International Conference on Whole Life Urban Sustainability and its Assessment
M. Horner, C. Hardcastle, A. Price, J. Bebbington (Eds)
Glasgow, 2007

Examining the Environmental Justice Component of Urban Sustainability: A Comprehensive Analysis Including Economics, Collective Action, Ethnicity, and Age

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ABSTRACT

A broader, more holistic understanding of urban sustainability includes social progress and sustainable governance. Within this context, environmental justice is an important component of sustainability. This paper assesses environmental justice using multivariate regression methods to analyze the factors that explain the location of United States Environmental Protection Agency Toxic Release Inventory facilities (TRIFs) within a large country containing 444 such facilities. The data overcomes prior research shortcomings by aligning residential characteristics before firm location over three decades, thereby ensuring that findings do not indicate the movement of residents into the firm's ambit, but location of the firm among the residents. The analysis tests poverty, race, and collective action hypotheses, including the relevance of age, to conclude that potential for collective action decreases the likelihood of TRIF location. Even controlling for other factors, evidence of environmental injustice based on race/ethnicity remains. Perhaps even more disturbing from a sustainability perspective, in these data areas with higher percentages of children have an increased likelihood of new TRIFs.

Key Words: Environmental Justice, Urban Sustainability

1 INTRODUCTION

As the concept of urban sustainability has developed, it has moved from a purely ecological focus to a broader and more holistic one that includes economic and governance systems. If a city is to be truly sustainable, it must "provide widespread economic and social progress" (SUEMoT 2007, p. 1) while also maintaining more traditionally understood ecological health. Within this broader context, one important issue is environmental justice. First, one element of social progress is improvement in the justice with which environmental burdens are distributed. Second, in the extreme, egregious injustice of any kind can lead to the breakdown of a society as those who are bearing excess burdens eventually may rebel. Third, even short of that point, if some groups feel that their situations are consistently unjust, they may withdraw from participation in governance, harming the ability of the city to inspire its residents to changes needed for either sustainability or progress.

In spite of several decades of research, the issue of whether environmental discrimination exists is still hotly debated and researched. One ongoing issue in the field of environmental justice (EJ) research is whether the undeniable disproportionate co-location of environmental disamenities with minority residents is due to efficient workings of the market, or something more invidious. If individuals make conscious trade-offs to accept more environmental harm in exchange for some other desired attribute, such as lower housing prices, this does not have the same implications for sustainable governance as does the situation in which environmental harms are imposed on existing residents with location influenced by race or ethnicity.

One reason for the continued debate is the difficulty, in much environmental justice work, of solidly linking the *ex ante* population with the *ex post* decision regarding disamenity location. Further, in 1995, Hamilton argued that the causes of firm location should not only include standard economic costs and potential legal costs, but also potential collective action costs; after all, we live in political-economies, so firms should consider the likelihood that residents will organize against them as they decide where to locate. Yet, much EJ research omits potential collective action costs, allowing for the possibility of omitted variable bias in statistical results.

The work presented here takes advantage of a unique dataset which identifies United States Environmental Protection Agency (US EPA) Toxic Release Inventory facility (TRIF) location dates, thus allowing analysis grounded in a time-based causal structure with clarity regarding the population that existed in a neighbourhood at the time that a new facility was located there. Further, it employs a thorough analysis not only of economic and potential legal compensation costs, but of potential collective action costs.

2 LITERATURE REVIEW

In 1995, James Hamilton published an article arguing that the causes of firm location decisions could be separated into three overarching categories. He referred to these as “pure discrimination; the Coase theorem [Coase, 1960]; and the theory of collective action [Olson, 1965]” (p. 109). In this way, he separated location determinants into factors of environmental discrimination, economic factors including transaction costs, and political-pressure factors. In the latter category, Hamilton (1995) was particularly interested in the potential for community members to engage in collective action. He argued persuasively that the firm’s environment has changed such that one of the most important siting considerations is a “neighbourhood’s likelihood of engaging in political opposition” (p. 117). Hamilton’s analysis uses voter turnout in one specification, and the difference between demographically predicted voter turnout and actual voter turnout in a second specification, to test the importance of potential collective action in the decision of treatment, storage, and disposal (TSD) facilities to expand. He finds strong evidence of the importance of the potential for political action, for the estimated coefficients on voting behaviour are both statistically significant and among the largest in magnitude in his estimates (pp. 124 and 126). Hamilton (1995) is the first work of which we are aware to provide such a thorough model of the political-economic elements that should affect firm location, and our study is grounded in this model.

Yet, we do not believe that Hamilton’s (1995) findings, particularly his conclusion that his analysis provides no evidence of pure discrimination once the economic cost and collective action variables are controlled for, are the last word on this topic. One factor that raises the possibility that there is more to learn is that the estimated coefficient for his pure discrimination variable, measured simply as percent of “non-white” population in his geographic area, carries the predicted sign under a hypothesis of environmental discrimination (is estimated to increase the likelihood of TSD expansion) and is statistically significant at greater than the 90-percent level, one-tailed. It is true that the magnitude of the estimated coefficient is fairly small, implying a change from the average likelihood of 0.359 of TSD expansion to 0.418 for a one-standard-deviation increase in the percent non-White (holding other variables at their means), whereas for the largest predictor (median household income) a one-standard-deviation increase results in a predicted probability change from 0.359 to 0.506. But, it is important to note that the work of Owens-Prindle (2004) and others indicates that different “non-white” groups may have very different environmental justice outcomes, with some groups actually less likely than Whites to receive environmental disamenities. For example, Burke (1993) finds disparate effects depending on minority group, with Hispanics and African-Americans disadvantaged, but Asian-American co-location not statistically different from that of non-Hispanic Whites. And, Sobotta et al. (2007) suggests regional variation in groups that are discriminated against. If these findings hold within Hamilton’s (1995) sample (which is US-wide), then the magnitude of the effect for those groups that are discriminated against will be dampened by the measurement of all non-White groups within a single category. Thus, though Hamilton’s evidence for the importance of collective action is strong, his conclusion against “pure discrimination” is weak.

Further, an unexamined implication of Hamilton’s (1995) work is that other factors that contribute to the potential for collective action may also matter to disamenity location. For example, firms that anticipate political opposition would do well to locate on political borders and in neighbourhoods where there are many children (who are not eligible to vote). This former prediction follows naturally from a public choice perspective because the firm thereby divides political opposition, making some potential complainants lack jurisdiction.

One possibility that often arises in the environmental justice (EJ) literature is that market rationality alone—absent any discrimination other than, perhaps, systemic—may explain the undeniable disproportionate co-location of racial and ethnic minorities with environmental disamenities in the US. One argument is that the presence of disamenities should reduce housing prices and, since minorities are disproportionately poor, we should expect market rationality to cause more minorities to be located near disamenities. Indeed, some researchers have pointed out that objecting to such a co-location based on income-based choices (assuming no information failure) is a form of paternalism (Noonan 2005). However, many EJ studies control for income, still finding disproportionate effects of minority status. For example, Burke (1993, p. 48) finds "When all census tracts were included in the analysis, the minority percentage of the tract appeared to have a slightly stronger relationship with TRI facility occurrence than does the median per capita income of the tract."

The other argument is related, though somewhat indirectly, to the first. As reviewed in Whittaker, et al. (2005), many authors have argued that racial and ethnic minorities are less focused on the environment. Though some arguments reduce to the income argument sketched above, others are grounded more theoretically in Maslow's (1970) hierarchy of needs: "the hierarchy of needs theory suggest[s] that poor or minority populations [have] more pressing day to day needs, and that concerns over extras like environmental protection [are] secondary" (Whittaker, et al. 2005, p. 435). Note that the focus on "poor" individuals may be similar to an income argument, but a focus on minorities regardless of income status could emphasize daily attempts to navigate more hostile social environments.

In contrast to these ideas, some evidence suggests that some minority groups may actually care more than dominant-group Whites about environmental hazards—or at least those of the type that might be located in their neighbourhoods, such as the TRIFs to be analyzed here and the TSD facilities analyzed by Hamilton (1995). Liu (2001, p. 200) reviews significant literature indicating that minorities may feel more dread about environmental risk because "Those of lower socioeconomic status have a sense of less control over and more concern about their exposure to risks." Whittaker, et al. (2005, p. 435) reviews an alternative to Maslow's (1970) theory, environmental deprivation theory, which posits "that concern is related primarily to exposure, that the more polluted the neighbourhood, the more concerned the residents of that neighbourhood." Since minorities are more exposed to environmental risks, this theory suggests they should be more concerned about those environmental hazards that pose direct risk to them. Further, Whittaker, et al. (2005)

finds empirical evidence of greater concrete environmental concern among Hispanics than non-Hispanic Whites, with African-American attitudes similar to those of Whites.

Note that, if minorities actually care more about close environmental risks than do Whites, then evidence of racial or ethnic minority status increasing likelihood of co-location with such environmental disamenities is even greater evidence of discrimination than previously understood. If minorities actually dis-prefer disamenities more than non-minority Whites, yet end up near them at a greater rate when controlling for other factors, then there must be strong social forces overcoming their own choice behaviour.

