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RESEARCH ARTICLE

The determinants of racial disparities in obesity: baseline evidence from a natural experiment

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Abstract
This article uses baseline data from an observational study to estimate the determinants of racial and gender disparities in obesity. Samples of low-income workers in Minneapolis and Raleigh reveal that respondents in Minneapolis have lower body mass indices (BMIs) than respondents in Raleigh. There are large, statistically significant race and gender effects in estimates of BMI that explain most of the disparity between the two cities. Accounting for intersectionality—the joint impacts of being Black and a woman—reveals that almost all the BMI gaps between Black women in Minneapolis and Raleigh can be explained by age and education differences.

Keywords: body mass index (BMI); food insecurity; minimum wage; racial disparity

JEL Codes: I14 Health and Inequality; J15 Economics of Minorities; Races; Indigenous Peoples; and Immigrants; J08 Labor Economics Policies

Introduction

Much of the literature on food insecurity and racial disparities in health outcomes begins with the underlying assumption that consumers' individual choices explain observed disparities across groups. For example, constraints faced by consumers via access to food markets or pricing among local food stores may also explain observed inequalities (Chung and Myers 1999). Often missing from conventional analyses is an examination of contextual factors that might offer policy insights about racial and ethnic disparities in diets, food consumption, and, ultimately, health outcomes.

This article utilizes survey data from the WAGE$ survey of low-wage workers in Minneapolis, Minnesota, and Raleigh, North Carolina. This data was collected to study the long-term health effects of introducing a phased in minimum wage in Minneapolis, with Raleigh serving as a control site, as there is no planned minimum wage increase and the state of North Carolina's preemption laws prevent cities or municipalities from establishing their own minimum wage. For the purposes of this article, which uses the baseline data from the WAGE$ sample collected in 2018, the minimum wage serves to identify low-wage workers in each city but will not serve as a bespoke causal determinant of BMI, but we will utilize this survey instrument as a tool to explore the determinants of BMI among low-wage workers in both sites.

The goal of this article is first to establish a baseline measure of the BMI differential between the two sites suggested by an OLS model. Second, this article will explore the extent to which differences in BMI are due to policy factors that are determined at the local level, due to personal factors, or may be due to differences in the formation of the survey sample by performing an Oaxaca decomposition for Black women in the sample and identifying the extent to which the observed BMI differential is explainable by observed factors in the study.

The article is organized in the following manner. First, we detail the design of the survey instrument we use in the study and provide background information on the two locations. We report the anomaly of racial differences in BMI between the subsamples according to geography for one demographic: Black women.

Next, we model the determinants of racial disparities in BMI across groups and differentiate between conventional race and gender measures and intersectionality measures of race and gender. Intersectionality is understood to be the concept that the sum of the separate impacts of race and gender is often exceeded by the joint impact of race and gender (Crenshaw 1989).

To identify BMI differentials based on the intersection of race and gender, we perform Oaxaca decompositions of the BMI among Black women between two locations. We interpret the explained vs. residual differences from the decompositions as measuring the behavioral or demographic aspects of these differences within race and gender differences vs. the contextual elements. We conclude by reporting the results and discuss their policy implications.

The WAGE$ observational study

In June 2017, the City of Minneapolis, Minnesota, set the city's minimum wage above the state level, joining a growing number of other local jurisdictions across the United States that have passed similar ordinances since 2012 (UC Berkeley Labor Center 2020). Minneapolis is in the process of incrementally increasing its minimum wage from $9.50 to $15 by July 1, 2022, for all businesses with more than 100 employees. The minimum wage will increase from $7.75 to $13.50 during the same period for smaller businesses (City of Minneapolis 2016). The ordinance specifically states that its purpose is to "maintain workers' health, efficacy, and general well-being."

Estimates from 2016 of the ordinance's potential effects predict that wages will increase by an average of 22 percent for the 71,000 workers in the city making the minimum wage or just above the minimum wage. Moreover, the higher minimum wage will affect 41 percent of non-Hispanic Black workers and 54 percent of Hispanic workers, compared with 17 percent of white workers. Projections estimate a postpolicy decrease in food insecurity of 3.8 percent and an increase in food expenditures of $26 per week among affected workers (Roy Wilkins Center for Human Relations and Social Justice 2016).

Evidence from previous studies suggest that minimum wage laws may be associated with a range of health outcomes, including obesity (Bhatia and Katz 2001; Meltzer and Chen 2009; Kim and Leigh 2010; Human Impact Partners 2014; Komro et al. 2016; Tsao et al. 2016). However, the current body of evidence is limited by design weaknesses and generally does not test causal mechanisms for the relationship between wages and health, either because the survey instruments used do not measure wages directly, or they do not measure health in sufficient detail. The minimum wage has been shown to reduce severe food insecurity, although the effects on overall food security remain less drastic (Rodgers, 2016). Obesity affects over one third of Americans and is disproportionately high among non-Hispanic Blacks and Hispanics (Centers for Disease Control 2013; Krueger and Reither 2015).

In the current study, the city of Minneapolis serves as the subject of observational interest since it has elected to adopt a new minimum wage regime, with the minimum wage for work in the city increasing incrementally over several years. The city of Raleigh was chosen as a control primarily due to its similarity in demographic characteristics. Raleigh's resident population, median household income, firm count, share of population with college education, and distribution of racial identities were similar to Minneapolis in the time before the passage of Minneapolis' minimum wage ordinance (Shanafelt et al. 2021). In addition, North Carolina's state minimum wage preemption reduces the likelihood that Raleigh will see an increase in the minimum wage during the time of the study. This allows Raleigh to serve as a reasonable control site for the scope of the study and motivated the selection of Raleigh as a comparison site.

This article uses baseline information from Minneapolis and Raleigh, North Carolina, that reflects wages before the implementation of the Minneapolis minimum wage ordinance to examine BMI differences between two cohorts of low-wage workers. The study follows low-wage workers over five data collection time points (annually 2018–2022). We examine baseline obesity-related measures among low-wage workers (earning ≤\$11.50 an hour at baseline) in Minneapolis ($n = 490$) with low-wage workers in a comparison city with no minimum wage increase (Raleigh, North Carolina, $n = 479$). We test the hypothesis that there are baseline BMI differences according to race and gender at the outset between low-wage workers in Minneapolis and Raleigh, controlling for nutrition-related and demographic differences between the cities. We interpret any residual differences between the cities to be attributable to contextual factors, such as a progressive political climate that (a) encourages a healthier lifestyle and (b) supports policy changes such as increases in the minimum wage.

Site population characteristics

Table 1 shows the city characteristics for Minneapolis and Raleigh, the control site. Raleigh has a larger Black population (29.3 percent) than Minneapolis (18.6 percent). Still, the two cities are remarkably similar on other demographics and critical characteristics relevant to this study, including population size, percent foreign-born residents, employment rate, cost of living, persons living in poverty, average BMI, and obesity rate.

