TITLE: Lingering Questions: Race, Health, and the Role of NGOs in Ohio

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ABSTRACT:

Using data from the 2008 Ohio Medicaid Assessment Survey (OMAS), we analyze the association between delay in treatment, self-rated health, race, and region in Ohio. We hypothesize that access to healthcare and region will play important roles in both self-rated health and the implications of delay in treatment. Aligning with the works of Montez et al. (2016 and 2017) and others, we do a state level analysis that draws on the impact of state context in driving health disparities. We focus specifically on Ohio because it borders Appalachia and contains the second largest Midwestern city, providing a population with a diverse racial makeup along different socioeconomic strata. Results show that race, gender, age, education, income, insurance coverage and region all matter for delay of treatment and self-rated health. One unexpected finding shows that Whites (in comparison to African Americans, Hispanics, and Asians) are most likely to delay treatment. Although Whites are more likely to delay treatment, they report better health outcomes than all other groups.

We thus propose a second layer of research to be added to the current analysis. This portion will be focused on the potential role of health Non-Governmental Organizations (NGOs) in filling the gap in access to healthcare that is theorized to directly impact delay in treatment. We believe that individuals who cannot afford healthcare costs may be seeking out health NGOs for basic medical needs. We expect NGO presence and access to differ by region in Ohio and we will collect data on the number of health-related NGOs in different regions of Ohio. Furthermore, we expect that people living in areas with access to NGOs will be less likely to delay treatment. Alternatively, those living in rural areas with restricted access to NGOs may report delaying treatment more often. Since Ohio contains large proportions of low SES Whites in rural areas, we suspect that this may drive the finding for White's delay in treatment. We will include this in the current analysis in order to see if health NGO existence helps mediate the relationship between race and delay in treatment.

Considering recent political and legislative shifts, we see the potential for NGOs to take a larger role in people's healthcare. This is especially true for areas where affordable healthcare is slim or largely unreachable (due to distance, costs, etc.). We hypothesize that health NGOs will fill an important gap for those who need health treatment but cannot afford it. With the Ohio population containing higher levels of poor whites than many other states, we expect that delay in treatment could be affected by access to treatment and want to explore the potential role of NGOs as a substitute for formal healthcare. We consider our findings in the context of local politics while also considering the broader policy impacts of non-traditional health provision.

PAPER:

Intro

Racial disparities in health are studied broadly across academia. Trends have been uncovered that reveal differences in mental and physical health outcomes based on racial/ethnic identity. Although racial/ethnic identity are socially constructed, the social institutions and micro-level processes within a racialized society create an environment wherein a person's racial and ethnic identity can have a tangible impact on their life outcomes as a result of inequality. In this analysis, we aim to examine the racial disparities in health for those living in Ohio.

Background

Historical analyses show that the Black/White racial gap in health has increased over time, in no small part due to the worsening health status of the Black population (Williams and Collins 1995). Furthermore, recent research has indicated that residential context may play a significant role in determining health outcomes for Blacks and Whites (Do 2008), and therefore, are crucial in explaining the Black/White racial gap in health. However, recent work concentrating on a race and age perspective show that while the gap itself has begun closing, Blacks under the age of 65 are still more likely than Whites to die from all leading causes (CDC 2017).

For other minorities, health related findings differ and much of the research has concentrated on showcasing lower health service use in comparison to native Whites (Mui et al. 2017; Salant and Lauderdale 2003). Within Asian populations in particular, health disparities vary based on ethnic group membership. Mayeda et al. (2017) found that the age of diagnosis for Alzheimer's differs for Asian minorities depending on ethnic identity. The authors found that South Asians have lower incidences of Alzheimer's than Chinese, and that Chinese have lower incidence rates than Japanese and Filipinos (p. 232). A study conducted by Park (2017) found similar disparities by ethnic group when analyzing the relationship between symptoms of depression and suicidal ideation among Chinese Americans and Filipino Americans. The dissimilarities between Asian subgroups reveals the heterogeneity among Asian ethnic groups.

