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Income, Healthy Food Availability, and Consumption Mediate Rural–Urban Health Disparities

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Abstract

Background: Examine the role of income, perceived healthy foods availability, and consumption as mediators of rural–urban health disparities.

Method: Pre-registered simple mediation models with post hoc multi-mediator models were tested using national- and state-level survey data. Oregon data was collected in an online Qualtrics survey between October 8 and November 9, 2021 using CloudResearch; Health Information National Trends Survey (HINTS) 5, a nationally representative dataset, was collected over 4 cycles from 2017 to 2020. Oregon residents ($n = 771$; rural = 313, urban = 458) self-reported online: income, perceived fruits and vegetable (FV) availability, FV consumption, and BMI measures (height, weight). HINTS respondents (rural $n = 1235$; urban $n = 13,912$) self-reported the same variables of interest without FV availability, and with an additional self-rated health variable detailed below.

Results: The effect of rurality on BMI ($b = 0.012$, $SE = 0.005$, $p = 0.01$) and self-rated health ($b = 0.003$, $SE = 0.001$, $p = 0.008$) when combining datasets was mediated by a series of income, perceived FV availability, and FV consumption.

Conclusion: To address rural–urban health disparities, individual (cognition, behavior), social (household income), and community (healthy food availability) factors should be targeted together.

Keywords

Rural health; Nutritional availability; Body mass index; High blood pressure; Income distribution

Introduction

Objective and subjective differences in resource availability in rural areas contribute to poorer health outcomes among residents when compared to urban populations. Previously

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observed poorer health outcomes include shorter life expectancy [1] and higher rates of metabolic and cardiovascular diseases [2] in rural USA, which appear to be worsening over time [1]. Identifying the individual and social mechanisms of the difference between rural and urban health is likely to highlight ways to address this growing health disparity.

Dietary quality relates with health and chronic disease outcomes via both obesity-related [3] and obesity-independent [4, 5] pathways. Food consumption patterns also, in part, explain some of the rural–urban obesity disparity: after adjusting for dietary and physical activity behaviors, the odds ratio for being categorized as obese ($\text{BMI} > 30 \text{ kg/m}^2$) was higher for rural (1.25) vs. urban (1.19) people [6].

Beyond this, evidence substantiating healthy food availability as an explanatory factor specific to rural health outcomes is sparse. Rurality has been linked to less healthy food consumption [6], availability, and access [7, 8]. In turn, food access and availability have been linked to health outcomes [9] though inconsistently [8, 10]. Within rural areas, poorer food availability and retail access have been linked to obesity [11] though not more direct health outcomes, and not always consistently or clearly [7, 12, 13]. Fresh fruit availability has been linked to lower obesity rates within rural populations [11]. Overall, existing research might imply that availability (and access) of healthy food is a mediator of rural health disparity, but we were unable to identify research directly testing that mechanism.

A recent presidential advisory and call to action by the American Heart Association and American Stroke Association identified income as a key social determinant of health (SDOH) in rural America [14]. People with less income may perceive restricted access to healthy food, and prior work has shown that neighborhood median income mediates rural–urban disparities in obesity prevalence [15]. Together, the strong evidence that income relates to urban–rural disparities and the lack of evidence linking healthy food availability to the rural–urban disparity leaves open two further questions: is food availability relevant to rural–urban health disparities, and if so, is food availability related to health in a way that is independent of income or that covaries with it?

This article presents three distinct research innovations: it is the first to directly test perceived food availability as a mediator of the rural–urban health disparity [11, 16]; the first to examine income, perceived healthy food availability, and consumption as joint explanatory factors of health outcome differences within a rural context; and the first to link health status indicators [17] other than BMI (which continues to be used as a proxy indicator of health though it has been credibly challenged on various grounds; see Hunger and colleagues [18] Tomiyama and colleagues) [19] to healthy food availability in a rural context.

In this paper, we propose a model in which rural context affects cardiometabolic outcomes through a serial mediation pathway of household income, healthy food availability, and fruit and vegetable consumption (Fig. 1). The model, framed broadly by social cognitive theory's reciprocally determined constructs [20] of individual factors, environmental influences, and behavior, is more focused on individual and social factors relative to prior models [21].

Both person-level factors and social-environmental determinants of health (SDOH) are responsible for poorer rural cardiovascular health outcomes [14]; therefore, one reasonable hypothesis is that person-level factors and SDOH are best understood as a chain of mediating causes that cascade from the environmental context to household economic resources to individual behaviors.

As a primary objective, Study 1 proposes a simple, pre-registered mediation model, in which rurality affects food availability which in turn affects health-related outcomes. Other pre-registered predictions were also made and are described below. Because Study 1's only outcome was BMI, Study 2 presents complementary evidence exploring disease outcomes in order to demonstrate the health relevance of our findings. Study 3 presents an exploratory investigation based on the conceptual mediation model of food-related health behavior described above.

Hypotheses for Study 1

A rural–urban disparity in the data collected was predicted and pre-registered¹ for two outcomes, (H1) eating behavior and (H2) BMI, after controlling for age and race/ethnicity. Although this dataset might be indicative of national trends, data collection was focused on Oregon as a first step due to the state's large rural area and relative lack of data on this topic.

It was further predicted in the pre-registration database² that people in (H3) community environments that were perceived safer and (H4) having perceived healthier food availability will (a) have healthier consumption behavior and (b) have lower BMIs, after controlling for perceived stress [22, 23], age, and race/ethnicity.

Finally, it was predicted³ (H5) that the rural–urban disparity would be partially explained by the perceived Healthy Food Availability in the community.

Hypotheses 1–5 were pre-registered⁴ and are tested in Study 1 below. There were no specific hypotheses about the relationships between the independent variable and the mediators.

Hypotheses for Study 2

Prior to analysis, a second set of predictions was registered⁵ describing the relationship between rurality and outcomes in the pre-collected open dataset National Information Health Trends Survey (HINTS). It was predicted that (H6) there would be poorer outcomes for rural areas compared to urban ones in terms of self-rated health (H6a), high blood pressure (H6b), overall cardiometabolic health (H6c), and ever having had cancer (H6d); that (H7) those outcomes would be mediated by fruit and vegetable consumption; and that (H8) they would also be mediated by household income. Fruit and vegetable consumption was chosen as a proxy of healthy food consumption; like healthy food consumption, it is inversely related to obesity in rural populations [11].

¹ https://osf.io/k7jav/?view_only=886fd119f07c4d9c80c206e436310933

² https://osf.io/k7jav/?view_only=886fd119f07c4d9c80c206e436310933

³ https://osf.io/k7jav/?view_only=886fd119f07c4d9c80c206e436310933

⁴ https://osf.io/k7jav/?view_only=886fd119f07c4d9c80c206e436310933

⁵ https://osf.io/h98wp/?view_only=c095f8a631474909bb7e2a910492dd0b

Hypotheses 6–8 are tested in Study 2 below.