Participants

In 2018, participants were enrolled and completed the first wave of data for the study. Recruitment of participants began in January of 2018 in Minneapolis and April of

Table 1. Key Characteristics of Minneapolis and Comparison City (Raleigh)

	Minneapolis, MN	Raleigh, NC
Population characteristics		
Population Estimate (7/1/2016)	413,651	458,880
Race[a]		
White, Not Hispanic, or Latino	60.3%	53.3%
Black, Not Hispanic, or Latino	18.6%	29.3%
American Indian or Alaska Native, Not Hispanic or Latino	2.0%	0.5%
Asian, Not Hispanic, or Latino	5.6%	4.3%
Any Race, Hispanic, or Latino	10.5%	11.4%
Multiracial Not Hispanic or Latino	3.0%	1.2%
Foreign Born[b]	15.5%	13.2%
Share of 25+ persons with Bachelor's Degree or Higher[b]	47.4%	48.2%
Median Household Income (2015 USD)[b]	51,480	55,398
Share of Persons in Poverty[b]	21.9%	16.0%
Working Age Civilian Labor Force Participation[b]	73.9%	70.6%
Weight measures		
Obesity Rate (2014)	22.2%	22.9%
Average Population BMI (2015)	27.2	27.1
State characteristics		
State Minimum Wage in 2017 (USD)[c]		
Large Firms	9.65	7.25
Small Firms	7.87	

Notes:
This excludes special classes of workers with bespoke minimum wage levels, including J1 visa recipients, Commensurate Wage recipients, and training wage recipient.
[a]From US Census Bureau as of 4/1/2010;
[b]From CDC BRFSS as of 2011–2015;
[c]Firm size based on annual sales <$500,000.
Sources: MN minimum wage: Berry (2021). NC minimum wage: North Carolina Department of Labor (2021). BRFSS SMART data for 2015 by Metropolitan Statistical Area accessed at https://www.cdc.gov/brfss/smart/smart_2015.html.

2018 in Raleigh, and the minimum wage in Minneapolis began to take effect that July (Shanafelt et al. 2021). Recruitment continued until at least 450 participants were identified in each test site. This ensured that the study was adequately powered to conduct future difference in difference analysis on BMI changes between the two sites over the study period, and to account for loss of participation to follow up. Participants were recruited through a variety of methods, including paid advertisements, posted fliers, and partnerships with community organizations with high visibility to low-wage workers.

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Participation was limited to those who report holding at least one job in either city with a wage of $11.50 or less. This cutoff reflects previous work that finds that earnings effects from the minimum wage ripple to those near 15 percent above the current minimum wage (Dube, Giuliano, and Leonard 2019). Minnesota in 2018 observed a minimum wage of $9.65, and $11.50 reflects a 15 percent increase above this wage, rounded up. Those with multiple jobs are included if one of these jobs pays $11.50 or less, even if their other jobs pay more.

Participants are compensated for their time in installments, based on their completion of the survey instrument, the verification of their wages with pay stubs, the verification of their food purchase history with receipts, and their measurement of height and weight for BMI calculation. Payment is scaled up to $70 USD based on the completion of these measures.

Body mass index

The primary outcome of interest for the WAGE$ study is body mass index (BMI). We measured BMI using standardized protocols from the University of Minnesota's Obesity Prevention Center (French, Wall, and Mitchell 2010). BMI is the recommended method of assessing overweight and obesity among adults and was calculated as weight in kilograms/height in meters squared. Measurements in Minneapolis and Raleigh were completed by trained and certified research staff who took height and weight measures in a private room with participants dressed in light clothing, shoes removed, and pockets emptied. Weight was measured in duplicate on a portable digital scale (Seca model) and recorded to the nearest 0.1 kg. If the two measures differed by more than 0.2 kg, a third measure was obtained. The mean of two or three values was used for analysis. The scale was calibrated with a 5 kg weight at regular intervals. Height was measured in duplicate, using a portable Schorr stadiometer (Schorr Production, Olney, MD) and recorded to the nearest 1.0 cm. If the two measures differed by more than 5 mm, a third measure was obtained. The mean of two or three values was used for analysis. In adults, in-person anthropometric data collection is more reliable and valid than self-reported data (US Department of Agriculture ERS 2020). Table 2 provides these and other definitions.

Employment characteristics

All current job(s), job title(s), employer name(s), employer address(es), job start date(s), weekly hours worked during the past two weeks, and hourly salary were recorded in an interviewer-assisted survey. Paystubs/proof of wages were requested from participants and provided by 66 percent of participants at baseline.

Survey measures

A survey, designed to be completed by participants in approximately 25 min, assessed psychosocial and behavioral mediators between wages and obesity as well as participant demographics.

The survey assessed, among other variables, demographics (age, gender, race, ethnicity, country of origin, education, marital status, household size), health insurance status (yes/no), physical activity (the count of times in a week that the respondent reports engaging in activity for at least 15 min, separated by mild, moderate, or strenuous

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Table 2. Definition of variables in regression models

Variable group	Variable label	Definition	N	Mean	St Dev.	Min	Max	Base category "Left Out" to avoid autocorrelation	Other notes
Dependent variable									
	height	Staff measured height in cm	974	169.0	9.2	146.1	198.6		
	weight	Staff measured weight in kg	974	86.9	23.3	40.8	195.6		
	BMI_kgm2	BMI calculated as weight kg/(height m)^2	974	30.5	8.1	15.0	65.2		
Base factors									
	location	Study site location (Minneapolis, Raleigh}	974					Raleigh	
	race	Self-reported race group (American Indian/ Alaska Native, Asian/ Pacific Islander, Black/ African American, White, Multiple, or Other}	909					White	Respondents may check all that apply; those that report multiple racial identities are designated
	ethnicity	Self-reported Hispanic Ethnicity {Hispanic, Non-Hispanic}	952					Non-Hispanic	
	sex	Self-reported gender {Female, Male, Nonbinary}	966					Male	

Truncated version only includes BMI and base factors. See the complete table in the Appendix .
Source: Caspi et al. (2021).

levels), banked status (yes/no to reported ownership of a checking or savings account with a bank or credit union), SNAP participation (yes/no), and food insecurity. Food insecurity is defined by at least two of six factors being true in the 12 months: the food you bought did not last and could not afford more; you could not afford a balanced meal; you cut your meal size because you were worried there was not enough money for food; you cut your meal size more than once or twice in the last 12 months; you were hungry because there was not enough money for food; or you ate less because you were worried you were going to run out of food.[1]

Survey measures also included questions about expenditures across 25 spending categories. These questions measure changes in expenditures, recognizing that many types of spending beyond food have implications for health (e.g., an increase in spending on rent could indicate improved housing conditions). We used a survey methodology employed by Hurd and Rohwedder (2012) in the American Life Panel (ALP), which asks about spending on a number of expenses, including housing and utilities, transportation, child-related expenses, clothing, personal care, health care, entertainment, education, insurance, and gifts (Albrecht et al. 2013). The ALP includes a reconciliation screen to avoid misreporting outliers, which reduces the standard deviation of responses by almost half (Albrecht et al. 2013). Total spending captured by the ALP has been found to be comparable to the more detailed Consumer Expenditure Survey (CEX).

All measures are designed to be repeated each year from 2018 through 2022 to form a panel design. Future waves of data collection will serve to causally identify the relationship between the minimum wage and the BMI, but this article includes the first baseline year to differentiate between BMI factors that are related to explainable characteristics measured in the study and factors that reflect unexplained factors that may limit the ability to use this sample to provide useful inference.

