The Effect of SNAP on Black Households' Nutritional Quality of Food Purchases

Duoyu Wang, Colorado State University, duoyu.wang@colostate.edu
Rebecca Cleary, Colorado State University, rebecca.cleary@colostate.edu

Selected Paper prepared for presentation at the 2024 Agricultural & Applied Economics Association Annual Meeting, New Orleans, LA; July 28-30, 2024

The Effect of SNAP on Black Households' Nutritional Quality of Food Purchases

Duoyu Wang *Rebecca Cleary †

Abstract

This study aims to measure the causal effect of the Supplemental Nutrition Assistance Program (SNAP) on the nutritional quality of food purchased separately for Black, non-Hispanic (BNH) and White, non-Hispanic (WNH) households. Using data from the National Household Food Acquisition and Purchase Survey (FoodAPS), we employ instrumental variable quantile regression to estimate the impact of SNAP participation on the Healthy Eating Index 2010 (HEI-2010) scores of household food purchases across the distribution of nutritional quality. This approach allows us to compare the difference in SNAP's effect between BNH and WNH households at the lower and upper tails of the HEI-2010 distribution. By estimating the models separately for each racial group, we account for potential heterogeneity in how households of different races respond to SNAP benefits and interact with their food environments and nutrition needs.

Key words: dietary quality, Healthy Eating Index (HEI), instrumental variables unconditional quantile regression, SNAP, nutrition

*Ph.D. student in the Department of Agricultural and Resource Economics, Colorado State University, duoyu.wang@colostate.edu.

†Assistant Professor, Department of Agricultural and Resource Economics, Colorado State University

1 Introduction

The Supplemental Nutrition Assistance Program (SNAP) plays a critical role in alleviating food insecurity and improving nutrition among low-income households in the United States. As the second largest means-tested food assistance program, SNAP served 12.5% of the U.S. population in an average month in fiscal year 2022. However, the program's effectiveness in promoting healthy food choices and improving diet quality remains a topic of intense debate. While SNAP aims to increase food expenditures and thereby improve nutrition, empirical evidence on its impact on the nutritional quality of food purchases is mixed.

Previous research has established that households participating in SNAP tend to increase their food expenditures by more than the amount of benefits received (Hastings and Shapiro, 2018). This finding suggests that SNAP has the potential to improve nutrition by enabling households to allocate more resources towards food purchases. However, whether this increase in food spending translates into better diet quality remains unclear. Some studies have found positive effects of SNAP on nutrient intake and diet quality (Anderson and Butcher, 2016; Mabli et al., 2010), while others have reported mixed (Yen, 2010; Gregory et al., 2013) or even negative impacts, particularly in terms of increased consumption of unhealthy items like sugar-sweetened beverages (Todd, 2014).

The complex relationship between SNAP participation and nutritional outcomes is further complicated by the significant racial disparities in program utilization and the persistence of nutrition-related health inequities. In 2022, Black, non-Hispanic (BNH) individuals comprised 27% of SNAP recipients but only 13.6% of the overall U.S. population, highlighting their over-representation in the program. In contrast, White, non-Hispanic (WNH) individuals accounted for 62.7% of SNAP recipients and 75.5% of the total population. Despite these disparities, the majority of research on SNAP and nutritional quality has not explicitly examined potential racial differences in the program's impact. Most studies have relied on models that assume a homogeneous response to SNAP participation across all racial groups, controlling for race with a simple categorical or binary variable that does not allow for interaction effects.

This approach fails to capture the unique challenges and contexts faced by BNH households, which may influence their food purchasing behavior and the effectiveness of SNAP in improving diet quality. Socioeconomic disparities, such as higher rates of poverty, lower levels of education, and larger household sizes among BNH families, may also contribute to differences in food purchasing behavior and nutritional outcomes (French et al., 2019; Smed et al., 2007; Hiza et al., 2013). Cultural and social factors, including dietary preferences and practices rooted in historical contexts, may influence how BNH households respond to

SNAP benefits and make food choices (Airhihenbuwa et al., 1996; Semmes, 1996). These factors, shaped by structural racism and systemic inequities, may limit the potential benefits of SNAP participation for BNH households.

Given these complex realities, it is crucial to examine the potentially differential effects of SNAP on the nutritional quality of food purchases for BNH and WNH households. This paper addresses this critical gap in the literature by separately estimating the impact of SNAP participation on diet quality across the distribution of nutritional quality for each racial group. We hypothesize that due to the unique challenges and contexts faced by BNH households, SNAP may have a different effect on their food purchasing behavior compared to WNH households, particularly at the extremes of the nutritional quality distribution.

Our study makes several important contributions to the literature on SNAP and racial disparities in nutrition. First, we challenge the conventional approach of comparing SNAP participants to eligible non-participants while controlling for race with a simple categorical variable. Instead, we estimate separate models for BNH and WNH households to allow for a heterogeneous response to SNAP participation and to capture the distinct factors shaping their food purchasing behavior. Second, we employ a distributional approach using Instrumental Variables with Unconditional Quantile Regression (IVUQR) (Imbens and Newey, 2009a; Rothe, 2010b) to examine how the impact of SNAP varies across the entire range of nutritional quality, rather than focusing solely on the mean. This enables us to identify potential differences at the tails of the distribution, where the consequences of inadequate or superior nutrition may be most pronounced (Onvani et al., 2017; Harmon et al., 2015). Third, by centering our analysis on the experiences and outcomes of BNH households, we challenge the white-dominated paradigms that often overlook the unique needs and challenges of minority populations in food assistance programs (Bowleg, 2021).