Hypothesis from Combined Datasets

Capitalizing on the availability of two large, independent datasets that contain overlapping variables, Hypothesis 9—not pre-registered—is that there is a non-zero serial mediation path from rurality to health outcomes via household income, fruit and vegetable availability, and fruit and vegetable consumption, measured across the Oregon data and HINTS dataset. Study 3 uses a path model, combining data across both the HINTS and Oregon datasets, to test this hypothesis.

Study 1: Oregon Rural Food Consumption Survey [A Priori Analysis]

Method

The research study employed the 2010 Rural Urban Commuting Area (RUCA) codes ZIP Code Approximation to classify regions of Oregon into two categories: “urban,” comprising “Metropolitan area” RUCA Codes, and “rural,” ZIP Codes associated with “micropolitan,” “small town,” or “rural” RUCA classifications.

The survey was approved by the University of Oregon IRB under MOD00000031 and data were collected via Qualtrics/CloudResearch between October 8 and November 9, 2021 [24] using targeted data collection to get balanced rural and urban samples of participants at least 18 years of age. The HINTS 5 survey described in the next study found that in the Pacific Census Division, which includes Oregon, 82% of Rural and 80% of Urban residents indicated internet use.

Participants

We aimed to collect 1034 participants, 517 in each of rural and urban groups, in order to detect small within-group effect sizes with partial $r^2 = 0.02$ and 90% power.

Prior to data cleaning, there were 1035 raw survey responses in the Oregon survey. Participant flowchart describing response removal is shown in Supplementary Material Figure S1. Following response removal for a cluster of responses under 60 s that were outside the normal distribution of responses, missing data (completed less than 5 min, or more than 200 missing columns missing with any completion time), and a post hoc attention check, 850 subjects remained, including 458 participants with urban ZIP codes, 313 with rural ZIP codes, and an additional 79 participants who did not provide a ZIP code. All analyses included age; age information for 109 participants was unavailable, leaving 735 data points to analyze. Of those 735, 109 were missing BMI data and could not be included in analyses using BMI, and an additional 6 remaining had gender data other than “Male” or “Female” and could not be included in bootstrapped mediation analyses due to low sample size, leaving 626 subjects available for the linear regressions and 620 subjects for the mediation analyses (see descriptive stats Table 1). All other data columns were complete. Anonymized data from this survey is available online at https://osf.io/uay6v/?view_only=1e6253bc53fc49b4be98e6ae8e8d7dff.

Of participants with rural ZIP codes, most (258; 83%) were in ZIP Codes associated with RUCA 4–6, described as primary flow within or to a large urban cluster of 10,000 to 49,999 people; further demographic information is reported in Table 1.

Measures

Each participant completed a modified 76-item Food Frequency Questionnaire (FFQ) [25], a 1-item supplementary homegrown vegetables frequency question, a Food Craving Inventory, 4-item Perceived Stress Scale (PSS) [22], Multi-Ethnic Study of Atherosclerosis (MESA) Perceived Healthy Food Availability, Safety, and Activities with Neighbors scales [9, 26], demographic data, and approximate address and GPS location.

To measure outcomes, we asked each participant to describe their height and current weight, which we used to calculate BMI; and to complete a modified 76-item Food Frequency Questionnaire (FFQ).

In the FFQ, participants were asked to indicate the number of servings of 76 food categories they had eaten in the last 2 weeks, choosing from 6 ordinal response bins (“never,” “1–3 times,” “4–6 times,” “7–9 times,” “10–13 times,” and “daily or more”), excluding dietary supplements. Serving sizes were noted next to each item. These responses were coded as ordinal scores from 1 to 6. Consumption of supplements was not measured.

We used both Healthy Food Consumption and Fruit and Vegetable Consumption to measure consumption behavior. Both of these measures were derived from the FFQ. Healthy Food Consumption was the aggregate of the 76-item FFQ as a net score of the consumption difference between cancer-preventing (e.g., green, leafy vegetables) and cancer-promoting (e.g., processed meats) items. Fruit and Vegetable Consumption was measured as the combination of only the fruit and vegetable items from the FFQ. We avoided bias arising from changes in habits by measuring only once, and by avoiding data imputation of the healthy food and fruit and vegetable scores. Healthy Food Consumption is heretofore measured as an “FFQ” score where higher scores indicate *less* healthy net consumption, whereas higher Fruit and Vegetable Consumption scores indicate *more* healthy consumption.

The MESA items include a 6-item perceived neighborhood Healthy Food Availability questionnaire (focusing on fruit and vegetable, fresh produce, and low-fat products), a 3-item neighborhood crime questionnaire, and a 5-item activities with neighbors questionnaire, all made up of 5-point Likert scales rated from “Strongly agree” to “Strongly disagree.” Participants were not given instructions on how to define their neighborhood with any particular radius.

Income was requested as “total household income, earned and unearned, before taxes during the past 12 months,” and possible answers were on an ordinal scale that approximated log of income, with item labels “Less than \$25,000,” “\$25,000 to \$34,999,” “\$35,000 to \$49,999,” “\$50,000 to \$74,999,” “\$75,000 to \$99,999,” “\$100,000 to \$149,999,” and “\$150,000 or more.”

Participants also self-identified on demographic questions including gender (Male, Female, or Other, with open-ended responses), race/ethnicity (including a Hispanic category), and income.

Data Analysis

For this and subsequent studies, questionnaire-derived measures including FFQ were z-scored, while other items (including Age and BMI) were measured unscaled.

Data exploration suggested including a quadratic effect for age explains additional variance. Consequently, we repeated some analyses in this Study with the quadratic included, and for Study 2 and Study 3 we included age² for all analyses.

Analyses tested the relationships between FFQ and BMI outcomes and MESA Healthy Food Availability and MESA safety from crime [9].

We tested the relationship between rurality, eating behavior, and BMI with linear models predicting eating behavior and BMI from rurality, the PSS, and demographic confounders relating to age and race/ethnicity. In a deviation from the pre-registered plan, we also added gender to the analysis.

Finally, we tested mediation of the rurality-BMI and rurality-FFQ relationships by Healthy Food Availability using the R mediation package (mediation 4.5.0, Dustin Tingley et al., Stanford, CA), with a 10,000-repetition nonparametric bootstrap and a biased-corrected and accelerated confidence interval. To reduce confounding, each linear model within the mediation analysis included terms for age, race/ethnicity, PSS, and gender. Due to the small sample size and a lack of a theoretical rationale, we avoided interaction terms. We aimed to test the natural, path-specific effect of rurality on BMI and FFQ by Healthy Food Availability.

