Distributional Changes in U.S. Dietary Quality 1989–2008

Timothy K.M. Beatty*
Department of Applied Economics
University of Minnesota

Biing-Hwan Lin†
Economic Research Service
U.S. Department of Agriculture

Travis A. Smith‡
Department of Applied Economics
University of Minnesota

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Abstract

This paper uses stochastic dominance to measure changes in the distribution of overall dietary quality in the U.S. over the period 1989–2008. Diet quality is often used as as a proxy for wellbeing and an outcome variable for a wide variety of interventions. For the population as a whole, we find significant improvements in diets across all levels of dietary quality. Further, we find improvements for both low-income and higher-income individuals alike. We show that the improvements vary between these groups with regards to the timing and distributional location. Further, we find that over half of the improvement for all individuals can be explained by changes in food formulation and changes in demographics.

Key Words: Stochastic dominance, dietary quality, deprivation.

JEL Classification: I14, D39, I32

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*tbeatty@umn.edu
†BLIN@ers.usda.gov
‡tasmith@umn.edu

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1. Introduction

Poor nutrition is a contributing factor to four of the ten major causes of death in the United States: coronary heart disease, cancer, stroke, and type 2 diabetes (Jemal et al., 2008). Diet-related illness and disease generate direct individual medical costs but also create negative externalities in the form of higher health insurance premiums, greater public health care expenditures, losses in worker-productivity and lower tax revenues (Cawley, 2004). Further, diet quality is an important contributor to the energy imbalance responsible for the rise in obesity. Finally, nutrition and diet quality are often used as measures of well-being in both developing countries (Ravaillon, 1996) and developed countries (Strauss and Duncan, 1998). As a result, diets have long been the focus of government policy. This paper studies the evolution of the distribution of U.S. dietary quality over the last two decades.

Promoting healthy eating, particularly among the poor, has been a long-term policy goal of State and Federal Governments. Policy prescriptions have included providing healthy foods directly to individuals (e.g., the School Breakfast Program, School Lunch Program, Special Supplemental Nutrition Program for Women, Infants, and Children–WIC, and Fresh Fruit and Vegetable Program) and increasing the resources available to households to buy food (e.g., Supplemental Nutrition Assistance Program–SNAP). Policies have also aimed at increasing the information available to individuals about what constitutes a healthy diet: the *Food Guide Pyramid* was released in 1992 and subsequently updated in 2005 as the *MyPyramid* and in 2011 as the *MyPlate*, Federally approved SNAP-Education programs grew from 7 active States in 1992 to 50 in 2004, mandatory nutrition labeling was enacted in 1994 and mandatory calorie postings in restaurants was introduced in 2011. Current policy proposals seek to change individual choice sets by restricting the set of foods available to purchase under SNAP and change the relative prices of foods via taxes or subsidies to promote healthier food choices.

This paper is one of the first to study the evolution of the entire *distribution* of U.S. dietary quality over a relatively long period (1989–2008) using a single, consistent measure.[1] We use stochastic dominance to compare diets over time and between income classes. Stochastic dominance is frequently used in the economics literature to analyze the distribution of income or wealth. This allows us to completely characterize the nature of the changes in dietary quality over time, paying close attention to low-income individuals whose diets are of particular concern to policymakers.

[1] Popkin et al. (1996, 2003) analyze average diet quality by socioeconomic status during an earlier period 1965–1996.

In addition, we construct counterfactual distributions of dietary quality to investigate the extent to which observed improvements can be explained by changes in the nutritional content of foods and by demographic changes. We ask, what would have the distribution of dietary quality looked like in 1989 had the demographic landscape of 2008 prevailed? How would the distribution of dietary quality change if food were formulated in 1989 as they were in 2008?

When comparing the observed distribution of dietary quality, we find a statistically significant and economically meaningful improvement across the entire population over 1989–2008. Comparable improvements are observed for low-income individuals. Counterfactual estimates indicate that 51.7 percent of the dietary improvement in the U.S. population can be explained by changes in demographics (i.e., an aging, more educated and ethnically diverse population) and an additional 10.5 percent of the improvement is due to changes in food composition (e.g., decreases in saturated fats, sugars and sodium). The remaining 37.8 percent is unexplained by either demographics or food composition.

The paper proceeds as follows. We begin by describing the widely used measure of dietary quality – the Healthy Eating Index (HEI-2005) – which forms the basis of our analysis. We then turn to a description of our primary data sources, the National Health and Nutrition Examination Survey (NHANES) and the earlier Continuing Survey of Food Intakes by Individuals (CSFII); we extend the HEI-2005 to the earlier study period 1989-91. We then motivate our empirical approach by providing a brief overview of stochastic dominance. Following the presentation of results, we discuss the economic and public policy implications in the final section.

2. Healthy Eating Indices

The Healthy Eating Index (HEI) – developed in 1995 in order to measure compliance with the U.S. government's recommendations for healthful eating – reflects a longstanding interest in constructing summary measures of dietary quality. Dietary indices date back to at least 1976 with the Index of Nutritional Quality (Sorenson et al., 1976) and the Mean Adequacy Ratio (Guthrie and Scheer, 1981); these indices focused on nutrients rather than foods. The Diet Quality Index (Patterson et al., 1994) was the first to incorporate both foods as well as nutrients.[2]

Every five years, based on an expert advisory panel, the *Dietary Guidelines for Americans* (DGA) are revised by the U.S. Departments of Agriculture (USDA) and Health and Human Services (HHS). These guidelines are the U.S. Government's official recommendations for healthful eating and form the basis for information provided to consumers. Many of the USDA's food-assistance programs must be in compliance with the DGA. The HEI was updated in 2005 to reflect the 2005 DGA,

[2] For a comprehensive review of dietary indices see Kant (1996) and Kourlaba and Panagiotakos (2009).

(henceforth, HEI refers to the most recent HEI, sometimes called the HEI-2005, see Guenther et al., 2008a). As the HEI was constructed with the 2005 DGA as its basis, one can think of using the HEI as a consistent dietary index with 2005 defined as the base period. Therefore, in this paper we measure the true latent variable *diet quality* based on the current stock of nutritional knowledge in 2005 using the HEI.

The HEI is the sum of 12 components based on the consumption of various foods or nutrients. Each component assigns a score ranging from 0 to 5 (total fruit, whole fruit, total vegetables, dark green/orange vegetables and legumes, total grains, whole grains), 0 to 10 (milk, meats and beans, oils, saturated fait, sodium) or 0 to 20 for the percentage of calories from solid fats, alcoholic beverages, and added sugars (SoFAAS) creating a maximum score of 100. Table 1 provides exact details of scoring. Note that components of the HEI are density based (the ratio of an individual's component intake to their total calorie intake) rather than quantity based and measure the relative quality of foods consumed.

Table 1: Healthy Eating Index-2005 standards for scoring.

	Score					
Component	0		5	8	10	20
Total fruit	0	$\longrightarrow$	$\geq$ 0.8 cup eq/1000 kcal			
Whole fruit	0	$\longrightarrow$	$\geq$ 0.4 cup eq/1000 kcal			
Total vegetables	0	$\longrightarrow$	$\geq$ 1.1 cup eq/1000 kcal			
Dark green/orange veg./legumes	0	$\longrightarrow$	$\geq$ 0.4 cup eq/1000 kcal			
Total grains	0	$\longrightarrow$	$\geq$ 3.0 cup eq/1000 kcal			
Whole grains	0	$\longrightarrow$	$\geq$ 1.5 cup eq/1000 kcal			
Milk	0	$\longrightarrow$			$\geq$ 1.3 cup eq/1000 kcal	
Meats and beans	0	$\longrightarrow$			$\geq$ 2.5 oz eq/1000 kcal	
Oils	0	$\longrightarrow$			$\geq$ 12 g/1000 kcal	
Saturated fat	$\geq$ 15	$\longrightarrow$		10 $\longrightarrow$	$\leq$ 7% of energy	
Sodium	$\geq$ 2.0	$\longrightarrow$		1.1 $\longrightarrow$	$\leq$ 0.7 g/1000 kcal	
Calories from SoFAAS†	$\geq$50	$\longrightarrow$				$\leq$ 20% of energy

Source: Recreated from Guenther et al. (2007)

†Solid Fat, Alcohol, and Added Sugar

There is debate among nutritionists about how a given HEI score maps into the notion of a "healthy" versus "unhealthy" diet. One generally accepted rule of thumb is that total scores of more than 80 are considered "good," scores of 51-80 as "needs improvement," and scores of less than 51 as "poor." Defining a healthy diet based on a single cut-off is difficult (analogous to characterizing what it means to be poor based on a poverty line). A key advantage of the stochastic dominance methods used in this research is that they allow general statements about improvements in dietary quality over time or between subpopulations without having to define a specific "healthy" score.

