

DIET QUALITY AND THE INCOME GRADIENT:
A NONPARAMETRIC ANALYSIS

by

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(Under the Direction of Travis A. Smith)

ABSTRACT

Utilizing NHANES data, our study seeks to further understand the relationship between income and diet quality by examining how the correlation between these two variables changes nonparametrically across the income spectrum using local polynomial regressions. Employing similar methods, we also attempt to explain the association between income and substitution between “healthy” and “unhealthy” food categories, and how this relationship changes with increasing levels of income. Preliminary results suggest that diet quality improvements associated with small income increases are much stronger and more positive for those at the low and high ends of the income distribution than for those at medium income levels. Analysis of the substitution between “unhealthy” and “healthy” food categories suggests that the relatively large improvements in diet quality among low-income individuals are likely due to substitution away from low-quality food categories as income increases, while the positive association observed at high income levels are the result of increases in consumption of high-quality foods.

INDEX WORDS: NHANES, poverty, nonparametrics, local polynomial regression

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Chapter 1

Introduction

According to a report by the Centers for Disease Control (CDC), more than 75% of US healthcare spending in 2009 was dedicated to the treatment of individuals with chronic diseases (CDC-NCCDPHP, 2009). Many of these diseases, which are among the leading causes of death in America, including stroke, certain cancers, heart disease, osteoporosis, and diabetes are significantly less likely to occur in individuals consuming diets of adequate nutritional quality (Ezzati & Riboli, 2013). Unfortunately, the majority of Americans regularly fail to meet the nutritional standards set forth by the USDA (Hiza et al., 2013). This is especially true among the low-income community, for whom consumption of nutrient-dense foods such as fresh fruits, vegetables, whole grains, and fish is much lower on average than those in other income groups (Leung et al., 2012).

In order to form hypotheses about which type of policy changes might be more effective in improving diet quality for disproportionately affected populations, one must first understand the relationship between food purchasing power and diet quality, and how that association could be different for small changes in income among low-income individuals. Many analyses have documented a positive relationship between socioeconomic status and diet quality (e.g. Loughrey et al., 2004). This is consistent with evidence that suggests high

income individuals tend to consume higher quantities of healthy foods, such as whole grains, fresh fruits and vegetables, low-fat dairy, and lean proteins, while low income individuals consume significantly more of items considered to be unhealthy, including refined grains, white potatoes, and high-fat foods (Darmon & Drewnowski, 2008).

Although this evidence is essential to understanding income as a likely determinant of diet quality, no study exists in the current literature regarding how this association varies nonlinearly by income level. Considering this, our study seeks to further understand this relationship by examining how the correlation between income and diet quality changes non-parametrically across the income spectrum using local polynomial regressions. Employing similar methods, we also attempt to explain the association between income and substitution between healthy and unhealthy food categories, and how this relationship changes with increasing levels of income. Finally, we compare the results for SNAP beneficiaries and nonparticipating SNAP eligible individuals.

The Food Stamp Program was first implemented in 1964 as a federal hunger relief program, addressing the problem of poor diet quality among impoverished Americans (USDA-FNS, 2014).¹ The program has two goals: hunger relief, and improving diet quality among low-income Americans through increasing grocery purchasing power and nutritional knowledge. However, SNAP, a program budgeted at over \$78 billion in 2015, has been widely accused of failing to accomplish its second goal, with many participants continuing to consume low-quality diets relative to non-participating SNAP-eligible households (CBO, 2015; Leung et al., 2012). Considering that there is a large degree of overlap between those eligible for SNAP and Medicaid, improving health among the SNAP population is frequently cited as a possible long-run cost-saving measure for welfare programs in the United States (Meyerhoefer & Pylypchuk, 2014). Because of this, many alterations to the program have

¹The Food Stamp Program was officially reorganized as the Supplemental Nutrition Assistance Program (SNAP) in 2008 (USDA-FNS, 2014).

been suggested. The effectiveness of each proposed amendment to the program, however, is highly dependent on the association between income and diet quality at low income levels.

This analysis utilizes data from the National Health and Nutrition Examination Surveys (NHANES) taken by the National Center for Health Statistics (NCHS) from 2007-2012. Diet quality is measured using the Healthy Eating Index (HEI). This holistic approach to measuring diet quality offers a modern, comprehensive, alternative view to that taken by studies utilizing a nutrient-by-nutrient method of analyzing diet quality. Preliminary results suggest that diet quality changes associated with marginal income increases are positive for those at the low and high ends of the income distribution and negative those at moderate levels of income. Put simply, for those with both low and high degrees of purchasing power, marginal increases in income are correlated with large, positive changes in overall diet quality. This is not the case for those in moderate income brackets, for whom marginal income increases are associated with decreased diet quality. Analysis of the substitution between unhealthy and healthy food categories suggests that the relatively large improvements in diet quality associated with income increases observed among low-expenditure individuals are likely due to substitution away from low-quality food categories as incomes increase, while improvements at the higher end of the income spectrum are attributable to increased consumption of high-quality food. Comparing SNAP participants and eligible non-participants, it appears that the association between income and diet quality is more positive for SNAP participants, but only for observations at income levels far below the upper bound for benefit eligibility.

Chapter 2

Background

In a study of the modifiable factors contributing to mortality in the United States, it has been estimated that roughly 400,000 deaths in the year 2000 could be attributed to “poor diet and physical inactivity” (Mokdad et al., 2004). The upward trend in medical conditions related to obesity in the United States, such as diabetes and stroke, suggests that poor diet quality and related lifestyle factors could soon become the leading cause of death in the United States, surpassing tobacco use, microbial agents, toxic agents, and motor vehicle crashes (Mokdad et al., 2004). A 2009 report by the CDC states that proper nutrition, especially adequate intake of fruits and vegetables is associated with reduced risk for heart disease and certain cancers. Kant’s 2004 review of the literature surrounding dietary patterns and associated health outcomes determined that, irrespective of how diet quality is measured (be it using an index or “factor or cluster analysis to derive dietary patterns”) diets rich in nutrient-dense foods such as whole grains, fruits, vegetables, and fish are associated with decreased disease risk.

Despite the wealth of evidence linking diet quality to health outcomes, Americans routinely fall short of dietary guidelines. In 2007, only 24 % of adults regularly met the minimum USDA recommendation for fruit and vegetable intake (CDC-NCCDPHP, 2009). Diet qual-

ity is even lower for low-income Americans, with low socioeconomic status (SES) associated with increased consumption of refined grains and added fats (Darmon & Drewnowski, 2008). As one might expect, this disparity has been associated with increased risk for diet related health problems among the low-income population (Shah et al., 2010). Numerous studies indicate that, while mean caloric intake has increased, overall diet quality in the United States has improved in recent years for the average citizen (Todd, 2014; Wang et al., 2014). Evidence regarding distributional effects is mixed. Some studies present evidence of a widening gap in diet quality between low- and high-income Americans (Wang et al., 2014). Others suggest that it is not the entire low-income population being left behind but only those at the lowest points on the diet quality spectrum (Beatty et al., 2014). However, the fact stands that the problem of a worsening disparity in diet quality between income levels exists for at least a portion of the low-income community. In order to understand this disparity, we must investigate possible determinants of an individual's diet quality.

A frequently cited place to begin is in discussing the relative price of high and low quality foods. Although there is research to suggest that relative price is highly dependent upon how "healthy food" is defined and how price is measured (e.g. by price per calorie or edible weight), there are numerous studies which assert that nutrient-dense diets are more expensive than energy-dense diets. (Carlson & Frazo, 2012, Darmon & Drewnowski, 2008). In a 2005 study, foods rich in refined grains, and added fats and sugars were found to be among the lowest-cost food items available to consumers, making them increasingly popular choices for low-income Americans (Drewnowski & Darmon, 2005).

Numerous social determinants of diet quality have been identified. In addition those who are low-income, those who are black, male, working-age, and those with low education levels are shown to have statistically poorer diet quality (Popkin et al., 1996; Kant & Graubard, 2007, Hiza et al., 2013). On an individual level, diet quality is a function of individual behavior with regard to food acquisition and preparation. Americans now source a greater proportion

of daily calories away from home than in previous decades (Nielsen et al., 2002). It is well established that food sourced away from home (FAFH) is of lower dietary quality than food purchased from a grocery store and prepared at home, containing less of essential dietary components such as calcium, and dietary fiber (Lin & Guthrie, 2012). This is likely the result of increasing wage rates and other factors which increase the opportunity cost of time, thus encouraging consumers to substitute away from more time-intensive preparation of higher-quality food at home (FAH) (Prochaska & Schrimper, 1973; Gottschalk & Danziger, 2005; Larson et al., 2006).

Reconciling an increasing mean diet quality with increasing consumption of restaurant and fast food items requires knowledge of the literature surrounding income elasticities for different types of food. Wage increases, although previously established as drivers of a substitution effect in favor of lower-quality food, also contribute to increases in the overall budget, therefore creating an income effect (Huffman, 2011; Larson et al., 2006). If the income elasticity of demand is positive for high-quality foods, and of sufficient magnitude to offset any substitution effect created by increasing wage, then diet quality could increase (Deaton & Muellbauer, 1980). Demand system analyses performed by Huang in 1996 show that income elasticities associated with many foods considered to be “healthy” (e.g. fish and some fresh produce items) are positive on average. There is also evidence, however, that income elasticities for both FAFH and common grocery items are higher for non-poverty status households (Park et al., 1996). This suggests that there may be some ambiguity regarding which effect, substitution or income, will outweigh the other at various points along the income spectrum.

This is a question of special interest to policy-makers, specifically with regard to SNAP, a program which relies on the power of the income effect to improve diet quality (USDA-FNS, 2014). Although unearned income increases may not directly impact the opportunity cost of time as defined by the wage rate, there is evidence that changes in unearned income

could change perception of relative food prices, producing a substitution effect (Liebman & Zeckhauser, 2004; Smith et al., 2016). Therefore, evidence of a strong, positive relationship between income and diet quality would be necessary to justify any proposed policy which would increase SNAP budgets.

Chapter 3

Data

This study utilizes data from three continuous waves of the National Health and Nutrition Examination Survey (NHANES, 2007-12) conducted by the the NCHS in partnership with the USDA (CDC-NCHS, 2016). NHANES is designed to provide nationally representative data including demographic and socioeconomic information as well as dietary and health-related measurements for respondents. Consumption is recorded using 24-hour dietary recall, and two days of intake data are recorded for each respondent (CDC-NCHS, 2016). Our study focuses on day-one dietary recalls from adults aged 20-79 who reported two days of reliable dietary intake data.

3.1 Measuring Family Income

In this study, income is measured using a ratio of family income to the poverty threshold for a given family size. This poverty ratio can also be interpreted as a “percent of the poverty threshold” (CDC-NCHS, 2009). For example, a poverty ratio of 4 indicates that annual family income is 400% of the poverty threshold. Scaling of the poverty threshold to account for family size is one way of applying an equivalence scale to the data. The “family unit” for

this measure of income includes individuals living in a single household who are “related by birth, marriage, or adoption...[including] step parents, children, or siblings...[and] unmarried partners if they have a biological or adoptive child in common” (CDC-NCHS, 2009). It should be noted that earnings of non-related individuals residing within the household are not included in calculating family income. Survey data is truncated at a poverty ratio of 0 on the bottom end and 5 on the upper end. For reference, a poverty ratio of 5 is equivalent to a yearly income \$55,805 for a single, adult individual under the age of 65 in 2009 (roughly the middle of the time span covered by the three surveys used) (USCB). Because there are a number of respondents whose income exceeds 500% of the poverty threshold, there is considerable potential for “bunching” at the upper bound of the income distribution. There is also the issue of zero-values. Because the survey question regarding family income was worded to include income from sources such as gifts and government transfers, it is possible that some degree of misunderstanding regarding this survey question occurred for individuals reporting zero income. For these reasons, observations at 0 and 500% of the poverty threshold were excluded from analysis.

3.2 Measuring Diet Quality

Diet quality is measured using the Healthy Eating Index-2010 (HEI-2010). The HEI-2010 was designed to measure adherence to the 2010 Dietary Guidelines for Americans, the set of U.S. Government-authorized recommendations for healthy eating (Guenther et al., 2013). To calculate an individual’s HEI score, subscores are assigned for each of 12 component categories of key food groups and nutrients. The maximum score for each category ranges from 5 to 20 points and is based on the amount of a specified nutrient or type of food consumed per 1000 calories.¹ For “adequacy components,” or categories of foods and nutrients for which

¹exceptions to this include the “fatty acids” category, for which the subscore is determined by the ratio of unsaturated to saturated fats, and the “empty calories” category, for which the subscore is based on the

increased consumption is recommended to improve the healthfulness of ones diet, subscores increase with increased consumption. The opposite is true of “moderation components,” for which increased consumption leads to movement away from dietary recommendations. For example, an individual may receive the maximum score of 5 points in the “greens and beans” category if they report consuming *at least* 0.2 cups of beans, peas, and/or dark green vegetables per 1000 total calories consumed. Conversely, the maximum score of 10 points in the “sodium” category is awarded if a respondent reports consuming *no more than* 1.1 grams of sodium per 1000 total calories. Put simply, higher scores reflect more complete adherence to dietary recommendations. The composite HEI score is simply the sum of these subscores. The maximum possible composite HEI score is 100, which reflects perfect compliance with dietary guidelines. Because sub-scores are determined on a “per 1000 calorie” basis, HEI scores can be calculated over a variety of time spans and are comparable across the spectrum of caloric needs (Guenther et al., 2013).

In order to analyze substitution between high and low quality food consumption, component categories were grouped according to their classification as “adequacy” or “moderation” components in HEI score calculation. Adequacy components represent foods or food groups of which nutritionists involved in the construction of government dietary guidelines believe individuals should eat sufficient amounts in specified proportions in order to maintain good health. Components for total fruit, whole fruit, total vegetables, beans and greens, whole grains, dairy, total protein, seafood and plant protein, and fatty acid ratio are considered to be adequacy components. Moderation components are those for which nutritionists recommend restricting consumption. Moderation components are refined grains, sodium, and extra (“empty”) calories (Guenther et al., 2013).

In order to determine how foods contribute to the fulfillment of individual goals set forth in the Dietary Guidelines for Americans, we utilize the Food Patterns Equivalents Database

percentage of total calories allocated to added sugars, excess alcohol, and solid fats.

(FPED) (Bowman et al., 2014). This “recipe database” deconstructs foods and beverages into Food Patterns (FP) components, defined as either cup, ounce, or teaspoon equivalents of key food groups or nutrients (Bowman et al., 2014). For example, if a respondent reports consuming a turkey sandwich with lettuce and cheese, this can be analyzed using FPED to determine the ounce equivalents of whole or refined grains and protein foods, and the cup equivalents of vegetables and dairy provided by the sandwich.

3.3 Summary Statistics

Table 3.1 contains Day 1 summary statistics for the sample, including variables of interest as well as standard demographic variables. The mean one-day HEI score for those included in the sample is approximately 54.23. This is consistent with previous studies which suggest that average diet quality in the U.S. is far from optimal as compared to government recommended guidelines (e.g. CDC-NCCDPHP, 2009). The average ratio of household income to the family size-adjusted poverty threshold is 2.3 (or 230% of the poverty threshold). Individuals 35-60 years old and comprise the largest age group, representing 48% of the sample. Just over half of the sample is female, and the majority of the sample, 63%, is white. 32% of the sample reports as having received at least some college education, representing the largest education-level group.

As a supplement to reporting summary statistics for the entire sample, means were calculated for SNAP participants as well as eligible non-participants and non-eligible respondents. Eligibility is determined here by a poverty ratio less than 1.85. Although the income cut-off for receiving SNAP benefits is technically 1.30, a more generous income threshold has been chosen in order to better reflect the population eligible to receive in-kind benefits for the purchase of food, and to account for the fact that reported income could include SNAP benefits (SNAP and WIC). These results can also be found in table 3.1. Roughly 18% of

the sample are SNAP participants (defined as having received SNAP benefits within the past 31 days). The most notable observation to be made is that mean HEI score seems to be increasing with income, with those in the subgroups having poverty ratios above 1.85 averaging the highest diet quality score. For SNAP participants, mean HEI is lower than for eligible non-participants. However, the association between marginal income changes and changes in diet quality for each subset of respondents remains unknown.

