costa Mesa shows that, in addition to oil businesses, metal product manufacturers, and boat building and repairing firms, car paint and body shops which are not present in the EPA's NET database also contribute significantly to odors pollution.[4] From the list of odor complaints for Costa Mesa, no other type of odor-generating business appears to be underrepresented on the EPA's NET list. We thus complement our list of polluters with addresses from automobile paint and body shops from the March 2002 edition of the Yellow Pages. For the four cities in our study area, we geocode the addresses of 106 automobile paint and body shops.

Painting automobiles is one of the most hazardous activities with respect to air pollution. On average, it takes 7940 liters of water and 23.3 liters of chemicals to paint one car (Mason, Dauksys, and Cullum,

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[3] Data are available from http://www.epa.gov/air/data/index.html. Date accessed: 1/30/2002

[4] The list of complaints should be interpreted with caution, however, because several complaints may be due to an isolated individual. In addition, a number of complains also deal with coffee roasting, which is typically not thought to be offensive. These complaints may have arisen because the emissions of the scorched mould-releasing agent of a local business sometimes smell like burnt coffee; there is, however, a coffee roaster in the area also, who may have burnt a batch of beans. However, several field trips to the West side of Costa Mesa, where a number of smelly polluters are located and where many complaints emanate from, revealed a distinctive and sometimes strong smell laced with VOCs.

1990). Many chemicals are used to paint automobiles. However, the primary air pollutants emitted during this process are volatile organic compounds (VOCs) (Kim, Adams, and Klaver, 2000). The Westside of Costa Mesa houses 56 car paint and body shops (Yellow pages, 2002). By comparison, only eight auto paint establishments are listed for Newport Beach.

Health impacts of these smelly pollutants could be quite significant. For example, general symptoms of exposure to VOCs include eye, nose, and throat irritation, headache, drowsiness, mental fatigue, respiratory distress, and impaired neurobehavioral function (Koren, Graham, and Devlin, 1992). Depending on the compound, consequences of exposure can be severe. For methanol, a common industrial solvent, acute exposure can cause visual disturbances such as blurred or dimmed vision; it can also lead to blindness, and neurological damage, including permanent motor dysfunction. Chronic exposure may lead to conjunctivitis, headache, giddiness, insomnia, gastric and visual disturbances, and blindness (EPA, 2001).

In addition, boating businesses, plastic manufacturers, as well as electronics or packaging firms release styrene into the air (EPA, 2001). Styrene is employed primarily in the production of polystyrene and resins. In liquid form, it is colorless and it has a sweet smell. Short-term exposure could lead to mucous membrane and eye irritation, but also to gastrointestinal problems. Chronic exposure can impact the central nervous system, creating headache, fatigue, weakness, and depression. Other effects include peripheral neuropathy, kidney dysfunction and disruption of hemoglobin formation. It could also be a human carcinogen (EPA, 2001).

Therefore, we added automobile paint and body shops to our list of polluters. While this addition was necessary to complement our database of polluters, it restricts our modeling methodology because no emissions data are available for these businesses. Therefore, we can only crudely estimate how far smelly pollutants impact property values.

4. Models

4.1. *Testing for the extent of the presence of polluters*

In order to estimate statistically if smelly pollutants have an impact on neighboring property values, in our GIS maps we draw around each house concentric circles of radius 1/4 mile, 1/2 mile, and 3/4 mile. We then define dummy variables that tell us whether any given house is located within 1/4 mile, 1/2 mile or 3/4 mile of any polluter. With this information, it is then easy to define other dummy variables, such as the one flagging polluters located between 1/4 mile and 1/2 mile from any given house. This simple approach enables us to roughly test how far the impacts of polluters can be detected on property values. These impacts include smells but also possibly noise, congestion, or visual impairment, which are often jointly present.

