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"I walk and bike because my neighbors do": Analyzing racial/ethnic disparities in active transportation using a neighborhood peer effects framework

A Thesis submitted in partial satisfaction of the requirements for the degree Master of Arts in Geography

by

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June 2024

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May 2024

“I walk and bike because my neighbors do”: Analyzing racial/ethnic disparities in active transportation using a neighborhood peer effects framework

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by

Brianna Chan

ACKNOWLEDGEMENTS

To all of my family, friends, and mentors who teach me, inspire me, and make my world so wide. Thank you for supporting me always.

ABSTRACT

"I walk and bike because my neighbors do": Analyzing racial/ethnic disparities in active transportation using a neighborhood peer effects framework

by

Brianna Chan

Not all racial/ethnic groups in the US have access to the health benefits of active transportation (AT) (i.e., walking and biking). While the physical drivers of racial/ethnic inequities in AT use, such as inaccessibility to safe infrastructure, are well-established in the literature, quantitative evidence for the contextual socio-cultural drivers that influence access to AT is sparse. Our goal is to use a neighborhood peer effects framework to investigate the question, "Are people more likely to engage in AT use in neighborhoods where more people of their same race/ethnicity engage in AT use?" We approach this question by estimating multilevel logistic regression models to measure the likelihood of an individual to engage in AT (i.e., walk or bike), based on the proportion of AT commuters of their same race/ethnicity within their neighborhoods. We define neighborhoods at the Public Use Microdata Area (PUMA) level and include all PUMAs (n = 265) in the state of California. We construct a PUMA same group AT use measure, which describes the proportions of AT commuters of each race/ethnicity for each PUMA, using commuting data from the 5-Year American Community Survey (2017). We merge neighborhood-level characteristics with our individual-level sample (n = 32,510) from the US National Household Travel Survey (2017) in order to analyze the variation in peer influence on AT use among racial/ethnic groups.

In both observed and adjusted models, we find a positive and significant association between individual-level AT use and PUMA same group AT rate for White, Asian, and Hispanic people. We do not find a significant association for the Black population. We find that PUMA same group AT rate has the strongest association with individual-level AT use for the White group, with Asians being the only group with an association significantly weaker than that of Whites. Our study provides key quantitative evidence of the systemic socio-cultural forces that could prevent racial/ethnic minorities from fully accessing AT systems, and broadly informs AT interventions that aim to create more equitable neighborhoods for any and all people.

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I. Introduction

Active transportation (AT), which refers to any human-powered, non-motorized mode of transportation (i.e., walking and biking), has been widely shown to improve overall health and sense of well-being (Glazener et al. 2021; Mueller et al. 2015). Beyond the individual health benefits of engaging in physical activity using AT, such as improved mental health and reduced risks of cardiovascular disease, cancer, and all-cause mortality (Checkroud et al. 2018; Mueller et al. 2015; Celis-Morales et al. 2017; Kelly et al. 2014), AT contributes to healthier environments by improving air quality and lessening exposures to harmful pollutants (Green et al. 2021). At an even broader scale, AT systems have the potential to mitigate climate change and its detrimental effects on population health by facilitating a shift from a car-centric transportation system to one that prioritizes more sustainable forms of transportation (Green et al. 2021; Brand et al. 2021). Evidence of the health benefits of AT illuminates the capacity of AT systems to facilitate healthier and livelier cities at a large scale, encouraging transportation planning agencies to invest in infrastructure that supports safe daily travel by walking or biking (Sciara and Lee 2018; Kärmeniemi et al. 2018).

However, not all people experience the same health benefits of AT, with racial/ethnic minorities experiencing the least access to AT-related health benefits (Barajas and Braun 2021; Adkins et al. 2017; August and Sorkin 2010). Research shows that although AT is positively associated with good health outcomes for all people, AT users of color are typically more likely to report worse health compared to their White counterparts, and the mechanisms for this disparity remain unclear (Barajas and Braun 2021). The growing amount of AT and transportation justice literature identifies the consequences of racial/ethnic disparities and corresponds to an intensifying urgency to better serve populations that have been historically excluded from AT spaces (Karner et al. 2020; Sadeghvaziri et al. 2023; Nguyen and Barajas 2023; Krapp et al. 2021; Golub 2016). Recently, research on social disparities in AT access and use has gained the most attention compared to other topics in the AT literature, emphasizing further the imperative need to address these disparities in our AT systems and identify the mechanisms that perpetuate them (Sadeghvaziri et al. 2023).

Racial/ethnic disparities in AT use are due to both inequalities in physically accessing AT infrastructure and contextual socio-cultural factors, like social norms, perceptions, and attitudes that prejudice some groups from using AT safely and willingly (Cusack 2021; Handy et al. 2010; van Acker et al. 2010). Most studies focus on quantifying how the presence of AT infrastructure varies by community and how these infrastructure inequalities fuel racial/ethnic inequities (Glazener et al. 2021; Barajas and Braun 2021; Knight et al. 2018; Lowe 2016; Rybarczyk 2014). Literature on the infrastructure-related drivers of AT inequities highlight lower levels of accessibility to AT infrastructure, such as reliable sidewalks and bike lanes, and lower walkability indices in neighborhoods with a high racial/ethnic minority population, which further inhibits minority groups from gaining the health benefits of AT (Sadeghvaziri et al. 2023; Adkins et al. 2017; Braun et al. 2019; Freeman et al. 2013).

Other studies investigate the contextual socio-cultural drivers of racial/ethnic disparities in AT use, using qualitative methods to illuminate the personal experiences and attitudes that racial/ethnic minorities have toward AT systems. Studies show that biking, for example, is perceived by the general public to be dominated by affluent, White males, which can deter people who do not fit that mold from engaging (Barajas and Braun 2021). Biking infrastructure is also considered a symbol of gentrification in minority communities, further perpetuating feelings of exclusion in racial/ethnic minorities and discouraging their engagement with biking systems, even if they have physical access to them in their neighborhoods (Braun 2024; Hoffmann and Lugo 2014; Lubitow and Miller 2013). Additionally, racial/ethnic minorities have expressed barriers such as safety concerns about the higher visibility of AT modes, like greater exposure to racialized attacks and police violence, compared to car travel (Lubitow et al. 2019).

Despite the merit of the existing literature on racial/ethnic disparities in AT, a gap lies in our current quantitative knowledge of socio-cultural drivers of AT disparities among racial/ethnic groups, especially regarding the impact these drivers have on individual-level AT use (Cusack 2021; Sallis et al. 2004). Addressing this gap provides insight into a more comprehensive, unified knowledge that captures the confluence of built environment and socio-cultural processes on AT access, which further helps guide interventions aimed to promote transportation justice and health equity.