To further explore this, we performed simple, linear OLS regressions of diet HEI on income, both for the entire sample and for subsets of respondents grouped by SNAP participation and then income level.² The results of these estimations are available in table 3.2. Regression results indicate that there is no significant relationship between income and HEI when whole sample is considered. This is an unexpected result, given previous studies regarding the correlation between income and the consumption of healthy foods (e.g. Darmon & Drewnowski, 2008). We also see no significant relationship between income and HEI for any SNAP participation or income subgroup examined. However, the parameter estimates associated with income, though statistically insignificant, do provide some insight into the relationship between income and diet quality in each income group. It appears that the association between income and diet quality is more positive in the eligible, non-SNAP participating group than for any other group, including the highest income group. Surprisingly, the parameter estimate on income is negative for the middle-income group. This could suggest that income is negatively correlated with diet quality for respondents in this group. Although the estimation method here is quite simplistic, results suggest that the association between diet and income could be different at various points along the income spectrum. These results also imply that standard, parametric estimation methods might not be capable of fully explaining the nature of the relationship between diet quality and income.

²The higher income group has been divided into two groups, in an effort to investigate how the relationship of interest changes at higher income levels

Table 3.1: Summary statistics, Adults

	Entire sample	SNAP	Eligible non-SNAP	Non-Eligible
HEI-2010	54.23 (0.30)	51.79 (0.56)	53.99 (0.38)	54.98 (0.38)
Poverty ratio	2.30 (0.04)	0.82 (0.02)	1.13 (0.02)	3.32 (0.03)
Female	0.53 (0.01)	0.61 (0.02)	0.53 (0.01)	0.51 (0.01)
<i>Education:</i>				
No high school	0.07 (0.01)	0.12 (0.01)	0.12 (0.01)	0.02 (0.00)
Some high school	0.15 (0.01)	0.30 (0.02)	0.19 (0.02)	0.09 (0.01)
High school	0.25 (0.01)	0.30 (0.02)	0.26 (0.01)	0.24 (0.01)
Some college	0.32 (0.01)	0.24 (0.02)	0.30 (0.02)	0.36 (0.01)
College or above	0.21 (0.01)	0.04 (0.01)	0.14 (0.01)	0.30 (0.01)
<i>Age:</i>				
20-34	0.32 (0.01)	0.41 (0.02)	0.38 (0.03)	0.27 (0.01)
35-60	0.48 (0.01)	0.47 (0.02)	0.42 (0.02)	0.52 (0.01)
>60	0.19 (0.01)	0.12 (0.01)	0.20 (0.02)	0.21 (0.01)
<i>Race/ethnicity:</i>				
White	0.63 (0.03)	0.47 (0.05)	0.52 (0.03)	0.73 (0.02)
Black	0.13 (0.01)	0.25 (0.03)	0.13 (0.02)	0.10 (0.01)
Hispanic	0.17 (0.02)	0.22 (0.03)	0.26 (0.03)	0.11 (0.01)
Other	0.06 (0.01)	0.05 (0.01)	0.08 (0.01)	0.06 (0.01)
Obs.	9809	1774	3638	4397

Standard errors in parentheses

Table 3.2: OLS regressions, Adults

	Entire sample	SNAP	Elig. non-SNAP	PR 1.86-2.99	PR \geq 3.00
Poverty ratio	0.25 (0.15)	0.33 (1.02)	0.86 (0.58)	-2.05 (1.67)	0.08 (0.61)
Female	2.59*** (0.33)	0.82 (0.84)	2.94*** (0.55)	2.80*** (0.71)	2.85*** (0.51)
35-60	1.40** (0.50)	0.79 (0.92)	0.59 (0.96)	0.79 (0.99)	2.80** (0.94)
>60	4.84*** (0.64)	2.38* (1.10)	3.26** (0.96)	6.60*** (1.14)	5.44*** (1.07)
Some high school	-1.05 (0.74)	-1.98 (1.43)	-0.43 (0.89)	-1.21 (1.66)	-1.29 (2.47)
High school	0.52 (0.62)	-0.79 (1.32)	0.40 (0.78)	0.25 (1.82)	1.02 (1.90)
Some college	2.32** (0.69)	2.37 (1.35)	2.19** (0.81)	2.92 (1.92)	1.34 (1.93)
College or above	5.38*** (0.89)	6.79** (2.34)	5.61*** (0.91)	4.38* (1.91)	5.24** (1.94)
Black	-0.68 (0.56)	-0.73 (1.04)	-1.01 (0.91)	-0.69 (0.94)	0.40 (0.84)
Hispanic	2.29** (0.72)	2.41* (1.10)	2.44** (0.87)	1.45 (1.26)	2.33 (1.51)
Other	1.54* (0.71)	-0.15 (1.58)	1.80 (1.15)	1.92 (1.61)	1.43 (1.14)
Constant	48.40*** (0.91)	49.99*** (1.88)	48.47*** (1.11)	53.56*** (5.01)	48.42*** (2.98)
Obs.	9809	1774	3638	2080	2317

Standard errors in parentheses, account for survey design

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

Chapter 4

Methods

Within the context of household production theory, households are considered to be utility-maximizing actors, interested in efficiently using market goods, skill, and time to produce consumption goods (Deaton & Muellbauer, 1980). Here, utility is derived from non-market consumption goods produced by the household, using time and market goods. Consider an example in which there are two consumption goods, z_1 and z_2 , which contribute to utility of the form

$$U(z_1, z_2; \tau). \tag{4.1}$$

τ is a fixed parameter representing the tastes and preferences of the household, which influence how z_1 and z_2 render utility. In this study, τ is proxied using a vector of observable demographic and human capital characteristics. We assume one good, z_1 , is more time-intensive than the other good, z_2 . For now, we can think of z_1 as “healthy” food, and z_2 as “unhealthy” food. The assumption of discrepancy in time-intensiveness between foods of different quality levels is based on previous research suggesting that higher quality meals are associated with greater time spent preparing food (Larson et al., 2006). As was previously stated, each consumption good z_i is produced using market goods, X_i , and time, t_i ,

according to a production function

$$z_i = f_i(X_i, t_i; k_i), \quad i = 1, 2 \quad (4.2)$$

where k_i is a constant efficiency or technology parameter. Here, k_i is proxied by an education variable, consistent with literature suggesting time previously invested in education is positively correlated with efficiency in production (Becker, 1965). With respect to food, this could translate to culinary skill or the ability to produce higher quality food using less time. Because individuals face a limited endowment of time in a given period, they must choose to allocate time between producing consumption goods, $(t_1 + t_2)$ or working for a wage, h as follows:

$$T = t_1 + t_2 + h. \quad (4.3)$$

The income constraint is defined by cash income, Y , which is acquired through earned labor wages w (for h units of time) and unearned income V (i.e. government transfers). The budget is distributed over market goods at prices P_i

$$Y = wh + V = P_1X_1 + P_2X_2. \quad (4.4)$$

The time and income constraints, equations 4.3 and 4.4, can be combined to form a full budget constraint.

$$F = wT + V = P_1X_1 + P_2X_2 + w(t_1 + t_2). \quad (4.5)$$

Maximizing utility with respect to this full budget constraint, the optimization problem is constructed as a Lagrangian

$$\mathcal{L} = U[f_1(X_1, t_1; k_1), f_2(X_2, t_2; k_2); \tau] + \lambda[wT + V - P_1X_1 - P_2X_2 - w(t_1 + t_2)] \quad (4.6)$$

where λ represents the marginal utility of full income. The first order conditions resulting from this optimization are

$$\mathcal{L}_{X_i} : MU_{z_i} MP_{X_i} = \lambda P_i \quad (4.7)$$

$$\mathcal{L}_{t_i} : MU_{z_i} MP_{t_i} = \lambda w \quad (4.8)$$

$$\mathcal{L}_\lambda : wT + V = P_1 X_1 + P_2 X_2 + w(t_1 + t_2) \quad (4.9)$$

Here, MU is the marginal utility of a consumption good z_i and MP is the marginal product of either a market good X_i or time. Taking the ratios of (4.7) and (4.8), we find the shadow price of z_i .

$$\pi_i(w, P_i; k_i) = MC_{z_i} = \frac{w}{P_i} = \frac{MP_{t_i}}{MP_{X_i}}. \quad (4.10)$$

Thus, we see that MC_{z_i} , the marginal cost of producing z_i , is a function of the opportunity cost of time (w), and the price of market goods (P_i) conditional on efficiency (k_i).

It should be noted that several assumptions are made here about the production functions for consumption goods. The simplest of these is that production functions are concave and free of fixed costs. It is further assumed that the production functions have constant returns to scale, or that they are homogeneous of degree one in both market inputs and time. Finally, we assume that both market and time inputs can be additively divided among production processes for each consumption good (Deaton & Muellbauer, 1980). This non-jointness assumption implies that no utility is directly derived from the purchase of market inputs or from time spent producing any consumption good z_i . Because it is feasible that an individual could derive some satisfaction from the active production of consumption goods (e.g. an individual who enjoys cooking), the assumption of nonjointness has been criticized as being overly restrictive (Pollak and Wachter, 1975). However, placing such restrictions on household production functions allows for a more tractable model by giving rise to three important implications: (1) independence of the relationship between individual preferences

and the budget constraint, (2) linearity of the budget constraint in z -space, and (3) reduction of the dimensionality of the problem to the number of consumption goods, thus simplifying analysis with regard to the impact of changes in wages, input prices, and endowments on demands.

With these assumptions in place, the new budget constraint is linear in consumption goods and their (shadow) prices (Deaton & Muellbauer, 1980).

$$F = wT + V = \pi_1 z_1 + \pi_2 z_2. \quad (4.11)$$

The optimization problem is now

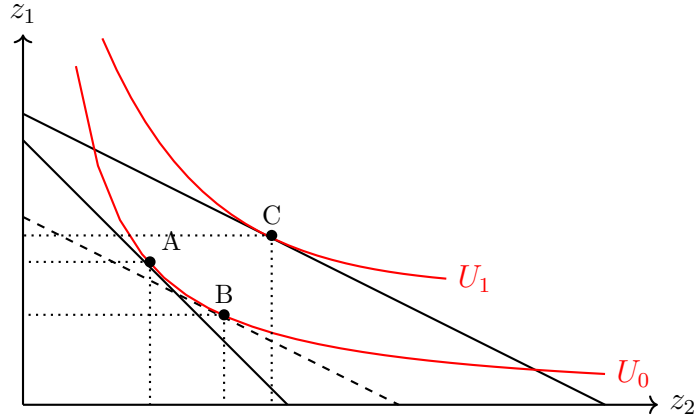
$$U = U(z_1, z_2; \tau) \quad \text{s.t.} \quad F = \pi_1 z_1 + \pi_2 z_2 \quad (4.12)$$

Keeping the nonjointness assumption in mind, the reduced-form demands for consumption goods are functions of the input prices conditional on taste and efficiency parameters. Thus, solutions to the above optimization problem can be written as:

$$z_i^* = z_i(\pi_1, \pi_2, F; \tau, k_i) = z_i(P_1, P_2, w, F; \tau, k_i). \quad (4.13)$$

This study investigates the relationship between marginal increases in overall income and associated diet quality changes. By decomposing the effect of a wage increase, we better understand how substitution and income effects occur for more and less time-intensive consumption goods.

Figure 4.1 depicts an increase in the wage rate from w to w' . An increase in the wage rate represents an increase in the opportunity cost of time. Because the budget constraints are linear, they also represent the ratio of the shadow prices of z_1 and z_2 , $\frac{-\pi_2}{\pi_1}$. This ratio changes with the cost of time, resulting in a change in the slope of the budget constraint.



Note: z_1 is higher quality food, which is relatively more time intensive to produce.

Figure 4.1: Impact of a wage increase in the z -space.

Therefore, a cost-minimizing actor will substitute away from producing a more time-intensive good, z_1 (moving from A to B). The wage increase will also increase the overall budget, pushing the constraint outward, and resulting in an income effect (moving from B to C). Considered together, these effects result in a movement from A to C and an increase in utility from U_0 to U_1 . Considering that z_1 and z_2 represent high- and low-quality foods respectively, a substitution away from z_1 should result in a decrease in overall diet quality as measured by the HEI, while the income effect will result in an increase in diet quality through increased consumption of z_1 . Whether the income effect outweighs the substitution effect is an empirical question.

4.1 Empirical Model

As was previously stated, the HEI-2010 has a known functional form that is assumed to be a valid measure of latent diet quality (Guenther et al., 2013),

$$DQ^* = HEI = f(z_1, \dots, z_{12}) = \sum_{j=1}^n z_j, \quad (4.14)$$

where DQ^* is true diet quality, HEI is the HEI-2010, and z_j is the j^{th} component of the HEI. Each subscore of the HEI is a linear function of a specific food attribute,

$$z_j = \sum_i b_{ji} x_i, \quad (4.15)$$

where each food x_i contains b_{ji} units of the j^{th} component of HEI. However, as it applies to the previously outlined model of household production, each subscore can be interpreted as a consumption good, produced using foods. These foods are the product of purchased ingredients, X and time t . This is to say that, although time is not explicitly included in the calculation of subscores, it influences the translation of market goods to food, and subsequently to diet quality. Subscores as consumption goods are simply linear transformations of foods as consumption goods, created by dividing foods into specific nutritional attributes. Because we have assumed constant returns to scale in production, we can continue to apply the theoretical framework outlined in the previous section.

With regard to our study, consumption goods are be interpreted as either the total HEI score, or adequacy and moderation groups of HEI component categories, where utility is a function of diet quality. Given that adequacy and moderation scores are additive combinations of component scores, we can simply consider the sum of all quantities of the given nutritional components which determine the scores in the adequacy categories to be a composite “adequacy feature,” b_a . The same can be said for the moderation categories, for which

the defining feature will be b_m . With this framework in mind, we can observe how households substitute between high and low quality food categories as the budget frontier moves outward.

It should be noted that the moderation component, z_m , is inversely related to consumption of “unhealthy” foods. Still, it remains a representation of an individual’s standing with regard to consumption of low-quality food items in accordance with government standards.

Consumption of these energy-dense, nutrient-poor foods is more often associated with low-income individuals than those in higher income groups, suggesting that people substitute away from these foods as incomes increase (Darmon & Drewnowski, 2008, Deaton & Muellbauer, 1980). Knowing this, one would expect both the adequacy and moderation scores to increase with income. However, considering that an increase in wage rate (the opportunity cost of time) has been found in previous research to be associated with substitution toward the production of less time-intensive meals, and that this likely translates to the production of lower quality foods, we might expect some non-linearities in the relationship between income and HEI subscores (Huffman, 2011; Larson et al., 2006). This implies that preferences for adequacy and moderation components could be nonhomothetic (Deaton & Muellbauer, 1980). With regard to unearned income in the form of SNAP benefits, there is research to suggest that, even with endowment increases (as opposed increases in wage rate), the perceived price of groceries could change relative to food purchased elsewhere due to a lack of fungibility between SNAP dollars and cash, resulting in a substitution effect which could also result in nonlinear relationships between income and aspects of diet quality (Leibman & Zeckhauser, 2004; Smith et al., 2016). Given that HEI is an additive function of components from both high and low quality food categories, the relationship between total HEI and income is also likely to be nonlinear, thus motivating the use of nonparametric methods to examine this association (Guenther et al., 2013). Assuming that all consumers face the same vector of prices, estimating the relationship between income and diet qual-

ity using nonparametric methods would allow us to estimate an “income elasticity” of diet quality at varying points along the income spectrum, and then determine if these estimates vary significantly from one another.

4.1.1 Local Polynomial Regression Analysis

As was suggested in previous sections, there is reason to believe that standard regression procedures may be ill-equipped to account for non-linearities in the relationship between income and diet quality. For this reason, this study utilizes semiparametric methods, a combination of purely nonparametric estimation and standard linear regression (Cameron & Trivedi, 2005).

Semiparametrics are preferable in this case for many reasons. First, the method is data-driven, meaning that we are able to estimate the “shape” of the relationship between income and diet quality without having to choose a functional form. This means that “elasticity” estimates will be more accurate, as compared to those for a linear model with higher-order terms added on a subjective basis (Cameron & Trivedi, 2005). Additionally, semiparametric methods permit the researcher to benefit from the accuracy of estimating one dimension of a model nonparametrically, while allowing covariates to enter parametrically, effectively acting as slope shifters. For this study, our measure of income enters the model in the nonparametric dimension, and demographic variables such as sex, race/ethnicity, age group, and SNAP participation are included linearly as follows

$$HEI = X'\beta + \lambda(y) + u. \tag{4.16}$$

where $\lambda(\cdot)$ is an unknown function, for which functional form is not assumed, y is income, as measured by the ratio of household income to the poverty threshold, and X is a vector of covariates with a vector of associated parameters β .

