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A Century of Eating:
revealed preferences for nutrients and foods in the United States

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*Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's
2014 AAEA Annual Meeting, Minneapolis, MN, July 27-29, 2014.*

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Abstract

People eat for two purposes: nutrition and taste. Both aspects of food affect consumption, which affects diet-related health issues and needs to be considered in light of policy changes. We use linear programming, maximum entropy and least squares to estimate consumer shadow prices for 18 nutrients and 21 food taste values from 1910-2006. From these estimations, we find annual taste and nutrition expenditures. This study explains correlations between taste and nutrient shadow prices as well as food expenditure shares with demographic composition of the U.S., which may unveil intuition behind unhealthy eating habits.

I. INTRODUCTION

The last four decades have witnessed a global phenomenon of skyrocketing obesity, hypertension, cholesterol problems, and type-II diabetes. According to the National Health and Nutrition Examination Survey (NHANES) in 2008, 34.2% of U.S. adults 20 years and older were overweight, 33.8% were obese, and 5.7% were extremely obese, based on body mass index (Ogden et al., 2010). That leaves only about a quarter of American adults at or below a healthy weight. Further, there was an observed doubling of type-II diabetes from the 1970's to the 1990's, according to a study from the American Heart Association (Fox et al. 2006). Between 90-95% of those diagnosed with diabetes have type-II diabetes, which is roughly 8% of the American population (CDC).

These diseases may directly result from or be exacerbated by the food people eat. Hypertension, diabetes and other diet-related health concerns often relate to excessive levels of individual nutrients, such as calories, sugar, sodium, and saturated fats. Conversely, other nutrients may cause health issues when under-consumed, especially many vitamins and minerals. Undoubtedly, food consumption affects human health.

People frequently eat for two purposes: nutrition and taste. Consumers buy food products for both taste value of the food and a collective bundle of nutrients. This follows from Lancaster (1966), who describes how consumers derive utility from the characteristics of a good. Often, a

tradeoff between nutrition and taste exists. We see this with the recommendation of a low-fat diet of the late 1970s (U.S. Senate Select 1977). However, a low-fat label does not limit the sugar content of a food. Without increased sugar content, a low-fat diet would be inherently less delicious. Thus, in maintaining a low-fat diet, Americans consumed increased levels of sugar, which may have ultimately reduced their health.

The objective of this study is to formally examine how the tradeoffs between tastes and nutrients have changed over time, and further to explore the demographic variables that influence these tradeoffs. We inspect three different methods of nutrient and taste valuation. We estimate shadow prices for 18 nutrients and taste values for 21 different food products from 1910-2006 using linear programming, least squares, and maximum entropy. This study estimates nutrient shadow prices and taste values over time, from which we estimate nutrition expenditure versus taste expenditure. The study then explains the relationships between these expenditure tradeoffs and U.S. demographic variables.

Numerous governmental programs provide food assistance for an increasing number of people in the U.S. For example, the Supplemental Nutrition Assistance Program (SNAP) constitutes the largest federal food assistance program. In 2006, an average of 26.5 million participants received SNAP benefits, with the number growing to 47.6 million by May 2013 (ERS 2013). The United States Department of Agriculture (USDA) originally launched SNAP as the Food Stamp Program in 1974. In late 2008, the Food Stamp Program became SNAP, with a new objective of increasing nutrition availability to low-income residents (Brownell et al. 2011). In pursuit of its mission, the USDA has furthered its efforts to suggest nutritional food bundles that align with Americans' tastes and preferences. SNAP calculates consumer benefits through its quadratic programming tool called the Thrifty Food Plan. Along with this increasingly palatable,

nutritious food bundle, the USDA also takes into account age and gender variables to better optimize participant benefits (USDA 2006). The USDA continues to move forward with incentive alignment when implementing food assistance policies, but no study offers an empirical assessment of Americans' tradeoffs between nutrition and tastes. This study aims to do so.

Examining annual taste and nutrition expenditure over the last century can help us understand consumer behavior with respect to food and nutrition. Policymakers have limited tools to provide incentives for consumers to make healthy eating choices (Faulkner et al., 2011). It may be helpful to shine light on discrepancies between the tradeoffs of nutrition versus tastes. Furthermore, the food and nutrient shadow prices may help predict how consumers might react to policy changes. If policymakers had better information about the tradeoffs between nutrition and taste, they could better understand which measures are critical for aligning food purchases with healthy lifestyles.

The literature investigating nutrient valuation began when Stigler (1945) developed an application of linear programming to minimize costs under essential nutrition constraints. His approach was least-cost food rationing, which estimates the least-cost bundle of food products to meet the nutritional criteria. Stigler constrained the nutrients to levels at or above the minimum recommended dietary allowances. Silberberg's (1985) work utilized this same method, but constrained nutrients at or above the *observed* levels of consumption to minimize expenditures under revealed and consistent nutrition habits. In this study, we modify the Silberberg approach by holding the minimum nutrition constraint *equal* to the observed, average consumption level.

An analyst looking to estimate nutrient valuation might use a relatively simple econometric tool - least squares. Ladd and Suvannunt (1976) used least squares to find the

hedonic prices of non-nutrient characteristics. We build off their study by further analyzing this collective “felicity of eating” factor of total utility in addition to that for individual nutrients. We can infer the taste value for individual food products by adding each product’s regression residual to the felicity of eating, from which we infer the total taste expenditure each year.

We would like to estimate a model consistently with Gorman’s (1956) theory of utility maximization, as well as the theory that characteristic (nutrient) prices and individual product value comprise the full product price. However, adding product-specific taste preferences increases the number of variables we must estimate without adding observations. When a question is ill-posed with more unknowns than equations (in this case due to the large number of product-specific as well as nutrient parameters), standard econometric modeling will not properly estimate the problem. We use information theory when there are necessary but unknown variables present (Mittelhammer, Judge and Miller, 2000). Beatty (2007) uses an entropy-based econometric approach to handle a similar problem to find nutrient and taste shadow prices. While Beatty (2007) uses a discrete maximum entropy model, our study estimates a continuous model of maximum entropy over a much larger time span.

We use maximum entropy to deal with this ill-posed problem. Maximum entropy is quite different from the two previously discussed models, because it allows us to consider the unique demand for individual food products. This assumes that consumers purchase a product partly due to the product's distinctive and unique quality. This model more accurately measures how people make food consumption choices. If nutrition shadow prices do not align with health requirements, it may be helpful to see if particular foods are causing this discrepancy.

This study contributes to the literature of consumer valuation of food and nutrition in multiple facets. First, this study estimates a longer time span of nutrient and food shadow prices

than any other study, offering insight to how these shadow prices change and evolve. It also compares findings across three models - linear programming, least squares, and maximum entropy - all using identical data. From these models' shadow prices, we estimate the portion of food expenditure consumers spend on taste versus nutrition, and how this has evolved over a century's time. These taste expenditures will allow policymakers to better understand what consumers pay for when they purchase food.

The upcoming section builds the theoretical foundation in a utility maximization setting, in which nutrient composition helps explain food prices. The basic theoretical discussion will follow with the three models employing linear programming, least squares, and maximum entropy. Next, we discuss the data as well as the empirical results. We then study the relationships between demographic composition with nutrition and taste expenditures. Last, the final section concludes and includes a discussion of policy implications.

