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A Census of the US Near-Roadway Population: Public Health and Environmental Justice Considerations

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Gregory M. Rowangould
Civil Engineering Department, MSC01 1070
University of New Mexico
1 University of New Mexico
Albuquerque, NM 87131, USA
Corresponding address: E-mail: rowangould@unm.edu

Abstract

This study estimates the size and distribution of the population living near high volume roads in the US, investigates race and income disparities in these near roadway populations, and considers the coverage of the national ambient air quality monitoring network. Every US census block is classified by traffic density and proximity to roads falling within several traffic volume ranges using year 2008 traffic data and the 2010 and 2000 US Census. The results indicate that 19% of the population lives near high volume roads. Nationally, greater traffic volume and density are associated with larger shares of non-white residents and lower median household incomes. Analysis at the county level finds wide variation in the size of near roadway populations and the severity of environmental justice concerns. Every state, however, has some population living near a high volume road and 84% of counties show some level of disparity. The results also suggest that most counties with residents living near high volume roads do not have a co-located regulatory air quality monitor.

Keywords: Air Quality, Environmental Justice, Vehicle Emissions, Public Health, Monitoring Network

1 Introduction

There is an accumulation of evidence that people living near high volume roads face elevated health risks from exposure to vehicle emissions. Given the nature of road networks and the geography of local residence and work places, there are disparities in exposure to mobile source emissions across socioeconomic and racial groups. While many studies document high levels of air pollutant concentrations and negative health outcomes alongside high volume roads, there is less information about the size and geographic distribution of the near-roadway population.

I create a national census of the US near-roadway population to offer insights into these issues. It is similar in spirit to Tian et al. (2013) but uses a more robust and spatially detailed set of roadway proximity and traffic exposure measures. The analysis is performed at the census block level rather than the census tract level using both traffic density and roadway proximity metrics. The finer spatial scale of the analysis aligns more closely with the spatial scale of near roadway emissions gradients. The approach is also broader and quantifies the size of the near roadway population both nationally and at the county level while also evaluating the spatial relationship between near roadway populations and the regulatory air quality monitoring network.

2 Methodology and Data

The area includes all US states. Average annual daily traffic (AADT) volume data for 2008 were obtained from the highway performance monitoring system (HPMS) road network included in the 2010 National Transportation Atlas Database (US Department of Transportation, 2010). The network includes the entire US highway network and most other primary roads. Block level population counts by race were obtained from the 2010 US Census while block-group level median household income data were obtained from the 2000 Census.

Proximity to high volume roads is measured using a series of distance buffers along roads with greater than 25,000 AADT in the HPMS dataset. High volume roads are defined as having greater than 25,000 AADT, generally corresponding to limited access divided highways and multi-lane urban arterials that are the class of roads considered in previous near-roadway population and health studies. Each HPMS road segment is classified by AADT in 25,000 AADT increments up to 200,000 AADT. Roads with greater than 200,000 AADT are classified into one category. Buffers are constructed parallel to each of the classified road segments at 100m intervals extending out to a maximum of 500m. These buffers cover an area where the greatest concentration of mobile source air pollutants are expected. Each census block, or portion of a census block, is then assigned to one of the distance-traffic buffers by computing a geographic intersection of the roadway buffers and census block boundaries using a GIS. For census blocks that were only partially intersected by a buffer, the census block is split into multiple parts. The population of each block part is estimated in proportion to the block part's area. The smallest spatial scale that income data were available is the block-group. Individual blocks in each block-group were assigned the block-group median household income. The 40 traffic-distance buffers contain 25.2% of populated US census blocks.

Traffic density is calculated for each US census block by constructing a 250m buffer around each block and then intersecting the buffered block with the HPMS road network

in a GIS following Gunier et al., (2003). Vehicle kilometers traveled (VKT) is then calculated for each road segment by multiplying each road segment's length by its AADT. The VKT in each block's buffered area is then divided by the block's area to estimate traffic density. The 250m buffer is used to capture traffic on roadways in close proximity to but not intersecting a block. Census blocks with no population or traffic density are discarded. The traffic density data set includes 52.2% of populated US census blocks.

The traffic-distance buffer dataset is used to count the population living within each traffic-distance buffer in each county and for the US. A cumulative plot of population by increasing levels of traffic and decreasing distance from the road is created. The county level results are also mapped to explore spatial patterns.

