

**STATE OF NEW MEXICO
ALBUQUERQUE-BERNALILLO COUNTY AIR QUALITY CONTROL BOARD**

IN THE MATTER OF THE PETITION FOR
A HEARING ON THE MERITS REGARDING
AIR QUALITY PERMIT NO. 3136

RECEIVED
ENVIRONMENTAL HEALTH
14 OCT - 7 PM 2:45

Arthur Gradi, Ruth A. McGonagil, Jerri Paul-Seaborn, Bernice Ledden, Susan Kelly, Americo Chavez, Pat Toledo, as individuals,

Petitioners,

v.

AQCB Petition No. 2014-3

City of Albuquerque Environmental Health Department, Air Quality Program, and Smith's Food & Drug Centers, Inc.,

Respondents.

NOTICE OF INTENT TO PRESENT TECHNICAL TESTIMONY

COME NOW the Petitioners, and hereby submit their Notice of Intent ("NOI") to Present Technical Testimony.

- (A) Name of persons filing the NOI: Arthur Gradi, Ruth A. McGonagil, Bernice Ledden, Susan Kelly, Americo Chavez, Pat Toledo, as individuals,

- (B) Statement clarifying whether the person filing the statement supports or opposes the petition at issue.

The Petitioners support the petition at issue.

- (C) Name of each witness to present technical testimony, estimated length of direct testimony and summary of anticipated direct testimony:

Dr. Dana (Rowan) Rowangould: *1 hour estimated direct testimony*

Summary of testimony

For a more detailed summary of Dr. Rowangould's anticipated technical testimony including her affiliation, qualifications, educational and work background please find: Rowangould Memorandum to Susan Kelly dated October 6, 2014, and CV, attached.

Rowangould is expected to testify to:

- 1) the direct vehicle emission is a function of number of vehicles entering and exiting the station and the degree to which their entry and exit slows traffic on adjacent streets. Applied to the specific permit of annual throughput of 7,000,000 gallons vs. the typical permit of annual throughput of 1,000,000, greater number of vehicles exiting and entering the Smith's gas station is expected to cause greater emissions from those vehicles and from other vehicles experiencing delays on adjacent streets. As a result, elevated levels of pollutants that are linked to health impacts increase the risk of respiratory inflammation, including asthma and related lung/ breathing disorders, non-fatal heart attacks, increased risk of cancer, premature death due to pre-existing conditions, and other neurophysiological symptoms among other health effects.

The elevated levels of pollutants of concern include carbon monoxide, nitrogen oxide, and toxic air pollutants including some volatile organic compounds and increased particulate matter.

- 2) Vapor losses which are not captured contain volatile organic compounds. Although the Smith station allows for "Stage I" recovery, the station is not required to have a "Stage II" vapor recovery at the pump, thus older vehicles without onboard vapor recovery systems will likely emit VOCs from the gas tanks into the air. Vapor losses are associated with health risks, and particularly the release of benzene is determined to elevate cancer risk among other health effects. Applying the quantitative study (South Coastal Air Quality Management District (CA), increased cancer risk is multiplied by a factor of 7 under the Smith permit.
- 3) Location of potential receptors are identified near the Smith's gas station on the basis of available data, including aerial imagery. These receptors include homes, and at least one school. Distance of receptors relevant to the Smith's station is a key factor in determining health impacts from vehicle pollution. Health risks from vehicle pollution/emissions are greater on vulnerable populations that include children, elderly, and people with respiratory conditions.

In conclusion and in light of the above technical testimony supported by the attached reliance materials, Dr. Rowangould recommends additional analysis be conducted to ensure potential air quality and health impacts associated with the proposed Smith's fueling station are better understood. If impacts are found to exceed acceptable levels on the basis of regulations, increased health risks and community sentiment then mitigation and or other alternatives should be explored.

NOI attachments:

-Memorandum of technical testimony (Dr. Rowangould).

-Dr. Dana (Rowan) Rowangould, CV

-Gregory M. Rowangould, *A Census of the U.S. Near-Roadway Population: Public Health and Environmental Justice Considerations*, Transportation Research Part D 25, 59-67 (2013).

-Alex A. Karner, et al., *Near-Roadway Air Quality: Synthesizing the Findings from Real-World Data*, Vol. 44, No. 14, *Envtl. Sci. & Tech.* 5334-5344 (2010).

The Petitioners may call the following witnesses to offer non-technical testimony:

1. Each of the Petitioners.
2. Individuals in other locations who live near GDFs in Albuquerque experiencing vapors and fumes.
3. The Petitioners reserve the right to call additional non-technical witnesses, including any witnesses/interested parties identified by Smith's and the City.
4. The above-listed fact witnesses/interested parties reserve the right to rely on the Administrative Record.
5. The above-listed fact witnesses/interested parties reserve the right to rely on and refer to reliance materials, such as the following:

-On Behalf of the American Lung Association and the American Thoracic Society Before the Senate Committee on Environment; Public Works Subcommittee on Clean Air; Nuclear Safety ; Subcommittee on Children's Health, and Environmental Responsibility, Air quality and Children's Health Hearing (2011) (Statement of Dona J. Upton, MD, MA).

-American Academy of Pediatrics (Policy Statement) Committee on Environmental Health, Ambient Air Pollution: Health Hazards to Children, Vol. 114, No. 6, Pediatrics, 1699-1707 (2010).

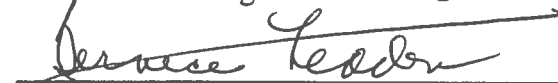
Respectfully Submitted, by co:Petitioners:



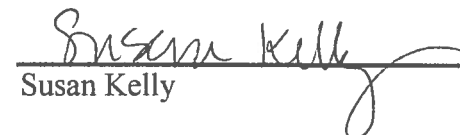
Arthur Gradi



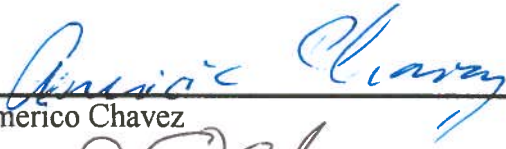
Ruth A. McGonagil



Bernice Ledden



Susan Kelly


Americo Chavez


Pat Toledo

The following Petitioners in this matter, Arthur Gradi, Ruth A. McGonagil, Bernice Ledden, Susan Kelly, Americo Chavez, and Pat Toledo hereby certify that the foregoing Notice of Intent to Present Technical Testimony was e-mailed or mailed on this 7th day of October, 2014, to the following:

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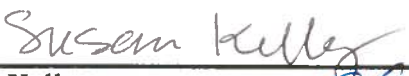
Arthur Gradi



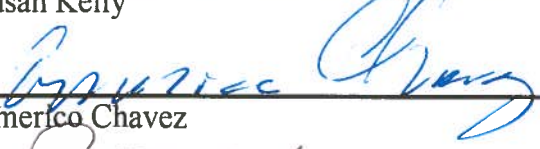
Ruth A. McGonagil




Bernice Ledden



Susan Kelly



Americo Chavez



Pat Toledo

MEMORANDUM

TO: Susan Kelly
FROM: Dr. Dana Rowangould, Sustainable Systems Research, LLC
DATE: October 6, 2014
RE: Air Quality and Health Risks of the Proposed Smith's Fueling Station at 6310 Fourth St. NW Albuquerque, NM 87107

Smith's Food and Drug has submitted a permit application for a high-throughput refueling station to the Albuquerque Environmental Health Department. The proposed refueling station will be located at 6310 Fourth St. NW Albuquerque, NM 87107. A vehicle refueling station has the potential to lead to air pollution from two types of sources: 1) direct emissions from vehicles entering and exiting the station and vehicles on feeder streets that slow or idle as a result of vehicle entry/exit, and 2) vapor losses from the refueling station's fuel storage tanks and some vehicles' fuel tanks occurring during refueling processes.

At your request I have reviewed the permit application and summarized insights from applicable scientific research and government agency guidance related to health risks from air pollution that may be associated with the proposed refueling station.

I have also attached my qualifications and two academic articles providing additional information about near-road health risks and exposures. One article describes the distances at which emissions from roads remain elevated above background levels (Karner et al. 2010) and the other characterizes the populations living near roads in the US (Rowangould 2013).

Direct Vehicle Emissions

The amount of air pollution directly emitted from vehicles will be a function of the number of vehicles entering and exiting the station and the degree to which their entry and exit slows traffic on adjacent streets (e.g. pass-by vehicles that slow or idle as a result of turning and queuing of entering and exiting vehicles). The proposed Smith's gas station will have a maximum permitted annual throughput of 7,000,000 gallons, much greater than for a typical refueling station, which might have a permitted annual throughput closer to 1,000,000 gallons. Fueling stations with greater throughput will have a greater number of vehicles entering and exiting and therefore greater direct emissions from those vehicles and from other vehicles experiencing delays on adjacent streets.

Vehicles directly emit several pollutants that can result in health impacts: carbon monoxide (CO), nitrogen oxides (NO_x), and toxic air pollutants (some of which are volatile organic compounds, or VOCs); diesel exhaust also contains these pollutants and

others, including particulate matter (PM). Exposure to these vehicle pollutants is associated with a number of adverse health outcomes:

- Nitrogen oxides (NO_x): Causes respiratory inflammation, increased symptoms in asthmatics (1).
- Carbon monoxide (CO): Reduces oxygen carrying capacity of the blood, leading to chest pain and myocardial ischemia in those with heart disease and even death at very high levels (2).
- Mobile Source Air Toxics (MSATs): Of particular health concern are benzene, 1,3-butadiene, formaldehyde, acrolein, acetaldehyde, polycyclic organic matter, and naphthalene. Human health effects studies are limited but evidence suggests that exposure to MSATs can increase cancer risks, respiratory irritation, and potentially lead to other health effects (3).
- Particulate matter (PM): Can lead to nonfatal heart attacks, irregular heartbeat, aggravated asthma, decreased lung function, irritation of airways, coughing, difficulty breathing, and premature death in people with preexisting health issues (4).
- Diesel exhaust (including diesel PM): In the short term can lead to acute irritation, neurophysiological symptoms, respiratory symptoms; in the long term it is associated with noncancer respiratory effects and elevated cancer risks (5).

