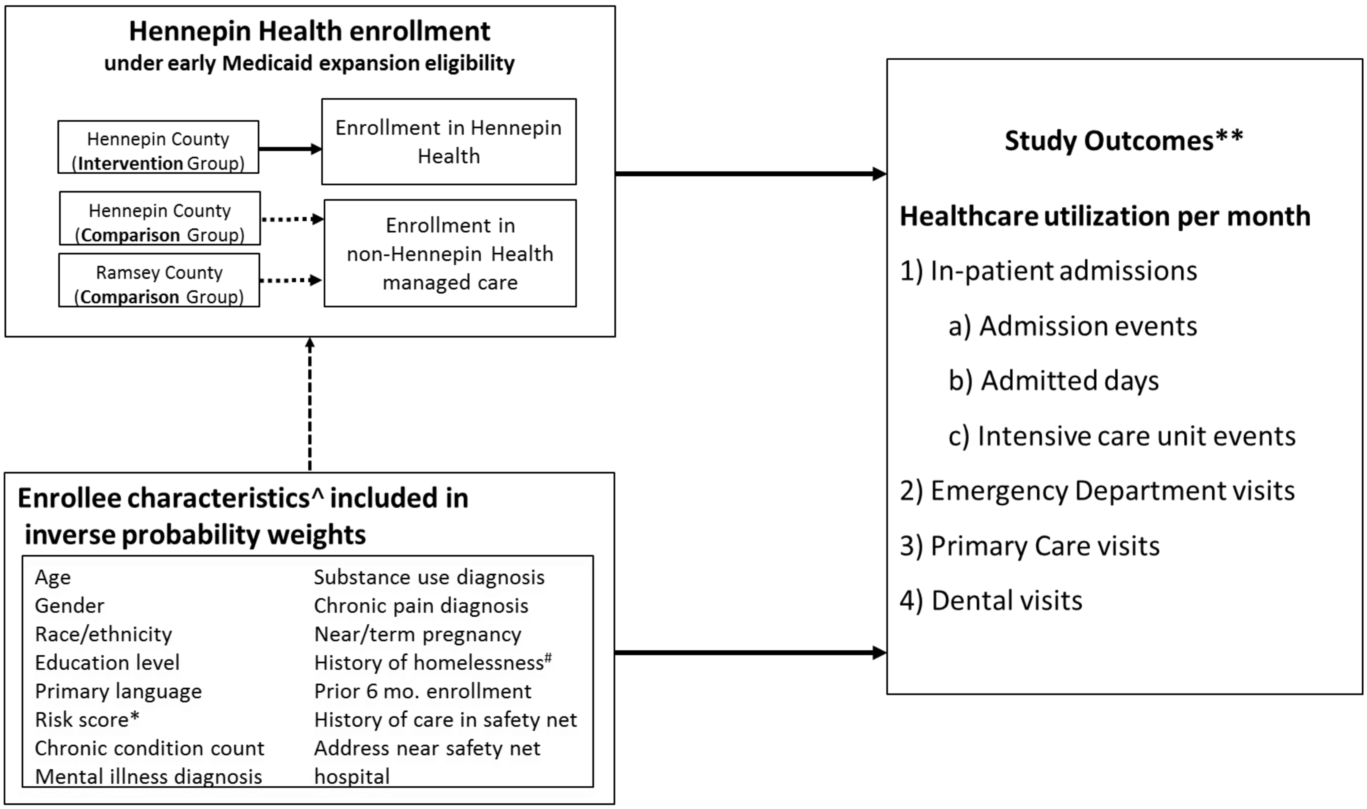
Technical Appendix to

Integrated, accountable care for Medicaid expansion enrollees: A comparative evaluation of Hennepin Health

Supplemental Figure 1. Conceptual model of the Hennepin Health comparative evaluation



^ For variable definitions, see Supplemental Table 1.
* Hierarchical condition category risk score (Pope, et al., 2000)
# Homelessness based on address used during Medicaid enrollment (Vickery et al., 2017.)
** For variable definitions, see Supplemental Table 2.