Roadway proximity and traffic density are used as proxy variables for emissions exposure. To evaluate disparities across the US, each region's baseline population characteristics is controlled for. This is accomplished by calculating the difference in the population share of minority residents and percent difference in median household income between each block and the county where the block is located. These two quantities are herein referred to as "race disparity" and "income disparity" respectively. One improvement made over past studies is that a range of traffic volume and proximity is considered rather than a single definition of being near a high volume road. This analysis also includes a much larger study area than most previous studies.

Demographic data are aggregated for each traffic-distance buffer and tabulated for the US and for each county. Population weighted mean values for each traffic-distance buffer are then estimated and plotted to identify potential associations between traffic level or proximity and race and income disparity.

Multinomial regression models were also created to test for associations between traffic-distance buffer levels and race and income disparity. The first model included the race and income disparity as covariates and the second model also included the log of population density as an additional covariate. Separate models were created for blocks in each of the five 100m buffer bands to explore differences in association at distances from the roadway. In each model the 200,000 AADT buffer was set as the reference category and the coefficient estimates are exponentially transformed to provide conditional odds ratios. The conditional odds ratios indicate the multiplicative effect that a unit increase in race disparity, income disparity, or logged population density has on the odds of a census block being located in the specified AADT buffer relative to the reference buffer.

There are several advantages to using traffic density over the buffer data. First traffic density is a continuous variable that does not require the researcher to define traffic level and proximity categories. Traffic density also captures the relatively worse-off condition of living at the intersection of multiple high volume roads (the buffer method categorizes blocks by the highest high volume road in this situation). One limitation of using traffic density is that the link between particular traffic density levels and emission concentrations is less understood.

As with the buffer data, the difference in each block's minority population share from county minority population share is calculated to control for regional differences in baseline population characteristics. This is repeated for median household income. The

traffic density data set is divided into traffic density quintiles for the US and individually for each county. The average race and income disparity is estimated for each quintile and compared.

Two linear regression models are also created to test for associations between traffic density, race disparity, and income disparity. Logged traffic density is regressed on race and income disparity for each block. A second model includes the logged population density as an additional covariate.

The location (x,y coordinates) of every air quality monitor used by EPA in 2010 to enforce the Carbon Monoxide (CO), Nitrogen Dioxide (NO₂), and particulate matter (coarse - PM10 and fine - PM2.5) NAAQS was downloaded from EPA's Air Explorer Website. Each monitor is classified by traffic volume and roadway proximity by intersecting the monitor data with the traffic-distance buffers using a GIS. Counties that do not have air quality monitors co-located with populations living in the near roadway buffers are identified.

