MOBILITY AND ENVIRONMENTAL EQUITY: DO HOUSING CHOICES DETERMINE EXPOSURE TO AIR POLLUTION?

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Abstract

U.S. Census data show that approximately 40 million Americans move each year, raising questions about the role of mobility in determining observed environmental risk exposure patterns. The literature in this area continues to be contested, and the relationship between household sorting and exposure is still not well understood. We offer a new assessment of this question with respect to the criteria air pollutants (focusing on ozone and particulate matter) using a unique data set that combines information from repeat real estate transactions by the same San Francisco Bay area homebuyers. Our hedonic results suggest a trade-off does exist between housing services and pollution (i.e., households can get more housing services for the same price by moving to a neighborhood with more pollution). Our results show poor/minority households are more likely to make this trade-off and that wealth taken from appreciating housing stocks increases their ability to avoid the conventional sorting induced-exposure story.

Keywords: Mobility, air pollution, household sorting, environmental justice

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1. Introduction

A variety of studies suggest that minority and low-income households often live in areas with poor environmental quality. Annual data also show that 14 percent of the U.S. population, or 40 million people, move to a new residence in each year (U.S. Census Bureau, 2004). Together, these facts raise questions about the role that moving decisions play in determining environmental risk exposure patterns. This is in contrast to previous research, which has posited that this exposure has been the result of the siting decisions of polluting firms. The literature in this area continues to be contested, and the role of mobility in exposure patterns is still not well understood.

We offer a new assessment of this question with respect to the criteria air pollutants (focusing on ozone and particulate matter) using a data set that combines individual real estate transactions with buyer attribute information for San Francisco Bay area homebuyers. Since we can observe individual choices and homebuyer economic circumstances on multiple occasions, we can test selected environmental justice (EJ) hypotheses in a new and more direct way that avoids many of the modeling assumptions that are typically required without these data (i.e., locational equilibrium models). As a result, we build on existing analyses that draw conclusions about sorting-induced exposure.

Specifically, we used a repeat-sales regression analysis for houses that sold two or three times during the years 1990 to 2004 to recover a hedonic price function controlling for time invariant unobservables. We found evidence that more ozone and particle pollution standard exceedences reduce Bay Area housing prices. This finding suggests that optimizing home buyers may indeed face an important trade-off—more housing services at the expense of lower environmental quality. The poor may be more likely to make this trade-off, and minorities are more likely to be poor. This provides a compelling explanation for observed racial correlations with criteria pollutants.

Specifically, since changes in common air pollutants appear to be reflected in housing prices, we looked for *direct* evidence that poor/minority homeowners trade more pollution exposure for cheaper housing and/or other desirable neighborhood attributes when they move, whereas other homeowners do not. This is an important addition to the environmental justice literature, because previous analyses that have looked for verification of the sorting explanation for environmental injustice used indirect evidence (i.e., do the percentages of poor and minority residents rise when pollution increases?). There are potential alternative explanations for such a finding. For example, do individuals actually move nearer to the pollution not because of cheaper housing but because of proximate job opportunities? We cannot answer this question without seeing both the house the individual bought and the house they sold. With a unique data set, we are able to follow buyers as they move from their old house to their new house, observing directly the trade-offs they make between housing services, pollution, and other determinants of neighborhood quality.

One interesting avenue we explore is the role that changes in wealth (as opposed to income) play in housing decisions of poor and minorities. To date, existing environmental justice stories have emphasized only one aspect of the household's economic circumstances—annual household income. To enhance our understanding of the role of changing wealth in pollution exposure, we considered whether large and small gains (or losses) from the previous home sales influence the housing trade-offs people make. We were able to calculate this amount by observing not only what Bay Area homeowners sold their previous houses for, but also what they had originally paid for them. The difference between these values is the amount of capital gain that they take with them into the house purchase that we examined. Do poor/minorities use large gains from a housing sale to buy more housing services *and* cleaner air when deciding to move? Are homeowners who move from declining neighborhoods more constrained in the housing services/pollution trade-off? Are environmental justice benefits associated with improving minority homeowners' access to credit?

2. Related Literature

A large number of papers in the environmental justice literature examine environmental equity questions. They do so from three perspectives. The first group of studies documents the correlation between pollution and community characteristics (e.g., Freeman, 1972; Asch and Seneca, 1978; UCC, 1987; GAO, 1983; GAO, 1995; Brooks and Sethi, 1997; Bullard, 2000; Houston et al., 2004). Fisher, Kelly, and Romm (2006) and Pastor, Saad, and Morello-Frosch (2007) are notable recent examples of typical EJ analyses, and they also focus on a similar geographic area of interest—the San Francisco Bay Area. The authors of the latter study were motivated to perform the analysis after finding that no existing empirical studies had addressed the overall distribution of air pollution exposure in this region. Entitled "Still Toxic After All These Years: Air Quality and Environmental Justice in the San Francisco Bay Area," the report uses a single-year cross-sectional design, a common method that is used to support claims of environmental injustice.

The authors leverage two data sets to compute census tract–level measures of hazardous air pollutant exposure and compare these to contemporaneous socioeconomic characteristics of the tracts. The first data set (EPA's Toxic Release Inventory [TRI]) is commonly used in the environmental justice literature and includes the location and emissions information on large industrial facilities. Using this data set, the authors specify a binary logit model where the dependent variable describes a census tract's proximity to a TRI facility (= 1 if less than 1 mile, 0 if greater than 1 mile). After controlling for selected factors (race, population density, and share of manufacturing employment), their analysis finds that census tracts with lower per capita incomes and home ownership rates were more likely to be in close proximity (i.e., within 1 mile) to stationary TRI facilities with air releases. Although the income and homeownership coefficients have intuitive (negative) signs, their magnitudes and standard errors are not reported; therefore, it is not possible to assess whether the coefficients are large or small. However, the authors are able to reject the hypothesis that these coefficients were zero at the 5 percent level. In addition to examining the influence of economic resources and proximity to toxic releases, the authors also found that black and Hispanic populations were more likely to live within a mile of a TRI facility with air releases after controlling for income and other tract-level characteristics.

The second data set used in the report (1999 National Air Toxics Assessment [NATA]) is unique because it considers mobile source emissions as well as large industrial facilities covered by TRI. In addition, procedures can be applied to the NATA data to describe a census tract's potential cancer and respiratory hazards. Regressing these tract level estimates of cancer and respiratory risk on income and share of homeownership shows that after controlling for race, population density, and percentage of industrial/ commercial/transportation land use, census tracts with lower incomes and home ownership rates appear to be at a higher risk for cancer and other respiratory hazards.

The results in Pastor, Saad, and Morello-Frosch (2007) correspond to six Bay area county visual patterns of the correlations between minority status (Figures 1 and 2) and high levels of criteria pollutants. As shown in Figures 3 and 4, we mapped air pollution exceedances (ozone and PM_{10}) reported by air quality monitors along with census-tract minority population share.