Access to resources

In addition to health outcomes, the survey also includes a number of measures that capture access to resources that may influence food purchases. SNAP usage is an indicator variable based on whether the respondent has reported a nonzero amount of SNAP benefits spent. This characterizes access to government transfer programs intended to reduce food insecurity. The USDA measure of food insecurity is operationalized based on a six-question panel. Food insecurity is defined by two or more of six factors being true in the 12 months prior to the survey: the food you bought did not last and could not afford more, you could not afford a balanced meal, you cut your meal size because you were worried there was not enough money for food, you cut your meal size more frequently than once or twice within a year, you ate less because you were worried about running out of food, you were hungry because there was not enough money for food. This food insecurity indicator is also included as a measure of access to resources.

Banking access is a proxy, intended to reflect the participant's disposable wealth, and their access to private sector resources, or inversely, reliance on the public sector.

[1]Respondents are asked to classify their responses to these questions in one of two ways: food lasting and not affording a balanced meal asked if this is often true, sometimes true, or never true. Cutting meal size, going hungry, or eating less asked if there is a time where this was ever true. Cutting meal size is also asked with what frequency over the last year. These questions also include some who respond they do not know, or leave the question blank, in which case, their response is treated as a missing value and is dropped from later regressions.

Banked status is based on reported ownership of a checking or savings account with a bank or credit union.

Race, gender, and intersectionality in the sample

The field of stratification economics seeks to identify ways in which economic phenomenon may serve as expressions of power that generate the treatment of less powerful groups as subaltern. In this field, it is common to see economics problems as problems of moving targets, where no one policy instrument or market activity is singled out as a causal determinant of this subaltern status. This suggests that researchers must adopt a variety of ways of measuring classes of economic power when exploring empirical questions and compare these varieties of results to understand the way in which this moving target may be present. Furthermore, researchers cannot assume independence of the boundaries of these classes, as these distinctions are created in the first place for the purpose of this stratification of power.

In the case of the WAGE$ study, we observe a differential in BMI with respect to one group in particular, Black women. We do not see a significant differential between sites for other groups (see Table 3), but we cannot suggest that this differential is from a stratification of economic power unless we compare the results of a model that treat those factors as fixed effects to a model that treats these factors together. Race and gender may each have a bespoke relationship with economic power; however, researchers should not treat each factor as independent. Differentials in policy and economic power are often observed to be greater in interactions of race and gender than in the sum of each of those identities alone (Crenshaw 1989). For this reason, we adopt a tiered approach to explore observed BMI differentials. First, we treat these differentials as fixed effects within the sample; second, we allow these differentials to be explained as a difference in treatment of several determining factors; and third, we compare the scope of the suggested differential between these models.

Table 3 reports that the BMI is lower in Minneapolis than it is in Raleigh. The mean of 29.832 in Minneapolis is lower than the mean of 31.199 in Raleigh. This difference of 1.367 is statistically significant at the 1 percent level for a two-tailed test. Most of this difference is driven by the lower BMI among Black women in Minneapolis vs. Black women in Raleigh, although the difference is barely significant at the 10 percent level for a two-tailed test.

Table 4 reports similar comparisons by SNAP usage. The higher SNAP usage in Minneapolis is consistently higher across race and gender groups. These differences are only statistically significant for Black women, Black men, White women, and White men.

A similar analysis including the probability of education in excess of High School and age is included in Tables A8 and A9, respectively. Education is not notably different according to race and gender, but the Raleigh cohort is younger than the Minneapolis sample.

The model

Although health-related outcomes are observed at the individual level, the determinants of health are based on both individual, environmental, and policy factors that are outside of the individual's control (Leigh and Du 2018). BMI as a health outcome is partially determined by personal behaviors like diet, sleep, and physical activity, partially

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Table 3. BMI differentials in the WAGE$ sample within racial group by location

		Count		Mean		Two-tailed T-test		
Sex	Race	Mpls, MN	Rale, NC	Mpls, MN	Rale, NC	Difference in Mean	(S.E.)	p-value
Female	Black	129	149	31.880	33.656	−1.777	(0.981)	0.071
	White	46	32	30.109	29.341	0.768	(1.624)	0.638
	Write in or Mixed Race	36	18	32.504	32.026	0.479	(2.295)	0.836
Male	Black	179	137	28.317	27.687	0.630	(0.722)	0.384
	White	35	21	29.672	28.341	1.331	(2.636)	0.616
	Write in or Mixed Race	27	14	26.750	28.617	−1.867	(2.083)	0.376
Whole sample		495	479	29.832	31.199	−1.367	(0.520)	0.009

Note 1: Asian, Pacific Islander, American Indian, Alaska Native, and Missing Race, and Gender Nonbinary are excluded from this table due to too few observations. If a race and gender group includes fewer than ten observations at a site, that group is not tested separately in this t-test, to avoid drawing comparisons driven by small sample size, but are included in the whole sample.
Note 2: Before each T-test, we conduct an F-test for unequal standard deviations of each group by location. If equal, a standard T-test is performed. If unequal, we use the Satterthwaite (1946) T-test with unequal variances.

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Table 4. SNAP usage differentials in the WAGE$ sample within racial group by location

		Count		Mean		Two-tailed T-test		
Sex	Race	Mpls, MN	Rale, NC	Mpls, MN	Rale, NC	Difference in Mean (S.E.)		p-value
Female	Black	125	248	0.712	0.556	0.156	(0.056)	0.006
	White	46	32	0.587	0.313	0.274	(0.112)	0.017
	Write in or Mixed Race	17	36	0.556	0.353	0.202	(0.147)	0.175
Male	Black	135	175	0.640	0.311	0.329	(0.057)	<0.001
	White	20	35	0.600	0.300	0.300	(0.137)	0.033
	Write in or Mixed Race	13	26	0.538	0.308	0.231	(0.187)	0.225
Whole sample		484	473	0.647	0.442	0.205	(0.033)	<0.001

Note 1: Asian, Pacific Islander, American Indian, Alaska Native, and Missing Race, and Gender Nonbinary are excluded from this table due to too few observations. If a race and gender group includes fewer than ten observations at a site, that group is not tested separately in this t-test, to avoid drawing comparisons driven by small sample size, but are included in the whole sample.
Note 2: Before each T-test, we conduct an F-test for unequal standard deviations of each group by location. If equal, a standard T-test is performed. If unequal, we use the Satterthwaite (1946) T-test with unequal variances.

determined by environmental factors like workplace conditions, household conditions, and partially determined by policy factors like access to healthcare services, food security assistance, and household income. The social determinant model of health differentiates between the factors that are in the individual's control and factors that are environmental or policy related, to identify plausible positive health effects that are associated with policy changes. Many of the policy interventions designed to ensure food security are means tested programs based on household income. These policies, however, often come with limitations, like requiring interaction with the state to prove eligibility, or limiting the kinds of goods that can be purchased with transferred funds like the SNAP program.