3 Results

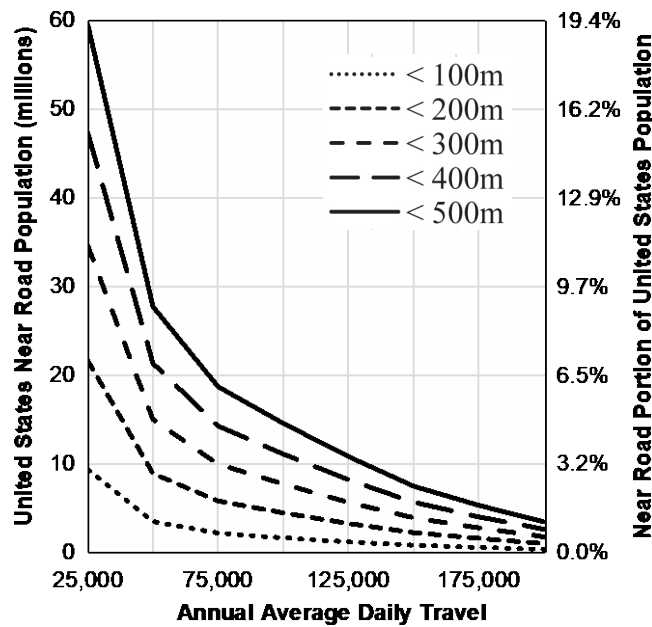
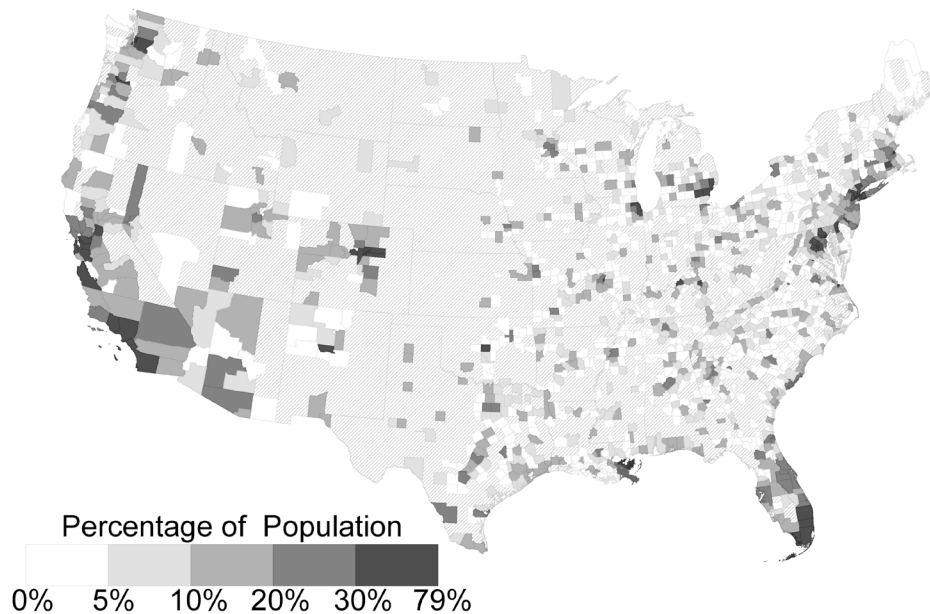


Figure 1. US population living near high volume roads during the year 2010.

The buffer analysis indicates that a large share of the US population lives near high volume roads (Figure 1). There are 59.5 million people living within 500m of roads with greater than 25,000 AADT, an area where residents are potentially exposed to elevated concentrations of many mobile source emissions. For individual states and counties the share of the population living near these roads can be much greater. For example, 40% of California's population lives near high volume roads; the largest share of any state excluding the District of Columbia where 62% of the population lives near high volume roads. In Falls Church County Virginia 79% of the population lives near high volume roads as does over 50% of the population in 14 other counties. Counties with the largest

share of their population living near high volume roads are mostly, but not entirely, confined to major urban areas (Figure 2).



Note: Hatched areas indicate counties with no population living near high volume roads.

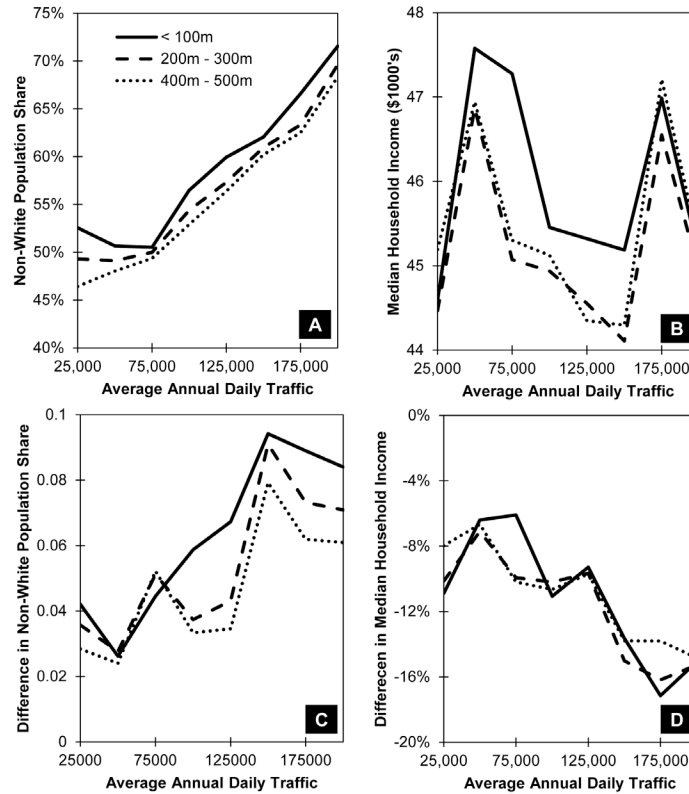
Figure 2. Percentage of the population living within 500m of a roadway with over 25,000 AADT in each county.

