S Supplementary Materials

S.1 ACS sampling design

The ACS relies on two distinct sampling units: housing unit addresses and residents of group quarters (e.g., college residence halls and correctional facilities). To create the housing unit sample, each county is divided into five sub-frames, which include about 20 percent of the entire county frame and are a representative sample. Each frame is used once every five years and new addresses are added to the five frames systematically each year. Census blocks, the smallest unit of geography used by the USCB (600-3,000 residents), within the annual relevant sub-frame are assigned sampling rates based on their population size, with lower population blocks being assigned higher sampling rates. Addresses are sampled from the census blocks according to the assigned sampling rates. Group quarters are separated into small ($<$ 15 people) and large quarters. Small group quarters are sampled similar to housing units. For large group quarters, groups of ten individuals are selected from each facility (United States Census Bureau, 2014).

S.2 Demographic data in USCB products

Within many public health settings it is important to have population counts by, at a minimum, sex, age, and racial/ethnic group to use in disease rate calculations. The decennial census provides estimates by sex and age for both racial and ethnic groups, allowing calculation of population counts by sex and age of Hispanic, non-Hispanic White, non-Hispanic Black, non-Hispanic Asian or Pacific Islander, and Non-Hispanic American Indian or Alaskan Native individuals. However, ACS 5-year estimates do not allow the separation of Hispanic compared to non-Hispanic individuals among those identifying as Black (it is available for those identifying as White) by sex and age at the census tract level (United States Census Bureau, 2019).

S.3 Worldpop models and covariates

The standard "top-down" modeling approach used by WorldPop disaggregates census data by building a random forest algorithm with geospatial covariates to predict population sizes on a high resolution grid. The top-down estimation approach is most appropriate for countries with a relatively recent and reliable census, which is why we chose the top-down models for our analysis using US data. For countries without a reliable census count, sample survey data are used either in place of or in addition to census data to build models that are used to predict population sizes at high resolution. This is referred to as the "bottom-up" modeling approach (WorldPop, 2020).

When using top-down modeling, WorldPop can estimate population sizes in either a constrained or unconstrained fashion (WorldPop, 2021). The unconstrained estimates are predictions directly from the disaggregation model– a limitation of these estimates is that they can be non-zero even in uninhabited areas. The constrained estimation approach produces non-zero estimates only for grid cells determined to be inhabited (containing buildings), based on detailed satellite imagery. For the time period considered in our study (2008-2010), only unconstrained estimates are available. Thus, we chose the unconstrained top-down US estimates for our analyses.

Although the list of covariates used in the models to create the US Worldpop estimates for 2008-2010 does not appear to be available, the Worldpop team has provided to us the list of covariates which were used to produce the US estimates for 2020:

- Distance to cultivated areas 2015
- Distance to woody areas 2015
- Distance to herbaceous areas 2015
- Distance to sparse vegetation areas 2015
- Distance to aquatic vegetation areas 2015
- Distance to urban area 2015
- Distance to bare areas 2015
- Distance to inland waterbodies 2000s
- Distance to urban area 2020
- Distance to settlement buildup areas 2000
- Distance to major road intersetcions multiple years
- Distance to major waterways multiple years
- Distance to major roads multiple years

- Current average total annual precipitation
- Current average annual temperature
- Slope
- Elevation
- Distance to coastline
- Nighttime lights 2016 VIIRS
- Distance to CAT1 protected areas 2017

S.4 Premature mortality modeling details and results

S.4.1 CT-aggregate models

Let $i = \{1, \dots, N\}$ index CTs so that Y_i is the number of observed premature mortalities in CT i, $PropBlack_i$ is the proportion Black in CT i (centered and scaled), and $PropPov_i$ is the proportion in poverty in CT i (centered and scaled). Let P_i be the CT expected number of premature mortalities computed using any of the 7 population datasets described above. Then we assume that $Y_i \sim Poisson(\lambda_i)$ and we fit the following spatial Poisson regression model:

$$log(\lambda_i) = \beta_0 + \beta_1 PropBlack_i + \beta_2 PropPov_i + \theta_i + \phi_i + log(P_i)$$

using a Bayesian approach proposed by Besag et al. (1991). Here θ_i is a random effect with a conditionally autoregressive spatial covariance structure and ϕ_i is an unstructured random random error term. We fit the model separately plugging in the P_i corresponding to each set of population size data. For convenience, when describing the results we refer to $PropBlack$ as the race variable and $PropPov$ as the poverty variable.

S.4.2 Race-stratified models

To formalize the race-stratified models, we now introduce a second index into our notation to differentiate the race-specific measures within CT. Let $i = \{1, \dots, N\}$ index CTs and $j = \{0, 1\}$ index race group, so that Y_{ij} is the premature mortality count in racial/ethnic group j within CT i. $I(Black)_{ij}$ is a binary indicator of Black race group, and $PropPov_i$ is the proportion in poverty in CT i (centered and scaled). Let P_{ij} be the CT- and racial/ethnic group-specific expected number of premature mortalities computed using any of the 7 population datasets described above. Then again we assume $Y_{ij} \sim Poisson(\lambda_{ij})$ and fit the following model using each of the 7 variants of P_{ij} formed from the different population data sources:

$$log(\lambda_{ij}) = \beta_0 + \beta_1 I(Black)_{ij} + \beta_2 PropPov_i + \theta_i + \phi_{ij} + log(P_{ij})$$

where θ_i is a CT-specific random effect with a conditionally autoregressive spatial covariance structure proposed by Leroux et al. (2000) and ϕ_{ij} is an unstructured CT- and race-specific error term. For convenience, when describing the results we refer to $I(Black)$ as the race variable and $PropPov$ as the poverty variable.