To quantify the effect of SNAP on nutritional quality by race, we use data from the National Household Food Acquisition and Purchase Survey (FoodAPS), a nationally representative survey of U.S. households' food purchases over a 7-day period. We also use the Healthy Eating Index (HEI)-2010 score to measure households' nutritional quality, which is a widely accepted, reliable, and valid measure of dietary quality (Guenther et al., 2014). Our empirical strategy employs IVUQR to estimate the causal impact of SNAP across the distribution of nutritional quality, separately for BNH and WNH households. We also explore the role of household-level factors, such as education, employment, and food spending, in shaping these relationships.

The remainder of this paper is structured as follows: Section 2 details the data used in the analysis, focusing primarily on the FoodAPS dataset and our measures of nutritional quality. Section 3 outlines our empirical strategy, including the IVUQR approach. Section

4 describes conclusion.

2 Data

To quantify the impact of the SNAP on the nutritional quality of food purchases among BNH and WNH households, we will utilize the National Household Food Acquisition and Purchase Survey (FoodAPS) as our primary data source. Additionally, we will draw on the USDA's SNAP Policy Database (Economic Research Service (ERS), U.S. Department of Agriculture (USDA)., 2019) and the U.S. Department of Labor's Comparison of State Unemployment Insurance Laws to provide state-level instrumental variables (IVs) for our analysis.

2.1 FoodAPS Data

FoodAPS, a nationally representative survey, offers a comprehensive examination of food acquisition patterns in U.S. households, encompassing both food at home (FAH) and food away from home (FAFH) purchases, as well as the role of food assistance programs in shaping these patterns. The survey, conducted between April 2012 and January 2013, collected data from 4,826 households over a week-long period. One of the distinguishing aspects of FoodAPS is its ability to capture household food acquisitions from two distinct perspectives: FAH and FAFH. FAH includes items obtained from various sources, including supermarkets, farmers' markets, home gardens, and food pantries, while FAFH includes meals and snacks purchased from restaurants, fast-food outlets, and entertainment venues.

During the survey period, the primary respondents (PRs) of each household, typically those responsible for the majority of the household's food acquisitions, participated in two face-to-face interviews and up to three telephone interviews. These interactions were designed to gather a wide range of information, including detailed demographic characteristics, income and employment status, food security status, and exhaustive data on all food acquisitions during the surveyed week. To ensure accurate data collection for FAH acquisitions, PRs were instructed to scan barcodes on packaged foods. For items without barcodes, such as fresh produce, they used generic codes and provided details regarding weight, quantity, and cost, as evidenced by store receipts. For FAFH acquisitions, receipts from restaurants and stores served as the primary data source, enabling researchers to track purchases made outside the home.

Due to policy adjustments in certain states that eased the eligibility criteria for SNAP participation, households earning more than 130% of the Federal Poverty Level (FPL) could qualify for SNAP benefits, as highlighted in the FoodAPS: Household-Level Public Use File Codebook 2016. In the period from 2002 to 2008, for instance, eleven states expanded their gross income thresholds beyond the traditional 130% limit. Arizona, Delaware, Massachusetts, Maryland, North Carolina, Washington, and Wisconsin set the bar at 200%; Maine and Oregon at 185%; and Minnesota and Texas at 165%. This change prompts a broader inclusion criterion for our analysis, extending our sample to households with a monthly gross income of up to 200% FPL (Feng et al., 2023).

The FoodAPS dataset initially covers data from 4,826 households. In our study, we focus on households living below 200% FPL, specifically targeting WNH and BNH groups. By applying these criteria, the dataset is narrowed down to 1,683 households. Among these, 842 households participate in SNAP, while the remaining 841 households do not. Households are identified as SNAP participants if they reported receiving SNAP benefits within the 30 days prior to the survey.

2.2 Healthy Eating Index

In this research, we utilize the Healthy Eating Index (HEI) as a principal metric to assess the nutritional quality of diets within our study population. The HEI is widely recognized for its validity and reliability, serving as a comprehensive measure that evaluates diet quality against the Dietary Guidelines for Americans (DGA) [1] benchmarks (Guenther et al., 2013, 2014). Our analysis specifically employs the HEI-2010 version, which aligns with the period of our data collection from the FoodAPS database, spanning 2012 to 2013 (Guenther et al., 2014).

The HEI-2010 is structured around twelve dietary components, which are categorized into two main groups: adequacy and moderation. Adequacy components include total fruits, whole fruits, total vegetables, greens and beans, whole grains, dairy, total protein foods, seafood and plant proteins, and fatty acids. These components are primarily assessed based on their nutrient density per 1,000 calories, except for fatty acids, which are evaluated through the ratio of polyunsaturated and monounsaturated fats to saturated fats (Guenther et al., 2013; Berube et al., 2017). Moderation components consist of refined grains, sodium, and empty calories, where scoring is similarly based on nutrient density per 1,000 calories, with the exception of empty calories, which are measured by their proportion of total caloric intake. The scoring system of the HEI ranges from 1 to 100, where higher scores in adequacy components and lower scores in moderation components signify better nutritional quality. Scores above 80 are indicative of good nutritional quality, scores between 51 and 80 suggest a

[1] For more in-depth information, visit this link.

need for dietary improvements, and scores below 50 point to poor nutritional quality (Beatty et al., 2014; Berube et al., 2017).

Given the absence of direct HEI-2010 scores in the FoodAPS dataset, we derived these scores for each household by analyzing their food acquisitions over a seven-day period, adhering to the scoring criteria specified by the HEI-2010 in Table 1 [2]. Through this process, we obtained HEI-2010 scores for a total of 1,683 households.