The HEI has been widely used and evaluated as a valid measure of diet quality (Guenther et al., 2008b). In the medical literature it has been found to be a significant predictor of medical outcomes, notably of all cause mortality, mortality due to malignant neoplasms (Ford et al., 2011), and overweight and obesity (Guo et al., 2004). Further, the HEI has been extensively used by economists to measure the outcome of policy interventions, for example the Welfare Reform (Kramer-Le Blanc, Basiotis, and Kennedy, 1997), School Breakfast Program (Bhattacharya, Currie, and Haider, 2006), Food Stamps and WIC (Wilde, McNamara, and Ranney, 1999), nutrition labeling (Kim, Nayga, and Capps, 2001) and unusually cold weather (Bhattacharya et al., 2003). Finally, it is has also been found to be associated with food insecurity (Bhattacharya, Currie, and Haider 2004) and has been proposed as a possible indicator of food deserts (Bitler and Haider, 2011).

3. Data

Our sample uses nationally representative individual intake data from two surveys: the Continuing Survey of Food Intakes by Individuals (CSFII, 1989-91 and 1994-96), and the continuous waves of the National Health and Nutrition Examination Survey (NHANES, 2001-08). In both surveys, respondents report 24-hour dietary intakes and demographic information including income and household size.[3] Finally, for consistency across samples, we focus on adults 20 years and older.

The HEI-2005 is calculated by linking the USDA's MyPyramid Equivalents Database (MPED) to food intake surveys. The MPED decomposes individual foods into proper MyPyramid equivalents so that each HEI component can be computed as shown in Table 1. There is no officially released MPED for the 1989-91 CSFII. Of the 3,953 unique foods reported by adults 20 and older on day one in the 1989-91 CSFII, 3,907 (98.8 percent) of these foods are also reported in the 1994-96 CSFII. We therefore use the 1994-96 MPED to calculate the HEI-2005 for individuals in 1989-91.[4]

We classify individuals as low-income if household income falls below 185-percent of the Federal poverty line, which is an upper bound on the cutoff for many Federal food assistance programs.[5] The Federal poverty line is updated each year and is a function of household income and size.

[3] For all surveys but the 2001-02 NHANES, a second non-consecutive day of dietary intake was obtained. In keeping with standard practice, we analyze the first day of intake. One alternative is to average day 1 and 2 intakes where available. Another approach is to estimate models of usual intake (see, Dodd et al., 2006). Assuming that measurement bias and within person variation, if present, is consistent across survey waves, our results are invariant to usual intake methods. As shown in Appendix A.3, results are robust to computing 2-day averages.

[4] Appendix A.1 contains a description of how to map the MPED for 1994-96 CSFII to the 1989-91 CSFII in greater detail.

[5] The cutoff for SNAP is 130 percent and 185 percent for WIC.

Table 2 reports the mean HEI scores for the population as a whole and for individuals above and below 185 percent of the poverty line for each of the periods in our sample.[6]

Table 2: Mean Health Eating Index–2005 scores.

Population	1989-91	1994-96	2001-04	2005-08
U.S. population	50.16 (0.30)†	51.10 (0.30)†	51.50 (0.34)	52.37 (0.42)
	[10.09, 96.42]	[10.69, 97.47]	[13.52, 99.46]	[8.78, 95.38]
N	9,498	9,867	8,640	7,765
Low-income	48.96 (0.35)†	49.36 (0.38)†	49.65 (0.53)†	51.45 (0.65)
	[10.09, 90.25]	[10.69, 93.81]	[15.08, 99.46]	[8.78, 94.60]
N	4,965	3,433	3,551	3,201
Higher-income	50.56 (0.36)†‡	51.73 (0.35)†‡	52.36 (0.33)‡	52.75 (0.38)‡
	[11.51, 96.42]	[13.63, 97.47]	[13.52, 93.97]	[14.91, 95.38]
N	4,533	6,434	5,089	4,564

Standard deviations in parenthesis. Maximum and minimum in brackets

†Within-population mean is significantly lower than 2005-08 at the 5-percent level.

‡Within-year higher-income mean is significantly different from low-income at the 5-percent level.

Table 2 shows a clear pattern of increasing dietary quality across all groups. Comparing the most recent period 2005-08 to the earlier periods, we see a significant increase (at the 5-percent level) for the population at large over 1989-91 and 1994-96. Low-income individuals appear to have a stagnant HEI score over 1989–2004, and then a significant increase in 2005-08. We also compare low- and higher-income individuals within year and find that higher-income individuals have significantly higher mean HEI scores for all years in the data, though in the final year of the data the mean HEI gap between groups is smallest.

4. Stochastic Dominance

We have seen that mean HEI scores have increased for all groups over the interval 1989–2008. But does the mean HEI obscure variation in dietary quality across individuals? For example, is the increase in diet quality due to general improvements across the population at a steady rate or due to larger improvements amongst those with the lowest (or highest) diet quality? To address

[6]There are various ways to calculate the HEI score for a population of interest (see Freedman et al. (2008, 2010) for in depth discussions). Because we are interested in the number and depth of *individuals* below a particular HEI score, we use the *mean score* of individuals instead of the more frequently used *score of the population ratio*. The mean score is computed by calculating each individual's HEI score and then averaging over the population, whereas the score of the population ratio is calculated as the population's total component intake over total calorie intake and then calculating each score from this population ratio.

these possibilities, we study the entire *distribution* of dietary quality for groups of interest using an approach common in the study of income and well-being, stochastic dominance.[7]

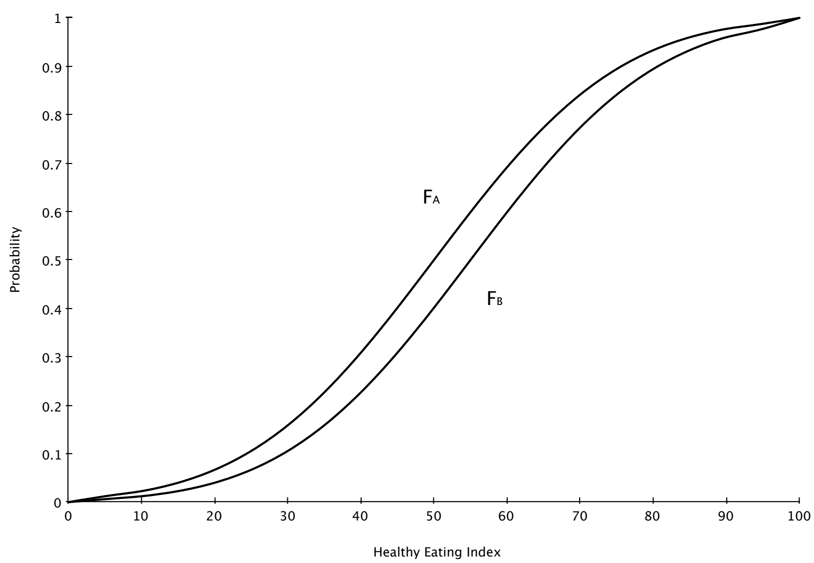
4.1. First Order Dominance

Consider two distributions of HEI scores with cumulative distribution functions $F_A(z)$ and $F_B(z)$, for a population of interest in two distinct time periods, or alternatively for two mutually exclusive subpopulations within a single time period. We say that distribution B *first-order* stochastically dominates (FOSD) distribution A if

$$F_B(z) \leq F_A(z) \,\forall\, z$$

with strict inequality for some z. If B FOSD A, then for any value of z, the share of the population with diets worse than z is higher under distribution A than under B. Figure 1 illustrates this relationship.

Figure 1: First Order Stochastic Dominance



Consider any arbitrary reference diet quality as shown in Figure 1. Under F_B the share of the population whose diet quality is below this arbitrary threshold will be smaller than under F_A. This relationship holds for all values in the domain of HEI scores. Thus by definition of first order

[7] Stochastic dominance approaches have also been used to study changes in body mass index (Madden, 2011) and environmental quality (Maasoumi and Millimet, 2005), and extended to qualitative health measures (Allison and Foster, 2004).

stochastic dominance, no matter how we define "healthy eating," more people in the population characterized by distribution B are eating better.

Stochastic dominance maps into social welfare under fairly standard assumptions about the utility derived from a healthy diet (Deaton, 1997). For example, if B FOSD A then for any social welfare function $\mathcal{W}$ defined on the distribution of diet quality $F(z)$ such that $\mathcal{W}(F) = \int U(z)dF(z)$ where U is *any* monotonically nondecreasing utility function of z ($U' \geq 0$), it must be true that social welfare derived from distribution B will be at least as good as the welfare derived from A.

4.2. Second and Higher Order Dominance

Distributional studies of well-being often look to higher orders of stochastic dominance, notably second-order stochastic dominance (SOSD). While FOSD counts the number of individuals falling below a given 'healthy diet threshold' (i.e., determines the "headcount ratio"), SOSD captures the depth, or severity of inadequate diets. SOSD is sensitive to the extent to which diets are falling in the lower tails.

