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Posted Date: 18 January 2024

doi: 10.20944/preprints202401.1409.v1

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Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 18 January 2024 doi:10.20944/preprints202401.1409.v1

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$PM_{2.5}$ Potential Indoor Exposures and Outdoor Concentrations Related to Smoking Prevalence by Zip Code in Three West Coast States

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Abstract: Low-cost monitors have made possible for the first time measurements of long-term (months to years) potential indoor exposures to fine particles. Indoor and outdoor measurements made over nearly 5 years (2017-2021) by the largest network of low-cost monitors in the United States (PurpleAir) are compared to the prevalence of adult smokers in 1650 Zip codes within the three West Coast states of California, Oregon, and Washington. The results show that mean indoor exposures above the 75th percentile of adult smoking prevalence are more than 50% higher than those below the 25th percentile. Mean outdoor concentrations are also elevated, but by a smaller amount (20%). Both comparisons are significant at the $p<0.001$ level. The elevation of the $PM_{2.5}$ concentrations with increasing smoking prevalence is evidence of environmental disparities in income, education, and other socioeconomic indices..

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1. Introduction

Over the last decade, the introduction of low-cost particle sensors has revolutionized our ability to estimate long-term potential indoor exposure. Previous studies of indoor particulate matter (PM) exposure have been largely restricted to just a few days or weeks at a time, due mainly to the cost, bulkiness, noise, and other drawbacks experienced by the persons in the homes selected for study. The new sensors are cheap, small, and virtually noiseless. They can sit on a shelf indoors virtually unnoticed and quietly build up a data record lasting for as much as 5 years. Adding the ability to share their data electronically on demand makes them invaluable to researchers. In the last few years, several studies have collected multiple years of data from thousands of indoor air monitors.

Epidemiological studies have suffered for many years from our lack of knowledge of indoor air quality. Epidemiologists are forced to estimate exposure from outdoor air measurements only. Since people spend most of their time indoors, this dependence on particles of ambient origin only means that the exposure-response curves are fundamentally flawed. The total indoor exposure is due to the sum of indoor-generated and outdoor-infiltrated particles. We can call this sum of indoor-generated and outdoor-infiltrated particles the *potential indoor exposure*. The term "potential" is necessary here, since exposure requires the presence of the person exposed and we are not always confined to our homes (with the major exception of the period following the Covid-19 epidemic).

Although their contribution to indoor air studies has been transformative, the low-cost sensors have also contributed to studies of outdoor air particles. Placing them in dense networks promises to provide far higher resolution of outdoor air quality than has been possible using the relatively small number of regulatory monitoring networks. A second contribution has been the ability to site many sensors near the regulatory networks, allowing calibration against the accurate Federal Equivalent Methods (FEM) or Federal Reference Methods (FRM) employed in the national monitoring system.

Another area where these low-cost monitors are beginning to be widely used is in environmental justice studies. Often, disadvantaged communities are exactly those with inadequate air quality monitoring, so the low-cost monitors can be used to better identify problem areas within the community.

1.1. PM Studies

A pioneering study of PM_{10} and $PM_{2.5}$ began in the 1970s. Called the Harvard 6-City Study, it used personal monitors as well as fixed indoor and outdoor monitors to measure exposure of persons living in six cities, chosen to represent low, medium, and high outdoor PM concentrations. Multiple follow-ups eventually resulted in 8111 participants who formed the basis for a connection between particle exposures and mortality [1]. The study had an important effect on the development of standards for outdoor particles by the US EPA.

A large study was mounted later by the US EPA. Called the Particle TEAM (PTEAM) Study, it also used personal and fixed indoor and outdoor monitors to measure $PM_{2.5}$ and $PM_{2.5}$ exposures and outdoor concentrations for 189 participants in Los Angeles [2].

1.2. PM and Smoking

Both the 6-City Study and the PTEAM Study found that smoking was one of the most important sources of indoor concentrations and personal exposure. The PTEAM Study estimated that 25% of both PM_{10} and $PM_{2.5}$ indoor concentrations in homes with smokers was due to smoking, with each cigarette contributing 13.8 (95% range of 10.2 to 17.3) mg of PM_{10} to indoor air [2].