A number of studies have measured elevated levels of vehicle pollutants in close proximity to busy roads; levels generally drop off between 115-570 meters, or 377 – 1870 feet (depending on local weather patterns, traffic volumes, etc.) (6). At the same time, 19% of the US population lives near busy roads and may be exposed to elevated air pollution levels (7)¹.

Vapor Losses

Vapor losses occur when the gases in fuel tanks are displaced by liquid fuel during refueling; if not captured, the gases escape from the fuel tank. Escaping gasoline vapors contain VOCs, including benzene. Stage I vapor losses refer to vapors that escape from a fueling station's storage tank when it is refilled. The permit application for the proposed Smith's station indicates that the station will have Stage I recovery which can be expected to capture most Stage I vapors. Stage II vapors are those that escape from a vehicle's fuel tank when it is refueled. Newer cars (2000 and later) and light trucks (2006 and later) have onboard refueling vapor recovery systems; however many older cars and light trucks do not. Fueling stations in Albuquerque are not currently required to have Stage II vapor recovery at the pump, so when older vehicles without onboard vapor recovery systems are refueling, VOCs are likely emitted from gas tanks into the air.

¹ This reference uses a criterion of 25,000 average annual daily traffic to define busy roads.

Gasoline vapors are associated with health risks. In particular, benzene is associated with elevated cancer risks and a number of other health problems (8).

In 2007, the South Coast Air Quality Management District (SCAQMD) quantified the cancer risks associated with gasoline vapors at typical fueling stations in southern California by modeling emissions and dispersion of gasoline vapors near 35 monitoring locations (9). There are differences between the fueling stations evaluated and the proposed Smith's station: evaluated stations were assumed to have Stage I and Stage II vapor recovery, local weather conditions may differ, and the assumed permitted throughput was lower at the evaluated stations. However, the SCAQMD findings can be adapted to higher throughput gas stations² (such as the proposed Smith's), providing a range of distances at which residential cancer risks due to vapor losses would exceed 1 in a million: 150 – 200 meters (492 – 656 feet) and at which occupational cancer risks would exceed 1 in a million: 60 – 100 meters (197 - 328 feet)³. Note that this is a rough estimate, assuming that that the effect of the weather conditions at the proposed Smith's location fall within the range of the 35 locations evaluated in southern California, and also assuming that current Stage II vapor losses in Albuquerque are equivalent to losses in southern California in 2007 with Stage II vapor recovery in place. The lack of a Stage II vapor recovery system means that risks from a gas station in Albuquerque could extend farther than those described above.

Location of Potential Receptors

As described above, evidence suggests that vehicle emissions from busy roads are elevated for distances as great as 377 – 1870 feet, and that residential cancer risks that exceed 1 in a million from vapor losses from the proposed fueling system could extend to distances of 492 – 656 feet, while occupational risks could extend to 197 – 328 feet.

Based on aerial imagery and the address of the proposed fueling station, we have identified a number of receptors located near the facility, including and businesses (Table 1). Note that health risks from vehicle pollution are greater for vulnerable populations, including children, the elderly, and people with respiratory problems (1, 4). In particular, a number of studies have found evidence of adverse health effects in children associated with air pollution from vehicle traffic (for example see refs. 10-13).

² SCAQMD estimates are based on an assumed permitted throughput of 1,000,000 gallons/yr. SCAQMD indicates that these estimates can be adapted to higher throughput stations by scaling their estimates proportionately. We therefore adapt SCAQMD estimates by multiplying their estimated cancer risks by 7 to reflect risks at stations permitted for 7,000,000 gallons/yr. The estimates presented here are the adapted estimates not the SCAQMD estimates.

³ Occupational exposure estimates assume a shorter duration of exposure, consistent with an 8-hour workday. This may apply to people working at the gas station itself or nearby.

Table 1: Distance from proposed fueling station property to potential receptors

Residences on Mullen Road	360+ feet
Residences on Vineyard Road	370+ feet
Likely residences on unnamed road off of 4 th Street, across from Mullen Road	180+ feet
Residences on Sabre Court	380+ feet

Conclusions

In light of the high throughput that is expected at the proposed Smith's gas station (and the resulting potential for greater than normal emissions), the potential health impacts associated with vehicle traffic and vapor losses, and the facility's proximity to residents, we recommend conducting additional analysis to ensure that the potential air quality and health impacts associated with the proposed Smith's fueling station are better understood. If the facility is found to result in air quality and/or health impacts that exceed levels that are acceptable, mitigations and/or alternatives should be explored.

Attachments

Curriculum Vitae of Dr. Dana Rowangould

Karner, Alex, Douglas S. Eisinger, Deb A. Niemeier, 2010. "Near-Roadway Air Quality: Synthesizing the Findings from Real-World Data" *Environmental Science & Technology* 2010 44 (14), 5334-5344

Rowangould, Gregory M. "A census of the US near-roadway population: Public health and environmental justice considerations", *Transportation Research Part D: Transport and Environment*, Volume 25, December 2013, Pages 59-67

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2. US EPA, 2012. "Health Effects | Carbon Monoxide | US EPA" Retrieved from <http://www.epa.gov/airquality/carbonmonoxide/health.html>. Updated on December 10, 2012. Accessed on August 7, 2014.
3. HEI Air Toxics Review Panel, 2007. Mobile-Source Air Toxics: A Critical Review of the Literature on Exposure and Health Effects. HEI Special Report 16. Health Effects Institute, Boston, Mass. Available at <http://pubs.healtheffects.org/getfile.php?u=384>

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EDUCATION

Ph.D., **University of California, Davis**, Ecology Graduate Group (Environmental Science and Policy Emphasis), 2013.

M.S., **University of California, Davis**, Agricultural and Resource Economics, 2009.

B.S., **Rice University**, Civil and Environmental Engineering, 2002.

EXPERIENCE

Affiliate Associate Professor. Department of Civil and Environmental Engineering, University of Washington, 2013 - Present

Principal. Sustainable Systems Research, LLC, 2012-Present

Recent Consulting:

Ecosystem Management, Inc. *Albuquerque Regional Transportation Infrastructure and Land Use: Climate Change Impacts And Adaptation*, 2014

Natural Resources Defense Council, *Review of the Air Quality Impacts of the WesPac Pittsburg Energy Infrastructure Project*, 2014.

Natural Resources Defense Council, *Review of Port Demand and Air Quality Impacts in the Bayonne Bridge Raising EA*, 2013-2014

Eastern Environmental Law Center and Natural Resources Defense Council, *Mapping Communities and Pollution Sources in NY/NJ*, 2013

Diesel Health Project and Natural Resources Defense Council, *Mapping Pollution Sources and Demographics in Kansas City, KS*, 2013

Save Our Creek, *Review of the Summerhill Homes/Magee Ranch Draft EIR*, 2013

Save Our Creek, *Danville General Plan Review*, 2012

Natural Resources Defense Council, *Review of Southern California International Gateway Project Recirculated Draft EIR*, 2012

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East Yard Communities for Environmental Justice and Natural Resources Defense Council, *Review of the Transportation and Air Quality Analysis in the I-710 Draft EIR*, 2012

Natural Resources Defense Council, *Ports and Air Quality: Moving Toward Clean Cargo*, 2012

TransForm, *Looking Deeper: A detailed review of the project performance assessment being used to develop OneBayArea*, 2011-2012

Postdoctoral Researcher. Center for Regional Change, University of California, Davis, Jan – Aug 2014

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Teaching Assistant. Department of Civil and Environmental Engineering, University of California, Davis, 2012 - 2013

Environmental Scientist. Groundwater Services, Inc., Houston, Texas, 2002-2004

PUBLICATIONS

- Rowangould, D. Karner, A., London, J. (submitted). Identifying Environmental Justice Communities for Transportation Analysis. Submitted for presentation at the Transportation Research Board's 94th Annual Meeting and for publication in the Transportation Research Record.
- Rowan, D., Eldridge, M., Niemeier, D. (2013). Incorporating regional growth into forecasts of greenhouse gas emissions from project-level residential and commercial development. *Energy Policy*, 62:1288-1300.
- London, J., A. Karner, J. Sze, D. Rowan, G. Gambirazzio and D. Niemeier. (2013). Racing Climate Change: Collaboration and Conflict in California's Global Climate Change Policy Arena. *Global Environmental Change* 23(4):791-799
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- Madani, K., Rowan, D., Lund, J. (2007). The next step in central valley flood management: Connecting costs and benefits. Proceedings of the University Council on Water Resources Annual Conference, Boise, ID. July 24-26, 2007.