S.4.3 Discussion of results

In the CT-aggregate models, we find IRRs significantly greater than 1 for the race covariate (proportion of CT population Black, centered and scaled), suggesting that communities with higher percent Black residents tend to have higher rates of premature mortality. All the CT-aggregate models also estimate an IRR for poverty larger than 1, indicating that higher poverty is associated with higher premature mortality rates.

In the race-stratified models, the race variable is a binary indicator of Black (Race=1) or non-Hispanic White (Race=0) racial/ethnic group. An IRR greater than 1 would indicate that on average premature mortality rates for Black populations are higher than that for non-Hispanic White populations within a CT. Across all models, the IRR estimate for the race variable is less than 1, but statistical significance is not consistently detected. While at face value this finding appears to be at odds with the findings of the CT-aggregate models, we note that the scientific questions being answered by these models are fundamentally different, providing insight into different aspects of health disparities. Poverty is associated with higher premature mortality rates in the race-stratified models.

S.5 Simulation study details

S.5.1 CT-aggregate data generation and modeling

We describe the simulations using expected premature mortality counts as the denominator. The simulations using crude population denominators proceed analogously, substituting population counts for expected counts below. We simulate CT-aggregate incidence data for MA, using the real covariate data used in the CT-aggregate analyses above. Namely, we include CT proportion Black and proportion in poverty from the 2010 ACS (both centered and scaled). The CT expected counts used to generate the data come from the 2010 decennial census (expected counts are created by combining information about CT total population count and age and sex distributions, see Section 2.4 for more detail). We use the same notation introduced for the CT-aggregate models in Section S.4.1, but letting P_i^c be the 2010 decennial census expected count. Incidences are simulated as $Y_i \sim Poisson(\lambda_{ij})$, with

$$log(\lambda_i) = \beta_0 + \beta_1 PropBlack_i + \beta_2 PropPov_{2i} + \theta_i + \phi_i + log(P_i^c).$$

Here θ_i is a random effect with a conditionally autoregressive spatial covariance structure. Explicitly, we generate $\theta_i \mid \theta_k, k \neq i \sim N(0.2 \sum_k w_{ik} y_k / w_{i+}, 1/w_{i+})$, where w_{ik} is the $(i,k)^{th}$ element of an adjacency matrix W, and w_{i+} is the sum of the elements in the i^{th} row of W. $\phi_i \sim N(0, 0.25)$ is an unstructured random error term.

S.5.2 Race-stratified data generation and modeling

We describe the simulations using expected premature mortality counts as the denominator. The simulations using crude population denominators proceed analogously, substituting population counts for expected counts below. We simulate CT race-stratified incidence data for MA, using the real covariate data used in the race-stratified analyses above. Namely, we include a binary indicator of racial/ethnic group and the CT proportion in poverty from the 2010 ACS. The CT racial/ethnic group-specific expected counts used to generate the data come from the 2010 decennial census. We use the same notation introduced for the race-stratified models in Section S.4.2, but letting P_{ij}^c be the 2010 decennial census expected counts. Incidence data are simulated as $Y_{ij} \sim Poisson(\lambda_{ij})$, with

$$log(\lambda_{ij}) = \beta_0 + \beta_1 I(Black)_{ij} + \beta_2 PropPov_i + \theta_i + \phi_{ij} + log(P_{ij}^c).$$

Here θ_i is a random effect with a conditionally autoregressive spatial covariance structure. Explicitly, we generate $\theta_i \mid \theta_k, k \neq i \sim N(0.2 \sum_k w_{ik} y_k / w_{i+}, 1/w_{i+})$, where w_{ik} is the $(i,k)^{th}$ element of an adjacency matrix W, and w_{i+} is the sum of the elements in the i^{th} row of W. $\phi_{ij} \sim N(0, 0.25)$ is an unstructured random error term.

S.6 Additional tables & figures

Table S.1: Massachusetts average (standard deviation) CT population size estimates and 2010 SMRs using each denominator source. CT proportion in poverty from the 2010 ACS, which is included as a covariate in our models, is also summarized.