The second group of papers in the EJ literature investigated the siting decisions of polluting firms. For example, Hamilton (1995) used contemporaneous community attributes to explain the planning decisions of commercial hazardous waste facilities. He tested three theories: (i) pure discrimination, (ii) Coasian bargaining (i.e., that plants are sited in places where the potential costs of compensating affected residents are low because their demand for environmental quality is weak), and (iii) collective action/political economy (i.e., that firms site plants in communities that are less likely to organize to collect compensation). Hamilton found that commercial hazardous waste facilities did avoid sites where potential compensation costs were high and areas more likely to mobilize against plans for expansion. Arora and Cason (1999) compare 1993 TRI data to 1990 neighborhood attributes in an attempt to limit reverse causality in correlation (i.e., 1990 neighborhood attributes could not be caused by 1993 TRI emissions). They performed tests similar to Hamilton's and found that race, income levels, and unemployment influence release patterns from TRI facilities. Community mobilization variables also influenced the level of TRI releases. Although these papers offer interesting hypothesis and empirical tests, siting explanations for exposure inequities are less relevant for criteria pollutants because mobile sources, rather than specific sites (e.g., TRI plants), are a substantial contributor to these air quality problems.

Figure 1. Share of Non-Hispanic Blacks by Census Tract: 2000

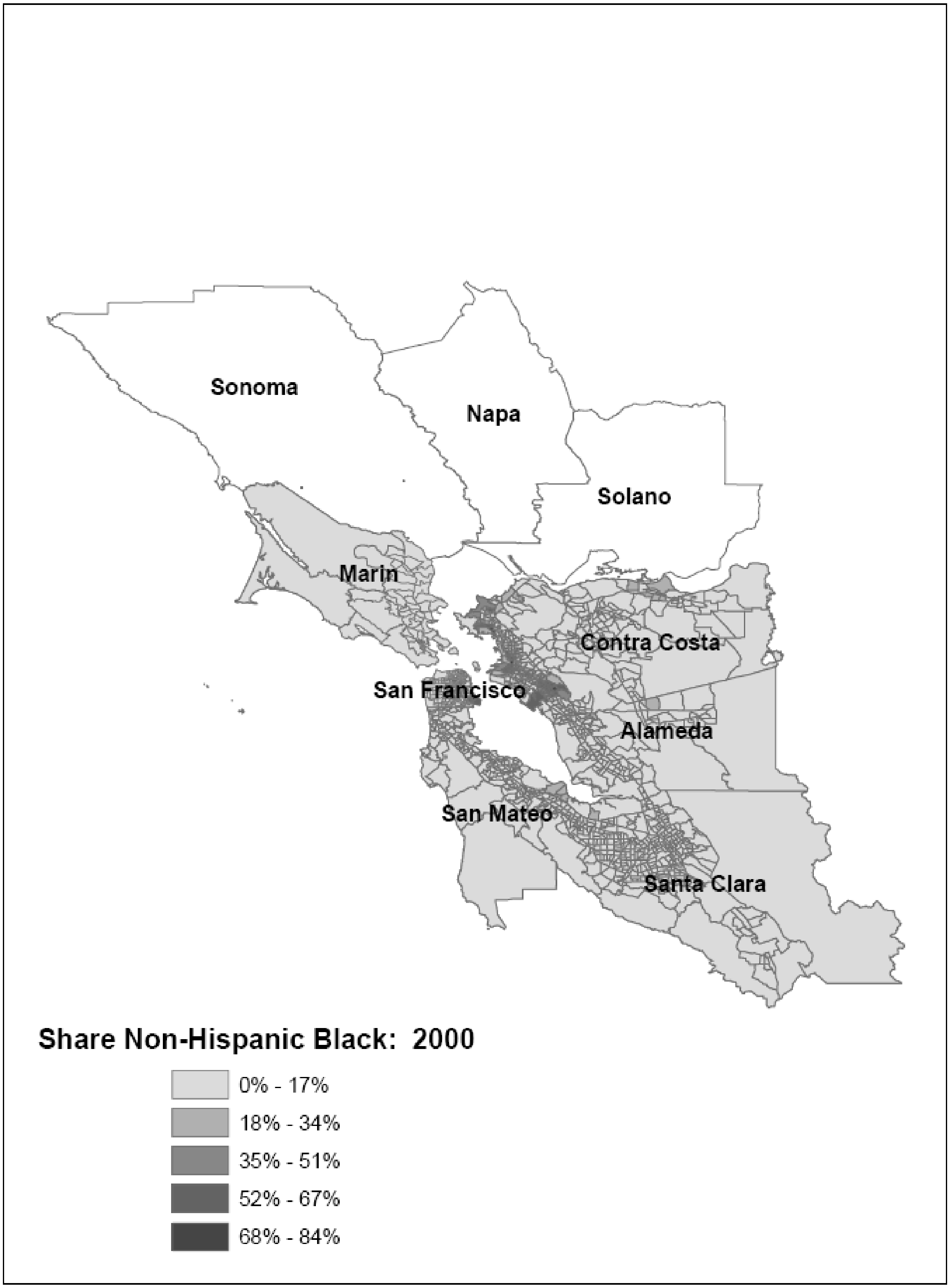


Figure 2. Share of Hispanics by Census Tract: 2000

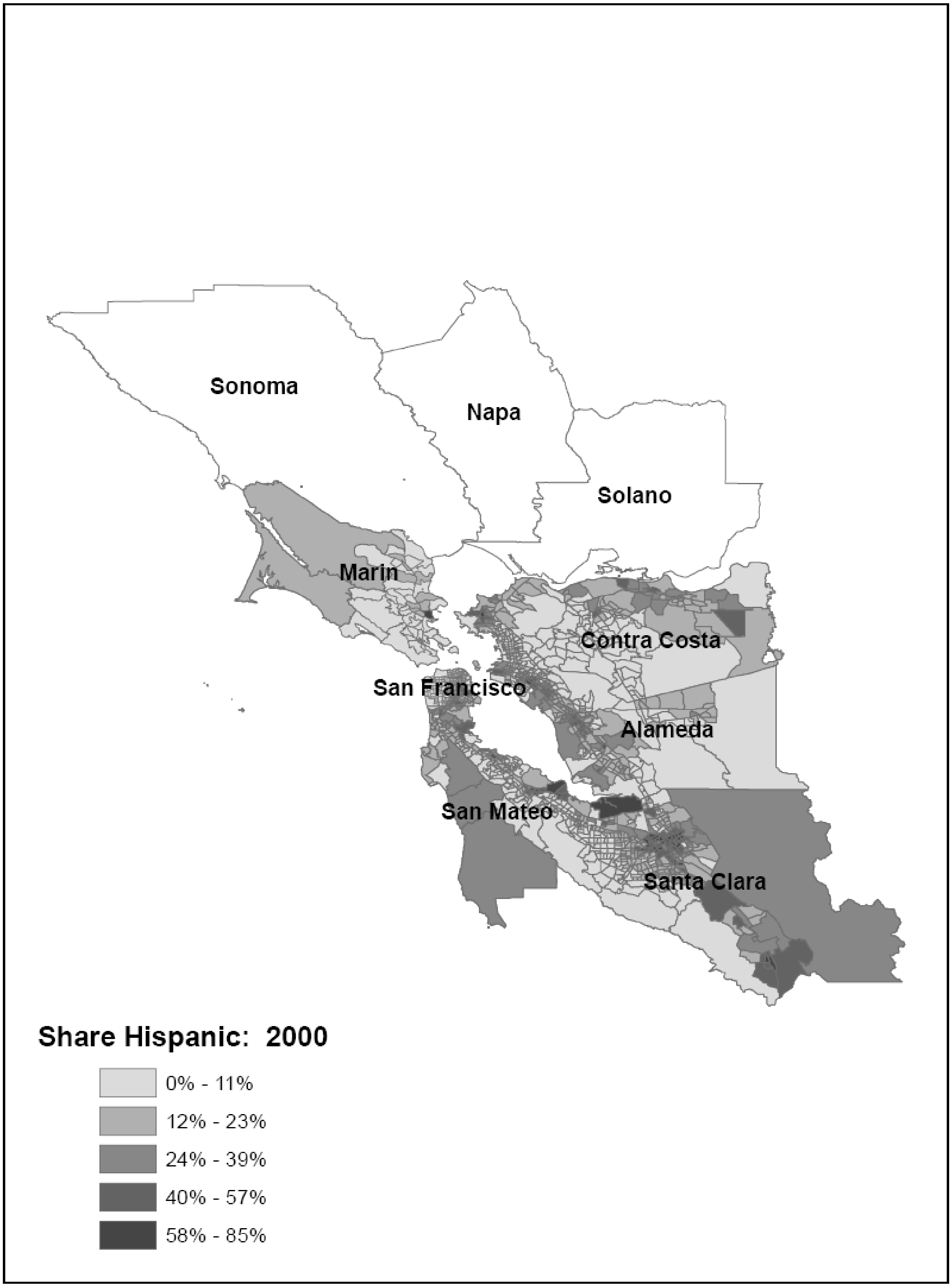


Figure 3. Minority Ozone Exposure (Days Exceeded) by Census Tract: 2000

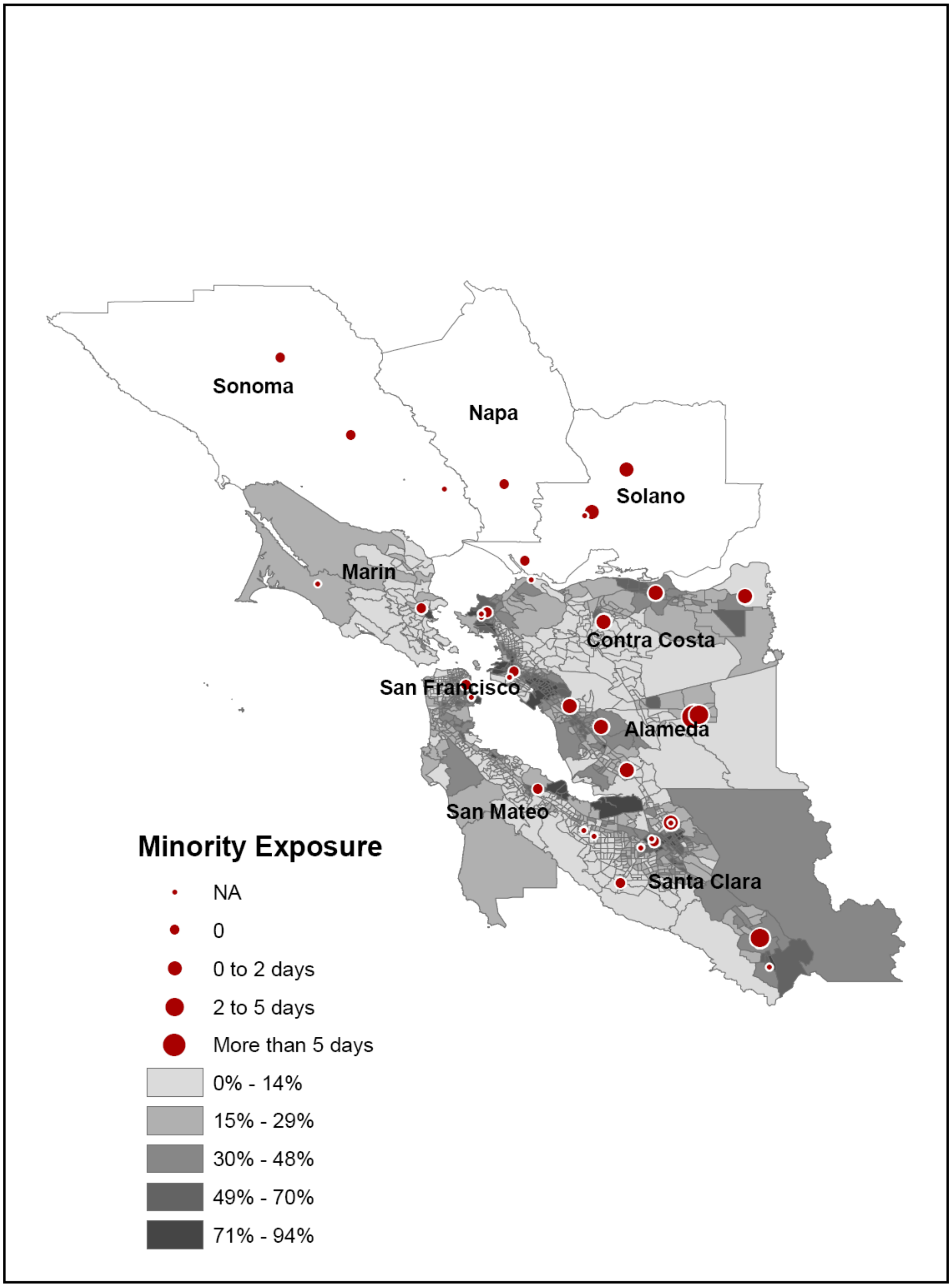
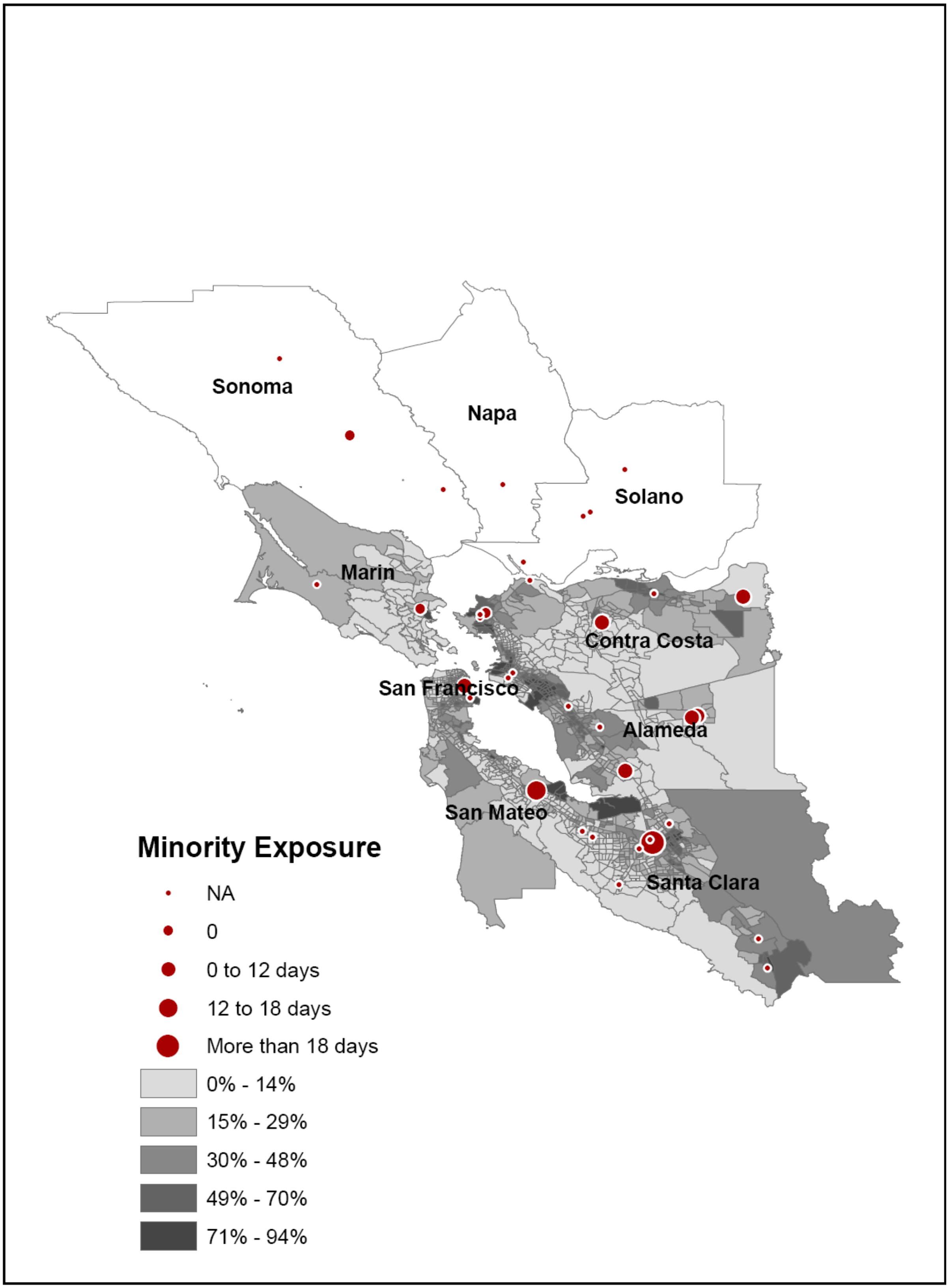