A. Neighborhood Peer Effects

The term neighborhood effects refers to a sociological framework that explains how individual-level outcomes are derived from ecological, cultural, and political forces that influence communities in a specific geographic area, or neighborhood (Mayer and Jencks 1989; Sampson et al. 2002; Sharkey and Faber 2014). Neighborhood effects theories were prompted by debate on the influence of living in a poor neighborhood on shaping individual outcomes (Mayer and Jencks 1989), and have since been used to identify the dynamic social mechanisms that influence individual outcomes, and explain the variation of spatial trends across neighborhoods, in domains such as health and human development (Sampson et al. 2002). In the health literature, research on neighborhood effects has been used to answer questions related to how neighborhood characteristics, like poverty, racial/ethnic composition, socioeconomic status, and community cohesion affect health and well-being outcomes (Diez Roux 2001), like the presence of mental health disorders (Ross 2000), risky adolescent behaviors (Kowaleski-Jones 2000; Ajilore 2015; Sampson et al. 1997), and academic performance (Nieuwenhuis and Hooimeijer 2016).

Neighborhood peer effects refer to a specific mechanism of neighborhood effects, where individual behaviors and attitudes are influenced by peers in an overarching social context (Durlauf 2004; Xiong et al. 2016). The framework of neighborhood peer effects is general and has been applied to study questions in a number of disciplines, including sociology (Salvy et al. 2008), politics (Fafchamps and Vicente 2020; Polipciuc et al. 2023), and human development (Havewala et al. 2021). In the existing health and well-being literature, neighborhood peer effects have been shown to be especially important as factors that drive outcomes related to physical activity rates (Salvy et al. 2008), academic achievement (Ajilore et al. 2015; Thrupp et al. 2002; Lavy and Scholsser 2011), and school enrollment (Bobonis and Finan 2008), as well as ways in which peers influence the outcomes of certain groups, such as racial/ethnic minorities, differently (Bobonis and Finan 2008). Research that applies neighborhood peer effects has implications for population-level health interventions and can inform key health policies, as shown in experimental studies that have identified how peers can encourage behaviors related to disease management (Webel et al. 2010), disease prevention (Pruckner et al. 2019), and exercise (Zhou and Zhang 2023; Sallis 1998). Peer effects have been shown to influence individual AT use outcomes in a recent study, which found that a desire to conform to peers' behaviors influenced active transportation choice in the workplace context of Grenoble University (Lambotte et al. 2023). This prompts further investigation into how peer effects can shape the varying trends in AT ridership among different racial/ethnic groups, which has not yet been quantitatively investigated in the literature.

B. Research Question and Hypotheses

In response to the literature, we pose the question, "Are people more likely to engage in AT use (i.e., walk or bike) in neighborhoods where more people of their same race/ethnicity engage in AT use?" To answer this question, we compare the relationship between neighborhood-level AT rates and individual-level AT rates of four racial/ethnic groups: (1) non-Hispanic White, (2) non-Hispanic Black, (3) non-Hispanic Asian, and (4) Hispanic groups.

We propose two hypotheses:

- **Hypothesis 1:** Higher rates of people of the same race/ethnicity who engage in AT in a neighborhood is associated with an increase in the likelihood of an individual of that race/ethnicity to also engage in AT, due to evidence that peers often have positive effects on individual-level behaviors related to physical activity (Zhou and Zhang 2023).
- **Hypothesis 2:** Neighborhood-level AT rates by race/ethnicity will have a stronger association with individual-level AT use for racial/ethnic minorities (i.e., non-Whites), due to evidence in the literature that racial/ethnic representation in the neighborhood has a positive impact on feelings of belongingness for racial/ethnic minorities (Graham et al. 2022).

II. Study Area

The study area spans all neighborhoods in the state of California. We define neighborhoods as Public Use Microdata Areas (PUMAs), which are Census-defined geographic units of analysis characterized by (1) boundaries that are based on aggregations of counties and Census tracts within a state, (2) a population between 100,000 to 200,000 people at the time of delineation, and (3) contiguity (i.e., each PUMA shares a border with another). We use the terms *PUMA-level* and *neighborhood-level* interchangeably throughout this paper. We choose the PUMA (n = 265) as the neighborhood-level unit of analysis because it is the finest scale of geography available for the Public Use Microdata Sample (PUMS) from the 5-Year American Community Survey (ACS). Each PUMA contains observations of AT use for at least 50 people of each racial/ethnic group of interest (i.e., each PUMA records AT use for at least 50 White individuals, 50 Black individuals, etc.), allowing us to construct PUMA-level AT use measures for each of these groups. We choose California as the study area because the state has (1) a larger sample size of individuals with travel data compared to other states, and (2) a high number of metropolitan areas that are considered to be friendly for walking and biking (The League of American Bicyclists 2022).

Important to note is that our study question may be relevant in only some PUMAs with high population density, as we include non-metropolitan areas in our study. The PUMAs that have low population density, and have predominantly suburban or rural characteristics, are especially at risk of not capturing an individual's true exposures to AT users and may include extremely low rates of AT, thereby limiting the applicability of our results (Pelletier et al. 2023). Nonetheless, there are benefits to setting our study area to the entire state of California, as this wider study area allows us to see a more holistic picture of the geographic variation in AT rates across the state and provides results that are generalizable to a wider variation of populations in active transportation contexts.

III. Data

A. Neighborhood-level Data: 5-Year American Community Survey (2017)

We use neighborhood-level demographic and AT commuting data from the 2017 ACS estimates, which we accessed from the *tidycensus* package in R (US Census Bureau 2017; Walker 2024). In our study, all neighborhood-level data are based on aggregations at the PUMA level.

The independent variable, or the exposure variable, is a PUMA-level AT rate that we construct for each racial/ethnic group. We refer to this measure as our *PUMA same group AT rate* throughout this paper. The PUMA same group AT rate describes the proportion of people of each race/ethnicity who use AT to commute to work within a PUMA. To create the PUMA same group AT rate, we calculate weighted proportions of AT commuters of each racial/ethnic group for each of the 265 PUMAs, using data from the PUMS survey item, *JWTRNS*, which contains 1,653,162 observations of individual-level commuting modes. Importantly, the ACS contains data only on means of transportation to work, excluding non-commuting trips like those with recreational or shopping purposes, and we nonetheless use this data because it is one of the only variables available to create a PUMA-level estimate of racial/ethnic levels of AT use. For the independent variable, we compile a dataset of the PUMA same group AT rates for each of the four racial/ethnic groups per PUMA. In Figure 1, we show an overview of the geographic variation of PUMA-level AT commuting rates by race/ethnicity across all 265 California PUMAs. Not only do different racial/ethnic groups have different exposures to AT commuters of their same race/ethnicity within each PUMA, but these exposures vary across PUMAs within the state.