4.2. *Functional forms*

The choice of a functional form for the relationship between house prices and various characteristics is always a question facing the empirical researcher conducting hedonic studies. Following a practice common in the empirical literature (e.g., see Palmquist, Roka, and Vukina, 1997), we estimate different popular functional forms and select the model that best fits our data based on the highest value of $\bar{R}^2$. After trying linear, log-linear, and linear-log functional forms, we find that log-linear models best fits our data; we thus report results only for this form.

We consider two types of models. Model 1 investigates the quantitative impacts of smelly polluters. It can be written:

$$\begin{aligned}\ln(PRICE_i) &= \beta_0 + \beta_1 AGE_i + \beta_2 LOT_i + \beta_3 BED_i \qquad (1)\\ &+\beta_4 BATH_i + \beta_5 OCEAN_i + \beta_6 MARKET_i + \beta_7 CRIME_i\\ &+\beta_8 API_i + \beta_9 HUNT_i + \beta_{10} NEWP_i + \beta_{11} SEAL_i\\ &+\beta_{12} Y97_i + \beta_{13} Y98_i + \beta_{14} Y99_i + \beta_{15} C1_i + \beta_{16} C2_i + \varepsilon_i\end{aligned}$$

where our variables are defined in table 1; $\beta_0, ..., \beta_{16}$ are unknown coefficients we want to estimate; ε_i is an error term; and i is an index designating the observation number. We first fit model (1) using ordinary least squares (OLS). A battery of diagnostic tests does not suggest any multicollinearity problem nor does it detect influential observations. However, it reveals the presence of heteroskedasticity. To obtain more formal evidence, we perform the 1982 Koenker-Basset test; it confirms the presence of heteroskedasticity with a p-value less than 1%. Since the form of the heteroskedasticity is *a priori* unknown in this context, we rely on the feasible generalized least squares approach (FGLS), which is particularly flexible (Wooldridge, 2000). It assumes that the error term can be explained by

$$\ln(\varepsilon_i^2) = \alpha_0 + \delta_1 AGE_i + \delta_2 LOT_i + ... + \delta_{16} C2_i + e_i, \qquad (2)$$

where the error e_i has a zero mean and is independent of the explanatory variables in (2); $AGE_i, ..., C2_i$ are the independent variables that appear in (1); and $\delta_0, ..., \delta_{16}$ are unknown coefficients we estimate by ordinary least squares (OLS) after replacing ε_i by its estimate $\hat{\varepsilon}_i$. Once the fitted values $\hat{g}_i \equiv \hat{\ln}(\varepsilon_i^2)$ for (2) are known, we estimate (1) with weighted least squares (WLS) and weights $w_i = \exp(-\hat{g}_i)$.

Model 2 investigates whether the impact of car paint shops and other polluters reach equally far. While all polluters are pooled for their impact on the first quarter of mile, we distinguish between car paint shops and other polluters for houses located between 1/4 mile and 1/2 mile from polluters. Other variables are similar so model 2 can be written:

$$\ln(PRICE_i) = \beta_0 + \beta_1 AGE_i + \beta_2 LOT_i + \beta_3 BED_i \qquad (3)$$

$$+\beta_4 BATH_i + \beta_5 OCEAN_i + \beta_6 MARKET_i + \beta_7 CRIME_i$$

$$+\beta_8 API_i + \beta_9 HUNT_i + \beta_{10} NEWP_i + \beta_{11} SEAL_i + \beta_{12} Y97_i$$

$$+\beta_{13} Y98_i + \beta_{14} Y99_i + \beta_{15} C1_i + \beta_{16} C2c_i + \beta_{17} C2o_i + \beta_{18} C2b_i + \varepsilon_i$$

We proceed as for model 1. An analysis of OLS residuals also reveals the presence of heteroscedasticity, which is confirmed by the 1982 Koenker-Basset test. We thus resort again to the FGLS approach described above.

Estimations are performed using SPSS on a PC. Results for model 1 and model 2 are respectively summarized in tables 2 and 3. They are discussed below.