To formally define SOSD, let $D_A^1(z) = F_A(z)$, and likewise for B, so that FOSD of B over A can be written as $D_B^1(z) \leq D_A^1(z)$. F_B will *second order* stochastically dominate F_A if

$$\int_0^z \left[D_B^1(y) - D_A^1(y)\right] dy \leq 0 \; \forall \, z$$

with a strict inequality for some value of z. This relationship is illustrated in Figure 2. Panel (a) shows the CDFs, which cross, ruling out FOSD over the entire range of HEI. Panel (b) shows the integrated difference, where the integrated difference between F_A and F_B is strictly positive, and thus F_B second-order stochastically dominates F_A.

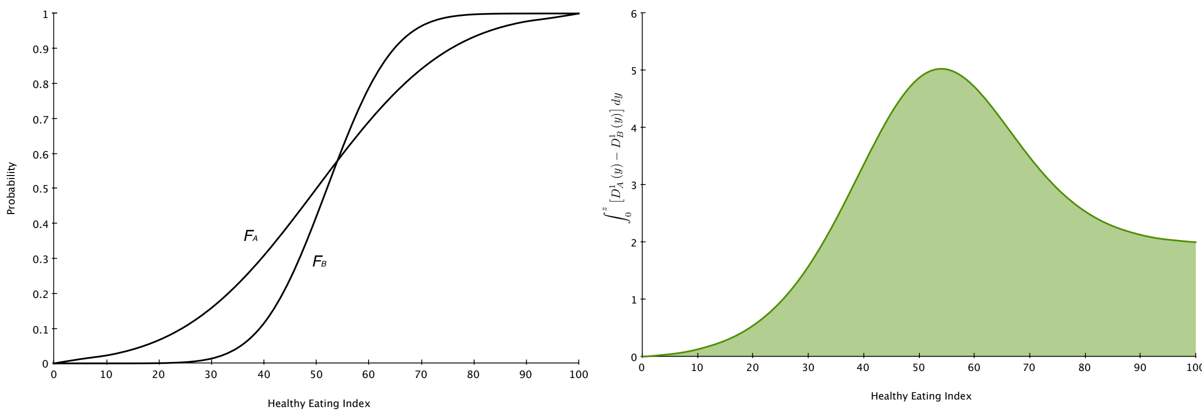
More generally, dominance at order s of B over A is then defined as $D_B^s(z) \leq D_A^s(z)$ where,

$$D_j^s(z) = \int_0^z D_j^{s-1}(y)dy \; \forall \, z \quad \text{for } j = A, B$$

with a strict inequality for some value of z. Note that because dominance of order s implies dominance of order $s+1$, it follows that dominance of order $s+1$ is a less stringent condition than dominance of order s. Thus, welfare implications are the strongest in the first-order case. We can extend the mapping of social welfare to SOSD by requiring U to be nondecreasing and concave in z ($U' \geq 0$, $U'' \leq 0$).

We are interested in testing the hypothesis that the distribution of dietary quality in one time period dominates the distribution in another time period. We formally test the null hypotheses of

Figure 2: Second Order Stochastic Dominance



(a) (b)

dominance at order $s \in \{1, 2\}$ as,

$$H_0^s : D_B^s(z) \leq D_A^s(z) \quad \forall\, z \quad \text{vs.} \quad H_a^s : D_B^s(z) > D_A^s(z) \quad \text{for at least one } z.$$

4.3. Estimation and Inference

4.3.1. Estimation

A useful expression for $D_j^s(z)$ in empirical analyses is

$$D_j^s(z) = \frac{1}{(s-1)!} \int_0^z (z-y)^{s-1} dF_j(y). \tag{1}$$

Integrating (1) by parts, a natural estimator of $D_j^s(z)$ which accounts for complex survey design (e.g., CFSII and NHANES) is

$$\hat{D}_j^s(z) = \frac{1}{\hat{N}_j (s-1)!} \sum_{i=1}^{n_j} \theta_i (z - y_i)^{s-1} I(y_i \leq z) \tag{2}$$

where θ_i is an individual's sample weight, $\hat{N}_j = \sum_{i=1}^{n_j} \theta_i$ is the population size in distribution j (with corresponding sample size n_j), and $I(\cdot)$ is an indicator function. The first-order case leads to the empirical CDF

$$\hat{D}_j^1(z) = \hat{F}_j(z) = \frac{1}{\hat{N}_j} \sum_{i=1}^{n_j} \theta_i I(y_i \leq z) \tag{3}$$

and the statistic for the second order case follows.

4.3.2. Inference

A variety of approaches to drawing inference from stochastic dominance methods have been proposed. Anderson (1996) and Davidson and Dulcos (2000) proposed calculating a set of t-statistics at a fixed number of points over the range of the distribution; Anderson (1996) uses a trapezoidal approximation and the Davidson and Dulcos (2000) test is based on inequality constraints. Note that both of these multiple comparison approaches are based on arbitrarily chosen ordinates, which can lead to test inconsistency. An alternative employs consistent tests that compare all objects within the support of the two distributions using a Kolmogorov–Smirnov (K-S) type statistic (McFadden, 1989; Barrett and Donald, 2003; Linton, Massoumi, and Whang, 2005). We draw from both literatures. In our application, we use the Davidson and Dulcos (2000) method to compute pointwise 95-percent confidence intervals around our estimates of the difference between the empirical CDFs in order to facilitate the graphical interpretation of our results. To test the null hypothesis of stochastic dominance we follow Barrett and Donald (2003).

To calculate the pointwise confidence intervals, we need an estimate of the variance and a corresponding critical value. As shown in Davidson and Dulcos (2000), under the assumption of independent distributions, the variance of $\left(\hat{D}^s_B(z) - \hat{D}^s_A(z)\right)$ is simply $\text{var}(\hat{D}^s_A(z)) + \text{var}(\hat{D}^s_B(z))$. The estimated variance can be calculated accounting for complex survey design with the appropriate software (here we use Stata's `svy` command). The critical value is drawn from the Studentized maximum modulus (SMM) distribution with K and infinite degrees of freedom (see Stoline and Ury (1979) for tables) where K is the number of test points. As noted by Davidson and Duclos (2000) and elsewhere, because there is no optimal choice of K, the number of test points is arbitrary (and hence the SMM critical value). We follow the custom of choosing deciles ($K = 10$), which corresponds to an upper 0.05 critical value of 2.80.[8]

To formally test the null hypothesis of dominance at order s, we use an extended K-S test following Barrett and Donald (2003) (see also, Linton, Massoumi, and Whang (2005) for a similar test). The K-S test utilizes all objects within the common support of the two distributions and thus can have more power than the two multiple comparison tests described above. Let $\mathcal{Z}$ be defined as

[8] Beach and Richmond (1985) first proposed calculating confidence intervals for Lorenz curves using a method similar to the one described here. They show that each ordinate of the confidence interval can be connected by a straight line. Lean et al. (2008) demonstrate via Monte Carlo simulation the use of 'minor' ordinates (e.g., choosing 10 minor ordinates between each of the 10 major ordinates for a total of 100 ordinates) but using the critical value corresponding to the number of major ordinates. Clearly, the independence assumption is problematic with the use of excessive grid points. Nevertheless, our use of the confidence interval is for graphical representation rather than formal hypothesis testing.

the union of the supports of A and B.[9] Define the following empirical functionals for each order s

$$\hat{d}_s = \sup_{z \in \mathcal{Z}} [\hat{D}^s_B(z) - \hat{D}^s_A(z)]. \tag{4}$$

When the distributions are independent (as we have assumed), tests based on $\hat{d}_s$ are consistent (McFadden, 1989). Test statistics are calculated using

$$\hat{T}_s = \left(\frac{n_A n_B}{n_A + n_B} \right)^{\frac{1}{2}} \hat{d}_s. \tag{5}$$

Because there are infinitely many $F_A(z)$ satisfying the null such that $F_B(z) \leq F_A(z)$, the limiting null distribution is undefined and depend on the underlying unknown distributions of F_A and F_B. Therefore, either simulation or bootstrap techniques are necessary to simulate p-values. Barrett and Donald (2003) use the *least favorable configuration* (LFC) to construct the null distribution. The LFC is the point in the null distribution that is least favorable to the alternative hypothesis. As a result, the test is conservative, rejection of the null under the LFC implies rejection at *any* point in the null distribution. It turns out that $\hat{T}^s$ is the LFC and we can construct a bootstrap distribution of $\hat{T}^{s*}$ to simulate the p-values.

We use a recentering bootstrap approach, which has been shown to perform well against alternative methods (see, Barrett and Donald, 2003 and Linton et al., 2005). Let $\hat{D}^{s*}_j(z)$ be defined as above from (2) but computed on a random bootstrap sample drawn with replacement from distribution j. The statistic is recentered by the observed values so that we have $\hat{D}^{s*}_{jc}(z) = \hat{D}^{s*}_j(z) - \hat{D}^s_j(z)$. We can then define the recentered bootstrap functionals as

$$\hat{d}^*_s = \sup_{z \in \mathcal{Z}} [\hat{D}^{s*}_{Bc} - \hat{D}^{s*}_{Ac}]$$

and the recentered bootstrap t-statistics as

$$\hat{T}^*_s = \left(\frac{n_A n_B}{n_A + n_B} \right)^{\frac{1}{2}} \hat{d}^*_s.$$

We approximate p-values from the distribution of bootstrapped test statistics by

$$\hat{p}_s \simeq \frac{1}{B} \sum_{i=1}^{B} I(\hat{T}^*_s > \hat{T}_s). \tag{6}$$

[9] In our empirical tests, we trim the top and bottom one percent of $\mathcal{Z}$ to focus attention away from outliers in the tails of the distributions.