2.3 Demographics and household characteristics

To investigate the distributional impact of SNAP on dietary quality by race, we incorporate several key variables into our analysis: education, marital status, employment status, household income, tobacco use, expenditures on food at home (FAH) per person, expenditures on food away from home (FAFH) per person, number of food shopping trips, and the driving distance to the primary food store. *Income* is measured as the average monthly household income, aggregating the income per member and standardizing it in units of $1,000. We also calculate *FAH expenditures per person* and *FAFH expenditures per person* by summing each household's weekly expenditures on FAH and FAFH, respectively, and dividing by the number of household members. Regional and rural information are included to control for fixed effects.

We calculate the variance inflation factor (VIF) [3] to identify potential multicollinearity among our independent variables. As indicated in Table 3, all VIF values fall below the threshold of 5, suggesting multicollinearity is not a significant issue. In Table 2, we observe distinct socio-economic differences between WNH and BNH households. In terms of education, BNH households have a slightly higher proportion of individuals with only primary school education compared to WNH households. WNH households are more likely to be married. However, despite the higher marriage rates, WNH households are less likely to have children than BNH households. Regarding food expenditures, WNH households allocate a larger portion of their budget to FAH expenses.

[2] For more information on calculating HEI-2010 scores, please refer to this link.

[3] The VIF assesses the extent of correlation between predictors in a regression model, with values greater than or equal to 1. A VIF of 1 indicates no correlation, while values between 1 and 5 suggest a moderate degree of correlation without severely impacting the model. A VIF exceeding 5 signals high correlation and potential multicollinearity concerns.

2.4 Instruments

To investigate the distributional impact of SNAP on dietary quality by race, we employ an instrumental variables (IV) approach that exploits exogenous variation in two state-level policy variables: maximum weekly unemployment insurance (UI) benefits and SNAP outreach spending per capita.

UI is a joint federal-state program that provides temporary financial assistance to eligible unemployed workers (Feng et al., 2023). The level of UI benefits, as measured by the maximum weekly benefit amount, varies considerably across states and is determined by state UI laws. Previous research has shown that UI benefit levels can influence SNAP participation through two potential channels. First, receiving UI benefits may increase awareness of other safety net programs like SNAP, leading to a positive "information effect" on SNAP participation (Finifter and Prell, 2013). Second, higher UI benefits may increase household income and reduce SNAP eligibility, resulting in a negative effect on SNAP participation (Reich and West, 2015). Crucially, the maximum weekly UI benefits, set by states, are plausibly exogenous to individual dietary quality, as they are determined by state-specific factors such as labor market conditions and policy preferences rather than individual characteristics. Several studies have utilized variation in UI benefit levels as a source of exogenous variation to estimate the causal effects of UI on various outcomes, such as job search behavior (Krueger and Mueller, 2010), and health (Kuka, 2020).

The second IV is the state's SNAP outreach spending per capita, calculated as total state outreach expenditures divided by the number of SNAP-eligible individuals in the state. SNAP outreach programs aim to increase program awareness and participation by providing information about eligibility criteria, application procedures, and program benefits, as well as assistance with the application process. Higher SNAP outreach spending in a state is expected to increase SNAP participation rates (Ratcliffe et al., 2011). Importantly, the variation in SNAP outreach spending across states is driven by factors such as state budget allocations and policy priorities, which are unlikely to be directly related to individual dietary choices. This suggests that SNAP outreach spending satisfies the exclusion restriction required for a valid instrument. The key identifying assumption is that state-level SNAP outreach spending affects individual dietary quality only through its impact on SNAP participation. Prior research has used SNAP outreach spending as an instrument to study the causal effects of SNAP on food insecurity (Ratcliffe et al., 2011) and child obesity (Schmeiser, 2012), providing support for the validity of this instrument.

We obtain data on maximum weekly UI benefit levels from the U.S. Department of Labor's Comparison of State UI Laws (U.S. Department of Labor., 2012, 2013)and state

SNAP outreach spending data from the USDA's SNAP Policy Database (Economic Research Service (ERS), U.S. Department of Agriculture (USDA)., 2019). We merge both IVs with the FoodAPS data by state, year, and month to construct a comprehensive dataset for analysis.

The validity of our IV approach relies on two key assumptions. First, the instruments must be strongly predictive of SNAP participation (the relevance condition). We assess this assumption by examining the strength of the first-stage relationship between the IVs and SNAP participation. Second, the instruments must affect dietary quality only through their impact on SNAP participation (the exclusion restriction). While this assumption is not directly testable, we argue that it is plausible given the institutional features of UI and SNAP outreach programs and the lack of obvious alternative pathways through which these state-level policies could influence individual dietary quality.

To further validate our instruments, we follow the approach of Feng et al. (2023) and conduct several tests. First, we examine the joint significance of the instruments in the first-stage regression and report the F-statistic and associated p-value. A sufficiently large F-statistic (typically greater than 10) indicates that the instruments are strong predictors of SNAP participation. Second, we use the Hansen J test of overidentifying restrictions to assess the validity of the exclusion restriction. A failure to reject the null hypothesis of the Hansen J test provides support for the exogeneity of the instruments. Finally, we estimate a reduced-form regression of dietary quality on the instruments among a sample of non-SNAP households. If the instruments are valid, they should not have a direct effect on dietary quality for households that do not participate in SNAP.

2.5 Stochastic Dominance

In this section, we employ a stochastic dominance approach to compare the distributions of nutritional quality, as measured by HEI scores, between SNAP participants and non-participants within each racial group. The stochastic dominance approach offers several advantages over traditional mean comparison methods, making it a more comprehensive and robust method for analyzing the quantile effect of SNAP on nutritional quality by race.