A much smaller share, 0.1%, of the US population lives within very close proximity to the highest traffic volume roads where exposure to elevated concentrations of mobile source emissions is extremely likely. While a small share of the population, this represents over 400,000 people. The population living close to the highest volume roads is confined to major metropolitan areas, most notably in California which is the only state where counties have greater than 10% of their population living near these very high volume roads.

The buffer analysis indicates that persons belonging to a racial minority group or with lower household incomes are more likely to live near a high volume road. While 19.3% of the US population lives near high volume roads, 27.4% of the non-white population (including 23.7% of the black population and 29.4% of the Latino population) live near high volume roads. The average median household income of census blocks near high volume roads is \$1,221 less than the US average of \$46,525.

There is also a strong association between race, income, and traffic volume as shown by the plots in Figure 3. The plots in Figure 3a and 3b do not control for baseline differences in each county's minority population share and median household incomes while the plots in Figures 3c and 3d do. Figures 3a and 3b show that on average the US population

living closer to higher traffic volume roads is disproportionately composed of non-white residents but that there is little association with median household income. In Figures 3c and 3d, where baseline population characteristics are controlled for, there is a clear association between increasing race and income disparity and increasing traffic volume. There is no apparent association with proximity within the range we considered.



Note: Relationship between the share of non-white residents and traffic volume (a), median household income and traffic volume (b), the difference in the share of non-white residents [near road – county] (c), and the percentage difference in median household income [(near road – county)/county x 100](d). Values for (c) and (d) represent the US population weighted mean difference between the population living within the indicated distance of a high volume road and the entire county population.

Figure 3. Relationships between traffic volume, roadway proximity, race and income.

For example, within 200m to 300m of roads with 25,000 AADT to 50,000 AADT the average share of non-white residents is 42.6% while the average share of non-white residents in the surrounding county is 39.8%, a difference of 2.8 percentage points. For roads with greater than 200,000 AADT the average share of non-white residents within 200m to 300m increases to 65.3% while the average share of non-white residents in the surrounding county increases to 56.6%, a difference of 8.7 percentage points. Additionally, populations living near roads with 25,000 AADT on average have median household incomes that are 8% to 11% less than the county average while populations

living near the highest traffic volume roads have median household incomes that are 18% less than the county average¹.

The traffic density and buffer data agree, with high traffic density quintiles having a much larger share of minority residents and lower median household incomes than lower traffic density quintiles (Table 1). The population share of non-whites is 3 times, Latinos 4 times, blacks 2.1 times, and Asians 5.9 times greater in the highest traffic density quintile as compared to the lowest traffic density quintile. The main exception to this pattern of disparity is for Native Americans (included in the “other” category) where their population share is greater in lower traffic density quintiles. The average median household income of residents in the highest traffic density quintile is \$1,339 less than that of households in the lowest traffic density quintile. However, unlike the ordinal increase in minority population shares across traffic density quintiles, the highest average median household income occurs in the 2nd quintile; this likely represents the generally lower incomes in very rural places.