II. DEVELOPMENT OF TASTE AND NUTRIENT SHADOW PRICES

We begin with a utility maximization problem where consumers make purchasing decisions over food products and all other goods. Consumers gain utility from each of the nutrients and from the food product itself. The optimality problem proceeds as follows:

$$(2) \quad \max \left\{ u(\mathbf{x}, \mathbf{y}, \mathbf{a} | \mathbf{s}), \mathbf{a} = \mathbf{A}\mathbf{x}, \mathbf{p}'\mathbf{x} + \mathbf{q}'\mathbf{y} = m \right\}.$$

We denote the quantity consumed of each $(1, \dots, I)$ food product a non-negative vector \mathbf{x} and all other $(1, \dots, N_y)$ goods consumed as a non-negative vector \mathbf{y} ¹. Let \mathbf{s} be an L -vector of demographic variables, preference parameters, or other variables that affect demand and preferences. The total amount of nutrients $(1, \dots, J)$ obtained from consuming food is vector

¹ We assume the independence of nutrients. While some nutrients may help augment or deplete absorption of other nutrients, this is not consistent for across consumption levels for these nutrients.

a . The nutrient amount per pound of food product i is denoted as $J \times I$ matrix A . The constraint $a = Ax$ requires that the nutrients consumed come from food products, x . The price of the food products (x) and all other goods (y) are respectively denoted by p and q . This optimality problem includes a budget constraint, $p'x + q'y = m$, where $m > 0$ represents total consumption expenditure, for which we use the sobriquet income.

We write the Lagrangian for this problem as

$$(3) \quad \mathcal{L} = u(x, y, a, s) + \lambda(m - p'x - q'y) + \mu'(Ax - a),$$

with first-order Kuhn-Tucker conditions²:

$$(4) \quad \begin{aligned} \frac{\partial \mathcal{L}}{\partial x} &= \frac{\partial u}{\partial x} - \lambda p + A'\mu \leq \mathbf{0}_I, x \geq \mathbf{0}_I, x' \frac{\partial \mathcal{L}}{\partial x} = 0; \\ \frac{\partial \mathcal{L}}{\partial y} &= \frac{\partial u}{\partial y} - \lambda q \leq \mathbf{0}_{N_y}, y \geq \mathbf{0}_{N_y}, y' \frac{\partial \mathcal{L}}{\partial y} = 0; \\ \frac{\partial \mathcal{L}}{\partial a} &= \frac{\partial u}{\partial a} - \mu \leq \mathbf{0}_J, a \geq \mathbf{0}_J, a' \frac{\partial \mathcal{L}}{\partial a} = 0; \\ \frac{\partial \mathcal{L}}{\partial \lambda} &= m - p'x - q'y = 0; \\ \frac{\partial \mathcal{L}}{\partial \mu} &= Ax - a = \mathbf{0} \end{aligned}$$

Summing the complementarity slackness conditions for goods and nutrition yields

$$(5) \quad 0 = x' \frac{\partial \mathcal{L}}{\partial x} + y' \frac{\partial \mathcal{L}}{\partial y} + a' \frac{\partial \mathcal{L}}{\partial a} = x' \frac{\partial u}{\partial x} + y' \frac{\partial u}{\partial y} + a' \frac{\partial u}{\partial a} - \lambda m.$$

Combining equations (4) and (5) yields the following, hedonic pricing model for each food product:

² Note that we treat the constraints as equalities, and monotonicity of $u(\cdot)$ implies $\lambda > 0$ and $\mu_j > 0$.

$$(6) \quad p = \frac{\frac{\partial u}{\partial x}}{(x'u_x + y'u_y + a'u_a)} + A' \frac{\frac{\partial u}{\partial a}}{(x'u_x + y'u_y + a'u_a)},$$

where $\frac{\frac{\partial u}{\partial x}}{(x'u_x + y'u_y + a'u_a)}$ represents the marginal dollar utility for food products, and

$\frac{\frac{\partial u}{\partial a}}{(x'u_x + y'u_y + a'u_a)}$ the marginal dollar utility for nutrients, or shadow prices for taste and

nutrition, respectively.

We rewrite the price equation (6) for each food product more succinctly as a function of the taste and nutrient shadow prices,

$$(7) \quad p = r + A' \pi.$$

Here, r is an I – vector representing the shadow price of each food product i , otherwise known as the taste for this food product, and π is a J – vector representing the shadow price for each nutrient, j .

III. EMPIRICAL MODELS

We compare three different approaches to generating shadow prices – linear programming, least squares, and information theory. We consider how each model describes the price of food products as a function of taste and nutrient prices as given in equation (7) and compare nutrition and taste expenditures annually.

3.1 Linear Programming

Using linear programming, only nutrient content and their shadow prices determine product prices. We use Silberberg's (1985) model, but constrain nutrients to the exact level observed. We write the minimization problem as:

$$(8) \quad \min \{C_N = p'x, a = Ax\}$$

We minimize the nutrition expenditure, which we denote as C_N , a J – vector of nutrient expenditures, while holding each level of nutrient consumption Ax at the observed nutrient consumption level a . Thus, we find a minimum expenditure level for a food bundle that satisfies the observed nutrient consumption level. Price in equation (8) consists of nutrient values only and excludes the taste value from equation (7), forcing taste value r to zero.

After obtaining the minimized nutrition expenditure, we compare the results to the observed level of food expenditure. Subtracting the minimum expenditures needed to obtain the observed nutrients from the observed expenditure levels yields the expenditure for taste in this model, C_T . This model assumes a product's entire price to originate from nutrition levels, so the residual expenditure represents the minimum possible level of C_T .

3.2 Least Squares

We consider a generalized least squares model for the hedonic price equation:

$$(9) \quad p = r + A'\pi + \varepsilon$$

Estimating equation (9) generates the shadow price for each nutrient, $\hat{\pi}$, as well as the marginal value of utility from eating, denoted as \hat{r} . Here, \hat{r} measures the common eating value that is not product specific. Adding this value with this I – vector of error terms for each food product, we infer a vector of the individual products' taste values. This provides us with an estimate of the food taste value \hat{r} from equation (7). Summing this food taste vector by the respective observed consumption levels allows us to find the total, annual taste expenditure $C_T = \sum_{i=1}^I \hat{r}_i x_i, i = 1, \dots, I$.

We allow both positive and negative values for the nutrient shadow prices π . Consumers might rationally consume where π is negative if the food product's taste value r outweighs the

disutility of nutrient j (Leathers 1979). People may consume more of any nutrient than they would if they could separate the nutrients from products they enjoy. We allow diminishing marginal utility to exist for all nutrients.

3.3 Maximum Entropy

Maximum entropy allows us to treat the product price as a function of both characteristic prices and product-specific taste value, where consumers make trade-offs between nutrition and taste. Adding product-specific taste preferences increases the number of variables without adding degrees of freedom, which leads to more unknown parameters than equations. With this ill-posed problem, standard econometric modeling will not properly estimate the parameters (Mittelhammer, Judge and Miller 2000). We extend this theory by using continuous probability distribution functions (PDFs), smoothed over a carefully defined support.