First and foremost, the stochastic dominance approach allows us to compare the entire distributions of HEI scores, rather than simply focusing on average differences. This is particularly important when the impact of SNAP participation on nutritional quality may vary across different quantiles of the HEI distribution. By examining the entire distribution, we can identify whether SNAP participation leads to improvements in nutritional quality for households at different levels of the HEI range.

Moreover, the stochastic dominance approach is robust to outliers and non-normality in the HEI distributions. Traditional mean comparison methods, such as t-tests, rely on assumptions of normality and can be sensitive to extreme values. In contrast, the stochastic dominance approach does not require any distributional assumptions and is less affected by outliers, ensuring a more reliable comparison of nutritional quality between SNAP participants and non-participants.

Another key advantage of the stochastic dominance approach is its ability to test for different orders of dominance, offering insights into the strength and nature of the relationship between SNAP participation and nutritional quality. First-order stochastic dominance implies that SNAP participation leads to an unambiguous improvement in nutritional quality across all quantiles, while second-order stochastic dominance allows for the possibility of overlapping distributions but still indicates an overall improvement in nutritional quality for SNAP participants.

By using the stochastic dominance approach, we can provide a more comprehensive and robust analysis of the quantile effect of SNAP on nutritional quality by race. This approach enables us to identify potential heterogeneity in the impact of SNAP participation across different levels of the HEI distribution and to draw more reliable conclusions about the effectiveness of the program in improving nutritional outcomes for Black and White households.

To implement this approach, we first compare the entire distributions of nutritional quality for SNAP participants and non-participants within each racial group. This comprehensive analysis involves two critical steps. Initially, we must ascertain if the differences observed in the HEI score distributions are statistically significant. Subsequently, we explore whether there is any overlap between the two nutritional quality distributions.

To accomplish this, we consider the cumulative distribution functions (CDFs) $F_{\text{SNAP}}(x)$ and $G_{\text{NONSNAP}}(x)$, representing the HEI scores of SNAP participants and non-participants, respectively, for a given racial group. If $D_1(x) \equiv G_{\text{NONSNAP}}(x) - F_{\text{SNAP}}(x) \geq 0$ for all x, this implies $F_{\text{SNAP}}(x)$ first-order stochastically dominates $G_{\text{NONSNAP}}(x)$, signifying that $F_{\text{SNAP}}(x)$ is consistently to the right of $G_{\text{NONSNAP}}(x)$ without any overlap. Conversely, if $D_2(x) \equiv \int (G_{\text{NONSNAP}}(x) - F_{\text{SNAP}}(x))\, dx \geq 0$ for all x, $F_{\text{SNAP}}(x)$ demonstrates second-order stochastic dominance over $G_{\text{NONSNAP}}(x)$. Here, the distributions may overlap, but the area under $G_{\text{NONSNAP}}(x)$ to the left of x is always greater than that under $F_{\text{SNAP}}(x)$.

To assess the statistical significance of the differences in HEI score distributions, we conduct a two-sample Kolmogorov-Smirnov (KS) test (Massey, 1951) for each racial group. The KS test is a non-parametric test that compares the CDFs of two samples to determine if they are drawn from the same underlying distribution. The null hypothesis of KS test posits identical distributions $F_{\text{SNAP}}(x) = G_{\text{SNAP}}(x)$ for all x. We reject this hypothesis with a p-value less than 0.01 for each racial group and conclude that the differences in the HEI score distributions between SNAP participants and non-participants are statistically significant for the given racial group.

To determine the presence of first-order stochastic dominance, we apply the Goldman-Kaplan test (Goldman and Kaplan, 2018) separately for both WNH and BNH households. The Goldman-Kaplan test is designed to compare the entire distributions and determine if one distribution lies above the other at all points.

Let $F^W_{\text{SNAP}}(x)$ and $G^W_{\text{NONSNAP}}(x)$ denote the CDFs of HEI scores for SNAP participants and non-participants, respectively, among WNH households. Similarly, let $F^B_{\text{SNAP}}(x)$ and $G^B_{\text{NONSNAP}}(x)$ represent the CDFs for BNH households. The Goldman-Kaplan test assesses whether the CDF of HEI scores for SNAP participants lies entirely below the CDF of HEI scores for non-participants within each racial group.

The Goldman-Kaplan test statistic for WNH households is defined as:

$$D^W_{\text{GK}} = \sup_x [G^W_{\text{NONSNAP}}(x) - F^W_{\text{SNAP}}(x)]$$

and for BNH households:

$$D^B_{\text{GK}} = \sup_x [G^B_{\text{NONSNAP}}(x) - F^B_{\text{SNAP}}(x)]$$

The null hypothesis of the Goldman-Kaplan test for each racial group is that the CDF of HEI scores for SNAP participants does not first-order stochastically dominate the CDF of HEI scores for non-participants. Formally, for WNH households:

$$H^W_0 : \sup_x [G^W_{\text{NONSNAP}}(x) - F^W_{\text{SNAP}}(x)] \leq 0$$

and for BNH households:

$$H^B_0 : \sup_x [G^B_{\text{NONSNAP}}(x) - F^B_{\text{SNAP}}(x)] \leq 0$$

In our analysis, we fail to reject the null hypothesis of the Goldman-Kaplan test for both WNH and BNH households. This suggests that the CDFs of HEI scores for SNAP participants and non-participants intersect at one or more points within each racial group, and first-order stochastic dominance cannot be established. This can be observed from Figure 1 for BNH households and 2 for WNH households. In other words, we cannot conclude that SNAP participation leads to consistently higher HEI scores across all levels of the distribution for either WNH or BNH households. Failing to establish first-order stochastic dominance for both racial groups does not necessarily imply that SNAP is ineffective in improving nutritional outcomes. It may indicate that the impact of SNAP participation on HEI scores varies across different levels of the distribution or that there are other factors influencing nutritional quality that need to be considered.