Figure 4. Minority PM_{10} Exposure (Days Exceeded) by Census Tract: 2000



Only a few empirical studies have departed from documenting correlation or testing the polluting firm's siting decision exposure hypothesis and looked at the influence of household mobility in generating the pollution exposure patterns observed in the data. For example, exposure patterns could be driven by a complex sequence of housing market changes and migration decisions that occur over time (e.g., households "vote" for the mix of environmental quality, housing stock, and local communities using their feet). In one of several versions of this migration story, declines in environmental quality cause households to leave and property values to fall. In response, low-income minority households may find these communities attractive because they are more willing to trade higher rates of exposure in exchange for a bigger (and now less expensive) house. This process has been referred to in the EJ literature as "housing market dynamics" (Been and Gupta, 1997), "white-flight" (Oakes, Anderton, and Anderson, 1996), and "minority-move in" (Morello-Frosch, et al., 2002). However, three early longitudinal studies examining this question found limited or no evidence of community demographic changes after the siting of hazardous waste storage and disposal facilities (Oakes, Anderton, and Anderson, 1996; Been and Gupta, 1997; and Pastor, Saad, and Hipp, 2001).

Recently, Banzhaf and Walsh (2008) published one of the most direct tests of migratory responses with the entry/exit of polluting facilities and emissions of air toxics. Using difference-in-difference and matching program evaluation methods, they found strong evidence of migration patterns that are consistent with the earlier work of Kahn (2000); communities where the air becomes cleaner see population gains, while communities where the air becomes dirtier experience population declines. In addition, they also found evidence of environmental gentrification similar to that found in Sieg et al.'s (2004) counterfactual simulations of household responses to air quality changes. Increases in air pollution levels appear to encourage rich households to exit a community, while poor households are more likely to enter.

One of Banzhaf and Walsh's important contributions is their attempt to better control for time-invariant unobserved local factors that determine residential location decisions. Many previous studies have not considered the role these amenities play in household sorting because numerous factors need to be considered; even if one was successful in developing a comprehensive and agreeable list, complete data would be to difficult and costly to collect. To overcome this challenge yet still address this issue, they used school district and zip codes fixed effects in addition to other demographic controls. We followed their lead and used zip code fixed effects to control for unobserved spatially distributed amenities.

The evidence presented by Banzaf and Walsh suggests that people migrate in response to environmental quality changes and consequently may help explain pollution exposure patterns that emerge over time. From a policy perspective, it suggests very different responses than would, for example, evidence of disproportionate siting. However, research to date has not addressed an important question about what types of constraints movers face, the consequences these constraints may have in terms of pollution exposure, and differences in the trade-offs they make in return for dirtier air (bigger houses, more other local amenities). Well-known environmental justice advocate Robert Bullard argues these mobility constraints are an important concern and that "poor whites and poor blacks do not have the same opportunities to 'vote with their feet'" when it comes to environmental quality choices (Bullard, 2000, p. 6). Mobility constraint questions (in particular, wealth effects associated with a previous home sale) have not been addressed to date in this empirical literature. This is the primary focus of our analysis.

3. Data

The new and unique data set we used to examine environmental justice questions combines information from three data sets:

- *Housing transactions*: Purchased from a national real estate company, these data provide actual transaction (instead of self-reported) prices and include key mortgage information such as loan amount and lender's name.
- *Home Mortgage Disclosure Act (HMDA)*: The HMDA data provide key demographic information about people (race and income) as well as mortgage information. Census tract, mortgage loan amount, and lender's name allow HMDA data matches with the housing transactions data set and links demographic information about the people who bought and sold the homes.
- *California Air Resources Board (CARB) Air Quality Data*: CARB provides the latest 27 years of air quality data (1980–2006). It also provides each monitor's geographic coordinates, which allowed us to compute a house-specific exposure measure using all air quality monitors in the area.