Results

Rurality, Physical Health, and Behavior Outcomes: Regressions on BMI and FFQ (Table 2) of rurality, controlling for age, gender, and race/ethnicity, revealed that rurality was related to higher BMI ($B = 2.01$ BMI points higher, $p = 0.001$, 95% CI = [0.805, 3.22]), confirming an a priori prediction (H1) we made, but not to reduced Healthy Food Consumption as measured by the FFQ ($p = 0.56$), failing to confirm a prediction (H2).

Mediators of the Relation of Rurality to Health Outcomes: A mediation analysis (Fig. 2) identified a significant mediation of the link between BMI and rurality by perceived Healthy Food Availability (8% proportion mediated, 95% CI [1%, 29%], $p = 0.05$ [2%, 32%]; average causal mediation effect unstandardized $B = 0.18$ [2%, 48%], $p = 0.05$) in the Oregon survey, confirming our a priori prediction H5, although we failed to observe our parallel prediction about a community healthy food environment mediation.

Regressions on BMI and FFQ (Table 3) of perceived Healthy Food Availability and Safety (from crime) revealed that perceived Healthy Food Availability was significantly and negatively related to the FFQ ($B = -0.13$, [-0.21, -0.06], $p < 0.001$) (confirming H4a)

and BMI ($B = 0.74$, $[-1.36, -0.12]$, $p = 0.02$) (H4b), but safety was not (H3a, H3b). A follow-up analysis showed that including the age quadratic term did not substantially change model fit.

Further analyses testing the robustness of these findings and other possible competing mediation effects are described in the Supplementary Materials.

Study 2: HINTS

Method

Data were obtained from the nationally representative HINTS 5 Cycles 1–4 [27] to better understand the relationship between rural ($N = 2180$) and urban ($N = 13,912$) residents in a larger dataset (see descriptive stats Table 1). HINTS 5 Cycle 1 was fielded over January–April 2017, and succeeding Cycles 2–4 were fielded through 2018–2020 during the same period of each year. HINTS 5 data collection has been previously described in detail [28] RUCA Codes 1–3 are classified in this study as urban and RUCA codes 4–10 as rural. All available data were used; Supplementary Material Figure S2 describes the data available for each analysis.

Measures

Predictors of interest were quantity of fruit and vegetables consumed, household income range, and rural status as described above. Confounders from the HINTS dataset used were age, age², gender, race, ethnicity, and survey cycle.

We selected health outcome measures related to cardiovascular or metabolic health, or cancers because links are often made between these health outcomes and food consumption [29–32]. We identified one measure of self-rated health, three relevant measures of medical conditions, and one additional measure of cancer diagnosis. The self-rated health measure (1) asked, “In general, would you say your health is excellent, very good, good, fair, or poor?” The three medical condition questions read:

Has a doctor or other health professional ever told you that you had any of the following medical conditions? 2a. Diabetes or high blood sugar; 2b. high blood pressure or hypertension; 2c. A heart condition such as heart attack, angina, or congestive heart failure?

The cancer diagnosis question (3) read, “Have you ever been diagnosed as having cancer?”.

Of the items in the HINTS “Overall Health” section, we excluded measures that were not direct consequences of excessive food consumption as described above, including the questions on:

1. The participant’s confidence in their ability to take care of their health
2. Deafness or hearing difficulty
3. Talking with friends and family about health
4. Lung disease

5. Depression or anxiety
6. Cognitive reactions to anxiety and threats
7. Attitudes towards medical appointments
8. Values. A cancer question was excluded because of the relatively small number of participants who indicated any type of cancer.

Fruit and Vegetable (FV) consumption was measured using two 7-level ordinal variables, each measured in a question asking about fruit or vegetables, of the form: “About how many cups of fruit/vegetables (including 100% pure fruit/vegetable juice) do you eat or drink each day?” Answers, coded, from 0 to 6, were “None,” “1/2 cup or less,” “1/2 cup to 1 cup,” “1 to 2 cups,” “2 to 3 cups,” “3 to 4 cups,” or “4 or more cups.” A survey guide quantified a cup in terms of pieces of commonly consumed fruits or vegetables. To get an overall FV consumption score, the two ordinal scales were simply summed together, and then the z-score of that sum was taken.

Household income was measured as a 9-level ordinal variable; participants were asked to consider “members of your family living in this household, what is your combined annual income, meaning the total pre-tax income from all sources earned in the last year?”; options were “\$0 to \$9999,” “\$10,000 to \$14,999,” “\$15,000 to \$19,999,” “\$20,000 to \$34,999,” “\$35,000 to \$49,999,” “\$50,000 to \$74,999,” “\$75,000 to \$99,999,” “\$100,000 to \$199,999,” and “\$200,000 or more.”

Data Analysis

Having selected these items, subsequent to data collection by the NCI, but prior to our analysis of the data, we registered heuristics for inclusion in analysis, based on observation of sufficient heterogeneity in the dataset. We created a combined cardiometabolic measure made up of the average of the answers to 2a, 2b, and 3c.

Age was centered at the US median population age of 38. The HINTS dataset does not include a comprehensive FFQ measure, so we used the FV consumption score in HINTS as a proxy for healthy food consumption.

Two sets of analyses were run: the first using regression to predict health outcomes from rurality, and the second to measure mediations of those relationships. The first analysis was multiple logistic regression predicting dichotomous outcomes, and multiple linear regression predicting other outcomes. To limit sources of confounding, each regression, including those within mediation models, included age, age², gender, race, ethnicity, and survey cycle as demographic covariates. Following our pre-registered predictions, we ran three sets of linear or logistic regression models, one set for each hypothesis. Each model was repeated once for each of the selected outcome measures. Mediations were calculated using the R mediation package (mediation 4.5.0, Dustin Tingley et al., Stanford, CA). Due to the lack of any theoretical rationale, we avoided interaction terms. We aimed to test the natural, path-specific effect of rurality on the three health outcome variables by FV consumption.

Results

Descriptive Statistics: We included all valid HINT Survey 4 Cycle 1–4 respondents; 13,912 were Metropolitan and classified as urban. Of 2180 rural participants, 1235 (57%) respondents had “Micropolitan” RUCA Codes 4–6; the remainder were classified as small town or rural. Of all respondents, 53% were female, 38% were male, and 8% had missing or multiple gender responses. Following grouping of race responses reported 20 or fewer times, 68% were classified White, 15% Black, 7% with race response missing, 4% as Multiple Races Selected, 1% as each of Chinese, Filipino, Asian Indian, Other Asian American, American Indian or Alaska Native, and Pacific Islander, and less than 1% classified each of Vietnamese, Korean, and Japanese. Subjects were grouped into self-reported ethnicity statuses including Mexican, Puerto Rican, Cuban, Multiple Hispanic Ethnicities, Unknown, and Not Hispanic. Responses reported a mean age of 57, median = 59, SD = 17. Correlations between key variables are described in Figure S3.