3 THE MODEL TO BE ESTIMATED

The decision to be modelled is the TRIF's location decision. As mentioned above, under Hamilton's (1995) basic, rationality-based model, the location decision should be determined by a combination of traditional economic ("Coasian") costs and political (collective action) costs. Controlling for both of these types of costs, factors such as race and ethnicity should not affect location. If race and/or ethnicity are found to have an effect when controlling for economic and political costs, then evidence of environmental discrimination exists.

As the above review of some of the EJ literature indicates, in spite of several decades of research, the question of whether disproportionate minority co-location is due to some form of discrimination is far from solved. One reason it is difficult to answer this question is that it has been difficult to obtain data that allow a clear time-based causal structure. Hamilton (1995) controls for this problem by examining TSD facility expansion plans—though this has the potential of including some TSD facilities that will not, in fact, be expanded. The analysis presented here deals with the timing problem by finding the location dates of US EPA Toxic Release Inventory facilities located in Maricopa County, Arizona. Arizona is in the Southwestern portion of the US. Figure 1 provides an illustration of our ability to match existing TRIFs, existing populations, and new TRIFs over three decades of Census data.

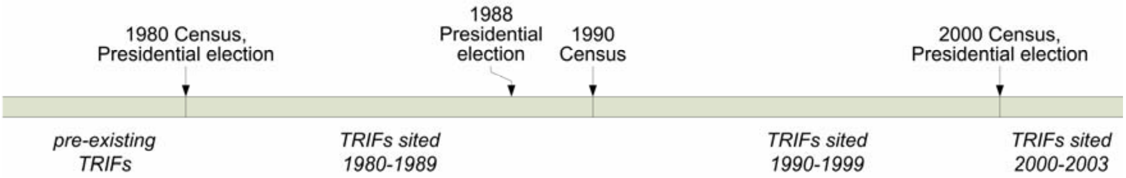

Figure 1: Analysis time-line

Maricopa County is a large county and is the most populous in the state of Arizona. It contains the city of Phoenix, which has grown rapidly over the last several decades to become the fifth-largest city in the US, as well as many other cities, Indian reservations, and unincorporated county lands, allowing for significant variation in terms of population densities, income patterns, ethnicity patterns, land uses, and city-based development policies. Maricopa County is larger than seven US states, and is about one-third the size of Scotland—about the same area as the Highland Council portion of Scotland (The Highland Council, 2006). However, while Scotland's Highland is home to around 200,000 persons (*Ibid*.), Maricopa County is home to over 3.6 million. Though cross-country comparisons are always fraught with potential pitfalls, the size and great variety of the study area increases the chances that its broad findings may be generalized beyond Arizona and the US.

Maricopa County contains 401 separate TRIFs, according to the TRI State Data Files for Arizona (EPA 2003). The US EPA Toxic Release Inventory is described as follows:

> The Toxics Release Inventory (TRI) is a publicly available EPA database that contains information on toxic chemical releases and other waste management activities reported annually by certain covered industry groups as well as federal facilities (EPA 2007).

We were able to obtain location date for 222 of these facilities; these 222 are the TRIFs studied in this analysis.[i] Knowing location date allows analysis of residential characteristics before firm location, ensuring that findings do not indicate the movement of residents into the firm's ambit, but location of the firm among the residents. Interestingly, in these data location dates range from 1912 to 2003, indicating that the known timing problem with EJ research can be severe.[ii] Figure 2 shows the TRIFs located in the Phoenix metropolitan area of Maricopa County, differentiating those with identified start dates from those without. Because a large number of TRI observations were excluded from the analysis for lack of a facility start date, we tested the distribution of these observations for clustering using the GeoDa spatial data analysis software package. We found that this distribution is not statistically significantly different from random.[iii]

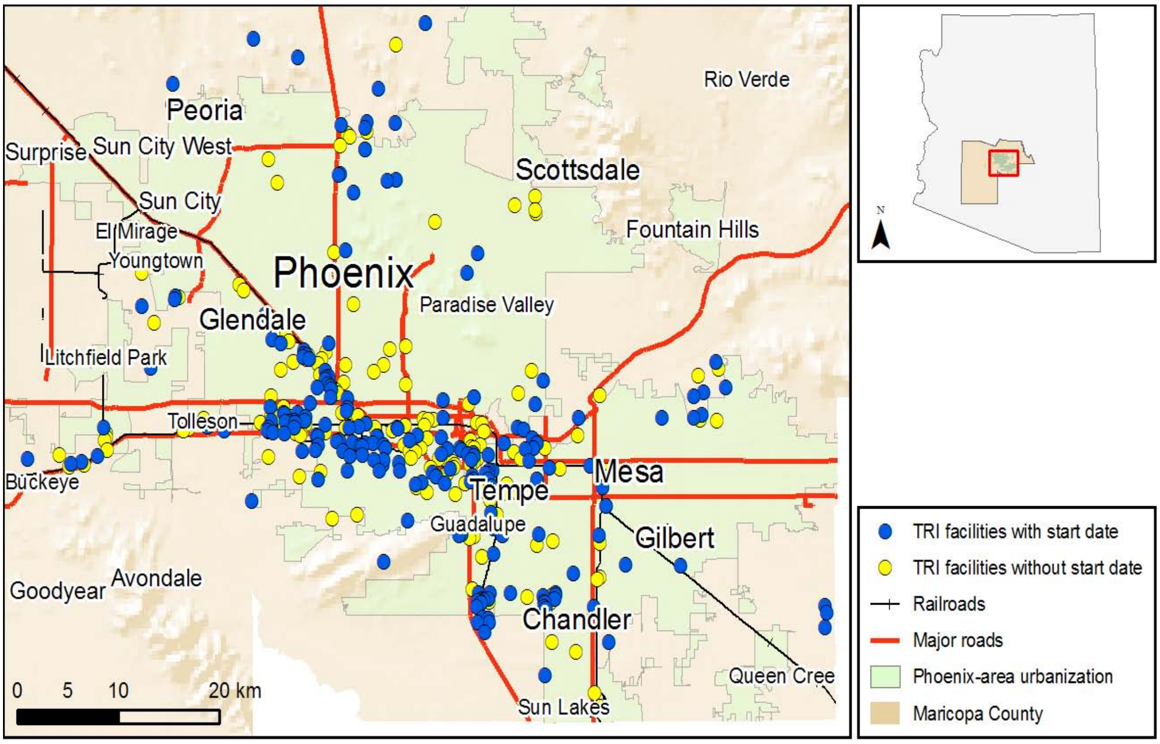

Figure 2: Urbanized Portion of Study Area Including Toxic Release Inventory Facilities With and Without Start Dates

The analysis uses three decades of US Census data at the Census Tract or Census Block Group (CBG) level in a type of pooled dataset. As can be seen in Figure 3, Census units are of widely varying sizes, necessitating controlling for size in some way: for each decade, the dependent variable is the number of TRIFs per square kilometre locating in each Census unit between the Census date and the next decennial Census (throughout, all distance variables are measured in kilometres). Thus, the first set of observations is all Census Tracts included in the 1980 Census, with all TRIFs that located in each 1980 Tract between 1980 and 1989. The next section of the panel uses 1990 CBGs, with all TRIFs/km^2 that located in each CBG between 1990 and 1999. For the 2000 CBGs, we include all TRIFs/km^2 that locate in each CBG between 2000 and 2005. Because of the large number of Census units that have no TRIFs locating in them each decade, we analyze our model using Tobit. In the analysis it is reasonable to consider that we are estimating the underlying probability that a TRIF will choose a given location, where we observe a TRIF's presence only when the probability achieves a certain threshold, but after that we can observe more than one in ratio data, which accords well with assumptions of the Tobit model.