Although household income is already an established determinant of BMI, wages may plausibly serve as a bespoke determinant. This is because monthly income is a function of both the wage rate, and the number of hours worked per month. If hours worked as employment status are fixed, increasing the minimum wage would lead to an unambiguous increase in household income. If hours are subject to change, however, an increase in the wage might be paired with a decrease in hours worked such that household income is unchanged. Hours worked may be reduced after an increase in the minimum wage through two channels. After an increase in the minimum wage, employers may cut hours and fire employees to cut costs. Economists debate the significance of this effect (Neumark et al. 2014; Cengiz et al. 2019). Also, households may request to reduce their hours worked so their monthly income is unchanged to maintain their eligibility for government programs. On average, for each $1 increase in household income, government transfer benefits are reduced by $0.30 (Reich and West 2015). This suggests that households might see more real spending power with an increase in income than reliance on these programs. Although household income would effectively replace the need for many of these programs, households that treat their income as variable and uncertain may prefer to maintain their use of these programs over a more volatile income situation from wages alone. This phenomenon is often referred to as the "Benefits Cliff."

The minimum wage increase in Minneapolis serves as an observational study to test this model, assuming that Minneapolis and Raleigh workers face similar determinants over time. Estimating the causal relationship between the minimum wage and the BMI is left as a topic of future research (Caspi et al. 2021). Although the minimum wage is an important factor that motivates the design of the WAGE$ survey, the goal of this article is to explore the extent to which existing determinants of health explain BMI differentials before the observed minimum wage policy. It is the purview of this article to explore the extent to which determinants at these sites are indeed similar.

We begin with a specification of the determinants of BMI that include measures, x_{in}, of race, ethnicity, gender, location, food insecurity, banked status, SNAP usage, physical activity, and primary job hourly wage. The subscript i refers to each included control, and n refers to each unique observation. This study uses the baseline time period only. Physical activity is based on the count of times in a week that the respondent reports engaging in activity for at least 15 min, separated by mild, moderate, or strenuous levels. Since all the workers in the experiment have the same range of wages, we do not directly control for income. Instead, we control for L, location. To determine whether racial and/or gender disparities cannot be accounted for by the controls or location, we also control for race, R, and gender, G, given by equation 1.

$$\text{BMI}_n = \alpha + \Sigma_i\, \beta_i\, x_{\text{in}} + \gamma R_n + \delta G_n + \phi L_n + \epsilon_n \tag{1}$$

We estimate the coefficients β_i, γ, δ, and ϕ to obtain the effects of each included covariates x_i, race, gender, and location on BMI in our survey sample of workers in Minneapolis and Raleigh. New controls x_i are added with each model. We test the underlying hypothesis that whether once we control for location, race and gender effects disappear, as one would expect for matched locations. To account for the possibility that between location j and location k there may be differential impacts of race and gender on BMIs, we re-estimate equation 1 separately for the two locations. These separate estimates are obtained from equations 2 and 3.

$$\mathrm{BMI}_n^k = \alpha^k + \Sigma_i\, \beta_i^k\, x_{in}^k + \gamma^k R_n^k + \delta^k G_n^k + \phi^k L_n^k + \epsilon_n^k \tag{2}$$

$$\mathrm{BMI}_n^j = \alpha^j + \Sigma_i\, \beta_i^j\, x_{in}^j + \gamma^j R_n^j + \delta^j G_n^j + \phi^j L_n^j + \epsilon_n^j \tag{3}$$

A direct test of whether any difference in BMI between the two locations is due to differences in the effects of race, gender, or other factors is to compute the counterfactual, $B\tilde{M}I^j$, or the predicted value of the mean BMI in location j when the effects of each x_i covariate, gender, and race on BMI in location j are the same as they are in location k. Equation 4 shows how this counterfactual is computed: we use the jth location's means of the independent variables, but the kth location's estimated coefficients to derive what the mean BMI in the jth location would be if the jth population had the kth location's treatment. Of course, when the estimated effects are the same between locations, $B\tilde{M}I^j = B\bar{M}I^j$, or the "equal treatment" BMI in location k is the same as the actual BMI in location j.

$$B\tilde{M}I^j = \hat{\alpha}^k + \sum\nolimits_i \hat{\beta}_i^k \bar{x}_i^j + \hat{\gamma}^k \bar{R}^j + \hat{\delta}^k \bar{G}^j + \hat{\phi}^k \bar{L}^j \tag{4}$$

Accordingly, we can decompose the actual gap in BMI between locations j and k into a portion that is due to differences in treatment (or coefficients) and differences in characteristics (each control x_i, race and gender). Equation 5 provides the decomposition. The second row of the equation reports the portion of the BMI gap between the kth location and the jth location due to differences in treatment (coefficients). The third line in the equation represents the portion of the BMI gap between the kth location and the jth location due to differences in each control x_i, race, and gender.

$$\begin{aligned} B\bar{M}I^k - B\bar{M}I^j &= [B\tilde{M}I^j - B\bar{M}I^j] + [B\bar{M}I^k - B\tilde{M}I^j] \\ &= [(\hat{\alpha}^k - \hat{\alpha}^j) + \sum\nolimits_i (\hat{\beta}_i^k - \hat{\beta}_i^j)\bar{x}_i^j) + (\hat{\gamma}^{-k}\hat{\gamma}^j))\bar{R}^j) + (\hat{\delta}^k - \hat{\delta}^j))\bar{G}^j) \\ &\quad + (\hat{\phi}^k - \hat{\phi}^j))\bar{L}^j)] + [\sum\nolimits_i \hat{\beta}_i^k(\bar{x}_i^k - \bar{x}_i^j)) + \hat{\gamma}^k(\bar{R}^k - \bar{R}^j)) + \hat{\delta}^k(\bar{G}^k \\ &\quad - \bar{G}^j)) + \hat{\phi}^k(\bar{L}^k - \bar{L}^j)] \end{aligned} \tag{5}$$

Equation 5 can be expanded further to account for the fact that there may be interactions between the differences in endowments vs. differences in treatment.[2]

[2]See, for example, Oaxaca and Ransom (1999), where algebraically, coefficient effects and endowment effects are not enough to explain the entire effect, and a third effect is needed to account for the interaction between coefficient and endowment effects.

One of the common limitations of the decomposition detailed in equation 5 is that it ignores what is called in the Critical Race Theory literature "intersectionality" (Crenshaw 1989). This concept posits that the sum of race and gender's separate effects underestimates the combined impacts of being a racial minority group member and being a woman. The cross-over from legal theory to econometrics is not yet settled. One approach is to incorporate interaction terms between race and gender in equations 1–3. The alternative, which we adopt here, is to perform a separate decomposition of BMI within race and gender pairs, which amounts to assuming interactions between race and gender within locations and interactions between each control x_i and race and gender between locations.

Comparing OLS and decomposition models

In an OLS regression approach, the relationship between the outcome variable and the included covariates is expressed as the slope of the covariate. This approach estimates the average rate of change between the outcome and the covariate, assuming no endogenous correlation between factors. This approach is best suited for empirical problems where variances in controls are independent of each other. In such a model, each control factor is presumed to parametrically represent this relationship linearly. In the case of categorical variables, each category may be represented as a vector of binary indicator variables, where the estimate of the average of this parameter reflects the average share of the sample that shares that category.