1.3. Environmental justice

Disparities in PM outdoor concentrations due to socioeconomic status (SES) have been noted for many years. An important review is Mohai et al., 2009 [3]. More recent studies have found such SES variables as income, education, housing, and ethnic groups to result in increased outdoor PM concentrations [4-11]. However, even with the advent of low-cost monitors, none of these studies were able to show an effect on indoor concentrations [12-16]. In the present study, we aim to use one of the largest studies employing low-cost monitors to explore the effect of smoking on indoor concentrations of more than 4000 residents of three West coast states.

2. Materials and Methods

2.1. Fine particle data

Hourly average $PM_{2.5}$ measurements were collected from about 10,000 outdoor and 4,400 indoor PurpleAir monitors in California, Oregon, and Washington covering the years 2017 through Sept. 8, 2021 [17]. About 85 million outdoor and 35 million indoor hourly averages were downloaded from the PurpleAir API site (https://api.purpleair.com/). The hourly averages were calculated from the raw 2-minute averages of the number of particles identified in the three smallest size categories (0.3-0.5 µm, 0.5-1 µm and 1-2.5 µm) using an algorithm known as ALT-CF3 or as "pm2.5_alt." All of the outdoor monitors were PA-II monitors with two Plantower PMS 5003 optical particle sensors in a single monitor. Data from the two sensors A and B were required to have a precision (abs(A-B/(A+B)) better (lower) than 20%. This corresponds to requiring a relative standard deviation (RSD) of the two sensors to be better (lower) than 28.28%. About 8% of measurements failed to reach this threshold, leaving about 77 million hourly outdoor measurements. About 1100 indoor measurements were also collected using PA-II monitors and the same corrections for precision were applied. The remaining 3300 indoor monitors were PA-I monitors with a single Plantower PMS 1003 sensor. These could not be corrected in the same way, but other quality assurance approaches were applied to remove outliers and other clearly erroneous measurements. This resulted in about 33 million hourly indoor averages. The hourly outdoor and indoor measurements were then averaged to create 3,529,229 quality-assured daily outdoor and 1,333,104 daily indoor measurements. A minimum of 30 full days (at least 18 of 24 hourly averages) was required for every monitor. The mean

 doi:10.20944/preprints202401.1409.v1

number of days per monitor was 220, or more than six months. All daily average measurements include information on the latitude, longitude, state, county, and Zip code of every monitor.

2.2. Calibration

Calibration of low-cost particle monitors is necessary to have confidence in the results. Multiple investigators have calibrated PurpleAir monitors in chamber and field studies. Most of these efforts have used the proprietary algorithms (CF_1 or CF_ATM) supplied by the Plantower manufacturer of the particle sensors. CF_1 is said to be used in "standard" environments (which appears to refer to indoor areas), and CF_ATM for "atmospheric" (outdoor) environments [18]. However, no information is supplied by Plantower regarding the composition or density of any test aerosol employed or the computations resulting in the estimates of PM1, $PM_{2.5}$ and PM_{10}. Most of these chamber and field studies find that the Plantower algorithms overestimate $PM_{2.5}$ by factors close to two [19-25].

An alternative algorithm, based on the method used by reputable manufacturers of multichannel optical particle monitors (e.g. the 16-channel Model 3330 of TSI (https://tsi.com/home/)) has been applied to PurpleAir monitors. This approach uses the particle number counts in the three smallest size categories (0.3-0.5 µm, 0.5-1 µm, and 1-2.5 µm) supplied by Plantower. Choosing a reasonable estimate for the diameter of an "average" particle in each size category, (e.g., the arithmetic or geometric mean of the category boundaries), and then calculating a volume based on assuming sphericity and a density (e.g. that of water) results in the following approach to calculating $PM_{2.5}$. The mass of all particles within the smallest size category is simply the mass m_1 multiplied by the number of particles N_1 in that category. The total mass $PM_{2.5}$ is the sum of the masses in the three size categories:

$$PM_{2.5}\,(\text{density } 1) = m_1N_1 + m_2N_2 + m_3N_3 \qquad (1)$$

But we know the masses m_i based on our selection of the diameter, our assumption of sphericity, and our choice of density, so we can write

$$PM_{2.5}\,(\text{density } 1) = 0.00030418\,N_1 + 0.0018512\,N_2 + 0.02069706\,N_3 \qquad (2)$$

where the N_i are calculated from the Plantower counts of particles in the >0.3 µm, >0.5 µm, >1 µm, and >2.5 µm. Since each of these "greater than" categories contain (like Russian dolls) the numbers of the next larger category, we have to subtract the numbers of the next larger category to obtain the number in a given size range. For example, the number N_1 of particles in the 0.3-0.5 µm category is the ">0.3" category minus the ">0.5" category.

This estimate of $PM_{2.5}$ for a density 1 aerosol can then be compared to reference monitors to determine a calibration factor (CF), resulting in the following equation:

$$PM_{2.5} = CF\,(0.00030418\,N_1 + 0.0018512\,N_2 + 0.02069706\,N_3) \qquad (3)$$

2.2.1. Calibration of outdoor PurpleAir monitors

33 PA-II PurpleAir monitors in California were compared to 27 nearby regulatory monitors using either Federal Equivalent Methods or Federal Reference Methods (FEM/FRM) [26,27]. The resulting CF was found to be 3.0 and the algorithm was named the ALT-CF3 (for alternative) algorithm. This is presently available on the PurpleAir API site as the "pm2.5 alt" algorithm.

Since that time the algorithm has been further tested for both the PMS1003 and PMS 5003 sensors used in the PurpleAir PA-I and PA-II monitors [28]. A revised CF of 3.4 was found. This new value will appear in future revisions of the API site. Until then, users of the PurpleAir data could, if they choose, multiply their results by the ratio of 3.4/3.

2.2.2. Calibration of indoor PurpleAir monitors

Two PurpleAir monitors were calibrated indoors over a 7-month period in 2019 in a room within a home [29]. A single puff of marijuana was emitted and the $PM_{2.5}$ concentration was followed for the next 6-16 hours. During the first part of this decay period, the marijuana smoke dominated the indoor air concentrations, but during the later stages, the normal background indoor air was comparable to or greater than the marijuana concentrations. 47 experiments took place between Jan 15, 2019 and July 21, 2019 using three SidePak monitors and two PurpleAir PA-II monitors (four Plantower PMS 5003 sensors). The SidePaks were tested separately using gravimetric methods and a SidePak calibration factor of 0.44 was calculated [30]. The PurpleAir indoor calibration factor was then determined by comparison with the SidePaks and found to be 2.93, quite close to the original value of 3.0 found for outdoor monitors but about 14% smaller than the later value of 3.4 (Figure S1 in Supplementary Information).

2.3. Smoking data

The US Centers for Disease Control (CDC) collects data on prevalence of tobacco smoking using telephone surveys in the Behavioral Risk Factor Surveillance System (BRFSS). The specific data set used in this study provides estimates of the prevalence of tobacco smoking by persons 18 and older in all US Zip Codes for the year 2021 (https://chronicdata.cdc.gov/500-Cities-Places/PLACES-Local-Data-for-Better-Health-ZCTA-Data-2023/qnzd-25i4/about_data.) The full dataset includes prevalence estimates for 31,435 Zip codes across the nation; for the tristate region, there are 3,036 Zip codes.

2.4. Census data

For income, education, housing characteristics, and ethnic populations, this paper uses the US Census-based American Community Survey (ACS) for the year 2021 available within the 5-year average data from 2017-2021 https://data.census.gov/table . These data use Zip Code Tabulation Area (ZCTA) codes, which generally have similar but slightly different geographic outlines to the Zip codes used by the US Postal Service. However, in multiple cases, the ZCTA 5-digit codes do not match the USPS Zip codes [31]. There were 1007 mismatches for the three states for the year 2021 and all were removed from the combined data sets using the Census Bureau Crosstalk ZCTA link https://udsmapper.org/zip-code-to-zcta-crosswalk/ .