The p-values allow for a test of stochastic dominances at order s based on the rule "reject H_0^s if $\hat{p}_s < \alpha$" where α represents the conventional levels of statistical significance. For example, if we observe a first-order statistic of $\hat{d}_1 = -0.001$ and the simulated $\hat{p}_1$-value is 0.90, we can infer that first-order dominance of B over A holds with 90-percent confidence.

Finally, our samples are constructed using multi-stage stratification where each strata is clustered by two primary sampling units (PSUs). Test statistics based on a simple random bootstrap samples drawn with replacement would be biased and inconsistent. Rao, Wu, and Yue (1992) show that bootstrap replicate weights can be obtained based on the complex survey design by randomly picking one PSU within each stratum and internally rescaling the sample weights. This is done B times (1,000 in this study) to create B replicate weights θ_i^* for each sample individual.[10] These weights are used in equation (2) to create the bootstrap distribution of $\hat{T}^{s*}$.

5. Results

Our main results are summarized in Tables 3 and 4, and depicted in Figures 3–5. In short, we find that there has been a statistically significant and economically important improvement in the HEI scores over the period under study; Americans at all ranges of dietary quality are eating better in 2005–2008 than they were in 1989–1991. Further, all pairwise comparisons, save one between the two earliest periods in our sample, show statistically significant patterns of increasing diet quality. However, there are differences between income groups with regards to when and where the improvements occurred (Table 5).

Table 3: Tests of stochastic dominance among U.S. adults

Distribution		Observed	First-order		Second-order	
A	B	Ranking	$\hat{d}_1$	$\hat{p}_1$-value	$\hat{d}_2$	$\hat{p}_2$-value
1989-91	1994-96	ND	0.003	0.904	0.014	0.660
	2001-04	$A \prec_1 B$	-0.004	1.000	-0.021	1.000
	2005-08	$A \prec_1 B$	-0.005	1.000	-0.026	1.000
1994-96	2001-04	$A \prec_2 B$	0.014	0.421	-0.025	1.000
	2005-08	$A \prec_1 B$	-0.001	0.999	-0.031	1.000
2001-04	2005-08	$A \prec_1 B$	0.000	0.980	-0.005	0.919

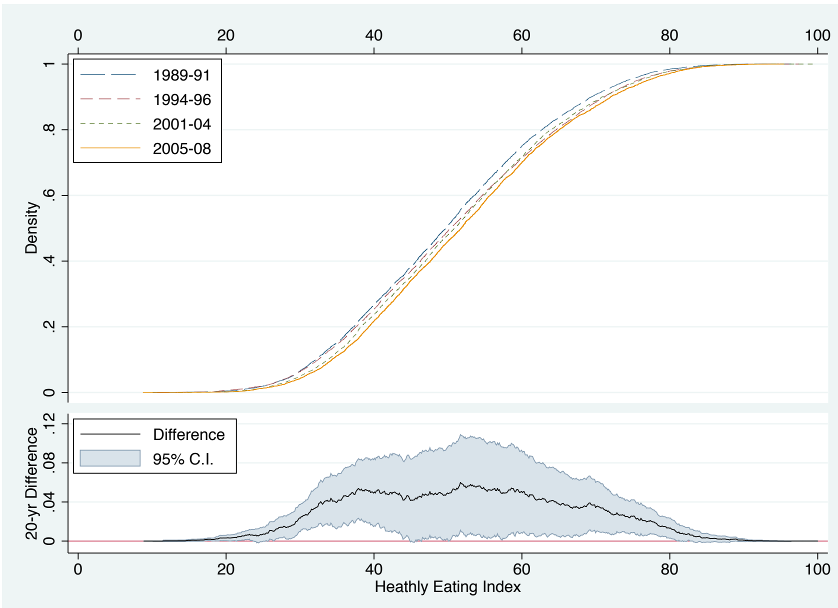
Notes: $A \prec_s B$ reads "Distribution B dominates distribution A at order s," while ND indicates no dominance at order 1 or 2. p_s-values indicate significance of the observed ranking.

[10] We use the user written Stata package `bsweights` (Kolenikov, 2010) to automate this process.

5.1. Between Periods

Figure 3 shows the empirical CDFs for the U.S. adult population in each period. Distributions shift systematically to the right over time, in other words towards a healthier diet. Because the shifts are relatively small, in this and subsequent figures, we present the estimated difference between 1989-91 and 2005-08 in a sub-panel. The area under the difference curve in the sub-panel is equal to the area between the 1989-91 and 2005-08 distributions. We can see the twenty-year improvement was positive and pointwise statistically significant for the empirically relevant range of HEI scores.

Figure 3: Distribution of adult HEI-2005 scores in the U.S. population

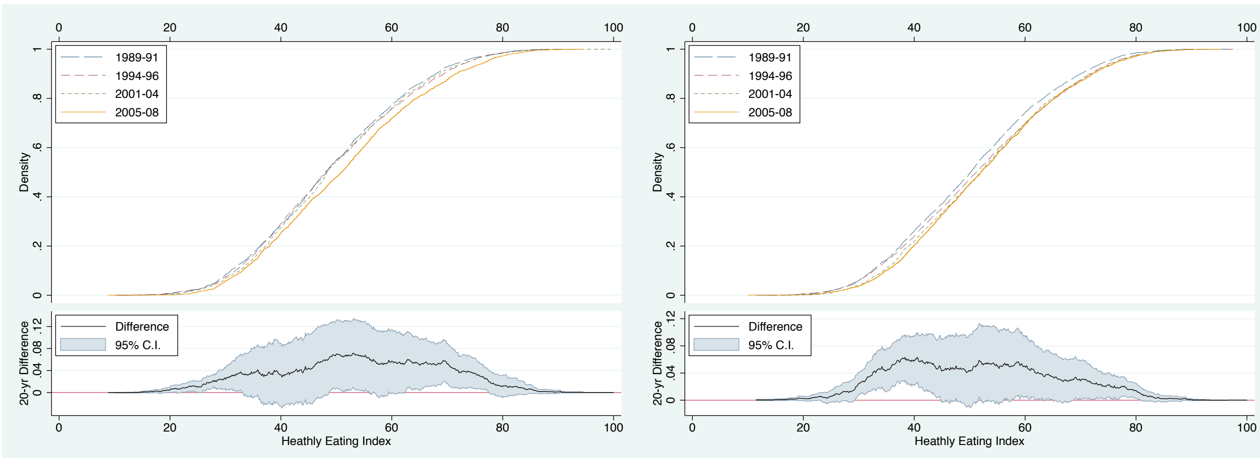


As shown in Table 3, the 2005-08 distribution significantly first-order stochastically dominates 1989-91, according to the K-S test ($\hat{p}_1 = 1.000$). We also observe that while improvements took place at all levels of dietary quality the largest improvements seem to have occurred for those at the lowest end of the HEI distribution. We investigate this observation further in Section 5.3.

5.2. Between Income Groups

We now turn our attention to direct comparisons of individuals above and below 185% of the poverty line. As noted above, we choose 185% of the poverty line as our cut-off because it is a threshold for many Federal nutrition assistance programs, and Federal nutrition policy has placed particular emphasis on the diets of low-income individuals. Panel (a) of figure 4 presents the empirical CDFs and the difference between 1989-91 and 2005-08 for low-income individuals; panel (b) likewise for higher-income individuals. Table 4 presents results from statistical tests of dominance by income group.

Figure 4: Distribution of adult HEI-2005 scores by income group



(a) Low-income

(b) Higher-income

For both groups, the distribution of dietary quality in 2005–2008 significantly first-order stochastically dominates the distribution in the earliest period, according to the K-S test ($\hat{p}_1 = 1.000$). For the low-income population, ranking of the most recent distributions show highly significant first-order dominance of 2005-08 over 2001-04 ($\hat{p}_1 = 0.999$) and 2005-08 over 1994-96 ($\hat{p}_1 = 1.000$) indicating a strong improvements in dietary quality. This is compared to the higher-income population which has seen relatively weaker improvements of recent by noting no dominance of 2005-08 over 2001-4 and second-order dominance of 2005-08 over 1994-96 ($\hat{p}_2 = 1.000$).