Introducing race, gender, ethnicity, or demographic factors as a vector of binary indicators allows the researcher to estimate the average correlation with the outcome of interest, but it is not appropriate to interpret this estimate as uncorrelated with other controls. Program participation is not randomly distributed throughout the population, and participation reflects a self-selection response to the constellation of factors that socially determine health. In such a case, interacting these fixed effects with each other will generate a new sort of average correlation with the outcome, but the resulting coefficient does not explain the underlying associations with that estimate.

To understand the nature of the BMI differential in the WAGE$ sample, the Blinder Oaxaca Decomposition is preferred to the OLS interaction term approach. While the OLS approach is useful to identify differences in the sample, the Blinder Oaxaca approach allows the researcher to explore between-group and within-group differences in the relationships between the effects, and the outcome of interest, BMI. While the OLS interaction term generalizes these effects into a singular fixed effect, the decomposition approach allows the researcher to rule out factors that are based on individual characteristics, social determinants, or policy factors. The cumulative effect of these covariates when estimated separately in a decomposition may uncover a scope of effects greater than the degree that would be estimated if these estimated were estimated as fixed effects (Best et al. 2011; Bright et al. 2016).

The OLS approach in this article is not included for the sake of identifying a causal relationship between race, gender, and BMI. The OLS approach is useful in this context because it allows the researcher to identify overall differences in the outcome variable by demographic. This serves to identify subgroups that may plausibly reflect biased selection into the survey sample. If the sample reflects unexplained differentials in BMI between test sites, it suggests a significant difference in the determinants of health between sites and may limit the usefulness of comparing the two sites. The OLS approach may identify BMI differentials, but the Oaxaca approach allows the researcher to establish if these differentials are explained by control covariates.

We identify BMI differentials for subgroups within OLS models based on gender, race, and ethnicity. We are only able to identify differentials between groups for which there are enough similar participants to who identify as such. We then deploy an Oaxaca decomposition approach to explore if these differentials are explainable by observable factors. We include four levels of controls to provide stratified estimates. We add new factors into each model to identify the simplest model that sufficiently explains the observed BMI differential.

Results and discussion

Pooled Minneapolis and Raleigh results

Table 5 reports the results of estimating the BMI equation as a function of race, ethnicity, gender, and location. Race and ethnicity are detailed as follows: American Indian/Alaska Native; Asian/Pacific Islander; Black/African American; Other/Multiracial; Hispanic; American Indian/Alaska Native and Hispanic; Black/African American and Hispanic; and Other/Multiracial and Hispanic. Column 1 has no other controls and shows that there are statistically significant impacts of Black/African American, Hispanic, their interaction, and gender.

Column 2 also controls for age and education.[3] The fixed effects of race and gender remain statistically significant and increase slightly from 1.949 to 2.100 for Black/African American and from 4.804 to 4.886 for Female. Notably, Hispanics alone have a larger and statistically significant impact. Columns 3 and 4 show models that control for education in excess of high school, food insecurity, banked status, SNAP usage, and physical activity. Controlling for physical activity leaves the marginal effects of race and gender largely unchanged, only changing the fixed effect of Black/African American by less than 0.2 points, and the Female fixed effect by less than 0.2 points.

Oaxaca decompositions: separate results for Minneapolis and Raleigh

Table 6 provides the results of estimating equations 2 and 3 separately for Minneapolis and Raleigh. Control variables include age,[4] education,[5] access,[6] physical activity,[7] and primary job wage. We highlight the coefficients on race and gender when statistically significant. The effects of gender are remarkably stable across all specifications. The effect of gender is larger in Raleigh than in Minneapolis, and the relative sizes of the gender effects are comparable across models. The marginal effects of the

[3]Age includes age and age squared. Education is a binary reported as education completed greater than a High School degree.

[4]Age includes self-reported age and age squared, unless otherwise stated as a range of ages.

[5]Education is the self-reported highest level of education from the following levels: Less than High School, Some High School, High School Diploma, Some College, Associate/Technical Degree, Bachelor's Degree, and Graduate Degree.

[6]Access is measured including food insecurity status as described in the section "Survey Measures," Banked status (reported ownership of a savings or checking account with a bank or credit union) and an indicator for SNAP usage.

[7]Physical activity asks the respondent to measure the number of times they engaged in an activity for at least 15 min that was a mild, moderate, or strenuous level of exercise within a typical month. Regressions include each of these frequencies of exercise as a parameter and the square of these frequencies of exercise.

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Table 5. BMI among the whole WAGE$ sample

	(1)	(2)	(3)	(4)	(5)
Race: American Indian/Alaska Native	0.549 (1.805)	0.627 (1.810)	0.568 (1.820)	0.356 (1.818)	0.174 (1.821)
Race: Asian/Pacific Islander	0.228 (5.710)	0.647 (5.712)	0.693 (5.721)	3.194 (5.866)	2.880 (5.867)
Race: Black/African American	1.949** (0.820)	2.100** (0.838)	2.076** (0.847)	1.937** (0.859)	1.624 (0.887)
Race: Other/Multiracial	1.744 (2.032)	1.722 (2.038)	1.744 (2.046)	1.407 (2.056)	1.122 (2.065)
Hispanic	4.851* (2.772)	4.786* (2.772)	4.946* 2.780	4.544 (2.777)	4.323 (2.780)
American Indian/Alaska Native and Hispanic	7.238 (6.515)	6.679 (6.520)	6.410 (6.533)	5.837 (6.539)	5.951 (6.535)
Black/African American and Hispanic	−6.524* (3.473)	−6.698* (3.474)	−6.851** (3.482)	−5.874* (3.518)	−5.726** (3.518)
Other/Multiracial and Hispanic	−4.061 (3.854)	−3.929 (3.853)	−4.050 (3.860)	−3.922 (3.857)	−3.649 (3.860)
Female	4.804*** (0.587)	4.886*** (0.591)	4.782*** 0.601	4.704*** (0.615)	4.724*** (0.615)
Nonbinary	0.712 (3.628)	1.102 (3.647)	0.994 (3.666)	0.813 (3.650)	1.152 (3.656)
Location—Minneapolis	−0.429 (0.591)	−0.460 (0.619)	−0.487 (0.682)	−0.300 (0.688)	−0.693 (0.744)
Constant	26.458*** (0.925)	21.214 (2.998)	20.937*** (3.088)	21.764*** (3.115)	19.582*** (3.491)
Age		0.248* (0.142)	0.238* (0.144)	0.251* (0.144)	0.258* (0.144)

(*Continued*)

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Table 5. (*Continued.*)

	(1)	(2)	(3)	(4)	(5)
Age Squared		−0.003* (0.002)	−0.003 (0.002)	−0.003* (0.002)	−0.003* (0.002)
Weekly Moderate Exercise Frequency				−0.405*** (0.143)	−0.395*** (0.143)
Weekly Moderate Exercise Frequency Squared				0.008** (0.003)	0.007** (0.003)
Age Quadratic	FALSE	TRUE	TRUE	TRUE	TRUE
Education Fixed Effects	FALSE	TRUE	TRUE	TRUE	TRUE
Access Fixed Effects	FALSE	FALSE	TRUE	TRUE	TRUE
Exercise Quadratics	FALSE	FALSE	FALSE	TRUE	TRUE
Wage Control	FALSE	FALSE	FALSE	FALSE	TRUE
N	805	805	805	805	805
R^2 Adjusted	0.10	0.09	0.08	0.09	0.09
F-Statistic	7.85	6.44	5.36	7.97	4.48