To directly measure the shadow prices for each nutrient and taste for each food product, estimating each element of equation (7), we minimize the average logarithmic height of the probability density functions (PDFs) of the shadow prices and food-specific taste attributes. These PDFs have a pre-specified support. We introduce the distributions of unknowns through moment conditions for each product, and the hedonic pricing model in equation (7) becomes

$$(10) \quad p = E(\mathbf{R}) + \mathbf{A}'E(\mathbf{\Pi}).$$

Here, \mathbf{R} and $\mathbf{\Pi}$ represent random variables for the food taste values and nutrient shadow prices. Price in equation (10) is a function of the mean of these, $E(\mathbf{R})$ and $E(\mathbf{\Pi})$.

The value r can take any value up to the price of food i . Hence, $r \in [0, p]$. We allow for the possibility of consuming at a negative π , as we did for least squares. The support is $\pi_j \in [-\tilde{\pi}_j, \tilde{\pi}_j]$, bounded symmetrically around zero, where

$$(11) \quad \tilde{\pi}_j \equiv \min_{\{a_{ij}>0\}} \frac{p_i}{a_{ij}}, \quad \forall j = 1, \dots, J.$$

We assume no nutrient can have a marginal value to consumers that exceeds the market price of that food. Otherwise, the consumption side of the market would tend to bid up the price of the food, leading to a higher market equilibrium price.

With the supports for both \mathbf{R} and \mathbf{II} , we can apply maximum entropy. Since we do not know the distributions of these two random variables, we consider a distribution with largest entropy, i.e. largest uncertainty. Jaynes (1957) maximizes entropy in a distribution by maximizing the negative integral of the PDF multiplied by the logarithm of the PDF. We write the maximum entropy equation as:

$$(12) \quad \begin{aligned} \max E &\equiv - \sum_{i=1}^I \int_0^{p_i} f_i(r) \ln f_i(r) dr - \sum_{j=1}^J \int_{-\tilde{\pi}_i}^{\tilde{\pi}_i} g_j(\pi) \ln g_j(\pi) d\pi \\ 1 &= \int_0^{p_i} f_i(r) dr, \quad i = 1, \dots, I, \\ s.t. \quad 1 &= \int_{-\tilde{\pi}_i}^{\tilde{\pi}_i} g_j(\pi) d\pi, \quad j = 1, \dots, J, \\ p_i &= \int_0^{p_i} r f_i(r) dr + \sum_{j=1}^J a_{ij} \int_{-\tilde{\pi}_i}^{\tilde{\pi}_i} \pi g_j(\pi) d\pi, \quad i = 1, \dots, I. \end{aligned}$$

The objective here is to maximize the entropy, or maximize the uncertainty under the information we have. This problem is constrained to the definition of the area under a probability distribution function as well as our hedonic price equation. Appendix A contains the detailed calculations to determine the expected values of the shadow prices.

Ultimately, we derive our hedonic pricing equation:

$$\begin{aligned}
(13) \quad \mathbf{p} &= p_i \left[\frac{1}{1 - e^{\gamma_i p_i}} \right] + \frac{1}{\gamma_i} + \mathbf{A}' \left[\tilde{\pi}_j \left[\frac{1 + e^{2\delta_j \tilde{\pi}_j}}{1 - e^{2\delta_j \tilde{\pi}_j}} \right] + \frac{1}{\delta_j} \right] \\
&= p_i \left[\frac{1}{1 - e^{\gamma_i p_i}} \right] + \frac{1}{\gamma_i} + \mathbf{A}' \left[\tilde{\pi}_j \left[\frac{1 + e^{2\tilde{\pi}_j \sum_{i=1}^I \gamma_i a_{ij}}}{1 - e^{2\tilde{\pi}_j \sum_{i=1}^I \gamma_i a_{ij}}} \right] + \frac{1}{\sum_{i=1}^I \gamma_i a_{ij}} \right].
\end{aligned}$$

The resulting price equation has 21 unknowns of parameter γ_i for each food product and 21 equations. Strict concavity implies a unique, optimal solution for γ_i^* . Since we know that $\gamma_i = 0$ violates this price constraint, we can assume that $\gamma_i \neq 0$. After solving for γ_i^* , we explicitly find $\delta_j^* = \sum_{i=1}^I \gamma_i^* a_{ij}$, $j = 1, \dots, J$ in the process of solving for nutrient shadow prices $\hat{\pi}$ and taste values \hat{r} . Finally, we find $C_T = \sum_{i=1}^I \hat{r}_i x_i$, $i = 1, \dots, I$, the annual expenditure for taste.

IV. DATA

We use an aggregate annual time series from 1910 through 2006. The per capita consumption of the 21 food products, nutrients and average retail prices come from USDA and U.S. Bureau of Labor Statistics (BLS) sources (LaFrance 1999a). The consumption data is from the USDA's *Food Consumption, Prices and Expenditures* and measures food *disappearance* as opposed to direct food consumption; that is, the difference between food available (the sum of production, beginning inventories and imports) and non-food use (exports, farm use and industrial consumption). Table 1 contains a detailed list of the 21 individual food products, consisting of four categories - dairy, meat, produce, and miscellaneous. We provide a complete

list of the 18 nutrients in Table 2, consisting of three categories - macronutrients, vitamins, and minerals.³

Tables 3 and 4 provide summary statistics of the consumption of these nutrients and foods, respectively. We have 97 years of observations for nutrients and food products, each of which scales down to daily consumption. Tables 3 and 4 present the mean, standard deviation, and minimum and maximum of daily intake of each nutrient and food product, respectively.

We see in Table 3 that over this span of time, the mean calorie intake of 3334 a day is quite a bit higher than what the Dietary Guidelines for Americans (USDA and USDHHS 2010) recommend; these guidelines estimate that women should consume between 1600 and 2400 calories, while men should consume between 2000 and 3000 calories. Similarly, Americans are over-consuming protein and vitamin C. The guidelines for adult women to consume protein is about 46 grams per day, and men should consume about 52-56 grams per day. However, Table 3 shows that we have consumed an average of about 97 grams of protein over our time span. While Americans have been over-consuming these nutrients, they are under-consuming calcium, which ideal consumption level is between 1000-1300 milligrams per day. Americans have also been under-consuming potassium by approximately 1200 milligrams per day. Notice the standard deviations in Table 3. Relative to the level of mean consumption, these nutrient consumption levels have not varied a lot over the 96-year time span.

Table 4 reveals which foods people consume. First, we see that Americans consume more milk than any other product category, at an average of 0.8 pounds per day. After milk, people consume cereals at just over half a pound a day. We find the level of sugars and sweets consumed starting at about a third of a pound per day. Considering all the fruits and vegetables,

³ We do not include carbohydrates, due to the linear relationship of calories with protein, carbohydrates and fats. We remove carbohydrates to avoid singularity without loss of generality and have checked for robustness.

Americans consume only more potatoes per day than sugars and sweets, while sugars and sweets surpass amounts from the rest of the individual fruits and vegetable products.