To further investigate the relationship between SNAP participation and nutritional quality for both WNH and BNH households, we proceed to test for second-order stochastic dominance using the consistent test proposed by Linton et al. (2005). This test is particularly useful when the CDFs of HEI scores for SNAP participants and non-participants intersect, as it allows for the possibility of intersecting CDFs while still assessing whether SNAP participation leads to an overall improvement in nutritional quality. The Linton, Maasoumi, and Whang test for second-order stochastic dominance compares the integrals of the CDFs for each group.

The test statistic for second-order stochastic dominance for WNH households is given by:

$$D_2^W(x) = \int_{-\infty}^{x} [G^W_{\text{NONSNAP}}(t) - F^W_{\text{SNAP}}(t)]dt$$

and for BNH households:

$$D_2^B(x) = \int_{-\infty}^{x} [G^B_{\text{NONSNAP}}(t) - F^B_{\text{SNAP}}(t)]dt$$

The null hypothesis for the Linton, Maasoumi, and Whang test for each racial group is that the CDF of HEI scores for SNAP participants does not second-order stochastically dominate the CDF of HEI scores for non-participants. Formally, for WNH households:

$$H_0^W : \sup_x D_2^W(x) \leq 0$$

and for BNH households:

$$H_0^B : \sup_x D_2^B(x) \leq 0$$

In this analysis, we reject the null hypothesis for both WNH and BNH households. This means that $F^W_{\text{SNAP}}(x)$ second-order stochastically dominates $G^W_{\text{NONSNAP}}(x)$ for WNH households, or $F^B_{\text{SNAP}}(x)$ second-order stochastically dominates $G^B_{\text{NONSNAP}}(x)$ for BNH households. Rejecting the null hypothesis suggests that SNAP is effective in improving the nutritional quality of food purchases for both WNH and BNH households across different levels of the HEI distribution.

3 Methods

SNAP is a crucial policy intervention aimed at improving nutritional outcomes for low-income households. However, investigating the impact of SNAP on nutritional quality is complicated by the endogeneity of SNAP participation. Endogeneity arises when there are unobserved factors that influence both the decision to participate in SNAP and the nutritional quality of an individual's diet. Failure to account for this endogeneity can lead to biased estimates of the effect of SNAP on nutritional quality.

To address the endogeneity of SNAP participation and investigate the quantile effect of SNAP on nutritional quality across race, we employ the Instrumental Variable Unconditional Quantile Regression (IVUQR) approach (Imbens and Newey, 2009b; Rothe, 2010a). IVUQR is an extension of the Instrumental Variable Quantile Regression (IVQR) method (Chernozhukov and Hansen, 2005), which allows for the estimation of the unconditional quantile treatment effects in the presence of endogeneity.

The choice of IVUQR over IVQR is motivated by several advantages that make IVUQR more suitable for our research. Firstly, IVUQR estimates the unconditional quantile treatment effects, which are the effects of SNAP participation on the quantiles of the marginal distribution of nutritional quality, without conditioning on the control variables. In contrast, IVQR estimates the conditional quantile treatment effects, which are the effects of SNAP participation on the quantiles of nutritional quality conditional on the control variables included in the model. The unconditional quantile treatment effects estimated by IVUQR are more interpretable and policy-relevant because they directly answer questions about the impact of SNAP on the overall distribution of nutritional quality, rather than the distribution conditional on specific values of the control variables.

Moreover, the unconditional quantile treatment effects estimated by IVUQR have a clear interpretation as the impact of SNAP on the quantiles of the marginal distribution of nutritional quality. For example, if IVUQR estimates that SNAP participation increases the 25th percentile of the nutritional quality distribution by a certain amount, this can be directly interpreted as the effect of SNAP on the nutritional quality of individuals at the lower end of the distribution, regardless of their characteristics. This interpretation is more useful for policymakers, as it provides insights into how SNAP affects the overall population and specific subgroups, rather than the effect conditional on specific values of the control variables.

Another advantage of IVUQR is its robustness to model specification. IVUQR is less sensitive to the choice of control variables included in the model compared to IVQR. In IVQR, the estimated conditional quantile treatment effects can change substantially depending on which control variables are included, as the effects are estimated conditional on those variables. IVUQR, on the other hand, estimates the unconditional quantile treatment effects, which are more robust to the choice of control variables, as they capture the overall impact of SNAP on the distribution of nutritional quality.

When investigating the quantile effect of SNAP on nutritional quality across race, IVUQR allows for a more straightforward comparison of the treatment effects across different racial groups. Since IVUQR estimates the unconditional quantile treatment effects, the estimated effects for each racial group can be directly compared to assess potential disparities in the impact of SNAP on nutritional quality. With IVQR, the estimated conditional quantile treatment effects for each racial group would be conditional on the control variables, making comparisons across groups more complex and less intuitive.

The IVUQR model is estimated in two stages:

$$SNAP_{ist} = \alpha Z_{st} + \beta X_{ist} + u_{ist} \tag{1}$$

$$Q_{h_{ist}}(\tau) = \gamma \widehat{SNAP}_{ist} + \delta(\tau) Xist + w_{ist} \tag{2}$$

where $SNAP_{ist}$ represents whether a household i, located in state s, participates in SNAP at time t. The vector Z_{st} includes IVs. The vector X_{ist} includes household and individual characteristics. u_{ist} and w_{ist} are error terms. In the second stage, $Q_{h_{ist}}(\tau)$ denotes the τ-th quantile of the unconditional distribution of dietary quality for household i residing in state s at time t, and $\widehat{SNAP}_{ist}$ is the predicted value of SNAP participation derived from equation 1. The α, β, and $\delta(\tau)$ are parameters to be estimated. γ represents the estimated impact of SNAP participation on the nutritional quality of household purchases.