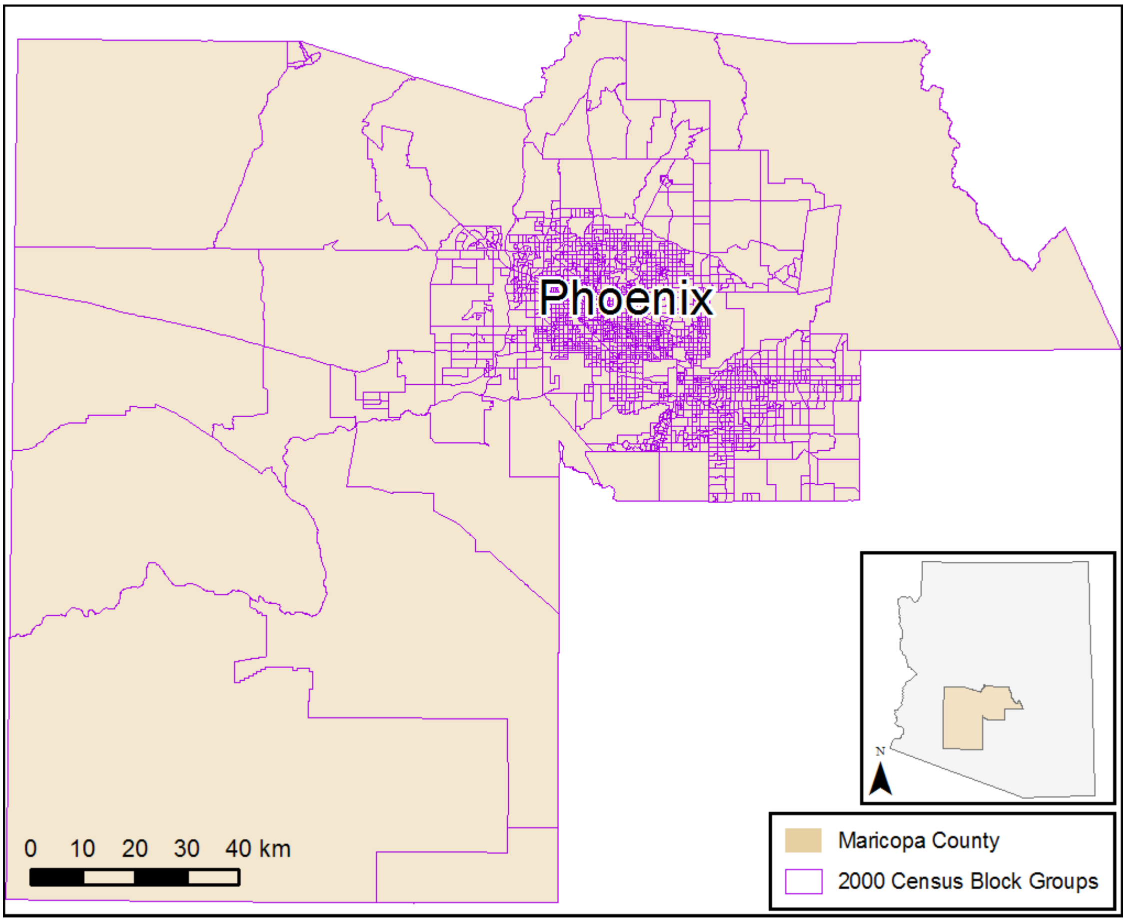

Figure 3: 2000 Census Block Groups of Maricopa County, Arizona, USA

3.1 Independent variables—Race and ethnicity

In order to control for the possibility of environmental discrimination—and to avoid the possibility of excessive aggregation muddying the waters—we measure the percent of each Census unit (Tract or CBG) composed of the following groups which are measured in the US Census and which may be discriminated against in the US: African-Americans (%Black), Hispanics (%Hispanic), Asians (%Asian), and American Indians (%AmerInd). As is usual, "Hispanics" are measured as those "of Hispanic origin," regardless of race.[iv] Because the hypothesis of environmental discrimination is that non-majority-White groups are treated differently from the majority, White-Non-Hispanics are the omitted (reference) group.[v]

3.2 Independent variables—Economic cost

As implied by microeconomic theory, an important determinant of the firm's location decision is economic costs. We include several variables to control for both production costs and potential lawsuit costs. Potential lawsuit costs, which depend on the potential for expensive harm which must be compensated, are a standard cost included in much of the environmental-policy firm-location literature.

Controls for economic costs include a measure of the distance to the nearest railroad (measured from the Census unit centroid), DistanceRR; a measure of the distance to the nearest major road (also measured from the centroid), DistanceMajorRd; measures of land type as a proxy for land cost because land cost was unavailable, measured as %Agriculture, %Urban, %Recreation, and %Water (%Desert, measuring unimproved land which should be a cheap land type, is the omitted group); and variables measuring what percent of the Census unit is contained within each of the 25 cities or five reservations that are located in the county (percent contained outside of any city or reservatioin is the omitted category). Cities and reservations take different policy approaches to development, zoning, and firm location, and the city and reservation measures are intended to control for this element of firm costs. However, though the analysis has an "n" of 4184, Tobit may have estimation difficulty when the number of independent variables is close to the number of positive observations. Since we have only 95 positive observations (95 Census units with one or more newly locating TRIF between 1980 and 2005), we also estimate the Tobit without the city and reservation location controls.

To control for potential lawsuit costs, we include a measure of population density, People/km^2; the number of persons in the Census unit, TotalPop; the average household income, MeanHHY; and the average house value; MeanHouseValue. The greater the population density, the greater the likelihood of harm requiring compensation. Controlling for density, the larger the number of people, the larger the required compensation is likely to be. The richer the average resident and the more expensive the average house, the higher the likely compensation per incident.

In addition, we include a measure of all TRIFs in place in each Census unit before the new TRIFs locating each decade, ExistTRIFs. We include this to control for two possibilities. First, we may not observe some attributes that make a location particularly suitable for TRIFs. If so, then the presence of existing TRIFs should increase the likelihood of a new TRIF locating there. Alternatively, the presence of TRIFs could sensitize residents of a Census unit to additional TRIFs (as suggested by Whittaker, et al., 2005), making the political costs higher for a new TRIF, and decreasing the likelihood of new TRIFs locating in that area.

3.3 Independent variables—Political and collective action

An insight of Hamilton's (1995) model is the explicit inclusion of costs to the firm posed by effective collective action of residents. Hamilton (1995) controls for this component using voting rates, and we also measure this using percent of adults voting in the closest preceding US Presidential race for each decade ('80 for the 1980 Census, '88 for 1990, and '00 for 2000, as shown in Figure 1) with the variable %VotePres. However, his work inspired us to go beyond this fairly basic measure of what is, after all, individual political engagement rather than collective action (Sobotta, 2002), and to use a public choice perspective to consider what other factors should impact collective action.

When approached in this way, a public-choice perspective implies that a strategic firm would choose to locate on political boundaries. For example, by locating on a boundary between two cities rather than in the middle of a city, a strategic firm could disenfranchise roughly half of affected residents. To test whether firms strategically take advantage of this opportunity to reduce the effectiveness of collective action, we measure the distance from each Census unit (based on its centroid) to the closest political boundary with the variable BoundaryDistance. Political boundaries can include county borders and reservations in addition to cities.

We also sought to measure factors that should change the likelihood that residents will engage in political or collective action. Much literature argues, for example, that homeowners, who have a higher stake in the effects of disamenities, are more likely to engage in political action against disamenity location in their neighbourhoods, so we measure the percentage of housing units that are owner-occupied with %HouseOwners.

Poverty and low educational attainment should generally decrease the ability effectively to engage in political action, so we control for these factors through the use of %LessThanHS and %Less150Poverty, measuring the percent of each Census unit's residents that have attained less than a high-school diploma, and the percent of residents living at less than 150% of the poverty line.[vi]

In Maricopa County, the dominant racial/ethnic minority group is composed of Hispanics, many of whom are recent immigrants who do not speak English or speak it only poorly. It seems that inability to speak the dominant language of government in the area would greatly decrease the ability to engage effectively in political action to stave off unwanted development in one's neighbourhood. So, we measure the percent of those in an area whose primary language is Spanish and who speak English poorly or not at all, %PrimarySpanish.

Demographic analysis indicates that older adults are more likely to engage in political action (see, for example, Centre for Research and Information on Canada, 2003). On the other hand, underage children are much less likely than normal to engage in political action (at least in part because they do not vote). Therefore, we measure %Age55-74 and %Age0-15, with the assumption that Census units that have more adults between the ages of 55 and 74 will (all else equal) have more likelihood for successful political action, whereas those with significant numbers of underage people will have less. We stopped measuring children at 15 because in Arizona 16-year-olds can drive and will be able to vote in two years, meaning that perhaps they can have more political influence than younger children.

Lastly, the public choice literature on collective action devotes significant attention to issues of homogeneity. Though there is some disagreement, much analysis finds that homogeneity increases the likelihood of successful collective action to provide public goods. In this vein, it is interesting to note that, contrary to their initial hypothesis, Sobotta et al. (2007) found that areas with high percentages of Spanish-only speakers actually had a reduced likelihood of being impacted by airport noise, controlling for other factors including Hispanic ethnicity and income. To allow for the possibility that increased homogeneity enables successful collective action, we included squares of the following variables: %Hispanic, %Black, %AmerInd, %Asian, and %PrimarySpanish. Inclusion of squared terms allows for the effect of variables to "flip," with their impact positive at some levels, but converting to negative at other levels. For example, if speaking primarily Spanish is truly a disadvantage in the political system, but having many neighbours that speak primarily Spanish aids in overcoming the collective action problem, then we would expect to estimate a positive coefficient on %PrimarySpanish while estimating a negative sign for $(\%PrimarySpanish)^2$. This implies a functional form for which increases in Spanish-speakers will increase the likelihood of a TRIF's location up to a point, but decrease that likelihood after there are "enough" Spanish-speakers to provide collective-action-aiding homogeneity.