In the multilevel models, we also incorporate PUMA-level variables from the ACS that may partially explain trends in AT use: median household income, average age, total population, total populations and population proportions of each of our racial/ethnic groups of interest, racial/ethnic segregation, and population density. We use the dissimilarity index to calculate the levels of Black-White, Asian-White, and Hispanic-White racial/ethnic segregation (Reardon and Sullivan 2004; US Census Bureau 2021), using estimated (weighted) tract population totals of each racial/ethnic group. Total White population and Hispanic-White dissimilarity variables are highly correlated (i.e., their correlation coefficient is 0.65 or higher) with other PUMA-level variables, so we did not include them in our models.

B. Individual-level Data: National Household Travel Survey (2017)

We use individual-level demographic and AT travel data from the geocoded version of the National Household Travel Survey (2017) (NHTS), a cross-sectional dataset that captures comprehensive data on nationwide travel patterns and infrastructure needs (Federal Highway Administration 2017). Survey respondents aged 5 or older record all of their trips taken over a 24-hour period, starting from 4 AM on the day of survey assignment to 4 AM of the following day, where they describe the trip purpose, transportation mode, and other travel characteristics. The NHTS encapsulates trips of all purposes, with main purposes falling under the categories of commuting, recreational, and shopping, and is recorded in person-trip format (i.e., each individual trip is recorded as an entry in the dataset, and each trip corresponds to a person identifier code). Along with travel data, the NHTS provides other individual-level demographic characteristics and geocodes of household addresses. We specifically use the 2017 iteration of the NHTS because of its add-on program, which provides additional household samples that reduce sampling error and increase precision in transportation-related analyses for participating states, like California. The NHTS dataset contains 26,095 household samples, which correspond to a total of 33,362 individuals.

The dependent variable, or the outcome variable, is individual-level AT use, which we code as a binary variable. To create this variable, we focus on the survey item, *TRPTRANS*, to identify AT users in our analysis. We code a binary indicator of whether or not an individual walked or biked for any of their recorded trips over the 24-hour period that the survey was administered (i.e., “0” identifies individuals who did not use AT at all in the 24-hour period and “1” identifies those who used AT at least once). Each individual also contains a PUMA indicator of their residential address denoted in the NHTS which is used to merge in PUMA-level data (described in Section III Part C).

Figure 1: PUMA same group AT rates, denoted as above or below the AT rate median for each respective group. Rates are shown for (1) Asian, (2) Black, (3) Hispanic, and (4) White groups. Data is from the ACS (2017).

In the multilevel models, we incorporate individual-level variables from the NHTS including race/ethnicity, age, sex, family household income, and health status. We code race/ethnicity as a categorical variable denoting either non-Hispanic White, non-Hispanic Black, non-Hispanic Asian, or Hispanic. We code sex as a binary variable, denoting either male or female. We also categorize family household income into low (<$50,000), middle ($50,000-199,999), and high (>$200,000) income categories. We dichotomize health status, which we derive from a self-rated health measure with five categories ranging from poor to excellent, into those who rated themselves as having good versus poor health. We regard self-rated health as a sufficient measure of health status, since perception of health has been shown in the literature to be a reliable indicator of actual health (Jylha 2009). We do not incorporate variables indicating education level, employment status, household size, and physical activity level, because these variables are highly correlated with other PUMA-level variables (i.e., their correlation coefficient is 0.65 or higher).

C. Data Integration

Using the relevant variables, we merge the PUMA-level data to each individual in the NHTS via their PUMA identifier, to assign each individual their respective PUMA same group AT rate and PUMA-level covariates. This merge results in a dataset with 33,362 entries that correspond to a unique individual and their respective individual-level and PUMA-level characteristics.

To avoid non-convergence issues when estimating our regression models, we remove individuals who have missing data on NHTS survey items from our sample. Individuals who responded with “prefer not to answer”, “other”, or “I don’t know” for any of the NHTS survey items are treated as having missing data and therefore also removed from our sample. Removing cases with missing or non-specific survey responses leads to a 2.55% reduction in the sample size, decreasing it from 33,362 to 32,510 individuals.

Nationally representative weights are incorporated into this dataset to account for sampling error and non-response bias. The descriptive tables and figures for the ACS are weighted using the variable, *PWGTP*, while those for the NHTS are weighted using the variable, *WTPERFIN*.

IV. Descriptive Statistics

Before proceeding, we remind the reader of the following terms used frequently throughout this paper:

- Same group AT rate: the proportion of individuals of the same race/ethnicity who use AT overall.
- PUMA same group AT rate: the proportion of individuals of the same race/ethnicity who use AT within a given PUMA.

A. Neighborhood-level AT Rates (ACS)

In Table 1, we show the weighted PUMA-level characteristics derived from the ACS, broken down by racial/ethnic group. The White group makes up the greatest percentage of the state population (57.0%), followed by the Hispanic (24.2%), Asian (12.5%), and Black (6.3%) groups. The Asian group has the highest same group AT rate across all PUMAs (1.6%), followed by White (1.6%), Black (1.2%), and Hispanic (1.2%) groups, which we visualize in Figure 2. The average PUMA same group AT rate is highest for Blacks (1.6%) and Whites (1.6%), whereas it is lowest for Asians (1.5%) and Hispanics (1.5%). Note that the AT rates derived from the ACS are lower than those in the NHTS, because they only identify those who commute using AT, and not those who use AT for other trips (e.g., recreation, shopping, errands).

	White	Black	Asian	Hispanic
Total population	20,554,862	2,237,593	4,387,340	8,782,073
	S.E. 22,112	10,025	11,660	18,357
Percentage of population	56.99	6.28	12.50	24.23
	S.E. 0.05	0.03	0.03	0.04
Avg. PUMA population	77,566	8,444	16,556	33,140
Avg. PUMA proportion (%)	56.99	6.28	12.50	24.23
Same group AT rate (%)				
Walk	1.15	1.05	1.26	0.95
	S.E. 0.01	0.03	0.03	0.02
Bike	0.43	0.19	0.35	0.23
	S.E. 0.02	0.02	0.02	0.01
Total	1.59	1.24	1.61	1.18
Avg. PUMA same group AT rate (%)				
Walk	1.15	1.34	1.21	1.18
Bike	0.44	0.28	0.27	0.29
Total	1.59	1.62	1.48	1.47
Total number of PUMAs	265			

Table 1: Weighted descriptive statistics and average PUMA-level estimates of the ACS (2017) population.

B. Individual-level AT Rates (NHTS)

In Table 2, we show the weighted individual-level NHTS population characteristics broken down by racial/ethnic group. Similar to the PUMA-level ACS results, the White group comprises the largest proportion of the NHTS sample (71.1%), followed by Hispanic (15.8%), Asian (9.9%), and Black (3.1%) groups. The White group has the highest same group AT rates (28.1%), followed by Asian (25.4%), Black (22.8%), and Hispanic (20.7%) groups, as shown in Figure 3. The average PUMA same group AT rate is highest for the White and Asian groups (2.0%), compared to their Black (1.6%) and Hispanic (1.5%) counterparts, indicating that Whites and Asians have more AT users of their same race/ethnicities within their neighborhoods, on average. When comparing Figures 2 and 3, we see a similar trend in AT rates among racial/ethnic groups in both the ACS and the

NHTS, with Whites and Asians consistently having higher AT rates than their Black and Hispanic counterparts.