Variable	Total	White	Black
Census Pop	3863.3 (1453.67)	2858.46 (1508.08)	273.22 (486.37)
Census SMR	1.13 (2.83)	1.34 (3.2)	1.29 (3.38)
ACS 2008 Pop	3831.44 (1480.72)	2889.1 (1533.12)	266.53 (516.48)
ACS 2008 SMR	1.08 (0.73)	1.33 (2.34)	3.16 (19.27)
ACS 2009 Pop	3846.42 (1476.89)	2877.26 (1524.06)	272.37 (524.81)
ACS 2009 SMR	1.08 (0.71)	1.32 (1.86)	10.59 (225.56)
ACS 2010 Pop	3866.15 (1484.7)	2867.86 (1521.6)	281.38 (537.82)
ACS 2010 SMR	1.07 (0.67)	1.3 (1.54)	6.87 (113.1)
WP 2008 Pop	3859.55 (1427.69)	2924.46 (1507.56)	265.49 (506.61)
WP 2008 SMR	1.05 (0.64)	1.22 (1.47)	3.84 (27.91)
WP 2009 Pop	3864.18 (1430.55)	2906 (1506.29)	270.84 (518.16)
WP 2009 SMR	1.05 (0.64)	1.24 (1.39)	9.29 (170.69)
WP 2010 Pop	3865.21 (1432.18)	2884.38 (1508.57)	277.55 (518.44)
WP 2010 SMR	1.05 (0.64)	1.25 (1.43)	5.7 (70.94)
Percent in Poverty, ACS 2010	12.42 (12.04)	-	-

Table S.2: Proportion of CTs with statistically significant changes in Black / non-Hispanic White ACS population size estimates for each pair of years.

	2008	2009	2010
2008	-	0.10 / 0.15	0.22 / 0.29
2009	0.10 / 0.15	-	0.14 / 0.13
2010	0.22 / 0.29	0.14 / 0.13	-

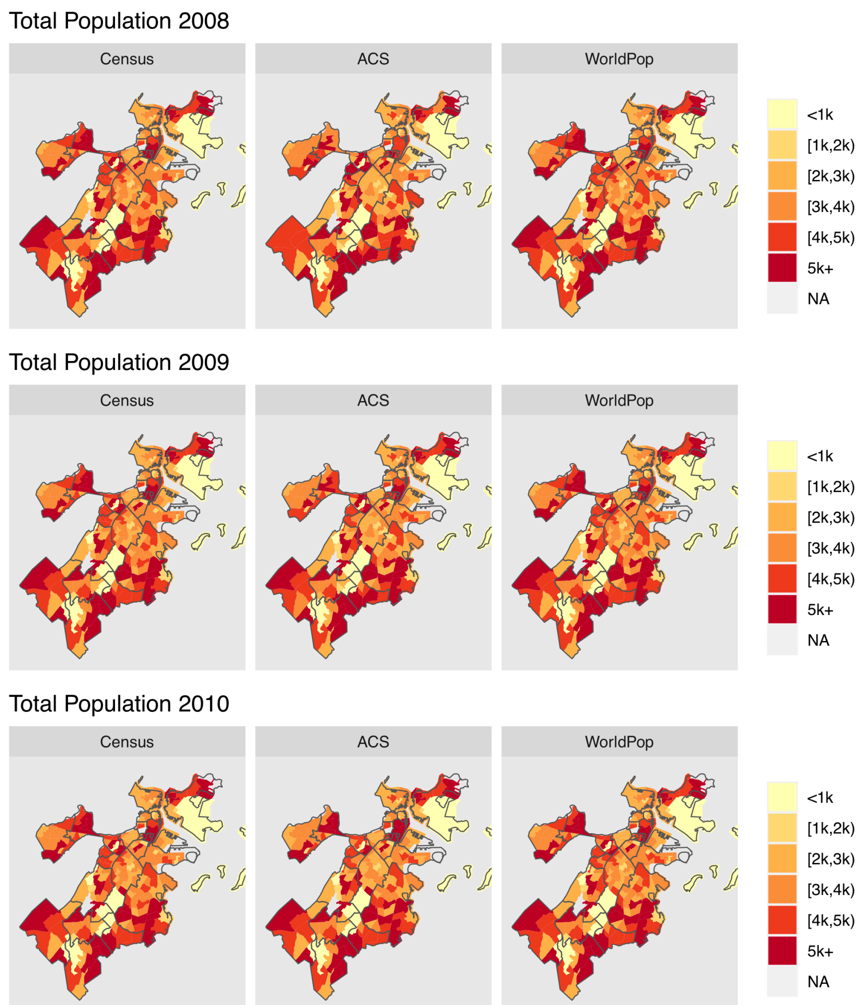

Figure S.1: Spatial distribution of census tract-level 2010 decennial census population counts compared to 5-year ACS and WorldPop population estimates for years 2008-2010 in Boston, Massachusetts USA.