The vector of household and individual characteristics, X_{ist}, includes variables such as gender, education, marital status, employment status, income, tobacco use, food at home expenditures per person, food away from home expenditures per person, house ownership, driving distance to the household's primary grocery store, number of food shopping trips, and whether living in a rural area. We use state-level maximum weekly unemployment insurance benefits and monthly SNAP outreach spending per capita as IVs (Z_{st}) (Feng et al., 2023), which are expected to influence SNAP participation but not directly affect dietary quality except through their impact on SNAP participation.

To investigate the quantile effect of SNAP on nutritional quality across race, we will estimate separate IVUQR models for each racial group. This approach allows us to compare the unconditional quantile treatment effects of SNAP on nutritional quality across different races, providing insights into potential disparities in the program's impact.

4 Conclusions

In this paper, we aim to address a critical gap in the literature on SNAP and its impact on the nutritional quality of food purchases by examining potential racial differences between BNH and WNH households. We challenge the conventional approach of controlling for race with a simple categorical variable and instead estimate separate models for each racial group to capture the unique challenges and contexts faced by BNH households that may influence their food purchasing behavior and the effectiveness of SNAP in improving diet quality. Our study employs a novel approach using IVUQR to estimate the causal impact of SNAP across the entire distribution of nutritional quality, separately for BNH and WNH households. This distributional approach allows us to identify potential differences at the extremes of the nutritional quality distribution, where the consequences of inadequate or superior nutrition may be most pronounced. Furthermore, our research emphasizes the importance of examining the effectiveness of food assistance programs through a racial equity lens. By challenging the assumption of a homogeneous response to SNAP participation across all racial groups, we encourage future research that explores the complex interplay between race, socioeconomic status, and nutritional outcomes. This understanding is crucial for developing more effective and equitable policies that promote food security and improve diet quality for all households, regardless of race.

References

Airhihenbuwa, C. O., S. Kumanyika, T. D. Agurs, A. Lowe, D. Saunders, and C. B. Morssink (1996). Cultural aspects of african american eating patterns. *Ethnicity health 1*(3), 245–260.

Anderson, P. M. and K. F. Butcher (2016). The relationships among snap benefits, grocery spending, diet quality, and the adequacy of low income families.

Beatty, T. K. M., B.-H. Lin, and T. A. Smith (2014). Is Diet Quality Improving? Distributional Changes in the United States, 1989–2008. *American Journal of Agricultural Economics 96*(3), 769–789.

Berube, L. T., M. Kiely, Y. Yazici, and K. Woolf (2017). Diet quality of individuals with rheumatoid arthritis using the Healthy Eating Index (HEI)-2010. *Nutrition and Health 23*(1), 17–24.

Bowleg, L. (2021). "the master's tools will never dismantle the master's house": Ten critical lessons for black and other health equity researchers of color. *Health education behavior 48*(3), 237–249.

Chernozhukov, V. and C. Hansen (2005). An iv model of quantile treatment effects. *Econometrica 73*(1), 245–261.

Economic Research Service (ERS), U.S. Department of Agriculture (USDA). (2019). SNAP Policy Database, SNAP Policy Data Sets. Retrieved from https://www.ers.usda.gov/data-products/snap-policy-data-sets/.

Feng, J., L. Fan, and E. C. Jaenicke (2023). The distributional impact of SNAP on dietary quality. *Agricultural Economics*.

Finifter, D. H. and M. A. Prell (2013). *Participation in the Supplemental Nutrition Assistance Program (SNAP) and unemployment Insurance : how tight are the strands of the recessionary safety net?* . United States Department of Agriculture, Economic Research Service.

French, S. A., C. C. Tangney, M. M. Crane, Y. Wang, and B. M. Appelhans (2019). Nutrition quality of food purchases varies by household income: the shopper study. *BMC public health 19*(1), 231–231.

Goldman, M. and D. M. Kaplan (2018). Comparing distributions by multiple testing across quantiles or cdf values. *Journal of econometrics 206*(1), 143–166.

Gregory, C., M. Ver Ploeg, M. Andrews, and A. Coleman-Jensen (2013). Supplemental nutrition assistance program (snap) participation leads to modest changes in diet quality. No. 1477-2017-3991.

Guenther, P. M., K. O. Casavale, J. Reedy, S. I. Kirkpatrick, H. A. Hiza, K. J. Kuczynski, L. L. Kahle, and S. M. Krebs-Smith (2013). Update of the Healthy Eating Index: HEI-2010. *Journal of the Academy of Nutrition and Dietetics 113*(4), 569–580.

Guenther, P. M., S. I. Kirkpatrick, J. Reedy, S. M. Krebs-Smith, D. W. Buckman, K. W. Dodd, K. O. Casavale, and R. J. Carroll (2014). The Healthy Eating Index-2010 Is a Valid and Reliable Measure of Diet Quality According to the 2010 Dietary Guidelines for Americans 1–3. *The Journal of Nutrition 144*(3), 399–407.

Harmon, B. E., C. J. Boushey, Y. B. Shvetsov, R. Ettienne, J. Reedy, L. R. Wilkens, L. Le Marchand, B. E. Henderson, and L. N. Kolonel (2015). Associations of key diet-quality indexes with mortality in the multiethnic cohort: the dietary patterns methods project. *The American journal of clinical nutrition 101*(3), 587–597.