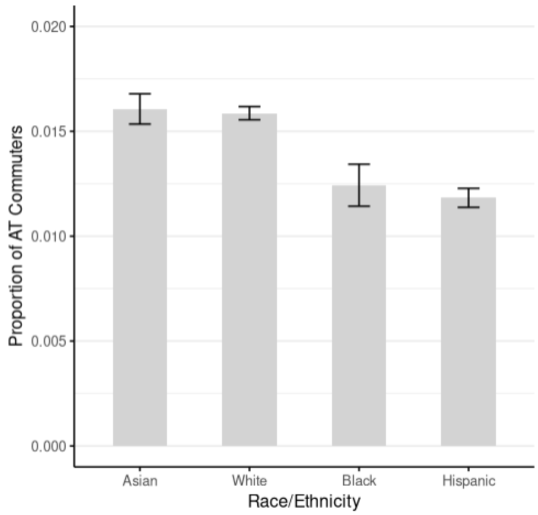


Figure 2: PUMA same group AT rates by race/ethnicity from the ACS (2017).

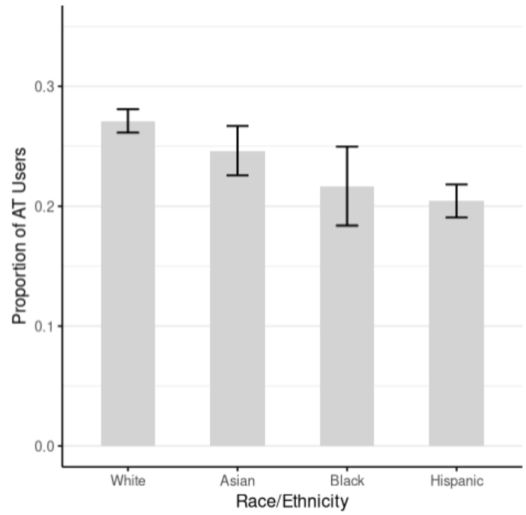


Figure 3: PUMA same group AT rates by race/ethnicity from the NHTS (2017).

As we show in Table 2, the individual-level and neighborhood-level characteristics of the NHTS population align with what we would expect. Regarding the individual-level characteristics of the NHTS population, this population consists mostly of middle-aged people around 30 and 40 years old, and males and females are relatively balanced, as the sample contains no extreme bias toward one sex in any of the racial/ethnic groups. White and Asian individuals have better health and higher family household incomes compared to their Black and Hispanic counterparts.

The neighborhood-level characteristics refer to PUMA-level measures derived from the ACS that were used to describe the neighborhoods of our individual-level NHTS sample. White individuals live in the wealthiest PUMAs, while Black individuals live in the poorest PUMAs. The average age of a PUMA is middle-aged, ranging from 35 to 39 years, for all racial/ethnic groups. Black and Asian individuals tend to live in denser neighborhoods compared to Whites and Hispanics. There is low variation in the level of PUMA-level racial/ethnic segregation for every racial/ethnic group, as all groups live in PUMAs with an average Black-White dissimilarity of about 40%, and an average Black-Asian dissimilarity ranging from about 31% to 35%.

	White	Black	Asian	Hispanic
Main Characteristics				
Sample size	23,128	1,018	3,232	5,132
Percentage of sample (%)	71.14	3.13	9.94	15.79
Same group AT rate (%)				
Walk	25.29	21.43	22.47	19.39
	S.E. 0.49	1.68	1.01	0.69
Bike	2.85	1.33	2.94	1.30
	S.E. 0.18	0.51	0.43	0.18
Total	28.14	22.76	25.41	20.69
Avg. PUMA same group AT rate (%)	1.95	1.62	1.95	1.52
Individual-level Characteristics				
Age (years)	42.57	40.68	37.64	33.59
	S.E. 0.01	0.83	0.43	0.32
Good health (%)	93.80	86.95	94.65	90.65
	S.E. 0.28	1.36	0.57	0.53
Sex (%)				
Male	53.59	45.94	52.60	50.49
	S.E. 0.57	2.08	1.22	0.88
Female	46.41	54.06	47.40	49.51
	S.E. 0.57	2.08	1.22	0.88
Household family income (%)				
Low	24.48	47.28	27.35	47.66
	S.E. 0.49	2.08	1.14	0.89
Middle	60.44	48.64	56.52	47.86
	S.E. 0.56	2.07	1.22	0.88
High	15.08	4.09	16.12	4.48
	S.E. 0.40	0.80	0.84	0.35
Neighborhood-level Characteristics	79,555	63,467	86,793	65,411
Median household income ($)				
	S.E. 304.15	945.24	673.35	392.67
Avg. age (years)	38.63	35.49	38.37	35.89
	S.E. 0.05	0.17	0.09	0.08
Population density (per sq. mi.)	6,601	9,094	8,607	6,652
	S.E. 83.44	269.92	197.73	269.82
Racial/ethnic segregation (%)				
Black-White dissimilarity	40.88	39.91	39.81	40.82
	S.E. 0.11	0.48	0.24	0.19
Asian-White dissimilarity	31.31	34.96	30.96	34.52
	S.E. 0.11	0.48	0.26	0.21

Table 2: Sample size and weighted descriptive statistics of the NHTS (2017) population. Neighborhood-level characteristics describe average PUMA statistics for the NHTS population at the PUMA level.

V. Analytical Approach

Using the R environment, we estimate multilevel logistic regression models to predict the likelihood of an individual to walk or bike, based on the proportion of AT commuters of their same race/ethnicity within their neighborhood. Multilevel logistic regression models account for the hierarchical structure of our data where individuals are nested within their neighborhoods (PUMAs). We estimate our models using the *glmer* command in R, which can be used to fit multilevel logistic regression models with binary outcomes. To estimate and visualize predicted values of our outcome variable, we use the *ggpredict* command in R, in which we set numeric covariates to their means and factor terms to their reference level.

We estimate several models:

- Base models, stratified by race/ethnicity, that show the association between PUMA same group AT rate and the log-odds of individual-level AT use for each of the racial/ethnic groups, excluding covariates.
- Adjusted models, which are the base models including covariates.
- A pooled model incorporating all racial/ethnic groups, including all individual-level and neighborhood-level covariates, in order to see the overall association between PUMA same group AT rate and individual-level AT use.
- The same pooled model, including interactions between individual race/ethnicity and PUMA same group AT rate, in order to compare the magnitude of this association among the racial/ethnic groups.