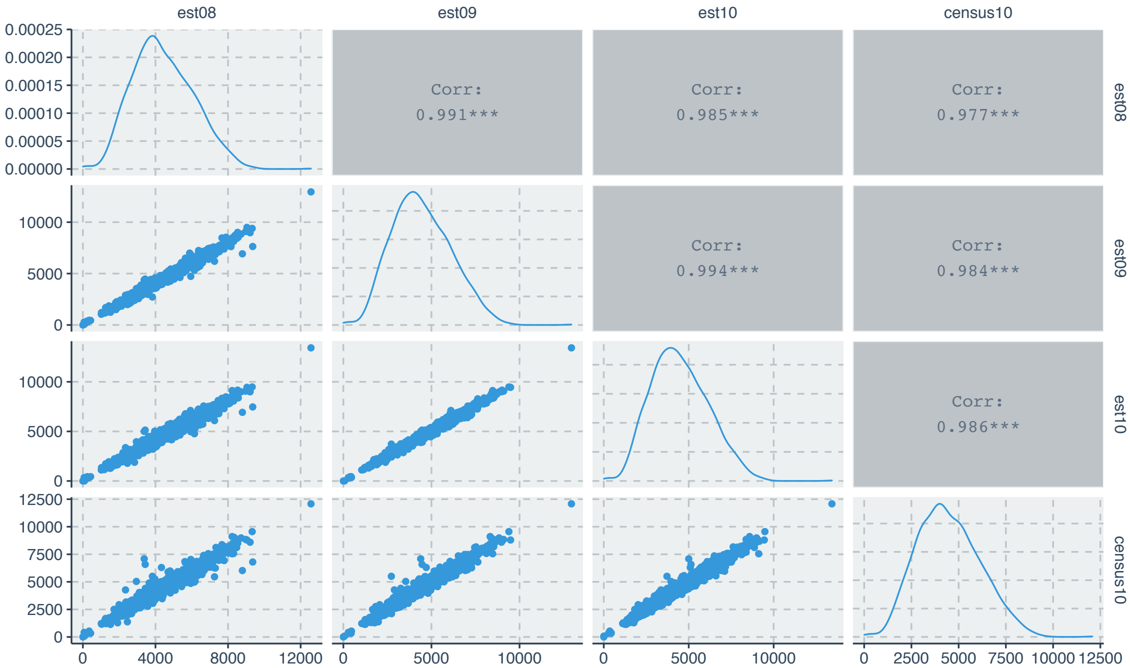

Figure S.2: Scatterplot matrix of ACS CT total population estimates for years 2008-2010 (est08, est09, and est10) and the 2010 decennial census CT total population counts.

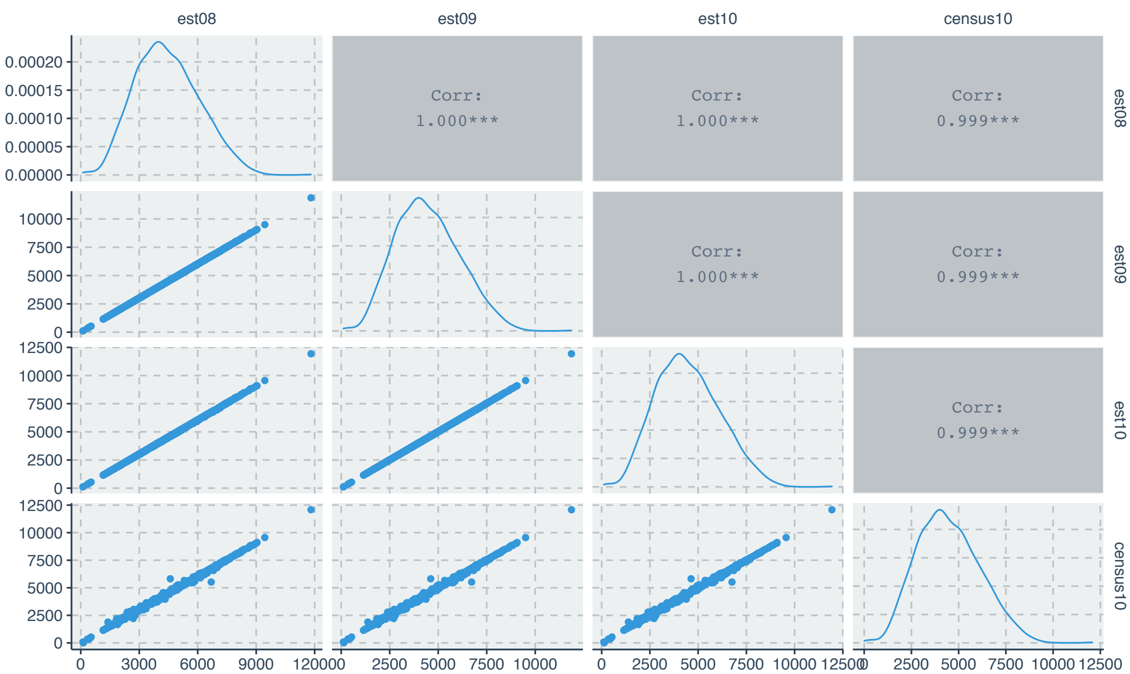

Figure S.3: Scatterplot matrix of WorldPop CT total population estimates for years 2008-2010 (est08, est09, and est10) and the 2010 decennial census CT total population counts.