5. Results

First, we see that our models explain approximately 68% of the variations in the logarithm of house prices. From tables 2 and 3, almost all the coefficients of variables describing the physical characteristics of houses have the expected sign and are statistically significant at 1%.

The exception is "number of bedrooms", which is negative and has a p-value of 0.06 for model 1 and of 0.13 for model 2. The negative sign for this coefficient makes sense for people who value space: since the area of the house is held constant, increasing the number of bedrooms shrinks the size of all other rooms. According to Boarnet and Chalermpong (2001), whose study area encompasses ours, the positive sign for the coefficient of "age" (statistically significant at 1%) may reflect improvements such as landscaping that were not present when the house was last on the market. Appreciation with age is often symptomatic of the presence of relatively new houses, although the mean house age in our sample is just above 34 years.

Likewise, the coefficients for all neighborhood characteristics have the expected sign and are statistically significant (negative for "distance to the coast" and "crime index", and positive for "API index"). The exception is "distance to the nearest supermarket", which is not significant. This can be explained by the presence of many supermarkets in our study area and the excessive crudeness of measuring proximity with a straight-line distance.

In addition, since housing prices have been increasing steadily since 1997, we expected the statistically significant negative coefficients for the dummy variables tracking the year in which sales took place, relative to 2000 (note that for 2000, our database includes sales for only the first 3 months). We also notice the very large positive premium for houses in Newport Beach (+45%), which may reflect the glamour attached to living there and the presence of Newport Bay, a natural reserve. Other things being equal, houses in Huntington Beach are on average 8% cheaper than in Costa Mesa (possibly because of the industrial nature of this city) while houses in Seal Beach are between 7% and 8% more expensive.

Environmental variables, which are the focus of this study, are statistically significant at 1% and have the expected sign (negative) for both models. When polluters are pooled together (i.e., car paint shops are included with polluters in NET), we find that the presence of a polluter within 1/4 mile of a house decreases its value by approximately 2.5% while polluters between 1/4 mile and 1/2 mile have a smaller impact (-2.0%). We also investigate the impact of polluters located between 1/2 and 1/4 miles of houses but find a statistically non-significant (at 10%) coefficient; the inclusion of this extra variable had only a very small impact on the other estimated coefficients of our model (these results are not presented herein). A look at the location of polluters (see figure 1) provides a possible explanation for the slow initial decrease in the impact of polluters with distance: we see that polluters tend to be clustered in a few corridors (especially one in Costa Mesa and another one in Huntington Beach) so emissions of pollutants tend to be concentrated in these areas and their immediate vicinities. As we move away from these clusters, the impact of these emissions tends to dissipate fairly quickly.

In model 2, we try to disentangle the respective impact of car paint shops and NET polluters beyond 1/4 mile. The coefficients of our environmental dummy variables still have the expected sign and they are statistically significant at either 1% or 2%. For polluters located within 1/4 mile of a house, we find a decrease in house value of approximately 2.9%, which is slightly higher than for model 1. This effect decreases slightly for car paint shops that are between 1/4 mile and 1/2 mile from a house (to ∼ -2.8%). Surprisingly, however, NET polluters do not appear to have any impact on properties located farther than 1/4 mile. This may result from the great variations in their level of emissions, whereas emissions from car paint shops are probably more homogeneous. The fourth environmental variable in model 2 tries to capture the combined effect of NET polluters and car paint shops: it equals 1 for houses located between 1/4 mile and 1/2 mile from at least one NET polluter and one car paint shop. Its coefficient is again negative and highly significant. We can explain its fairly large magnitude (∼ 3.4%) by the clustering of polluters, which increases the intensity of bad smells, although as mentioned above, other forms of pollution may also be present (such as noise, traffic congestion, etc.).