Prior to estimating models, we standardize the covariates by using the scale command in R, which converts each original value to a z-score. Doing so prevents convergence issues that arise from variation of scales and units among variables.

VI. Results

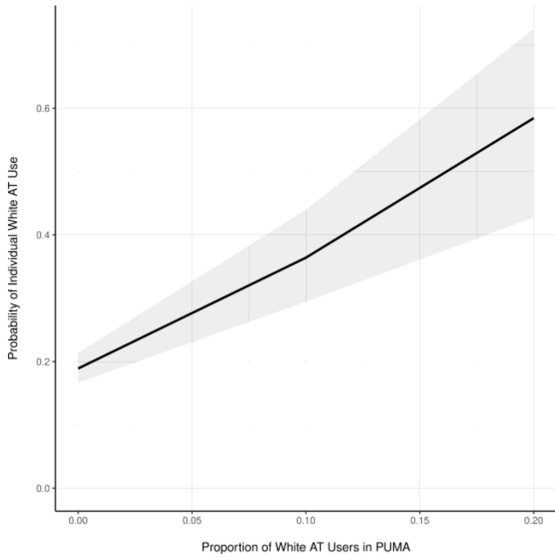
We find several notable trends in the models stratified by race/ethnicity. First, we find a positive and significant association between PUMA-level AT rates and individual-level AT use for all racial/ethnic groups, excluding covariates, as shown in Table 3. It is important to note that because the outcome variable is binary, we interpret a one unit increase as a jump from no AT users of the same race/ethnicity in one's neighborhood to 100% AT users of the same race/ethnicity. In the White group, we find that for each one unit increase in the proportion of White AT users, the log-odds of a White individual choosing to walk or bike increases by 16.32, whereas in the Black, Asian, and Hispanic groups, a one unit increase in their respective PUMA same group AT rate corresponds to a respective increase in their log-odds of individually using AT by 7.88, 8.75, and 16.66.

	White			Black			Asian			Hispanic		
	Est.	S.E.	P	Est.	S.E.	P	Est.	S.E.	P	Est.	S.E.	P
Intercept	−1.371	0.042	***	−1.435	0.107	***	−1.381	0.064	***	−1.640	0.058	***
Main Effects												
Prop. White AT users	16.324	1.630	***									
Prop. Black AT users				7.878	3.442	*						
Prop. Asian AT users							8.745	1.696	***			
Prop. Hispanic AT users										16.663	2.305	***
Random Effects												
Variance	0.12			0.10			0.09			0.11		
Standard deviation	0.342			0.319			0.303			0.331		
Number of Observations	23,128			1,018			3,232			5,132		
Number of PUMAs	263			209			245			265		
BIC	25,724.8			1,087.8			3,534.8			5,170.6		
RMSE	0.43			0.41			0.42			0.40		

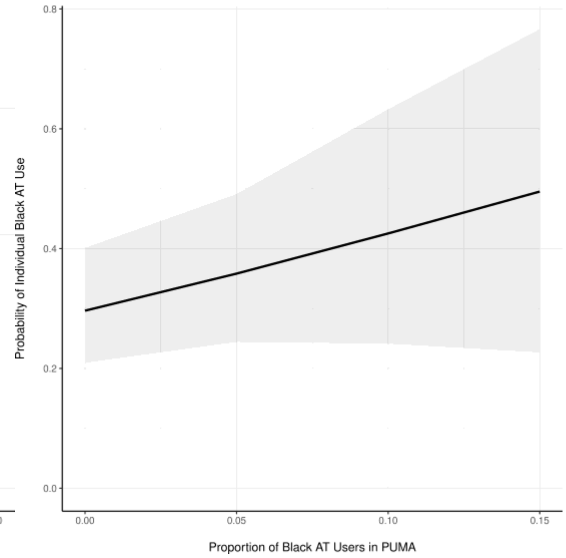
Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '+' 0.1 '' 1

Table 3: Base multilevel logistic regression models for individual-level AT use by race/ethnicity. Estimates are log-odds.

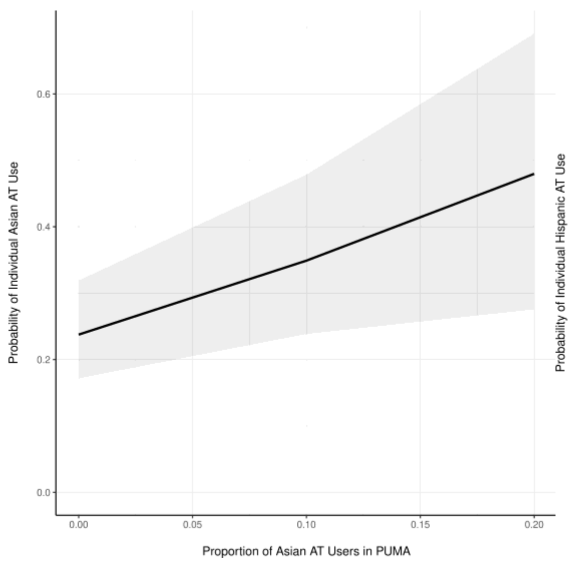
In Figure 4, we show that full models after adjusting for covariates for each race/ethnicity indicate a positive and significant association between PUMA same group AT rate and individual-level AT use for the White, Asian, and Hispanic groups, which show an increase in log-odds of individually using AT by 8.98, 5.64, and 10.97 with every one unit increase in PUMA same group AT rate, respectively (see Appendix for specific estimates). The association is positive for the Black group as well, although it is not significant. Before and after adjusting for covariates, the models stratified by race/ethnicity show an overall positive trend, supporting our first hypothesis so far.



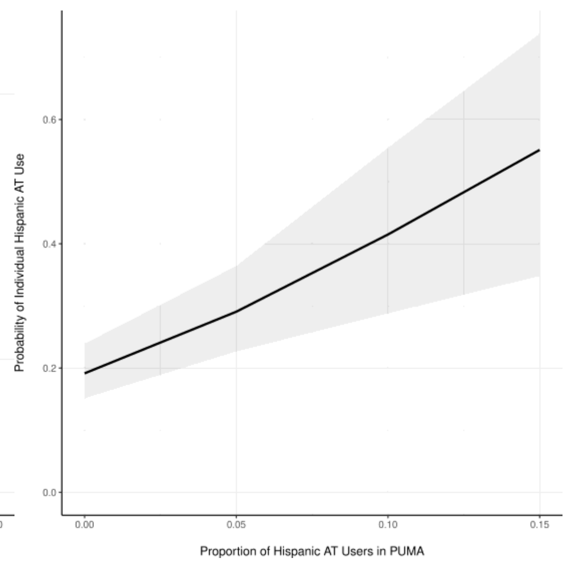
(a)



(b)



(c)



(d)

Figure 4: The predicted probability of individual-level AT use for (a) White, (b) Black, (c) Asian, and (d) Hispanic groups based on proportion of PUMA same-race/ethnicity AT users, after adjusting for covariates. The shaded gray area represents the 95% confidence interval of the estimates.