PRESENTATIONS

- Rowangould, D. Niemeier, D. (2014). Smart growth policy and practice: Retrospective evaluation of residential development in the Sacramento region. Poster presentation at the Transportation Research Board's 93rd Annual Meeting. Washington, DC. January 12-16, 2014.
- Rowan, D., Karner, A. (2011). Moving toward equity: The ongoing struggle for environmental justice in California. Session co-organizer and moderator. Interdisciplinary Graduate and Professional Symposium, UC Davis, Davis, CA. April 23, 2011.
- Rowan, D., Niemeier, D. (2011). Greenhouse gas emissions inventories of proposed residential and commercial developments: Dealing with growth. Poster presentation at the Transportation Research Board's 90th Annual Meeting. Washington, DC, January 23-27, 2011.
- Karner, A., Rowan, D., London, J., Sze, J., Niemeier, D. (2009). Environmental justice, gender, and conflict in California climate policy. Poster presentation at the 4th International Conference on Women's Issues in Transportation. Irvine, CA, Oct. 27 – 30, 2009.
- Rowan, D., Kirk, C., Girn, V., Stasio, K., Stillwater, T., Vassilian, C., Gunda, S., Hsieh, T. (2009). Campus energy solutions: Innovations and results from a collaborative program. Poster presentation at the International Energy Program Evaluation Conference. Portland, OR., August 12-14, 2009.
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Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

A census of the US near-roadway population: Public health and environmental justice considerations



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ARTICLE INFO

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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.

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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](#)

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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 100 m intervals extending out to a maximum of 500 m. 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 250 m 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 250 m 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 are 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 are 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 100 m buffer bands to explore differences in association at different 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 – PM_{2.5}) 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.

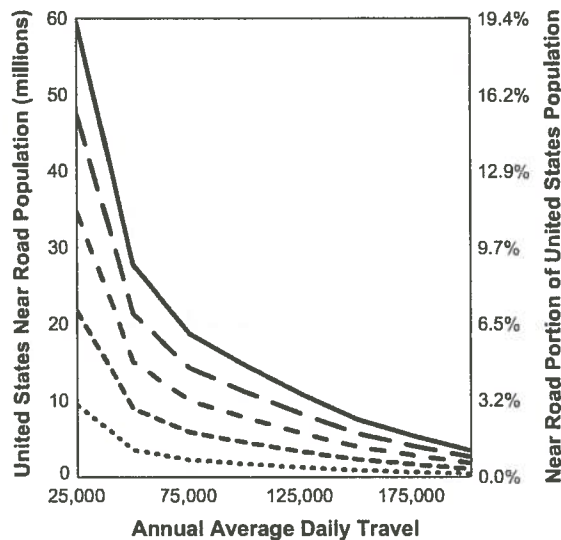


Fig. 1. US population living near high volume roads during the year 2010.

3. Results

The buffer analysis indicates that a large share of the US population lives near high volume roads (Fig. 1). There are 59.5 million people living within 500 m 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 (Fig. 2).

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 \$1221 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 Fig. 3. The plots in Fig. 3a and b do not control for baseline differences in each county's minority population share and median household incomes while the plots in Fig. 3c and d do. Fig. 3a and b shows 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 Fig. 3c and d, 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 considered range.

For example, within 200–300 m 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 200–300 m 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 8–11% 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 average.¹

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

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



Fig. 2. Percentage of the population living within 500 m of a roadway with over 25,000 AADT in each county. Note: Hatched areas indicate counties with no population living near high volume roads.

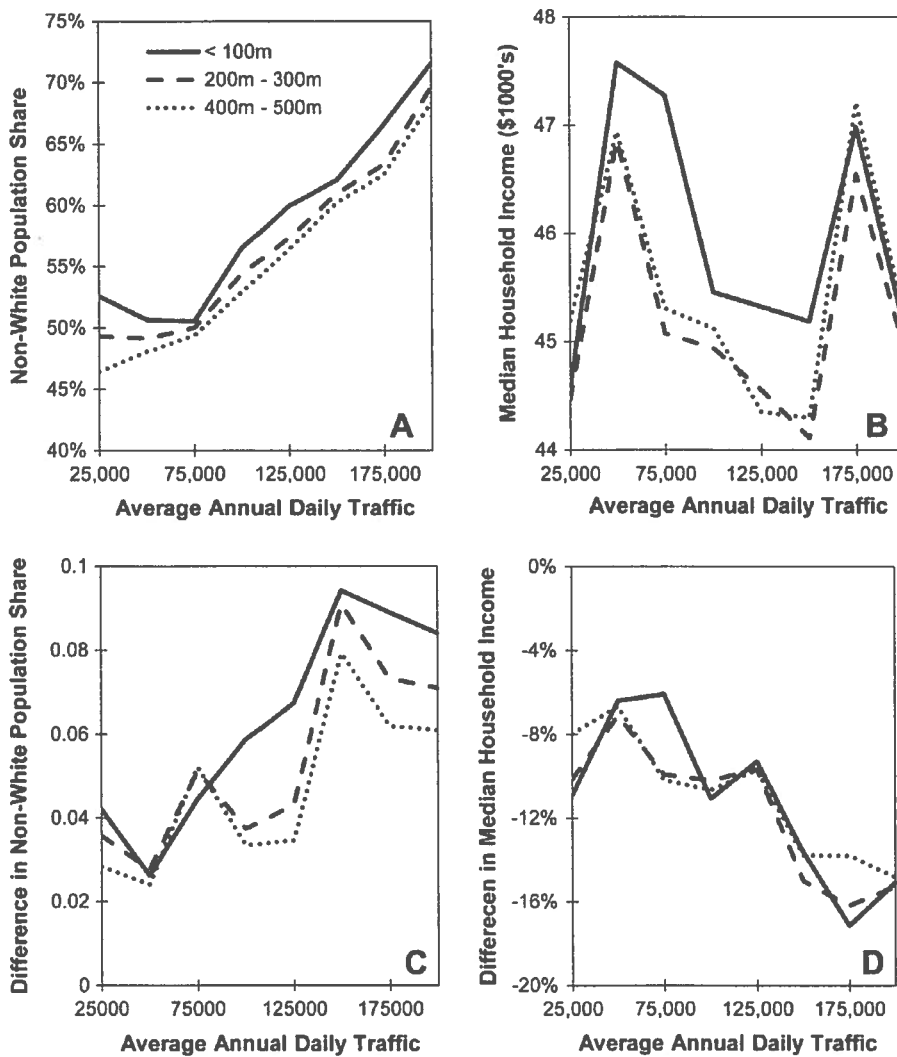


Fig. 3. Relationships between traffic volume, roadway proximity, race and income. Note: Relationship between the share of non-white residents and traffic volume (a), median household income and traffic volume (b), the difference in the share of non-white residents [near road – county] (c), and the percentage difference in median household income [(near road – county)/county × 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.

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>							
1st	6825	\$43,466	19%	7%	8%	1.6%	2.8%
2nd	66,118	\$47,421	31%	13%	11%	4.0%	3.0%
3rd	240,948	\$44,813	41%	19%	13%	5.7%	3.3%
4th	633,366	\$42,648	49%	24%	15%	7.2%	3.3%
5th	3,761,149	\$42,127	57%	28%	17%	9.4%	3.2%
<i>Difference relative to country population^e</i>							
1st	6825	\$2901	−4.3	−1.9	−1.9	−0.38	−0.16
2nd	66,118	\$1415	−0.7	−1.0	−0.1	0.33	0.08
3rd	240,948	−\$3486	3.5	1.4	1.4	0.43	0.22
4th	633,366	−\$6464	5.8	3.1	2.2	0.26	0.21
5th	3,761,149	−\$7591	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.

^e Mean population weighted difference between block and county populations by traffic density quintile.

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 \$1339 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.

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 incomes are \$2901 greater than county averages in the lowest traffic density quintile and \$7591 less than county averages in the highest traffic density quintile.

Large minority and low-income populations in urban areas could drive the aggregate results in Fig. 1 and Table 1. The maps in Fig. 4 shows the difference in population characteristics between the lowest and highest traffic density quintiles for each county in the US. Fig. 4a and b 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 (Fig. 4c and d) 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).

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.

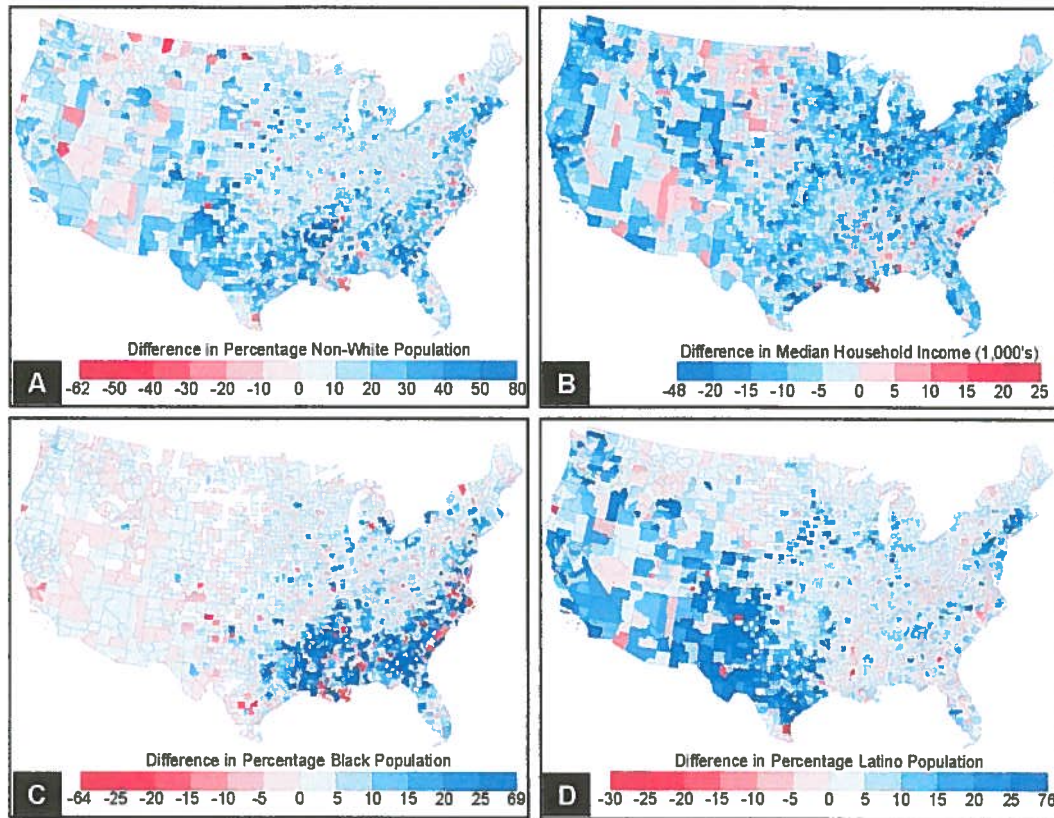


Fig. 4. Spatial distribution of county level income and race disparities. Note: Difference in the percentage of non-white population (a) average median household income (b), percentage black population (c), and percentage Latino population (d) between the lowest and highest traffic density quintile for each US county.