3.1 Housing Transactions

The data purchased from DataQuick included real estate transactions for 1990–2004 covering six key counties of the San Francisco Bay Area (Alameda, Contra Costa, Marin, San Francisco, San Mateo, and Santa Clara). Transaction variables for this analysis included a unique parcel identifier, transfer value (sale price), sales date, and geographic information (census tract, latitude, longitude). DataQuick also provides several useful housing characters observed at the last transaction: lot size, square footage, number of baths, and number of bedrooms. In addition to these data, we used GIS software to assign a 5-digit U.S. zip code to each house.[1]

We reviewed the data set and dropped observations meeting the following criteria. First, we restricted our analysis to houses that sold two or three times during the sample period. Within this group, we dropped properties sold multiple times on the same day or the same year. Next, we screened properties for land-only sales or rebuilds and dropped all transactions where year built is missing or with a transaction date that is prior to year built. To compute distances between houses and air quality monitors, we needed the property's geographic coordinates. Therefore, we dropped properties where latitude and longitude were missing. We also eliminated transactions without a sales price and dropped 1 percent of observations from each tail of the price distribution to minimize the effect of outliers. Finally, we restricted the sample to include only houses with identifiable zip codes and the following ranges of attributes: lot size (1,000 to 30,000 square feet), square feet (800 to 3,000 square feet), bathrooms (1 to 5), and bedrooms (1 to 8). Housing variable descriptions are included in Table 1, and the resulting sample statistics are reported in Table 2. This sample is very similar to the full sample reported in Bayer et al. (2008).

Table 1. Housing Variable Descriptions

DataQuick Variable	Data Set Name	Description
SA_PROPERTY_ID	*Idp*	Primary key. Unique parcel identifier
SA_DATE	*Date*	Document date for the transaction
SA_VAL_TRANSFER	*Price*	Transfer value of the property, AKA sale amount or sale value
SA_CENSUS_TRACT	*Tract*	Census tract
SA_X_COORD	*Longitude*	Longitude coordinate
SA_Y_COORD	*Latitude*	Latitude coordinate
SA_LOTSIZE	*Lotsize*	Lot size expressed in square feet
SA_SQFT	*Sqft*	Total living and/or heated and/or air condition area square feet
SA_NBR_BATH	*Baths*	Number of bathrooms
SA_NBR_BEDRMS	*Bedrooms*	Number of bedrooms

Table 2. Housing Variables: Subsample of Houses with 2 Sales

Variable	Mean	Standard Deviation	Minimum	Maximum
2 Sales				
price($1,000)	$361	$214	$15	$1,500
lotsize	6,258	3,526	1,000	30,000
sqft	1,616	497	800	3,000
baths	2.0	0.64	1	5
bedrooms	3.2	0.82	1	8
Number of Observations: 195,426 (97,713 houses)				
3 Sales				
price($1,000)	$342	$210	$15	$1,500
lotsize	5,885	3,339	1,000	30,000
sqft	1,560	481	800	3,000
baths	2.0	0.63	1	5
bedrooms	3.1	0.80	1	8
Number of Observations: 76,563 (25,521 houses)				

Table 3. Housing Variables: Full Sample

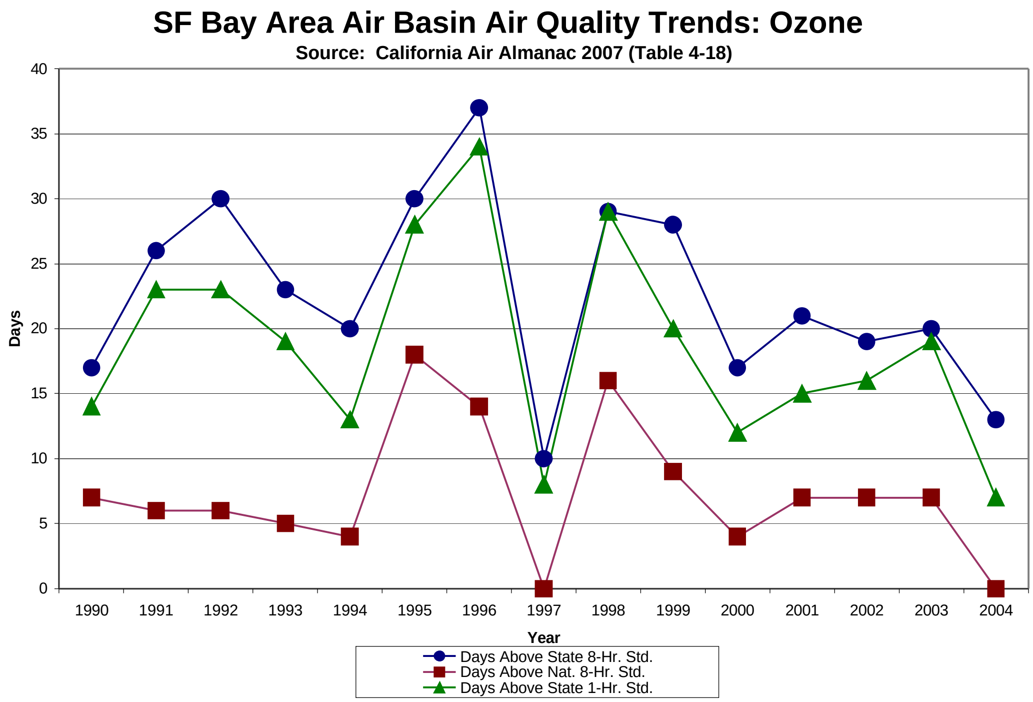
Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
price($1,000)	1,232,575	$352	$222	$16	$1,505
Lotsize	1,105,557	6,884	11,385	0	199,940
Sqft	1,106,305	1,647	720	400	10,000
Bedrooms	1,106,360	2.9	1.13	0	8

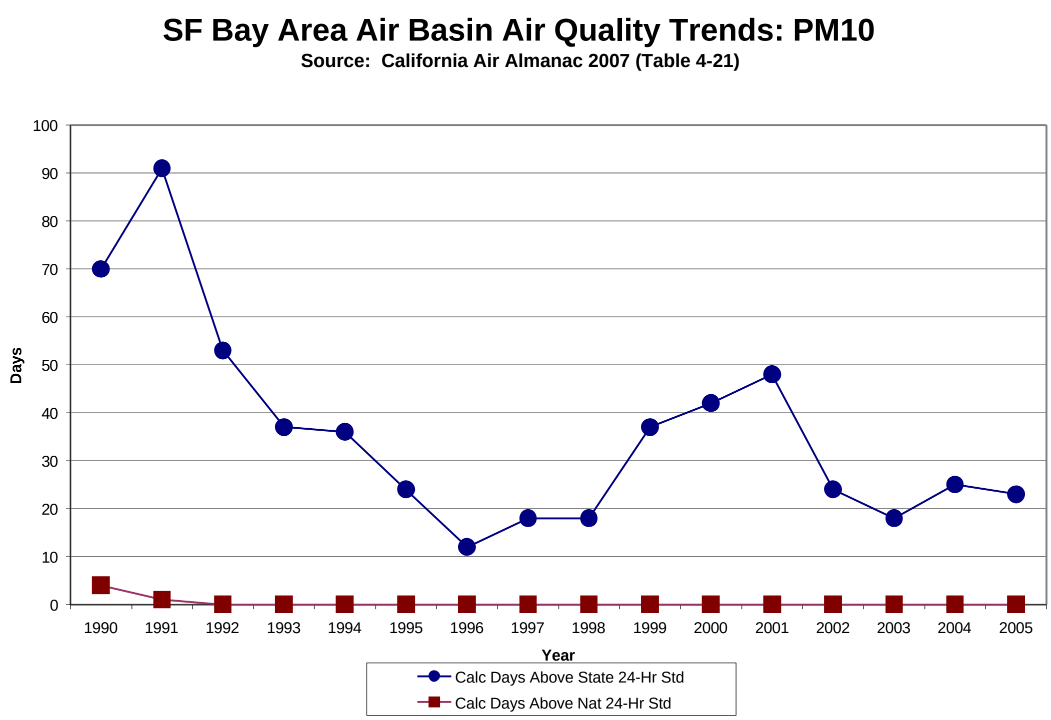
Source: Bayer et al. 2008. Table 2.