For the nonparametric dimension of the model, we utilize local polynomial regression. Local polynomial regression is a special type of kernel regression, a weighted running average method. This method was developed to yield smooth estimations for the case where there is a continuous independent variable for which the number of associated values of the dependent variable may vary. To accommodate for this, a “neighborhood” or bandwidth, h , is defined around a given value of the independent variable, x_0 . Observations within this neighborhood are then weighted according to a kernel function such that observations further from x_0 are given less weight, where the kernel weight for a given value of x is $m(x)$. A weighted least squares regression is then conducted at each evaluation point. For local polynomial regression, $m(x)$ is equal to a polynomial rather than a constant, as with local linear regression, to remedy boundary problems and allow for an even smoother estimation of the relationship in question. This study utilizes a local polynomial estimator of degree 2, is written as

$$\sum_{i=1}^N K\left(\frac{x_i - x_0}{h}\right) \left(y_i - a_{0,0} - a_{0,1}(x_i - x_0) - a_{0,2}\frac{(x_i - x_0)^2}{2}\right)^2 \quad (4.17)$$

yielding the point estimate of $\hat{m}^{(2)}(x_0) = \hat{a}_{0,0}$. K is the chosen kernel. Here, the optimal Epanechnikov kernel has been chosen (Cameron & Trivedi, 2005).

To estimate the parametric portion of the model, a differencing method outlined by Yatchew in 2003 was applied to the data. Intuitively, differencing relies on the assumption that, when ordered according to values of the variable entering the model nonparametrically, consecutive values values of the estimated function will occur very close together. Therefore, differencing the model allows the nonparametric dimension to simply “fall out” of the model, enabling estimation of the linear parameters which remain. To accomplish this quickly for large data sets, Yatchew suggests applying a “differencing matrix,” D to the model, such

that we have

$$D \cdot HEI = DX'\beta + D\lambda(y) + Du \cong DX'\beta + Du. \quad (4.18)$$

Predicted values of the dependent variable from this first-stage regression are then subtracted from observed values to create a new dependent variable, HEI^* . HEI^* is net of variation that can be attributed to variables within X . Nonparametric estimation of HEI^* is then performed via local polynomial regression according to the equation

$$HEI - X'\hat{\beta} = HEI^* = \lambda(y) + u. \quad (4.19)$$

The same procedure is applied to analyze the association between income and the adequacy and moderation components of HEI by simply replacing the HEI with the appropriate grouping of subscores as the dependent variable. Local polynomial regression estimates are achieved using the `lpoly` package for Stata 14 statistical software. The optimal bandwidth is automatically calculated and applied by the software (using the rule-of-thumb value) for each estimation.¹

In order to confirm that nonparametric estimation is appropriate, procedures consistent with recommendations by Yatchew (2003) are employed to test the semiparametric regression against linear regression.

Finally, to compare the association between income and diet quality across income levels and subgroups of the sample, we first calculate point estimates numerically for the first derivative of the local polynomial regression at specific income levels, consistent with Rilestone and Ullah (1989), as follows:

$$\hat{f}'_s(x) = \frac{1}{2h}(\hat{f}_s(x+h) - \hat{f}_s(x-h)) \quad (4.20)$$

¹Although technically sub-optimal, the rule-of-thumb bandwidth is used due to computational and practical limitations. The bias imposed is negligible (Yatchew, 2003).

where $\hat{f}_s(x)$ is the point estimate, $\hat{a}_{0,0}$, given by function s at a specified income level, and $h \rightarrow 0$ with increasing sample size. For the sake of simplicity in calculation, h is held equal to .1. Due to computational limitations associated with obtaining predicted function values at every observed income value, first derivative estimates are calculated using estimated function values at every ten percentage points of the poverty threshold, thus reducing the number of income observation values to 49, and necessitating the use of a higher bandwidth. Further, it is customary to estimate derivatives using an oversmoothed function (Yatchew, 2003). For this purpose, rule-of-thumb bandwidths are increased by a factor of 1.1 for each estimation. It should be noted that this necessary oversmoothing, combined with the decreased number of income level observations increases the possibility for bias in estimation of the function and is therefore only applied during the generation of first derivative estimates and related calculations (Yatchew, 2003).

In order to obtain a more interpretable measure of association between income and dietary quality, first derivative estimates are used to calculate elasticities

$$\hat{e}_s = \hat{f}'_s(x) \frac{x}{\hat{f}_s(x)} \quad (4.21)$$

where $\hat{e}_{s,x}$ is the estimated elasticity at income level x using function s . These elasticities, loosely interpreted as indicators of the strength and direction of association between income and diet quality, can be contrasted across income levels and demographic groups.

Chapter 5

Results

The first hypothesis to be tested is that of whether the relationship between income and diet quality is indeed nonlinear for our sample, once covariates have been considered. Based on results of the test comparing the semiparametric model to a linear model, it seems that the true relationship between income and diet quality (for the entire sample) differs enough from the linear model to justify the use of semiparametric methods (the p-value for the test statistic is .000077, far below the threshold for significance at the 95% level). Given this, we can move on to more detailed examination of the estimated functions for both the sample as a whole, as well as for specific attributes of diet quality and subsamples of the larger sample group. Elasticity estimates are depicted graphically in figures 7.11-7.20. Taken in combination with depictions of the estimated function for each subgroup one can gain a more detailed understanding of how the relationship between HEI (or subsets of HEI) and income changes with marginal income increases.

The estimated relationship between HEI score and income for the entire sample is depicted in figure 7.1. Consistent with earlier test results, the association appears to be very nonlinear, with a strong, positive association between diet quality and income occurring in the areas around 100 and 350% of the poverty threshold, and a negative association occurring

at the upper and lower extremes of the income spectrum, as well as in the range between 150 and 300% of the poverty threshold. This result is also reflected in the elasticity estimates depicted in figure 7.11, where we see a positive elasticity in the function at both lower and higher ends of the income spectrum, and a negative elasticity at the center of the range. For individuals whose income is equal to the poverty threshold (poverty ratio=1), a 1% increase in poverty ratio (approximately \$123.31 annually for a single individual under the age of 65 in 2015) is associated with a 0.019% increase in HEI score. A 1% increase in poverty ratio at 200% of the poverty threshold is associated with a decrease in HEI score of 0.008. This suggests that, for individuals at the lower and higher ends of the income spectrum (with the exception of those at extreme high and low income values¹) marginal increases in income are associated with improved diet quality as measured by HEI scores. This does not seem to be the case for respondents in the center of the income spectrum. Although this may seem counter-intuitive, examination of the estimated relationship between adequacy and moderation components and income is helpful in explaining the shape of the diet quality-income association.

As can be seen in figure 7.2, it appears that increases in income are more positively related to moderation component scores at lower income levels and adequacy component scores at higher income levels. This implies that improvements in diet quality associated with increasing income are likely due to decreased consumption of “unhealthy” foods at lower income levels, and increased consumption of “healthy” foods at higher income levels. In the middle of the income range, however, we see a strong negative association between income and moderation component scores (with an estimated elasticity of the moderation function of -0.017 at 200% of the poverty threshold). Applying theoretical framework outlined in the

¹Although choosing a local polynomial approach lessens bias at extreme values of the independent variable, the bias is not completely eliminated. It is customary in nonparametric analysis to place more emphasis on results at non-extreme values of the independent variable where estimates are less vulnerable to bias resulting from border problems (Yatchew, 2003).

previous section, one can suppose that this is due to an increase in consumption of lower-quality, less time-intensive foods (e.g. highly processed foods or FAFH) as the opportunity cost of time increases with wage. This effect is likely offset by a positive income effect on the consumption of high-quality foods at the upper end of the income spectrum.

5.1 Dividing analysis by population groups

Dividing the sample based on demographic characteristics provides insight regarding how the association between income and HEI score changes across groups. Figure 7.3 suggests that women exhibit more variation than men in how income relates to diet quality as income changes, given that the estimated function for women is highly non-linear, like that for the entire sample, while the estimated function for men appears nearly linear in shape. When comparing across education groups, in figure 7.4, the most interesting observation to be made is that a negative association between income and diet quality toward the center of the income spectrum occurs primarily for respondents with some level of college education. If we assume that wage increases with education level, this supports the idea that the downward-sloping section of the overall function can be attributed to increased opportunity cost of time. Breaking down the sample by age, figure 7.5, we see that the positive association between income and diet quality at lower income levels is strongest for respondents older than 60, while the negative association in the middle of the income range only occurs for those in the 20-34 age group. Income is positively associated with diet quality between 300 and 400% of the poverty threshold for all three age groups. When race-ethnicity is considered in figure 7.6, both the positive association at lower income levels and the negative association at moderate income levels is strongest for white respondents, while the positive elasticity at higher income levels is present among black respondents. This can be seen more clearly in figure 7.7.

5.2 SNAP comparisons

In order to provide an appropriate comparison between SNAP participants and eligible non-participants, only the income range between the poverty ratios of 0 and 1.85 was considered. As before, elasticities were evaluated along the observed income interval. Although the estimated functions in figure 7.8 appear flat, observation of the elasticities presented in figure 7.18 indicate that diet quality improvements associated with marginal income increases are higher for non-SNAP participants than for SNAP beneficiaries below approximately 75% of the poverty threshold. However, there is evidence that the difference in elasticity between the two groups is insignificant at this range of income levels. For participants in the area surrounding the poverty level, diet quality elasticity is much higher than for non-participants. As one approaches the upper bound for eligibility, the association between diet quality and income becomes negative for SNAP beneficiaries. This suggests that the association between SNAP participants' diet quality and marginal income changes is only positive and stronger than that of eligible non-participants at income levels far below the upper bound for benefit eligibility, namely, income levels surrounding the poverty threshold. Comparing substitution between adequacy and moderation components of HEI across SNAP and eligible non-SNAP respondents, it appears that the improvements diet quality for SNAP participants associated with income increases around the poverty threshold correspond with higher elasticities in moderation component scores and smaller, but still positive elasticities in adequacy scores.

Chapter 6

Conclusions

Based on the results presented here, there is evidence that the correlation between diet quality and income varies significantly across income levels. These estimations also indicate that the degree to which this association varies is observably different for individual subsets of the population. Perhaps most importantly, it seems that the association between diet quality and income is positive and significant at low income levels, providing support for policies aimed at improving diet quality outcomes by increasing food purchasing power for this group. Even for SNAP participants, for whom diet quality is shown in this study to be lower on average, the association between diet quality (as well as the adequacy and moderation components of diet quality) and income is positive at lower income levels. Although predicted elasticities suggest apparently small diet quality changes for marginal income increases, it is pertinent to note that research exists which shows that even very small increases in diet quality are associated with significant improvements in health outcomes, with higher scores for multiple variants of the HEI scoring system ¹ correlating with reduced risk of death by any major, chronic disease (e.g. cardiovascular disease, coronary heart disease, stroke, diabetes, and cancer) (Chiuve et al., 2012).

¹HEI-2005 and the Alternative HEI-2010

An example of a policy approach compatible with the results of this study can be found in the Healthy Incentives Pilot (HIP). The HIP program effectively increased participants grocery budget by reducing the price of specific fruits and vegetables when purchased by SNAP participants (USDA-FNS, 2014). Results of this pilot show an increase in consumption of targeted food items after implementation of the program (USDA-FNS, 2014). Although this program only increased grocery budgets with respect to fruits and vegetables, if we consider that food purchased from the grocery store and prepared at home is, on average, of higher quality than foods purchased away from home, then the same general idea can be applied to the overall SNAP budget, which can only count toward grocery purchases (Lin & Guthrie, 2012, USDA-FNS, 2014). Given what our study shows about the relationship between diet quality and income, an increase in food purchasing power among low-income populations, such as that benefiting from SNAP, is likely to be correlated with increased diet quality for those most in-need.

6.1 Limitations and Future Research

A number of limitations are observable in this study, the first of which is the necessity of using aggregate data in the absence of appropriate panel data. Since diet quality observations do not correspond to one individual over a range of income levels, we are not technically observing the diet quality response of individuals as incomes increase (Deaton and Muellbauer, 1980). We are merely estimating the association between income and diet quality for the sample population.

This study is also limited by the absence of price data, which would allow for a more complete disentanglement of substitution and income effects. The inclusion of prices would also allow the researcher the opportunity to determine what portion of the substitution effect can be attributed to observable relative price differentials, and what portion could be

connected to the opportunity cost of time in household production.

If this line of research is to be applied to the formulation of nutrition-based welfare policy, future studies should strive to further understand the effect of unearned income (such as government transfers) on the perceived opportunity cost of time as well as the effect of incomplete fungibility between earned and unearned income in order to better understand substitution effects between high- and low-quality foods as unearned income changes.

With regard to nonparametric estimation methods, results presented here would benefit from the application of cross-validation methods to ensure optimal bandwidth choice (Yatchew, 2003).