Model based on Andersen, 1995; Cooper, Hill, & Powe, 2002; Gelberg, Andersen, & Leake, 2000; Smedley & Syme, 2001; Shippee, Shah, May, Mair, & Montori, 2012.

Supplemental Table 1. Definition of adjustment variables constructed from DHS data files

Adjustment Variable	**Definition**
Age	Current age at the start of each month
Gender	Male (1/0) as there are more males in the program than females.
Race/ethnicity	Race and ethnicity were combined into a categorical variable as: Asian, Black, Hispanic, Native American, White, and Unknown
Education level	Categorical variable with the categories: <12, 12-14, 15+
Primary language	Data was categorized as primary language of English or non-English.
History of seeking care in safety net setting	Previous receipt of care in the past (rolling) 12 mo. of Medicaid enrollment at safety net care systems, defined as: Federally Qualified Health Centers, HCMC and affiliated clinics, and Regions Hospital. See full NPI list in Appendix A.
Zip code surrounding largest safety net hospital in Hennepin county urban core	Address at time of enrollment in first MCO (or HH) with zip code in Hennepin County urban core using HH selection zip codes: 55403, 55404, 55405, 55406, 55407, 55408, 55409, 55411, 55412, 55413, 55414, 55417, 55418, 55419, 55422, 55423, 55428, 55429, 55430, 55440, 55441, 55443, 55454
Zip code surrounding largest safety net hospital in the Ramsey county urban core	Address at time of enrollment in first MCO Ramsey County urban core 55101, 55102, 55103, 55104, 55105, 55106, 55107, 55108, 55109, 55114, 55116, 55117, 55119, 55155, 55130
Mental Illness Diagnosis	Any diagnoses during all enrolled months consistent with mental illness: HCC categories 57 [Schizophrenia], 58 [Major Depressive, Bipolar, and Paranoid Disorders] *and/or* Clinical Classification Software mental health categories 650 (Adjustment disorders), 651 (Anxiety disorders), 652 (Attention-deficit, conduct, and disruptive behavior disorders), 653 (Delirium, dementia, and amnestic and other cognitive disorders) , 654 (Developmental disorders), 655 (Disorders usually diagnosed in infancy, childhood, or adolescence), 656 (Impulse control disorders, NEC), 657 (Mood disorders), 658 (Personality disorders), 659 (Schizophrenia and other related disorders), 662 (Suicide and intentional self-inflicted injury), and 670 (Miscellaneous mental health disorders) ("CCS Category Names," n.d.)
Substance Use Disorder Diagnosis	Any diagnoses during all enrolled months consistent with substance use disorder: ("CCS Category Names," n.d.) HCC categories 54(Drug/Alcohol Psychosis), 55 (Drug/Alcohol Dependence) *and/or* Clinical Classification Software substance use categories 660 (Alcohol-related disorders) and 661 (Substance-related disorders)
Chronic pain diagnosis	Diagnosis codes consistent with chronic pain according to the CCW definition of "Fibromyalgia, Chronic Pain and Fatigue" in the past (rolling) 12 months of enrollment.

	Presence of ICD-9 codes 338.2, 338.21, 338.22, 338.23, 338.29, 338.3, 338.4, 780.7, 780.71, 729.1, 729.2
Unstable housing	Use of homeless address at any time during the study (known shelter, general delivery address in Hennepin or Ramsey county, single site supportive housing facilities) *and/or* Hotel/motel address (per Dunn & Bradstreet), Hospital address (MN hospital list and D&B), Places of worship (per Dunn & Bradstreet), Free text comment synonymous with one of the above categories *and/or* "Homeless" including "No permanent address."(Vickery et al., n.d.)
Enrollment patterns	Enrollment (in a Medicaid managed care program, and separately in HH versus non-HH), as a time-varying measure, was the primary outcome in the creation of the inverse probability of treatment weights for the marginal structural models (see vector *A* in the model equations listed in Appendix A, below).
Prior 6 month enrollment history	Categorical variable summarizing pattern of last enrollment
Pregnancy diagnoses	Due to observations of fewer pregnancy-related diagnoses in the HH group (likely driven by the of males in this group), the following pregnancy-related CCS categories were added to the IPW model: Other pregnancy and delivery including normal (196), Other complications of pregnancy (181), Early or threatened labor (184), Forceps delivery (194) ("CCS Category Names," n.d.)
Hierarchical condition category risk score	HCC community-based risk score calculated over the enrollee's first 12 (or as close to 12 as exists) months.
Number of chronic CCS conditions per month	Number of different chronic CCS categories present per month. The list of qualifying CCS conditions was based on the work of Magnan.[1]