We can compare the total twenty year improvements in each income group by examining subpanels (a) and (b) in Figure 4. We see that low-income individuals experienced relatively lower increases over the bottom tail of relevant range of HEI as compared to their higher-income counterparts. We can more formally investigate this finding by taking the difference (between above and below 185% of the poverty line) in the differences (between the earlier and later periods). Figure 5 superimposes the subfigures in panels (a) and (b) of Figure 4 in the top panel and then plots the difference between the two in the bottom panel. That is, in the subpanel of Figure 5 we plot:

$$DD = \left[\hat{D}^1_{high,89}(z) - \hat{D}^1_{high,08}(z)\right] - \left[\hat{D}^1_{low,89}(z) - \hat{D}^1_{low,08}(z)\right].$$

As shown in Figure 5, considering lower levels of dietary quality below a HEI of 45 we find higher-income individuals experienced a greater improvement over 1989–2008 than low income individuals.

Table 4: Tests of stochastic dominance among U.S. adults by income group

Distribution		Observed	First-order		Second-order	
A	B	Ranking	$\hat{d}_1$	$\hat{p}_1$-value	$\hat{d}_2$	$\hat{p}_2$-value
Low-income						
1989-91	1994-96	ND	0.015	0.559	0.019	0.665
	2001-04	$A \prec_2 B$	0.001	0.966	-0.018	0.971
	2005-08	$A \prec_1 B$	-0.008	1.000	-0.035	1.000
1994-96	2001-04	$A \prec_2 B$	0.016	0.582	-0.026	0.992
	2005-08	$A \prec_1 B$	-0.007	1.000	-0.039	0.999
2001-04	2005-08	$A \prec_1 B$	-0.005	0.999	-0.014	0.934
Higher-income						
1989-91	1994-96	ND	0.005	0.843	0.015	0.672
	2001-04	$A \prec_1 B$	-0.004	1.000	-0.027	1.000
	2005-08	$A \prec_1 B$	-0.003	1.000	-0.023	1.000
1994-96	2001-04	$A \prec_2 B$	0.012	0.576	-0.029	1.000
	2005-08	$A \prec_2 B$	0.007	0.781	-0.026	1.000
2001-04	2005-08	ND	0.004	0.908	0.007	0.716

Notes: $A \prec_s B$ reads "Distribution B dominates distribution A at order s," while ND indicates no dominance at order 1 or 2. p_s-values indicate significance of the observed ranking.

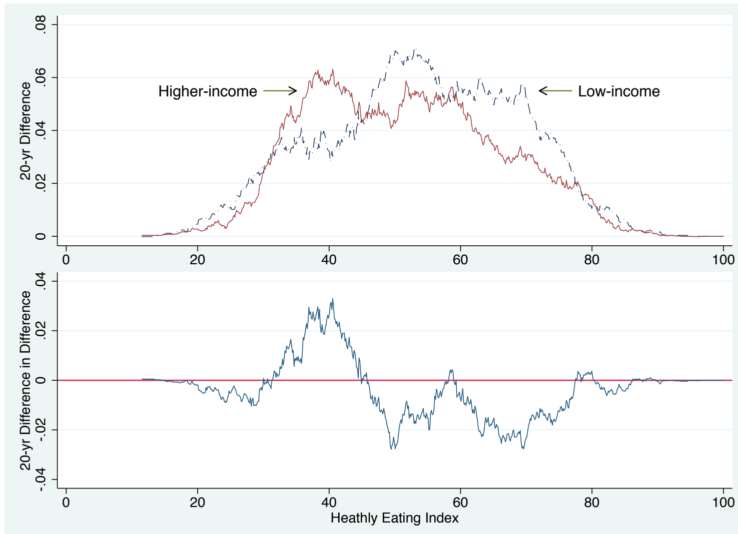
Whereas at higher levels of the HEI distribution, low income individuals experienced greater increases in dietary quality. In other words, we find some evidence that low income individuals with poor dietary quality in 1989–1991 experienced less improvement over the 20-year period compared to higher income individuals with poor dietary quality in the base period.

5.3. Rate and Location of Change

Given the differential gains in dietary quality noted above, we now investigate *when* in time and *where* in the distribution of dietary quality these improvements took place. For consistency and cross sample/population comparisons, we focus on fixed portions of the distribution of dietary quality. An obvious choice is to use quartiles, which are all roughly segmented by HEI scores of 40, 50 ,60.[11] Table 5 measures the amount of dietary improvement occurring in a particular quartile between two time periods as the percentage of total improvement ($\hat{F}_{1989-91}$ - $\hat{F}_{2005-08}$). That is, we measure the area bounded by the two empirical CDFs within each quartile range of the HEI scores. For example, the percentage of improvement in the U.S. over the 20-year period that occurred in

[11] Quartile estimates for the U.S., low-, and higher-income populations when samples are pooled across the 20-year period reveal cutoffs of (40.3, 50.7, 61.5), (39.0, 48.7, 59.9), and (40.8, 51.3, 62.0), respectively.

Figure 5: Differences in dietary improvements amongst low- and higher-income populations



the bottom quartile (< 40) between 1989-91 and 1994-96 was 2.9 percent. The last column of Table 5 measures the overall improvements over 1989–2008 within each quartile of the distribution of dietary quality.

For the U.S. adult population, improvements below the median (HEI < 50) occurred steadily over the period 1989–2008. Individuals in the upper range of dietary quality (HEI above 50) experienced virtually all of their gains over the periods 1989–1996 and 2001–2008. Overall, there were slightly higher gains in the upper quartiles compared to the lower quartiles for the U.S. population.

Comparing the between period improvements by income group, we see that 72.3% of the total improvement in the diets of the low-income population occurred more recently over 2001–08. This is in contrast to the higher-income population which saw the majority of their improvements occurring over 1989–1996 (54.1%) and 1994–2001 (29.2%). Improvements in the lower quartiles for the higher-income population have been relatively steady over the 20-year period, whereas most of the improvement in low-income diets within the lower quartiles occurred more recently over 1994-2008. In other words, at the lower end of the distribution of dietary quality, low income individuals have seen comparatively limited or lagging improvements.

Table 5 underscores the policy justification for targeting the most vulnerable group at risk of poor diets – the low-income, low dietary quality population. This is best seen by examining the last column of Table 5, which measures the total gains over the 20-year period within each quartile. The higher-income population has had almost proportional gains across all levels of HEI, whereas the low-income population has seen less improvement in the lower quartiles.

Table 5: Location and time-path of dietary improvement

HEI range	Between period $\hat{F}_{89} - \hat{F}_{94}$	Between period $\hat{F}_{94} - \hat{F}_{01}$	Between period $\hat{F}_{01} - \hat{F}_{08}$	Total $\hat{F}_{89} - \hat{F}_{08}$
All adults				
0 - 40	2.92	13.13	7.21	23.26
40 - 50	5.88	7.12	8.49	21.49
50 - 60	12.91	1.94	9.35	24.20
60 - 100	21.23	-3.79	13.62	31.06
0 - 100	42.94	18.39	38.67	100.00
Low-income				
0 - 40	2.61	8.21	8.87	19.69
40 - 50	-1.85	6.77	13.93	18.85
50 - 60	4.24	0.79	19.96	24.98
60 - 100	10.97	-4.05	29.56	36.47
0 - 100	15.96	11.72	72.32	100.00
Higher-income				
0 - 40	3.23	16.36	5.36	24.94
40 - 50	9.27	9.15	4.46	22.88
50 - 60	16.46	4.72	2.72	23.89
60 - 100	25.18	-1.07	4.18	28.29
0 - 100	54.05	29.16	16.71	100.00

Note: Numbers represent the percentage of the 20-year improvement coming from the area bounded by the HEI range and the two distributions.

6. Counterfactual Analysis

We now explore whether factors that evolve naturally over time within the population can explain observed improvements in the distribution of HEI scores between 1989–2008. We focus on two factors in particular: changes in food formulation and changes in the demographic landscape.[12]

6.1. Food Reformulation

The composition of the food supply has changed considerably over the last twenty years in response to changes in policy, regulation, technology and consumer tastes. For example, Vesper et al. (2012) find that levels of transfats in the population declined after new labeling requirements were put

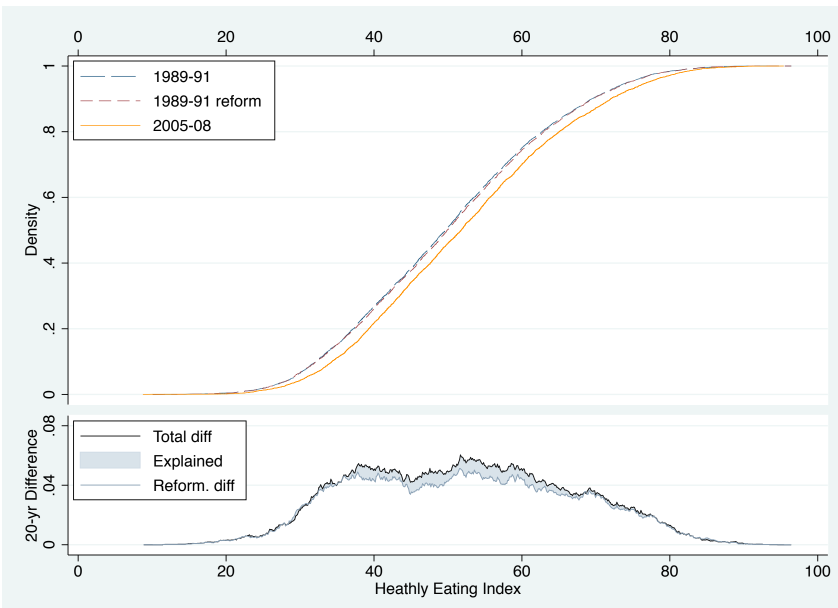
[12]Educational attainment is missing for 121 individuals in 1989-91 CSFII. They are dropped from the preceding analysis and all counterfactual analyses.

in place in 2003. We now investigate how much of the improvement in dietary quality can be explained by changes in food composition.