Table 1. Mean Disparity in Income and Race/Ethnicity by Traffic Density Quintile

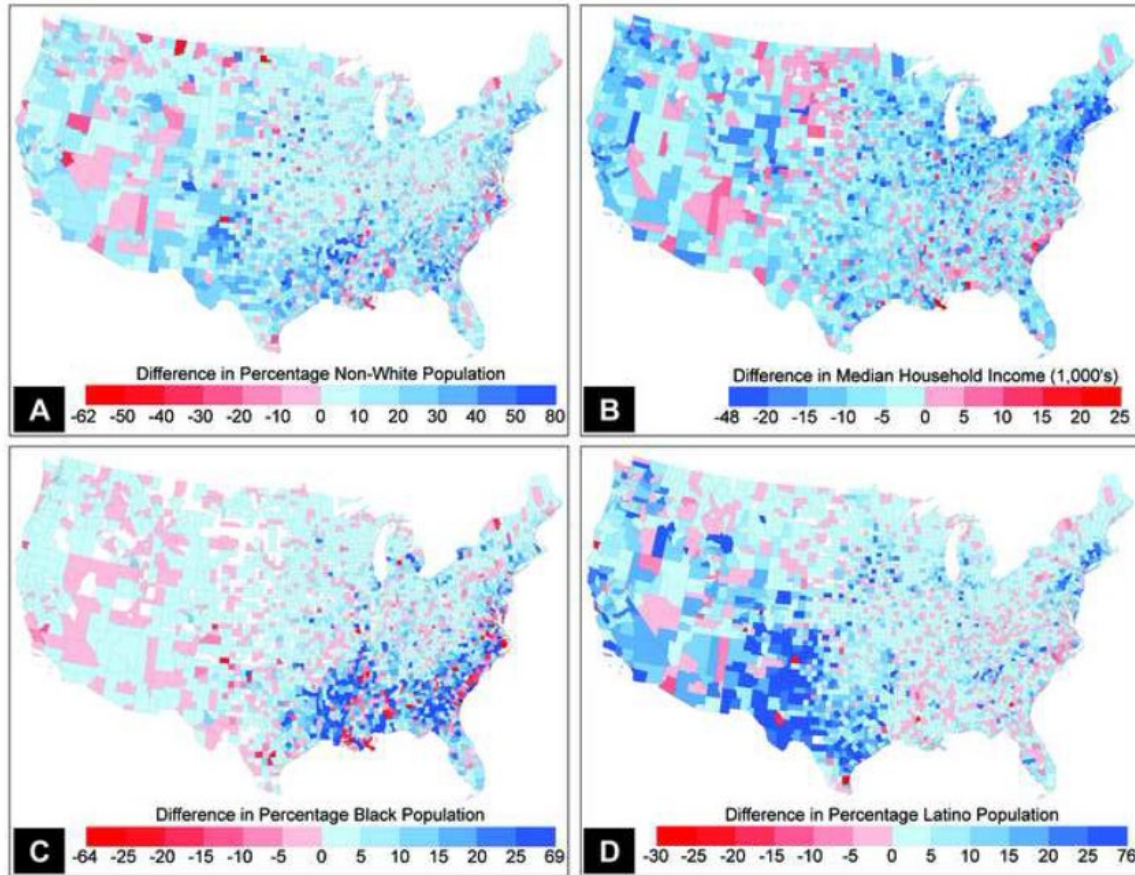
Quintile	Traffic Density ^a	Income ^b	Share of Population by Race/Ethnicity				
			Non-White	Latino	Black	Asian	Other ^c
<i>Aggregate^d</i>							
1 st	6,825	\$43,466	19%	7%	8%	1.6%	2.8%
2 nd	66,118	\$47,421	31%	13%	11%	4.0%	3.0%
3 rd	240,948	\$44,813	41%	19%	13%	5.7%	3.3%
4 th	633,366	\$42,648	49%	24%	15%	7.2%	3.3%
5 th	3,761,149	\$42,127	57%	28%	17%	9.4%	3.2%
<i>Difference Relative to County Population^e</i>							
1 st	6,825	\$2,901	-4.3	-1.9	-1.9	-0.38	-0.16
2 nd	66,118	\$1,415	-0.7	-1.0	-0.1	0.33	0.08
3 rd	240,948	-\$3,486	3.5	1.4	1.4	0.43	0.22
4 th	633,366	-\$6,464	5.8	3.1	2.2	0.26	0.21
5 th	3,761,149	-\$7,591	6.1	4.0	1.6	0.30	0.15

^a Mean daily vehicle kilometers traveled per square meter; ^b Mean block-group median household income from the 2000 US Census; ^c All other races/ethnicities excluding white, includes Pacific Islanders and American Indians; ^d Mean values by traffic density quintile; and ^e Mean population weighted difference between block and county populations by traffic density quintile

The trends noted also hold when baseline county population characteristics are controlled for (lower half of Table 1). For example, the percentage of non-white residents in the lowest traffic density quintile is 4.3 percentage points lower than the percentage of non-white residents in the surrounding counties and the percentage of non-white residents in the highest traffic density quintile is 6.1 percentage points greater than the percentage of non-white residents in the surrounding counties. Similarly, average median household

¹ All averages are population weighted mean values of block level data.

incomes are \$2,901 greater than county averages in the lowest traffic density quintile and \$7,591 less than county averages in the highest traffic density quintile.



Note: Difference in the percentage of non-white population (a) average median household income (b), percentage black population (c), and percentage Latino population (d) between the lowest and highest traffic density quintile for each US county.