Our estimated housing price decreases resulting from smelly urban polluters are in fact smaller than some of the findings reported in the literature. For example, Nelson, Genereux, and Genereux (1992) find that a house located on the boundary of a landfill could see its value reduced by approximately 12%; this falls to 6% for houses approximately a mile away. Reichert, Small, and Mohanty (1992) report a 6% drop in value for houses sold one or more years after the opening of one of the landfills they study. For odors originating from large-scale hog-operations, Palmquist, Roka, and Vukina (1997) find decreases in value of up to 9% for the closest and most affected houses. Such large decreases may come from the social stigma of living too close to a landfill or simply from the unbearable smell of pig manure.

6. Concluding Remarks

Even without emissions data, we find that local smelly pollutants cause a statistically significant decrease in the value of neighboring house of up to 3.4%. This impact is larger in areas with a high concentration of polluters, and it appears quite strong for car paint shops. It may be argued that only part of this effect should be attributed to smelly pollutants because the polluters considered may also generate noise and worsen traffic congestion: more traffic may be expected and less parking may be available in the vicinity of car paint shops, for example. However, our results are also likely to undervalue the true costs of smelly pollutants because the exposed population may not have full information about the potentially serious health risks of these pollutants. Indeed, in our study, a large part of the affected population consists of recent immigrants, chiefly from Mexico, who are not very fluent in English and have limited schooling.

These results have implications for public policy at the local level. In order to protect public health and to restore property values, cities might consider ordinances restricting or banning the emission of local, smelly pollutants (none of the four cities in our study area does at the moment). If applied too brutally, such measures could, however, also have a number of adverse effects. First, they could erode a city's tax base if they drive away too many businesses. Second, they could adversely affect the renters currently living in the polluted areas. While their health would most likely improve, a cleaner environment might encourage zoning changes and significant rent hikes that may price current renters out of the housing market at a time when affordable housing is very scarce in Orange County.

An alternative or complementary solution could be for municipalities to provide subsidies to small businesses for purchasing pollution control equipment. Ideally, this measure could be partly self-financing, as a cleaner environment would result in slightly higher property values, and thus increased property tax revenues. In addition, municipalities may be able to negotiate moderate rent increases. Unfortunately, this approach appears difficult to implement in California since Proposition 13 has capped increases in property taxes and municipalities are currently facing very tight budget constraints.[5]

[5] Proposition 13 was passed on June 6th, 1978, by nearly two-thirds of California's voters. It reduced property taxes by about 57%, limited the assessment rate to 1% for all California property and capped annual tax increases to no more than 2%. When property is sold it is then reassessed at market value. Prior to Proposition 13, the average property tax rate in California was 3% of assessed value and there was no limit on annual increases. Proposition 13 made headlines around the country (http://www.hjta.org/prop13.htm

For future work, it would be useful to collect actual pollutant emission, especially from car paint shops, in order to model the dispersion of smelly pollutants. In addition, a health survey of people residing in the areas affected by smelly pollutants could be conducted in order to assess the health risks they are facing.

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Table 1

Variables of the Hedonic Models and Descriptive Statistics

Variable	*Description*	*Units*	*Min.*	*Max.*	*Mean*	*Std. Dev.*
PRICE	Sale price of a house	$	51,000	11,000,000	394,320	342,545
AGE	Number of years since the house was built	#	0	94	34.35	11.28
LOT	Lot size	Feet^2	104	823,588	6,818.5	14,970
BED	Number of bedrooms	#	1	9	3.30	0.84
BATH	Number of bathrooms	#	1	10	2.16	0.68
OCEAN	Distance to the ocean	Feet	37	28523	9885	6740
MARKET	Distance to the nearest supermarket	Feet	42	10664	3376	1717
CRIME	Crime index	/1000 inhab.	63	196	131.5	25.94
API	Weighted 1999 API score	#	510	867	742.8	69.69
HUNT	Huntington Beach	0/1	0	1	.51	.500
NEWP	Newport Beach	0/1	0	1	.24	.427
SEAL	Seal Beach	0/1	0	1	.03	.169
Y97	Sale in 1997	0/1	0	1	.29	.453
Y98	Sale in 1998	0/1	0	1	.33	.470