Rurality and Physical Health Outcomes: Consistent with the prediction made in the blind ex-post registration, rural compared to urban populations had poorer health outcomes. In multiple linear regressions, rural respondents had poorer self-rated health on a 5-point scale (0.2 points higher [1.2, 2.1], $t = 7.4$, $p < 0.001$), confirming H6a; a greater odds of high blood pressure (OR = 1.23 [1.11, 1.36], $z = 3.9$, $p < 0.001$), confirming H6b; and scored 0.07 [0.04, 1.10] points higher ($t = 3.9$, $p < 0.001$) on a 3-point scale tallying reports of high blood pressure, diabetes, or a heart condition, confirming H6c. Rural (vs. urban) respondents did not have significantly different odds of cancer, failing to confirm the last element of H6d.

Mediators of the Relation of Rurality to Health Outcomes: Mediation analyses of HINTS tested whether FV consumption statistically accounted for the relationships between rurality and health outcome measures. Table 4 describes mediation analyses for FV consumption. Both mediated effects and direct effects were found, indicating that FV consumption explained some but not all of the relationship between rurality and outcome for all three cases (confirming H7).

We also tested whether household income mediated the relationship between rurality and health outcome measures. As shown in Table 4, there were significant direct and mediated effects of rurality on self-rated health and high blood pressure (confirming H8).

Study 3: Hybrid Analysis

Method

We ran a hybrid mediation analysis combining each dataset to test for parallel and sequential mediations between all the variables of interest in our model. The Oregon survey is comprised of roughly equal samples of rural and urban Oregon populations respectively, which are subsets of population from which the nationally representative HINTS dataset is drawn, allowing us to supplement the broad applicability of the HINTS dataset with a targeted sample measuring data of interest not measured in HINTS (perceived Healthy Food Availability). The HINTS dataset also quantifies associations of rurality, income, and

FV consumption with self-rated health, cardiometabolic health, and high blood pressure. By creating a hybrid of the two models, we can test the mediating effect of perceived availability of health food within the full conceptual pathway from rurality to a broad range of health outcomes that is illustrated in Fig. 1.

Data Analysis

In a standard bootstrapped mediation analysis, mediation effects are estimated by multiplying the individual effects of regression models at each stage of the analysis, a “product of paths” procedure [33]. To illustrate, it can be observed in Fig. 2 that the average causal mediation effect is equal to the product of the two paths from independent variable to mediator and from mediator to outcome. This is repeated a large number of times with resampling following using a bootstrapped design, identifying a significant causal mediation effect if the bootstrap distribution of beta value estimates obtained significantly differs from zero. We extended this methodology obtaining beta value estimates from two separate datasets where those datasets share some but not all overlapping variables, and then applying the same bootstrapped product of paths test to estimate mediation effect sizes. We call this extension a *hybrid mediation analysis*.

Because the HINTS dataset contains a larger number of samples and thus more precise population estimates can be obtained, we started with the HINTS dataset and added data from the Oregon survey where necessary (Supplementary Materials Figure S3). Data modeling relationships between rurality, household income, FV consumption, and physical and health outcomes were obtained from the HINTS dataset. Estimates of the relationships between household income, perceived Healthy Food Availability, and Fruit and Vegetable Consumption were obtained from the Oregon survey.

In order to do this, we ran three sets of mediation analyses: an Oregon survey mediation, HINTS mediations measuring outcomes on each of five outcome variables, and hybrid mediations measuring outcomes of each of five outcome variables. The R mediation package used previously cannot model multi-variable serial mediation pathways, and so in this analysis, we used the R lavaan package (lavaan 0.6.12, Yves Rosseel), rather than the R mediation package.

Within the Oregon survey, each regression in the overall path model included age, age², gender, and race/ethnicity to reduce confounding. The HINTS dataset also included these variables, with race and ethnicity recorded separately.

Measures

In both datasets, FV consumption was measured as ordinal variables describing the number of cups of fruit and vegetables consumed. Both surveys measured household income along an ordinal scale roughly linear to log of income. RUCA codes were used to classify participants as urban or rural in both datasets.

Results

Data Pre-processing: Because the HINTS dataset only measured healthy food consumption in Fruit and Vegetable Consumption, we also replaced the “FFQ” measure used in the first analysis with a measure of Fruit and Vegetable Consumption in the Oregon survey. FFQ (in which higher scores are less healthy) and Fruit and Vegetable Consumption correlated with $r = -0.58 [-0.59, -0.49]$ ($p < 0.001$).

Path Models: In the Oregon survey (Fig. 3), there was a marginal indirect effect of rurality on BMI via household income, perceived Healthy Food Availability, and Fruit and Vegetable Consumption, $b = 0.009$, 95% CI [0.002, 0.019] ($p = 0.05$); although the p -value is at marginal significance, it assumes normality, whereas the CI does not, and hence the significant indication from the CI may be the more reliable indicator here.

We ran five path mediation analyses for the HINTS: one for BMI and four for the health outcomes (self-rated health, high blood pressure, cardiometabolic health, and cancer). These are presented in Table 5, grouped by their effect.

In a hybrid mediation model using HINTS data to estimate the indirect effect of rurality via household income and Fruit and Vegetable Consumption and using the Oregon data to estimate the indirect effect of income on Fruit and Vegetable Consumption via perceived availability (Table 5; Fig. 3), we found an indirect effect of rurality on BMI ($b = 0.012$, $SE = 0.004$, 95% CI = [0.004, 0.023], $p = 0.01$), self-rated health ($b = 0.003$, $SE = 0.001$, CI = [0.001, 0.005], $p = 0.008$), and cardiometabolic health ($b = 0.0007$, $SE = 0.0003$, CI = [0.0002, 0.0014], $p = 0.04$). The direct effect of rurality on BMI was significant ($b = 0.96$, $SE = 0.27$, 95% CI = [0.43, 1.50], $p < 0.001$), while the direct effects of rurality on other health measures were not significant. Figure 3 shows the magnitude of effects in the self-rated health hybrid path model.