3. Results

The three datasets described above were merged by ZCTA Zip Code. Statistics for the merged data sets are provided (Table 1).

Table 1. Statistics for the merged smoking, fine particle, and SES variables datasets.

Statistic	Mean indoor $PM_{2.5}$ (µg/m³)	Mean outdoor $PM_{2.5}$ (µg/m3)	Median household income (2021 $)	Prevalence of smoking (%)	Percent over 25 with bachelor's degree	Percent Hispanic or Latin (of any race)
N Zip codes	733	1549	1578	1578	1578	1578
Mean	4.6	8.3	88720	12.3	37.1	25.0
Standard error	0.13	0.10	947	0.09	0.50	0.54
Lower quartile	2.9	6.0	62303	9.5	21.0	9.1
Median	3.8	7.6	80582	12.2	33.6	17.2
Upper quartile	5.2	9.8	106575	14.8	51.4	34.5

There were 1652 Zip codes with either indoor or outdoor measurements lasting at least 30 days and 1384 Zip codes had no $PM_{2.5}$ measurements. These two datasets are compared in Table 2. The total population of the three states in 2021 was 49.9 million, with 38.9 million residing in Zip codes with indoor or outdoor $PM_{2.5}$ measurements compared to 11 million residing in Zip codes with no $PM_{2.5}$ measurements. The Zip codes without monitors had a considerably higher mean prevalence of smoking (17.2%) compared to those with monitors (12.4%). Since the population without monitors

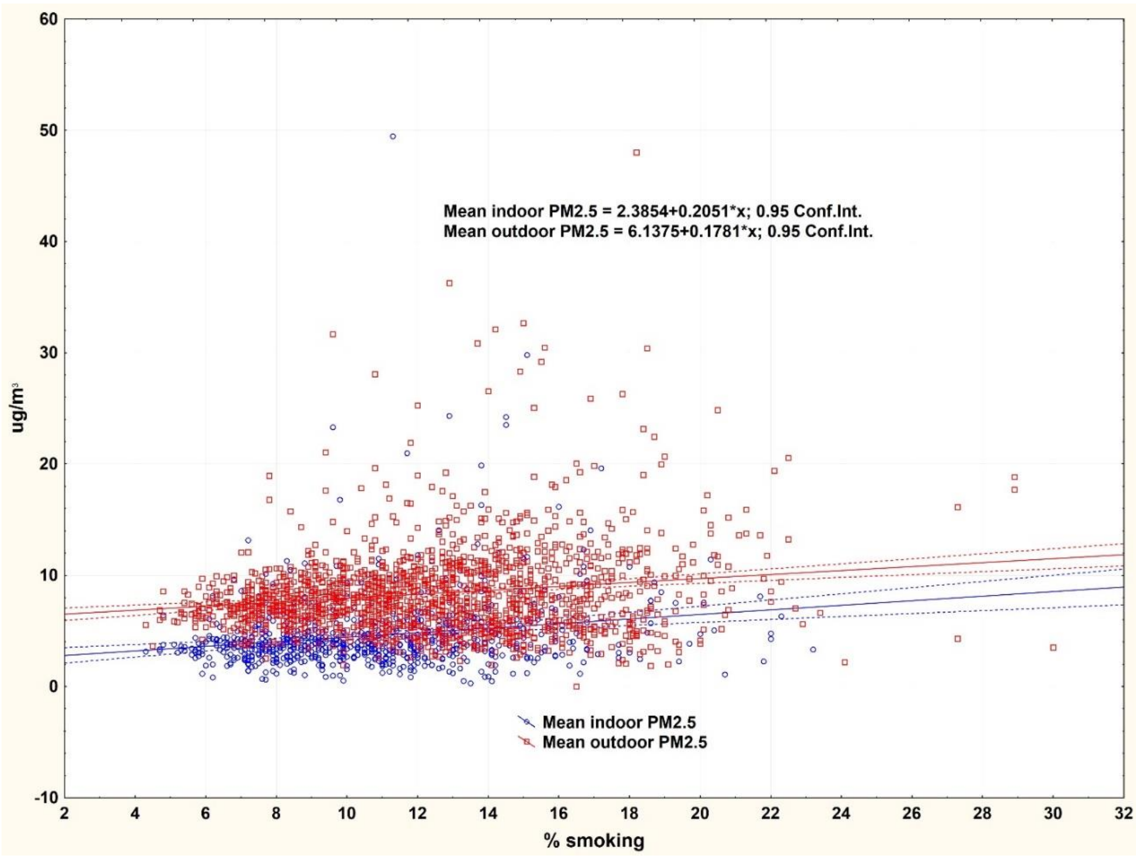
Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 18 January 2024 doi:10.20944/preprints202401.1409.v1