To identify foods and food mixtures that have undergone food reformulation (e.g., changes in the type of fat used in processed foods), we use the USDA Food and Nutrient Database for Dietary Studies (FNDDS). FNDDS consists of a series of databases updated every two years in conjunction with the continuous waves of NHANES to reflect the current state of food formulation and packaging. All together, we combine the FNDDS to cover 1994–2008. We briefly explain the method here with more details in Appendix A.2.

To construct the distribution of dietary quality in 1989–1991 as if food were formulated in 2005–2008, we first identify all foods coded as reformulated in the 1994–2008 FNDDS. We then replace the nutrient values for these food items in the 1989–1991 CSFII with the reformulated values found in the FDNNS. We also replace the MPED values of the 1989–91 reformulated foods with their 2005–08 values. We then construct a new HEI-2005 score based on updated nutrient and MPED values for each respondent in the 1989–1991 sample. Figure 6 displays the results.

Figure 6: Distribution of HEI-2005 scores accounting for reformulation



The distribution of HEI that accounts for reformulation lies everywhere to the right of the original 1989–1991 distribution over the relevant range of the HEI. The implication is that changes in food composition have lead to improvements in dietary quality. As before the the sub-panel plots the difference between the CDFs. In Figure 6, the shaded area represents the change in the empirical CDFs explained by reformulation. The ratio of the shaded area to the total area provides a scalar measure of change. Here, improvements due to reformulation represent about 10.5% of the total difference between 1989–91 and 2005–08.

An important caveat is that this exercise captures partial equilibrium effects and some care must be taken interpreting these results. Our counterfactual analysis cannot account for the fact that individuals in 1989–1991 might have chosen different foods had their foods been formulated as they were in 2005–2008. Nevertheless, it shows how reformulation, all else equal, can play an important role in altering dietary quality.

6.2. Demographic Changes

The United States of 2005–2008 is an older, more diverse, and better educated country than the United States of 1989–1991. To the extent that these factors are correlated with healthy eating, they may explain some of the improvements in dietary quality. Table 6 illustrates demographic changes using data from our sample and from the U.S. Census. There is a clear decrease in the 30 to 44 year old population and a concomitant rise in the 45 to 64 year cohort. The decrease in the non-hispanic white population has come from an increase in the Hispanic and other race/ethnicity groups. The overall educational attainment in the population has also increased.

Table 6: U.S. population characteristics, adults 20 and older

Demographic	1989-91 CSFII	2005-08 NHANES	1990 Census†	2005-07 Census‡
Age 20 − 29	21.7	19.1	22.7	19.1
Age 30 − 44	35.9	28.4	33.5	29.1
Age 45 − 64	26.2	35.2	26.1	35.0
Age 65+	16.3	17.3	17.6	16.8
Non-hispanic white	78.8	71.9	78.4	69.5
Non-hispanic black	10.8	11.5	10.6	11.3
Hispanic	7.7	11.5	7.6	12.8
Other race/ethnicity	2.7	5.1	3.4	6.4
Did not attend high school	8.5	6.0	9.6	6.1
High school, no college	46.2	37.7	44.5	39.7
Attended college	45.2	56.2	45.9	54.2
N	9,377	7,765		

†U.S. Census Bureau, General Population Characteristics (CP-1, 3-4)

‡U.S. Census Bureau, 2005-07 Annual Community Survey 3-year sample

To investigate the effect of evolving population characteristics, we construct counterfactual distributions of HEI scores following an approach proposed by DiNardo, Fortin, and Lemieux (1996).

We ask, "What would the distribution of HEI scores look like had the demographic landscape of 2005–08 prevailed in 1989–91?" We focus on age, race/ethnicity, and educational attainment, all of which have been found to be correlated with diet healthfulness (Popkin et al., 1996). The intuition is to adjust each individual's sampling weight in the base period 1989-91 conditional on a set of demographics such that it captures the relative probability that the individual would be represented in the more recent 2005–08 sample.

To briefly describe the methodology, let each individual observation be a vector (y, h, t), where y is HEI, h is vector of demographic characteristics, and t is time. Thus, all individuals belong to the joint distribution $F(y, h, t)$. The static joint distribution of HEI and demographics in time t is $F(y, h|t)$. The density of HEI at any point in time $f_t(y)$ can be written as the integral of the HEI density conditional on a set of demographics $f(y|h, t_y)$ at a specific date t_y, over the distribution of demographics $F(h|t_h)$ at date t_h

$$\begin{aligned} f_t(y) &= \int_{h\in\Omega_h} dF(y, h|t_{y,h} = t) \\ &= \int_{h\in\Omega_h} f(y|h, t_y = t)dF(h|t_h = t) \\ &= f(y; t_y = t, t_h = t) \end{aligned}$$

where Ω_h is the domain of individual demographics. Therefore, our question posed earlier can be written with the above notation as the density of HEI scores in 1989-91 had the 2005-08 demographic landscape prevailed: $f(y; t_y = 89, t_h = 08)$. This density is written as

$$\begin{aligned} f(y; t_y = 89, t_h = 08) &= \int f(y|h, t_y = 89)dF(h|t_h = 08) \\ &= \int f(y|h, t_y = 89)\psi(h)dF(h|t_h = 89) \end{aligned}$$

where $\psi(h)$ is a reweighting function defined as $\psi(h) = dF(h|t_h = 08)/dF(h|t_h = 89)$. Applying Bayes' rule to the function we can rewrite $\psi(h)$ as

$$\psi(h) = \frac{\Pr(t_h = 08|h)}{\Pr(t_h = 89|h)} \cdot \frac{\Pr(t_h = 89)}{\Pr(t_h = 08)}.$$

To obtain an estimate $\hat{\psi}(h)$, notice the conditional probabilities $\Pr(t_h = t|h)$ can be estimated using a probit model by pooling the data and estimating the probability an individual is observed in time t conditional on a set of characteristics.[13] As we only compare two dates, the unconditional

[13]The conditional probability model includes 20 cells: gender fully interacted with four age dummies, and four

probabilities $\Pr(t_h = t)$ are simply the weighted sums of individuals in period t_h over the weighted sums of individuals in both periods. Because we are interested in applying the above methodology to tests of stochastic dominance, we replace an individual's sampling weight θ_i with $\omega_i = \theta_i \hat{\psi}_i(h)$ in equation (2).

Figure 7 plots four empirical CDFs. We compute the demographic counterfactual for the reformulated density. For reference we plot the original distribution of HEI for 1989–1991 and the original distribution of HEI for 2005–2008, as well as the reformulated 1989–91 distribution. We see the counterfactual HEI distribution lies everywhere to the right of the original and reformulated 1989–91 distributions. The implication is that the majority of the improvement in HEI scores over the last 20 years can be explained by shifts in the demographic make-up of the population.

Figure 7: Distribution of HEI-2005 scores accounting for reformulation and demographic changes

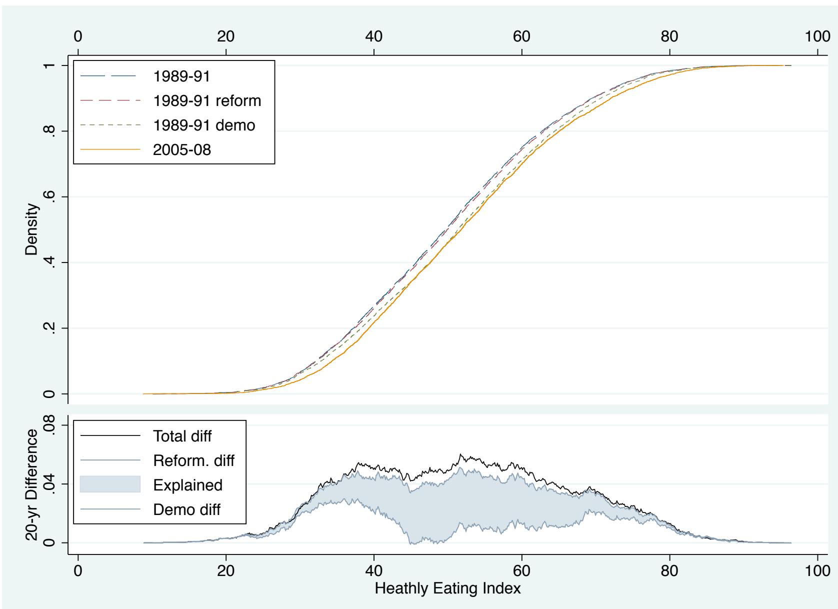


Figure 7 decomposes the change in the distribution of HEI into three main parts: improvements explained by reformulation (as shown in the previous section), additional improvements explained by changes in demographics, and finally unexplained changes. As noted above, 10.5% of total improvement can be explained by changes in food composition. Here we find that an important proportion of the total improvement in HEI scores, 51.7%, can be explained by changes in population demographics over the twenty year period. This leaves 37.8% of the improvement unexplained by reformulation and demographics, which represents a significant portion: the 2005-08 distribution

dummies for race/ethnicity groups fully interacted with three education dummies, all as described in Table 6 for adults 20 and older. Results available from the authors upon request.