For Hispanics, the findings are less clear but distinctions in health by migration status have been found (i.e. Healthy Immigrant Paradox; Roura 2016). While Hispanics fare better than Whites in terms of heart disease, and strokes, they fare worse in terms of diabetes and liver disease (Vega et al. 2009; CDC 2004). Additionally, Hispanics have higher rates of mortality related to diabetes, stomach cancer, HIV, and liver cancer compared to their White counterparts (Vega 2009). The authors found that these disparities are often related to differences in nativity and socioeconomic indicators such as education and income. Like Asians, this speaks to the heterogeneity of the Hispanic population.

The disparities in health outcomes among different minority groups may be related to differences in their historical racialized experiences within America. Blauner (1982) argues that the circumstances of arrival for minority groups is an important factor in explaining the differences in their racialized experiences. Since health is part of the everyday experiences of minority groups, it is fair to assume that their health experiences may differ based on their historical racialized experiences within America.

Research suggests that racial disparities in health may be partially linked to cumulative exposure to prejudice, discrimination, and racism (Geronimus 1992; Sue 2007). Scholars have found that subtle and persistent racism, or microaggressions, can have a lasting impact on the psychological outcomes of minorities (Sue 2007). Furthermore, the impact of discriminatory actions such as microaggressions have a cumulative effect. Geronimus (1992) argues that this cumulative effect has a physical impact on Blacks, leading to declines in health at an earlier age. Furthermore, she argues that Blacks are aware of this premature decline in health and make personal adaptations in anticipation of a decline in health. If this holds true, then this suggests that individuals are not only intimately aware of their own health status, but that their health status is ultimately linked to larger structural factors, and in particular, structural discrimination.

This structural perspective to racial disparities is common in sociological research. Eduardo Bonilla-Silva (1997) argues that a structural approach to racism and discrimination is important to better understand the pervasiveness of racial inequality in society. Structural understandings of racial inequality and discrimination can help explain and address social inequality, and in particular, health disparities. Structural approaches are particularly important in racialized societies because individually focused approaches may not be broad enough to address day to day discrimination and its cumulative impacts on health. Discrimination is an important factor to consider when measuring racial inequality in health because of the psychological toll that is associated with it.

Health disparities research within the United States, as mentioned above, has largely focused on racial and ethnic disparities. Internationally, consideration of a wider set of characteristics (gender, sexuality, socioeconomic status (SES) and disability status) has inspired more current U.S. based health research (Dehlendorf et al. 2011). Sociologists have played a leading role in emphasizing the primacy of social structure (and thus its measures) in considerations of health disparities (Williams and Sternthal 2010). Structural research has emphasized the important role that socioeconomic status plays in social inequality (Wilson 1980; Lareau 2002). In his 1980 book *The Declining Significance of Race*, Wilson argues that socioeconomic status is inextricably linked to racial inequality in America because of America's long history of racially exclusionary economic policies. For Wilson, socioeconomic status acts as an additional layer of stratification on top of race, and in recent years has become a more prominent driver of inequality.

Similarly, Lareau (2002) argues that socioeconomic status is an important factor in determining life outcomes through the acquisition of social and cultural capital. Social and cultural capital can be transmitted along class lines, providing those with higher socioeconomic status access to beneficial resources that can improve their life outcomes, including those related to health. In particular, Lareau (2002) finds that children of higher socioeconomic statuses are more assertive with their healthcare providers and about their health. This difference in approaches may impact health outcomes for children based on socioeconomic status. The extensive research showing the impact of socioeconomic status on social outcomes, warrants the inclusion of socioeconomic variables in analyses of health inequality.

Among others, Braveman et al. (2005) and Salant and Lauderdale (2003) show that findings differ widely depending on which measure of SES researchers choose to use. Dehelendr et al. (2011) suggests using multiple factors and measures of SES, as available in data sets. We will use two common measures of SES: income and education. We will centrally consider race, but control for additional characteristics including gender, age, and insurance coverage status. In the chosen data set, variables for race, gender, and income were imputed, in order to account for missing data. We did not square the age term, as we expected the relationships of self-rated health and delay in care to be linear.

Despite significant bodies of work surrounding health theory (from life course analysis to cumulative disadvantage and the weathering hypothesis) and large national level studies of health disparities, regional studies such as this one are often fewer and far between (Elder 1998;

Dannefer 2003; Geronimus 1992). Further, we argue that treatment and insurance coverage must be included as part of the disparity question. Since we know that affordable care and community based social ties impact levels of healthcare usage and thus health (Lillie-Blanton and Hoffman 2005; Thoits 2011), we can assume that delay in treatment could be a mediator in that relationship.