Table 1
(continued)

Variable	*Description*	*Units*	*Min.*	*Max.*	*Mean*	*Std. Dev.*
Y99	Sale in 1999	0/1	0	1	.33	.469
C1	House $\leq 1/4$ mi of a polluter	0/1	0	1	.11	.311
C2	House $\in (1/4,\ 1/2)$ mi of a polluter	0/1	0	1	.29	.432
C2c	House $\in (1/4,\ 1/2)$ mi of a cps but no other polluter	0/1	0	1	.08	.273
C2o	House $\in (1/4,\ 1/2)$ mi of a polluter but not a cps	0/1	0	1	.03	.162
C2b	House $\in (1/4,\ 1/2)$ mi of ≥ 1 cps and ≥ 1 other polluter	0/1	0	1	.08	.275

Notes: cps = Car paint shop. Our sample is of size 7726.

Table 2

FGLS Coefficients for Model 1

	Coefficients	*Standard Error*	*p-value*
Constant	11.563	.080	.000
Age (sale year-year built)	6.135E-03	.000	.000
House square footage	3.795E-04	.000	.000
Number of bedrooms	-9.094E-03	.005	.058
Number of bathrooms	5.205E-02	.008	.000
Lot square footage	1.090E-06	.000	.000
Straight line distance to the ocean	-1.613E-05	.000	.000
Crime index	-1.259E-03	.000	.000
Dummy variable for 1997	-.221	.015	.000
Dummy variable for 1998	-.145	.015	.000
Dummy variable for 1999	-4.559E-02	.015	.002
API compound index	7.767E-04	.000	.000
Straight line distance to nearest supermarket	3.988E-07	.000	.840
Dummy for 1/4 mile distance from all polluters	-2.528E-02	.011	.016
Dummy for houses between 1/4 and 1/2 mile from all polluters	-2.019E-02	.007	.005

Table 2
(continued)

	Coefficients	*Standard Error*	*p-value*
Dummy for Huntington Beach	-8.477E-02	.010	.000
Dummy for Newport Beach	.372	.018	.000
Dummy for Seal Beach	6.838E-02	.020	.001
Adjusted R^2		0.677	

Table 3
FGLS Coefficients for Model 2

	Coefficients	*Standard Error*	*p-value*
Constant	11.571	.079	.000
Age (sale year-year built)	6.355E-03	.000	.000
House square footage	3.771E-04	.000	.000
Number of bedrooms	-7.280E-03	.005	.131
Number of bathrooms	5.976E-02	.008	.000
Lot square footage	1.236E-06	.000	.000
Straight line distance to the ocean	-1.615E-05	.000	.000

Table 3
(continued)

	Coefficients	*Standard Error*	*p-value*
Crime index	-1.284E-03	.000	.000
Dummy variable for 1997	-.224	.016	.000
Dummy variable for 1998	-.148	.015	.000
Dummy variable for 1999	-4.758E-02	.015	.001
API compound index	7.365E-04	.000	.000
Straight line distance to nearest supermarket	-2.516E-07	.000	.903
Less than or equal to 1/4 mile distance from any polluter	-2.879E-02	.012	.013
Between 1/4 and 1/2 mile from mp but not within 1/2 mile from cps	7.469E-03	.021	.721
Between 1/4 and 1/2 mile from cps but not within 1/2 mile from mp	-2.769E-02	.010	.004
Between 1/4 and 1/2 mile from at least one mp and one cps	-3.396E-02	.010	.001
Dummy for Huntington Beach	-8.246E-02	.010	.000
Dummy for Newport Beach	.375	.018	.000
Dummy for Seal Beach	7.495E-02	.020	.000

Table 3

(*continued*)

	Coefficients	*Standard Error*	*p-value*
Adjusted R^2		0.676	

Notes: The dependent variable is the logarithm of sale price for sale price $>$ 50,000.

Figure 1

Location of polluters and houses sold