The demographic data described in Table 5 consists of three different categories – family, income and economic health, and food policy. The *family* category includes average family size, population proportions of age groups (both of which come from BLS data), and population proportion of ethnicity (which are derived from Bureau of Census figures). Ethnicity categories are white, black, and other. The category “other” consists of all races other than white or black, and this comprised less than one percent of the total population until 1963. Age groups consist of population proportions: under 15 years old, 15 to 54 years old, and 55 years and older. The *income* category comes from BLS data and includes per capita disposable income in real 1967 dollars and the unemployment rate. The *food policy* category consists of variables denoting policy events, including mandatory pasteurization of milk in 1917, the fortification of vitamin D in milk in 1932, the Social Security Act of 1935, the Food Stamps Program nationwide in 1974, the nationwide spread of the Women, Infants, and Children (WIC) in 1975, and the mandatory labeling of Nutrition Facts in 1992. We also use dummy variables for the periods during and post-World War II. We see that the average family size over this time span has been just under four people, the largest age group has been 15-54 years of age, the largest ethnicity group has been white, and the mean unemployment rate has been just under 7%.

V. EMPIRICAL RESULTS

5.1 Shadow Prices and Taste Expenditure

We found 18 nutrient shadow prices for each model and 21 food taste values for the least squares and maximum entropy models. Appendices C and D contain graphs for all nutrient shadow prices and taste values, which are available from the authors.

Linear programming, maximum entropy, and least squares were used to calculate nutrient shadow prices and taste values. Linear programming directly estimates only nutrient shadow prices, forcing taste value for individual food products to zero. The least squares model estimates a taste value, which is common across food products. Summing product specific residuals from least squares to this common taste value generates our inferred, food specific taste values. Maximum entropy estimates all nutrient shadow prices as well as food taste values directly.

The three estimation techniques each yield unique shadow price trends. The distinctions between each model ultimately cause unique taste and nutrition expenditure trends. Linear programming estimates the smallest absolute nutrient shadow prices between the three models, and it forces the individual food taste value to zero. Compared to linear programming, least squares estimates more volatile shadow prices, and it occasionally yields negative nutrient shadow prices. Maximum entropy directly estimates each individual food taste and nutrient shadow price, and it yields consistently positive nutrient shadow prices and taste values, which is compatible with positive market prices for food.

Figure 1 presents the annual taste expenditure as estimated by linear programming. This annual expenditure ranges from just over \$2 in 1983 to roughly \$53 in 1912, all in real U.S. dollars. Positive taste expenditure means that consumers spent more than the minimum possible cost for nutrition. If consumers were attempting to save money by spending money more efficiently on nutrition rather than taste, we would expect to see lower taste expenditure. For example, taste expenditure dipped during the years of WWII, when rationing may have influenced food expenditure to focus primarily on nutrients. We see a steep decrease in taste expenditure in the early 1970s, and a gradual increase beginning in the 2000s.

Also estimated through linear programming, Figure 2 presents the annual nutrition expenditure. This ranges from under \$200 in 1912 to over \$400 in 1975. While taste expenditure decreased upon the start of the 1970s, the nutrition expenditure increased between 1967 and 1979. About the last 30 years of this nutrition expenditure holds between \$350 and \$400. Under the linear programming model, nutrition expenditure seems to have stabilized within this range. This model estimates a higher level of nutrition expenditure relative to taste expenditure.

Figures 3 and 4 present the taste and nutrition expenditures results from least squares, respectively. Figure 3 shows least squares to predict minimum taste expenditure at just under \$0 in 1989 and a maximum taste expenditure of \$630 in 1962. Our model allows for negative expenditure estimates, and similarly taste expenditure estimates higher than the observed food expenditure level, because the model allows for negative shadow prices due to diminishing marginal returns. Negative taste expenditure implies that the level of nutrition expenditure exceeds the observed food expenditure. Similarly, the least squares model estimates negative levels of nutrition expenditure, which balances with a higher level of taste expenditure in those years. The annual nutrition expenditure in Figure 4 ranges from about negative \$250 in 1962 to above \$400 in 1989. Notice that these years are the same as the least squares' taste expenditure extremes. Least squares does not consistently yield one type of expenditure higher than the other.

Figures 5 and 6 present the estimates of taste and nutrition expenditure trends from maximum entropy. The minimum level this model estimates for taste expenditure is just over \$200 in 1910, and the maximum level reaches over \$400 in 1974. Similar to the nutrition expenditure as estimated through linear programming, the taste expenditure from maximum entropy almost stabilizes from the 1980s onward. Figure 6 presents the annual nutrition expenditure from maximum entropy. We see a minimum nutrition expenditure at just over \$1 in

1912, and a maximum nutrition expenditure of \$23 in 1973. Interestingly, the minimum taste and nutrient expenditures are around the same time, and the case is similar with the maximum taste and nutrient expenditures.

Figures 7 and 8 compile the annual taste and nutrition expenditures, respectively, from each of our three models. From these figures, we can see that maximum entropy estimates the smoothest expenditure levels, while least squares estimates the most volatile of the three models. This volatility from least squares is due to the stochastic nature of the regression's residual terms. Maximum entropy yields the highest trend of taste expenditure, while linear programming yields the smallest trend. Similarly, linear programming yields the largest nutrition expenditures, because the equality constraints for nutrition levels in our cost minimization problem are quite binding, and thus the minimized nutrition expenditure was close to the observed food expenditure.

Figures 9 through 13 present expenditure levels for macronutrients plus cholesterol. Since maximum entropy best represents reality, in which consumers likely consider both taste and nutrition when shopping, we present these expenditure levels for calories, protein, fat, and cholesterol in Figure 9. From this graph, we see that protein expenditure is the highest and is continually increasing over time. Further, we see that calorie expenditure is increasing slightly, cholesterol expenditure increases up until WWII before it falls back down, and fat expenditure is the lowest of the four presented nutrients. While high cholesterol levels are an increasingly present medical concern for the average American, the average American seems to be spending less money each year on cholesterol. This provides evidence that instead of paying for cholesterol itself, people tend to pay for a complementary taste value associated with cholesterol.

Figures 10 through 13 compare these individual nutrient expenditures across the three estimation techniques. For each of these figures, maximum entropy likely best reflects consumer behavior, since it represents a consumer who directly values both nutrition and taste simultaneously. Figure 10 compares calorie expenditure levels over time, presenting that the level predicted by maximum entropy is consistently higher than that from linear programming after the early 1920s. As we have seen from previous results, least squares again yields the most volatile levels, showing a general increase since roughly 1960. In Figure 11, we see that the least squares' estimated protein expenditure has a higher absolute value than the other two models. However, in Figure 12, we see that the least squares' estimated expenditure level for fat is much closer to the other two models than for protein. Maximum entropy finds that fat expenditure increased up until WWII, following with a decrease in expenditure. Linear programming estimates a slight increase in fat expenditure, while least squares estimates an increasing fat expenditure since the early 1980s. Figure 13 presents the expenditure levels for cholesterol. Similar to fat expenditures, maximum entropy finds decreasing cholesterol expenditure levels since WWII. Again, linear programming expenditure is rather stable, and least squares is predicting a decrease since the 1980s.