Several delay in treatment studies have researched specific health outcomes i.e. breast cancer, and how delay in treatment may vary by race and ethnicity, often finding that minority groups are more likely to delay treatment in comparison to their White counterparts (i.e. Smith et al. 2013).

Our work will fill in the gap for regional level health disparity analysis, while also laying down the foundation for further, more socially informed, regional analyses of health in Ohio. As research progresses, we see that social determinants of health, particularly poverty, poor housing, and environmental factors add additional layers which may increase risk for poor health outcomes, often through the concepts of stress and allostatic load (Alder and Rehkoph 2008).

The Ohio Medicaid Assessment Survey (OMAS; 2008), previously known as the Ohio Family Health Survey (OFHAS; 2004) has collected data regarding healthcare access, utilization, and health status at the state, regional, and county levels from 1997 to 2017, with the transition in name from OFHS to OMAS in 2008. We selected the 2008 survey because of the transition period and because it was the most recent iteration which contained measures for self-rated health, as well as delay in access to care, both variables which we argue depict two racial and ethnic health disparities across different regions of Ohio. It also contains larger numbers of responses. The OMAS data also satisfies the requirement for regional level data. The original dataset from 2008 contained 50,944 individuals. This OMAS study can provide a basis for racial/ethnic disparities in health off of which future research can build to help disentangle mechanisms and general trends for state, and regional level minority populations.

Data and Methods

OMAS data that included both of our dependent variables (delay in treatment and self-rated health) in relation to race, gender, age, income, education, insurance coverage, and regionality gave us a working sample of 50,013 individuals. With the later given justification for removing outliers, our regression sample was 50,0000. Since we were able to use the imputed variables for income and education, our working sample contained less missing data points and thus we were able to maximize our sample size. Gender and race were also imputed variables in this sample. Most respondents rated their health as being either very good or good, 32.15% and 30.10% of the sample, respectively. Of the sample, a majority of respondents did not have to delay treatment (80.91%). Our sample is largely White or Other (83.95%), but also contains racial/ethnic minorities, with 11.06% of the sample classifying as African American/Black, 3.72% classifying as Hispanic and 1.27% classifying as Asian.

Data collecting entities combined the categories of White and Other, and thus this analysis will have to use this category, despite potential known and unknown differences among those who classify as White versus those who may classify as Other. However, despite this caveat, the percentages within racial categories of our sample closely mirror those same percentages in the state of Ohio according to the U. S. Census Bureau. Our sample contains more women than men, at 63.90% female, which does not mirror the state of Ohio as a whole. However, this is not unexpected as women are typically overrepresented in samples.

Additionally, since this was a phone survey conducted on landlines, women could have been more likely to be at the home and thus to respond.

The average age and annual household income of respondents in our sample were 53.81 and $51,323.11. We tested age using the ladder function, which showed that our variable for age did not need to be transformed. Further, we do not suspect delay in treatment or self-rated health to vary across different age categories in particular or distinct ways. Thus, our sample tended to be middle aged and had slightly higher income than the average income of $47,988.00 for Ohio in 2008 (U.S. Census Bureau).

Similar to national education trends, more than half of our sample had a high school education (62.92%) and most respondents had some sort of insurance coverage (88.53%). The education variable was originally composed of 8 categories, which included Less than 1st Grade, First through 8th Grade, Some High School, but No Diploma, High School Graduate or Equivalent, Some College, but no Degree, Associate Degree, Four Year College Graduate, and Advanced Degree. We combined these into the 4 categories of High School, Associates, Bachelor's, and Advanced degrees, adding all lower level educational categories to the High School degree. We also added some college but no degree to the Associates category.

Our region variable was a string variable and appeared as the first letter of each regional category (A=Appalachian, M=Metropolitan, R=Rural (Non-Appalachian) and S=Suburban). We had to destring the variable and label the categories. We also had to destring the respondent's assigned IDs. Most respondents lived in a metropolitan region of the state of Ohio (44.41%), while the next highest category was split between Appalachia (22.73%) and rural non-Appalachia (11.51%).