[1] Magnan, 2015

Supplemental Table 2. Definitions of outcome variables constructed from Medicaid claims data

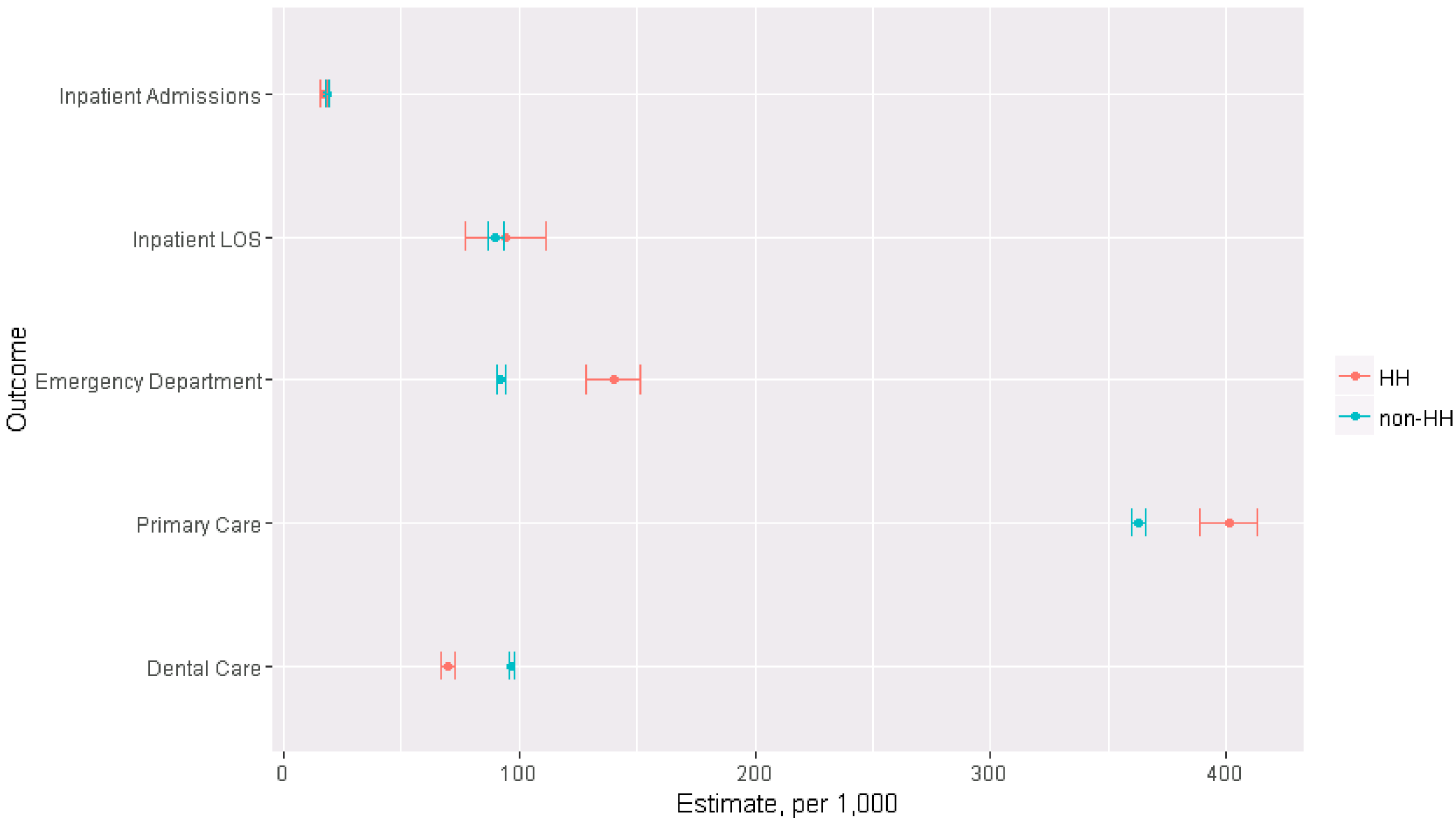
Outcome	**Definition**
In-patient admission	Claim for beginning of in-patient or facility-based care episode on given date
In-patient length of stay (LOS)	Total number of admitted days rolled back to month of the index admission (to any in-patient hospital).
Intensive Care Unit (ICU) visits	Visit to the ICU based on revenue code (20X). These were counted in the month of the first day of the hospital admission during which the ICU visit occurred.
Emergency Department (ED) visit	Claim with charges consistent with care at an emergency department per DHS specifications on given date (Wholey et al., 2016). This included all ED visits which led to discharge or admission to the hospital.
Primary care visits	Evaluation & Management CPT code on given date indicating a visit with a generalist provider (by National Provider Index directory) including Family Medicine, Internal Medicine, Geriatricians, Pediatricians, Preventive Medicine, Nurse Practitioners, or Obstetrics and Gynecology; following ACG approach (Weiner & Abrams, 2011).
Dental visits	Claim for dental care on given day within the month