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.

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

AADT ^b	Model 1		Model 2		
	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 × 100).

^e Natural log of population density.

^f values in parentheses are 95% confidence intervals for the conditional odds ratios.

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 × 100].

^d Natural log of population density.

Table 4
Count of counties with co-located air quality monitors.

Pollutant	AADT	Distance from road		
		<100 m	<300 m	<500 m
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.

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.

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

Table 5
Population (millions) living near high volume roads in counties without co-located air quality monitors.

Pollutant	AADT	Distance from road		
		<100 m	<300 m	<500 m
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.

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 PM_{2.5} 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 PM_{2.5} 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 100 m of roads with greater than 200,000 AADT have a co-located PM_{2.5} monitor. The findings are similar for CO, NO_x, and PM₁₀ monitors.

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 exposure.²

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

Additionally, 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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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.

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Near-Roadway Air Quality: Synthesizing the Findings from Real-World Data

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Despite increasing regulatory attention and literature linking roadside air pollution to health outcomes, studies on near roadway air quality have not yet been well synthesized. We employ data collected from 1978 as reported in 41 roadside monitoring studies, encompassing more than 700 air pollutant concentration measurements, published as of June 2008. Two types of normalization, background and edge-of-road, were applied to the observed concentrations. Local regression models were specified to the concentration-distance relationship and analysis of variance was used to determine the statistical significance of trends. Using an edge-of-road normalization, almost all pollutants decay to background by 115–570 m from the edge of road; using the more standard background normalization, almost all pollutants decay to background by 160–570 m from the edge of road. Differences between the normalization methods arose due to the likely bias inherent in background normalization, since some reported background values tend to underpredict (be lower than) actual background. Changes in pollutant concentrations with increasing distance from the road fell into one of three groups: at least a 50% decrease in peak/edge-of-road concentration by 150 m, followed by consistent but gradual decay toward background (e.g., carbon monoxide, some ultrafine particulate matter number concentrations); consistent decay or change over the entire distance range (e.g., benzene, nitrogen dioxide); or no trend with distance (e.g., particulate matter mass concentrations).

Introduction

Since the early 2000s, there has been increased regulatory interest in understanding and mitigating near-road air pollution in the United States. The U.S. Environmental Protection Agency's 2001 Mobile Source Air Toxics (MSAT) Rule identified locations near heavily trafficked roads as important microenvironments for MSAT exposure (1). In 2003, California Senate Bill 352 classified freeways and other busy traffic corridors as facilities with the potential to emit hazardous air pollutants (2). The bill required environmental review of proposed school sites located within a quarter mile (~400 m) of urban or rural roads with average daily traffic exceeding 100,000 and 50,000 vehicles, respectively. In 2004, the Sierra Club litigated to prevent expansion of highway US 95 in Las Vegas, Nevada, citing concerns regarding near-road air pollutants. The lawsuit settlement agreement committed state and federal agencies to monitoring at several

roadside locations and to pilot mitigation strategies at nearby schools (3). A 2005 California Air Resources Board (CARB) land use guide recommended siting "sensitive land uses" further than 500 feet (~150 m) from a freeway or high-traffic road (4).

Concern over near-road pollution is motivated by a growing body of literature examining associations among pollutant concentrations, health impacts, and road proximity. To date, empirical findings on health effects related to near-road pollutant exposures have been mixed (5–17), and there have been few attempts to synthesize what is known about real-world near-road pollutant concentrations. This study begins to fill this gap by synthesizing and evaluating approximately three decades of published real-world monitoring data and characterizing the relationships that exist between pollutant concentrations and road proximity.

Two meta-analyses of near-road air quality have been undertaken in recent years. In the first, Brugge et al. (13) reviewed cardiopulmonary health risks associated with near-road exposures and concluded, from a review of eight studies, that ultrafine particle number, black carbon, carbon monoxide (CO), and oxides of nitrogen (NO_x, including nitric oxide [NO], and nitrogen dioxide [NO₂]) are elevated near roadways and the most important exposure zone extends to those individuals residing 30 m from freeways. In the second study, Zhou and Levy (18) performed a meta-analysis to determine important parameters affecting the "spatial extent" of impacts resulting from mobile source air pollution. They reviewed 33 studies; 18 were monitoring studies; the remainder involved dispersion modeling, land use regression, biomonitoring, and epidemiology. Spatial extent was defined as the distance at which roadway effects were no longer observable; it focused on measures of pollution concentration or health impacts. Their findings varied as a function of the spatial extent definition (concentration vs. health impacts), pollutant type, and local meteorology. Overall, they observed that the concentration-based spatial extent of mobile source impacts ranged from 100–500 m from roads. One limitation to this study, as noted by Zhou and Levy, was that results for particulate pollutants were not disaggregated by particulate size and mass fraction, a limitation that has been addressed in this study.

This paper advances understanding of the dispersion of near-road air pollutant concentrations by synthesizing findings from 41 monitoring studies undertaken beginning 1978 and published by June 2008. The findings document, by individual pollutant type, the distances over which near-road concentrations decay to background. Concentration measurements are normalized using two techniques: normalizing to a background and an edge-of-road concentration.

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The findings also complement other work describing the physical and atmospheric processes governing the shape and rate of decay curves for individual pollutants (18); such prior work has dealt mostly with chemical reactivity and dispersion impacts on the atmospheric transport and fate of given pollutants such as NO₂ and ultrafine particles (19). Finally, our results will help validate modeling tools or assess under which conditions model estimates are most robust. Pollutant exposure is determined by many factors such as time of day and location of activities (20); to the extent that exposure occurs in the near-road environment, this study provides a stronger scientific context for designing buffer zones to avoid exposure to higher pollution concentration levels.

Methods

Data Assembly and Preparation. To populate our database, we included reported distance/concentration pairs from all monitoring studies we identified that included information or findings on near-road concentration gradients. If upwind or background data were unavailable, downwind data were still included in the database. A comprehensive literature search was completed to identify and include data available as of June 2008; however, it is possible that studies not previously cited or widely distributed were missed. No judgment was made regarding the quality of the fieldwork or the instrumentation used. Rather, we assumed that study authors performed the necessary quality assurance and quality control to validate their data.

Although a diversity of measurement approaches and technologies have been used to assess near-road concentrations, the most frequently applied method was to arrange pollutant monitoring equipment along a vector approximately perpendicular to the road. Distances and pollutants varied among studies, as did motivation. Some studies collected data solely to observe near-road conditions; others were designed to improve model verification or calibration. Collected measurements typically involved measurement campaigns conducted over periods ranging from several hours to several weeks or longer. Meteorology also varied widely.

Our analysis unit was one distance/concentration pair (e.g., a single CO measurement at 30 m from the edge of road). We identified 780 such pairs from 41 papers (8, 21–60); the literature represents wide geographic, meteorological, and traffic operational variation. (The Supporting Information includes an annotated bibliography of all studies.)

Our final database includes distance/concentration pairs that spanned 263 unique measurement sets. A measurement set is defined here as a group of distance/concentration pairs originating from the same study and representing one pollutant under one set of measurement conditions. Many studies reported results from different observation days, seasons, or traffic conditions. If these data were available from the study results, we recorded them as separate measurement sets for analysis.

To partially control for the important influence of wind direction on observed concentration (31), data were only entered into the database for concentrations measured when wind was approximately from the road or was aggregated over meteorological conditions including winds from the road. Studies typically used prevailing wind patterns to orient monitors to measure downwind impacts, but four studies (13 measurement sets total) reported observations under parallel wind conditions (31, 44, 58, 59). These measurements were not included.

Field measurements were grouped by pollutant type or surrogate (EC includes black carbon, black smoke, and the reflectance of PM filters). Ultrafines were also grouped but as a separate category. The term “ultrafine” typically refers to particles less than 100 nm in diameter (61), and particle

number concentrations (as opposed to mass concentrations) are typically used to quantify ultrafine roadside concentrations. We categorized particle number concentration into three groups: UF1 particle number denotes data collection beginning at 3 nm, UF2 particle number signifies data collection beginning at 15 nm, and fine particle number begins at 300 nm (0.3 μm, just above the ultrafine classification). We also grouped volatile organic compounds (VOC) into two categories. The first was VOC1 including eight VOCs whose concentrations generally varied with distance from road; examples include 1,3-butadiene and methyl tert-butyl ether. VOC2 included four VOCs whose concentrations generally did not vary with distance from road; examples include propane and *n*-butane. (The Supporting Information contains further details on data reduction and complete information on pollutant grouping.)