Table 1: Descriptive Statistics for Variables of Interest (n=50,000)	
Variable	**Mean (SD) or Percent**
Self-Rated Health	
Excellent	16.04%
Very Good	32.15%
Good	30.10%
Fair	15.81%
Poor	5.91%
Delay in Treatment	
Yes	19.09%
No	80.91%
Race	
White/Other	83.95%
Black/AA	11.06%
Hispanic	3.72%
Asian	1.27%
Sex	
Male	36.10%
Female	63.90%
Income	51323.11 (71717.51)
Age	53.81(16.92)
Education	
High School	62.92%
Associates	11.57%
Bachelor's	13.09%
Advanced Degree	12.42%
Insurance Coverage	
Covered	88.53%
Not Covered	11.47%
Region	
Appalachia	22.73%
Metropolitan	44.41%
Rural/Non-Appalachia	21.35%
Suburban	11.51%

Analyses:

In efforts to further understand local versions of national trends, we will consider the following two research questions.

1. Does **delay in treatment** differ by race/urbanicity in Ohio?
2. Does **self-rated health** vary by region in Ohio?

<u>Analysis 1</u>

We use binary regression models to assess delay in treatment by race, age, gender, income, and education as well as by region. Our focus will be on race, with a supplemental focus on region. To begin, when checking for multi-collinearity, we find that our predictor variables are not highly correlated (mean VIF=1.20; highest VIF=1.83). In terms of outliers, we took out the top 14 earners in our dataset of 50,000+ whose incomes were more than $1,000,000 per year (up to over 12 million). While these 14 cases were not outliers visually, we suspect that they were high enough earners that they kept our models from converging (removing the cases allowed the models to converge and produce output).

As seen in Table 2 (below), delay in treatment is impacted by race, gender, age, income, education, insurance coverage, and region. In Model 1 we begin by adding demographic variables of race, gender and age. Our Model 2 adds our SES variables of income and education. Next, Model 3 includes an insurance coverage variable, and lastly Model 4 includes our regional comparison variable. From this point on, when saying Whites, we mean to imply Whites and Others. To begin, when running a Hosmer-Lemeshow goodness of fit test on the data, we find that our best model (Model 4) is acceptable and fits our data (Ch^2= 163.65; $p<0.001$).

Per Block 1, our Model 1 with demographic variables predicts our delay in treatment outcome better then chance alone (Chi^2=1565.37; $p<0.001$). Per Block 2, Model 2 with SES variables predicts our outcome better then chance alone (Chi^2=2898.24; $p<0.001$). When performing a likelihood ratio test between block 1 and 2, we find that our overall Model 2 fits the data better than Model 1 (Chi^2=1332.88; $p<0.001$). However, while the Hispanic/White comparison was not significant in Block 1, it became significant in Block 2. Additionally, the Black/White comparison lost significance with the addition of the education variables in Block 2. To note, the Black/White comparison also changed direction, making Whites more likely to delay treatment when considering SES. Per Block 3, Model 3 with the insurance coverage variable predicts our outcome better then chance alone (Chi^2=5481.19; $p<0.001$). When performing a likelihood ratio test between block 2 and 3, we find that our overall Model 3 fits the data better than Model 2 ((Chi^2=2582.95; $p<0.001$). Model 3's addition of the insurance coverage variable brought back significance to the Black/White comparison, thus making all race comparisons (versus White) significant. However, we lose the significance of the bachelor's versus high school comparison. This significance lasts throughout to the last model, Model 4. Per Block 4, Model 4 with the region variables predicts our outcome better then chance alone (Chi^2=5489.56; $p<0.001$). When performing a likelihood ratio test between block 3 and 4, we find that our overall Model 4 fits the data better than Model 3 (Chi^2=8.37; $p<0.05$). Essentially, each subsequent model with additional variables improved our model fit, with Model 4 being our best model. This can also be seen as the Chi-Square test of fit increases across Models. Thus, analysis and interpretation will focus around Model 4.