Chapter 7

Additional Figures

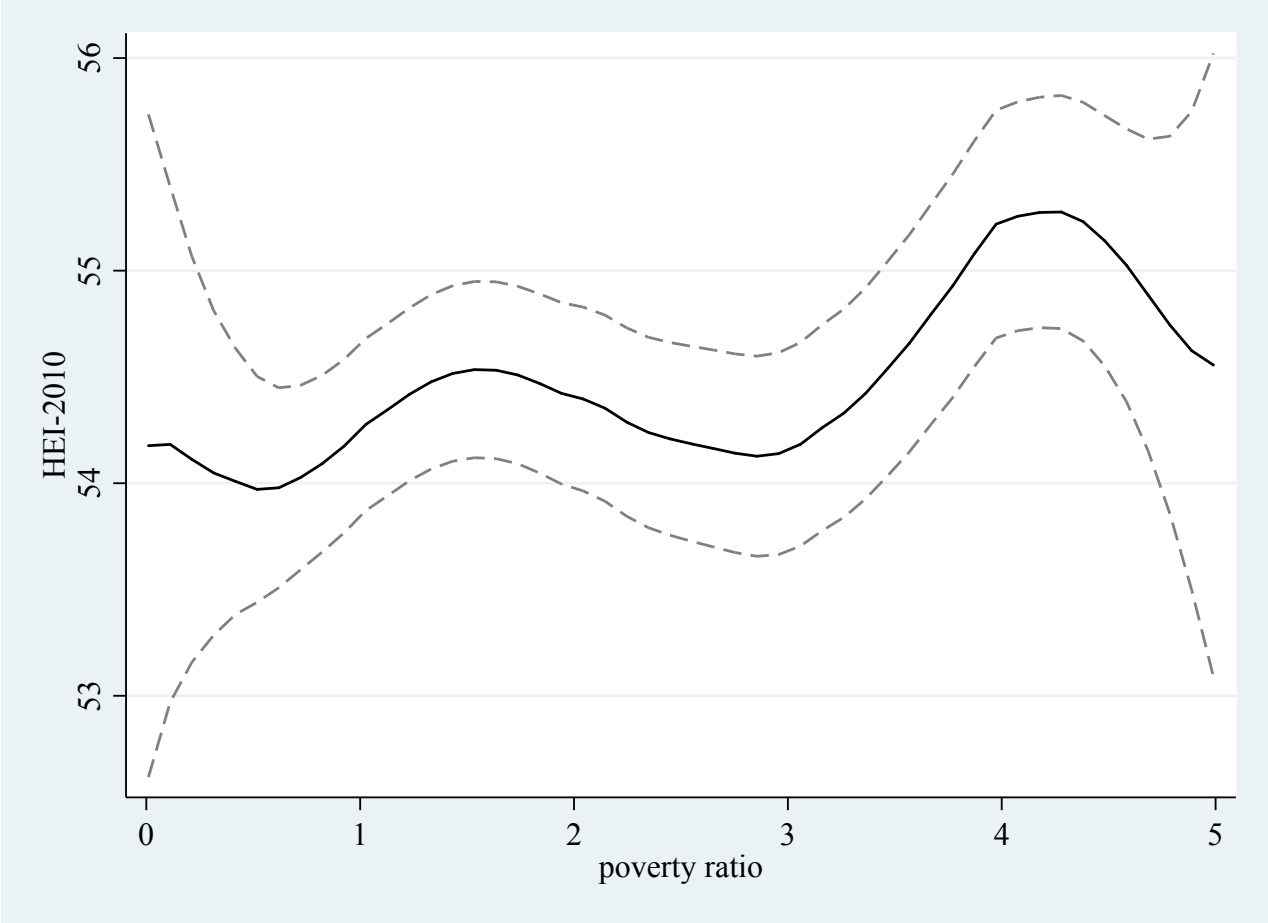


Figure 7.1: Local polynomial estimation, Entire sample

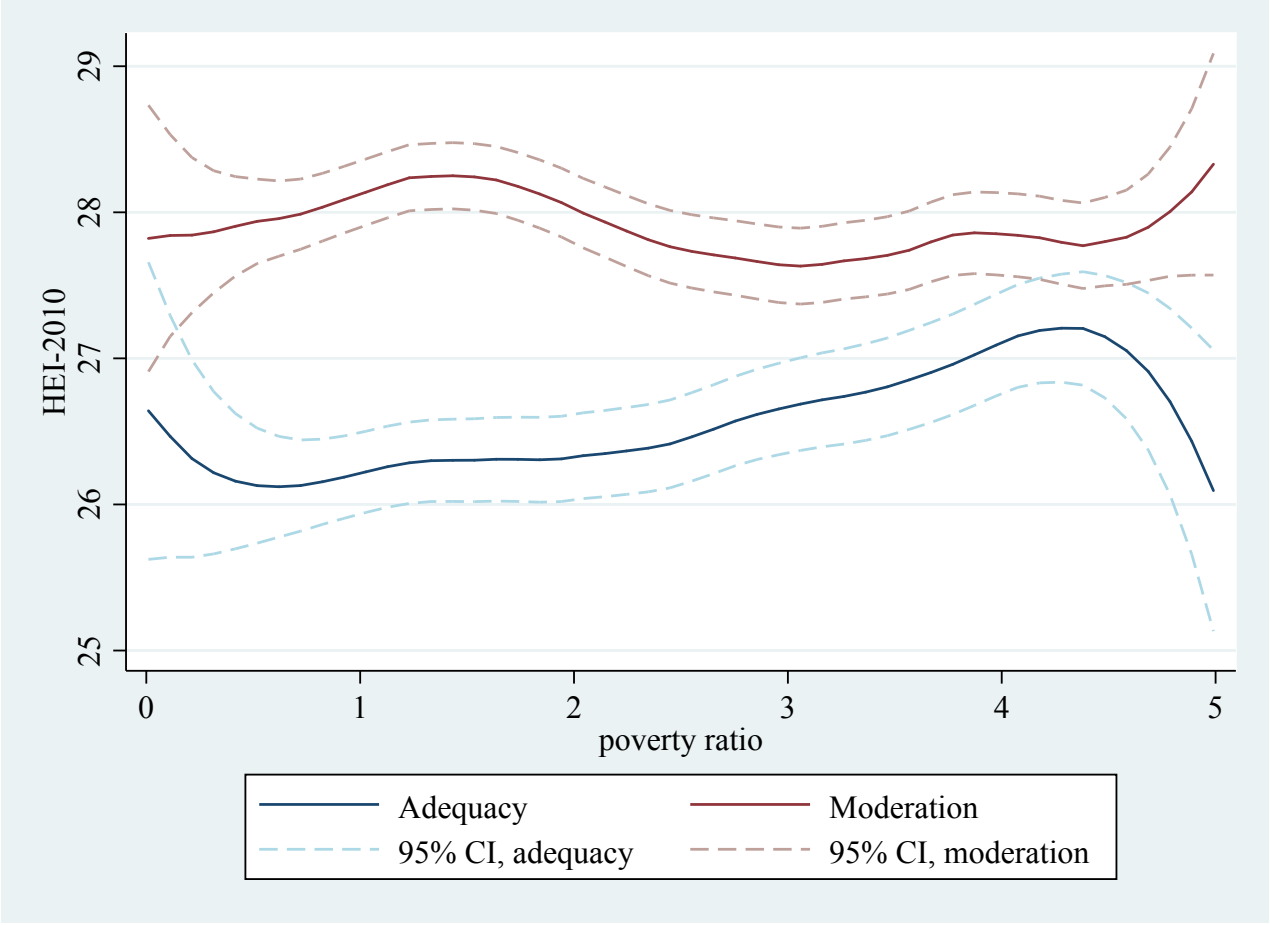


Figure 7.2: Adequacy vs. moderation, Entire sample

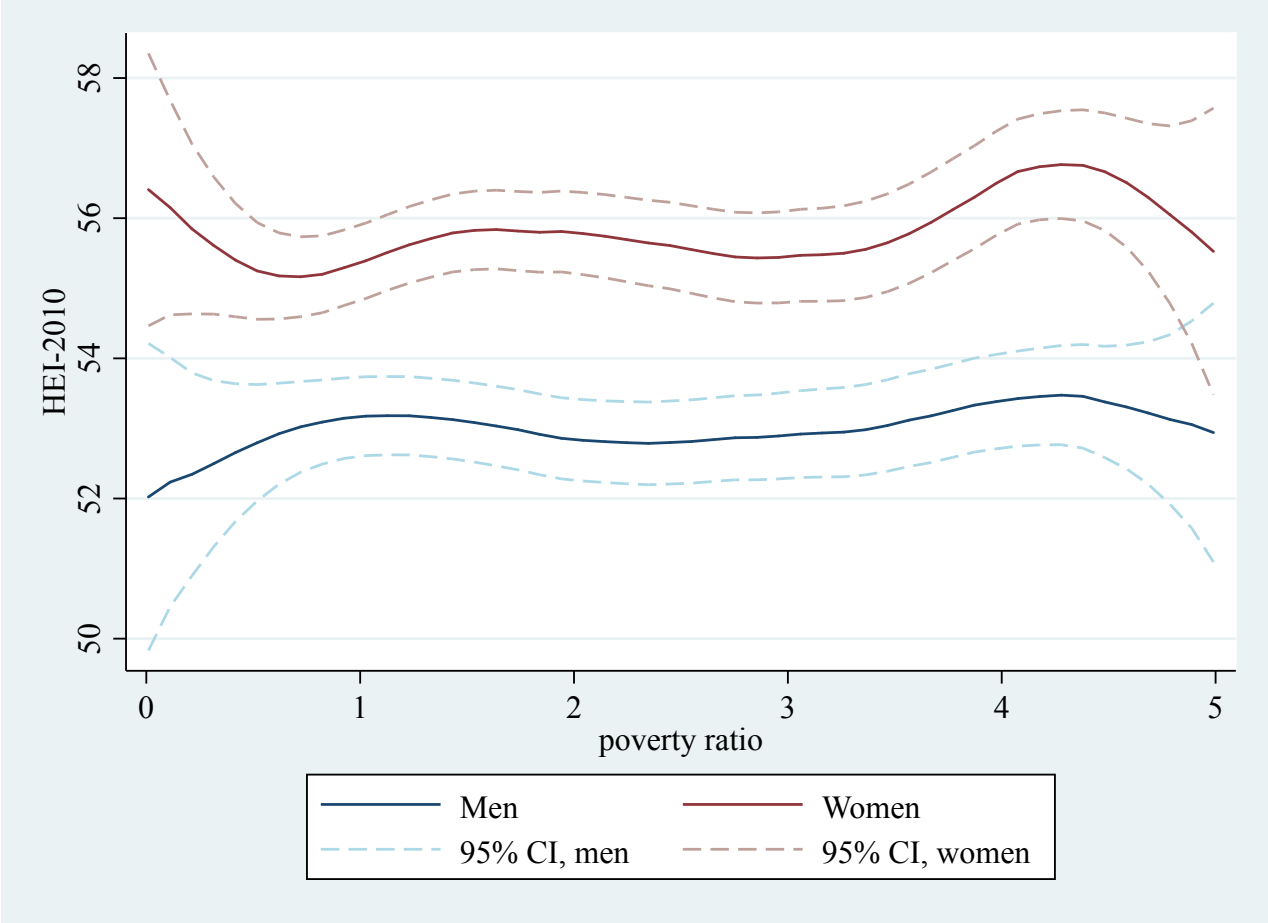


Figure 7.3: Men vs. women

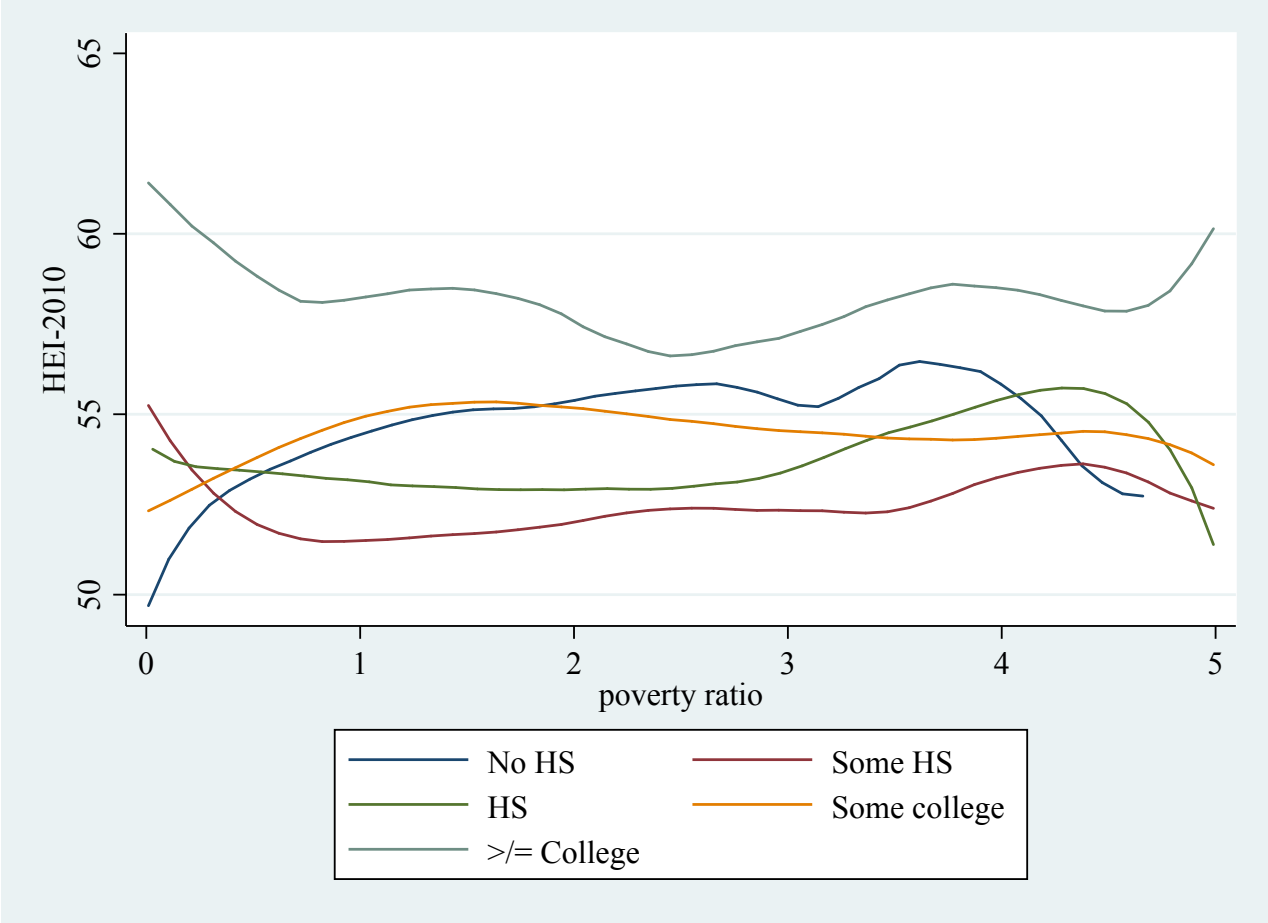


Figure 7.4: Education level

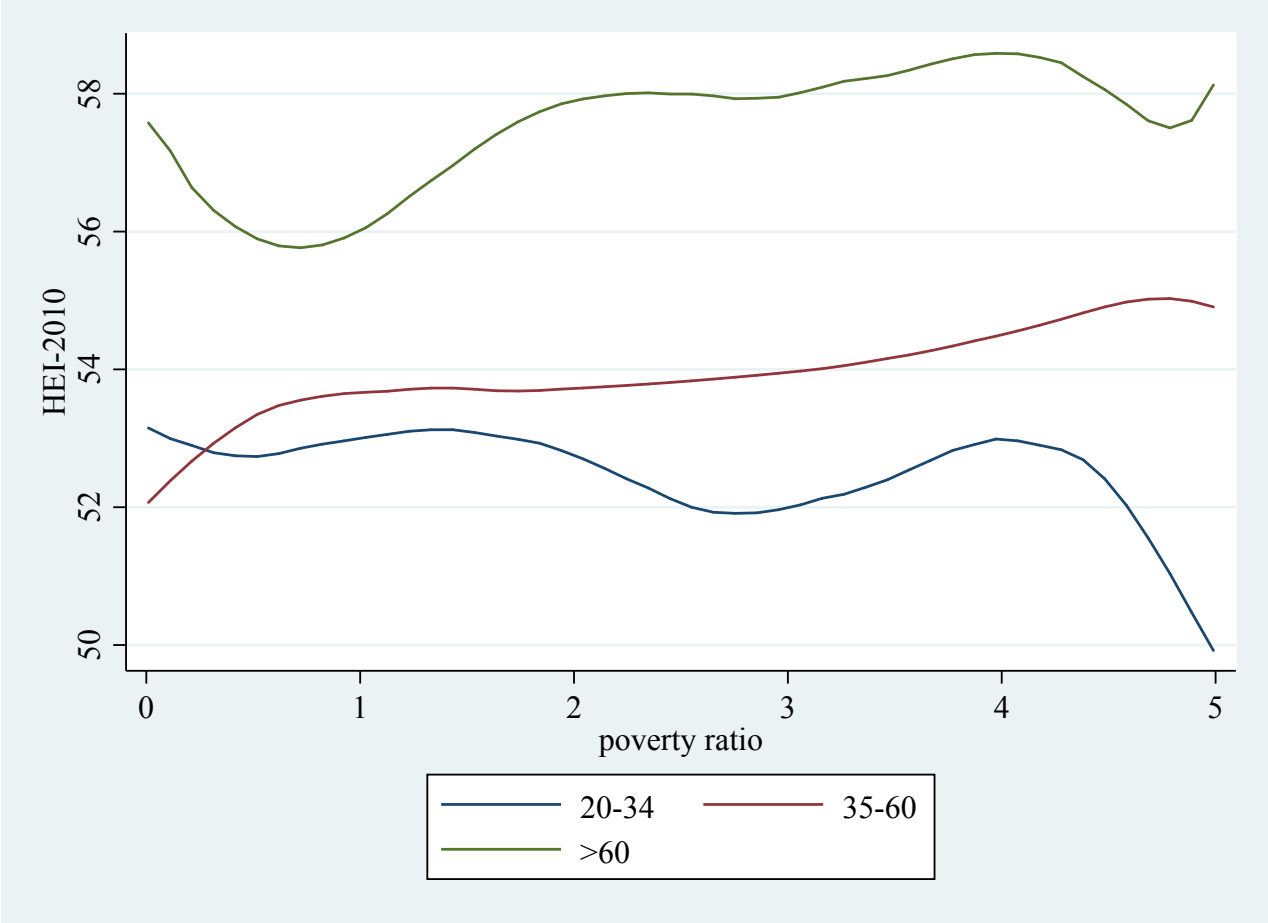


Figure 7.5: Age category

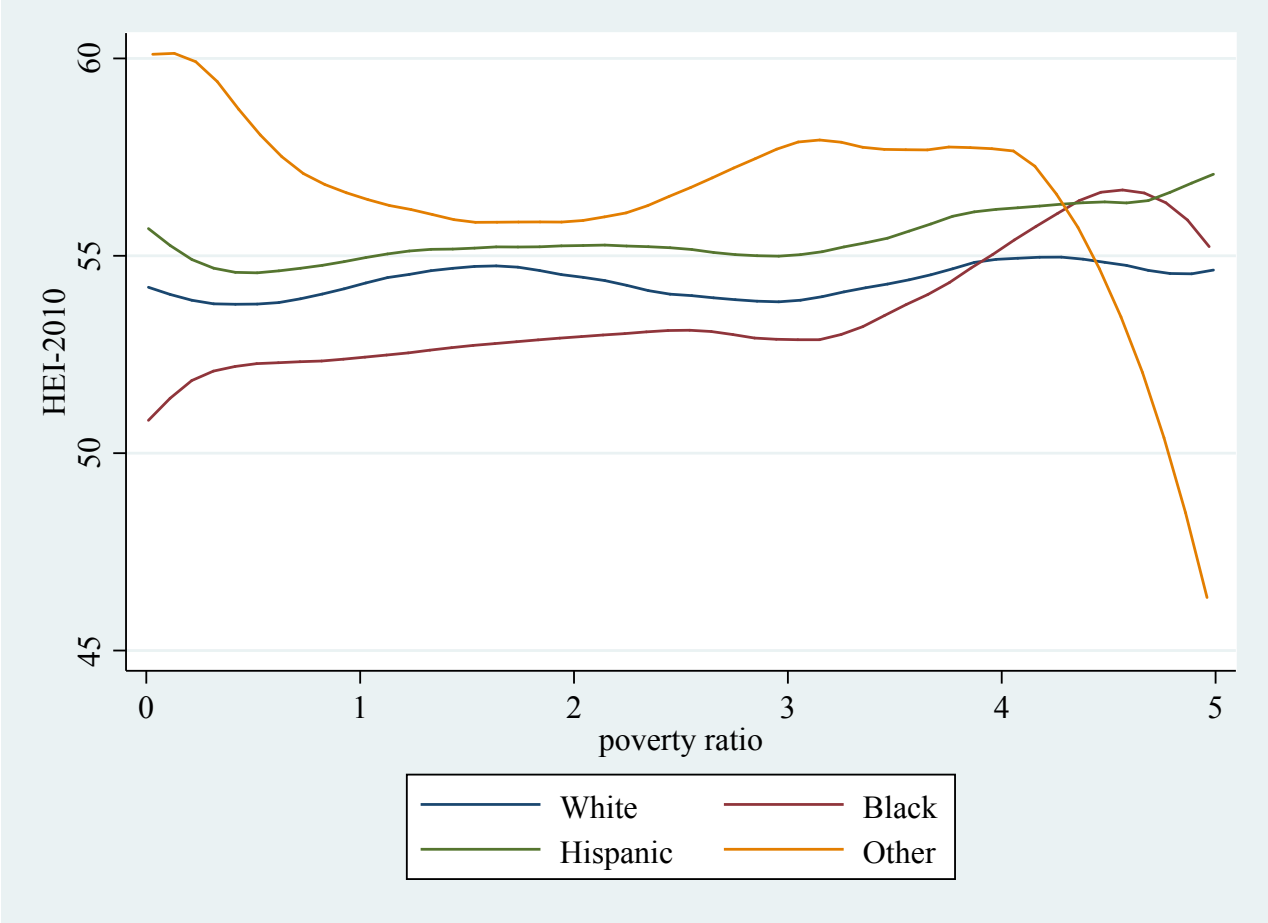


Figure 7.6: Race\ethnicity

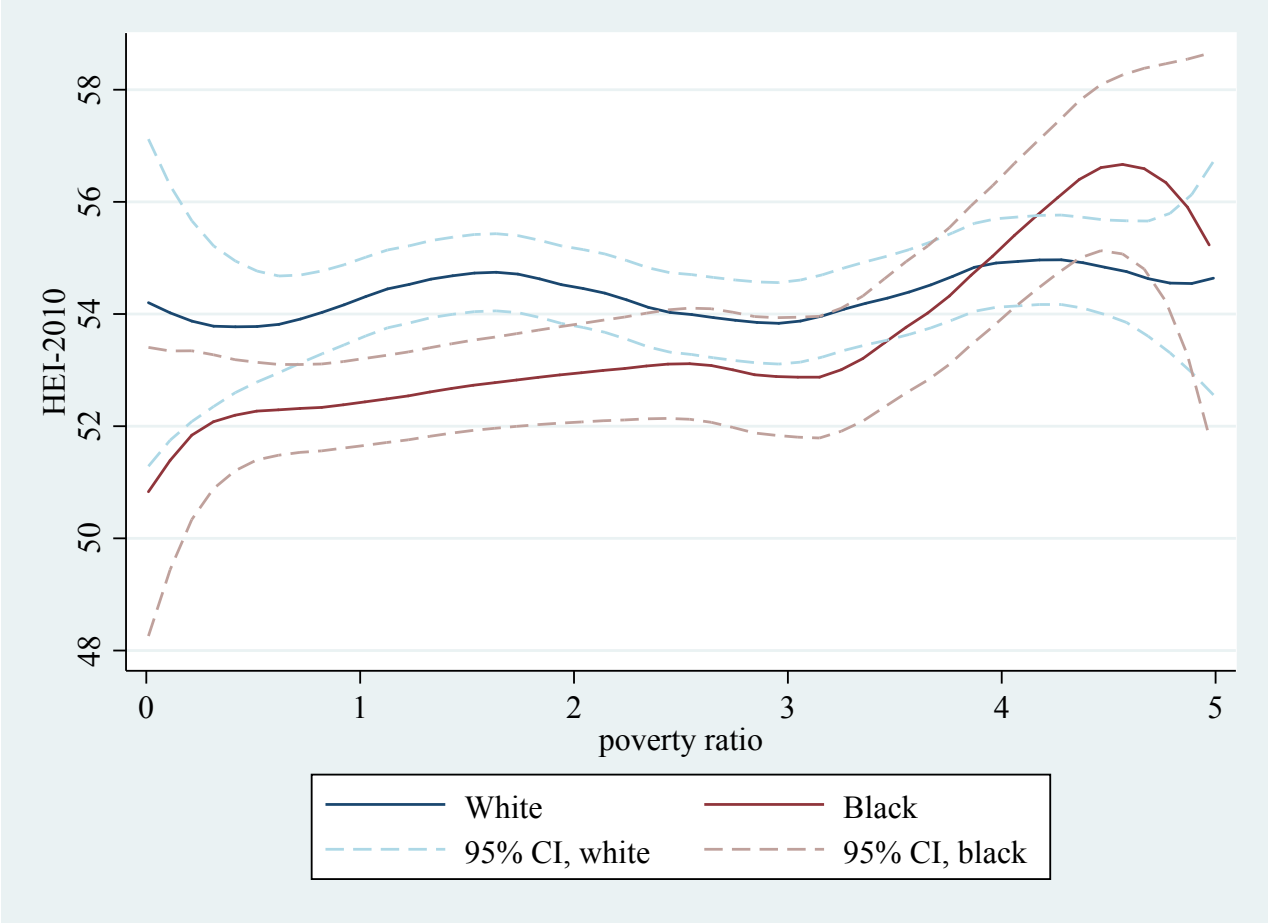


Figure 7.7: White vs. black respondents

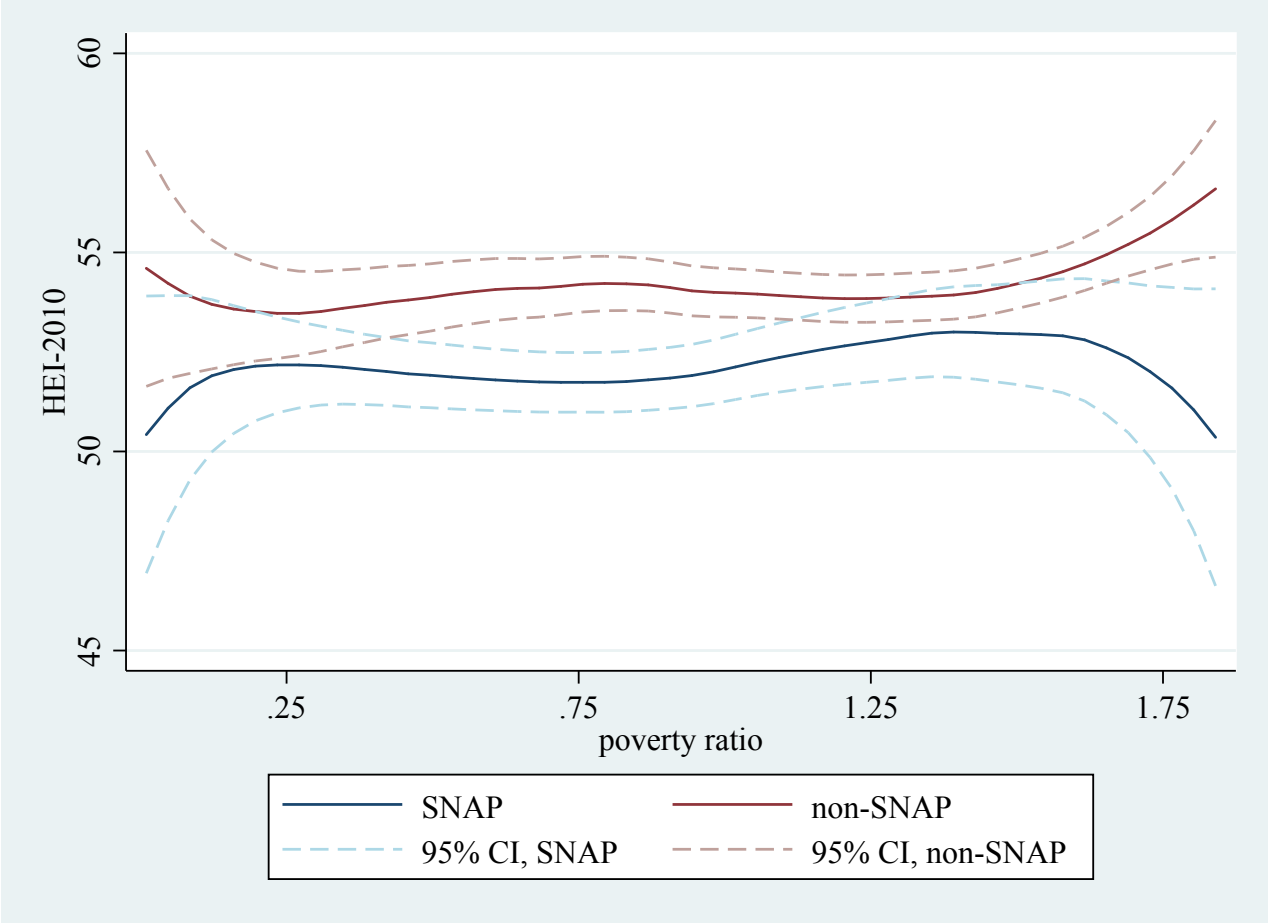


Figure 7.8: SNAP vs. eligible Non-SNAP

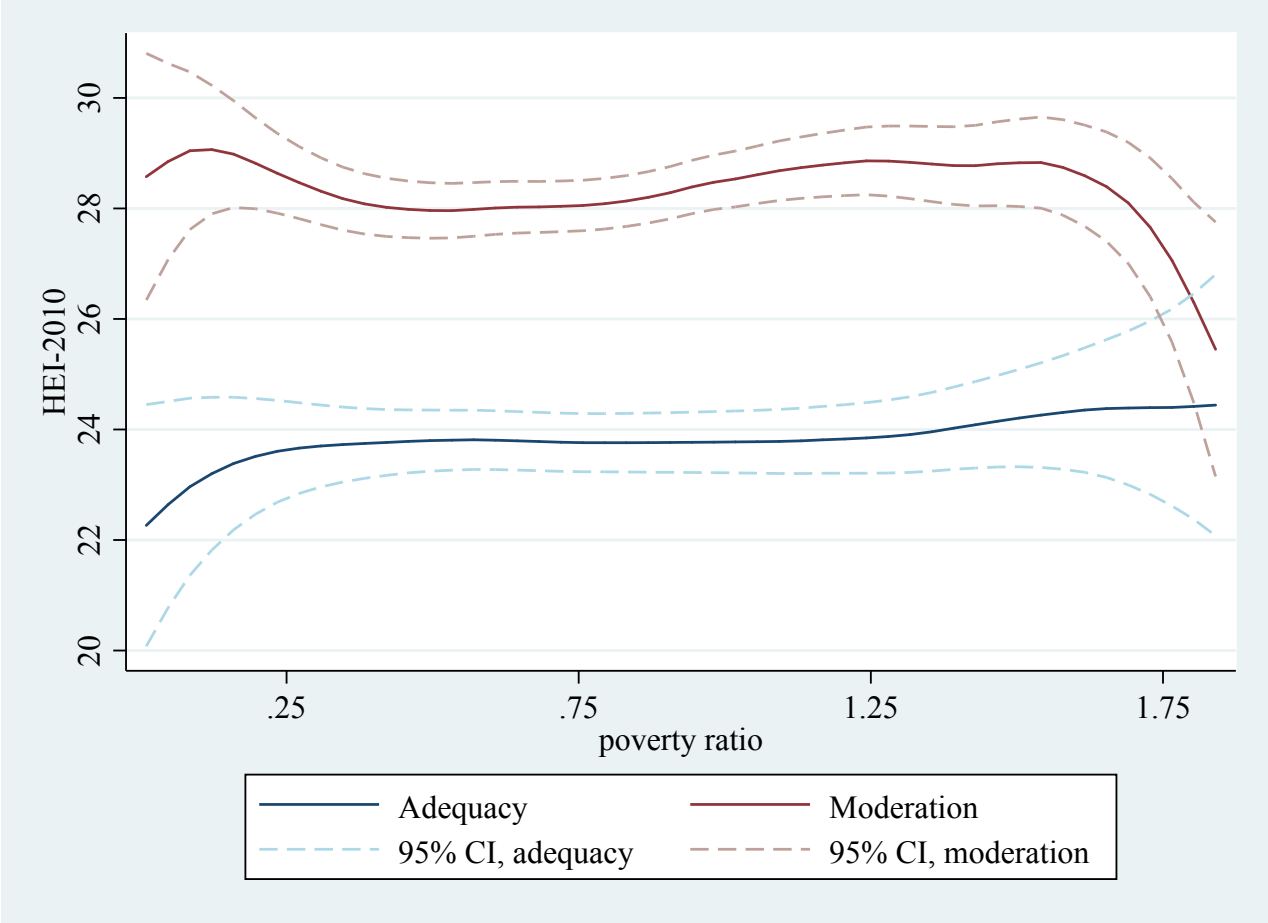


Figure 7.9: Adequacy vs. moderation, SNAP

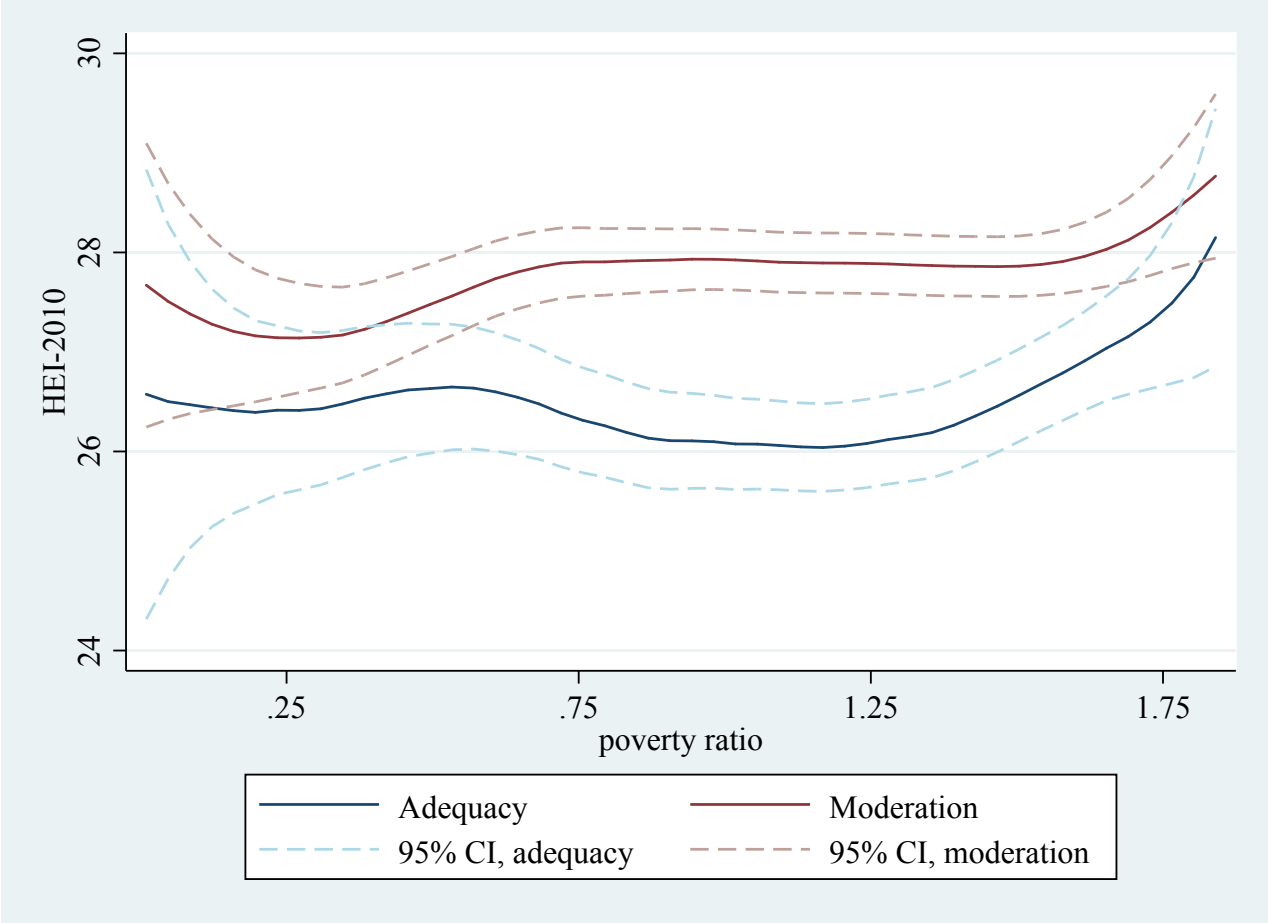


Figure 7.10: Adequacy vs. moderation, Eligible non-SNAP

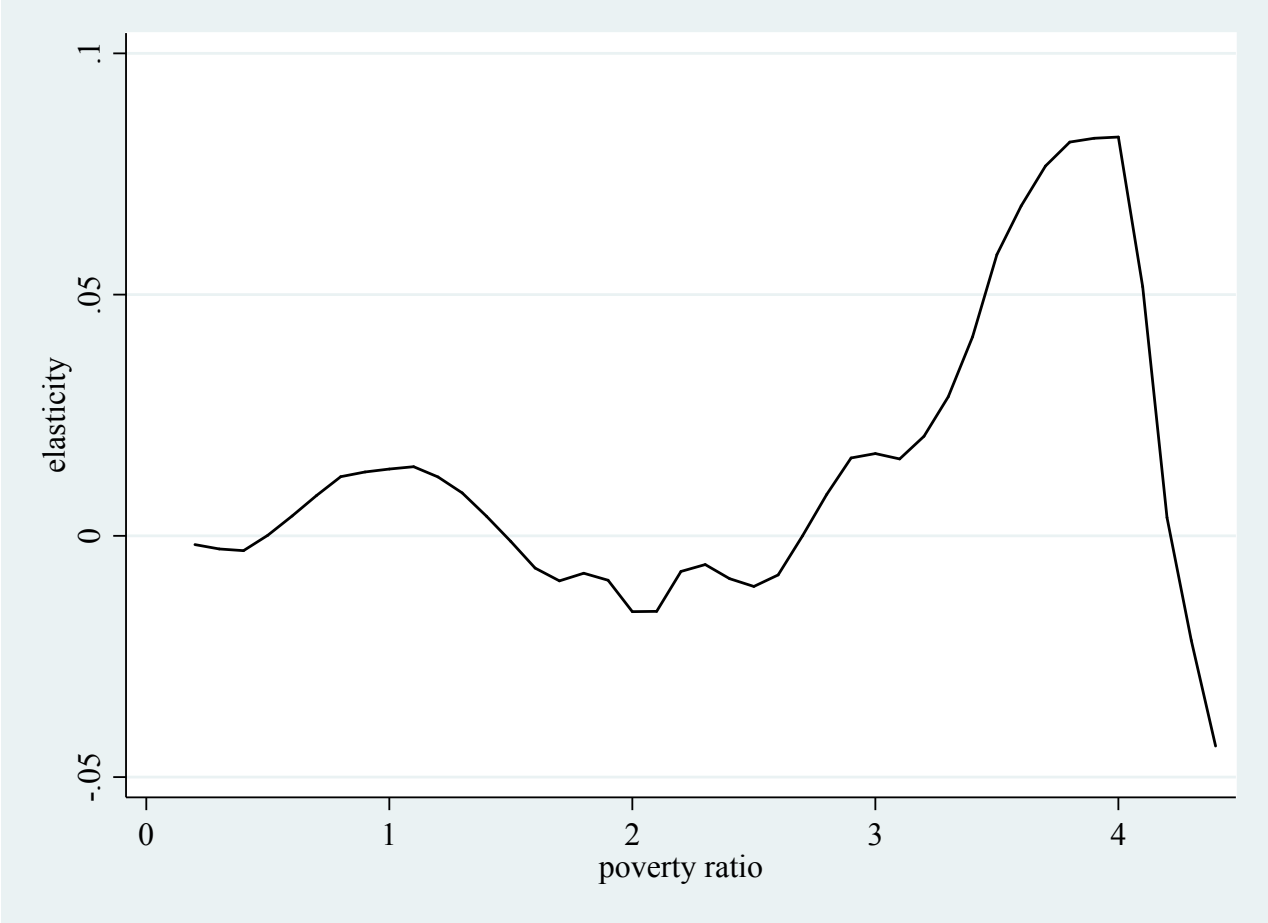


Figure 7.11: Elasticities of HEI, Entire sample

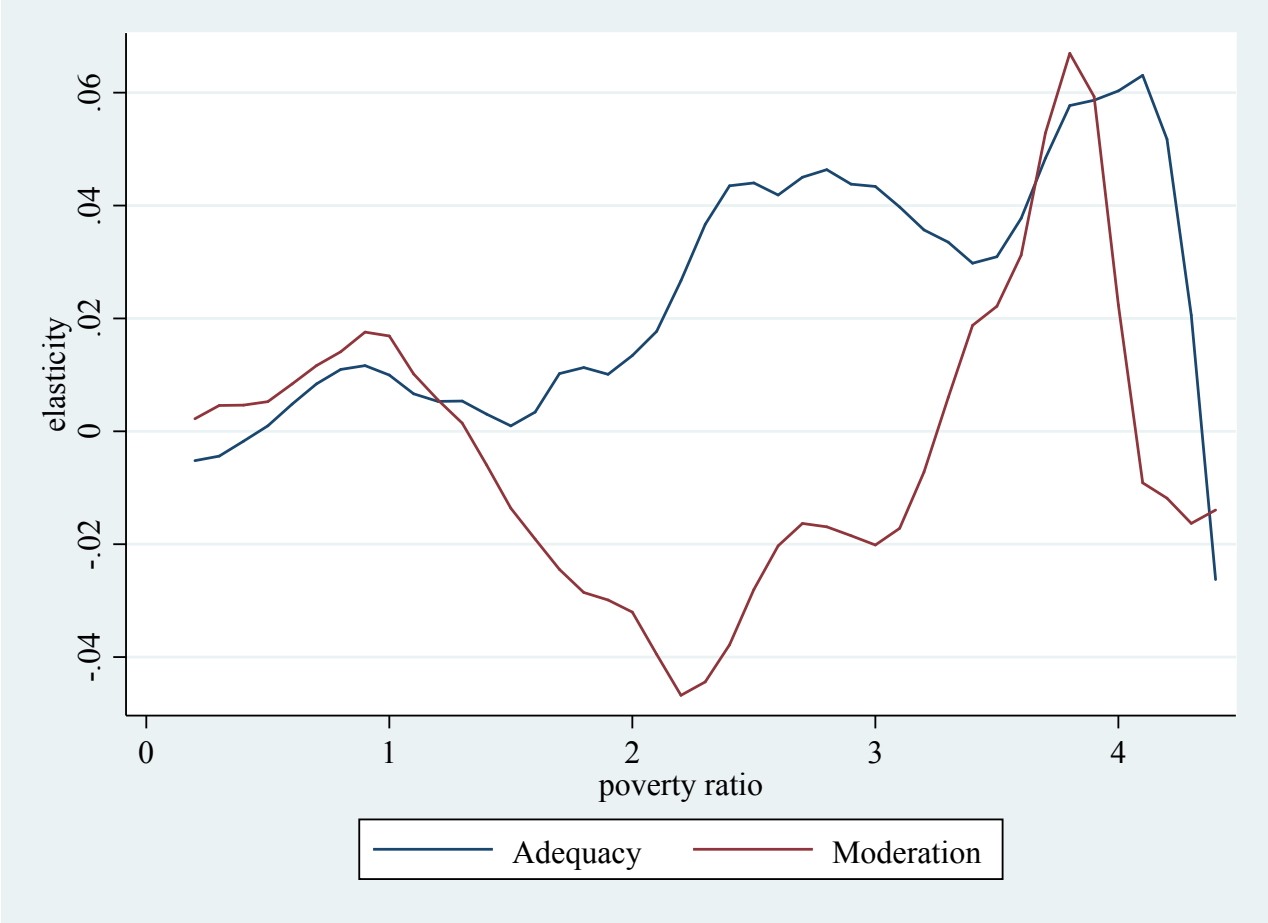


Figure 7.12: Elasticities of components, Entire sample

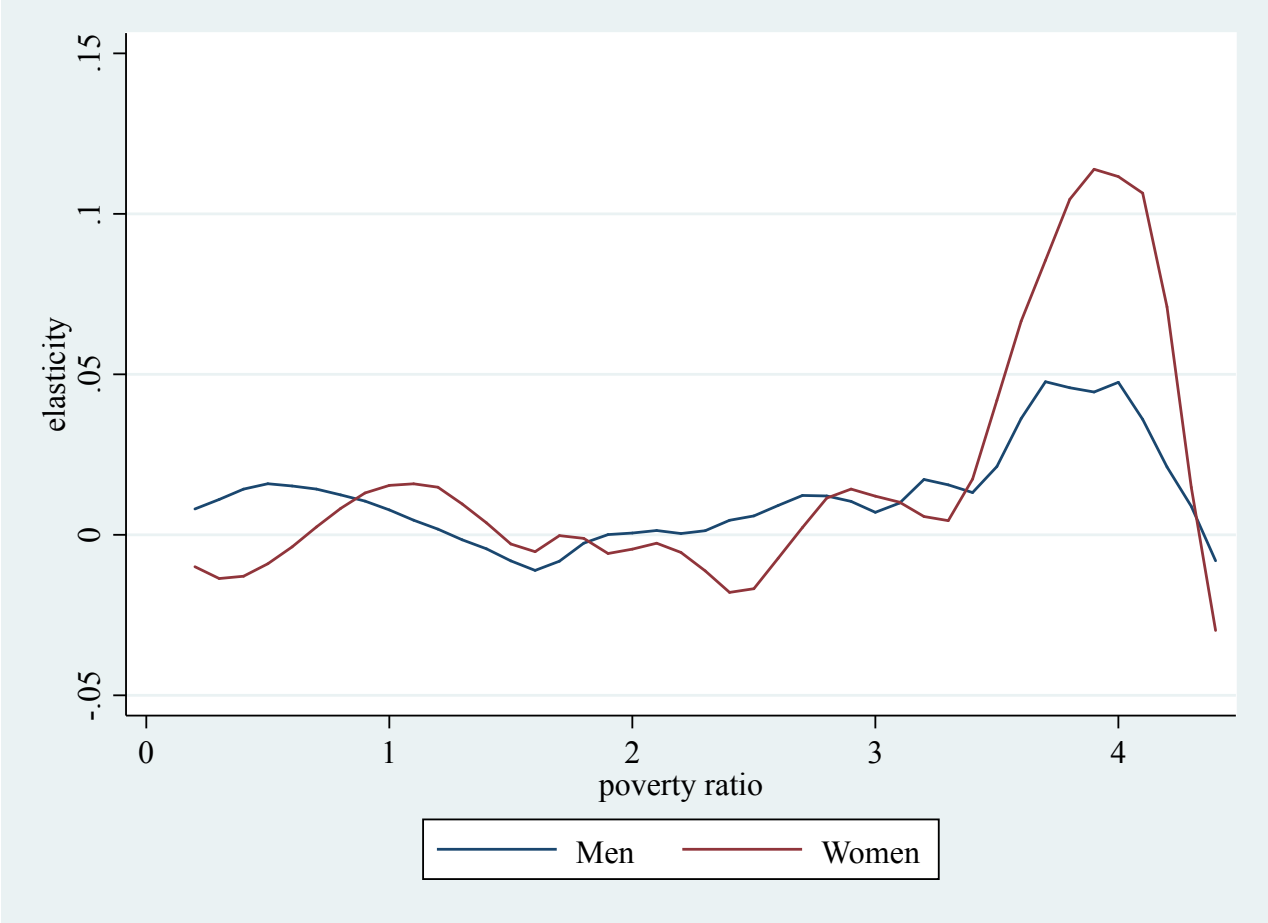


Figure 7.13: Elasticities of HEI, Men vs. women

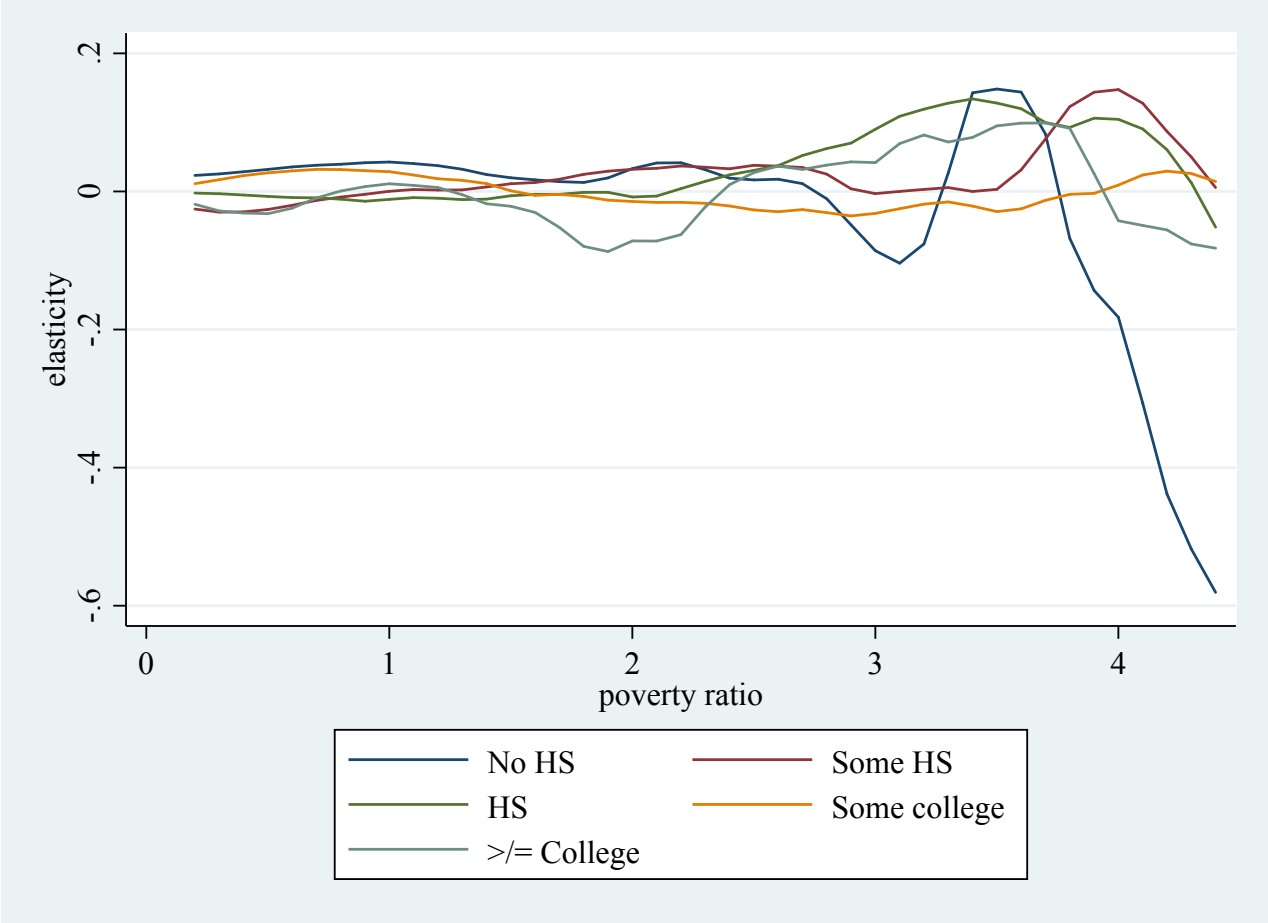


Figure 7.14: Elasticities of HEI, Education level

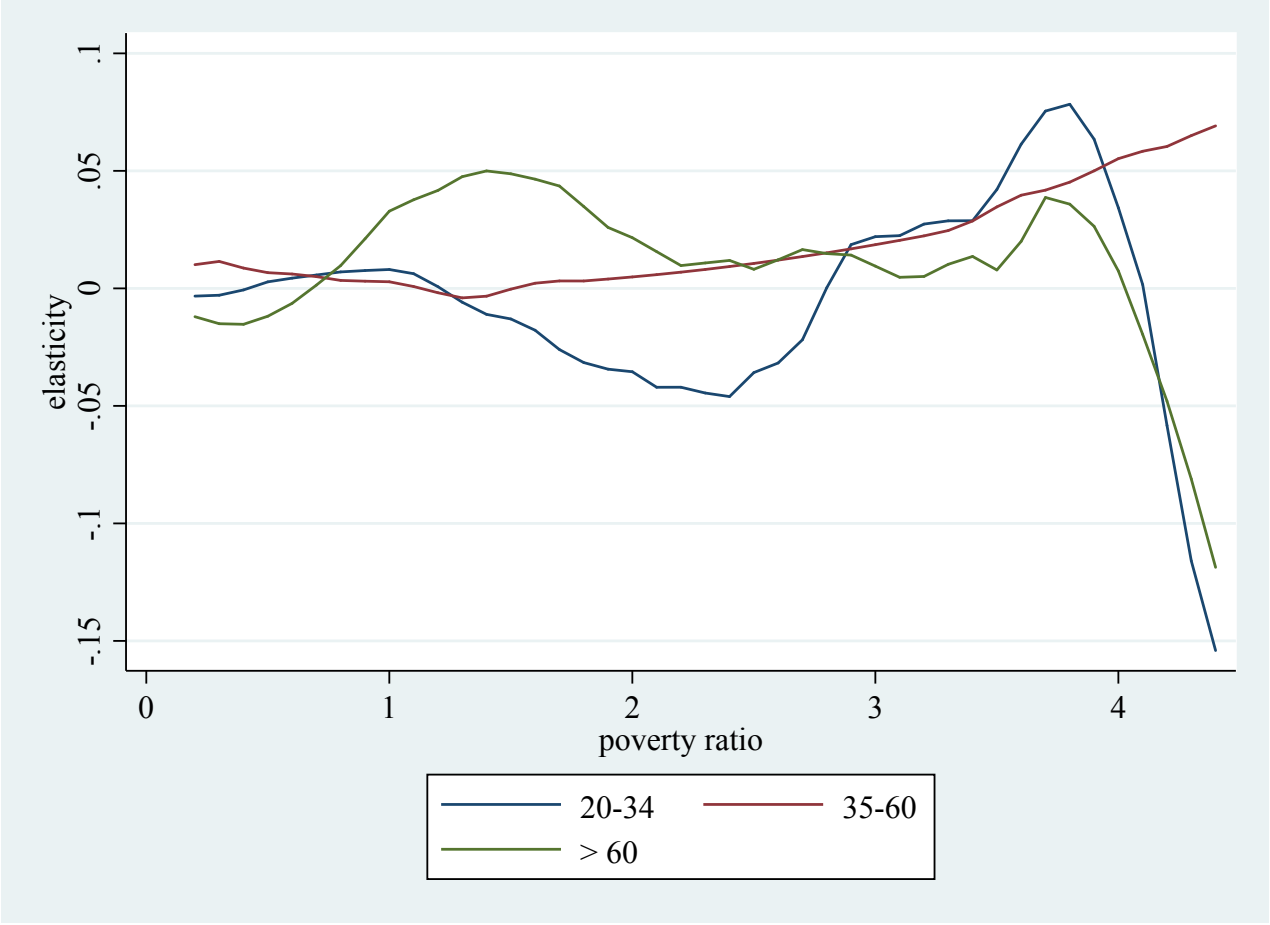


Figure 7.15: Elasticities of HEI, Age category

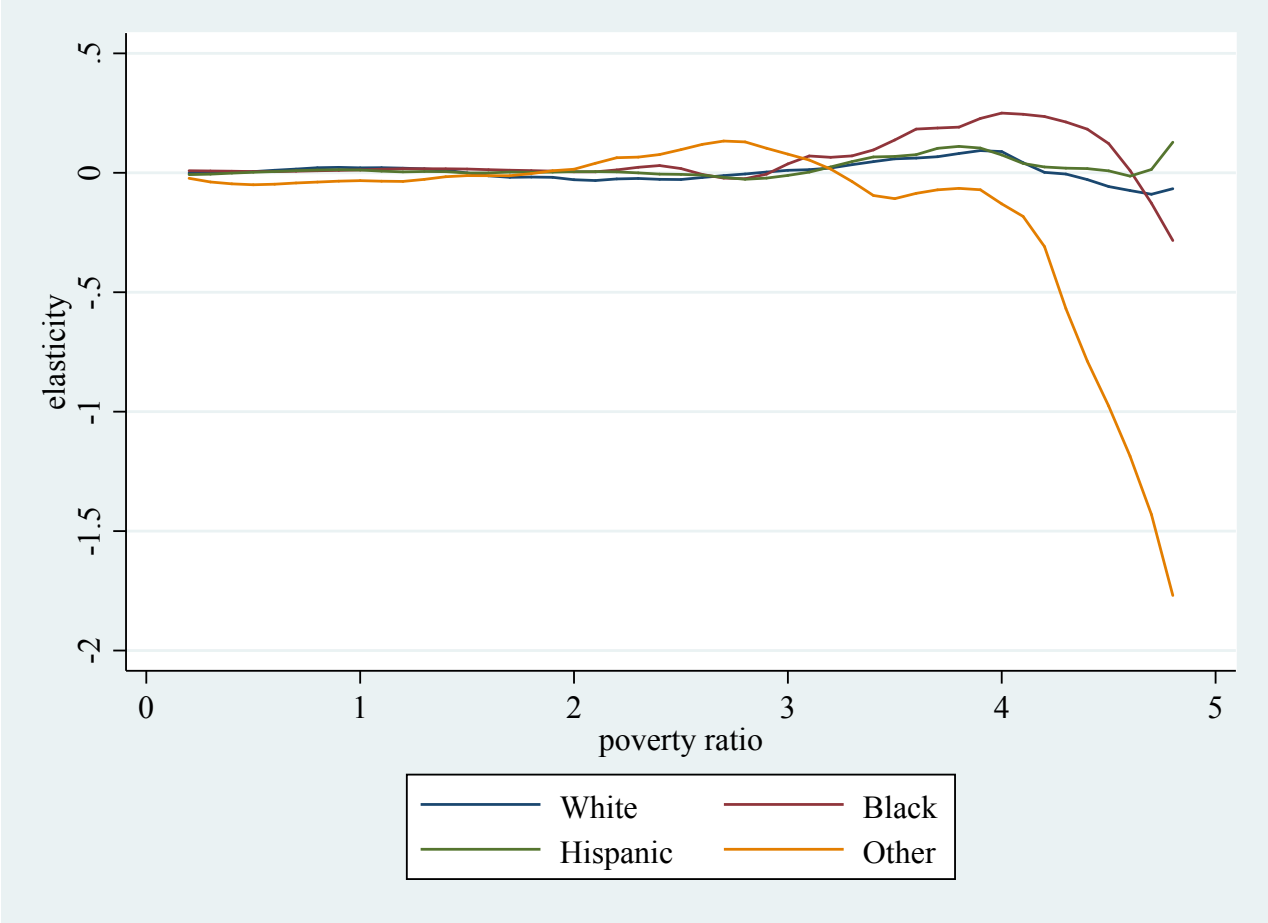


Figure 7.16: Elasticities of HEI, Race\ethnicity

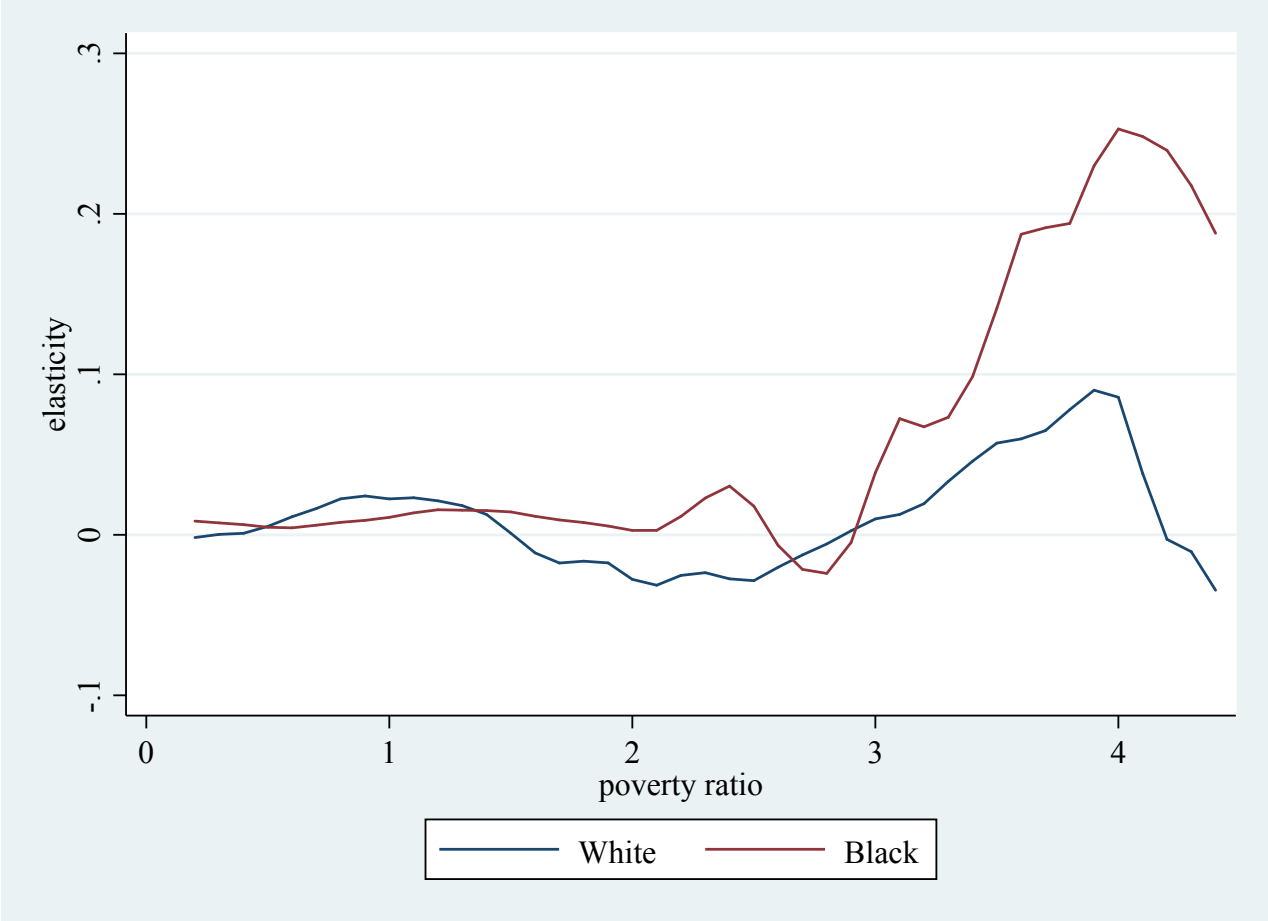


Figure 7.17: Elasticities of HEI, White vs. black respondents

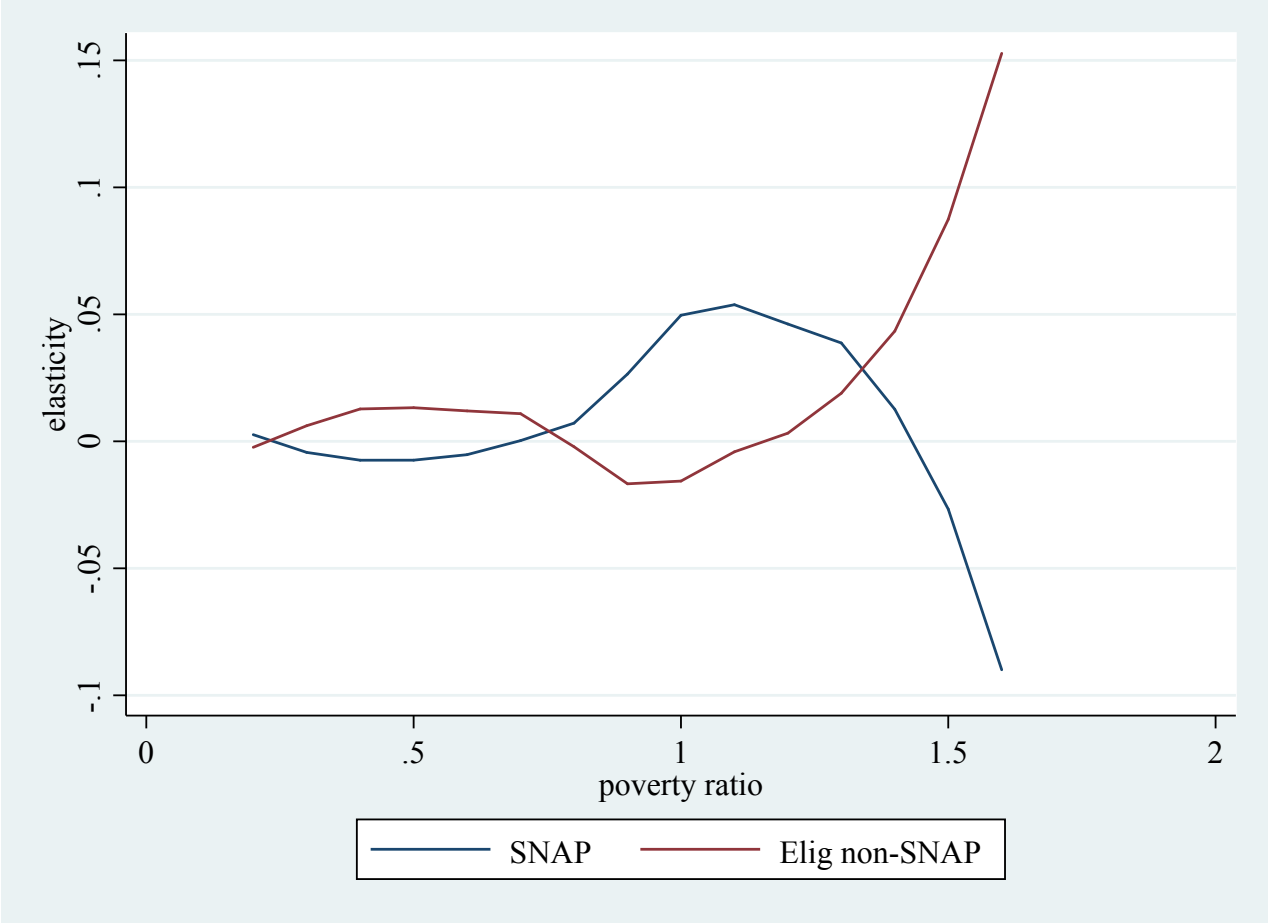


Figure 7.18: Elasticities of HEI, SNAP vs. eligible Non-SNAP

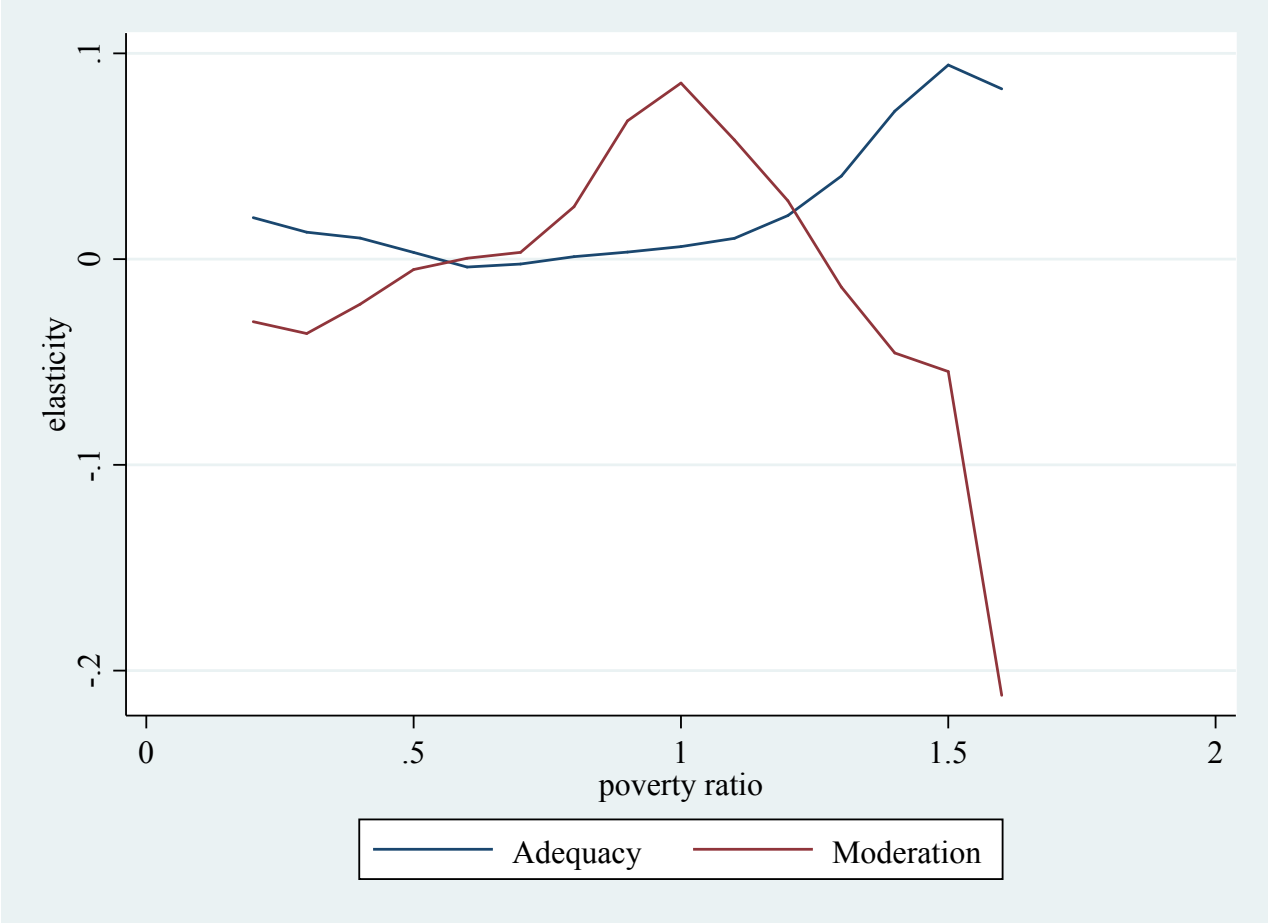


Figure 7.19: Elasticities of components, SNAP

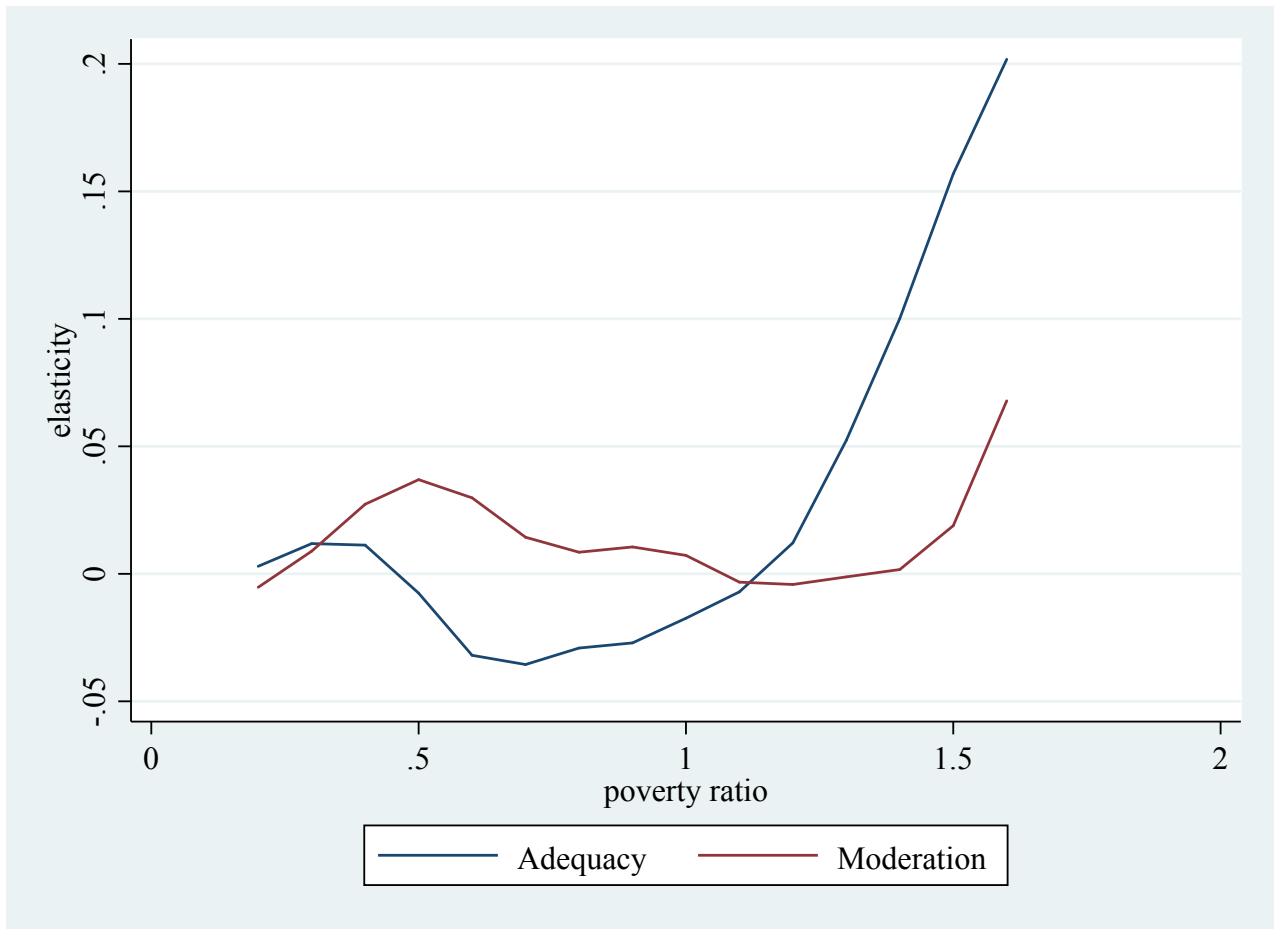


Figure 7.20: Elasticities of components, Non-SNAP

Bibliography

- [1] Beatty, T. K. M., Lin, B. H., and Smith, T. A. (2014). Is diet quality improving? Distributional changes in the United States,1989-2008. *American Journal of Agricultural Economics*, 96(3):769789.
- [2] Becker, G. S. (1965). A Theory of the Allocation of Time. *The Economic Journal*, 75(299): 493-517.