3.4 The complete model

As described above, the conceptual model to be estimated is the following:

(1)

$$
\begin{aligned}
\mathrm{TRIF/km^2} = {} & \beta_0 + \beta_1\mathit{\%Black} + \beta_2\mathit{\%Hispanic} + \beta_3\mathit{\%Asian} + \beta_4\mathit{\%Amerind} - \beta_5\mathit{DistanceRR} \\
& - \beta_6\mathit{DistanceMajorRd} - \beta_7\mathit{\%Agriculture} - \beta_8\mathit{\%Urban} - \beta_9\mathit{\%Recreation} - \\
& \beta_{10}\mathit{\%Water} - \beta_{11}\mathit{People/km^2} - \beta_{12}\mathit{TotalPop} - \beta_{13}\mathit{MeanHHY} - \\
& \beta_{14}\mathit{MeanHouseValue} + \beta_{15}\mathit{ExistTRIFs/km^2} - \beta_{16}\mathit{\%VotePres} - \\
& \beta_{17}\mathit{BoundaryDistance} - \beta_{18}\mathit{\%HouseOwners} + \beta_{19}\mathit{\%LessThanHS} + \\
& \beta_{20}\mathit{\%Less150Poverty} + \beta_{21}\mathit{\%PrimarySpanish} - \beta_{22}\mathit{\%Age55\text{-}74} + \\
& \beta_{23}\mathit{\%Age0\text{-}15} - \beta_{24}\mathit{(\%Black)^2} - \beta_{25}\mathit{(\%Hispanic)^2} - \beta_{26}\mathit{(\%Asian)^2} - \\
& \beta_{27}\mathit{(\%Amerind)^2} - \beta_{28}\mathit{(\%PrimarySpanish)^2} + \beta_{29}\mathit{1980} + [\text{25 City and 5} \\
& \text{Reservation indicators}] + \varepsilon
\end{aligned}
$$

Where

TRIF/km² is the geographic density of new TRIFs in each Census unit (number of new TRIFs divided by the size of the Census unit in square kilometres)

%Black is the percent of each Census unit's residents who describe themselves as Black or African-American

%Hispanic is the percent of each Census unit's residents who describe themselves as of Hispanic ethnicity

%Asian is the percent of each Census unit's residents who describe themselves as Asian

%Amerind is the percent of each Census unit's residents who describe themselves as American Indian

DistanceRR is the distance from each Census unit's centroid to the nearest railroad (in kilometres)

DistanceMajorRoad is the distance from each Census unit's centroid to the nearest major road

%Agriculture is the percent of each Census unit that is agricultural land

%Urban is the percent of each Census unit that is urbanized

%Recreation is the percent of each Census unit that is recreational land

%Water is the percent of each Census unit that is water
People/km^2 is the population density of each Census unit
TotalPop is the total population of each Census unit
MeanHHY is the mean household income of the households in each Census unit (in constant 2000 dollars)
MeanHouseValue is the mean value of single-family houses (not apartments/flats) in each Census unit (in constant 2000 dollars)
ExistTRIFs/km^2 is the density of TRIFs located in a Census unit before the current decade
%VotePres is the percent of those members of a Census unit who are old enough to vote (18 and older) who voted in the most recent Presidential election preceding the most recent Census
BoundaryDistance is the distance from each TRIF to the closest political boundary (whether county, city, or reservation)
%HouseOwners is the percentage of each Census unit who live in housing they own (as opposed to housing they rent)
%LessThanHS is the percent of each Census unit's residents over the age of 18 (for the 1980 and 1990 Censuses; over 25 for the 2000 Census) who have not graduated from high school (in the US, high school is the last mandatory level of education)
%Less150Poverty is the percent of each Census unit's residents living at 150% or below of the US Federal "poverty line" (i.e., the annual household income below which one is considered to be in poverty)
%PrimarySpanish is the percent of each Census unit's residents who speak Spanish and speak English poorly or not at all
%Age55-74 is the percent of each Census unit's residents who are between the ages of 55 and 74
%Age0-15 is the percent of each Census unit's residents who are between the ages of 0 and 15
1980 is a dummy variable taking on a 1 if the Census year is 1980, 0 otherwise, included to control for the fact that 1980 data are observed at the Census tract level while 1990 and 2000 are observed at the level of the CBGs
25 City and 5 Reservation indicators are 30 dummy variables taking on a value indicating what percentage of each Census unit is contained within each of the 25 cities and 5 Indian reservations in Maricopa County (what percent is contained in the county is the omitted group)
β_0 through β_{29} are regression coefficients to be estimated and
ε is the stochastic error

Generally, the signs above are as predicted by the hypotheses, discussed above, leading to each variable's inclusion. In brief, under an environmental discrimination hypothesis, β_1 through β_4 should be positive as increases in the percentage of a Census unit's residents who are ethnic or racial minorities will increase the likelihood of a TRIF locating there. Since %Desert is the omitted category of land-use-type, β_7 and β_8 are expected to have negative coefficient estimates because Agricultural and

Urban lands should be more expensive than unimproved desert land; also, it may be very costly to locate in either water or recreation areas. β_{15} is shown with a positive sign though, as mentioned above, different hypotheses lead to different sign predictions; we consider the cost hypothesis more likely than the sensitization hypothesis, but estimation will show. Please note the inclusion of the dummy variable 1980, included because 1980 geographies are Tracts but 1990 and 2000 geographies are CBGs. We lack sign hypotheses for the coefficients of the 25 city and five reservation dummy variables, because we believe their signs will depend on each locale's attitude toward economic development, with some locales seeking new firms even of this type and others repulsing them.

Table 1 shows descriptive statistics for the variables used in the model except for the city and reservation indicators (shown in Appendix A Table 1A). Note that in only 95 of 4184 observations is at least one new TRIF located, making the mean of the dependent variable particularly small, at approximately 0.012. This is important information when interpreting the estimation results.

Table 1: Descriptive Statistics of Analyzed 1980, 1990 and 2000 Maricopa County Census Units

Variables	Mean	Std Dev	Minimum	Maximum
DV: TRIF/km2	0.012	0.117	0.000	3.090
%Black	3.501	6.944	0.000	91.757
%Hispanic	20.156	22.519	0.000	100.000
%Asian	1.725	2.797	0.000	33.668
%AmerInd	1.767	5.497	0.000	96.259
DistanceRR	6.237	6.285	0.002	50.108
DistanceMajorRd	2.559	2.592	0.000	32.310
%Agriculture	5.468	16.276	0.000	100.000
%Urban	83.837	25.135	0.000	100.000
%Recreation	2.363	7.274	0.000	93.914
%Water	0.538	2.339	0.000	33.116
%Desert	7.791	17.066	0.000	99.831
People/km2	2,014.9	1,457.9	0.072	21,858.3
TotalPop	1,569.7	1,317.0	4.0	14,658.0
MeanHHY	57,297.4	31,416.6	0.0	345,957.0
MeanHouseValue	120,271.9	88,124.6	0.0	1,250,000.0
ExistTRIFs/km2	0.042	0.264	0.000	3.153
%VotePres	41.787	17.159	0.000	219.281
BoundaryDist	2.182	2.101	0.000	28.710
%HouseOwners	64.938	26.844	0.508	100.000
%LessThanHS	20.737	17.649	0.000	100.000
%Less150Pov	21.025	18.024	0.000	100.000
%PrimarySpanish	4.660	8.462	0.000	91.667
%Age55-74	15.953	13.055	0.000	100.000
%Age0-15	23.157	10.379	0.000	60.000

Note: All Census units without population are omitted. Included N = 4184

The case of Census Tracts and CBGs that have no populations or such small populations that data on race and ethnicity are not reported presents an awkward analysis puzzle. In our dataset there are 11 Tracts or CBGs out of the total 4344 original observations which must be omitted because there is no population, but another 149 that must be omitted because some variables are missing. Including observations with no population would make the meaning of zero in, for example, the race measures non-continuous: 0 observed for the percent Hispanic could mean either no Hispanics in that tract—which should decrease the likelihood of a TRIF, all else equal, under an environmental discrimination hypothesis—or else no population at all—which should, under cost hypotheses, increase the likelihood of a TRIF, all else equal. Out of 4344, 160 is too small a number to allow for including measures of all groups (i.e., adding in the omitted groups), because the matrix would still be virtually singular with the percent variables summing to 100% in all but 3.7% of the cases. We also considered measuring variables that are currently measured as percents as raw numbers—for example, measuring the numbers of Hispanics, African-Americans, White, Asians, and American Indians in each area—but this can only make sense with the inclusion of total population, in which case those variables would be perfectly collinear with the total population variable. Therefore, very-small-population observations must be omitted from the analysis, yet that too seems problematic for, from several perspectives, it would be best of all to locate TRIFs—and other disamenity-bearing facilities—where there is no human population. Unfortunately, though only 3.5% of CBGs (and 1.8% of the repeated geography of the county) are excluded, 10.5% of newly locating TRIFs are excluded from the analysis, indicating that some TRIFs are, in fact, locating in areas that may be ideal from the perspective of human impacts. This represents a weakness of our analysis which we have not yet figured out how to solve. However, many of the Census units omitted due to missing data are large, with the population of the average omitted CBG at around 500 (over 3000 for the average omitted Tract), which should decrease the extent of this problem. Also, we think this may be an unidentified weakness in much of the EJ literature which relies on Census data.

As described in this section, the model to be estimated is not spare. Its very comprehensiveness, combined with its clear matching of existing residents to new disamenity locations, makes it a strong test of the hypothesis of environmental discrimination (at least within fairly populous Census units). If, carefully controlling for factors that should affect standard firm economic costs, and carefully controlling for factors that should affect political costs—and within a setting where we can carefully match location decisions to the population at the time of location—we find evidence of race or ethnicity increasing the likelihood of TRIF location, then this provides strong evidence environmental discrimination exists at least sometimes. If not, we would find support for those who argue that evidence of environmental discrimination may simply fail appropriately to measure all elements of economic rationality.