3.2 Air Quality Data

Currently, the San Francisco Bay Air Basin remains one of the cleanest of California's air basins. Its coastal climate (cooler temperatures and better ventilation) makes its air quality better relative to other inland regions such as the San Joaquin Valley and South Coast air basins (CARB, 2007). However, the region continues to deal with air quality issues associated with ground-level ozone and particle pollution. Between 1990 and 2004, Bay Area pollution levels exceeded state and federal air quality standards (see Figure 5). The number of ozone excess days reached a peak in 1996 but has gradually declined since that year. In 2004, monitors measured ozone concentrations that exceeded the air quality standards on fewer than 15 days. Currently, California designates the Bay Area as a nonattainment area for ground-level ozone and coarse (PM_{10}) and fine ($PM_{2.5}$) particle pollution. Using federal standards, the Bay Area is a nonattainment area for ozone only.

Figure 5. Bay Area Air Quality Has Improved but Pollution Levels Continue to Exceed State Air Quality Standards





Source: CARB (2007). Table 4-18 and Table 4-21

The Bay Area air quality monitors are part of a statewide system of over 250 common pollutant monitors. Each year, CARB uses these monitors to collect millions of measurement observations. CARB is also responsible for ensuring data quality and reporting and storing these results. For this study, 37 monitors were identified and provided air pollution measurements related to ozone and particle pollution (PM_{10}).

In February 2008, the California Environmental Protection Agency Air Resources Board (CARB, 2008) provided the latest DVD-ROM with 27 years of air quality data (1980–2006). The data set covers all monitors located in the six counties covered by the real estate transactions data (Alameda, Contra Costa, Marin, San Francisco, San Mateo, and Santa Clara) and the three counties on the boundaries of this area (Napa, Solano, and Sonoma). The data set provides a variety of air quality measures for ozone. For this study, we used a simple 3-year moving average of annual days exceeding California's 1-hour ozone standard and annual days exceeding California's 24-hour PM_{10} standard.[2] We used a moving average because pollution levels tend to fluctuate from year to year (especially in the case of ozone); when making purchase decisions, homebuyers may recognize this and take into account where the pollution level had been in the previous year and where it is likely to go in the following year.

In addition to these pollution readings, CARB provides information on each monitor's coverage. This variable ranges from 0 to 100 and indicates the extent of monitoring performed during months where high pollution concentrations are expected. For example, a coverage number of 50 indicates that monitoring occurred 50 percent of the time during high-concentration months. We dropped monitors with less than 60 percent coverage for a given year.

With the geographic information (latitude and longitude), we computed a house-specific exposure measure using a weighted average of all monitors' exceedances with one over distance as the weight. The distance in kilometers between each house and monitor is calculated using the "Great Circle" estimator. Table 4 provides summary air quality data for houses included in our housing sample.

Table 4. Housing-Specific Pollution Measures Summary Statistics

	Days Exceeding California Standard			
Variable	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
		2 Sales		
Ozone (1 hour)	3.1	1.4	0.1	14.1
PM_{10} (24 hour)	17.7	11.0	2.5	59.7
Number of Observations: 195,426 (97,713 houses)				
		3 Sales		
Ozone (1 hour)	3.1	1.5	0.1	14.1
PM_{10} (24 hour)	17.7	10.8	2.3	60.2
Number of Observations: 76,563 (25,521 houses)				

Note: Pollution measured as 3-year moving average (t, t-1, t-2).

3.3 Home Buyer Characteristics

DataQuick data and HMDA data were merged on the basis of census tract, loan amount, date, and lender's name. People were then linked across time using an algorithm that compares characteristics of names and dates and is described in Bayer et al. (2008) and Bishop and Timmins (2008). Bayer et al. (2008) validated the algorithm by comparing the matched data set to public access Census micro data from IPUMS and the original real estate transaction data set. The matched buyers are representative of all the buyers and the housing attributes as well.

We reviewed the data set and dropped observations meeting the following criteria. First, we restricted the sample to people who appear as buyers twice. We restricted the sample to white, black, Hispanic, and Asian households. In cases where conflicting race information was provided in the first and second observations (or was missing), we used the reported race in the second observation or replaced missing information with the race of the first sale. We dropped observations where no race information was available, where income was missing, or when we could not compute the capital gain buyer. Buyer sample statistics are reported in Table 5 and are compared to the full sample reported in Bayer et al. (2008) (see Table 6).

Table 5. Buyer Characteristics: Subsample

Variable	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Income ($1,000)	$138	$88	$3	$1,527
Share White	0.63	0.42	0	1
Share Asian	0.23	0.15	0	1
Share Black	0.02	0.32	0	1
Share Hispanic	0.12	0.35	0	1
Number of Observations:		*4,889*		

Table 6. Buyer Characteristics: Full Sample

Variable	Mean	Standard Deviation	Minimum	Maximum
Income ($1,000)	$119	$129	0	11,200,000
Share White	0.60	0.49	0	1
Share Asian	0.24	0.43	0	1
Share Black	0.03	0.18	0	1
Share Hispanic	0.11	0.31	0	1

Source: Bayer et al. 2008. Table 3.

4. Housing Prices and Pollution: The Hedonic Gradient

Our basic specification of the hedonic price equation for a sample observation (house *i* located in zip code *j* selling in year *t*) is as follows:

(1) $$\ln P_{i,j,t} = \beta_0 + Z'_j\phi + H'_i\lambda + Y_t\theta + A'_{i,j,t}\alpha + \varepsilon_{i,j,t}$$

(2) $$\varepsilon_{i,j,t} = \omega_i + u_{i,j,t}$$

where Z_j is a vector of zip code indicators, H_i is a vector of variables describing housing attributes, Y_t is a vector of year indicators, and $A_{i,j,t}$ is a vector of variables describing the air quality associated with house *i*. We assumed that the error term ($\varepsilon_{i,j,t}$) can be decomposed into a fixed component that is specific to house *i* (ω_i) and a time-varying component ($u_{i,j,t}$). Year indicators are included to control for the effects of unusually rapid growth in Bay Area-wide housing prices while overall air quality improved. Failure to control for these effects would lead us to overestimate the positive effect that air quality improvements might have on housing prices.