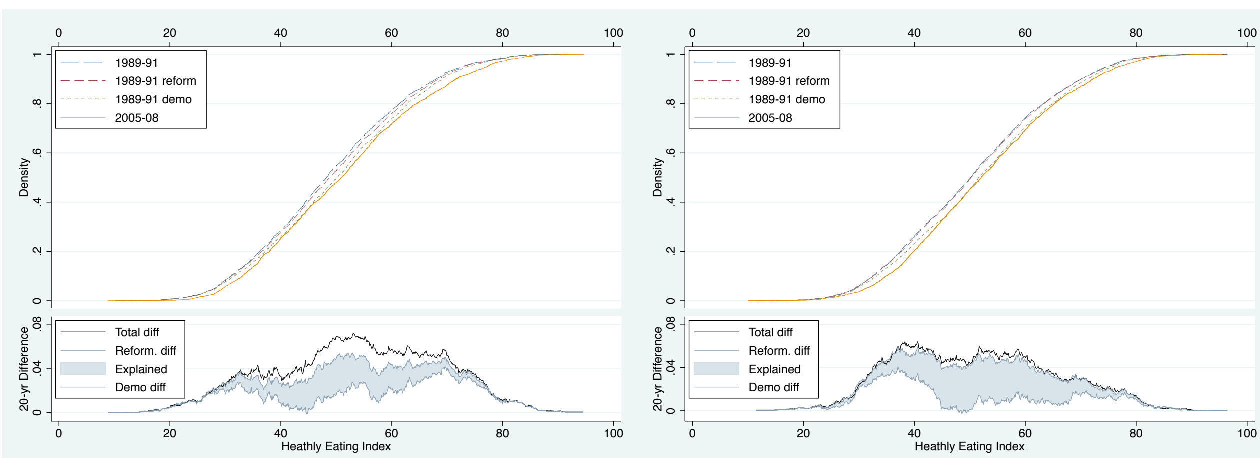
second-order stochastically dominates the 1989-91 counterfactual distribution accounting for both reformulation and demographic changes ($\hat{p}_2 = 1.000$).

Again some care must be taken in interpreting these results. One important limitation of the partial equilibrium nature of the counterfactual analysis is that food choices in the counterfactual population would not affect the set of foods made available by food manufacturers. While this assumption is economically unappealing, the exercise still provides valuable information pertaining to the effects of demographics on diet quality via clear and tractable analytical techniques.

6.3. Counterfactuals by Income Group

The counterfactual analyses above suggest that an important part of the improvement in dietary quality can be explained by changes in food composition and demographics. Given that improvements occurred at different rates for different parts of the HEI distribution for low-income versus higher-income individuals, we now ask whether changes in food composition and demographics account for differing amounts of improvement by income group. Results are presented in Figure 8.

Figure 8: Counterfactual distribution of adult HEI-2005 scores by income group



(a) Low-income

(b) Higher-income

Changes in food composition account for a substantially larger percentage of the dietary improvement for lower-income individuals (18.8%) as compared to their higher-income counterparts (6.9%). This is consistent with the observation that lower-income individuals eat more processed foods (Drewnowski and Barratt-Fornell, 2004), where much of the reformulation is occurring. Changes in demographics explain a smaller share of the improvement for low-income (34.2%) than higher-income individuals (54.8%). The remaining unexplained share of the twenty-year improvement is larger within the low-income population (47%) as compared to higher-income (38.3%).[14] This suggests that further research into the determinants of diet quality of low-income individuals may be warranted.

7. Discussion and Conclusion

This paper documents a previously unknown consistent improvement in U.S. dietary quality over the period 1989–2008, at all levels of dietary quality. While we find that high income individuals consistently have higher dietary quality than low-income individuals, we also find some evidence that the gap is shrinking over time. An important caveat is that the diets of low-income individuals in the lowest portion of the HEI distribution continue to lag.

We also show that most of the improvement in dietary quality is explained by changes in food formulation and changes in demographics. Moreover, we find that changes in food formulation explain considerably more of the improvement in dietary quality for low-income individuals than for higher-income individuals. These findings suggest that the direct and indirect effects of policy on food composition may represent understudied policy levers.

How large are these results? Ford et al. (2011) classify individuals as having a healthy diet if they are in the upper 40% of the distribution of dietary quality. All else equal these individuals are found to be at lower risk of all cause mortality. One way to asses the magnitude of changes in HEI over time is to see how many individuals move from unhealthy to healthy diets over the period under study. In 1989, the 60$^{\text{th}}$ percentile of the HEI distribution was 53.6. In 2008, a HEI value of 53.6 represented the 54.4$^{\text{th}}$ percentile of the HEI distribution. In other words 5.6 percent of individuals moved out of the higher risk category between 1989–2008 due to improvements in diet quality.

An important share of the change in dietary quality over the period remains unexplained. Because of the sheer number of overlapping and time varying policy initiatives, particularly those that target less affluent Americans, credibly identifying the effects of specific policies remains a challenging task for future work.

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A. Appendix

A.1. Extending HEI-2005 to CSFII 1989–1991

Extending the HEI-2005 to the 1989-91 CSFII allows us to create a consistent dietary index spanning 1989–2008. As mentioned in the text, the HEI-2005 is calculated by linking the MyPyramid Equivalents Databases (MPED) to food intake surveys via unique food codes. To do so, we use the MPEDv1 for 1994-96 CSFII, 1999-2000 NHANES and the accompanying whole fruit and fruit juice data.[15] In the 1994-96 CSFII and the 2001–08 NHANES, some foods have modification codes (for example, there are modification codes for the type of milk used in a scrambled egg) but these do not appear in the 1989-91 CSFII. The first step is to drop all duplicate food codes that have modifications in the MPEDv1. Previous research has shown that these modifications do not have significant impacts on nutrient intakes (Ahuja et al, 1999).

Of the 3,953 unique foods reported by adults 20 and older on day one in CSFII 1989-91, 3,907 (98.8 percent) of these foods are in the MPEDv1. A total of 10,439 adults reported complete intakes on day one in 1989–91, and 941 adults (9 percent) reported consuming one of the forty-six foods not found in MPEDv1. These individuals are dropped from the sample. Table 7 and Figure 9 below show the proportion of calories, grams, and selected nutrient intakes coming from these 46 foods for the 941 adults. The steep slope of the CDF shows that these foods make up a very small proportion of food calories and nutrients for those that have consumed them. Specifically, for the 941 adults that consumed at least one of the 46 foods that do have full information, for at least 80% of these adults, these 46 foods represent less than 20% of each particular nutrient's intake.

Table 7: Percent of nutrient intake from foods not matched to the MPED, $N = 941$

Nutirent	Mean	Std. dev.	Min.	25$^{\text{th}}$ percentile	Median	75$^{\text{th}}$ percentile	Max.
Grams	5.78	8.65	.01	0.72	2.89	6.63	76.7
Kcal	7.04	7.33	0	2.57	5.12	8.78	76
Total fat	7.88	11.8	0	.223	3.34	10.20	84.5
Sat. fat	5.88	10.2	0	.159	2.36	7.08	92
Carbs	8.55	10.6	< 0.01	.044	5.46	13	97.8

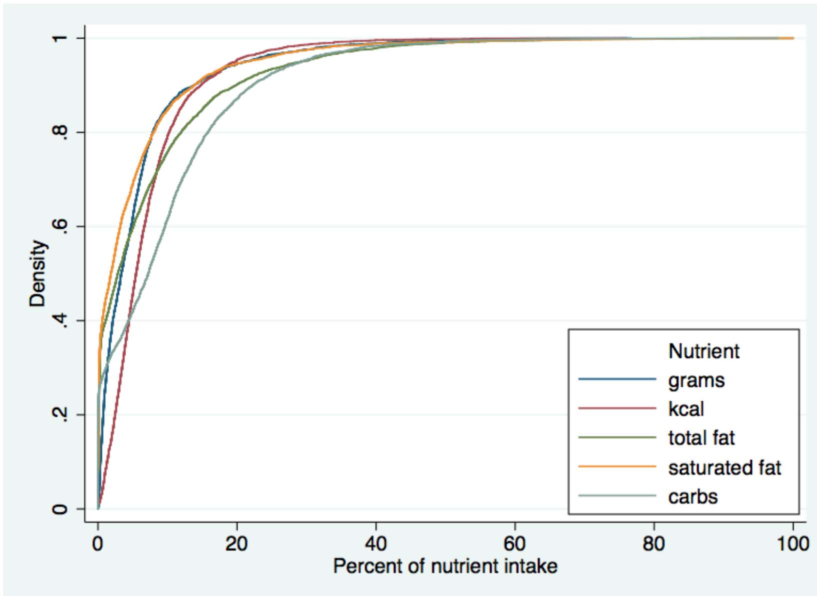
Note: Numbers are percent of the nutrient intake.