In the first pooled model (Model 1 in Table 4), we analyze the overall association between PUMA same group AT rate and individual-level AT use. We find a strong positive association between PUMA same group AT rate and individual-level AT use across all racial/ethnic groups combined, after adjusting for covariates. As seen in Model 1 in Table 4, a one unit increase in PUMA same group AT rate corresponds to an increase in the log-odds of choosing to walk or bike by 7.49. In Figure 5, we plot the positive relationship between PUMA same group AT rate and individual-level AT use for all racial/ethnic groups combined (denoted by the line labeled "All").

The second pooled model (Model 2 in Table 4) shows adjusted pooled estimates when incorporating interactions between PUMA same group AT rate and individual race. We find that the association between PUMA same group AT rate and individual AT log-odds differ only for the Asian group relative to the White group, which is lower than the White group. We visualize the predicted values of individual-level AT use for each racial/ethnic group in Figure 4; our predicted values show a larger increase in predicted probability of individual-level AT use per unit increase for the Hispanic group, followed by Black and Asian groups, although the predicted values corresponding to the Black and Hispanic groups are not significantly different from the values for the White group.

Results for the covariates align with literature on neighborhood-level and individual-level characteristics known to affect AT use. From the individual-level characteristic estimates in both Model 1 and Model 2 in Table 4, we find that young and old age, good health status, and low family household income are significantly associated with a higher likelihood of an individual to use AT, regardless of race/ethnicity. At the neighborhood level, there is a higher likelihood of walking and biking for those who live in PUMAs that are characterized by relatively higher median household incomes, have a higher composition of older-aged people, are denser, and/or have a higher proportion of Black people, which are indicators characteristic of urban core areas (Shutters et al. 2022; Parr 2007; Pew Research Center 2022) known to be more conducive to better AT infrastructure (Pelletier et al. 2023). While we control for the neighborhood-level and individual-level variables to isolate our measured association between PUMA same group AT rate on individual AT behaviors, we acknowledge the possibility of omitted variable bias, due to the difficulty of capturing all of the external factors that influence the association between our two main variables of interest. Additionally, this issue may also lead to an endogeneity problem, where the independent variable, PUMA same group AT rate, is correlated with a variable captured in the error term.

	Model 1: No Interactions			Model 2: Interactions		
	Est.	S.E.	P	Est.	S.E.	P
Intercept	−1.27	0.06	***	−1.29	0.06	***
Main Effects						
PUMA same group AT rate	7.49	1.22	***	8.84	1.30	***
Race (ref: White)						
Black	−0.33	0.08	***	−0.26	0.10	*
Asian	−0.33	0.05	***	−0.22	0.06	***
Hispanic	−0.36	0.05	***	−0.34	0.07	***
Interaction effects						
PUMA same group AT x Black				−2.85	3.28	
PUMA same group AT x Asian				−4.55	1.48	**
PUMA same group AT x Hispanic				−0.73	1.90	
Individual-level Effects						
Female *(ref: male)*	0.00	0.03		0.00	0.03	
Age	−0.14	0.06	*	−0.13	0.06	*
Age-squared	0.15	0.05	**	0.15	0.05	**
Good health *(ref: poor health)*	0.23	0.06	***	0.23	0.06	***
Family household income (ref: low)						
Middle	−0.25	0.03	***	−0.25	0.03	***
High	−0.27	0.05	***	−0.27	0.05	***
Neighborhood-level Effects						
Median household income	0.12	0.03	***	0.12	0.03	***
Average age	0.08	0.03	**	0.08	0.03	**
Population density	0.21	0.03	***	0.20	0.03	***
Total population	0.03	0.02		0.03	0.02	
Racial/ethnic total population						
Black	0.05	0.02	*	0.05	0.02	*
Asian	0.00	0.03		0.00	0.03	
Hispanic	−0.02	0.03		−0.02	0.03	
Racial/ethnic segregation						
Black-White dissimilarity	0.00	0.03		0.00	0.03	
Asian-White dissimilarity	0.03	0.03		0.03	0.03	
Random Effects						
Variance	0.06			0.06		
Standard deviation	0.24			0.24		
Number of observations	32,510			32,510		
Number of PUMAs	265			265		
BIC	35.48			35.51		
RMSE	0.42			0.42		

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘+’ 0.1 ‘’ 1

Table 4: Multilevel logistic regression models for individual-level AT use by race/ethnicity. Estimates are in log-odds.