Hastings, J. and J. M. Shapiro (2018). How are snap benefits spent? evidence from a retail panel. *The American economic review 108*(12), 3493–3540.

Hiza, Hazel A.B., P. R., P. R. Casavale, Kellie O., P. R. Guenther, Patricia M., and M. R. Davis, Carole A. (2013). Diet quality of americans differs by age, sex, race/ethnicity, income, and education level. *Journal of the Academy of Nutrition and Dietetics 113*(2), 297–306.

Imbens, G. W. and W. K. Newey (2009a). Identification and estimation of triangular simultaneous equations models without additivity. *Econometrica 77*(5), 1481–1512.

Imbens, G. W. and W. K. Newey (2009b). Identification and estimation of triangular simultaneous equations models without additivity. *Econometrica 77*(5), 1481–1512.

Krueger, A. B. and A. Mueller (2010). Job search and unemployment insurance: New evidence from time use data. *Journal of public economics 94*(3), 298–307.

Kuka, E. (2020). Quantifying the benefits of social insurance: Unemployment insurance and health. *The review of economics and statistics 102*(3), 490–505.

Linton, O., E. Maasoumi, and Y.-J. Whang (2005). Consistent Testing for Stochastic Dominance under General Sampling Schemes. *The Review of Economic Studies 72*(3), 735–765.

Mabli, J., L. Castner, J. Ohls, M. Fox, M. Crepinsek, and E. Condon (2010). Food expenditures and diet quality among low-income households and individuals. Mathematica Policy Research.

Massey, F. J. (1951). The Kolmogorov-Smirnov Test for Goodness of Fit. *Journal of the American Statistical Association 46*(253), 68–78.

Onvani, S., F. Haghighatdoost, P. J. Surkan, B. Larijani, and L. Azadbakht (2017). Adherence to the healthy eating index and alternative healthy eating index dietary patterns and mortality from all causes, cardiovascular disease and cancer: a meta-analysis of observational studies. *Journal of human nutrition and dietetics 30*(2), 216–226.

Ratcliffe, C., S.-m. McKernan, and S. Zhang (2011). How much does the supplemental nutrition assistance program reduce food insecurity? *American journal of agricultural economics 93*(4), 1082–1098.

Reich, M. and R. West (2015). The effects of minimum wages on food stamp enrollment and expenditures. *Industrial relations (Berkeley) 54*(4), 668–694.

Rothe, C. (2010a). Identification of unconditional partial effects in nonseparable models. *Economics letters 109*(3), 171–174.

Rothe, C. (2010b). Nonparametric estimation of distributional policy effects. *Journal of econometrics 155*(1), 56–70.

Schmeiser, M. D. (2012). The impact of long-term participation in the supplemental nutrition assistance program on child obesity. *Health economics 21*(4), 386–404.

Semmes, C. (1996). *Racism, health, and post-industrialism: A theory of African-American health.* Westport, CT: Praeger.

Smed, S., J. D. Jensen, and S. Denver (2007). Socio-economic characteristics and the effect of taxation as a health policy instrument. *Food policy 32*(5-6), 624–639.

Todd, J. E. (2014). *Changes in eating patterns and diet quality among working-age adults, 2005-2010.* Economic research report ; number 161. Washington, D.C: United States Department of Agriculture, Economic Research Service.

U.S. Department of Labor. (2012). Comparison of State Unemployment Insurance Laws. Retrieved from https://oui.doleta.gov/unemploy/pdf/uilawcompar/2012/monetary.pdf.

U.S. Department of Labor. (2013). Comparison of State Unemployment Insurance Laws. Retrieved from https://oui.doleta.gov/unemploy/pdf/uilawcompar/2013/monetary.pdf.

Yen, S. T. (2010). The effects of snap and wic programs on nutrient intakes of children. *Food policy 35*(6), 576–583.

Table 1: HEI-2010 Components and Scoring Standards

Component	Maximum points	Standard for maximum score	Standard for minimum score of zero
Adequacy:			
Total Fruit[1]	5	$\geq$ 0.8 cup equiv. per 1,000 kcal	No Fruit
Whole Fruit[2]	5	$\geq$ 0.4 cup equiv. per 1,000 kcal	No Whole Fruit
Total Vegetable[3]	5	$\geq$ 1.1 cup equiv. per 1,000 kcal	No Vegetables
Greens and Beans[3]	5	$\geq$ 0.2 cup equiv. per 1,000 kcal	No Dark Green Vegetables or Beans and Peas
Whole Grains	10	$\geq$ 1.5 oz equiv. per 1,000 kcal	No Whold Grains
Dairy[4]	10	$\geq$ 1.3 cup equiv. per 1,000 kcal	No Dairy
Total Protein Foods[5]	5	$\geq$ 2.5 oz equiv. per 1,000 kcal	No Protein Foods
Seafood and Plant Proteins[5,6]	5	$\geq$ 0.8 oz equiv. per 1,000 kcal	No Seafood or Plant Proteins
Fatty Acids[7]	10	(PUFAs + MUFAs)/SFAs $\geq$ 2.5	(PUFAs + MUFAs)/SFAs $\leq$ 1.2
Moderation:			
Refined Grains	10	$\leq$ 1.8 oz equiv. per 1,000 kcal	$\geq$ 4.3 oz equiv. per 1,000 kcal
Sodium	10	$\leq$ 1.1 gram equiv. per 1,000 kcal	$\geq$ 2.0 gram equiv. per 1,000 kcal
Empty Calories[8]	20	$\leq$ 19% of energy	$\geq$ 50% of energy

Note: 1: Includes 100% fruit juice. 2: Includes all forms except juice. 3: Includes any beans and peas not counted as Total Protein Foods. 4: Includes all milk products, such as fluid milk, yogurt, and cheese, and fortified soy beverages. 5: Beans and peas are included here (and not with vegetables) when the Total Protein Foods standard is otherwise not met. 6: Includes seafood, nuts, seeds, soy products (other than beverages) as well as beans and peas counted as Total Protein Foods. 7: Ratio of poly- and monounsaturated fatty acids (PUFAs and MUFAs) to saturated fatty acids (SFAs). 8: Calories from solid fats, alcohol, and added sugars; threshold for counting alcohol is $\geq$ 13 grams/1000 kcal.