Discussion

This research confirms prior findings (and H1) that when compared to urban residents, people living in rural areas report higher BMI, poorer self-rated health, and worse cardiometabolic and hypertension health outcomes. These rural health findings are related to household income, which in turn is related to perceived availability and reported consumption of healthy foods, specifically fruits and vegetables. Perceived availability of healthy food, a socio-environmental factor, which relates with healthy food consumption, a behavioral factor, is linked to BMI, a relative indicator of weight health (confirming H3), and in fact, appears to partially explain the rural–urban disparity in health outcomes (confirming H5). The relations among the rural community context, residents’ perceived healthy foods availability and consumption behavior variables, remained even when controlling for household income.

To our knowledge, this work is the first to specifically report this mediation in rural–urban comparisons and elevates the importance of conceptualizing food systems in context via reciprocally determined, social cognitive [20] interactions of *residents* (e.g., food and nutrition knowledge, lived/learned experiences, social well-being), *environments*

(e.g., food resources (availability, accessibility, affordability/assistance), food cultural array, local food system (production/processing, packaging/marketing), and *behaviors* (e.g., food purchasing, preparation, consumption, culture) as an explanatory factor of rural–urban health differences [34]. The effect of rurality on consumption behaviors was mediated entirely through residents’ perceptions of place-based availability of healthy foods (i.e., fruits and vegetables), while household income mediated the rurality–health-outcomes relationship independently of residents’ perceptions of healthy foods availability.

Populations identified as low-income, whether by household, neighborhood, or community socio-economic status, tend to register a disproportionately high prevalence of dietary and lifestyle influenced chronic disease [35]. Socio-environmental factors associated with intersectional income and health inequities could include neighborhood access to supermarkets (e.g., food deserts), monetary access to local produce (e.g., seasonal farmer markets, rural farm-direct sales), and socio-cultural variables like cultural diversity, regional cuisines, or food processing economies, none of which was factored in these rural–urban comparisons. Furthermore, in a nationally representative sample, consumption of fruits and vegetables seemed to mediate rural–urban disparities in self-rated health and aggregated cardiometabolic health outcomes. Behavioral factors, such as FV consumption, as well as SDOH, such as household income and community food systems, each contribute to rural health outcomes, as described in a recent presidential advisory and call to action from the American Heart and Stroke Associations on rural health [14]. Our results confirmed the joint contributions of individual, behavioral, and socio-environmental factors, and are directionally consistent with the hypothesis that household income influences perceived FV availability, which in turn influences FV consumption, which ultimately affects cardiometabolic health outcomes. However, the reverse directionality is possible (i.e., cardio-metabolic health influencing FV consumption) though less likely without intervention [36].

The mediating chain from rurality through income, FV availability, and FV consumption to health outcomes was significant for BMI, self-rated health, and aggregate cardiometabolic health, although the mediating effect size was small. Even small effects, when found at the population level, can reveal meaningful and noteworthy health benefits and costs, particularly if examined for differential effects and sensitivities within geographically defined populations. For example, urban and rural areas differ in definition of healthy food availability, i.e., supermarket within ½ mile (urban) compared to 10 miles (rural), as well as distance, transportation modes, and cost to access healthy food with urban residents incurring a lower cost to access healthy food when driving and walking compared to people residing in rural areas [37]. The nationally representative HINTS sample confirmed our model, excepting of FV availability, and the mediation model is likely to apply across rural–urban populations and places in the USA. However, to better understand downstream effects and disparities within diverse rural (or urban) populations that moderate the mediation chain from rurality through food to health, an upstream, place-based approach and critical, intersectional analyses are warranted. Working at the intersection of rural cultural studies and food justice, Thompson and Carter (2022) explain how and why critical theories (e.g., white supremacy, intersectionality, social justice) and participatory or engaged research can advance the study and intervention of food injustice in rural settings [38]. For example, the

hybrid model including FV availability (an attribute of food justice), even if tested using data from a nationally representative sample, would more likely generalize to a greater within-group diversity of rural populations (including those historically marginalized) with intersectionality analyses.

Limitations

The Oregon survey targeted 517 participants per group, but data collection yielded only 458 and 313 usable responses from rural and urban ZIP codes, respectively. This reduced sample size increases the risk of false negative errors and may explain some unconfirmed pre-registered predictions. However, the key finding—that healthy food availability mediates rurality and BMI—was confirmed using the pre-registered design, suggesting the effect size might be even larger than anticipated.

The “hybrid analysis” combines data from two datasets: a cross-sectionally representative US sample and an Oregon sample not controlled to be demographically representative. While not identical, the populations appeared reasonably similar. For instance, the relationship between standardized Fruit and Vegetable Consumption and BMI was -0.975 [$-1.56, -0.34$] in the Oregon survey and -0.61 [$-0.78, -0.45$] in HINTS.

The mediation analysis examined associations between rurality and health outcomes, quantifying pathway strengths across datasets. While the method tests associations, not causation, prior evidence suggests a likely causal direction: rurality and income influence food availability, food availability influences food consumption, and fruit and vegetable consumption impacts health outcomes [39].

Mediation analyses not only assume causal directionality; they also assume confounders are controlled for in each leg of the pathway, that mediator-mediator confounds are controlled, and that mediator-outcome confounders are not independently affected by the exposure [40]. We controlled for demographic factors known to affect model components (age, sex, race/ethnicity). Although community crime levels and perceived stress were not significantly related to BMI or FFQ outcomes, we acknowledge the potential for unidentified confounders.

Implications for Research and Practice

Rural–urban health disparities are increasing [1] and understanding the avoidable reasons for those disparities, particularly persistent deprivation of health protective socio-environmental resources, such as local availability and secure healthy foods access, and exposure to health risks, such as nutritional insecurity and easy access to unhealthy dietary options, could help us to identify avenues for improving rural health [41]. The work confirms the relevance of poorer HF consumption for high rural BMIs, but also underscores that healthy eating is related to perceptions of healthy food availability, which seems to be related to household income levels. Perceptions act as a lens through which we view reality. For lower income households, increasing or assisting HF affordability may increase perceived healthy food availability and HF consumption, and improve rural health outcomes.

