For Online Publication
Appendix for:
Measuring Changes in Disparity Gaps: An Application to Health Insurance

A. Details on the Behavioral Risk Factor Surveillance System (BRFSS)

In this section, we provide some additional details on the Behavioral Risk Factor Surveillance System (BRFSS) and our sample selection. The BRFSS was established in 1984 and now completes more than 400,000 adult interviews annually. Additional information on the BRFSS (including survey response rates) can be found in Wallace et al. (2021) or online at https://www.cdc.gov/brfss/index.html.

To construct our analytic sample, we first limited to 2010-2018 BRFSS data and respondents aged 51-79 years. We retained respondents whose self-identified race/ethnicity was either non-Hispanic Black, Hispanic, or non-Hispanic White and additionally excluded observations with missing data.

From the BRFSS we assessed respondent age in years and self-identified race/ethnicity. To measure health insurance rates, we assessed whether respondents reported having any source of health insurance coverage. To measure access to health care, we assessed whether respondents reported having a usual source of care within the past year or being unable unable to see a physician due to cost. Finally, we assessed whether respondents reported being in "poor" self-reported health.

B. Regression discontinuity design

Two features of our setting complicate the estimation of equation 6. Both stem from the discreteness of our running variable. First, for each of our access measures the respondents to the BRFSS answered based on their experience over the past year, rather than their situation at the time of the interview. Hence, we have to omit observations at age 65 years for these variables because respondents' answers reflect their access at ages 64 and 65 years.

As a result, we have to employ a 'donut" RD in the estimation of equation 6 (e.g., Barreca et al., 2011), omitting age 65 which requires further extrapolation of the age trends on each side of the discontinuity. To account for this, we estimate "honest" confidence intervals using the methods in Kolesár and Rothe (2018), and Armstrong and Kolesár (2018*b*,*a*), an approach that uses on bounds the second derivative of the true $f(\cdot)$ and $g(\cdot)$ functions to estimate (and incorporate) the potential bias due to extrapolation into our estimation. To obtain our bound on how quickly the functions $f(\cdot)$ and $g(\cdot)$ can change we follow the approach outlined in Imbens and Wager (2019), wherein we fit our outcome as a quadratic function of age to the left of the discontinuity, take the coefficient on the quadratic term (i.e., the second derivative).

Figure A1 presents visual evidence of the regression discontinuity models for our primary and secondary outcomes. Table A1 provides estimates for our secondary outcomes in tabular form.