Supplemental Table 3. Estimated probability and conditional rates of health care utilization in Hennepin Health versus non-Health Hennepin by person-months based on the fitted marginal structural models[a]

	Hennepin Health		Non-Hennepin Health	
	Estimate per 1,000 person-months	95% CI	Estimate per 1,000 person-months	95% CI
Inpatient admissions				
Probability of any use	0.016	0.014-.017	0.017	0.0166-.0174
Rate of use among participants with any use	1,078.4	1,060.3-1,096.6	1,084.1	1,079.3-1,089.0
Admitted days				
Probability of any use	0.015	0.014-.017	0.017	0.016-.017
Rate of use among participants with any use	6,294.1	5,366.9-7,221.4	5,383.8	5,232.5-5,535.0
Intensive care unit visits				
Probability of any use	0.0006	0.0005-0.0008	0.0005	0.0004-0.0005
Rate of use among participants with any use	999.5	998.6-1,000.4	1,036.3	1,020.9-1,051.8
Emergency department visits				
Probability of any use	**0.107**	**0.103-.110**	**0.074**	**0.073-.075**
Rate of use among participants with any use	1,313.1	1,214.6-1,411.7	1,249.4	1,230.2-1,268.5
Primary care visits				
Probability of any use	**0.221**	**0.215-.227**	**0.252**	**0.250-.253**
Rate of use among participants with any use	**1,813.2**	**1,788.9-1,837.6**	**1,442.1**	**1,437.0-1,447.2**
Dental visits				
Probability of any use	0.050	0.048-.052	0.070	0.069-.070
Rate of use among participants with any use	1,406.6	1,386.7-1,426.4	1,389.6	1,384.8-1,394.5

[a] Bold text indicates significant difference between HH and non-HH with non-overlapping confidence intervals of estimates, or confidence interval of difference not crossing zero.

Supplemental Figure 2**.** Adjusted/expected rates of healthcare utilization in Hennepin Health vs. non-Hennepin Health Medicaid expansion enrollees per- 1,000 member months



Supplemental Table 4. Change in health care use over 6-month periods of time among Hennepin Health (HH) in comparison to non-Hennepin Health (nHH) Medicaid Expansion enrollees[a]

	Hennepin Health (HH), six-month change		Non-Hennepin Health (nHH), six-month change		Difference between change for HH vs. nHH	
	Estimate per 1,000 enrollees	95% CI	Estimate per 1,000 enrollees	95% CI	Estimate per 1,000 enrollees	95% CI
In-Patient admissions	-0.34	-1.06 – 0.39	**0.39**	**0.26 – 0.53**	-0.73	-1.47 – 0.01
Emergency dept. visits	**-3.97**	**-6.85 – -1.10**	**-1.73**	**-2.31 – -1.15**	-2.24	-5.19 – 0.71
Primary care visits	**-8.42**	**-13.3 – -3.50**	**-4.97**	**-5.94 – -4.00**	-3.45	-8.50 – 1.60
Dental visits	**3.45**	**2.62 – 4.29**	**-4.72**	**-5.23 – -4.21**	**8.18**	**7.19 – 9.16**

[a] Bold text indicates significant difference between HH and non-HH with non-overlapping confidence intervals of estimates, or confidence interval of difference not crossing zero.