Truncated version includes only statistically significant nondemographic controls. Refer to full version in the Appendix section.
Note 1: Food Insecurity defined by two or more of six factors being true in the 12 months [the food you bought did not last and could not afford more, you could not afford a balanced meal, you cut your meal size because you were worried there was not enough money for food, you were hungry because there was not enough money for food, you ate less because you were worried you were going to run out of food, the number of times you cut your meal size due to fear of running out of food was more than one or two times].
Note 2: Exercise level based on the count of times in a week that the respondent reports engaging in activity for at least 15 min, separated by mild, moderate, or strenuous levels.
Note 3: Banked status based on reported ownership of a checking or savings account with a bank or credit union.
Note 4: Access Fixed Effects include Food Insecurity, Banked Status, and SNAP User Indicator.
Note 5: Regression results reported in terms of BMI units. Standard Errors in parentheses.
Note 6: p-values 0.10*; 0.05**; 0.01***.
Note 7: For categorical variables, the following values are used as the baseline: {(Location: Raleigh), (Education: High School Degree or Less), (Bank Status: No bank or credit union account), (SNAP User Status: Non-user), (Food Insecurity: Food Secure)}.
Note 8: Each regression is run with the same sample of respondents with no item nonresponse, even if that item is not included in that regression version column. This is done for the sake of comparability.
Note 9: Asian/Pacific Islander and Hispanic not included in chart due to a lack of sufficient observations.

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Table 6. Decomposition of the determinants of BMI among the whole WAGE$ sample

	(1)		(2)		(3)		(4)		(5)	
	Raleigh, NC	Minneapolis MN	Raleigh, NC	Minneapolis MN	Raleigh, NC	Minneapolis MN	Raleigh, NC	Minneapolis MN	Raleigh, NC	Minneapolis MN
Race: American Indian/Alaska Native	5.093 (4.359)	0.242 (1.855)	5.296 (4.360)	0.133 (1.869)	5.276 (4.375)	−0.198 (1.895)	6.020 (4.394)	−0.624 (1.903)	5.713 (4.395)	−0.622 (1.906)
Race: Asian/ Pacific Islander	2.180 (8.461)	−2.872 (7.687)	4.425 (8.472)	−2.740 (7.723)	5.218 (8.584)	−1.972 (7.759)	3.924 (8.567)	10.558 (9.017)	3.087 (8.580)	10.581 (9.040)
Race: Black/ African American	2.645** (1.289)	0.674 (1.001)	3.025** (1.302)	0.472 (1.051)	3.035** (1.317)	0.461 (1.069)	3.103** (1.324)	0.151 (1.103)	2.336 (1.438)	0.157 (1.109)
Race: Other/ Multiracial	−1.527 (2.939)	2.036 (1.913)	−1.337 (2.937)	1.788 (1.949)	−1.254 (2.952)	1.816 (1.961)	−1.877 (2.968)	1.201 (1.993)	−2.400 (2.990)	1.205 (1.997)
Hispanic	2.137 (2.041)	1.468 (1.887)	1.710 (2.040)	1.559 (1.900)	1.709 (2.047)	1.594 (1.907)	1.767 (2.099)	1.653 (1.907)	1.589 (2.101)	1.656 (1.911)
Female	5.821*** (0.860)	3.708*** (0.799)	5.880*** (0.863)	3.736*** (0.811)	5.809*** (0.902)	3.724*** (0.813)	5.612*** (0.923)	3.574*** (0.846)	5.740*** (0.927)	3.575*** (0.847)
Nonbinary	3.098 (5.986)	−1.146 (4.473)	2.892 (5.981)	−1.165 (4.548)	2.613 (6.020)	−0.648 (4.591)	2.769 (6.003)	−1.129 (4.576)	3.830 (6.047)	−1.127 (4.583)
Constant	25.164*** (1.324)	27.454*** (0.990)	15.831*** (4.271)	27.252*** (4.483)	15.274*** (4.452)	26.599*** (4.553)	16.848*** (4.492)	27.291*** (4.593)	14.162*** (4.902)	27.452*** (5.507)
Age			0.444** (0.211)	0.028 (0.207)	0.444** (0.217)	0.050 (0.209)	0.441** (0.217)	0.058 (0.209)	0.450** (0.217)	0.058 (0.209)

(Continued)

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Table 6. (*Continued.*)

	(1)		(2)		(3)		(4)		(5)	
	Raleigh, NC	Minneapolis MN	Raleigh, NC	Minneapolis MN	Raleigh, NC	Minneapolis MN	Raleigh, NC	Minneapolis MN	Raleigh, NC	Minneapolis MN
Age Squared			−0.005** (0.003)	0.000 (0.002)	−0.005** (0.003)	−0.001 (0.002)	−0.005** (0.003)	−0.001 (0.002)	−0.005** (0.003)	−0.001 (0.002)
Weekly Moderate Exercise Frequency							−0.527** (0.210)	−0.248 (0.204)	−0.507** (0.210)	−0.248 (0.204)
Location BMI Estimate	31.296*** (0.433)	29.834*** (0.402)	31.296*** (0.434)	29.834*** (0.403)	31.296*** (0.435)	29.834*** (0.405)	31.296*** (0.438)	29.834*** (0.408)	31.296*** (0.438)	29.834*** (0.408)
Difference		1.463** (0.590)		1.463** (0.592)		1.463** (0.594)		1.463** (0.598)		1.463** (0.599)
Endowments		0.712*** (0.263)		0.685* (0.367)		0.553 (0.548)		0.618 (0.574)		0.638 (0.684)
Coefficients		0.162 (0.647)		0.116 (0.710)		−0.051 (0.833)		−0.292 (0.844)		0.326 (0.958)
Interaction		0.588 (0.397)		0.662 (0.559)		0.961 (0.815)		1.137 (0.843)		0.500 (1.027)
Age Quadratic	FALSE		TRUE		TRUE		TRUE		TRUE	
Education Fixed Effects	FALSE		TRUE		TRUE		TRUE		TRUE	
Access Fixed Effects	FALSE		FALSE		TRUE		TRUE		TRUE	
Exercise Quadratics	FALSE		FALSE		FALSE		TRUE		TRUE	

(*Continued*)

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Table 6. (*Continued.*)

	(1)		(2)		(3)		(4)		(5)	
	Raleigh, NC	Minneapolis MN	Raleigh, NC	Minneapolis MN	Raleigh, NC	Minneapolis MN	Raleigh, NC	Minneapolis MN	Raleigh, NC	Minneapolis MN
Wage Control	FALSE		FALSE		FALSE		FALSE		TRUE	
N	421	384	421	384	421	384	421	384	421	384
R^2 Adjusted	0.098	0.046	0.107	0.040	0.102	0.038	0.110	0.048	0.112	0.045
F-Statistic	7.52	3.66	6.03	2.60	4.65	2.16	3.73	2.02	3.64	1.91
Endowment Effect Share of Total Differential	48.68		46.81		37.80		42.24		43.58	
Coefficient + Interaction Effect Share of Total Differential	51.32		53.19		62.20		57.76		56.42	