is thus likely to have higher PM exposure, this suggests that our estimates of $PM_{2.5}$ exposure are likely to be underestimates if applied to the entire population.

Table 2. Comparison of total population and prevalence of smoking in Zip codes with and without PM measurements.

	Zip codes with PM measurements (N = 1652)		Zip codes with no PM measurements (N=1384)	
Statistic	% smoking	Population	% smoking	Population
Mean	12.4	23523	17.2	7958
Standard error	0.09	491	0.18	388
Lower quartile	9.6	4783	13.5	366
Median	12.3	21237	15.8	1315
Upper quartile	14.9	36174	18.6	7333
Sum		38860515		11013276

The indoor and outdoor daily average $PM_{2.5}$ measurements are regressed on the smoking prevalence data (Figure 1). There is a strong (p<0.0001) increase in both indoor and outdoor concentrations with increasing prevalence of tobacco smoking. (Note: all p-values are based on Ordinary Least Squares (OLS) regressions, which treat x-values (% smoking) as without error. In fact the Relative Standard Error (RSE) of the smoking prevalence variable is about 0.0075. This error is likely to reduce the calculated significance of all regressions.) The increase in the outdoor concentration is most likely due to socioeconomic factors, since it is known that smoking is greater for persons with lower incomes, less education, and belonging to certain ethnic groups. The larger increase in the indoor concentration is due to a combination of these SES factors and the known major source of indoor $PM_{2.5}$ due to smoking [2].



 doi:10.20944/preprints202401.1409.v1

Figure 1. Regression of mean daily average indoor and outdoor $PM_{2.5}$ on prevalence of tobacco smoking by persons 18 and over within all Zip codes in Washington, Oregon, and California. About 740 Zip codes included indoor air monitors and about 1650 Zip codes included outdoor air monitors.

Comparing the lower half of the smoker prevalence data to the upper half, the mean indoor $PM_{2.5}$ ranged from 4.18 (SE 0.13) to 5.58 (SE 0.29) ug/m^3, a 33% difference, whereas the mean outdoor $PM_{2.5}$ ranged from 7.86 (SE 0.10) to 8.87 (SE 0.17), only a 13% difference (Table 3). Both differences were significant at the p<0.001 level.

Table 3. Comparison of $PM_{2.5}$ concentrations in the upper half of the smoking prevalence data to the lower half.

Upper half	Valid N	Mean	Standard error
Mean indoor $PM_{2.5}$	212	5.58	0.29
Mean outdoor $PM_{2.5}$	800	8.87	0.17
% smoking	820	15.46	0.09
Lower half			
Mean indoor $PM_{2.5}$	523	4.18	0.13
Mean outdoor $PM_{2.5}$	807	7.86	0.10
% smoking	818	9.41	0.06

A stronger relationship is shown if the upper quarter of the smoking prevalence data is compared to the lower quarter (Table 4). Now the increase in the mean indoor $PM_{2.5}$ is from 3.9 (SE 0.10) to 6.01 (SE 0.49), a difference of 54%. The increase in outdoor $PM_{2.5}$ remains smaller at 7.55 (SE 0.11) to 9.23 (SE 0.41), a 22% difference. Again both differences are significant at the p<0.001 level.