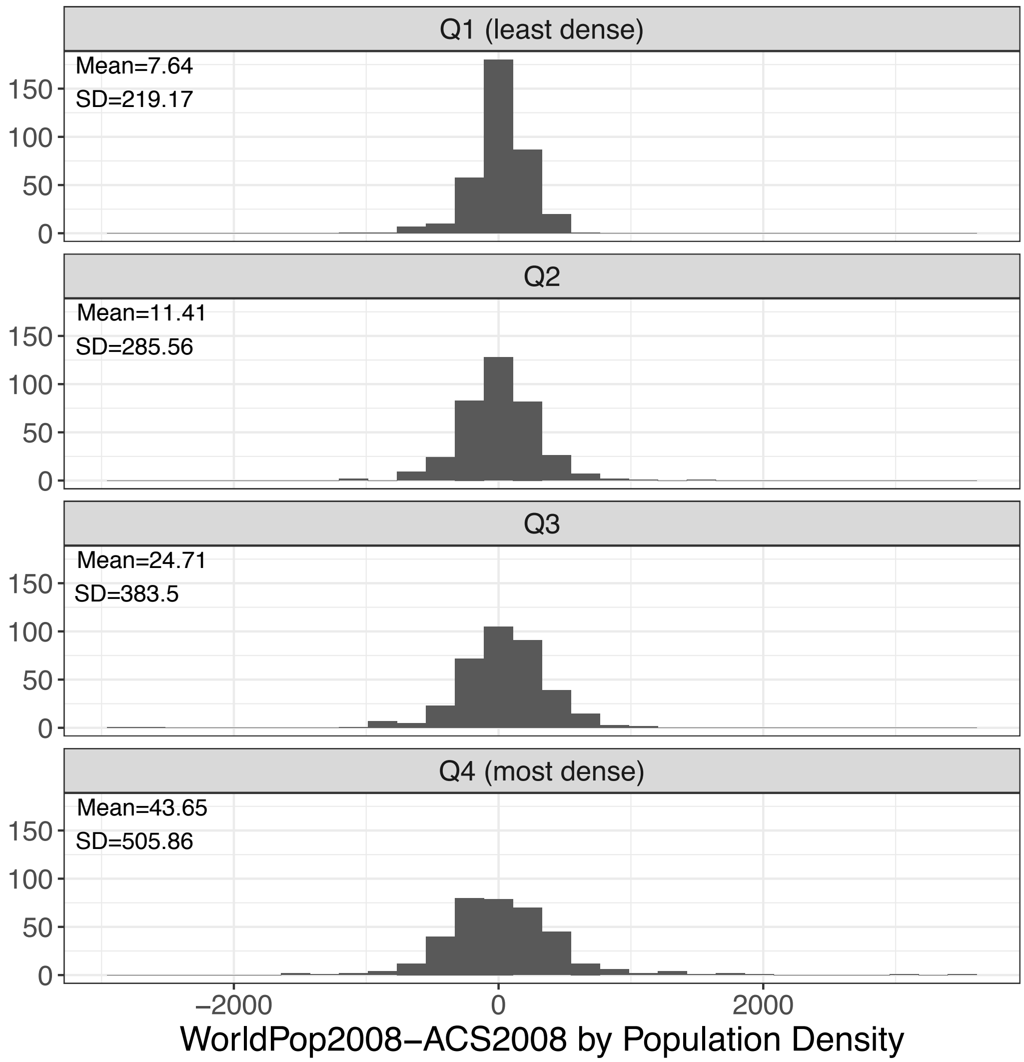

Figure S.4: Census tract level differences in ACS and WorldPop 2008 population estimates by population density quartile, Massachusetts USA.