Normalization. Monitored concentration data are typically normalized to wind speed or traffic volume (58), to a reference near-road distance (43, 44), or by subtracting out background concentration (41, 53). There are problems in normalizing to traffic volume or meteorological conditions when aggregating data across numerous studies. First, many studies do not provide sufficient information (e.g., temporal resolution) to derive similar measures of traffic or meteorological conditions elsewhere. Second, even when data can be gathered, studies frequently aggregate or resolve data to the units most useful for that particular study interest. For example, daily traffic might be used for cumulative effects, whereas peak hour traffic might be applied for a study interested in acute effects.

We have chosen two types of normalization procedures that can easily be replicated in future studies and rely on factors that are usually readily available from or described in published work. The first, normalizing to background, yields the relative concentration of pollutants measured in the near-road zone compared to nearby concentrations unaffected by (typically upwind of) the road. This normalization can directly identify whether and where measured concentrations fall to background levels. The normalization divides observed near-road concentrations by the reported background value; as values approach one, near-road concentrations approach background.

The second approach, normalizing to edge-of-road, yields the relative concentration of pollutants in the near-road zone compared to concentrations measured at the point of expected maximum roadway influence: the roadway edge. This type of normalization indirectly allows assessment of whether and where measured concentrations fall to background levels. This approach has two benefits relative to background normalization. First, it enables use of data from (many) studies for which no background measurements were published or recorded. Second, it avoids data comparison problems—since there is no standard protocol in use to measure near-road background concentrations, background concentrations reported in monitoring may result from a variety of measurement approaches and locations relative to the road being studied.

Edge-of-road normalization involves dividing all concentrations in a measurement set by the edge-of-road concentration. If the edge concentration was unavailable, in most cases an exponential fit of the individual measurement set was used. Previous work has shown that an exponential decay describes the atmospheric fate of pollutants which vary by distance (43, 55, 56, 59). We also used linear regression to estimate an edge concentration for pollutants that showed little variation with distance according to the supporting annotated bibliography. This did not affect the shape of the decay curve in the event that the concentration actually varied exponentially with distance. The estimated value was used simply to normalize the rest of the measurement set. If the

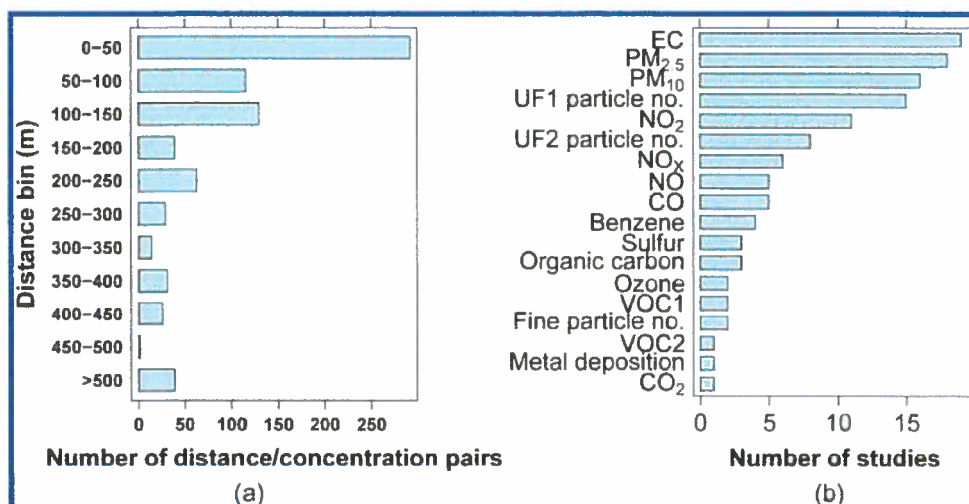


FIGURE 1. Database summary: (a) observations grouped by 50 m distance bin and (b) studies grouped by pollutant. EC in (b) refers to direct and surrogate measures; measures of particle number (UF1, UF2, Fine) and VOCs (VOC1, VOC2) are discussed in the text and the Supporting Information. The sum of bars in (b) exceeds the 41 studies in our database—some studied several pollutants.

edge concentration was underpredicted by linear regression, then normalized downwind values were artificially increased relative to the edge-of-road concentration; however, the point at which background was reached should not have been affected. We also used ANOVA assessments (discussed below) to quality check the assignment of edge concentrations. The ANOVA coefficients for near-road values confirmed that the assigned edge concentrations were reasonable.

The edge-normalized values indicate whether and at what distance from the road concentrations reach a stable value. In concept, stability is indicative of near-road concentrations approaching or reaching background, although it is numerically possible (though physically less likely) that stability could also represent a steady concentration above background. (See the Supporting Information for further edge normalization details.)

While many factors affect the magnitude of observed near-road concentrations (22, 35, 40, 59, 62), if the *shape* of the concentration decay curve is expected to be roughly similar across multiple studies for a given pollutant, dividing by the roadway edge concentration should preserve the shape while removing the absolute magnitude of the observations. This intuition has been confirmed by recent work on the influence of roadway configuration and sound/vegetation barriers on observed concentrations (62) and in other normalized comparisons undertaken by Zhu et al. (58) for three facilities normalized to unit wind speed and traffic volume. Others have taken a similar approach with more limited data; for example, Pleijel et al. (43) compared Swedish and Canadian monitoring data for NO₂ by dividing all observations by the NO₂ concentration at 10 m from the road.

Local Regression. Locally weighted regression (loess) was used to regress concentration on distance for both sets of normalized data. Loess is a robust smoother that does not impose a functional form on the relationship between the dependent and independent variables (63). The smoother uses a specified data window that moves along the *x* axis of a scatterplot. At each data point a fitted value is calculated using the subset of the data contained within the moving window. The size of the subset is defined as a percentage of total data and is referred to as the smoothing parameter; larger smoothing parameter values produce smoother concentration vs distance curves. Local regression has previously been applied to near roadway data by Gramotnev and Ristovski (59). However, the authors did not specify the value of the smoothing parameter used. We set the smoothing parameter by visual inspection. Parameter values of 0.75 and 0.70 (background normalization and edge normalization,

respectively) produced smoothed curves sufficient for the purpose of our research.

Analysis of Variance. Discussion of statistical significance is rare in the near-road literature. In studies that do conduct statistical analysis, paired *t*-tests comparing observed concentrations to a reference group typically located closest to the roadway are used (46, 50). Sabin et al. (47) used paired *t*-tests and an analysis of variance (ANOVA) to test differences in the dry deposition rates of metals between downwind locations. However, there is some question as to whether near-road pollution concentrations (in addition to other meteorological and traffic measurements) meet the normality criteria for a *t*-test, and in at least one study the nonparametric Mann–Whitney test has been used (22). The distribution of observed near-road concentrations may be skewed since there are generally a large number of low-concentration observations. If deviation from normality is very large, then ANOVA results may not be robust. To overcome this possibility, we performed an ANOVA to identify the magnitude and significance of changes in concentration by distance from road and augmented the ANOVA results with the nonparametric Kruskal–Wallis test [ref 64, pp 103–104]. R was used for all statistical analyses (65) and figure preparation (66).

Results and Discussion

The literature confirms intuition: meteorology—wind speed and direction—strongly affects near-road pollutant concentrations. When wind flows from the road to receptors, concentration gradients are more pronounced and extend to a greater distance than when wind is parallel to or away from receptors (31). Traffic volume and fleet composition (22, 59) and other factors such as the presence of a noise barrier (62) can also contribute to differences in observed concentrations of traffic-related air pollution. In general, concentrations decay to background within a few hundred meters downwind of a road, although studies measuring pollutants solely in the evening hours indicate that higher concentrations persist beyond 500 m (57). Most of the observations collected from the studies were obtained within 150 m of the roadway (Figure 1a). Studies focused on particulate matter (PM) mass, particle number concentrations, elemental carbon and surrogates (EC), and all oxides of nitrogen (Figure 1b). Approximately 68% of included studies involved some measurements near freeways or highways; the remainder involved measurements only near arterial and/or local roads.

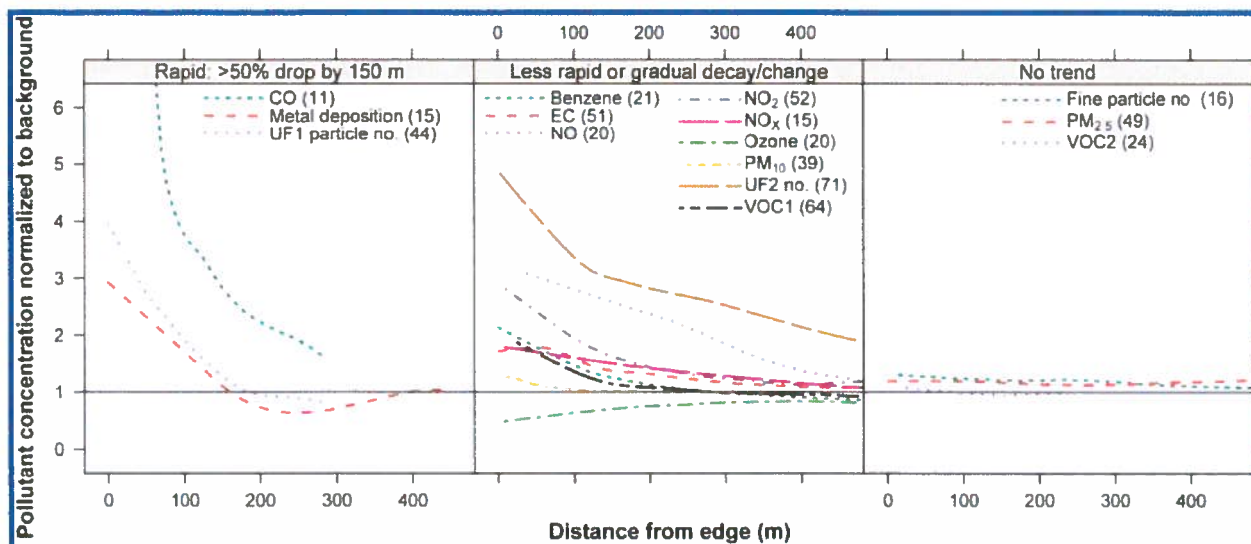


FIGURE 2. Local regression of background normalized concentrations on distance. The horizontal line indicates background concentration. A loess smoother ($\alpha = 0.75$, degree = 1) is fitted to each pollutant which is placed into one of three groups. The regression sample size, n , is given in parentheses after each pollutant.