Table 4. Comparison of the upper quarter of the smoking prevalence data to the lower quarter.

Upper quarter	Valid N	Mean	Standard error
Mean indoor $PM_{2.5}$	81	6.01	0.49
Mean outdoor $PM_{2.5}$	385	9.23	0.27
% smoking	400	17.38	0.11
Lower quarter			
Mean indoor $PM_{2.5}$	306	3.91	0.10
Mean outdoor $PM_{2.5}$	401	7.55	0.11
% smoking	407	7.85	0.06

A comparison of the relative strength of the relationship between smoking on indoor and outdoor $PM_{2.5}$ is given by the Spearman correlations in Table 5. The correlation with indoor $PM_{2.5}$ (0.18) is nearly twice that for outdoor $PM_{2.5}$ (0.10). This table also includes the very strong (negative) relationships of income and education with smoking.

Table 5. Spearman correlations between smoking prevalence vs. $PM_{2.5}$ and SES variables.

Variable	% smoking
Mean indoor $PM_{2.5}$	0.18
Mean outdoor $PM_{2.5}$	0.10
Median household income ($)	-0.81

 doi:10.20944/preprints202401.1409.v1

Percent over 25 with bachelor's degree	-0.85
Percent Hispanic or Latin (of any race)	0.18

The extremely powerful (negative) relationship between smoking and education is compared to the less powerful (but strongly significant) relationship between smoking and indoor and outdoor $PM_{2.5}$ in Figure 2.