4 RESULTS

Table 2 shows the results for the Tobit analysis omitting the city and reservation location indicator variables, with the results of the Tobit analysis including them shown in Appendix A, Table 2A. From comparing the two sets of results, we conclude that the location indicators are not necessary to include in this case, and we focus on the results from the second (shorter) Tobit. None of the location variables is statistically significant at even the 90% level under a two-tailed test, and the Tobit procedure fails to converge when these 30 location indicators are included. Omitting them, Tobit converges in only 8 iterations, and most signs, magnitudes, and *t*s are essentially the same between the two models. We infer from this that cities and reservations are not engaging in significant policies either to attract or to repel the new TRIFs in our study.

Table 2: Tobit Model Analytic Results, Excluding City and Reservation Indicators

Variable	Parameter Estimate	Average Effect of a 10-Unit Change (10[dP/dX])	10-Unit Effect as Percent Change from Mean	t-statistic
Discrimination				
%Black	-0.0014	-0.0000	-3.8%	-0.08
%Hispanic	0.0140	0.0004	37.7%	1.06
%Asian	0.1566	0.0049	421.5%	2.12*
%AmerInd	0.0160	0.0005	43.0%	0.64
Economic Costs				
DistanceRR	-0.0052	-0.0002	-13.9%	-0.38
DistanceMajorRd	-0.0399	-0.0012	-107.3%	-1.31+
%Agriculture	-0.0038	-0.0001	-10.2%	-0.86
%Urban	0.0026	0.0001	7.0%	0.67
%Recreation	-0.0301	-0.0009	-81.1%	-1.58+
%Water	0.0125	0.0004	33.7%	0.60
ExistTRIFs	0.5204	0.0161	1400.8%	3.60*
Legal Costs				
People/km^2	0.0008	-0.0000	-2.1%	-6.13*
TotalPop	0.0001	0.0000	0.3%	2.12~
MeanHHY (000s)	0.0052	0.0002	14.1%	1.30+
MeanHouseVal (000s)	-0.0023	-0.0001	-6.2%	-1.44+
Collective Action				
%VotePres	-0.0121	-0.0004	-32.5%	-1.85*
BoundaryDistance	0.0048	0.0001	12.9%	0.17
%HouseOwners	-0.0053	-0.0002	-14.2%	-1.38+
%LessThanHS	0.0055	0.0002	14.7%	0.73
%Less150Poverty	0.0002	0.0000	0.6%	0.04
%PrimarySpanish	0.0243	0.0008	65.3%	0.93
%Age55-74	0.0047	0.0001	12.7%	0.60
%Age0-15	0.0175	0.0005	47.2%	1.69*
%PrimarySpanish^2	-0.0005	-0.0000	-1.4%	-0.74
%Black^2	-0.0001	-0.0000	-0.3%	-0.34
%Hispanic^2	-0.0002	-0.0000	-0.6%	-1.65*
%Asian^2	-0.0126	-0.0004	-33.8%	-1.52+
%AmerInd^2	-0.0003	-0.0000	-0.7%	-0.84

(Table 2 continues next page)

Table 2: Tobit Model Analytic Results, Excluding City and Reservation Indicators (continued)

Variable	Parameter Estimate	Average Effect of a 10-Unit Change (10[dP/dX])	10-Unit Effect as Percent Change from Mean	t-statistic
Other Controls				
Yr1980	0.6188	-0.0192	-1665.6%	2.49*
Intercept	-2.0296	0.0629		-3.20*
Model Fit				
Log of Likelihood Function	-364.09			

Note: Standard errors computed using Newton (analytic second derivatives)
* statistically significant, p<0.05, one-tailed test
~ statistically significant, p<0.05, two-tailed test
+ statistically significant, p<0.10, one-tailed test

4.1 Race and Ethnicity Variables

Noting that we have controlled for many factors that are correlated with race and ethnicity, including income levels, population densities, and education levels, one of our most important findings is that the results of our analysis indicate environmental discrimination. The signs are positive for all races and ethnicities measured except for %Black, and are statistically significant for %Asian, giving us confidence in the magnitude of its coefficient estimate. Further, %Asian is estimated to have the largest effect of any variable in the model except for ExistTRIFs (and the uninteresting 1980 dummy).

Coefficient magnitudes are difficult to interpret in this analysis because of both the use of the Tobit model and the rarity of the phenomenon studied. Consider again the average value of the dependent variable (DV), which is 0.0115 per square kilometre; slightly more than 2% of the observations are non-zero. Thus, though coefficient magnitudes look small, they may imply important effects. In order to help interpret the Tobit coefficients, we provide two non-standard statistics.[vii] The first non-standard statistic is 10 times the dP/dX (labelled as "Average Effect of a 10-Unit Change" on the Table). The dP/dX is the average effect of a marginal change in each independent variable on the probability that the dependent variable will be positive—over the various possible combinations of independent variables.[viii] Use of the dP/dX statistic takes into account the interactive nature of the Tobit model without the necessity of choosing specific values for the other independent variables when interpreting the effect of any one.

The second non-standard statistic we report tells the average predicted effect of a 10-unit change in the independent variable on the probability that the dependent variable will be positive in terms of the percent increase or decrease from the mean of the DV. For variables measured as percents, such as the race and ethnicity variables, a 10-unit increase is an increase of 10 percentage points (say, from 6% to 16%). Looking at the results for %Asian alone, we see that its average effect for a 10-percentage-point change is 0.05, which looks very small but results in more than a 450% increase (from the mean of the dependent variable) in the predicted probability that a new TRIF will locate in a Census unit.

4.2 Collective action variables

Though some specific hypotheses are not supported, overall the results indicate the importance of potential collective action in fending off TRIFs. Of the 13 variables included to control for potential collective action, all but two have estimated coefficients of the predicted signs. The percent of those voting for President in the most recent election (%VotePres) is of the correct sign to support the importance of collective action and is statistically significant, as is %HouseOwners (at the 90% level). %LessThanHS, %Age0-15, %Less150Poverty, and %SpanishSpeakers are also of the correct signs, though we have less confidence in these findings. Further, all five squared terms are of the correct sign, and two are statistically significant, giving support to the collective-action value of homogeneity.

BoundaryDistance and %Age55-74 have unexpected signs (though neither are statistically significant). The first indicates that TRI firms are not strategic with respect to their ability to split collective action by jurisdictions, or perhaps that jurisdictions work well together in this area.

The unexpected sign for %Age55-74 is potentially the more important. Though we have less confidence in the estimated signs for this variable, considering it in conjunction with %Age0-15, the results suggest that TRIFs are more likely to locate both where there are higher percentages of children and where there are higher percentages of older adults. Physiological research indicates that these two populations are more susceptible to the harm caused by pollutants than are people between these age groups (Liu 2001). To the extent these findings are true in this population and/or are generalizeable, they mean that the TRIF location procedure causes more harm than it would if TRIFs were located more evenly with respect to age.[ix]

Interestingly, though the sign of %150Poverty is as predicted, its magnitude indicates that, controlling for many other factors associated with poverty, simply being poor does not materially increase the likelihood that TRIFs will locate in one's area. This may demonstrate an important failing of studies without the ability precisely to match disamenity location time to the population, for often other studies find the importance of poverty (e.g. Brooks & Sethi 1997, and others referenced above).

4.3 Economic and compensation cost variables

In general, the estimates for the cost factors are as expected. Increasing the distance to the railroad and to major roads is estimated to decrease the likelihood of TRIF location. The presence of existing TRIFs is estimated greatly to increase the likelihood of another one locating there, suggesting that this variable is picking up some otherwise-unaccounted-for cost or benefit of certain Census units. Increased population density and increased housing values are estimated to decrease the likelihood of TRIF location. Also, the land-use variables indicate, as expected, that agricultural land is more expensive than desert, and it is far most costly to locate where there is significant recreational land.

However, the coefficients for %Urban and %Water are of unexpected signs. Most surprising, total tract population and mean household income are, quite contrary to expectation, both estimated to increase the likelihood of TRIF location, and TotalPop's coefficient estimate is statistically significant at the 99% level under a two-tailed test, with MeanHHY being statistically significant at the 90% level, two-tailed. Given these high t-values, it is difficult to dismiss these as accidents (though of course they still may be), though the magnitude of their estimated effects is small. If we take these sign estimates seriously, perhaps they—along with %Urban—indicate the presence of potential customers of the TRIF companies themselves, a benefit to TRIF location that outweighs increased land cost and potential increased legal compensation costs. An alternative explanation would be that TRIFs select densely populated areas because their potential employees live there, but Peck & Godchaux (2003) indicates this is unlikely in the Phoenix metropolitan region.