Alternatively, we could have constructed 'best matches' for each of the 46 foods, as done by the National Cancer Institute when creating a equivalents database for NHANES III (1988-94) for the original HEI (National Cancer Institute website, accessed February, 2012). We tried this for the 46 foods, allowing us to keep all 10,439 adults; results were robust to this approach.

The validity of backdating the food codes has not previously been attempted, and we make no attempts here. However, we do note that the MPEDv2 created for 2003-04 was recently appended with some 800 foods to create the 2005-08 MPED. Thus, if mapping forward is appropriate then mapping backwards seems reasonable.

[15]Data can be obtain from the ARS-USDA website `http://www.ars.usda.gov/Services/docs.htm?docid=17558`

Figure 9: Distribution of the percentage of nutrient from foods with no MPED values



A.2. Calculating Reformulated Nutrient Values

The FNDDS codes nutrients that have been updated due to reformulation.[16] Reformulation can occur for a whole host of nutrients: water, calories, sodium, fats, ect. We code a food as reformulated if any of these nutrients we reformulated. The logic being that we do not know what or how the food was reformulated (e.g., Raisin Bran added more raisins which would affect many of the listed nutrients). We replace values for calories, sodium, carbohydrates, alcohol, and saturated fat in the 1989-91 CSFII with the most recent updated value in FNDDS (i.e., if a food was reformulated in 2002 and then again in 2005, we use the 2005 value). As noted in Table 1 these nutrients directly affect calculation of the HEI-2005. We then replace the MPED values in the 1989-91 CSFII with those from 2005-08 if the food was reformulated.

[16]The FNDDS corresponding to NHANES 2001–08 can be found on the ARS-USDA website `http://www.ars.usda.gov/services/docs.htm?docid=12089`. We obtained a multi-year version dating back to 1994 by submitting a request to ARS-USDA.

A.3. Two Day Average

Table 8: Mean Health Eating Index–2005 scores, 2 day average.

Population	1989-91	1994-96	2005-08
U.S. population	52.35 (0.34)[a]	53.16 (0.30)[a]	55.09 (0.36)
	[13.43, 91.72]	[16.65, 94.85]	[11.34, 96.83]
N	7,439	9,323	8,165
low-income	50.76 (0.40)[a]	51.49 (0.44)[a]	54.05 (0.52)
	[13.43, 89.83]	[16.65, 94.85]	[11.34, 94.71]
N	3,860	3,236	3,112
Higher-income	52.88 (0.42)[ab]	53.77 (0.33)[ab]	55.33 (0.38)[b]
	[15.64, 91.72]	[17.84, 93.03]	[16.781, 96.83]
N	3,579	6,087	4,527

Standard deviations in parenthesis. Maximum and minimum in brackets

[a]Within-population mean is significantly lower than 2005-08 at 5-percent level.

[b]Within-year higher-income is significantly different from low-income at 5-percent level.

Figure 10: Two-day average HEI scores, U.S. population

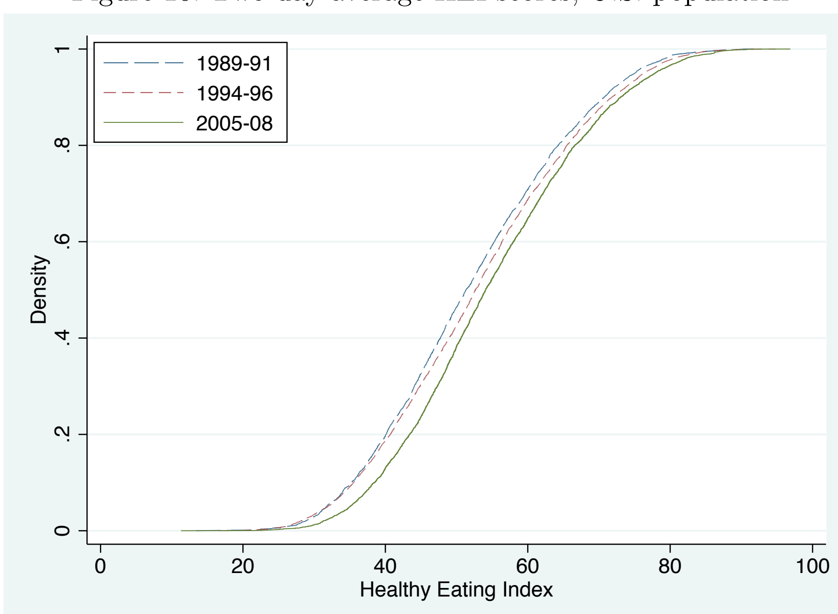
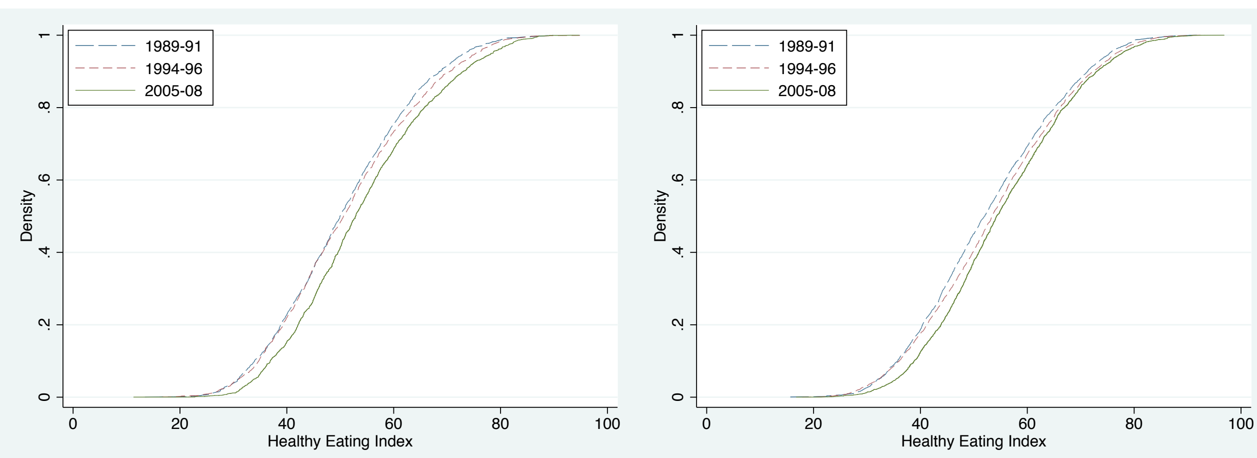


Table 9: Tests of stochastic dominance among U.S. adults, two day average

Distribution		Observed	First-order		Second-order	
A	B	Ranking	$\hat{d}_1$	$\hat{p}_1$-value	$\hat{d}_2$	$\hat{p}_2$-value
1989-91	1994-96	ND	0.007	0.722	0.025	0.600
	2005-08	$A \prec_1 B$	-0.007	1.000	-0.026	1.000
1994-96	2005-08	$A \prec_1 B$	-0.007	1.000	-0.026	1.000

Notes: $A \prec_s B$ reads "Distribution B dominates distribution A at order s," while ND indicates no dominance at order 1 or 2. p_s-values indicate significance of the observed ranking.

Figure 11: Two-day average distribution of HEI scores by income group



(a) Low-income (b) Higher-income

Table 10: Tests of stochastic dominance by income group, two day average

Distribution		Observed	First-order		Second-order	
A	B	Ranking	$\hat{d}_1$	$\hat{p}_1$-value	$\hat{d}_2$	$\hat{p}_2$-value
Low-income						
1989-91	1994-96	ND	0.008	0.810	0.012	0.660
	2005-08	$A \prec_1 B$	-0.007	1.000	-0.032	0.998
1994-96	2005-08	$A \prec_1 B$	-0.006	1.000	-0.040	1.000
Higher-income						
1989-91	1994-96	ND	0.007	0776	0.018	0.646
	2005-08	$A \prec_1 B$	-0.008	1.000	-0.030	0.994
1994-96	2005-08	$A \prec_1 B$	-0.006	1.000	-0.022	0.974

Notes: $A \prec_s B$ reads "Distribution B dominates distribution A at order s," while ND indicates no dominance at order 1 or 2. p_s-values indicate significance of the observed ranking.

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