The impact of fruit and vegetable consumption on a variety of health outcomes beyond BMI is clear, and consumption practices appear to explain part of the rural health disparity. However, the effect of fruit and vegetable consumption is entirely explained by perceived healthy food availability, underscoring perceived and actual healthy food availability as a challenge for resolving the rural health disparity. Household income partially but not fully explains the mediation of healthy food availability and consumption, indicating that characteristics of the rural environment independent of household income seem to be related to health disparity. The best interventions should consider individual factors as well as larger structural factors in order to improve health: healthy food availability and perceptions thereof, how these can be achieved in a rural context at rural income levels, and the extent to which these will influence consumption. Further work should explore opportunities to improve health by improving environmental affordances for behavior as well as opportunities to assist households in making healthier choices when situated within impoverished food environments.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Conflict of Interest

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Data Availability

Links to data, analysis code, and materials are available on OSF (https://osf.io/uay6v/?view_only=8f31f576816f431ca3b0a6c0fb1bbe58). The data available includes deidentified participant data from the Oregon dataset, a PDF of the Qualtrics survey used to collect this data, and the code that was used to transform data from the raw Qualtrics format to deidentified participant data. Code written in R to perform all the analyses presented in this paper and a link to the HINTS dataset is also made available with the link above. Timestamped registration of one study pre-registration and one blind ex post study registration are provided as links within the paper's hypothesis section. Informed consent form will not be made available, but IRB approval information is described in the text. Data are available immediately and will remain available as long as the Open Science Foundation

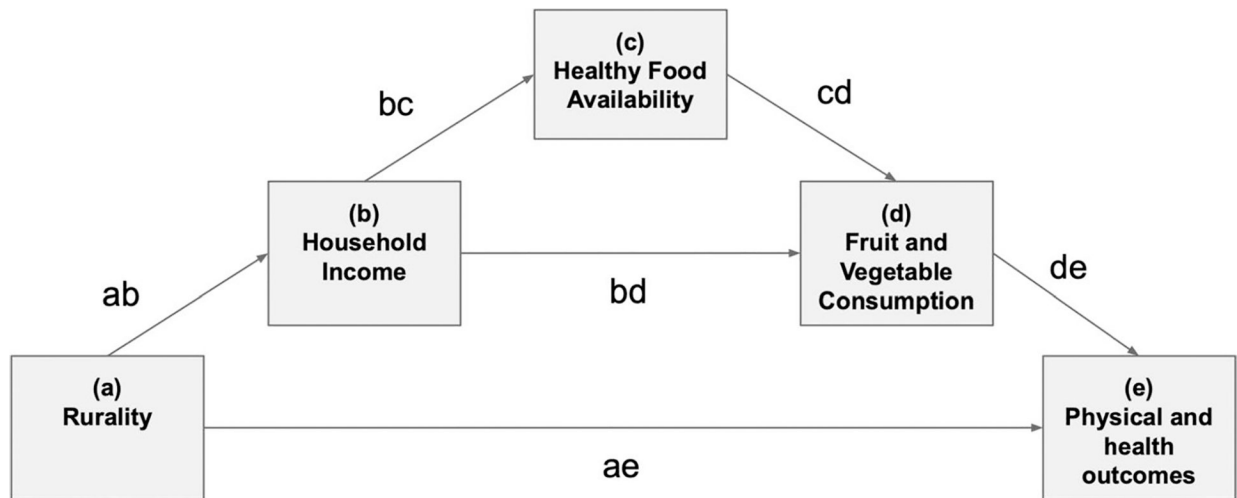
continues to host it at the repository in which it was deposited. All materials hosted are made available to anyone accepting them under the terms of the GNU General Public License v.3.0.

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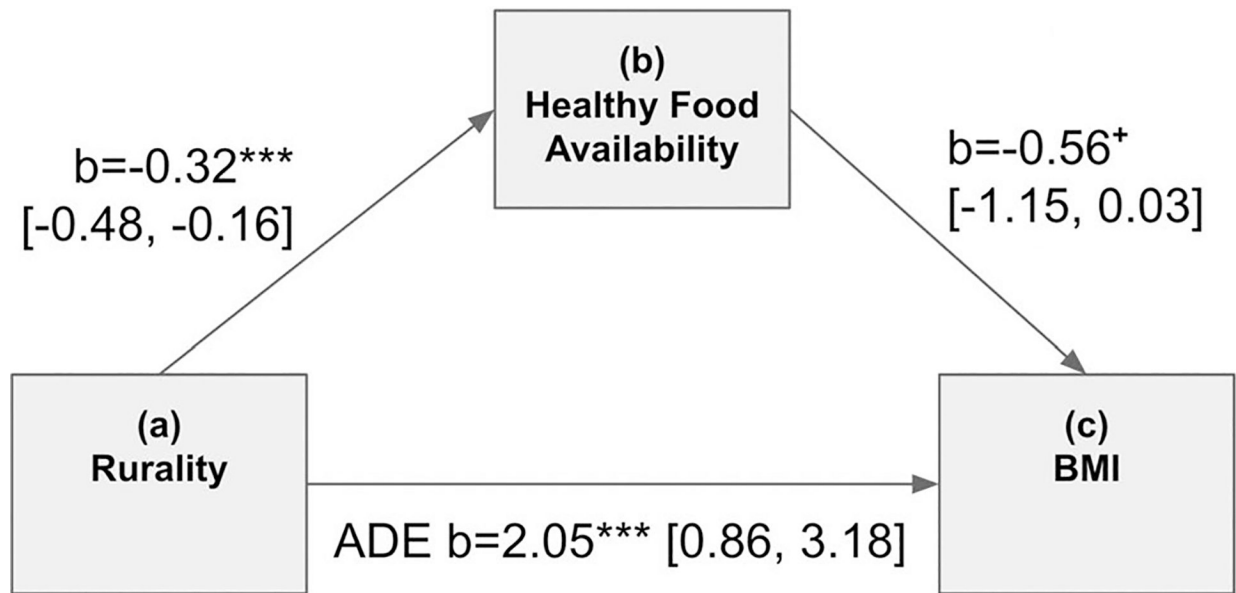
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Each regression also includes controls for Age, Gender, and Race, and the Perceived Stress Scale.

Fig. 1.

Conceptual mediation model for the hybrid analysis across the Oregon dataset and HINTS dataset. Study 1 and Study 2 investigate subsets of this model, while Study 3 describes the entire model



Average Causal Mediation Effect $b=.1808^*$ [0.02, 0.48].

Fig. 2.