4.4 Error Considerations

As pointed out by a reviewer, Tobit is biased when the errors are heteroskedastic (see, e.g., Arabmazar & Schmidt 1982 and work referenced therein). In the analysis presented here, the most likely culprit for heteroskedastic errors would be the size of the geography itself, with larger Census units more likely to exhibit greater error variance than smaller. However, we do not expect heteroskedastic errors in this case because the dependent variable is normalized by the size of the Census units, and examination of a plot of the residuals versus area (in square kilometres) indicates no such pattern. However, in order to insure that we do not make much of findings of which we cannot be confident, we re-ran the model with Eicker-White standard errors, which are robust to heteroskedasticity.[x] For Table 2, in every case where we have flagged an estimate as being statistically significant, the Eicker-White standard errors were *smaller* than the Newton standard errors (the default SE estimator in TSP's Tobit procedure), resulting in *larger* t-statistics and *more* confidence in the estimates. Because we do not believe the errors are heteroskedastic, we retain the t-statistics based on Newton, but this extra analytic step increases our confidence in the usability of our results.

As a further test of robustness, we re-ran our model using a Poisson regression, which is ideal for count data with many zero observations. The results are only reinforcing. In fact, the few anti-prior signs (that were not statistically significant in the Tobit) change to match our expectations in the Poisson model. Main findings regarding Asians, young age, and other economic and political factors remain, providing evidence that our analytic results are not a mere function of our specification choice.[xi]

4.5 Overall

Overall, 3 of 4 signs support hypotheses of environmental discrimination, 7 of 11 support legal and economic cost theories, and 11 of 13 support hypotheses of the importance of potential collective action. Together, these suggest—as we would expect—that the firm takes into account many factors in deciding where to locate. Other than the coefficient for the 1980 dummy variable, by far the largest estimated magnitudes for a 10-unit change are for the presence of existing TRIFs and the percent of the Census unit population that is Asian. Both of these factors are also statistically significant, so the results strongly suggest the importance of economic factors—and also the presence of environmental discrimination.

Fully to understand the effect of the percent of a Census unit that is made up of residents who identify themselves as Asian, however, we should consider the combined effect of %Asian and $\%Asian^2$. Taken alone, the effect of %Asian indicates the presence of environmental injustice founded in ethnicity. Taken alone, the effect of $\%Asian^2$ indicates the effect of homogeneity in enhancing collective action. Taken together, the coefficients of these two variables can indicate the net effects on different Census units of their Asian demographic makeup.

As estimated, on average the net (marginal) effect of a 1-unit increase in %Asian is equal to

(2)

$$0.00049 + 2(-0.00004)(\%Asian) = 0.00049 - 0.00008(\%Asian)$$

As shown in Table 1, the average %Asian is a very low 1.7, but some Census units have as many as 34 percent Asian residents. If 2 percent of residents are Asian, the average effect of a 1-unit (1 percentage-point) increase in %Asian is estimated to be 0.00027—or, in terms comparable to those in Table 2, a 10-unit increase at this level is estimated to cause about a 232% increase (from the mean) in the likelihood of a new TRIF locating in a given Census unit. Of course, the implication of a squared term that has a coefficient of a sign opposite to that term's coefficient in the level is that the estimated sign of the effect may change from positive to negative. Here, the estimated average effect of an increase becomes zero once %Asian reaches 6.1 percent. Therefore, according to the estimated net effects of Asian composition, Census units with Asians are targeted by TRIFs. Asians living in Census units with few others are disadvantaged. Yet, in the event that Asians cluster together so as to become more than 6 percent of the tract, their homogeneity allows them to exercise collective action and fend off TRIFs.

Figure 4 shows the distribution of Asians in Maricopa County in 2000.

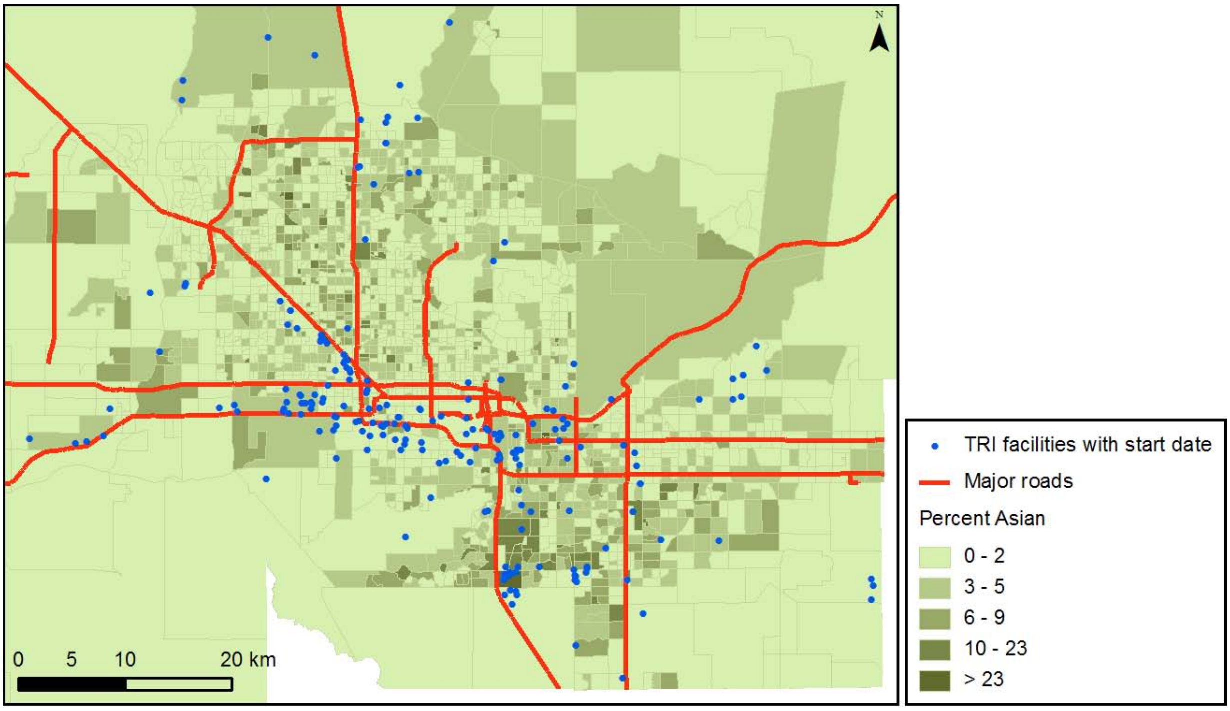

Figure 4: Distribution of Asians by 2000 Census Block Group, Urbanized Portion of Study Area

As shown in the figure, the majority of CBGs have fewer than 2 percent Asian residents. However, the next most common composition is from 3-5 percent Asian. Taking into account other factors, particularly economic factors, these tracts are particularly at risk for new TRIFs.

5 CONCLUSIONS

In spite of decades of research into the issue of environmental justice, many still question the extent to which environmental disamenities are disproportionately co-located with racial and ethnic minorities even after taking into account other factors that should matter. Many of the reasons for continued disbelief in findings of environmental discrimination boil down to methodological criticism of earlier research (see, e.g., discussion in Liu 2001, Hamilton 1995, Bowman 1997, and Anderton, et al. 1994).

We hope this study may put some methodological concerns to rest, and may assist in the eventual development of a tool-kit of acceptable methods for understanding the many facets of sustainability. First, we use a method in which we match new TRIF locations to populations that were there before the TRIFs located. Second, we take into account traditional economic cost factors, potential legal compensation cost factors, and potential collective action factors. The importance of all of these is supported, indicating that attempts to understand whether environmental injustice exists within a specific urban setting requires controlling for all these categories.

Yet, we still find evidence of environmental discrimination, with the evidence of discrimination against Asians particularly strong. Further, the estimated effects of increasing percents of Asians, Hispanics, and American Indians is much higher than the estimated effect of increasing percents of residents in poverty, though some researchers have assumed that correlational findings of disproportionate co-location of minority groups and environmental disamenities are really findings of the importance of poverty.

The finding with respect to Asians—which we did not expect—motivates us to make another methodological critique: we urge researchers not to aggregate several minority groups that may be viewed quite differently by decision-makers. Along this vein, it is possible that environmental discrimination may occur differently–or not occur at all—depending on the disamenity and the region of the world. For one thing, the decision-makers can be quite different. In the case studied here, over 200 location decisions are made by individual private firms and governmental entities. In the case of aviation noise analyzed by Sobotta et al. (2007), decisions were made by a single quasi-public organization. Different people may discriminate against different groups; different organizations, industries, and cities will have their own cultures. Therefore, demonstrating environmental discrimination in one industry or setting indicates that it exists. Showing no evidence of environmental discrimination in another industry or setting may show that it does not exist *there*, but does not necessarily invalidate other findings.

We consider the analysis presented here to provide a strong test of the possibility of environmental discrimination. Not only are we able to match new TRIF locations to their extant populations, but we study TRIF location over three recent decades in a rapidly growing county that exhibits significant diversity of many types, including unimproved lands, agricultural lands, cities of widely varying sizes, and Indian reservations. It is no surprise economic factors matter in TRIF location decisions. It is little surprise that collective action factors matter to TRIF location. But it is sad, surprising, and important that race and ethnicity matter to this process.

It is further important that age matters in TRIF location. Within the context of sustainability, the targeting of neighbourhoods with high percentages of children is particularly problematic, for sustainability by its very nature focuses on the future, and children are the future of our cities.