Appendix A

Weights for marginal structural models

Inverse probability of treatment weights were used in marginal structural models to address time-varying confounding. Let A_{ij} be a categorical variable for insurance enrollment type (HH, non-HH, or not-enrolled in a Medicaid program) for subject i at month j of the study, X_i are the baseline (time-invariant) characteristics and V_{ij} are the time-varying characteristics for subject i at month j. The stabilized weighted for person i at calendar month j are given by

$$SW_{ij} = \frac{\prod_{k=1}^{j} P(A_{ik}|X_i, \bar{A}_{i,j-1})}{\prod_{k=1}^{j} P(A_{ik}|X_i, \bar{A}_{i,j-1}, \bar{V}_{i,j-1})},$$

where $\bar{X}_{i,j-1} = (X_{i1}, X_{i2}, \ldots, X_{i,j-1})$ and similarly for $\bar{A}_{i,j-1}$. That is the denominator is the probability subject i follows his/her exposure history through month j given the time-invariant characteristics and the history of time-variant characteristics and exposure before month j. The numerator is the probability subject i follows his/her exposure history through month j given just time-invariant characteristics and exposure history before month j.

To estimate the stabilized weights, we ran four separate logistic regression models. The first two models were used to estimate the probability of being enrolled versus not being enrolled in Medicaid. The second two models were used to estimate the probability of being enrolled in HH conditioned on being enrolled in Medicaid.

1) A logistic regression model was used to estimate the probability of being enrolled for a given month with time-varying confounders, baseline covariates, and a categorical variable for the number of months enrolled during the preceding six months;
2) A logistic regression model was used to estimate the conditional probability of current enrollment using a categorical variable for the number of months enrolled

during the preceding six months and baseline covariates as predictors to compute a standardized weight;

3) A logistic regression model was used to estimate the conditional probability of the person's current enrollment status in HH conditioned on being enrolled in Medicaid. Again, this model included time-varying confounders and baseline covariates, as well as a categorical variable for the number of months enrolled on HH during the preceding six months as an indicator of past exposure to HH; and,
4) A logistic regression model was used to estimate the conditional probability of current enrollment in HH conditional on being enrolled in Medicaid, using baseline covariates and a categorical variable for the number of months enrolled on HH during the preceding six months as an indicator of past exposure to HH to compute a standardized weight.

We note the probability of being enrolled in HH given baseline characteristics and the history of time-varying covariates, and exposure is the product of the conditional probability of being enrolled in a Medicaid managed care program given baseline characteristics and the history of time-varying covariates and exposure (Model 1) and the probability of being in HH given enrolled in Medicaid, baseline characteristics and the history of time-varying covariates and exposure (Model 3). Similarly, the probability of being enrolled in HH given baseline characteristics and the history of exposure is the product of the conditional probability of being enrolled in a Medicaid program given baseline characteristics and the history of exposure (Model 2) and the probability of being in HH given enrolled in Medicaid, baseline characteristics and the history of exposure (Model 4).

Assuming that there is no unmeasured confounding and the probability of treatment is non-zero for all levels of the covariates, the standardized weights provide a method of obtaining an unbiased estimator of the HH exposure effect by creating a pseudo-population with no confounding assuming the logistic regression models are correct.

Modeling

The first part of the two part model used a general linear model to model any utilization in a month for each of the outcomes separately assuming covariates (described below) were linearly associated with the outcome on the logit scale. Robust standard errors were used to account for the fact that a single subject contributed multiple person-months to the project with an auto-regressive-1 working correlation structure. The second part used a general linear model to model the conditional utilization, conditioned on at least some use for each of the outcomes separately assuming covariates were linearly associated with the outcomes on the log scale. Again, robust standard errors were used with an auto-regressive-1 correlation structure.