When observing these nutrient expenditures and taste expenditures, it is important to look at the evolution of food prices. Figure 14 shows the food price index over this time span for urban consumers (Federal Reserve Economic Data 2014). Food prices experience a trough between about 1930 until 1943. These prices then begin a long stretch of exponential increase, where the food price index increases exceedingly rapidly after about 1970. This rapid increase in food price may seem to correlate to the steady decrease in fat and cholesterol expenditure levels, supposing that consumers switch to value other nutrients more under a more constraining food

price. Further, maximum entropy shows a decrease in nutrition expenditure throughout the period that food prices are increasing. It is plausible that food prices are increasing partially due to the increasing taste values that maximum entropy yield, which directly relates to an increase in demand for taste.

5.2 Effect of Demographic Variables on Nutrient Shadow Prices and Taste

To examine the relationships between demographic variables and the estimated shadow prices, we estimate a seemingly unrelated regression (SUR) for each model. The dependent variables for these SURE models are the estimated nutrient shadow prices and the taste values, and the independent variables are the demographic variables discussed previously. We estimate a separate SUR model for the nutrient shadow prices and food taste values found using the three previously discussed models, totaling six SUR models. The detailed theoretical model is located in Appendix B.

In order to minimize unnecessary complexity, Tables 6 and 7 present representative nutrient shadow price and food taste value SUR coefficients. The representative nutrient shadow prices are these for calcium, fat, protein, and calories. The representative food taste values are those for milk, beef, poultry, processed non-citrus fruit, sweets, and coffee. The detailed results are available upon request from the authors.

5.2.1 Seemingly Unrelated Regression, Nutrient Shadow Prices

In Table 6, positive coefficients for disposable income for nutrient shadow prices under linear programming and maximum entropy suggest normal goods. As income rises, so does consumers' WTP for the next unit of nutrient, increasing the quantity consumed. Only in the SUR for our least squares shadow prices do we see statistically significant, negative coefficients for disposable income with regard to vitamin A, riboflavin and magnesium.

The variable of average family size has a negative coefficient for protein shadow prices under least squares and maximum entropy models. As the average family size increases by one person, the least squares' model of protein shadow price should decrease by about 11 cents a gram according to our least squares model. A larger family may value the next amount of protein less, perhaps since they will switch to cheaper foods in order to feed more people. This coefficient for the maximum entropy protein shadow price is -.05 cents, an absolute value that is smaller than that for least squares.

A population proportionally higher in non-white and non-black ethnicities indicates a higher shadow price for many nutrients. For example, black and white dummy variables have negative coefficients when explaining the shadow price for calories using maximum entropy. As seen from Table 6, both least squares and maximum entropy suggest that non-white and non-black populations value calcium more than black and white ethnicities. However, linear programming's calcium, iron, and fat shadow prices have positive black and white coefficients. Each of the three models implies a unique relationship between nutrient shadow prices and race.

5.2.2 Seemingly Unrelated Regression, Food Taste Values

Consider Table 7, which is representative of demographic coefficients explaining food tastes. Average family size has positive coefficients for many least squares taste values. The least squares coefficient for milk taste value is positive, implying that larger families value milk more than smaller families. The statistically significant, negative coefficients for average family size are maximum entropy's taste values of meats and coffee. As with the negative coefficients for protein, this may occur if larger families move away from meats to other, cheaper foods. Larger families may value coffee less, since children drink coffee at a lower rate than adults.

While the non-white/non-black ethnicities category often has a positive influence on nutrients, it has a mixed influence on food products. For example, we estimate the non-white/non-black ethnicities to value milk, beef and coffee less, but value processed, non-citrus fruits higher. It is possible that this portion of the population values nutrients relative to tastes more than the white and black populations. However, some foods that are positively related to the non-white, non-black ethnicity group under maximum entropy are fish, fruit, vegetables, as well as coffee, teas and spices. Since a substantial portion of this category is Asian, it is plausible that fish and teas may have higher values due to cultural tastes and preferences.

The variable of WIC becoming a national program in 1975 has a negative coefficient for milk and beef, but a positive coefficient for coffee and butter under maximum entropy. Most WIC beneficiaries are mothers with infants, who may not buy liquid milk if they use powder formulas and other baby foods. These are suggestive reasons for such coefficients. This dummy variable may capture other things occurring at this time. For example, this negative coefficient of beef taste value may track the national trend away from beef consumption.

5.2.3 Demographics and Taste Share of Food Expenditures

Table 8 provides the dependent variable coefficients from regressions over taste share of food expenditures. The linear programming regression has an adjusted R-squared of 0.48, the least squares regression has an adjusted R-squared of 0.30, and the maximum entropy regression has an adjusted R-squared of 0.84.

We see quite a few variables in the linear programming regression with at least a 10% significance level. Average family size is negatively correlated with taste share of food expenditure. It is plausible that larger families are going to spend more of the food expenditure on nutrition than those with fewer or no children. Next, while black ethnicity is largely and

positively correlated with taste share, the non-black and non-white ethnicities are negatively correlated to taste share; both these variables are in comparison to the white ethnicity. Further, as real per-capita disposable income increases, we estimate that taste share will decrease, and nutrition share will increase. This implies evidence that taste is an inferior good, negatively correlated with disposable income. However, we also estimate that as the unemployment rate increases, the expenditure on taste share will decrease. It is plausible that those with no job may have more time to prepare food at home, which is more likely to be nutritious.

Our least squares regression with demographics only has two significant variables at the 10% level or better. This model predicts that average family size is positively correlated with taste share, which directly counters our findings from the other two models. Further, we find that an aging population (as seen through the variable of age 54 or older) correlates with an increase in taste share of food expenditure. As we can see from the maximum entropy regression for this variable, this finding also disagrees with those of the other models.

The maximum entropy model is the best-fitted model in comparison with the first two. First, we estimate average family size to have a negative coefficient, similar to our linear programming model. We also find that an aging population correlates with a decrease in taste share on food expenditure. This relates to the plausibility that more time (e.g. through retirement) will allow more opportunity to prepare nutritious food at home. Next, we find that the black proportion as related to white will relate to an increase in taste share. This finding also matches that from the linear programming taste share. Also matching the qualitative findings from the linear programming dependent variable, we find that real per-capita disposable income negatively relates to taste share. Again, this provides evidence of taste as an inferior good.

Lastly, this model finds that the dummy variable from WWII onward is positively correlated with taste share.

VI. CONCLUSION

While the USDA utilizes quadratic programming to estimate optimal levels of benefits for SNAP, this paper has formally found nutrient shadow prices, food taste values, as well as both nutrition and taste expenditures. The shadow prices of nutrients under each model describe how much the consumer would pay for one more unit of each nutrient. These models use a linear hedonic price function, which represents the equilibrium of individuals' preferences with suppliers' cost functions. From these shadow prices, this study calculates the annual taste expenditure and nutrition expenditure for the average consumer in the U.S. Individual consumers will make purchasing decisions with taste values in mind, and policy changes should be in light of these taste values.

Diet related health issues are preventable. Many Americans continue to eat unhealthy foods, likely because of the taste value of these products. Heart disease is one of the many diet related health problems, and it is one of the top five causes of death in the U.S. (Frieden 2014). By tracking the evolution of taste expenditure relative to nutrition expenditure, we are able to see a clearer connection to the increasing presence of diet related health problems.