Figure 4. Spatial distribution of county level income and race disparities.

Large minority and low-income populations in urban areas could drive the aggregate results in Figure 1 and Table 1. The maps in Figure 4 show the difference in population characteristics between the lowest and highest traffic density quintiles for each county in the US. Figures 4a and 4b indicate that in most counties a disproportionate number of non-white residents live in high traffic density areas (84% of US counties) as do a disproportionate number of residents with lower median household incomes (83% of US counties). The disparities among non-whites are greatest in the southern states; however, there is no general geographic region of the country without any disparity. When the non-white population is isolated to just black or Latino residents (Figures 4c and 4d) strong spatial patterns of disparity emerge. Blacks are much more likely to live in high traffic density areas in a region following the coast from East Texas to Virginia while Latinos are much more likely to live in high traffic density areas in a region extending from Texas to the West Coast and also a small area in the Northeast. These areas correspond to regions with higher baseline populations of black and Latino residents. Disparities in

median household income are greatest in urbanized areas, most notably in the Northeast, along the West Coast, and the Great Lakes region.

The buffer and traffic density data both provide evidence that living near a high volume road or in a high traffic density area is associated with larger race and income disparities. The regression analysis results further confirm these findings while also disentangling the relationship between race and income (Table 2).

TABLE 2 Conditional Odds Ratios^a for Census Blocks in 100m Traffic-Distance Buffers

	Model 1		Model 2		
AADT ^b	Exp(β_{dNW}) ^c	Exp(β_{pdInc}) ^d	Exp(β_{dNW})	Exp(β_{pdInc})	Exp($\beta_{\log(density)}$) ^e
25,000	0.58 (0.54, 0.63) ^f	1.21 (1.15, 1.29)	0.68 (0.63, 0.73)	0.97 (0.91, 1.02)	0.70 (0.69, 0.71)
50,000	0.63 (0.58, 0.69)	1.51 (1.42, 1.61)	0.74 (0.68, 0.81)	1.19 (1.12, 1.27)	0.69 (0.68, 0.70)
75,000	0.82 (0.75, 0.90)	1.33 (1.24, 1.42)	0.95 (0.87, 1.04)	1.05 (0.98, 1.12)	0.70 (0.69, 0.71)
100,000	0.75 (0.68, 0.82)	1.03 (0.96, 1.11)	0.82 (0.74, 0.90)	0.89 (0.83, 0.95)	0.79 (0.78, 0.81)
125,000	1.07 (0.97, 1.18)	0.93 (0.86, 1.01)	1.15 (1.04, 1.27)	0.85 (0.79, 0.92)	0.84 (0.83, 0.86)
150,000	1.21 (1.08, 1.34)	0.91 (0.83, 0.99)	1.30 (1.16, 1.45)	0.84 (0.77, 0.91)	0.85 (0.83, 0.87)
175,000	0.83 (0.74, 0.94)	0.82 (0.74, 0.90)	0.84 (0.74, 0.95)	0.79 (0.72, 0.86)	0.93 (0.91, 0.95)
n	325,140		325,140		
AIC	791,502		797,591		

^a Conditional odds ratios derived by exponential transformation of coefficients estimated by multinomial logistic regressions where the 200,000 AADT category is the basis for comparison; ^b Values represent lower bound of each 25,000 AADT interval.; ^c dNW = race disparity, defined as the difference in the non-white population share between near road and county populations (% non-white near road - % non-white in county); ^d pdInc is income disparity, defined as the percentage difference in average median household income between near road and county populations ((near road income – county income)/county income x 100); ^e Natural log of population density; and ^f values in parentheses are 95% confidence intervals for the conditional odds ratios

The conditional odds ratios shown in Table 2 indicate the relative odds of a census block being located near a roadway in a particular traffic volume category relative to being located near a roadway with greater than 200,000 AADT. The odds ratios for each parameter indicate the multiplicative effect that a unit change in the parameter would have on the conditional odds ratio. For example, a one unit increase in racial disparity (β_{dNW}) would decrease the odds of a census block being located near a road with 25,000 to 50,000 AADT by 0.58 times, while increasing the odds of a census block being located near a road with 150,000 to 175,000 AADT by about 20%, relative to the block being located near a road with greater than 200,000 AADT. The odds ratios in Model 1 indicate an association between increasing race and income disparity and increased odds of living near higher volume roads. These associations could occur if race and income disparities are larger in dense urban areas where all census blocks have relatively high odds of being located near a high volume road. Model 2 controls for population density and continues

to find that increasing disparities in race and income are associated with greater odds of a census block being located near higher volume roads.