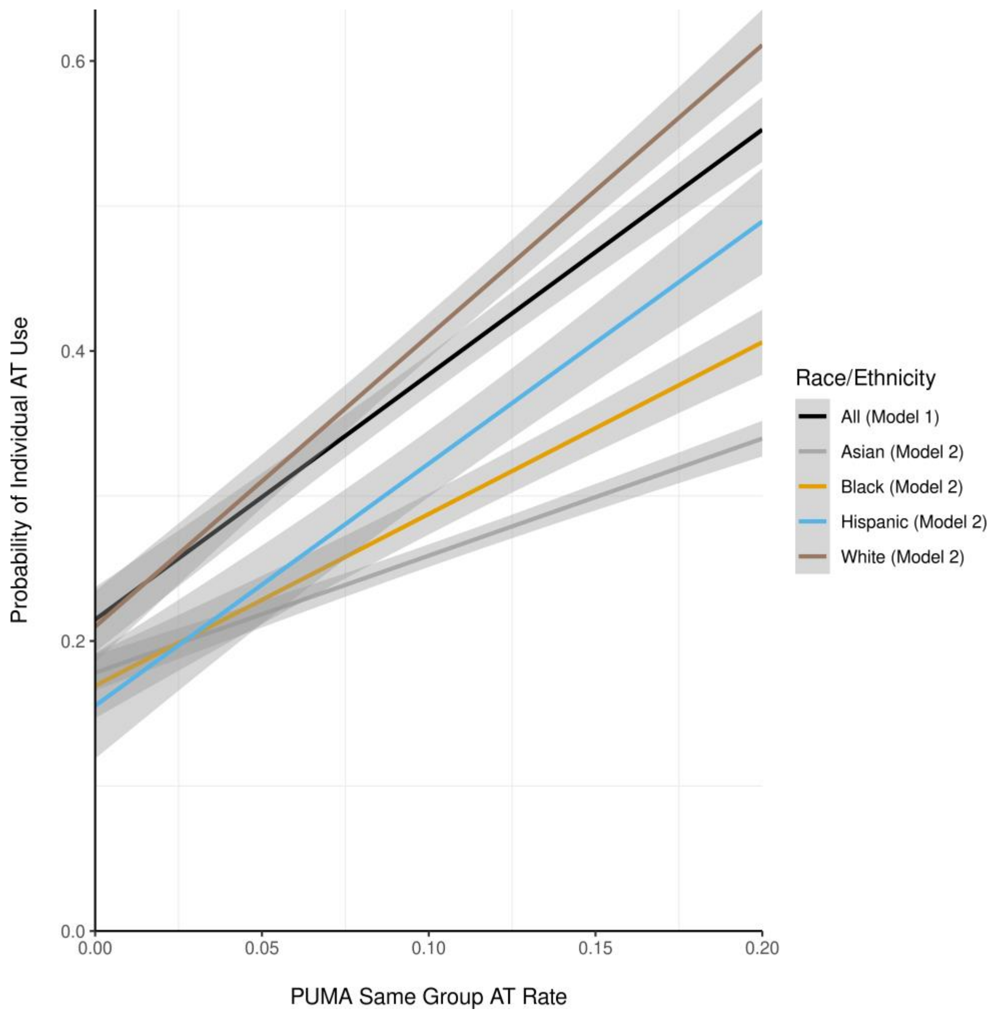


Figure 5: Predicted probability of individual-level AT use for each of the racial/ethnic groups based on PUMA-level AT use (Model 2). "All" refers to the base relationship between PUMA same group AT rate and the likelihood of an individual to use AT for all racial/ethnic groups combined (Model 1). Both models are adjusted for covariates, which are held at their means.

VII. Discussion

In this study, we address the research question, "Are people more likely to engage in AT use in neighborhoods where more people of their same race/ethnicity engage in AT use?" We compare the associations between PUMA same group AT rate and individual-level AT use among four racial/ethnic groups. We hypothesize that (1) having more AT commuters of the same race/ethnicity in one's neighborhood is associated with an increased chance of choosing to walk or bike, and (2) this association is larger for racial/ethnic minorities. The results partially align with what we expect.

Our findings corroborate established neighborhood peer effects literature where peers have a positive influence on physical activity rates, which support our first hypothesis (Salvy et al. 2008). The positive association between PUMA same group AT rate and individual-level walking and biking provides supporting evidence for racial/ethnic representation empowering racial/ethnic minorities to engage in AT, as they may feel a greater sense of comfort and familiarity when using AT if they see others who look like them using AT in their neighborhoods (Egalite et al. 2015). The feelings of belonging that may result from seeing other racial/ethnic minorities using AT may also help individuals to overcome fears of racialized attacks due to the higher visibility of AT modes compared to car modes, as well as skepticism toward AT developments associated with gentrification in their neighborhoods (Graham et al. 2022; Hoffmann and Lugo 2014; Lubitow and Miller 2013). Our findings potentially reinforce the sociological literature, which establishes a positive impact of minority group representation on individual outcomes in a variety of contexts, namely academic contexts, and suggest that this representation phenomenon may also apply to the active transportation context (Gershen et al. 2021; Ijoma et al. 2022). Our findings further remind us that access to AT relies on the cumulative impacts of a variety of factors related to both safe infrastructure and socio-cultural aspects (Cusack 2021; Handy et al. 2010). Not only do equitable AT systems require thoughtful and safe infrastructure placement, but the greater culture surrounding AT affects how an individual may or may not identify with being an AT user (Zhou and Zhang 2023).

From a policy standpoint, our findings suggest that racial/ethnic representation may matter in AT contexts, and further highlight the need to investigate more deeply the implications of peer effects on the health outcomes of marginalized groups within this context. It is possible that boosting AT participation among different racial/ethnic groups and encouraging more integrated, racially and ethnically diverse AT systems may be important for minimizing barriers to access to AT for racial/ethnic minorities. Greater racial/ethnic representation in our AT systems could, in theory, help improve social access to AT for racial/ethnic minorities by means of an improved sense of belongingness for these minorities, and further contribute to more equitable health outcomes (Barajas 2021).

After comparing the associations between neighborhood-level and individual-level AT among each racial/ethnic group, we find evidence refuting our second hypothesis that the association between PUMA same group AT rate and individual-level AT use is largest for racial/ethnic minorities. We find that the association between peer AT use and individual-level AT use for Black and Hispanic groups is not larger than, but comparable to that of the White group, which is counter to our expectations. We speculate that the White group has a larger likelihood of using AT based on PUMA same group AT rate, compared to the Asian group, due to their structural privilege that allows them to have better access to resources like AT (Kwate and Goodman 2014), assume a dominant position in AT spaces (Braun et al. 2019), and avoid socio-cultural barriers to AT related to racialized attacks and policing that other racial/ethnic minorities do (Lubitow et al. 2016). The White population generally being the dominant group using AT may overshadow the influence of PUMA same group AT rate on the AT outcomes of Asian individuals (Kunst et al. 2017; Ho et al. 2012). Because Asians are the only group with an association significantly lower than that of the White group, we are limited in our ability to make further inferences about the relative magnitude of influence that peers have on individual-level AT use based on race/ethnicity.

While the NHTS is an optimal dataset to conduct our AT analysis, it brings with it some limitations. The primary strength of the NHTS is that it records a large amount of AT data, as it contains trips of all purposes and captures a large number of samples in our study area of California. Its main limitation is that it is a cross-sectional dataset, which limits our ability to make causal claims about the direction of the associations we find. To address this uncertainty concerning causality and strengthen our claims, we base our study on a well-established theoretical framework of neighborhood peer effects, which allows us to make strong inferences about the directionality of associations. An overarching strength of the NHTS is that its large sample size allows us to distinguish differences in associations among different racial/ethnic groups, giving way to a more nuanced understanding of the way that people of color are disadvantaged in AT systems. While we considered including other marginalized groups, like Native Americans and Pacific Islanders, we were limited by the data, as we required at least 50 people of each group per PUMA to conduct a valid analysis. Better data on these underserved groups would allow for even more comprehensive analyses of the socio-cultural drivers of AT disparities, which would better inform health interventions and policies that aim to use AT as a way to promote health equity in our communities.

Using the PUMA to define neighborhoods presents several limitations, despite it being the finest possible scale of analysis in publicly available data that contains at least 50 people of each racial/ethnic group in our study area of California. Firstly, the relatively large size of a PUMA, which captures at least 100,000 people, may overestimate the amount of direct exposure an individual has to other AT users within their neighborhoods, lending itself to a modifiable areal unit problem (Fotheringham and Wong 1991). An individual is likely to travel within a much smaller area within a PUMA in their daily life, which can be defined as one's "activity space" (Golledge and Stimson 1996; Browning and Calder 2021). Additionally, an individual's activity spaces may span beyond their residential PUMAs, and into neighboring PUMAs, but we do not take this into account when we define neighborhoods at the PUMA level. However, a potential strength of the PUMA is that one's perception of the amount of people of their same race/ethnicity who are using AT may span beyond their direct activity spaces, as socio-cultural norms and attitudes are commonly placed in the contexts of broader areas (Yu et al. 2019; Orstad et al. 2016). Better information on the perceptions of who is using AT, and how these perceptions are affected by the spatial scale of activity spaces, would improve our ability to measure the neighborhoods of AT users most accurately (Orstad et al. 2016). Ensuring that the neighborhood is defined in a way that is most relevant to our outcome is essential for strengthening inferences about the impact of neighborhood effects (Diez Roux 2001). Future iterations of this study may attempt to redefine the study area and the geographic extent of the neighborhood.