One of the strengths of our data is that we can match houses over time. As such, we estimate a differenced regression for houses that sold at least twice during the period between 1990 and 2004. We found strong evidence that more ozone and PM_{10} exceedences reduce Bay Area housing prices (see Table 7). Using superscripts to denote either the first or second sale of house *i*:

$$(3) \qquad \ln P_{i,j,t}^{2} - \ln P_{i,j,t}^{1} = (Y_t^{2} - Y_t^{1})\theta + (A_{i,j,t}^{2} - A_{i,j,t}^{1})'\alpha + (u_{i,j,t}^{2} - u_{i,j,t}^{1})$$

All house and neighborhood attributes (including the zip code fixed effects and unobserved ω_i's) are differenced away in Equation (3). Assuming that only fixed house and neighborhood attributes might have been correlated with pollution, this eliminates any potential source of bias in our estimate of *a*. To the extent that neighborhood attributes change over time in a manner correlated with our pollution measures, we still have a potential source of bias.[3]

To highlight the advantages of the differencing approach, we estimate one other specification that does not leverage house fixed effects. In this regression, we include house and neighborhood attributes in the hedonic price equation instead of differencing them away. As shown in Table 7, more PM_{10} exceedances are associated with a small *increase* in housing prices in that specification. One might argue that this result is driven by the omission of unobserved location attributes that are positively correlated with PM_{10}. For example, houses located near major roadways may be attractive because it is easier to commute to work or access public transit; however, these roadways would also be more likely to be used by vehicles emitting diesel exhaust.

Table 7. Hedonic Prices and Pollution: Bay Area Results

	No House Fixed Effects	**House Fixed Effects (Differences)**
Dependent Variable:	ln(price)	$\ln(price_{t+1}) - \ln(price_t)$
Explanatory Variables:		
Lot size	<0.01* <(0.001)	NA
Square feet	<0.01* <(0.001)	NA
Bathrooms	0.05* (0.003)	NA
Bedrooms	-0.09* (0.002)	NA
Days exceeded state 1 hour ozone standard (3 year moving average)	-0.05* (0.001)	-0.09* (0.002)
Days exceeded state 24 hours PM10 standard (3 year moving average)	0.03* <(0.001)	-0.01* <(0.001)
Constant	10.2* (0.026)	-0.08* (0.017)
Year indicators	Yes	Yes
Observations	271,989	148,755
R-Squared	0.38	0.07

**Statistically different than zero at a=0.01.*
Note: Quantities in parenthesis below estimates are the panel robust standard errors.

With respect to housing services, both of these models show that holding other factors constant, increases in housing services increase housing prices. Lot size, square feet, and number of bathrooms coefficients are generally small but positive and statistically different from zero. The one sign exception is the bedroom coefficient. Since a homeowner may not consider the partial effect of an additional bedroom (holding the total number of rooms fixed) desirable, this makes sense.[4]

These hedonic results constitute our first two pieces of empirical evidence: (i) a trade-off does exist between house price and pollution, and (ii) increased housing services do indeed result in a higher housing price. An individual can, therefore, get more housing services for the same price by moving to a neighborhood with more pollution. Whether poor/minority individuals are more likely to make this trade-off is the subject of the remainder of our analysis.

5. Following the Decisions of Bay Area Home Buyers

In this section, we look for *direct* evidence that poor/minority homeowners trade more pollution exposure for cheaper housing and/or other desirable neighborhood attributes when they move, whereas other homeowners do not. In addition, we leverage the fact that we can see homeowners on multiple purchase occasions to explore the role of housing wealth in the purchase decisions of the poor and minorities.

5.1 Method

We constructed year-specific housing service and neighborhood quality indices using a regression model similar to that used above to document the capitalization of pollution into housing prices. In particular, we specified the log of housing price as a function of neighborhood (i.e., zip code) dummies, housing characteristics, air pollution, and other unobserved factors. Importantly, we allowed all the parameters in this regression to vary by year; this allowed for the most flexible calculation of neighborhood and housing services indices possible. We estimated the following model with ordinary least-squares:

$$\ln P_{i,j,t} = \beta_{0,t} + Z_j'\phi_t + H_i'\lambda_t + A_{i,j,t}'\alpha_t + \eta_{i,j,t} \tag{4}$$

For each house, we then used the estimated housing and zip code coefficients (i.e., λ_t and ϕ_t, respectively) to compute a housing services ($H_i'\lambda_t$) and neighborhood quality index for each home in the sample in each year. Next, we computed the differences in housing services index, house-specific air pollution (measured using the 3-year moving average number of days exceeded for ozone and PM_{10}), and other neighborhood services (i.e., zip code fixed effects) associated with the move from a first home to a second home. As a last step, we computed the correlation coefficients across these variables for different groups.

5.2 Results

Arguments based on sorting-induced exposure suggest that poor and minority households are willing to live in a house with dirtier air in exchange for receiving more housing services (and possibly a neighborhood with better overall quality). Initially, we looked for patterns in correlation coefficients that are consistent with this story. We paid particular attention to differences across racial groups, income levels, and wealth derived from the previous home sale.

As shown in Table 8, minorities bought bigger homes that had more air pollution exposure. Compared with white and Asian homeowners, minorities also took on more pollution (both ozone and PM_{10}) to get more housing services; evidence that is consistent with the simple sorting story. The minority household's housing service/ozone correlation coefficient is nearly two times higher than white and Asian groups.

Table 8. Housing, Pollution, and Neighborhood Correlation Coefficients by Race and Income

	Ozone	PM10	Neighborhood Quality
Minority	0.22	0.04	0.02
High Income	0.10	0.08	- 0.08
Low Income	0.27	0.03	0.02
White	0.09	- 0.07	- 0.10
High Income	0.11	- 0.09	- 0.17
Low Income	0.09	- 0.05	- 0.07
Asian	0.11	- 0.09	- 0.05
High Income	0.08	- 0.10	- 0.08
Low Income	0.14	- 0.07	- 0.08
Minority White Diff: High Income	- 0.01	0.17	0.08
Minority White Diff: Low Income	0.18	0.08	0.09
Double Difference:	- 0.19	0.09	- 0.01
Asian White Diff: High Income	- 0.03	0.00	0.08
Asian White Diff: Low Income	0.05	- 0.02	- 0.01
Double Difference:	- 0.08	0.02	0.09

Note: Correlation coefficients with respect to housing services

Next, we looked more closely at the differences between low- and high-income groups to see what role that distinction plays in mobility-induced exposure patterns. As shown in Table 8, the racial difference in house-ozone correlation disappears for high-income homeowners. However, the house-PM_{10} correlation persists. In contrast, low-income Asians and minorities take on significantly more pollution to get more housing services. Therefore, the observed correlation between race and air pollution exposure can really be explained by income differences. We also note that income does not seem to influence the trade-offs white homeowners make (i.e., poor white homeowners do not seem to have to give up cleaner air to get more housing services). In contrast, Asians and minorities do.