Race

Race was significant as a whole in increasing fit of the model (Chi^2=67.25; $p<0.001$). The odds of delaying treatment are 8.6% lower for Blacks, relative to Whites controlling for all other predictors ($p<0.05$). The odds of delaying treatment are 39.0% lower for Hispanics, relative to Whites controlling for all other predictors ($p<0.001$). The odds of delaying treatment are 37.0% lower for Asians, relative to Whites controlling for all other predictors ($p<0.001$). The odds of delaying treatment are 33.23% lower for Hispanics, relative to Blacks controlling for all other predictors ($p<0.001$). The odds of delaying treatment are 31.06% lower for Asians, relative to Blacks, controlling for all covariates ($p<0.001$). The odds of delaying treatment are not significantly different for Asians in comparison to Blacks. This shows us that overall, in the state of Ohio, Whites are more likely than Blacks, Hispanics, or Asians to delay treatment. Further, Hispanics are least likely to delay treatment.

Region

Region was significant as a whole in increasing the fit of the model ($Chi^2=8.33$; $p<0.05$). The odds of delaying treatment are 7.6% lower for rural (non- Appalachian) regions in comparison to Appalachian regions controlling for all other predictors ($p<0.05$). The odds of delaying treatment are 10.1% lower for suburban regions in comparison to Appalachian regions controlling for all other predictors ($p<0.05$). The comparisons between rural (non-Appalachian) and metropolitan regions, between suburban and metropolitan, and the comparisons between suburban and rural (non-Appalachian) regions in terms of delay in care were all surprisingly not significant. Succinctly, Appalachian regions are more likely to delay treatment than rural (non-Appalachian) regions as well as suburban regions in the state of Ohio.

Other Predictors and Control Variables

Female The odds of delaying treatment are 55.6% higher for females, relative to males controlling for all other predictors ($p<0.001$). For every 1-year increase in age, the odds of delaying treatment decrease by 2.1%, controlling for all other predictors ($p<0.001$).

For every 1 unit (1 dollar) increase in income, the odds of delaying treatment decreases by less than 0.0%, controlling for all other predictors ($p<0.001$). Education was significant as a whole in increasing fit of the model ($Chi^2=63.32$; $p<0.001$). The odds of delaying treatment are 19% higher for those with Associates degrees in comparison to those with high school education, controlling for all other predictors ($p<0.01$). The odds of delaying treatment are 15.2% lower for those with Advanced degrees in comparison to those with high school education, controlling for all other predictors ($p<0.001$). Differences in delay in treatment were not significant for those with bachelor's degrees in comparison to those with a high school education. Essentially as income increases, the chances of delaying treatment decreases, taking into considerations other variables, especially insurance coverage. This finding is intuitive. Interestingly an Associates level of education compared to high school education makes persons more likely to delay treatment. Those with Advanced degrees are less likely to delay treatment than those with high school education, which aligns with previous literature that finds that as SES increases, health tends to increase.

The odds of delaying treatment are 5.16 higher for those who are not covered by insurance, in comparison to those who are covered, controlling for all other predictors ($p<0.001$).

Table 2 Nested Binary Logistic Regression Predicting Delay in Treatment (n=49,878)								
	Model 1		**Model 2**		**Model 3**		**Model 4**	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Race (vs. White/Other)								
Black/AA	0.19(0.03) ***	1.2	-0.03(0.04)	0.97	-0.08(0.04) *	0.92	-0.09(0.04) *	0.91
Hispanic	-0.09(0.06)	0.92	-0.25(0.06) ***	0.78	-0.49(0.06) ***	0.61	-0.49(0.06) ***	0.61
Asian	-0.64(0.12) ***	0.53	-0.43(0.12) **	0.65	-0.46(0.13) ***	0.63	-0.46(0.13) ***	0.63
Female (vs. Male)	0.38(0.03) ***	1.46	0.32(0.03) ***	1.38	0.44(0.03) ***	1.56	0.44(0.03) ***	1.56
Age	-0.02(0.00) ***	0.98	-0.03(0.00) ***	0.97	-0.02(0.00) ***	0.98	-0.02(0.00) ***	0.98
Income			-0.00(0.00) ***	1.00	-0.00(0.00) ***	1.00	-0.00(0.00) ***	1.00
Education (vs. High School)								
Associates			0.11(0.04) ***	1.11	0.17(0.04) ***	1.19	0.17(0.04) ***	1.19
Bachelor's			-0.15(0.04) ***	0.86	-0.06(0.04)	0.94	-0.06(0.04)	0.94
Advanced Degree			-0.26(0.04) ***	0.77	-0.16(0.04) ***	0.85	-0.17(0.05) ***	0.85
No Insurance Coverage (vs. Covered)					1.64(0.03) ***	5.17	1.64(0.03) ***	5.16
Region (vs. Appalachia)								
Metropolitan							-0.02(0.03)	0.98
Rural (Non-App)							-0.08(0.04) *	0.92
Suburban							-0.11(0.05) *	0.9
Constant	-0.42(0.04) ***		0.33(0.05) ***		-0.60(0.05) ***		-0.56(0.06) ***	
LR Test	1565.37***		1332.88***		2582.95***		8.37*	
Log-Likelihood	-23533.08		-22866.64		-21575.17		-21570.99	
Model Chi^2	1565.37***		2898.24***		5481.19***		5489.56***	
** p<0.05, ** p<0.01, *** p<0.001*								