TABLE 1. Summary of Background Normalized Data

group	pollutant	approximate multiplier above background concentration at edge-of-road	approximate distance required to reach background concentration (m) ^a
rapid: >50% drop by 150 m	CO	21 ^b	— ^c
	metal deposition	2.9	161
	UF1 particle no.	4.0	189
less rapid or gradual decay/change	benzene	2.1	280
	EC	1.7	420 ^d
	NO	3.3	565 ^e
	NO ₂	2.9	380 ^f
	NO _x	1.8	570 ^e
	PM ₁₀	1.3	176
	UF2 particle no.	4.8	910 ^e
VOC1	2.0	270	

^aThe approximate distances were derived from an expanded version of Figure 2; the distance point at which the smoothed line reached a value of one on the y-axis is cited here as background. ^bNear-road CO concentrations extended outside of the range plotted in Figure 2. ^cCO concentrations did not reach background within the 285 m for which data were measured. ^dBackground normalized concentrations attained an approximate minimum value of 1.1 at this distance from the road. ^eReached background concentrations outside of the range plotted in Figure 2. ^fBackground normalized concentrations attained an approximate minimum value of 1.08 at this distance from the road.

Background Normalization. The background-normalized concentrations are shown in Figure 2, and near-road concentrations and distance-to-background values are summarized in Table 1. (The Supporting Information contains supplemental figures illustrating the data used to produce Figures 2 and 3.)

In Figure 2, the range on the y-axis has been constrained to six times above background concentration. The only pollutant exceeding this is CO, which was observed to reach 20 times above background at the roadway edge. The range on the x-axis in Figure 2 has been constrained to 0–450 m from the edge of road where most of the data fall (Figure 1a). We also excluded data from two studies because the sampling and vehicle fleet characteristics were very unique relative to the rest of the studies. One study measured concentrations only at night; another study measured near-road conditions in 1978, when vehicle emissions and near-road concentrations were substantially higher than the values reported in other studies (45, 57). Organic carbon and sulfur are not shown in Figure 2 due to limited data. (See the Supporting Information for further discussion of omitted data.)

Changes in pollutant concentrations over distance generally fell into three groups. The first showed rapid initial concentration decay—defined here as at least a 50% decrease in peak/edge-of-road concentration by 150 m—followed by consistent but more gradual decay toward background; the second consistently decayed or changed over the entire distance range, while the third showed no trend with distance.

One pollutant, ozone, which is shown in the second panel, displayed a unique increasing trend, beginning below background near the road and gradually approaching background by 400 m from the edge. However, ozone values were consistent with expected near-road titration due to interaction with direct vehicle emissions of NO to form NO₂ (67).

All pollutants except for CO, UF2 particle number, NO, and NO_x, reached background by approximately 400 m. UF2 particle number concentrations should generally be lower than UF1 particle number concentrations (38, 48, 68). Reasons for anomalously high UF2 particle numbers are discussed below along with other study limitations. Generally, the high concentrations shown in the first 100 m drop off by 400 m, even considering the between-study differences in methods

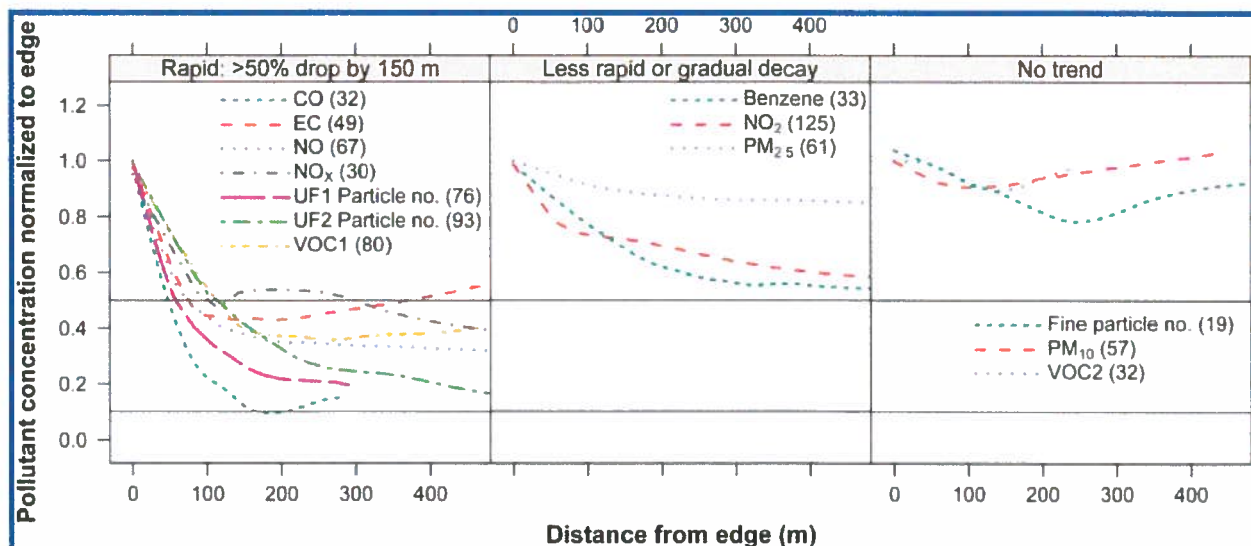


FIGURE 3. Local regression of edge normalized concentrations on distance. The horizontal black lines show a reduction from the edge-of-road concentration of 90% (at 0.1) and 50% (at 0.5). A loess smoother ($\alpha = 0.70$, degree = 1) was fitted to pollutant data which was placed in one of three groups. The regression sample size, n , is given in parentheses after each pollutant. The n includes an estimated (not in the literature) edge-of-road value to facilitate normalization.

TABLE 2. Summary of Edge Normalized Data^a

group	pollutant	percentage decrease ^b	distance (m)	reached background
rapid: >50% drop by 150 m	CO	90	170	yes
	EC	56	130	yes
	NO	65	200	yes
	NO _x	52	115	yes
	UF1 particle no.	79	210	yes
	UF2 particle no.	86	570 ^c	yes
	VOC1	62	180	yes
less rapid or gradual decay	benzene	45	320	yes
	NO ₂	42	550 ^c	yes
	PM _{2.5}	22	986 ^d	no

^a Distances and percentage decreases were derived from an expanded version of Figure 3. ^b For pollutant concentrations that reached background: defined as percent decrease in edge-of-road concentration at the stabilization distance. For pollutants that did not reach background: defined as percent decrease in edge-of-road concentration at the furthest distance for which measurement data were available. ^c Reached background outside of the range plotted in Figure 3. ^d Data for PM_{2.5} extended to 986 m from the edge of road.

and traffic characteristics; this is notable considering the wide variation in data and the inherent limitations of this normalization method (i.e., the lack of common protocols used to define background). The curves indicate (ignoring ozone) that concentrations of certain pollutants are elevated near roadways and decrease as the distance increases, while other pollutants show no roadway influence. These background normalized results suggest that a range of approximately 160–400 m is sufficient to reach background concentrations for the majority of pollutants.

Edge Normalization. The results for the normalization to roadway edge are shown in Figure 3 and summarized in Table 2. We were able to include more data in the edge normalization than background normalization since background measurements or estimates were not required for normalizing in this method. Of the 138 total measurement sets comprising Figure 3, 114 did not include an edge-of-road concentration. Exponential fits (total number of measurement sets for each pollutant in parentheses) were used to determine edge concentrations for benzene (6), CO (3), EC (6), NO (5), NO₂ (14), NO_x (4), UF1 particle number (6), UF2 particle number (14), and VOC1 (16). Linear regression was used to estimate an edge concentration for PM₁₀ (9), PM_{2.5} (11), fine particle number (3), and VOC2 (8). The remaining nine measurement sets contained only two

distance/concentration pairs. Edge-of-road concentrations for these pollutants were also estimated using linear regression including EC (1), NO_x (1), UF1 particle number (3), and UF2 particle number (2). We omitted organic carbon, sulfur, and metal deposition from Figure 3; the data for these pollutants were too sparse to smooth without significantly increasing the smoothing parameter. We also omitted ozone because its increasing concentration with increased distance from the road would plot outside the range of Figure 3. Data from the nighttime-only Zhu et al. (57) study were also excluded. (See the Supporting Information for details on omitted data and edge normalization.)

Edge normalization provides the percentage decrease in pollution concentration as measured from the roadway edge to the distance of interest (Figure 3). For concentrations that varied by distance, the percentage of the near road high concentration at which leveling occurred represents a proxy of that pollutant's background concentration; this assumes that the roadway influence has dropped to approximately zero when no further changes occur in the smoothed curve.

Figure 3 shows CO, benzene, EC, NO, NO_x, NO₂, PM_{2.5}, and UF1 particle number, and UF2 particle number, and VOC1 all decreased as distance from road increased. PM₁₀, fine particle number, and VOC2 showed ambiguous or little to no trend with distance.