Environmental justice stories emphasize the role annual household income plays in determining exposure. To enhance our understanding of the relationship between economic circumstances and pollution exposure, we also considered whether information about changes in homeowner wealth that have not been typically observed in the data (e.g., large and small percentage gains [or losses] from the previous home sale) influences the housing trade-offs people make. Intuitively, households that make more money from the previous home sale relative to the initial purchase price may be better positioned to avoid the housing services/pollution trade-off.

As shown in Table 9, a big relative gain does seem to help poor minorities avoid the ozone trade-offs. The difference between low- and high-income with low gain correlation coefficients is 0.19 for ozone. In contrast, the difference between low- and high-income is smaller (0.15) for high-gain households. This suggests poor minorities do use housing wealth to "buy" their way out of high pollution when they move to a bigger house (difference of -0.04). Similar effects occur for PM, but the difference is more than twice as large (-0.10).

For Asians (see Table 10), the wealth effect suggests they are more likely to make the ozone trade-off; the ozone difference between low and high income for low gain households is -0.02, while it is 0.16 for high gain households, a difference of 0.17. However, housing wealth does appear to help low-income households escape higher levels of PM pollution.

For white homeowners, housing wealth doesn't seem necessary for low income households to avoid the trade-off (see Table 11). Instead, it appears that low income households can escape pollution just as easily as high income households.

Table 9. Minority Housing, Pollution, and Neighborhood Correlation Coefficients by Race, Income, and Housing Wealth Change

	Ozone	PM10	Neighborhood Quality
Minority	0.22	0.04	0.02
Low Income	0.27	0.03	0.02
High % Gain	0.27	0.04	0.00
Low % Gain	0.27	0.03	0.00
High Income	0.10	0.08	- 0.08
High % Gain	0.12	0.12	- 0.06
Low % Gain	0.08	0.01	- 0.10
Diff Income Groups: High % Gain	0.15	- 0.09	0.05
Diff Income Groups: Low % Gain	0.19	0.02	0.10
Double Difference:	- 0.04	- 0.10	- 0.05

Note: Correlation coefficients with respect to housing services

For Asians (see Table 10), the wealth effect suggests they are more likely to make the ozone trade-off; the ozone difference between low and high income for low gain households is -0.02, while it is 0.16 for high gain households, a difference of 0.17. However, housing wealth does appear to help low-income households escape higher levels of PM pollution.

For white homeowners, housing wealth doesn't seem necessary for low income households to avoid the trade-off (see Table 11). Instead, it appears that low income households can escape pollution just as easily as high income households.

6. Conclusion

We offer a new assessment of environmental equity questions in the San Francisco Bay area using a unique data set that combines individual real estate transactions with homebuyer mortgage information. The key advantage of this data is that we observe Our hedonic results document two pieces of empirical evidence necessary for a sorting-induced exposure story: (i) a trade-off does exist between house price and pollution, and (ii) increased housing services do indeed result in a higher housing price. An individual can, therefore, get more

Table 10. Asian Housing, Pollution, and Neighborhood Correlation Coefficients by Race, Income, and Housing Wealth Change

	Ozone	PM10	Neighborhood Quality
Asian	0.11	- 0.09	- 0.05
Low Income	0.14	- 0.07	- 0.08
High % Gain	0.19	- 0.05	- 0.11
Low % Gain	0.10	- 0.09	- 0.06
High Income	0.08	- 0.10	- 0.08
High % Gain	0.02	- 0.05	- 0.09
Low % Gain	0.12	- 0.14	- 0.08
Diff Income Groups: High % Gain	0.17	0.00	- 0.02
Diff Income Groups: Low % Gain	- 0.02	0.06	0.02
Double Difference:	0.19	- 0.06	- 0.04

Note: Correlation coefficients with respect to housing services

Table 11. White Housing, Pollution, and Neighborhood by Race, Income, and Housing Wealth Change

	Ozone	PM10	Neighborhood Quality
White	0.09	- 0.07	- 0.10
Low Income	0.09	- 0.05	- 0.07
High % Gain	0.08	- 0.06	- 0.07
Low % Gain	0.10	- 0.04	- 0.08
High Income	0.11	- 0.09	- 0.17
High % Gain	0.10	- 0.11	- 0.20
Low % Gain	0.12	- 0.08	- 0.13
Diff Income Groups: High % Gain	- 0.02	0.05	0.13
Diff Income Groups: Low % Gain	- 0.02	0.04	0.05
Double Difference:	0.01	0.01	0.09

housing services for the same price by moving to a neighborhood with more pollution. Analysis of differences in the correlation patterns between changes in housing service indices and house-specific ozone and PM_{10} pollution suggests that poor/minority households are more likely to make this trade-off. Moreover, it provides additional support for the sorting (versus discriminatory siting) explanation for observed patterns of race, wealth, and air pollution exposure.

Our hedonic results document two pieces of empirical evidence necessary for a sorting-induced exposure story: (i) a trade-off does exist between house price and pollution, and (ii) increased housing services do indeed result in a higher housing price. An individual can, therefore, get more housing services for the same price by moving to a neighborhood with more pollution. Analysis of differences in the correlation patterns between changes in housing service indices and house-specific ozone and PM_{10} pollution suggests that poor/minority households are more likely to make this trade-off. Moreover, it provides additional support for the sorting (versus discriminatory siting) explanation for observed patterns of race, wealth, and air pollution exposure.

Our analysis also finds that wealth taken from appreciating housing stocks can increase the ability of poor/minority individuals to avoid the conventional sorting story. This has two implications. First, poor minority households living in a declining neighborhood that want to improve their housing situation could be at a significant disadvantage because they own a house that will not appreciate by as much as a house in an improving neighborhood. If an individual is a high-income minority, this effect appears to be diminished and if an individual is white, it seems to go away altogether. This finding has dynamic implications. Poor minority households are likely to be constrained in their housing choices by wealth effects, which will force them to buy houses in polluted neighborhoods. If those neighborhoods continue to deteriorate, those homeowners are going to be even further constrained when it comes time to buy a house with even greater housing services. Second, policies that help minorities gain access to credit may have an indirect benefit that enhances their ability to move to neighborhoods with cleaner air. Policy makers could consider this factor as they weigh the many other benefits and costs of relaxing credit constraints.

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[1] ESRI Data: U.S. Zip Code Areas: 2000.

[2] The CARB DVD variable name for ozone is "OZEX1HST." For PM_{10}, CARB's variable name is "PM10CX1S."

[3] Our identification assumption would be violated if, for example, improving employment opportunities in a neighborhood led to increased pollution and higher housing prices. Whereas this might be the case with TRI pollutants, we believe that this assumption is a reasonable one in the case of criteria pollutants. These pollutants tend to be produced by automobiles traveling on highways to jobs in other parts of the city, and the distribution of their ambient concentrations is driven, in large part, by wind patterns and geography.

[4] For a given size of home (square feet) and bathrooms, adding an additional bedroom means the average size of these rooms will necessarily be smaller. In addition, the same number of bathrooms would now have to be used by presumably more people.