- [3] Bowman, S. A., Clemens, J. C., Thoerig, R. C., Friday, J. E., Shimizu, M., and Moshfegh, A. J. (2014). Food Patterns Equivalents Database 2011-12 : Methodology and user guide. Report, U.S. Department of Agriculture Agricultural Research Service (USDA-ARS), Beltsville Human Nutrition Research Center, Beltsville, MD.
- [4] Cameron, A. and Trivedi, P. (2005). Microeconometrics: Methods and applications. *Cambridge University Press*, Cambridge, UK.
- [5] Carlson, A. and Frazao, E. (2012).Are healthy foods really more expensive? It depends on how you measure the price. Report 96, United States Department of Agriculture, Economic Research Service (USDA-ERS).
- [6] U.S. Census Bureau (USCB). Poverty Thresholds 2009. Retrieved February 9, 2016, from: [:https://www.census.gov/hhes/www/poverty/data/threshld/thresh09.html](https://www.census.gov/hhes/www/poverty/data/threshld/thresh09.html)

- [7] Centers for Disease Control, National Center for Chronic Disease Prevention and Health Promotion (CDC-NCCDPHP) (2009). The power of prevention: Chronic disease, the public health challenge of the 21st century. Available from: <http://www.cdc.gov/chronicdisease/pdf/2009-Power-of-Prevention.pdf>.
- [8] Centers for Disease Control and Prevention, National Center For Health Statistics (CDC-NCHS) (2016). National Health and Nutrition Examination Survey 1999-2016 survey content brochure. Available from: http://origin.glb.cdc.gov/nchs/data/nhanes/survey_content_99_16.pdf.
- [9] Centers for Disease Control, National Center for Health Statistics (CDC-NCHS). National Health and Nutrition Examination Survey data (2007-2012). Available from: http://www.cdc.gov/nchs/nhanes/nhanes_questionnaires.htm
- [10] Centers for Disease Control, National Center for Health Statistics (CDC-NCHS) (2009). National Health and Nutrition Examination Survey: 2007 - 2008 data documentation, codebook, and frequencies. Available from: http://www.cdc.gov/nchs/nhanes/search/nhanes07_08.aspx
- [11] Chiuve, S. E., Fung, T. T., Rimm, E. B., Hu, F. B., McCullough, M. L., Wang, M., Stampfer, M. J., and Willett, W. C. (2012). Alternative dietary indices both strongly predict risk of chronic disease. *Journal of Nutrition*, 142(C):10091018.