In Study 1, MESA Healthy Food Availability mediates Rurality and BMI in the Oregon dataset. Models also included the following variables not shown as predictors for both Healthy Food Availability and BMI: race, gender (male or female), and PSS. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, “n.s.” $p \geq 0.1$. *ADE* average direct effect, the average of direct effects over the 10,000 sampled bootstrap iterations; *ACME* average causal mediation effect, over the same bootstrap process

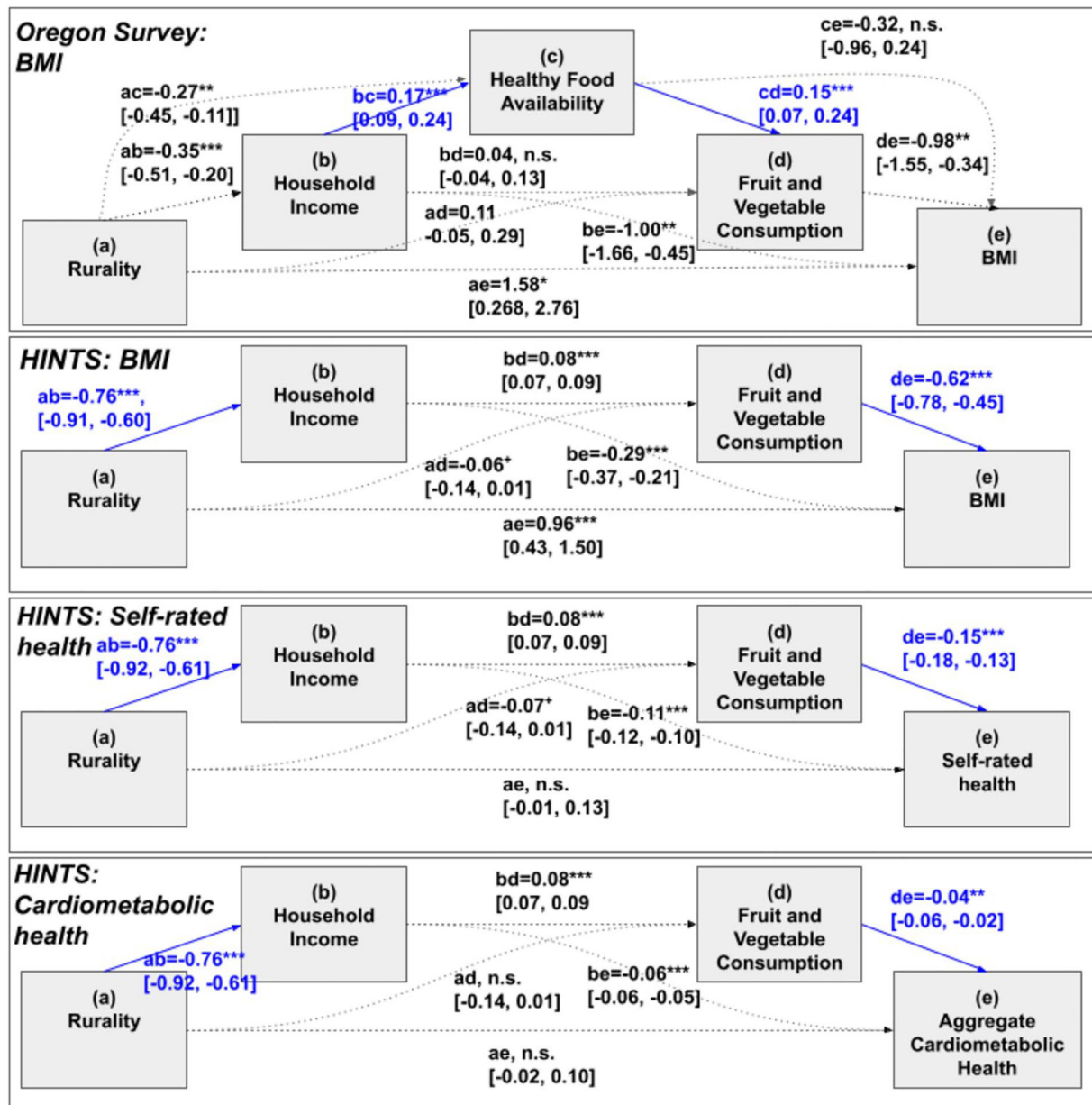


Fig. 3.

Study 3 draws on the Oregon Survey (Study 1) and HINT (Study 2). Oregon survey and HINTS path model effects of rurality on BMI, self-rated health, and cardiometabolic health. Each of the three hybrid models includes the two effects in solid lines in the first (Oregon survey) panel, and then two effects from the respective HINTS panel. Note. Unstandardized beta effect sizes for the hybrid path model from rurality to BMI, self-rated health, and cardiometabolic health outcomes. Solid lines indicate effects used to calculate the primary hybrid model indirect effect. All others illustrated in dashed lines. Significance is indicated by a suffix next to the effect size, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1

Descriptive stats for populations included in regressions and mediation analyses in Study 1 and Study 2. Because bootstrap analyses are difficult to run with very small groups, although participants had reported race/ethnicity demographic data following the US census categories, categories with fewer than 20 respondents were amalgamated as shown in the table below, including grouping Asian subcategories together and other categories with other or unreported race/ethnicity

		Study 1	Study 2
	<i>N</i> (total)	626	16,091
	<i>N</i> (urban)	379	13,912
	<i>N</i> (rural)	241	2179
	Female	69%	53%
Age, M	Rural	49	56
	Urban	51	60
Race/ethnicity	Non-Hispanic White	81%	56%
	Black	0%	15%
	Asian	7%	5%
	Hispanic	6%	13%
	Hawaiian or other Pacific Islander	3%	1%
	Other or unreported	3%	10%

Table 2

Rurality regressed on BMI and FFQ

Predicting Predictor	BMI		FFQ	
	<i>b</i>	<i>b</i> 95% CI [LL, UL]	<i>b</i>	<i>b</i> 95% CI [LL, UL]
(Intercept)	28.18**	[27.27, 29.09]	- 0.17**	[- 0.23, - 0.11]
MSE	2.01**	[0.80, 3.22]	0.02	[- 0.05, 0.10]
Rural ZIP (vs. urban)				
Perceived Stress Scale (z-scored)	- 0.45	[- 1.07, 0.17]	- 0.01	[- 0.05, 0.02]
		[- 0.01, 0.02]	- 0.00*	[- 0.00, - 0.00]
Gender (vs. female)		[- 0.82, 1.75]	0.03	[- 0.05, 0.12]
		[- 0.73, 11.32]	- 0.03	[- 0.32, 0.26]
Age	0			
Male	0.46			
Other	5.3			
		[- 3.04, 1.58]	- 0.11	[- 0.26, 0.04]
		[- 6.09, - 1.06]	0.11	[- 0.05, 0.27]
		[- 3.66, 3.04]	- 0.1	[- 0.31, 0.11]
Asian	- 0.73	[- 5.61, 1.11]	- 0.06	[- 0.27, 0.16]
Hispanic, any race	- 3.57**	- 5.61, 1.11]		
Hawaiian or other Pacific Islander	- 0.31	<i>R</i> ² = 0.04**		<i>R</i> ² = 0.018
Other race or race not reported	- 2.25	95% CI [0.01, 0.06]		95% CI [0.00, 0.03]