An objective of this study is to assess nutrition and taste expenditures from 1910-2006. We explain relationships between shadow prices, taste values, and shares of food expenditures each with U.S. demographic variables. While both linear programming and least squares models estimate decreasing taste expenditure levels, maximum entropy estimates increasing taste expenditure. Further, this study extends theory to a new and continuous application of maximum entropy.

If maximum entropy is the best estimator for food and nutrient valuation, as it seems to be, then the increasing taste expenditure may play a role in increasing food prices in general. This increase in taste expenditure is likely due to an increase in demand for taste. It is plausible that consumers' taste values are rather inelastic, in which case they will often continue to pay for the good despite a price increase, thus increasing taste expenditure. Maximum entropy estimates a recent taste expenditure level between \$350 and \$400 per year. On the other hand, maximum entropy estimates much lower nutrition expenditure levels most recently around \$15 per year. Further, annual nutrition expenditure seems to drop around the same time that food prices take off, from the 1970s onward. This provides evidence that the increasing prices of differentiated foods increasingly comprise taste value more than nutritional value.

A basic question motivating this research is whether to include food shadow prices in the utility for eating. Of the three models, maximum entropy is most realistic when considering how consumers make choices influenced by tastes and preferences. When consumers are shopping for groceries, they simultaneously consider both taste and nutritional values of the food products. This method of maximum entropy estimates the highest level of taste expenditures when compared to the other estimation techniques.

Through regressing maximum entropy's taste share of food expenditure with demographic characteristics, we find the expenditure of taste share to be negatively related to family size, an aging population, and disposable income. This provides evidence that taste is an inferior good, and that families with more children and the older population will buy more nutritious versus tasteful foods. We also find that this taste share is positively correlated with the size of black ethnicity proportion relative to white, as well as with the time from WWII onward.

Food assistance programs need to consider these taste expenditures when making policy changes. By doing so, these policies will be better prepared to align consumer spending on tastes and preferences with food assistance costs. Since maximum entropy directly estimates food taste values in conjunction with nutrient shadow prices, it best models realistic consumer behavior and nutrient valuation. Estimating nutrient shadow prices while simultaneously considering food tastes will best model how people choose to eat the way they do.