Table 2: Summary Statistics Across Race Status

Variables	WNH_mean	WNH_s.d.	BNH_mean	BNH_s.d.
HEI-2010	48.149	13.202	47.606	12.556
Male	0.263	0.440	0.253	0.435
Married	0.346	0.476	0.182	0.386
Primaryschool	0.172	0.378	0.217	0.413
Some_college	0.342	0.475	0.359	0.480
BA	0.096	0.295	0.083	0.276
MS_above	0.021	0.142	0.017	0.128
Worked	0.007	0.084	0.007	0.084
Tobacco	0.394	0.489	0.343	0.475
FAH_expenditures	40.650	39.491	30.656	36.335
FAFH_expenditures	14.173	23.503	14.846	28.796
Primstoredist	5.220	6.415	3.361	5.252
Age5	0.344	0.696	0.437	0.791
Age6_11	0.328	0.682	0.402	0.754
Age12_18	0.311	0.689	0.442	0.806
Rural	0.406	0.491	0.175	0.380
Income	1.755	1.018	1.586	1.072
Midwest	0.279	0.449	0.255	0.437
South	0.395	0.489	0.553	0.498
West	0.160	0.367	0.116	0.320
FAH_shopping_trips	3.387	2.514	3.270	2.577
FAFH_shopping_trips	7.299	7.569	8.310	8.163

Note: Region- and rural-fixed effects are omitted here for brevity

Table 3: Variance Inflation Factor between Independant Variables

Variables	VIF
Male	1.538
Married	1.494
Primaryschool	1.728
Some_college	2.130
BA	1.325
MS_above	1.126
Worked	1.071
Tobacco	1.653
FAH_expenditures	2.161
FAFH_expenditures	1.469
Primstoredist	1.610
Age5	1.541
Age6_11	1.575
Age12_18	1.694
Rural	1.599
Income	4.078
Midwest	2.516
South	4.341
West	1.724
FAH_shopping_trips	3.374
FAFH_shopping_trips	2.972

Note: VIF = 1: No correlation between the independent variable and the other variables. VIF between 1 and 5: Generally, it indicates a moderate level of multicollinearity. VIF greater than 5: This might be a cause for concern, indicating a high level of multicollinearity. From table 3, all VIFs are less than 5, meaning the independent variables are not highly correlated.

Figure 1: Cumulative Distribution of HEI scores for Black Non-Hispanic (BNH) SNAP and Black Non-Hispanic Non-SNAP households

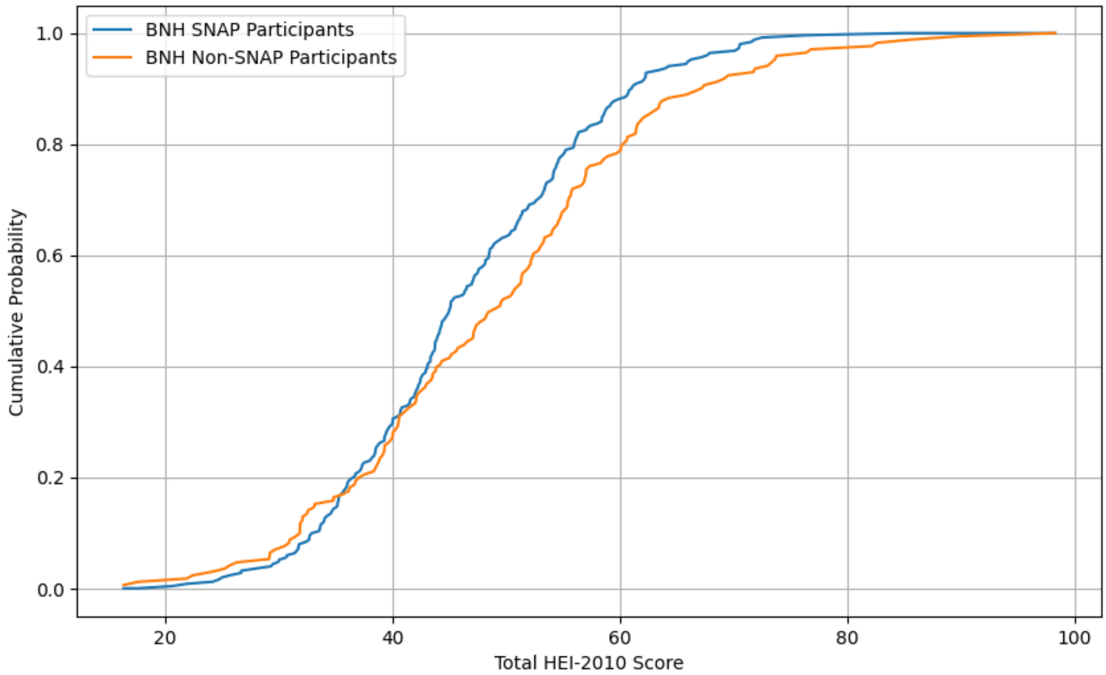

Figure 2: Cumulative Distribution of HEI scores for White Non-Hispanic (WNH) SNAP and White Non-Hispanic Non-SNAP households