TABLE 3. ANOVA and Kruskal-Wallis Results: Background Normalization^a

	ANOVA		Kruskal-Wallis <i>p</i> -value ^e	0-80 m		80-120 m		>120 m	
	Df	F		coeff. ^f	n	coeff. ^f	n	coeff. ^f	n
benzene	(2,18)	17.13 ^d	0.0027	1.967	6		1	-0.968 ^d	14
CO	(1,9)	6.14 ^b	0.0140	12.41	7			-9.97 ^b	4
EC	(1,49)	9.62 ^c	<0.001	2.41	36			-1.119 ^c	15
metal deposition	(1,13)	30.8 ^d	0.0022	3.06	5			-1.947 ^d	10
NO	(2,17)	4.48 ^b	0.0320	5.13	4		1	-3.22 ^b	15
NO _x	(1,13)	4.80 ^b	0.0022	5.55	5			-4.26 ^b	10
NO ₂	(2,49)	13.49 ^d	<0.001	2.63	21		10	-1.378 ^d	21
UF1 p.m. no.	(2,41)	6.06 ^c	<0.001	4.72	29		4	-3.46 ^c	11
UF2 p.m. no.	(2,68)	8.90 ^d	<0.001	6.84	27	-3.46 ^b	10	-4.34 ^d	34
VOC1	(2,61)	37.6 ^d	<0.001	2.09	18	-0.826 ^b	2	-1.037 ^d	44
VOC2	(1,22)	4.31 ^b	0.0431	1.053	8			-0.0817 ^b	16
fine PM no.	(2,13)	3.48	0.1426		4		2		10
ozone	(2,17)	1.64	0.547		5		1		14
PM ₁₀	(2,36)	3.00	<0.001	1.424	27		3	-0.412 ^b	9
PM _{2.5}	(2,46)	0.383	0.791		24		3		22
sulfur	(2,3)	0.987	0.1717		2		1		3

^a The last five rows contain those pollutants with insignificant *F* statistics. ^b Statistical significance is indicated as follows: *p* < 0.05. ^c Statistical significance is indicated as follows: *p* < 0.01. ^d Statistical significance is indicated as follows: *p* < 0.001. ^e The Kruskal-Wallis *p*-value is taken from the nonparametric Kruskal-Wallis test whose null hypothesis is that there is no difference in the mean ranks of the groups. ^f Refers to the regression coefficients extracted from a linear regression of normalized concentrations on distance bin. The coefficient in the 0-80 m bin was the model intercept which represents the mean normalized value in that range, while the coefficients in the other two distance bins represent mean changes relative to the first bin. Missing values in the table indicate insignificant results as judged by the omnibus *F* and the Kruskal-Wallis *p*-value, or no data, evidenced by a blank *n* for the cell.

We again categorized rapidly decaying pollutants as those which decreased at least 50% from their peak value by 150 m. Several pollutants exhibited sharp declines within the first 100-150 m before leveling off. CO and UF1 particle number showed the greatest declines. Benzene, NO₂, and PM_{2.5} showed gradually decreasing trends. NO₂ declined continuously to 450 m indicating that background concentrations were not reached over the plotted distance range but flattened beginning at approximately 550 m from the roadway edge. UF2 particle number showed substantial declines over the entire plotted distance range but did not appear to level until approximately 570 m from the road. The majority of the edge-normalized pollutant concentrations appear to reach background by 115 to 300 m from the edge of road.

Analysis of Variance. Some of the most frequently cited studies using real-world observations (55, 56) show substantial pollutant reductions by 80 m from the road, only slightly shorter than the 100 m zone of highest exposure for some pollutants found in a recent meta-analysis (18).

Near-road concentrations have traditionally been modeled as a Gaussian plume [e.g. ref 11] with as much as 96% of the concentration dissipating by 150 m (69). Our work, however, suggests that decay regimes may be more complex and possibly organized into those pollutants that, under certain conditions, decay rapidly, those that decay gradually, and those that do not decay. To test this hypothesis, we divided our data into three different groups organized by findings in the literature. Specifically, the first bin (0-80 m) represents the window of anticipated peak concentration, as evidenced by our synthesis and widely referenced work (55, 56), the second bin (80-120 m) captures the window which some of the literature has flagged as the end of the spatial extent of mobile source impacts (18), and finally, the third bin (120 m and beyond) represents a reference for the distance range where the literature (modeled and monitored) suggests a substantial decline in observed roadway influence. Some pollutants have no data in the second bin, but this simply reduces the test to a comparison between the first and third groups. The null hypothesis in this case is that there is no difference in mean observed

concentrations between observations near the road (i.e., the first distance bin) and observations further downwind of the road (distance bins two and three).

The mean values (coefficients) for the pollutant within distance category are reported in Tables 3 and 4 for background and edge normalized data, respectively. The coefficients in the second and third distance bins (i.e., 80-120 m and >120 m) are mean changes relative to the first category. It should be noted that the means are not directly comparable to the loess plots, since the loess algorithm uses a weighting function to calculate its fitted values at each data point.

All coefficients in the second and third bin for both normalization methods are negative, since concentrations generally decrease when moving from the first to the second and third distance categories. Results from the Kruskal-Wallis test and ANOVA are generally in agreement, indicating that any deviations from normality are generally not severe enough to affect the ANOVA results.

Background Normalized Concentrations. Mean values of multipliers above background in the first 80 m from the road range from a factor of 1.05 for VOC2 to 12.4 for CO. For PM₁₀, the ANOVA *F*-statistic differs from the Kruskal-Wallis *p*-value. PM₁₀ is on average 1.42 times above background concentrations (0-80 m) and declines by an average of approximately 0.4 from the near road value beyond 120 m (28% decrease). Benzene also shows a small but significant increment above background at 1.97, declining to 1.0 past 120 m (49% decrease). Each of the remaining pollutants that vary by distance both begin at a higher above-background increment than PM₁₀ and decrease more sharply. Thus, the relationship of PM₁₀ with distance appears to be weak, if it exists. PM_{2.5}, fine particle number, and sulfur do not vary by distance, and VOC2 shows a small but statistically significant relationship with distance bin, decreasing by 8% over the distance range greater than 120 m from the road.

Edge Normalized Concentrations. Results show that 10 pollutants out of 11 had mean concentration values less than or equal to one in the 0-80 m range. Mean concentration values for PM₁₀, PM_{2.5}, and VOC2 for the same distance range

TABLE 4. ANOVA and Kruskal-Wallis Results: Edge Normalization^a

	ANOVA		Kruskal-Wallis <i>p</i> -value ^a	0-80 m		80-120 m		>120 m	
	Df	<i>F</i>		coeff. ^f	<i>n</i>	coeff. ^f	<i>n</i>	coeff. ^f	<i>n</i>
benzene	(2,24)	4.40 ^b	0.0282	0.876	7		3	-0.255 ^c	17
CO	(2,24)	15.42 ^c	<0.001	0.652	16	-0.564 ^c	2	-0.477 ^d	9
EC	(2,37)	6.16 ^c	0.0057	0.740	20		1	-0.264 ^c	19
fine PM no.	(2,13)	3.86 ^b	0.0184	1.018	4		2	-0.202 ^b	10
metal deposition	(1,13)	144.7 ^d	0.00182	1.000	5			-0.615 ^d	10
NO	(2,52)	16.02 ^d	<0.001	0.751	25	-0.574 ^d	3	-0.385 ^d	27
NO _x	(2,22)	3.95 ^b	0.0369	0.737	8	-0.609 ^b	2		15
NO ₂	(2,97)	34.8 ^d	<0.001	0.883	41	-0.248 ^d	17	-0.1777 ^d	42
UF1 p.m. no.	(2,61)	15.04 ^d	<0.001	0.611	41	-0.277 ^c	7	-0.353 ^d	16
UF2 p.m. no.	(2,74)	40.5 ^d	<0.001	0.763	29	-0.239 ^d	12	-0.445 ^d	36
VOC1	(2,61)	6.83 ^c	0.0042	0.730	18	-0.448 ^b	2	-0.241 ^c	44
ozone	(2,17)	0.807	0.319		5		1		14
PM ₁₀	(2,41)	1.507	0.214		22		7		15
PM _{2.5}	(2,46)	0.877	0.0334		16		5		28
sulfur	(1,2)	0.061	0.655				1		3
VOC2	(1,22)	3.71	0.066		8				16

^a The last five rows contain those pollutants with insignificant *F* statistics. ^b Statistical significance is indicated as follows: *p* < 0.05. ^c Statistical significance is indicated as follows: *p* < 0.01. ^d Statistical significance is indicated as follows: *p* < 0.001. ^e The Kruskal-Wallis *p*-value is taken from the nonparametric Kruskal-Wallis test whose null hypothesis is that there is no difference in the mean ranks of the groups. ^f Refers to the regression coefficients extracted from a linear regression of normalized concentrations on distance bin. The coefficient in the 0-80 m bin was the model intercept which represents the mean normalized value in that range, while the coefficients in the other two distance bins represent mean changes relative to the first bin. Missing values in the table indicate insignificant results as judged by the omnibus *F* and the Kruskal-Wallis *p*-value, or no data, evidenced by a blank *n* for the cell.

not shown in Table 4 averaged 0.98, providing evidence that edge concentrations were not consistently underestimated.

Concentrations were significantly different for CO, NO, NO₂, VOC1, UF1, and UF2 particle number when comparing the second (80-120 m) and third distance bins (>120 m) to the first (0-80 m). NO_x concentrations were significantly different when comparing the second distance bin to the first. Benzene, EC, metal deposition, and fine particle number showed significant decreases in concentration when comparing the third distance bin to the first. Ozone, PM₁₀, PM_{2.5}, sulfur, and VOC2, all show insignificant *F* statistics.