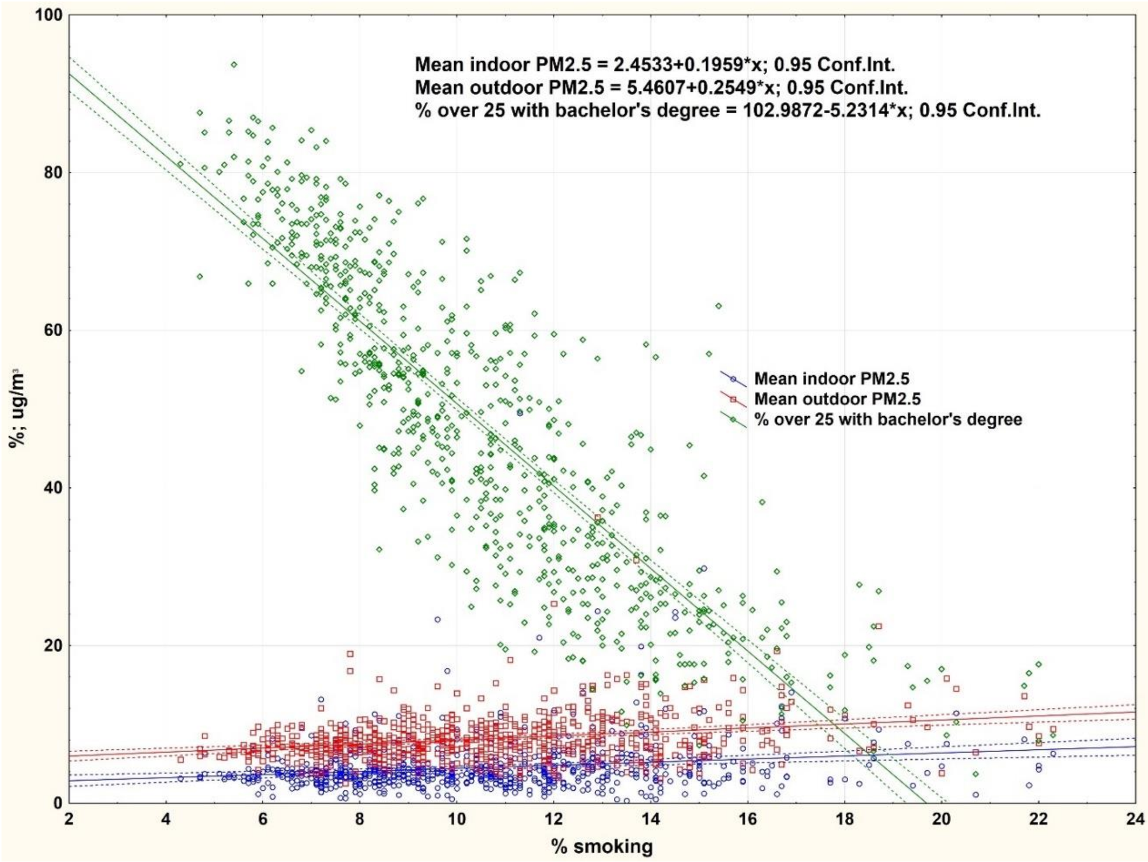


Figure 2. The relationship of % smoking in Zip codes with educational attainment and with indoor and outdoor $PM_{2.5}$ concentrations. Here only Zip codes with both indoor and outdoor air monitors are included (N = 704). .

4. Discussion

Recently, a major nationwide study employing the pm2.5 alt algorithm has considered the indoor and outdoor $PM_{2.5}$ concentrations at about 4000 locations in multiple states during the years 2021 and 2022 [32]. The study was able for the first time to separate indoor-generated particles from those with sharp peaks produced by indoor sources such as smoking and cooking, and those with slow increases found from normal activities such as walking across floors. The two source types contributed equally to indoor-generated particles. The study also found that indoor-generated particles produced 48% of the total indoor concentrations. This result was in close agreement with the 49-50% estimated from the database used in this study, based on about 4400 locations in three West Coast states over the 4.7 years from 2017 through Sept. 8, 2021 [17].

The addition of indoor air measurements to the outdoor measurements employed in previous environmental justice studies have added strength to the conclusions of the earlier studies. This has been the case for such measures as income, education, housing characteristics, and ethnic groups, all explored in many existing studies but limited to estimates of outdoor concentrations. In one recent study all four of these SES variables were found to result in differences on the order of 10-30% for outdoor $PM_{2.5}$ and 30-50% for indoor $PM_{2.5}$, all at significant (p<0.01) levels (Wallace (2024), submitted to *Indoor Environments*). In this case of using a variable (smoking) associated directly with increasing indoor concentrations, the level of significance reached $p<0.001$ for both indoor and outdoor air concentrations. Another case that deserves consideration for future studies might be underage smoking or vaping of marijuana, which can produce 2-7 times the mass of $PM_{2.5}$ per puff as tobacco [29, 33, 34]. However, nationwide data on this possibly increasing risk are impossible to collect due to differing State and Federal laws on the legality of marijuana.

5. Conclusions

Almost all previous environmental justice studies have been forced to use outdoor concentrations as a surrogate for actual exposure. This study provides one of the first large-scale studies of how actual measured indoor $PM_{2.5}$ is related to tobacco smoking prevalence in all Zip codes in three States. Evidence has been presented that indoor air is a stronger predictor of smoking prevalence, and therefore conditions associated with unhealthful exposures, than outdoor air. Because potential indoor air exposures are much more closely associated with actual total exposure than outdoor concentrations, future studies, particularly environmental justice studies, will benefit from adding indoor air measurements to their outdoor datasets. The relationship among tobacco smoking prevalence and several SES indicators has also been presented.

Supplementary Materials: The following supporting information can be downloaded at: www.mdpi.com/xxx/s1, Figure S1: Calibration of indoor PurpleAir monitors based on 47 experiments vaping marijuana in a single room of a home [1].

Author Contributions: The single author performed all activities required for initiating, writing, and editing of the article

Funding: This research received no external funding

Institutional Review Board Statement: No Institutional Review Board approval was required, since no human subjects were interviewed or otherwise asked for information.

Informed Consent Statement: All data obtained was publicly available from subjects who did not avail themselves of the option to remove their data from the dataset.

Data Availability Statement: All PurpleAir data are available from the author on request.

Acknowledgments: PurpleAir is acknowledged for their contribution to science by maintaining an openly available data base on all measurements made by their monitors for personsagreeing to public availability.

Conflicts of Interest: The author reports no conflicts of interest

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