Table 3
Healthy food availability and safety from crime regressed on BMI and FFQ

Predicting Predictor	BMI		FFQ_z	
	<i>b</i>	<i>b</i> 95% CI [LL, UL]	<i>b</i>	<i>b</i> 95% CI [LL, UL]
MESA		[28.24, 29.77]	- 0.02	[- 0.11, 0.07]
(Intercept)	29.01**	[- 1.36, - 0.12]	- 0.13**	[- 0.20, - 0.05]
Healthy Food Availability (z-scored)	- 0.74*	[- 0.98, 0.26]	- 0.01	[- 0.09, 0.06]
Safety from Crime (z-scored)	- 0.36			
Perceived Stress Scale (z-scored)	- 0.31	[- 0.95, 0.32]	- 0.04	[- 0.11, 0.03]
Age	0.02			
Age ²	0			
Gender (vs. female)		[- 0.01, 0.06]	- 0.01**	[- 0.01, - 0.00]
		[- 0.00, 0.00]	0.00**	[0.00, 0.00]
		[- 0.99, 1.60]	0.1	[- 0.06, 0.25]
		[- 2.17, 9.15]	- 0.28	[- 0.81, 0.26]
Male	0.3			
Other	3.49			
Race and ethnicity (vs. White)		[- 2.64, 2.03]	- 0.18	[- 0.46, 0.10]
		[- 5.71, - 0.62]	0.13	[- 0.17, 0.43]
		[- 3.46, 3.34]	- 0.25	[- 0.65, 0.16]
		[- 5.54, 1.08]	- 0.18	[- 0.58, 0.22]
Asian	- 0.31	$R^2 = 0.036^*$		$R^2 = 0.048^{**}$
Hispanic, any race	- 3.16*	95% CI [0.00, 0.05]		95% CI [0.01, 0.07]
Hawaiian or other Pacific Islander	- 0.06			
Other race or race not reported	- 2.23			

Table 4
Size of mediators of the relationship between rurality and each listed outcome in the HINT Survey in a simple 1-variable mediation model

Mediator of rurality effect	Outcome	Average direct effect	Average causal mediation effect	Proportion mediated
Fruit and Vegetable Consumption	Self-rated health	0.14 [0.07, 0.21] ***	0.03 [0.02, 0.04] ***	17% [9%, 35%] ***
	High blood pressure	0.04 [0.00, 0.07] *	0.004 [0.002, 0.01] ***	10% [7%, 966%] *
	Cardiometabolic health	0.06 [0.01, 0.12] ***	0.008 [0.004, 0.01] ***	11% [6%, 757%] *
Income	Self-rated health	0.08 [0.03, 0.12] ***	0.09 [0.07, 0.10] ***	52% [41%, 77%] ***
	High blood pressure	0.03 [0.00, 0.05] *	0.01 [0.01, 0.02] ***	36% [26%, 150%] ***
	Cardiometabolic health	0.03 [− 0.01, 0.07] <i>n.s</i>	0.03 [0.03, 0.04] ***	56% [41%, 240%] ***

Note.

* $p < 0.05$,

** $p < 0.01$,

*** $p < 0.001$.

All mediations controlled for age², gender, race (including ethnicity), and survey cycle

Table 5
Direct and indirect unstandardized effects in (a) HINTS mediation model and (b) hybrid mediation model

Outcome	(a) Oregon mediation model		(b) HINTS mediation model		(c) Hybrid mediation model	
	Estimate	CI	Estimate	CI	Estimate	CI
Indirect effect						
BMI	0.009 ⁺	[0.002, 0.019]	0.0375 ^{***}	[0.0250, 0.0524]	0.0119 [*]	[0.0043, 0.0227]
Self-rated health			0.0093 ^{***}	[0.0067, 0.0123]	0.0029 ^{**}	[0.0011, 0.0054]
Aggregate cardiometabolic health			0.0021 ^{**}	[0.0009, 0.0036]	0.0007 [*]	[0.0002, 0.0014]
High blood pressure/hypertension			0.0009 [*]	[0.0002, 0.0017]	0.0003 ⁺	[0.0000, 0.0007]
Ever had cancer			-0.0003	[-0.0008, 0.0003]	-0.0001	[-0.0003, 0.0001]
Via fruit and vegetable availability and consumption						
BMI	0.04 ⁺	[0.008, 0.090]	(Not available in this dataset)		0.0269 [*]	[0.0074, 0.0550]
Self-rated health					0.0066 [*]	[0.0018, 0.0131]
Aggregate cardiometabolic health					0.0015 ⁺	[0.0003, 0.0034]
High blood pressure/hypertension					0.0006 ⁺	[0.0001, 0.0015]
Ever had cancer					-0.0002	[-0.0007, 0.0002]
Via fruit and vegetable consumption only						
BMI	-0.109	[-0.319, 0.044]	0.0479 ⁺	[0.0016, 0.1019]	-0.074	[-0.1849, 0.0295]
Self-rated health			0.0123 [*]	[0.0004, 0.0244]	-0.0181	[-0.0437, 0.0073]
Aggregate cardiometabolic health			0.0027	[-0.0002, 0.0066]	-0.0042	[-0.0114, 0.0017]
High blood pressure/hypertension			0.0014	[0.0000, 0.0035]	-0.0018	[-0.0053, 0.0007]
Ever had cancer			-0.0004	[-0.0015, 0.0003]	0.0005	[-0.0007, 0.0023]
Via income only						
BMI	0.35 [*]	[-0.319, 0.019]	0.2184 ^{***}	[0.1452, 0.3002]	(Not distinguishable from the HINTS model)	
Self-rated health			0.0852 ^{***}	[0.0662, 0.1055]		
Aggregate cardiometabolic health			0.0414 ^{***}	[0.0306, 0.0533]		
High blood pressure/hypertension			0.0177 ^{***}	[0.0126, 0.0233]		
Ever had cancer			-0.0014	[-0.0046, 0.0017]		
Direct effect						

Outcome	(a) Oregon mediation model		(b) HINTS mediation model		(c) Hybrid mediation model	
	Estimate	CI	Estimate	CI	Estimate	CI
BMI	1.583 *	[0.268, 2.757]	0.9600 ***	[0.4309, 1.5057]		(Not distinguishable from the HINTS model)
Self-rated health			0.0639 +	[- 0.0041, 0.1336]		
Aggregate cardiometabolic health			0.0404	[- 0.0201, 0.0983]		
High blood pressure/hypertension			0.0269	[- 0.0081, 0.0611]		

Note. BMI body mass index.

+ $p < 0.10$,
* $p < 0.05$,
** $p < 0.01$.
*** $p < 0.001$.

(a) "Indirect effect" is a path to rurality via income and Fruit and Vegetable Availability; consumption not available.

(b) "Indirect effect" is a path to rurality via income, Fruit and Vegetable Availability, and Fruit and Vegetable Consumption