The Kruskal-Wallis *p*-value indicates significant differences among means by distance group across all pollutants (*p* < 0.05) except for ozone, sulfur, PM₁₀, and VOC2. PM_{2.5} is the only pollutant which shows disagreement between tests. This is likely due to the distribution of PM_{2.5} measurements. When distributions are non-normal, Kruskal-Wallis is more likely to reject a false null hypothesis than ANOVA. A significant decrease in concentration with increasing distance for PM_{2.5} is consistent with graphical evidence from Figure 3. A similar explanation likely holds for background-normalized PM₁₀.

Limitations and Differences between Normalization Methods. We have introduced the first comprehensive use of the edge normalization technique to the literature, partially to offset limitations of using the standard background normalization. We find that normalizing on the basis of the edge-of-road concentration offers advantages to normalizing by the background concentration because the definition of background concentrations differs across studies in the absence of a standard protocol. If, in a particular study, background is mischaracterized as either too high or too low, that study's results can obscure or overstate trends when pooled with other findings. Different studies variously defined background as concentrations measured at the edge of the upwind lanes, some distance from the upwind lanes, the nearest stationary monitoring site, or other locations. These inconsistencies also raise the possibility that our database may include "background" concentrations which reflect roadway influence. This situation could have occurred if

investigators measured background during very low wind speed (meandering wind), when roadway pollutants could drift toward the background monitor. If such situations occurred, they would have artificially increased background values and reduced the observed near-road (downwind) impacts. In general, high background concentrations will tend to generate flatter gradients, and low background concentrations will generate steeper gradients.

For example, background measurements of PM₁₀ for a study in Macao, China were taken on a separate island at sites located 2-4 km away from the roadways under study (54). The resultant low background measurements tended to inflate the background-normalized Macao concentrations relative to other studies in our database that typically measured background just upwind of the roadway under study.

As another illustration, different background measurement protocols resulted in anomalous UF2 particle number findings. Particle number concentrations increase with measurement of smaller-diameter particles (38, 48, 68). However, in Figure 2, normalized UF2 particle number (>15 nm diameter) concentrations exceeded UF1 particle number (>3 nm diameter) concentrations. Part of the explanation involves a study by Hitchins et al. (31) which measured UF2 particle numbers. The authors did not take background measurements but did report concentrations when the wind direction was from the receptors to the road—a background estimation approach that has been used in some other studies [e.g. ref 27]. Additionally, Hitchins et al. (31) reported concentration values under several different wind speed scenarios. The highest values of UF2 particle number were reported at the lowest wind speed, but the background value was given for conditions with a higher wind speed. In this case, normalizing by the reported background concentration resulted in exaggerated concentration values. If another study contemporaneously reported background and near road values, it would likely show lower normalized concentrations. This highlights the difficulties associated with pooling data from studies that frequently employ different measurement and reporting protocols. Depending upon the sample size

TABLE 5. Summary of Pollutant Profiles under Both Normalization Methods^{a,e}

	distance from road at which leveling begins or background reached (m)		percentage of near-road high concentration at which leveling begins or background is reached		edge-of-road multiplier above background concentration (multiples of background)	
	EN	BN	EN	BN ^b	EN ^c	BN
NO _x	115	570	48	56	2.1	1.8
EC	130	420	44	59	2.3	1.7
CO	170	— ^d	10	5	10	21
VOC1	180	270	38	50	2.6	2.0
UF1 particle no.	210	189	21	25	4.8	4.0
NO	200	565	35	30	2.9	3.3
benzene	320	280	55	48	1.8	2.1
NO ₂	550	380	58	34	1.7	2.9
UF2 particle no.	570	910	14	21	7.1	4.8
metal deposition	—	161	—	34	—	2.9

^a Table entries are sorted based on the edge normalized distance at which background concentrations are reached (**bold**). Pollutants that showed significant results in both ANOVA models are included. ^b Calculated as the inverse of the edge-of-road multiplier above background concentrations. ^c Calculated as the inverse of the percentage of near road high at which leveling occurs. ^d Missing values indicate no smoothed data for estimation (e.g., metal deposition) or similar limitations. ^e Abbreviations: EN is edge normalization; BN is background normalization.

across studies, a single study can substantially alter the position of a pollutant's background normalized curve by reporting a background concentration much higher or lower than the background values found in other studies.

In general, it is likely that the bias across studies is for some reported background values to underpredict (be lower than) actual background, due to lengthy averaging periods for background vs near-road measurements, or use of monitoring locations at relatively unpolluted sites distant from areas immediately upwind of the roads studied. This bias would tend to increase the background normalized values estimated here and lengthen the estimated distance required to reach background (affecting results shown in Figure 2). Biasing the distance required to reach background could result in a pollutant being placed into a different decay category depending on the normalization method used.

When normalizing by edge concentrations, the data yield their own background value by virtue of leveling off. The general assumption with edge normalization is that, when pooling data from numerous studies, if the regression approaches a horizontal line, this approximately signifies that roadway influence has diminished to background.

A limitation of the information derived from edge normalization is the possibility that concentrations level off at values which are site-specific—for example, due to abnormally high background concentrations or due to conditions that inhibit dispersion and result in stabilized concentrations above background. If site-specific situations caused the distance at which background was reached to vary across studies, or caused the stabilized value to be an unusually large fraction of the edge-of-road concentration, the regression results (Figure 3) may be biased (e.g., stabilized values higher than background, or the point of stabilization at a shorter distance than would be expected without unusually high background). Finally, while predicting an edge-of-road concentration does not affect the shape of an individual measurement set, it may affect the shape and position of the smoother. If the edge concentration were consistently underpredicted, Figure 3 would show an initial increase in concentrations moving away from the edge of road. Similarly, if the edge concentration was consistently overpredicted, the observed decrease in concentrations would be exaggerated.

Table 5 summarizes the concentration gradients of each pollutant that showed a significant variation with distance in both ANOVA models (see Tables 3 and 4 for significance). Overall, compared to background normalization, edge nor-

malization showed a more rapid decline to background concentrations for EC, NO_x, NO, UF2 particle number concentrations, and VOC1, and a less rapid decline for NO₂. Benzene and UF1 particle number concentrations declined to background at similar distances from the road under both normalization methods. Background normalization has more pollutants in the "gradual decay" category than edge normalization (nine and three, respectively). These results are consistent with the hypothesis that background normalization results in increased distance-to-background values and partially explains why pollutants can change decay categories depending on the normalization method. These differences would likely be smaller if studies better matched background concentrations to the location of near-road measurements.

The findings show that, for almost all pollutants, the influence of the roadway on air pollution concentrations decays to background between 115–570 m according to edge normalization and between 160–570 m based on background normalization. These ranges cover all background normalized pollutants except for CO, which declines continuously to 285 m (end point of available CO data), and UF2 particle number, which achieved background after 910 m; and all edge-normalized pollutants except for metal deposition which was too sparse to smooth and PM_{2.5}, which achieved background by 990 m. Edge-of-road concentrations were elevated from 1.7–20 times above background.

The trends indicated by both normalization methods are broadly consistent, not considering the specific distance at which background is reached. As Table 5 indicates, there is general agreement in terms of the increment at the roadway edge relative to background concentrations (at least to an order of magnitude, in the case of CO, and much closer for benzene, EC, NO_x, and UF1 particle number).

Relevance for Future Research. Key considerations for future near-road work include the following: standardizing the location and method of obtaining background measurements and reporting more completely on site conditions. Some studies at specific sites have assessed how changes in traffic volumes or meteorological characteristics affected near-road concentrations (40, 70, 71). Greater and more consistent specification of site conditions in future work will broaden understanding of the key factors that contribute to near-road concentrations. This study is based on published, mostly daytime, data available as of June 2008. These data were aggregated from studies with nonuniform sampling procedures and nonuniform locations (i.e., different roadway,

geographic, and meteorological conditions). The majority of field studies were conducted at-grade with no obstructions to air flow between the road and the pollution monitors. Such obstructions have been shown to affect observed concentrations (62). Data were only entered when wind direction was approximately from the road to the receptors. Additionally, the sampling periods employed by each investigator typically varied from several hours to several weeks or longer. Concentrations averaged over longer periods will likely vary less than those measured during shorter intervals. Background concentrations were not always averaged over the same period as the associated near-road measurements, nor were they taken in similar locations relative to the road. The choice of background measurement technique can over- or understate roadway increments for a single study; as evidenced by Table 5, the variability in reporting background concentrations may result in an overall bias to overestimate the distance at which pollutant concentrations decay to background.

Some omitted data (57) (described in the Supporting Information), combined with more recent findings (72), indicate that nighttime or presunrise conditions can lengthen, to perhaps two or three thousand meters, the distance at which near-road pollutant concentrations decay to background. Additionally, nighttime near-road ultrafine particle number concentrations can occasionally exceed daytime conditions, despite reduced traffic volumes (72). Further work is needed to integrate daytime and nighttime findings and to assess their relative importance given daytime and nighttime differences in travel activity, near-road pollutant concentrations, and factors affecting human exposure.

In addition to integrating nighttime and daytime near-road findings, future work should update the findings presented here to reflect ongoing research. Additional near-road measurement results were published following assembly and analysis of the data presented in this paper [e.g. refs 73–75]. Findings from recent studies are consistent with results presented here—they show that daytime near-road concentrations are generally indistinguishable from background within several hundred meters from the road.

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Supporting Information Available

Annotated bibliography of all studies included in the synthesis, further discussion on data reduction, omitted data, and edge normalization as well as supplementary figures. This material is available free of charge via the Internet at <http://pubs.acs.org>.

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