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APPENDIX A: Tables of Descriptive Statistics for City and Reservation Variables, and Tobit Output for Analysis Including These Variables

Table 1A: Descriptive Statistics for 25 City and 5 Reservation Indicators

Community	Mean, %	Std Dev	Minimum, %	Maximum, %
PctApacheJ	0.010	0.459	0	25
PctAvondal	0.642	7.400	0	100
PctBuckeye	0.142	2.796	0	73
PctCarefre	0.045	1.636	0	77
PctCaveCre	0.082	2.352	0	85
PctChandle	3.799	18.864	0	100
PctElMirag	0.145	3.380	0	100
PctFountai	0.242	4.752	0	100
PctGilaBen	0.001	0.038	0	2
PctGilbert	1.482	11.478	0	100
PctGlendal	7.662	26.324	0	100
PctGoodyea	0.436	6.051	0	99
PctGuadalu	0.101	3.042	0	99
PctLitchfi	0.058	2.182	0	97
PctMesa	8.548	27.462	0	100
PctParadis	0.471	6.485	0	100
PctPeoria	3.193	16.926	0	100
PctPhoenix	46.579	49.540	0	100
PctQueenCr	0.089	2.389	0	96
PctScottsd	5.010	21.562	0	100
PctSurpris	0.516	6.619	0	100
PctTempe	4.925	21.417	0	100
PctTolleso	0.082	2.604	0	100
PctWickenb	0.143	3.357	0	97
PctYoungto	0.105	2.983	0	96
PctFortMcD	0.050	2.173	0	99
PctSaltRiv	0.130	3.360	0	100
PctGilaBIR	0.000	0.002	0	0
PctGilaRiv	0.104	3.088	0	100
PctTohonoO	0.002	0.126	0	8

Table 2A: Tobit Results Including 25 City and 5 Reservation Indicators (Table continues on next page)

Variable	Parameter Estimate	Average Effect of a 10-Unit Change (10[dP/dX])	10-Unit Effect as Percent Change From Mean	t-statistic
Discrimination				
%Black	-0.0004	-0.0001	-1.1%	-0.02
%Hispanic	0.0110	0.0033	28.9%	0.82
%Asian	0.1740	0.0529	459.3%	2.26*
%AmerInd	0.0184	0.0056	48.5%	0.65
Economic Costs				
DistanceRR	-0.0025	-0.0008	-6.6%	-0.16
DistanceMajorRd	-0.0392	-0.0119	-103.5%	-1.16
%Agriculture	-0.0033	-0.0010	-8.8%	-0.70
%Urban	0.0015	0.0005	4.0%	0.34
%Recreation	-0.0396	-0.0120	-104.4%	-1.78*
%Water	0.0094	0.0029	24.8%	0.42
ExistTRIFs	0.4757	0.1445	1,255.5%	3.29*
Legal Costs				
People/km^2	-0.0008	-0.0002	-2.1%	-6.11*
TotalPop	0.0001	0.0000	0.3%	2.18~
MeanHHY (000s)	0.0035	0.0011	9.3%	0.82
MeanHouseVal (000s)	-0.0023	-0.0007	-6.1%	-1.42+
Collective Action				
%VotePres	-0.0121	-0.0037	-31.9%	-1.77*
BoundaryDistance	0.0114	0.0035	30.2%	0.39
%HouseOwners	-0.0052	-0.0016	-13.8%	-1.33+
%LessThanHS	0.0118	0.0036	31.1%	1.45+
%Less150Poverty	-0.0026	-0.0008	-6.9%	-0.36
%PrimarySpanish	0.0291	0.0088	76.7%	1.07
%Age55-74	0.0066	0.0020	17.4%	0.80
%Age0-15	0.0173	0.0053	45.7%	1.63+
%PrimarySpanish^2	-0.0005	-0.0001	-1.3%	-0.65*
%Black^2	-0.0001	-0.0000	-0.3%	-0.38
%Hispanic^2	-0.0002	-0.0001	-0.6%	-1.55+
%Asian^2	-0.0149	-0.0045	-39.3%	-1.72*
%AmerInd^2	-0.0004	-0.0001	-1.0%	-1.06
Other Controls				
Yr1980	0.3461	0.1052	913.5%	0.99
PctApacheJ	-0.3228	-0.0981	-851.9%	0.00
PctAvondal	0.0016	0.0005	4.2%	0.24
PctBuckeye	-0.0354	-0.0108	-93.4%	-0.83
PctCarefre	-38.2471	-11.6220	==	-0.04
PctCaveCre	-0.0014	-0.0004	-3.6%	-0.01
PctChandle	0.0032	0.0010	8.4%	0.74

Variable	Parameter Estimate	Average Effect of a 10-Unit Change (10[dP/dX])	10-Unit Effect as Percent Change From Mean	t-statistic
PctElMirag	-22.2767	-6.7691	==	-0.05
PctFountai	-4.2809	-1.3008	==	-0.01
PctGilaBen	-1.8871	-0.5734	==	-0.39
PctGilbert	-0.0279	-0.0085	-73.5%	-0.61
PctGlendal	0.0016	0.0005	4.3%	0.41
PctGoodyea	-0.0009	-0.0003	-2.3%	-0.12
PctGuadalu	-0.0019	-0.0006	-4.9%	-0.07
PctLitchfi	-88.8365	-26.9944	==	-0.07
PctMesa	0.0019	0.0006	4.9%	0.49
PctParadis	0.0123	0.0037	32.5%	1.24
PctPeoria	-0.0078	-0.0024	-20.7%	-1.05
PctPhoenix	-0.0029	-0.0009	-7.6%	-0.88
PctQueenCr	-0.0255	-0.0078	-67.4%	-0.31
PctScottsd	-0.0200	-0.0061	-52.8%	-0.67
PctSurpris	-66.1919	-20.1134	==	-0.14
PctTempe	0.0043	0.0013	11.4%	0.98
PctTolleso	-0.0205	-0.0062	-54.2%	-0.42
PctWickenb	-8.6678	-2.6338	==	-0.03
PctYoungto	-23.8614	-7.2507	==	-0.09
PctFortMcD	-412.9710	-125.4876	==	-0.09
PctSaltRiv	-0.0109	-0.0033	-28.8%	-0.49
PctGilaBIR	57.9160	17.5987	==	0.67
PctGilaRiv	0.0163	0.0049	43.0%	1.30
PctTohono	-689.0870	-209.3897	==	-0.30
Intercept	-1.7848	-0.5423	==	-2.44
Model Fit				
Log of Likelihood Function	-347.38			

* statistically significant, p<0.05, one-tailed test
~ statistically significant, p<0.05, two-tailed test
+ statistically significant, p<0.10, one-tailed test
== percent effect size very large (exceeds 1,000%)

APPENDIX B: List of Analyzed TRIFs (some organizations have more than one facility)