Ultimately, our study serves as a jumping-off point to quantify how peers of the same race/ethnicity may influence AT behaviors among wider groups of people, paving the way for future studies to investigate other socio-cultural drivers of AT use. In the broader literature, future studies should quantify other contextual socio-cultural drivers of racial/ethnic disparities in AT access in the US, as it is essential for AT system policies to address the structural inequities that prevent racial/ethnic minorities from receiving the health benefits of AT. To initiate more effective implementation of AT health policies and interventions, these studies should be used in combination with community collaborations that aim to serve the needs of those who have historically been excluded from AT contexts.

VIII. Conclusion

Using the neighborhood peer effects framework to contextualize behaviors in AT use among different racial/ethnic groups, we find that White, Asian, and Hispanic people in California may be more likely to engage in AT if there are more people of their same race/ethnicity engaging in AT in their neighborhood, defined at the PUMA level. Additionally, we find that the association between PUMA same group AT rate and the probability of an individual to use AT is significantly larger for Whites, with Asians being the only group with an association significantly lower than that of Whites. Our study suggests that socio-cultural factors such as peer AT behaviors within racial/ethnic groups, may be important when investigating the systemic forces that prevent racial/ethnic minorities from fully accessing AT systems, and merit further scrutiny. At a broader scale, our study may provide broad guidance for interventions and plans that improve public health, promote transportation justice, and create more equitable, livable neighborhoods for any and all people.

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Appendix

	Individual-level White AT Use		
	Est.	S.E.	P
Intercept	−1.46	0.08	***
Main Effect			
Proportion of White AT Users in PUMA	8.98	1.71	***
Individual-level Effects			
Age	0.05	0.07	
Age-squared	0.00	0.07	
Female *(ref: male)*	0.01	0.03	
Good health *(ref: poor health)*	0.35	0.07	***
Family Household Income (ref: low)			
Middle	−0.23	0.04	***
High	−0.24	0.06	***
Neighborhood-level Effects			
Median household income	0.10	0.04	*
Average age	0.12	0.04	**
Population density	0.19	0.04	***
Total population	0.01	0.03	
Racial/ethnic Total Population			
Black	0.06	0.03	*
Asian	0.06	0.03	+
Hispanic	−0.01	0.04	
Racial/ethnic Segregation			
Black-White dissimilarity	0.00	0.04	
Asian-White dissimilarity	0.04	0.03	
Random Effects			
Variance	0.08		
Standard deviation	0.28		
Number of observations	23.128		
Number of groups (PUMAs)	263		
BIC	25.734		
RMSE	0.43		

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '+' 0.1 '' 1

Table A1: Multilevel logistic regression model for White AT use.

	Individual-level Black AT Use		
	Est.	S.E.	P
Intercept	−0.88	0.26	***
Main Effect			
Proportion of Black AT Users in PUMA	5.64	4.15	
Individual-level Effects			
Age	−0.32	0.33	
Age-squared	0.12	0.33	
Female *(ref: male)*	0.07	0.16	
Good health *(ref: poor health)*	−0.28	0.23	
Family Household Income (ref: low)			
Middle	−0.68	0.17	***
High	−0.47	0.40	
Neighborhood-level Effects			
Median household income	−0.05	0.14	
Average age	0.18	0.15	
Population density	0.22	0.08	**
Total population	0.04	0.09	
Racial/ethnic Total Population			
Black	−0.04	0.05	
Asian	−0.11	0.11	
Hispanic	−0.03	0.12	
Racial/ethnic Segregation			
Black-White dissimilarity	−0.17	0.10	
Asian-White dissimilarity	−0.04	0.10	
Random Effects			
Variance	0.06		
Standard deviation	0.24		
Number of observations	1.018		
Number of groups (PUMAs)	209		
BIC	1.155		
RMSE	0.40		

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘+’ 0.1 ‘’ 1

Table A2: Multilevel logistic regression model for Black AT use.

	Individual-level Asian AT Use		
	Est.	S.E.	P
Intercept	−1.31	0.22	***
Main Effect			
Proportion of Asian AT Users in PUMA	5.42	2.20	*
Individual-level Effects			
Age	−0.25	0.18	
Age-squared	0.26	0.16	
Female *(ref: male)*	−0.01	0.08	
Good health *(ref: poor health)*	−0.16	0.20	
Family Household Income (ref: low)			
Middle	0.03	0.11	
High	−0.03	0.14	
Neighborhood-level Effects			
Median household income	0.11	0.06	+
Average age	0.06	0.08	
Population density	0.12	0.06	*
Total population	0.10	0.05	*
Racial/ethnic Total Population			
Black	0.10	0.05	*
Asian	−0.03	0.05	
Hispanic	−0.03	0.07	
Racial/ethnic Segregation			
Black-White dissimilarity	0.08	0.07	
Asian-White dissimilarity	−0.02	0.05	
Random Effects			
Variance	0.05		
Standard deviation	0.23		
Number of observations	3.232		
Number of groups (PUMAs)	245		
BIC	3.631		
RMSE	0.42		

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '+' 0.1 '' 1

Table A3: Multilevel logistic regression model for Asian AT use.

	Individual-level Hispanic AT Use		
	Est.	S.E.	P
Intercept	−1.86	0.17	***
Main Effect			
Proportion of Hispanic AT Users in PUMA	10.97	3.00	***
Individual-level Effects			
Age	−0.89	0.14	***
Age-squared	0.78	0.13	***
Female *(ref: male)*	0.01	0.07	
Good health *(ref: poor health)*	0.08	0.14	
Family Household Income (ref: low)			
Middle	−0.37	0.08	***
High	−0.66	0.17	***
Neighborhood-level Effects			
Median household income	0.17	0.07	*
Average age	0.09	0.06	
Population density	0.22	0.06	***
Total population	0.02	0.04	
Racial/ethnic Total Population			
Black	0.00	0.04	
Asian	−0.13	0.06	*
Hispanic	−0.01	0.05	
Racial/ethnic Segregation			
Black-White dissimilarity	−0.04	0.05	
Asian-White dissimilarity	0.02	0.05	
Random Effects			
Variance	0.08		
Standard deviation	0.29		
Number of observations	5.132		
Number of groups (PUMAs)	265		
BIC	5.213		
RMSE	0.39		

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '+' 0.1 '' 1

Table A4: Multilevel logistic regression model for Hispanic AT use.