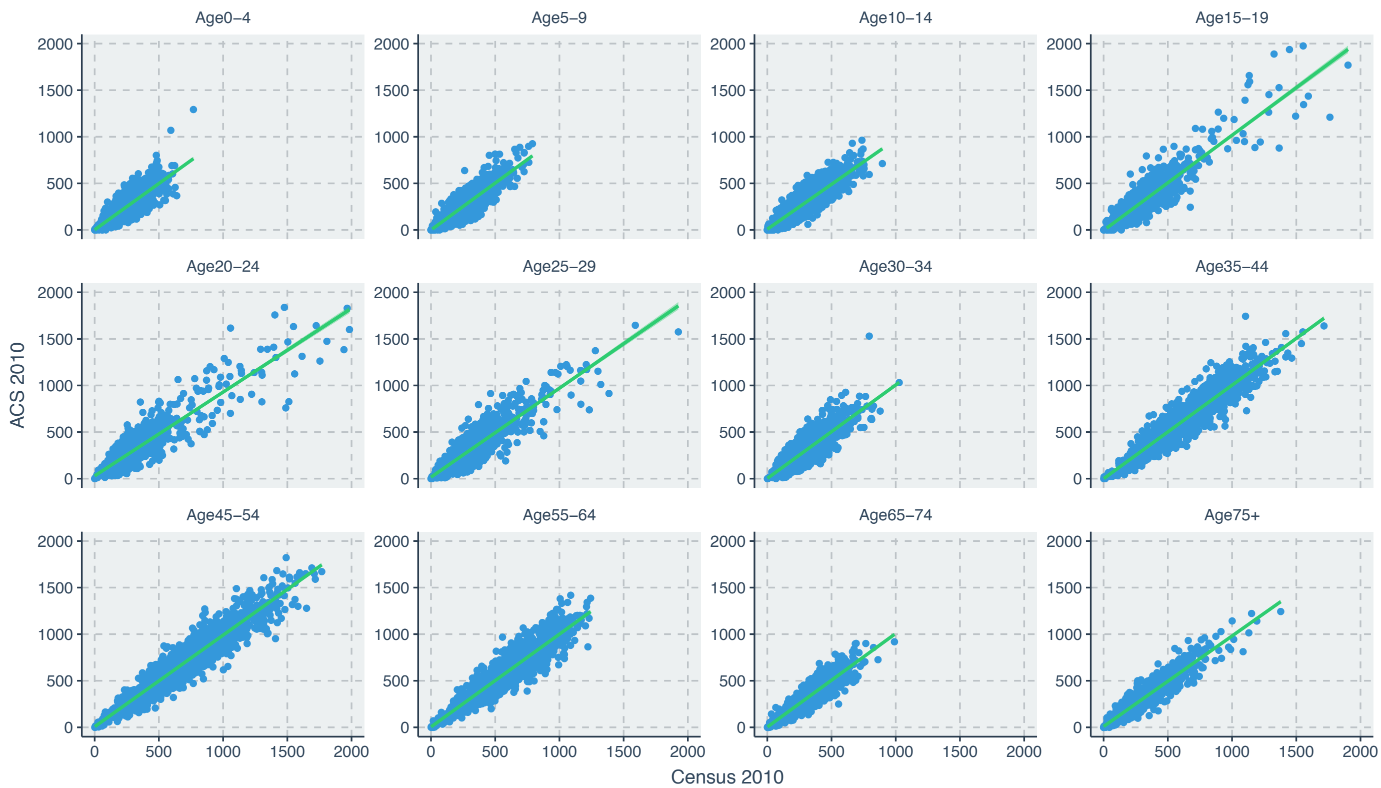

Figure S.5: Scatterplots of ACS 2010 age-stratified CT population estimates vs. 2010 decennial census age-stratified CT population counts.

Figure S.6: Scatterplots of WorldPop 2010 age-stratified CT population estimates vs. 2010 decennial census age-stratified CT population counts.

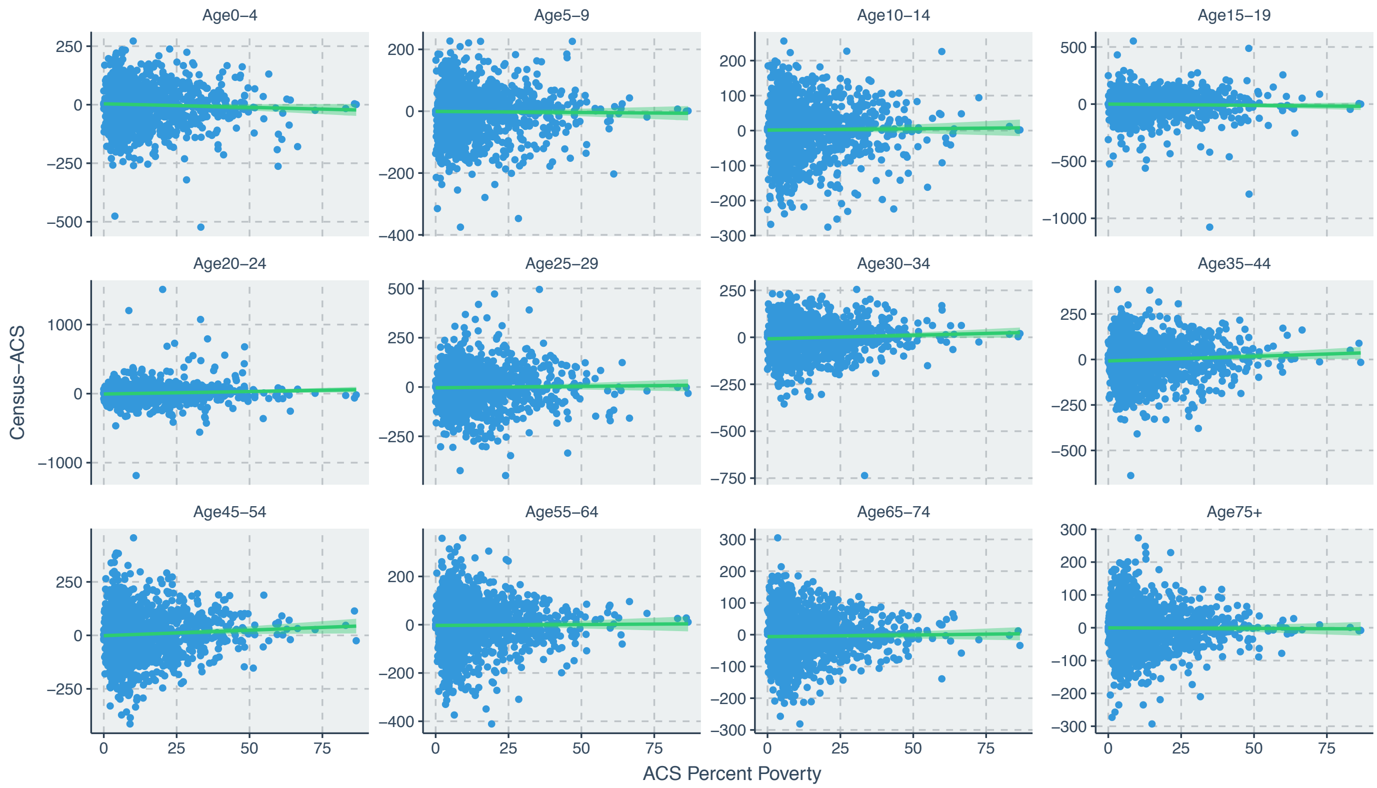

Figure S.7: Scatterplots of difference in decennial census and ACS 2010 age-stratified CT population estimates vs. percent of the CT in poverty.