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FIGURES

Figure 1. Annual Taste Expenditure using Linear Programming

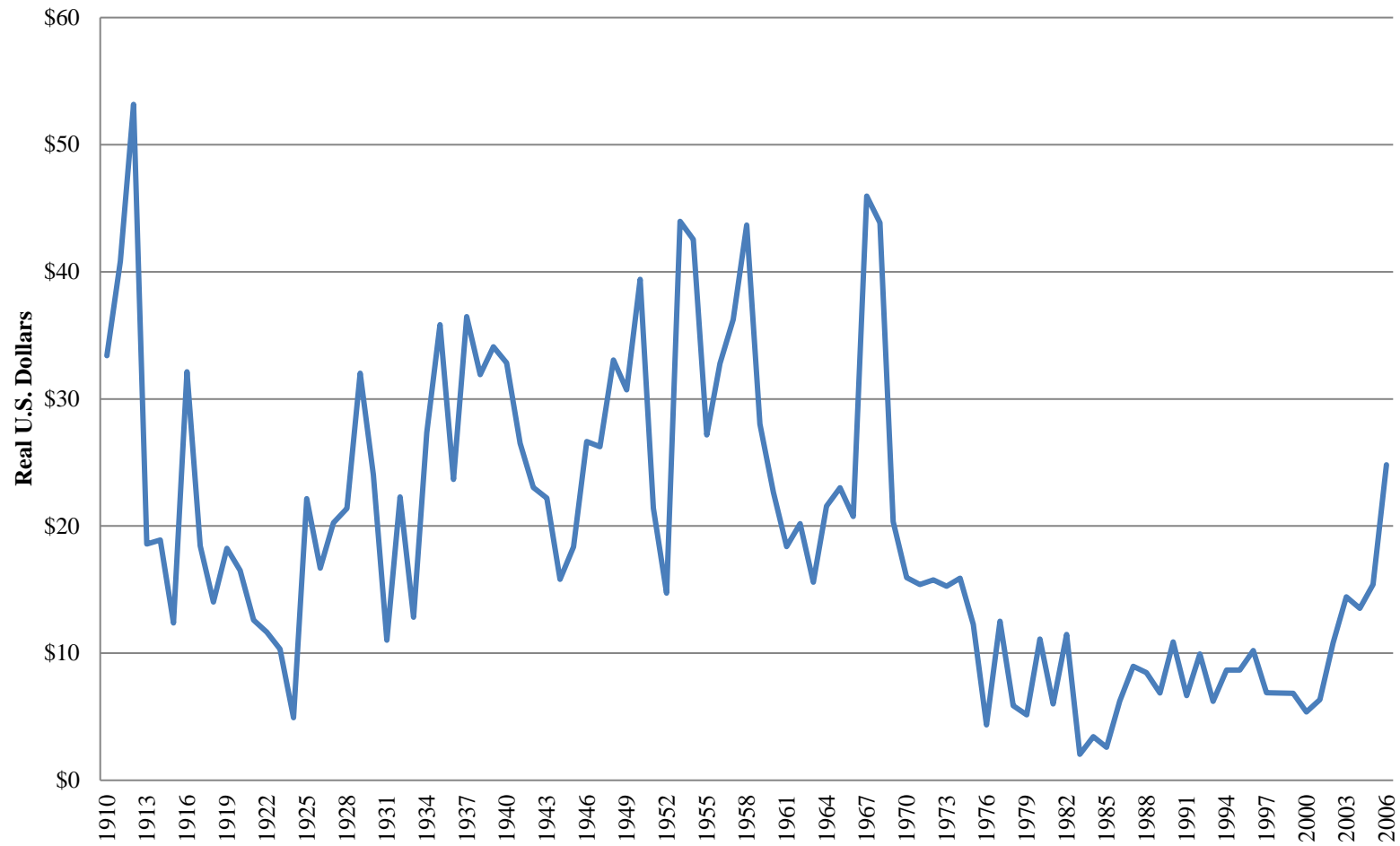


Figure 2. Annual Nutrition Expenditure using Linear Programming

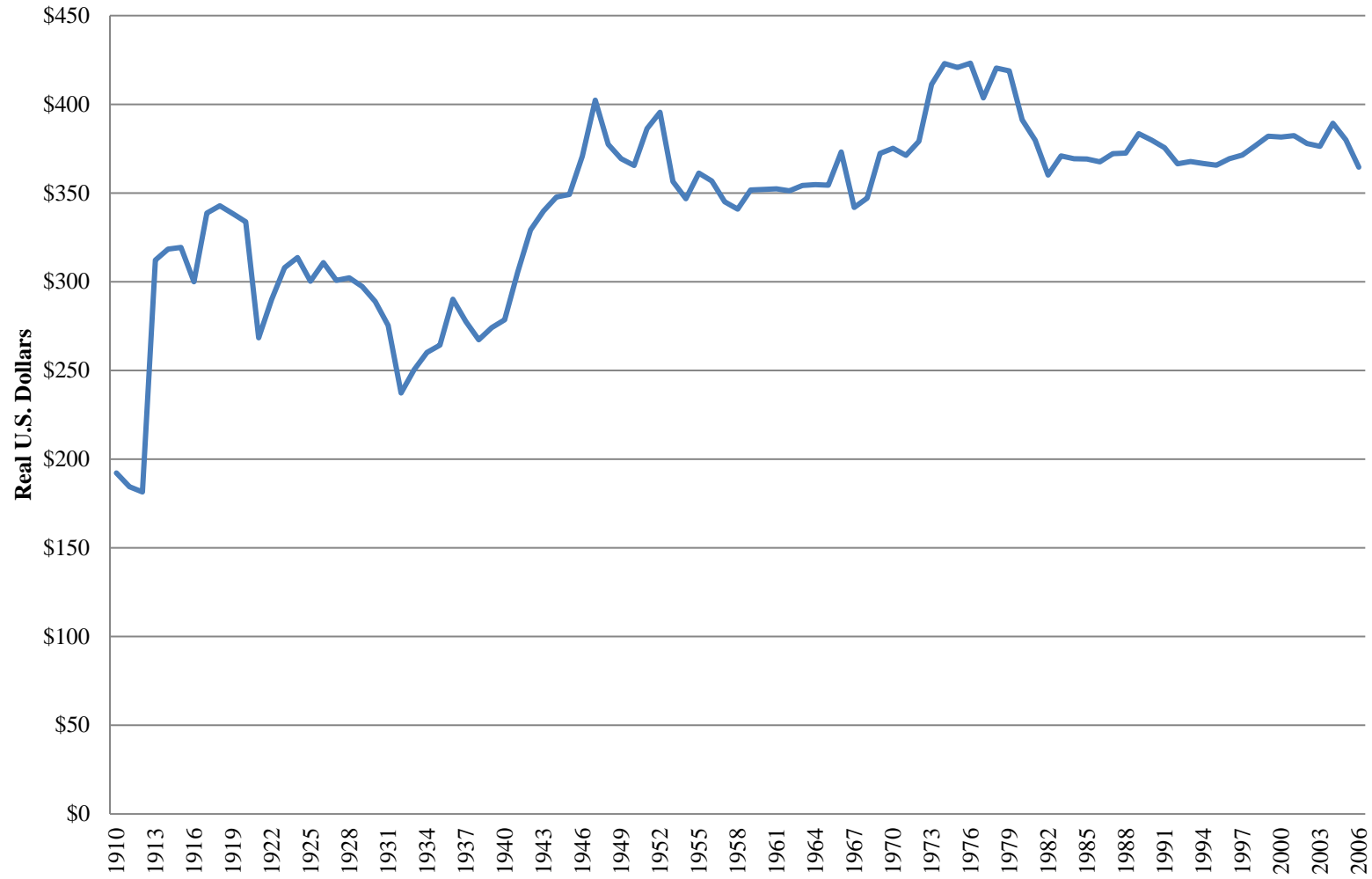


Figure 3. Annual Taste Expenditure using Least Squares