Truncated version includes only statistically significant nondemographic controls. Refer to full version in the Appendix section.
Note 1: Food Insecurity defined by two or more of six factors being true in the 12 months [the food you bought did not last and could not afford more, you could not afford a balanced meal, you cut your meal size because you were worried there was not enough money for food, you were hungry because there was not enough money for food, you ate less because you were worried you were going to run out of food, the number of times you cut your meal size due to fear of running out of food was more than one or two times].
Note 2: Exercise level based on the count of times in a week that the respondent reports engaging in activity for at least 15 min, separated by mild, moderate, or strenuous levels.
Note 3: Banked status based on the reported ownership of a checking or savings account with a bank or credit union.
Note 4: Access Fixed Effects include Food Insecurity, Banked Status, and SNAP User Indicator.
Note 5: Regression results reported in terms of BMI units. Standard Errors in parentheses.
Note 6: p-values 0.10*; 0.05**; 0.01***.
Note 7: For categorical variables, the following values are used as the baseline: {(Location: Raleigh), (Education: High School Degree or Less), (Bank Status: FALSE), (SNAP User: FALSE), (Food Insecurity: Food Secure)}.
Note 8: Each decomposition is run with the same sample of respondents with no item nonresponse, even if that item is not included in that decomposition version.
Note 9: Asian/Pacific Islander and Hispanic not included in chart due to a lack of sufficient observations.

Female indicator variable in Raleigh range from 5.880 for the model with age and education controls the least controls, to 5.612 in the model with the most controls for food insecurity, SNAP usage, and bank account status, physical activity, age, and education controls, but not hourly wage. The same effects range from 3.736 through 3.574 for Minneapolis, respectively. Adding controls posits a difference of less than 0.5 BMI units, where the scale of BMI is on average around 30 (see Table 3).

The effects of race differ between Raleigh and Minneapolis. However, the only statistically significant impacts are for Black/African American respondents, and then only in Raleigh. The marginal effect of being Black in Raleigh is to increase the BMI by 2.645 to 3.103 units depending on the model specification, and not significant in the model including wages. The marginal effects of race are all statistically insignificant in Minneapolis, with the effects among Blacks diminishing nearly to zero when the effects of age, education, access, and physical activity are considered.

The bottom panel of Table 6 reports the percentage of the BMI gap between Minneapolis and Raleigh that can be explained by the variables included in Models (1)–(5) in the table. Controlling only for race and gender, 51 percent of the gap is explained by differences in the endowment of determinants, and the remaining percent is the residual and interaction. With a full set of controls, this explained gap drops to 56 percent. This means that the bulk of the difference in BMI between Minneapolis and Raleigh is unexplained by the endowment of variables and may be due to the residual and the interaction between the effects of differential marginal impacts of the included variables and endowments.

Notably absent from the specification detailed in Table 6 is any direct account for intersectionality or the interaction between race and gender. One way of capturing the joint effects of being, for example, Black and a woman, is to estimate the models separately for Black women in Minneapolis and Raleigh. This is the aim of our next series of tests, by using Blinder Oaxaca decomposition, which we deploy in the following section.

Oaxaca decompositions for Black women: tests of intersectional effects

In Table 7, the estimates of the coefficients in the BMI equation are obtained separately for Black women in Minneapolis and Raleigh. Column 1 reports the effects of only controlling for ethnicity. Not surprisingly, the Oaxaca decomposition results in virtually none of the BMI gap between Black women in Minneapolis and Raleigh being explained by ethnicity. The rest of the gap is due to the residual and the interaction between endowments and the residual.

Columns 2–5 report the results with combinations of controls for age, education, access, physical activity, and primary job wage. With full controls, no control stands out as statistically significant. Notably, the adjusted R^2 are near zero, the F-statistics for the goodness of fit for the equations are often insignificant, and in the underlying regressions, the coefficients on the independent variables used to produce the counterfactuals are statistically insignificant. In short, if Black women in Raleigh had the same coefficients as Black women in Minneapolis, their BMIs would be no different.

The Blinder Oaxaca decomposition separates the relative effects of each factor according to the difference in return on those factors, and the difference in the allocation of those factors. The factors of control in this model are social determinants of health that are theorized to influence BMI; however, these relationships are not necessarily uniform. If policies or social forces are different between study sites, the slope of the return on factors may vary greatly, and the coefficient estimate of this slope may

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Table 7. Decomposition of the determinants of BMI in the WAGE$ sample among Black women participants by geography

	(1)		(2)		(3)		(4)		(5)	
	Raleigh, NC	Minneapolis, MN	Raleigh, NC	Minneapolis, MN	Raleigh, NC	Minneapolis, MN	Raleigh, NC	Minneapolis, MN	Raleigh, NC	Mpls, MN
Hispanic	2.575 (5.390)	−3.801 (6.548)	1.598 (5.417)	−2.878 (6.391)	1.799 (5.464)	−2.627 (6.459)	1.216 (5.562)	−4.270 (8.206)	1.371 (5.572)	−4.371 (8.250)
Constant	33.905*** (0.614)	32.274*** (0.899)	26.401*** (5.732)	49.991*** (8.740)	26.200*** (6.084)	51.552*** (9.147)	28.559*** (6.092)	50.448*** (9.982)	32.100*** (7.733)	52.925*** (12.194)
Location BMI Estimate	33.939*** (0.611)	32.203*** (0.892)	33.939*** (0.615)	32.203*** (0.904)	33.939*** (0.619)	32.203*** (0.916)	33.939*** (0.626)	32.203*** (0.940)	33.939*** (0.627)	32.203*** (0.945)
Difference		1.736 (1.081)		1.736 (1.093)		1.736 (1.105)		1.736 (1.130)		1.736 (1.134)
Endowments		0.022 (0.070)		1.682** (0.656)		1.567 (1.217)		0.340 (2.570)		0.654 (2.699)
Coefficients		1.751 (1.084)		1.406 (1.200)		1.413 (1.407)		0.412 (1.466)		0.021 (1.562)
Interaction		−0.037 (0.109)		−1.352 (0.834)		−1.244 (1.503)		0.984 (2.739)		1.061 (2.909)
Age Quadratic	FALSE		TRUE		TRUE		TRUE		TRUE	
Education Fixed Effects	FALSE		TRUE		TRUE		TRUE		TRUE	
Access Fixed Effects	FALSE		FALSE		TRUE		TRUE		TRUE	
Exercise Quadratics	FALSE		FALSE		FALSE		TRUE		TRUE	
Wage Control	FALSE		FALSE		FALSE		FALSE		TRUE	
− *N*	231	106	231	106	231	106	231	106	231	106

(*Continued*)

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Table 7. (*Continued.*)

	(1)		(2)		(3)		(4)		(5)	
	Raleigh, NC	Minneapolis, MN	Raleigh, NC	Minneapolis, MN	Raleigh, NC	Minneapolis, MN	Raleigh, NC	Minneapolis, MN	Raleigh, NC	Mpls, MN
R^2 Adjusted	−0.003	−0.006	−0.002	0.056	−0.014	0.044	0.025	0.021	0.023	0.011
F-Statistic	0.23	0.34	0.87	2.56	0.56	1.68	1.45	1.17	1.38	1.08
Endowment Effect Share of Total Differential	1.29		96.89		90.27		19.59		37.67	
Coefficient + Interaction Effect Share of Total Differential	98.71		3.11		9.73		80.41		62.33	