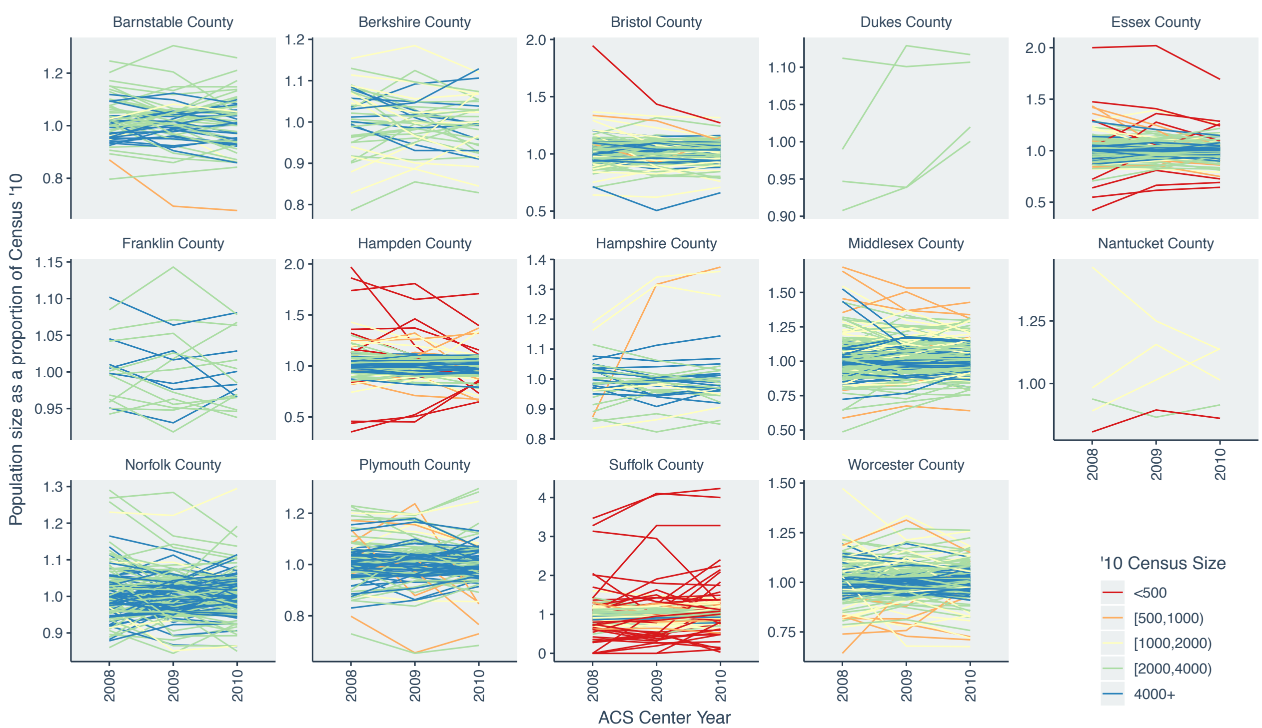

Figure S.8: MA census tract ACS population size estimates for non-Hispanic Whites over time as a proportion of 2010 decennial census population size. Colors represent 2010 decennial census population size bins.