Analysis of the traffic density data produces similar conclusions (Table 3). Model 1 indicates that increasing levels of race and income disparity are associated with increasing traffic density. Negative values indicate greater income disparity so that negative income disparity coefficient estimates indicate greater income disparity is associated with greater traffic density. When population density is controlled for in Model 2 the association between race disparity and traffic density is reversed and the association between income disparity and traffic density is reduced. These results indicate that the apparent association between race and income disparity in Model 1 may be explained by larger race and income disparities occurring in dense urban areas where the probability of living near a high volume road is also greater.

TABLE 3 Traffic Density Ordinary Least Squares Regression Results

	Model 1	Model 2
intercept	11.80 (11.80, 11.81) ^a	5.94 (5.93, 5.95)
dNW ^b	0.50 (0.48, 0.51)	-0.33 (-0.34, -0.32)
pdInc ^c	-1.03 (-1.04, -1.02)	-0.06 (-0.07, -0.06)
log(density) ^d		0.84 (0.84, 0.84)
n	1,693,957	1,693,957
adj-R ²	0.05	0.61

^a values in parentheses are 95% confidence intervals for the parameter estimates; ^b dNW = race disparity, defined as the difference in the non-white population share between near road and county populations (% non-white near road - % non-white in county); ^c pdInc = income disparity, defined as the percentage difference in average median household income between near road and county populations [(near road income – county income)/county income x 100]; and ^d Natural log of population density

The buffer and traffic density results do not correspond when population density is controlled for. This may be explained by limitations in the buffer data set. First, only census blocks near high volume roads are considered. This was done out of convenience for counting the size of the near roadway population and making the GIS analysis more tractable. Additionally, the relatively small number of census blocks in the highest traffic volume category were located near roads having a wide range of traffic volume. The buffer data were also not able to account for the relative worse off condition of living near multiple high volume roads.

While I find that a large share of the US population lives near high volumes roads, very few air quality monitors are located in these areas (Table 4). For example, only 14% of counties with residents living near high volumes roads also have a co-located and active PM2.5 air quality monitor. The percentage of counties that have co-located monitors in areas closer to higher volume roads is much smaller. Overall 18 million people live near high volume roads in counties where there are no co-located PM2.5 monitors (32% of the US population living near high volume roads) (Table 5). Very few monitors are placed near roads with the highest traffic volumes. For example, only three counties out of 63

with population living within 100m of roads with greater than 200,000 AADT have a co-located PM2.5 monitor. The findings are similar for CO, NO_x, and PM10 monitors.

TABLE 4 Count of Counties with Co-Located Air Quality Monitors

Pollutant	AADT	Distance from Road		
		< 100m	< 300m	< 500m
CO	> 25,000	48 (4%) ^a	83 (6%)	103 (8%)
	> 100,000	14 (5%)	26 (10%)	38 (14%)
	> 200,000	2 (3%)	5 (8%)	11 (17%)
NO _x	> 25,000	32 (2%)	64 (5%)	88 (6%)
	> 100,000	10 (4%)	21 (8%)	31 (11%)
	> 200,000	2 (3%)	4 (6%)	11 (17%)
PM10	> 25,000	65 (5%)	106 (8%)	138 (10%)
	> 100,000	22 (8%)	42 (15%)	53 (19%)
	> 200,000	4 (6%)	11 (17%)	14 (22%)
PM2.5	> 25,000	82 (6%)	146 (11%)	195 (14%)
	> 100,000	21 (8%)	42 (15%)	54 (20%)
	> 200,000	3 (5%)	9 (14%)	13 (20%)

^a As percentage of all counties with near road population in given traffic-distance buffer

TABLE 5 Population (millions) Living Near High Volume Roads in Counties without Co-Located Air Quality Monitors