In the first set of models, only a current enrollment indicator for Hennepin Health was included in the model, fitted using the stabilized inverse probability weights described earlier. Probabilities of any use were estimated from the first part of the two part model and the Delta method was used to derive standard errors. Conditional rates were estimated from the second part of the two part model and the Delta method was again used to derive standard errors. To estimate the expected rate of use, the probability of use and the conditional rate of use were multiplied together and the Delta method was again used to estimate standard errors.

Finally, to estimate the probability of utilization over time, the conditional rate of use over time, and the expected rate of use over time, we fit a second set of marginal structural models which included covariates for the indicator for Hennepin Health enrollment, calendar month, and the interaction of the two. Two separate parameterizations of calendar month were used. One included calendar month as a factor and the second included calendar month as a continuous monthly count from January 2012. The model with the continuous count was used to test the hypothesis that the expected rate of use improved for HH over time compared to non-HH. The model with calendar month as a factor was included to plot monthly point estimates along with the linear trends.

Missing data

Missing data due to non-enrollment (censoring) were estimated by last observation carried forward for time-varying variables (i.e., chronic pain diagnoses; censoring did not create missing in time-constant variables). This method was used because patients were assumed to receive little to no medical care during periods of non-enrollment and their last health status was felt to be the best estimate of their subsequent health status in the absence of enrollment. The imputed data was used when constructing the weights for the MSM.

Appendix B

National Provider Indices consistent with safety net care sites in Hennepin and Ramsey Counties

We used the definition of safety net proposed by the Institute of Medicine (IOM) as "those providers that organize and deliver a significant level of health care and other health-related services to uninsured, Medicaid, and other vulnerable patients." The IOM report goes on to detail that "core safety net providers typically include federal, state, and locally supported community health centers…public hospital systems, and local health departments" (Lewin, Altman, & Institute of Medicine (U.S.), 2000). Therefore, we found national provider indices (NPI) consistent with the following provider types in Hennepin and Ramsey counties. This included all federally qualified health centers (community health centers) from this list (http://mnachc.org/documents/MNACHCMemberFQHCsbyRegion2015_000.pdf) in St. Paul and Minneapolis.

a. Hennepin Healthcare and affiliated primary care clinics (http://www.hcmc.org/clinics/index.htm)
b. Hennepin County Human Services and Public Health Department clinics
c. Regions and St. Joseph's Hospitals in St. Paul
d. HealthPartners Midway Clinic (per recommendation of HP ED physician)
e. Ramsey County public health clinics

Appendix C

Construction of Ramsey County urban core zip codes

Construction of Ramsey County urban core addresses was informed by census data on zip code tabulation areas (ZCTAs). Using American Community Survey 5-year estimates for 2008-2012, selected Ramsey County urban core areas were comparable to the Hennepin County urban core on median income, unemployment rate, and proportion African American.

Appendix D

Definition of race/ethnicity

1. Race/ethnicity was based on DHS' codebook definitions, which allowed for recording of multiple races (White, Black, Asian, Pacific Islander, Native American), and Hispanic/Latino ethnicity as a separate indicator.
2. For the purposes of this study, we combined A = Asian and P = Pacific Islander as Asian-Pacific Islanders; and also combined U=unknown and blanks who do not claim Hispanic identity as "unknown."
3. For analysis, White individuals with no listing of other groups or Hispanic/Latino Ethnicity were coded as White, non-Hispanic. Where individuals reported multiple racial groups, or were listed as Hispanic/Latino ethnicity, were coded into the less frequent group to preserve smaller groups, in the following order:

    White (no other racial categories and no Hispanic ethnicity);

    Black (non-Hispanic);

    Hispanic/Latino;

    Asian/Pacific Islander (Hispanic or not); and

    Native American (Hispanic or not).

    Individuals with Hispanic/Latino ethnicity (any race) were coded as Hispanic.

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