- [12] Congressional Budget Office (CBO) (2015). Supplemental Nutrition Assistance Program CBO baseline, January 2015. Available from: <https://www.cbo.gov/sites/default/files/51312-2015-01-SNAP.pdf>
- [13] Darmon, A. and Drewnowski, N. (2008). Does social class predict diet quality? *The American Journal of Clinical Nutrition*, 87(5):11071117.

- [14] Deaton, A. and Muellbauer, J. (1980). Economics and consumer behavior. *Cambridge University Press*, Cambridge, UK.
- [15] Drewnowski, A., and Darmon, N. (2005). Food choices and diet costs: an economic analysis. *The Journal of Nutrition*, 135(4), 900-904.
- [16] Ezzati, M. and Riboli, E. (2013). Behavioral and dietary risk factors for noncommunicable diseases. *New England Journal of Medicine*, 369(10):954-964.
- [17] Gottschalk, P. and Danziger, S. (2005). Inequality of wage rates, earnings and family income in the United States, 1975-2002. *Review of Income and Wealth*, 51(2):231-254.
- [18] Guenther, P. M., Casavale, K. O., Reddy, J., Kirkpatrick, S. I., Hiza, H. A., Kuczynski, K. J., Kahle, L. L., and Krebs-Smith, S. M. (2013). Update of the Healthy Eating Index: HEI-2010. *Journal of the Academy of Nutrition and Dietetics*, pages 121.
- [19] Hiza, H. A. B., Casavale, K. O., Guenther, P. M., and Davis, C. 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.
- [20] Huang, K. S. (1996). Nutrient elasticities in a complete food demand system. *American Journal of Agricultural Economics*, 78(1):21-29.
- [21] Huffman, W. E. (2011). Household production theory and models. *The Oxford Handbook of Food Consumption and Policy*, pages 35-74.
- [22] Kant, A. K. (2004). Dietary patterns and health outcomes. *Journal of the American Dietetic Association*, 104(4):615-635.
- [23] Kant, A. K. and Graubard, B. I. (2007). Secular trends in the association of socioeconomic position with self-reported dietary attributes and biomarkers in the US pop-

- ulation: National Health and Nutrition Examination Survey (NHANES) 1971-1975 to NHANES 1999-2002. *Public Health Nutrition*, 10(2):15867.
- [24] Larson, N. I., Perry, C. L., Story, M., and Neumark-Sztainer, D. (2006). Food preparation by young adults is associated with better diet quality. *Journal of the American Dietetic Association*, 106(12):20012007.