ABLE STEEL FABRICATORS INC.
ABS METALLURGICAL PROCESSORS INC.
ACME ELECTRIC CORP AEROSPACE DIV
ADAPTO INC.
ADOBEAIR INC.
ADVANCED MATERIALS TECHS. INC.
AERO SPRING & MFG. CO. INC.
AIR PRODS. & CHEMICALS INC.
ALAMEDA CHEMICAL HTP
ALLIED TOOL & DIE CO. INC.
ALLIED TUBE & CONDUIT - PHOENIX OPERATIONS
ALLIED-SIGNAL INC. AIRLINE SERVICES
ALLIED-SIGNAL INC. GARRETT AUXILIARY POWER DIV.
AMERICAN AEROSPACE TECHNICAL CASTINGS INC.
AMERICAN BEST LLC
AMERICAN FIBERGLASS
AMERICAN IND. DIVERSIFIED INC.
AMERON CONCRETE & STEEL PIPE GROUP
ANR MANUFACTURING LTD
APEX CHEMICAL CO
ARCH CHEMICALS INC.
ARIZONA CASTINGS INC.
ARIZONA GALVANIZING INC.
ARIZONA MARBLE INDUSTRIES INC.
ARIZONA POLYMER FLOORING INC.
ARIZONA PUBLIC SERVICE OCOTILLO POWER PLANT
ASHLAND DISTRIBUTION CO
ASPEN FURNITURE L.L.C.
ATLAS ROOFING CORP
AVANTI CIRCUITS
AVONTI MANUFACTURING INC.
AVONTI MFG. INC.
BOC EDWARDS KACHINA
BP PHOENIX TERMINAL
BULK TRANSPORTATION BUCKEYE TERMINAL
CAVCO INDS INC. SPECIALTY DIV
CAVCO INDUSTRIES INC. DURANGO
CEMEX - MESA PLANT
CEMEX - SUN CITY
CEMEX - WEST PLANT
CHEMRESEARCH CO INC.
CHEVRON USA INC. PHOENIX ASPHALT TERMINAL
CHROMALLOY ARIZONA
CIRCUIT EXPRESS INC.
CLEAN HARBORS ARIZONA LLC
COLUMBUS CHEMICAL INDUSTRIES INC.
CONTRACT MANUFACTURING SERVICE INC.
COPLIN MFG. INC.
COPPER STATE RUBBER OF ARIZONA INC.
CORNING GILBERT INC.
CRAFCO INC. CHANDLER
CUSTOM BOLT MFG.
D-VELCO MFG. OF ARIZONA INC.
DITRON MANUFACTURING INC.
DOLPHIN INC.
DUNN DEL RE STEEL
DYNACO CORP
EARL'S FIBERGLASS INC.
EARTH PROTECTION SERVICES INC.
EATON ELECTRICAL
EBERLE DESIGN INC.
ELECTRONIC DEVICES INC.
ESCO INTEGRATED MANUFACTURING
F & B MFG. CO.
FLEETWOOD HOMES OF ARIZONA INC. # 21
GANNON & SCOTT
GEM MICROELECTRONIC MATERIALS
GENERAL DYNAMICS DECISION SYSTEMS
GOLD TECH INDUSTRIES AEROSPACE TELECOMMUNICATIONS DIV
GOODRICH CORP UNIVERSAL PROPULSION CO INC.
GOODRICH TURBOMACHINERY PRODUCTS
GRIGGS PAINT
HAMILTON SUNDSTRAND
HANSON PIPE & PRODUCTS INC. PHOENIX 39TH AVE PLANT
HARTSON-KENNEDY CABINET TOP CO INC.
HERAEUS INC. MATERIALS TECHNOLOGY DIV
HERITAGE GRAPHIC
HONEYWELL ENGINES SYSTEMS & SERVICES
HONEYWELL INTERNATIONAL AIR TRANSPORT
HUHTAMAKI PLASTICS PHOENIX
HYDRO ALUMINUM NORTH AMERICA
IMC MAGNETICS CORP
IMSAMET OF ARIZONA
IN-CIDE TECH. INC.
INNOVATIVE SURFACES
INTEL CORP
INTEL MAIN CHANDLER CAMPUS
INTERNATIONAL TECHNICAL COATINGS INC.
INX INTERNATIONAL INK CO
IONICS PURE SOLUTIONS
ISOLA USA CORP
J. B. RODGERS MECHANICAL CONTRACTORS INC.
KIRKWOOD SHUTTERS LTD.
KULICKE & SOFFA FLIP CHIP DIV
KYRENE GENERATING STATION
KYSOR PANEL SYSTEMS
L & M LAMINATES & MARBLE
LINCOLN LASER CO.
LOS ANGELES CHEMICAL CO CHA NDLER
MAAX SPAS ARIZONA INC.

MAPEI CORP.
MARLAM INDUSTIES INC.
MARSH AVIATION INC.
MASTERCRAFT CABINETS INC.
MCDONNELL DOUGLAS HELICOPTER CO
ME GLOBAL INC.
MECHTRONICS OF ARIZONA
MEDTRONIC TEMPE
MESA FULLY FORMED INC.
METAL PRODUCTS CO INC.
METCO METAL FINISHING INC.
MGC PURE CHEMICALS AMERICA INC.
MICOM CIRCUITS WEST
MICROCHIP TECH. INC.
MICROCHIP TECHNOLOGY INC.
MICROSEMI CORP
MICROSI INC.
MONIERLIFETILE L.L.C.
MOTOROLA CHANDLER
MOTOROLA SCG
MOTOROLA TEMPE
MURCO WALL PRODS. INC.
NELTEC INC.
NESCO MANUFACTURING INC.
NESTE OIL SERVICES
NIKKO MATERIALS USA INC. (DBA GOULD ELECTRONICS INC.)
OBERG ARIZONA
OHLINGER IND. INC.
ONYX SPECIAL SERVICES INC.
PACIFIC SCIENTIFIC ENERGETIC MATERIALS CO
PALM HARBOR HOMES
PAN GLO SERVICES L.L.C.
PARAGON VISION SCIENCES
PATRICIAN MARBLE CO. L.L.P.
PENN RACQUET SPORTS
PHOENIX BRICK YARD
PHOENIX COCA-COLA BOTTLING CO.
PHOENIX HEAT TREATMENT
PHOENIX METALLICS
PIMA VALVE INC.
PING INC.
PIONEER DISTRIBUTING CO. INC.
POLYONE CORP GLENDALE PLANT
PORCHER
PORT-A-STALL INC.
PRAXAIR DISTRIBUTION INC.
PRECISION DIE & STAMPING INC.
PREMIER BUILDING SYSTEMS
PRESTO CASTING CO
PRO PETROLEUM
PROCTER & GAMBLE MFG. CO.
PROFESSIONAL CHEMICALS CORP
QUINCY JOIST CO.
REDDY ICE - PHOENIX 2
REDMAN HOMES INC. (DBA CHAMPION HOME BUILDERS)
ROGERS CORP
ROGERS CORP ADV CIRCUIT MATERIALS FLEXIBLE PRODUCTS
ROMIC ENVIRONMENTAL TECHNOLOGIES SOUTHWEST
ROYAL STONE INDS.
SAFEWAY
SAFEWAY MILK PLANT
SANMINA-SCI CORP PHOENIX DIV
SANTAN GENERATING STATION
SANTOKU AMERICA INC.
SCA PACKAGING NORTH AMERICA
SCHREIBER FOODS INC.
SCHUFF STEEL CO.
SCHULT HOMES
SCI LLC (ON SEMICONDUCTOR)
SHAMROCK FOODS CO
SOUTH BAY CIRCUITS INC.
SOUTHWEST ALUMINUM SYS. INC.
SOUTHWEST DISTRIBUTING CO
SOUTHWEST METAL FINISHING LLC
STMICROELECTRONICS INC.
SUB ZERO FREEZER CO INC.
SUMCO SOUTHWEST CORP
SUN LAND BEEF CO
SUNTRON
SUPERLITE BLOCK
SURFACE MOUNT COMPANY
TALLEY DEFENSE SYS. INC.
TALLEY DEFENSE SYS. INC. BURN GROUND
TALLEY DEFENSE SYS. INC. PLANT 4
TARR ACQUISITION LLC
TEMPO RESEARCH CORP (MESA AZ)
TESSENDERLO KERLEY INC.
TRANS-MATIC MANUFACTURING CO
TRANSPRO INC.
TREFFERS PRECISION INC.
TRENDWOOD INC.
TRENWYTH INDUSTRIES
TRIUMPH CORP
TRW VEHICLE SAFETY SYSTEMS MESA II FACILITY
U.S. AIR FORCE LUKE AFB
U.S. AIR FORCE LUKE AFB AZ BARRY M. GOLDWATER RANGE
UCSC LTD CO
UNION DISTRIBUTING CO. INC.
UNITED DAIRYMEN OF ARIZONA
UNIVAR - PHOENIX
VALLEY INDL. PAINTING
VALLEY MACHINE WORKS
VERCO MFG. CO.
W.R. GRACE & CO CONN GRACE CONSTRUCTION PRODUCTS
WALLNOX ENTERPRISES (DBA DESERT SUN FIBERGLASS)
WATER ENG. SERVICES INC.
WEAVER QUALITY SHUTTERS
WESTERN BONDED PRODUCTS INC. FLEX FOAM
WESTERN STATES PETROLEUM
WORLD RESOURCES CO
WR MEADOWS OF ARIZONA INC.
ZIEMAN MANUFACTURING PHOENIX DIV

ENDNOTES

[i] Appendix B lists the TRIFs analyzed.
[ii] Hamilton (1995) also finds significant variation in when his treatment, storage, or disposal plants began operation. See Table 1, p. 119.
[iii] GeoDa, 2006, Spatial Analysis Lab, University of Illinois, Urbana-Champaign, https://www.geoda.uiuc.edu
[iv] Because of the Census categories available in 1980, this means that %Hispanic can overlap with the other minority racial categories (White, Non-Hispanic does not overlap with Hispanic).
[v] Some readers may be concerned that there is no “All Other” racial category. In our data, the correlation between %Hispanic and %AllOther was 0.98. Inspection suggests that in our area the large majority of those who list their race as something other than Black, Asian, or AmerInd (with their included categories of Pacific Islander and Eskimo or Aleut) list it as something indicating Hispanic ethnicity, such as “Mexican,” “Chicano,” or “La Raza.” Therefore, we have omitted the All Other category, which means that some very small percent of the omitted group may be of some unmeasured minority status (not Hispanic, Black, Asian, or American Indian). This may increase SEs slightly, but should have little other effect.
[vi] We chose 150 percent of the poverty line because public opinion research places the threshold for being “poor” at roughly one-half of the median income, which falls at roughly 150 percent of the official US Federal poverty line. Using this public opinion measure is in line with our interest in capturing the public’s collective action.
[vii] All regression computations were performed using PowerMac TSP 4.3, copyright 1996 by TSP International.
[viii] According to Clint Cummins, co-developer with Bronwyn Hall of TSP, “It is an average derivative, computed for each observation in the sample and then averaged” (personal email communication, 24 October, 2006).
[ix] As Liu (2001) points out, this statement implicitly assumes that all TRIFs are equally noxious (which we know is not true), or that TRIFs are randomly located with respect to noxiousness.
[x] TSP 4.5 allows for estimation of such robust errors in Tobit analysis.
[xi] These results are not reported but are available from the authors.