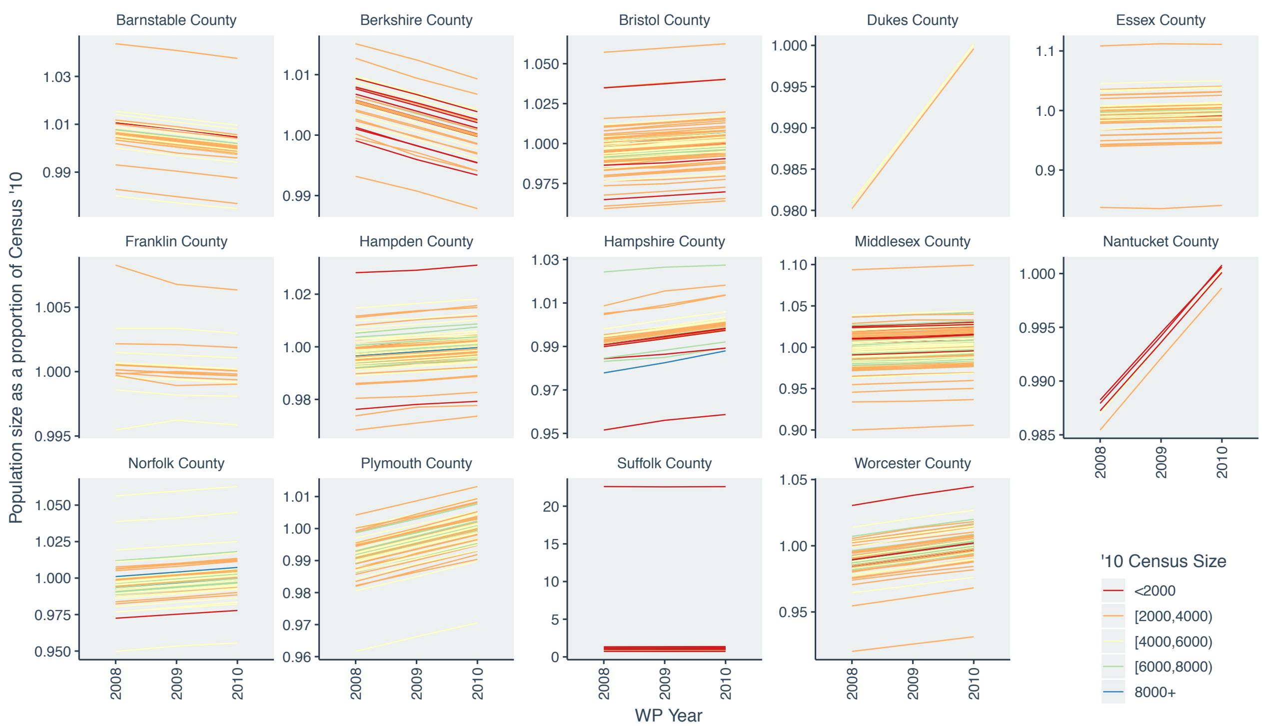

Figure S.9: MA census tract Worldpop population size estimates over time as a proportion of 2010 decennial census population size. Colors represent 2010 decennial census population size bins.

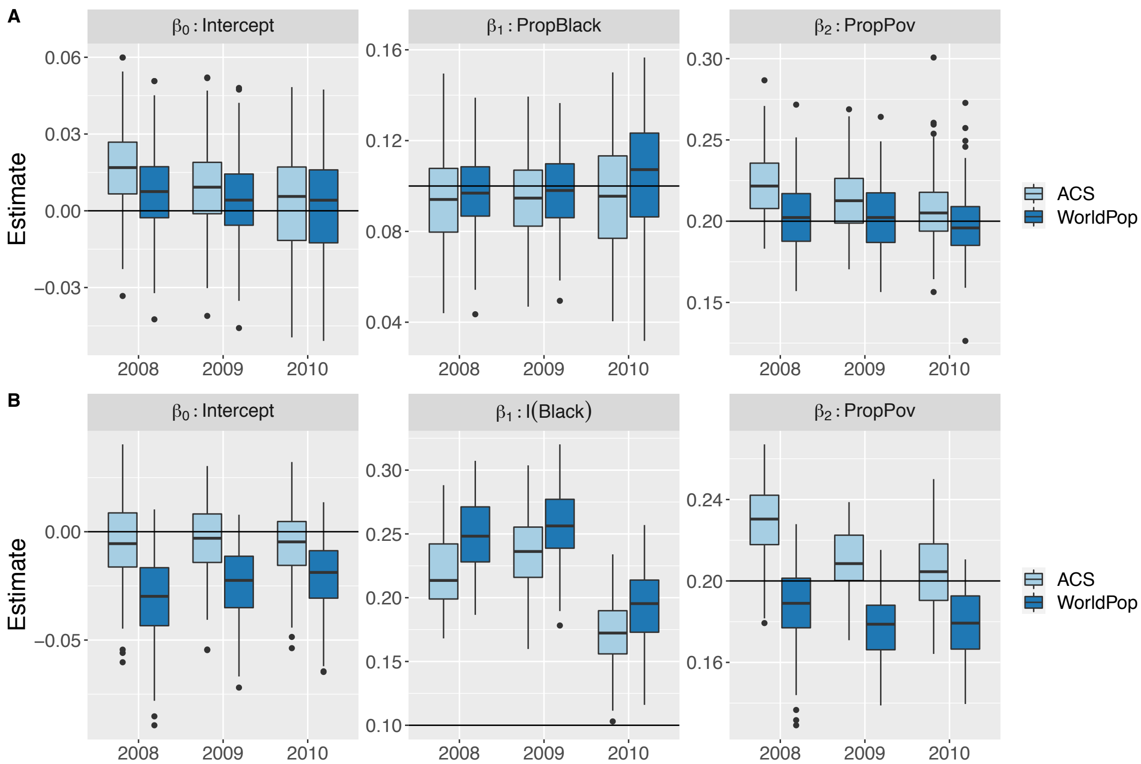

Figure S.10: Simulation results using crude denominators. Parameter estimates using ACS and Worldpop population size estimates in CT-aggregate (A) and race-stratified (B) models. Data are generated using 2010 decennial census population sizes. True values of each parameter are denoted by the black horizontal lines.