Truncated version includes only statistically significant nondemographic controls. See full version in the Appendix section.
Note 1: Food Insecurity defined by two or more of six factors being true in the 12 months [the food you bought did not last and could not afford more, you could not afford a balanced meal, you cut your meal size because you were worried there was not enough money for food, you were hungry because there was not enough money for food, you ate less because you were worried you were going to run out of food, the number of times you cut your meal size due to fear of running out of food was more than one or two times].
Note 2: Exercise level based on the count of times in a week that the respondent reports engaging in activity for at least 15 min, separated by mild, moderate, or strenuous levels.
Note 3: Banked status based on the reported ownership of a checking or savings account with a bank or credit union.
Note 4: Access Fixed Effects include Food Insecurity, Banked Status, and SNAP User Indicator.
Note 5: Regression results reported in terms of BMI units. Standard Errors in parentheses.
Note 6: p-values 0.10*; 0.05**; 0.01***.
Note 7: For categorical variables, the following values are used as the baseline: {(Location: Raleigh), (Education: High School Degree or Less), (Bank Status: FALSE), (SNAP User: FALSE), (Food Insecurity: Food Secure)}.
Note 8: Each decomposition is run with the same sample of respondents with no item nonresponse, even if that item is not included in that decomposition version.
Note 9: Asian/Pacific Islander and Hispanic not included in chart due to a lack of sufficient observations.

even take on a new sign. In such a situation, it is possible that the amount of the decomposed effect from the return on factors is counteracted by effect from the allocation of factors. This may lead to a situation where the absolute value of the sum of gross differentials totals to greater than 100 percent of the observed group net differential.

In the case of the decomposition in Table 7, Model (1), we see that a difference in endowments only explains a marginal amount of the difference in BMI between study sites (less than 2 percent). In this model, the only endowment of control factors that will vary across sites is the share of respondents identifying as Hispanic.

In the case of Model (2), age, age squared, and the probability of education in excess of High School are added as control factors. Most of the difference in BMI can be explained by differences in the endowments of these factors (almost 97 percent). The endowment effect seems to play a significant role; however, this finding is not robust to the inclusion of more determinants.

In the case of Model (3), access to resources is included as a control factor by including SNAP recipiency, food insecurity, and an indicator if they have access to a bank account. These inclusions suggest that if the Raleigh sample had a similar age distribution as Minneapolis, Raleigh would have an even lower BMI level than Minneapolis, and some differential would remain unexplained. The inclusion of these new factors removes any significance of the endowment effect but maintains a relatively high share of the decomposition's explained endowment share (90 percent).

Model (4) introduces physical activity polynomials as control factors, described as the number of times the respondent reports mild activity, moderate activity, or strenuous activity for at least 15 min in a typical month. This also includes the square of each of these terms. This model suggests that endowment effects explain a smaller degree than Model (3) (only about 20 percent).

The last model, Model (5), introduces the hourly wage at the workers' primary job as a linear control. Including this term leaves over 37 percent of the observed differential explained by the endowment effect.

In comparison, Model (1) does not sufficiently explain the observed differential in BMI between test sites for Black women. Model (2) explains almost all the observed differential, suggesting that although the OLS regressions from Table 5 might appear to suggest that Black women face fundamentally different determinants of health in the WAGE$ sample, this difference is only an artifact of the difference in age and education for this subgroup.

Age and education are not expected to vary between sites in a major way within the duration of the WAGE$ study, so this explainable observed differential does not suggest a threat to later studies that may seek to determine causal inferences between plausible determinants of health, like the minimum wage, and BMI. Although Models (3) and (4) do suggest large endowment effects, the scale of this increase is minimal compared with simply including age and education in Model (2). This suggests that with regard to access and personal behavior as determinants of BMI, we do not get that much more explanatory power. This suggests that researchers cannot just explain away the difference in BMI between sites by citing differences in personal behaviors. This reinforces the plausibility of policy level factors, like the minimum wage, as determinants of health.

Summary and conclusion

There are notable differences in BMI values across races and ethnicities in the current study. Because obesity and high BMI are predictors of adverse health outcomes, policymakers and health advocates have sought economic interventions that might narrow the racial gaps in BMI. The data gathered in the current project promises to shed light on whether one policy intervention—increasing the minimum wage—might promise to remedy the problem of racial disparities in obesity. The logic is that through higher incomes produced via increases in the minimum wage, Blacks and other minority group members who are disproportionately located at the lower end of the wage distribution will have access to healthier diets and, with physical activity, will reach healthier weights.

In our baseline data, however, we observe an anomaly. Black women in Minneapolis have lower BMIs than Black women in Raleigh. The two cities are nearly matched in demographic characteristics, so it is surprising that within one demographic group between the two cities, there is a nontrivial difference in baseline BMIs. The reason why this difference requires careful decomposition is that any finding in future years of the natural experiment that BMIs or other measures of health improved in Minneapolis relative to Raleigh would be contested by the fact that at the outset of the experiment, there were favorable outcomes for this demographic group in Minnesota relative to the comparison group in North Carolina.

The intersectionality concept is useful for explaining why there might be an unexplained gap in BMIs between Black women in Minneapolis and Black women in Raleigh. Although our analysis conceptually can control for differences in location and a host of other demographic, access, social, and physical activity measures, intersectionality theory suggests that the separate impacts of race and gender underestimate race and gender's joint effects for Black women.

We have modeled this intersectionality—or differential effects arising from being a Black woman in Minneapolis vs. a Black woman in Raleigh—as a combination of a residual and the interaction of residuals and endowments in an Oaxaca decomposition exercise. We interpret the residual in the decomposition as arising from differential treatment of identically situated Black women in the two locations. Although we can only speculate about why there might be differential treatment in Minneapolis vs. Raleigh, we note that Minneapolis has a history and legacy of progressive politics and higher health care access and SNAP usage than Raleigh (Myers and Ha 2018). For example, in 2017, Minnesota SNAP usage was about 10.09 percent, while North Carolina's was about 17.14 percent, but among African Americans only, Minnesota was 40.95 percent and North Carolina was 31.87 percent (Ruggles et al. 2020).

Although the OLS model of fixed effects suggests large significant differences in BMI between Black/African American respondents and female respondents between study sites, the Oaxaca decomposition of the gap in BMI between Black women in Minneapolis and Raleigh reveals that all the observed gap can be explained by age and education differences. Virtually none of the gap is attributable to the differential treatment of Black women in Raleigh vs. Minneapolis–at least as we have measured it in the model. Adding more controls for access and physical activity leaves the results unchanged. At least in this analysis, we do not find any support for the claim that the observed differences in baseline BMI are accounted by behavioral, policy, or access factors that may correlate with increasing minimum wages in Minneapolis.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/age.2021.21.

Data availability statement. Deidentified microlevel data can be obtained upon request from the PI after obtaining IRB approval. Requests should be directed to Caitlin Caspi, ScD (caitlin.caspi@uconn.edu). A

dashboard of aggregated statistics derived from the WAGE$ survey can be found at the following URL: http://z.umn.edu/wages-dashboard.

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