Analysis 2

We use ordinal regression models to assess self-rated health by race, age, gender, income, and education as well as by region. Same as above, when checking for multi-collinearity, we find that out predictor variables are not highly correlated (mean VIF=1.20; highest VIF=1.83). When considering the parallel assumption, also known as the proportional odds assumption, by conducting a Brant test, we were unable to get the test to run on our data set, despite multiple attempts on multiple computers and on several versions of STATA and thus proceed as if this assumption is passed.

As seen in Table 3 (below), self-rated health is also impacted by race, gender, age, income, education, insurance coverage, and region. As in the previous analysis, in Model 1 we begin by adding the demographic variables of race, gender and age. Our Model 2 adds SES measures of income and education, while Model 3 includes the insurance coverage variable, and lastly Model 4 additionally looks at regional differences. From this point on, when saying Whites, we again mean to imply Whites and Others. To begin, when running a Hosmer-Lemeshow goodness of fit test on the data, we find that our best model (Model 4) is acceptable and fits our data (Ch^2= 174.70; $p<0.001$).

Per Block 1, Model 1 with demographic variables predicts our outcome better then chance alone (Chi^2=2364.56; $p<0.001$). Per Block 2, Model 2 with SES variables predicts our outcome better then chance alone (Chi^2=6250.10 $p<0.001$). When performing a likelihood ratio test between block 1 and 2, we find that our overall Model 2 fits the data better than Model 1 (Chi^2=3388.54; $p<0.001$). Looking between Model 1 and Model 2, we can see that the addition of SES variables (income and education) takes away significance from the gender and the Asian vs. White comparison, both of which become not significant. Per Block 3, Model 3 with the coverage variable predicts our outcome better then chance alone (Chi^2=6416.06; p<0.001). When performing a likelihood ratio test between block 2 and 3,wefind that our overall Model 3 fits the data better than Model 2 (Chi^2=165.96; p<0.001). Adding the insurance variable in Model 3 brings back significance to the gender comparison. Per Block 4, Model 4 with the region variables predicts our outcome better then chance alone (Chi^2=6561.96; p<0.001). When performing a likelihood ratio test between block 3 and 4, we find that our overall Model 4 fits the data better than Model 3 (Chi^2=145.90; p<0.001). Therefore, like before our Model 4 fits the data better then previous models, all which added to our analysis in each stage, per Chi-Square tests of fit.

Race

Race was significant as a whole in increasing fit of the model (Chi^2=338.51; p<0.001). The odds of being one category higher on the self-rated health scale (better health) are 38.9% lower for Blacks, relative to Whites controlling for all other predictors (p<0.001). The odds of being in a higher self-rated health category are 26.5% lower for Hispanics, relative to Whites controlling for all other predictors (p<0.001). The odds of being in a higher self-rated health are 20.20% higher for Hispanics, relative to Blacks controlling for all other predictors (p<0.001). The odds of being in a higher self-rated health category are 73.87% higher for Asians, relative to Blacks controlling for all other predictors (p<0.001). The odds of being in a higher self-rated health category are 44.64% higher for Asians, relative to Hispanics controlling for all other predictors (p<0.001). The Asian/ White comparison for self-rated health was not significant.