- [25] Leung, C. W., Ding, E. L., Catalano, P. J., Villamor, E., Rimm, E. B., and Willett, W. C. (2012). Dietary intake and dietary quality of low-income adults in the Supplemental Nutrition Assistance Program. *American Journal of Clinical Nutrition*, 96(5):977988.
- [26] Liebman, J. B. and Zeckhauser, R. J. (2004). Schmeduling. *Harvard University and National Bureau of Economic Research (NBER) Working Paper Series*. Available from: <http://www.hks.harvard.edu/jeffreyliebman/schmeduling.pdf>
- [27] Lin, B. H., Guthrie, J. (2012). Nutritional quality of food prepared at home and away from home, 1977-2008. Report 105, United States Department of Agriculture, Economic Research Service (USDA-ERS).
- [28] Loughrey, K., Basiotis, P. P., Zizza, C., and Dinkins, J. M. (2001). Profiles of selected targeted audiences: Promoting the dietary guidelines for Americans. *Family Economics and Nutrition Review*, 13(1):314.
- [29] Meyerhoefer, C. D., and Pylypchuk, Y. (2014). The Effect of Chronic Illness on Participation in the Supplemental Nutrition Assistance and Medicaid Programs. *American Journal of Agricultural Economics*, 96(5), 1383-1401.
- [30] Mokdad, A., Marks, J., Stroup, D., and Gerberding, J. (2004). Actual causes of death in the United States. *The Journal of the American Medical Association*, 291(10):12381246.

- [31] Nielsen, S. J., Siega-Riz, A., and Popkin, B. (2002). Trends in food locations and sources among adolescents and young adults. *Preventive Medicine*, 35(2):107113.
- [32] Park, J., Holcomb, R., Raper, K., and Capps, O. (1996). A demand systems analysis of food commodities by US households segmented by income. *American Journal of Agricultural Economics*, 78(2):290300.
- [33] Pollak, R. A. and Wachter, M. L. (1975). The relevance of the household production function and Its implications for the allocation of time. *Journal of Political Economy*, 83(2):255278.
- [34] Popkin, B., Siega-Riz, A., and Haines, P. (1996). A comparison of dietary trends among racial and socioeconomic groups in the United States. *The New England Journal of Medicine*, 335(10):716720.