Pollutant	AADT	Distance from Road		
		< 100m	< 300m	< 500m
CO	> 25,000	5.9 (62%) ^a	16.9 (51%)	25.9 (46%)
	> 100,000	1.6 (91%)	6.2 (81%)	7.1 (50%)
	> 200,000	0.4 (96%)	1.6 (91%)	1.2 (34%)
NO _x	> 25,000	6.2 (65%)	18.6 (56%)	27.5 (49%)
	> 100,000	1.7 (93%)	6.1 (80%)	7.5 (53%)
	> 200,000	0.4 (96%)	1.6 (91%)	1.1 (33%)
PM10	> 25,000	5.3 (56%)	16.1 (49%)	25.4 (45%)
	> 100,000	1.6 (87%)	5.2 (69%)	7.0 (49%)
	> 200,000	0.4 (94%)	1.5 (85%)	1.3 (38%)
PM2.5	> 25,000	5.1 (54%)	13.1 (40%)	18.0 (32%)
	> 100,000	1.5 (85%)	5.3 (70%)	5.8 (41%)
	> 200,000	0.4 (98%)	1.7 (93%)	1.4 (43%)

^a Percentage of population living within the indicated traffic-distance buffer without a co-located air quality monitor

4 Conclusions

I find that a large portion of the US population lives near high volume roads where the concentration of mobile source air pollutants is typically elevated. This is true in almost every region of the country. While prior research has focused on the largest urban areas, these results indicate that exposure to high concentrations of mobile source emissions from living in close proximity to high volume roads is potentially a much larger and more widespread public health concern.

I also find that minority and low-income households are on average more likely to live near a high volume road or in an area with higher traffic density. The results also align with those of prior studies. As with Guiner et al. (2003) and Houston et al. (2004), I find that higher traffic density areas in California and the Los Angeles California metropolitan area have larger proportions of low income and minority residents. The results also agree with studies that have used the US Environmental Protection Agency's National-Scale Air Toxics Assessment database to assess health risks from mobile source emissions exposure².

Aggregate results, however, do not tell the complete story. For example, when county level results are compared with prior studies that find an association between greater shares of minority residents and increasing levels of traffic density or health risk in California, the Los Angeles area, the Tampa Bay area, and Maryland, a more complex picture is revealed. There are counties where no disparities are apparent, or where disparities work in the opposite direction, as well as a wide range in the magnitude of disparities. There are also areas of the country where environmental justice concerns appear much larger than others. While the areas of highest concern include regions considered in past studies, it is notable that many areas across the south also tend to have large disparities in who lives and does not live near high volume roads. While some regions have greater disparities; overall, the findings demonstrate that environmental justice concerns are not isolated to any particular state or region but that they are widespread and very common.

In aggregate, at the national scale, my results also partially agree with Tian et al. (2013). Both studies find that increasing traffic density is associated with greater shares of minority residents but Tian et al. find little or no association with income while I do. Tian et al. also find little correlation between race and traffic density in the northeast; whereas, my analysis indicates that there are greater shares of minority residents in higher traffic density census blocks in most counties in the northeast. Furthermore, Tian et al. provide a top ten list of states with the greatest correlation between share of minority residents and household income, and traffic density. Most of the states on the top ten lists are located in the northern half of the country. In contrast I find that the greatest disparities in race tend to occur in the southeastern quadrant of the country while income disparities are more

² For example, Chakraborty (2009) finds that census tracts with greater health risks from vehicle emissions exposure in the Tampa Bay metropolitan area have higher shares of minority residents and in Maryland Apelberg et al. (2005) find that high risk census blocks have higher shares of minority and low income residents.

scattered. The differences between the studies likely stem from the spatial scales used in the underlying data analysis and presentation of the results.

Further, I control for regional differences in baseline population characteristics when analyzing the complete national data set by measuring disparity as the departure from a county's mean population characteristics. As shown controlling for baseline population characteristics can result in different findings. Differences in each study's findings highlight the role of spatial scale when investigating spatial phenomena and how various definitions of disparity can influence aggregate results.

Further, I find that very few monitors used to enforce the NAAQS are co-located with near road populations. This is significant because a violation of the NAAQS generally requires a region to reduce emissions from mobile sources and perform more detailed air quality analysis when developing transportation plans. While current federal law requires "hotspot" analysis for CO and PM_{2.5} when building new transportation infrastructure in non-attainment areas there is currently no method to enforce possible violations of the NAAQS alongside existing transportation corridors or in attainment areas lacking air quality monitors.

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