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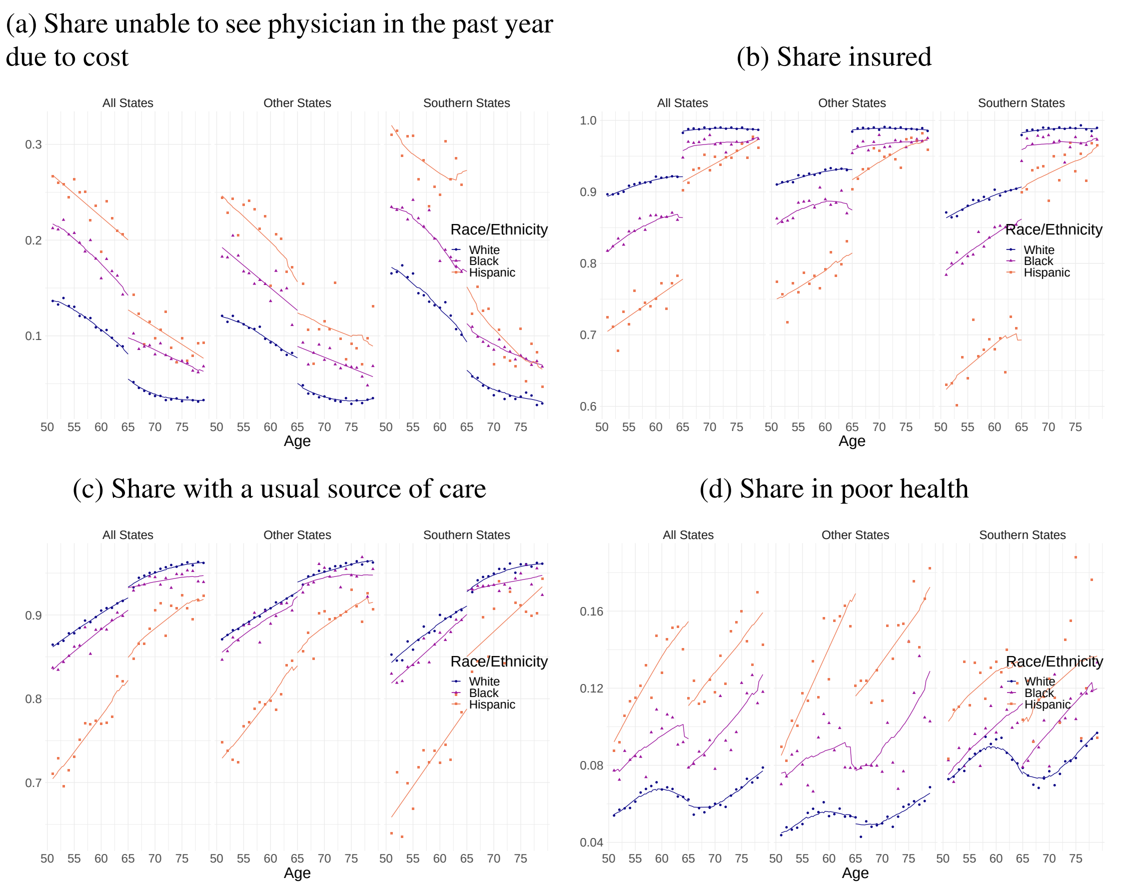
Figure A1. : Effect of Medicare eligibility at age 65



Source: This figure presents the graphical estimated effect of Medicare on different outcomes. Fitted lines are estimated using local linear regression separately on each side of age 65. Southern States are defined as Alabama, Kentucky, Mississippi, Tennessee, Arkansas, Louisiana, Oklahoma, Texas, Florida, Georgia, North Carolina, South Carolina, and Virginia.

Table A1—: Additional Effects on Changes in Racial and Ethnic Gaps and the Effects of Medicare Eligibility at Age 65

	Share of Change in Gap Explained (κ)		Estimated Effect (τ)			Change in Gap (δ)	
Share in Poor Health	Black Americans	Hispanic Americans	White Americans	Black Americans	Hispanic Americans	Black Americans	Hispanic Americans
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Overall			-0.0016	-0.019	-0.044	-0.017	-0.042
			(0.003)	(0.01)	(0.01)	(0.01)	(0.015)
Breakdown by Region	1.1	1.0					
Non-South			-0.0033	-0.00092	-0.053	0.00240	-0.05
			(0.003)	(0.01)	(0.02)	(0.014)	(0.013)
South			0.00120	-0.032	-0.029	-0.033	-0.03
			(0.005)	(0.01)	(0.02)	(0.02)	(0.02)
Share with a usual source of care							
Overall			0.014	0.019	0.034	0.0054	0.021
			(0.003)	(0.01)	(0.02)	(0.015)	(0.02)
Breakdown by Region	0.79	0.99					
Non-South			0.012	0.00580	0.016	-0.0059	0.0039
			(0.003)	(0.01)	(0.015)	(0.015)	(0.018)
South			0.017	0.029	0.062	0.012	0.045
			(0.005)	(0.01)	(0.025)	(0.015)	(0.03)

Source: Authors analysis of the Behavioral Risk Factor Surveillance System (BRFSS), 2010-2018. This table reports estimated effects from the Medicare RD regression, for White, Black, and Hispanic Americans. Columns 1 and 2 explain the share of the change in the gap explained by heterogeneity within covariates (see text for details). Columns 3, 4 and 5 report estimates of the RD regression by racial and ethnic group. Columns 6 and 7 report the difference between columns 4 and 3, and 5 and 3, respectively. These can be interpreted as the discontinuity in the disparity at age 65.