- [35] Prochaska, F. J. and Schrimper, R. A. (1973). Opportunity cost of time and other socioeconomic effects on away-from-home food consumption. *American Journal of Agricultural Economics*, 55(4):595603.
- [36] Rilestone, P. and Ullah, A. (1989). Nonparametric estimation of response coefficients. *Communications in Statistics-Theory and Methods*, 8(17):26152627.
- [37] Shah, B. S., Freeland-Graves, J. H., Cahill, J. M., Lu, H., and Graves, G. R. (2010). Diet quality as measured by the Healthy Eating Index and the association with lipid profile in low-income women in early postpartum. *Journal of the American Dietetic Association*, 110(2):274279.
- [38] Smith, T. A., Berning, J. P., Yang, X., Colson, G., and Dorfman, J. H. (2016). The effects of benefit timing and income fungibility on food purchasing decisions among Supplemental Nutrition Assistance Program households. *American Journal of Agricultural Economics*, (2014):aav072.

- [39] Todd, J. E. (2014). Changes in eating patterns and diet quality among working-age adults , 2005-2010. Report 161, United States Department of Agriculture, Economic Research Service (USDA-ERS).
- [40] U.S. Department of Agriculture, Agricultural Research Service (USDA-ARS). Food Patterns Equivalents Database (2007-2012). Available from: <http://www.ars.usda.gov/Services/docs.htm?docid=23869>
- [41] U.S. Department of Agriculture, Food and Nutrition Service (USDA-FNS), Office of Policy Support (2014). Evaluation of the Healthy Incentives Pilot (HIP) final report-Summary. Available from: <http://www.fns.usda.gov/sites/default/files/HIP-Final-Summary.pdf>
- [42] U.S. Department of Agriculture, Food and Nutrition Service (USDA-FNS) (2014). Supplemental Nutrition Assistance Program (SNAP): A short history of SNAP. Available from: <http://www.fns.usda.gov/snap/short-history-snap>
- [43] Wang, D.D., Leung, C.W., Li, Y., Ding, E.L., Chiuve, S.E., Hu, F.B., Willett, W.C. (2014) *Journal of the American Medical Association Internal Medicine*, 174(10):1587-95.
- [44] Yatchew, A. (2003). Semiparametric regression for the applied econometrician. Cambridge University Press, Cambridge, UK.