Essentially Whites have the highest (best) levels of self-rated health followed by Asians, Hispanics, then Blacks.

Region

Region was significant as a whole in increasing the fit of the model (Chi^2=145.84; p<0.001). The odds of being in a higher self-rated health category are 24.4% higher for metropolitan in comparison to Appalachian regions controlling for all other predictors (p<0.001). The odds of being in a higher self-rated health category are 29.2% higher for rural (non-Appalachian) regions in comparison to Appalachian regions controlling for all other predictors (p<0.001). The odds of being in a higher self-rated health category are 29.5% higher for suburban regions in comparison to Appalachian regions controlling for all other predictors (p<0.001). The comparisons between rural (non-Appalachian) and metropolitan regions, between suburban and metropolitan, and the comparisons between suburban and rural (non- Appalachian) regions in terms of self-rated health were all surprisingly not significant. The Appalachian region stands out in comparison to others, exhibiting lower levels of self-rated health over all.

Other Predictors and Control Variables

The odds of being in a higher self-rated health category are 3.4% lower for females, relative to males controlling for all other predictors (p<0.001). For every 1-year increase in age, the odds of being in a higher self-rated health category decreases by 1.8%, controlling for all other predictors (p<0.001).

For every 1 unit increase in income, the odds of being in a higher self-rated health category increases by less than 0.00%, controlling for all other predictors (p<0.001). Education was significant as a whole in increasing the fit of the model (Chi^2=1542.69; $p<0.001$). The odds of being in a higher self-rated health category are 39.2% higher for those with Associates degrees in comparison to those with high school education, controlling for all other predictors ($p<0.01$). The odds of being in a higher self-rated health category are 97.8% higher for those with bachelor's degrees in comparison to those with high school education, controlling for all other predictors ($p<0.001$). The odds of being in a higher self-rated health category are 2.38 times higher for those with Advanced degrees in comparison to those with high school education, controlling for all other predictors ($p<0.001$). Essentially, as education goes up, self-rated health also tends to increase in Ohio.

In terms of insurance, the odds of being in a higher self-rated health category are 28.7% percent lower for those who are covered, in comparison to those who are not covered, controlling for all other predictors ($p<0.001$). So those with insurance coverage tend to have better self-rated health than those without coverage.

Table 3 Nested Ordinal Logistic Regression Predicting Self Rated Health (n=49,891)

	Model 1		**Model 2**		**Model 3**		**Model 4**	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Race (vs. White/Other)								
Black/AA	-0.63(0.03) ***	0.53	-0.46(0.03) ***	0.63	-0.45(0.03) ***	0.64	-0.49(0.03) ***	0.61
Hispanic	-0.46(0.04) ***	0.63	-0.32(0.04) ***	0.72	-0.28(0.04) ***	0.76	-0.31(0.04) ***	0.73
Asian	0.45(0.07) ***	1.57	0.09(0.07)	1.10	0.09(0.07)	1.10	0.06(0.07)	1.06
Female (vs. Male)	-0.09(0.02) ***	0.92	-0.02(0.02)	0.98	-0.03(0.02) *	0.97	-0.03(0.02) *	0.97
Age	-0.02(0.00) ***	0.98	-0.02(0.00) ***	0.98	-0.02(0.00) ***	0.98	-0.02(0.00) ***	0.98
Income			0.00(0.00) ***	1.00	0.00(0.00) ***	1.00	0.00(0.00) ***	1.00
Education (vs. High School)								
Associates			0.35(0.03) ***	1.42	0.34(0.03) ***	1.40	0.33(0.03) ***	1.40
Bachelor's			0.72(0.03) ***	2.05	0.70(0.03) ***	2.01	0.68(0.03)	1.98
Advanced Degree			0.89(0.03) ***	2.43	0.87(0.03) ***	2.38	0.86(0.03) ***	2.35
Insurance Coverage (vs. No Coverage)					-0.35(0.03) ***	0.71	-0.34(0.03) ***	0.71
Region (vs. Appalachia)								
Metropolitan							0.22(0.02) ***	1.24
Rural (Non-App)							0.26(0.02) ***	1.29
Suburban							0.26(0.03) ***	1.29
Constant 1	-4.05(0.04)		-3.38(0.04)		-3.53(0.04)		-3.38(0.04)	
Constant 2	-2.54(0.03)		-1.83(0.03)		-1.98(0.04)		-1.83(0.04)	
Constant 3	-1.13(0.03)		-0.35(0.03)		-0.50(0.04)		-0.34(0.04)	
Constant 4	0.50(0.03)		1.37(0.03)		1.23(0.04)		1.40(0.04)	
Log-Likelihood	-72578.73		-70635.96		-70552.98		-70480.03	
Model Chi^2	2364.56***		6250.10***		6416.06***		6561.96***	

** p<0.05, ** p<0.01, *** p<0.001*

Conclusion:

According to our OMAS data, we find that race, gender, age, education, income, insurance coverage and region all matter in terms of delay in treatment and self-rated health. Whites, surprisingly, are more likely to delay treatment than Blacks, Hispanics and Asians, with Hispanics being least likely to delay treatment. If this holds true in other cases, the Hispanic finding (assuming that a substantial portion of the Hispanic variable is made up of immigrants) may provide support for one of the mechanisms that helps produce the Healthy Immigrant Paradox. If Hispanics are least likely to delay treatment, this could help explain why they also tend to be healthier than many native populations, as studies regarding the Immigrant Health Paradox point out.

However, we must also realize that the treatment variable may not accurately account for the severity of health problems in seeking treatment. Thus, Whites may be most likely to delay treatment because their health problems are less severe. Alternatively, Whites may be more likely to delay treatment because overall, they may get more physicals and regular checkups allowing them to keep up with their health more closely and make decisions on delay more often. Essentially, they may discover a problem earlier than other racial minorities, and thus have more time to delay treatment while figuring out the next steps. This would be the case if upon detection the problem needing treatment could be put off a bit more. Whereas, if a racial minority discovers their problem in the thrones of the disease, they may be forced to take action more swiftly and immediately, not allowing for delay. More research needs to be done in order to directly untangle these possibilities.

In terms of self-rated health, Blacks and Hispanics have worse self-rated health outcomes than Whites, while Asians have better health outcomes. Blacks still have the worst levels of self-rated health in the Ohio region. This connects well to several past findings. In particular, this provides evidence to support Geronimus' (1992) weathering hypothesis, which indicates that the discrimination and prejudice that Blacks experience may build up to affect their health outcomes.

Further research addressing the mechanisms by which this racial gap occurs, especially in relation to other non-White minorities is needed. Works like that of Umberson (2017) show that Blacks disproportionally face deaths of family members compared to other racial groups, leading to an overlooked source of racial disadvantage. More of these types of sources must be uncovered in order to fully understand the relationships between race and health. Furthermore, we found racial disparities in self-rated health that persisted regardless of considerations of income and education. However, for Asian respondents, we found that race became an insignificant factor after adding in socioeconomic variables. This is consistent with previous literature which has indicated that class distinctions provides an additional layer to (and sometimes act as a protective buffer against) racial stratification (Lareau 2002; Wilson 1980).

Additionally, in regard to both delay in treatment and self-rated health, we see that the Appalachian region stands out from the rest of the regional comparisons, as other past findings support. More research needs to be undertaken in order to fully comprehend what about this region makes health and treatment look differently. We also find that females have lower levels of self-rated health, and tend to delay treatment more than males, also falling in squarely with past findings. In an interesting twist on insurance findings, we also see that insurance coverage is associated with worse self-rated health. Intuitively this makes sense, as those with worse health are likely to have steeper medical expenses, thus justifying the need for insurance.

Along with interesting findings regarding delay of treatment in Ohio and results bolstering previous findings on self-rated health, also come limitations. One of the bigger limitations of the study revolves around the combination of the White and Other categories mentioned previously. Additionally, Asians and Blacks are slightly underrepresented in our sample, while females are over represented in our data compared to the actual demographics of Ohio. Further, our data considered a binary delay variable, but future studies should consider looking at data that disentangle more nuanced levels of measuring different stages of delay in treatment. Future research should also search for the mechanism(s) that drive Whites to delay treatment more frequently than other racial groups.

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