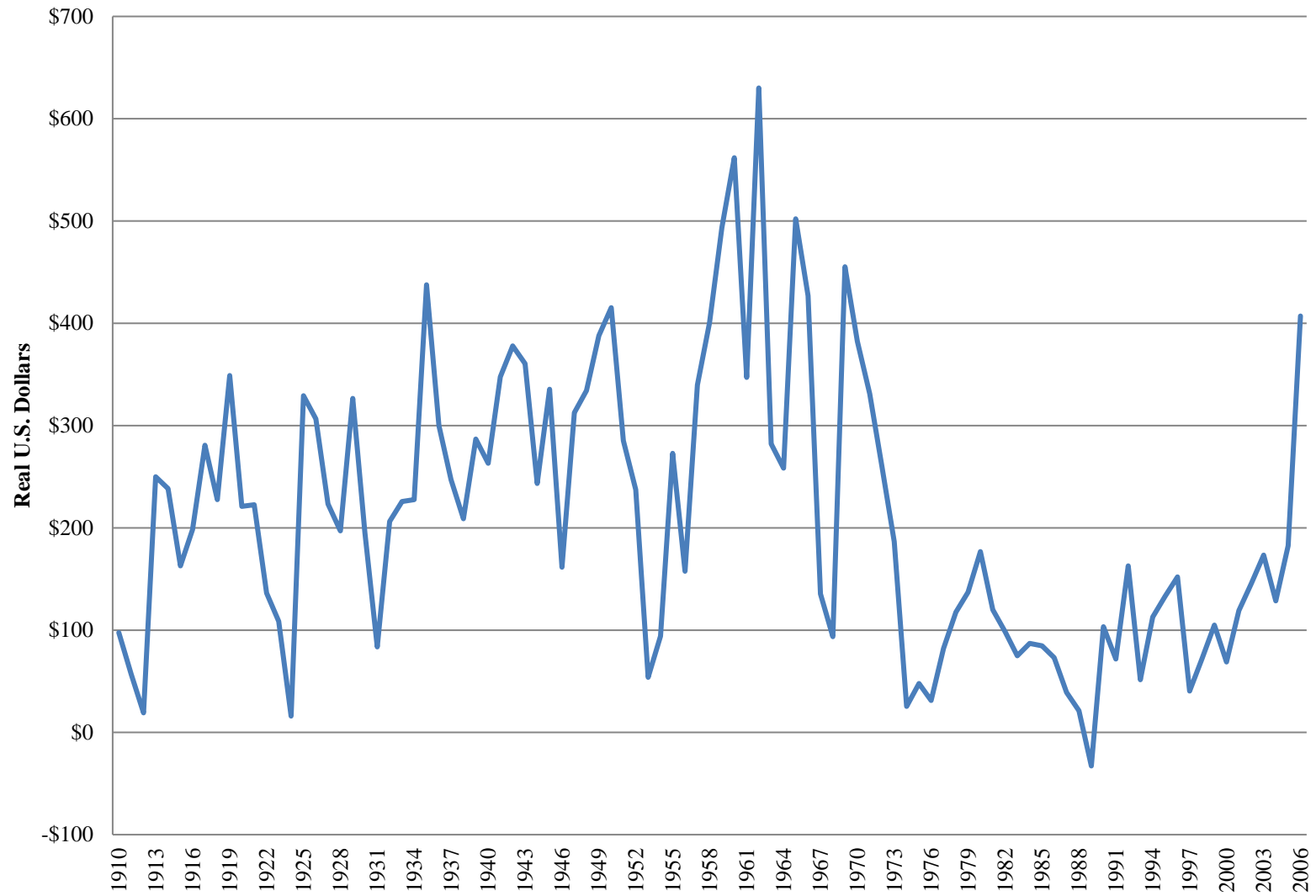


Figure 4. Annual Nutrition Expenditure using Least Squares

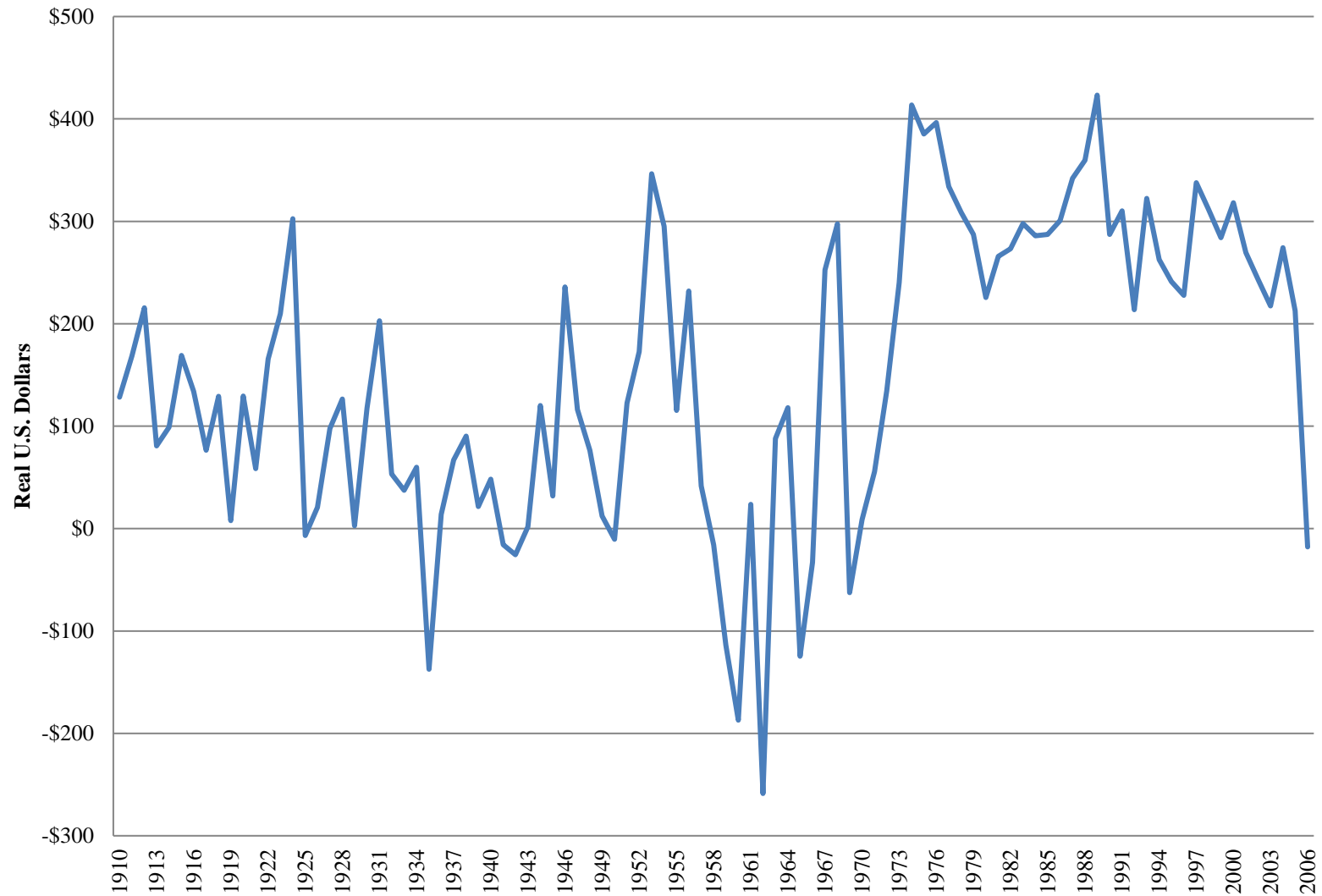


Figure 5. Annual Taste Expenditure using Maximum Entropy

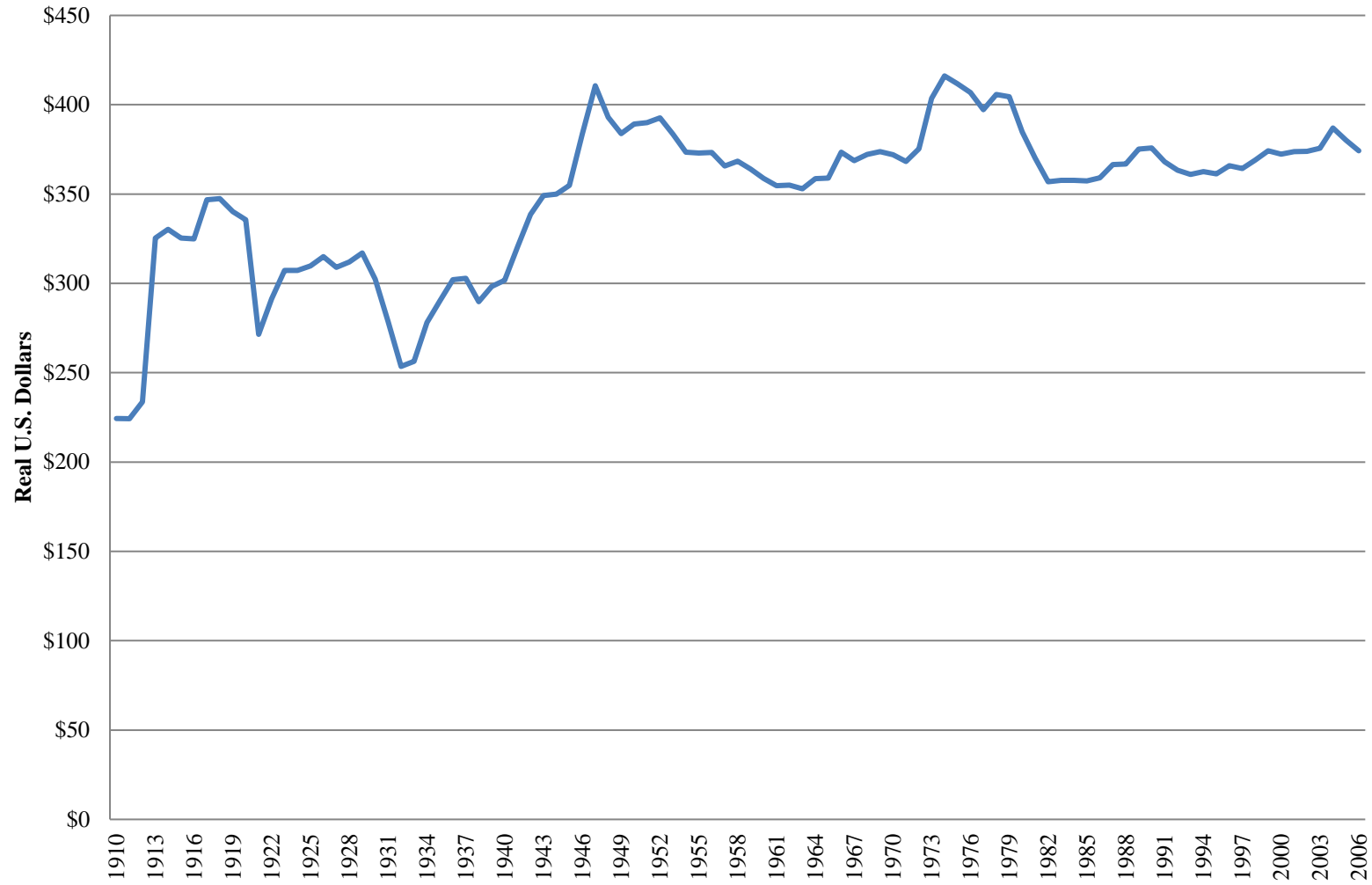


Figure 6. Annual Nutrition Expenditure using Maximum Entropy

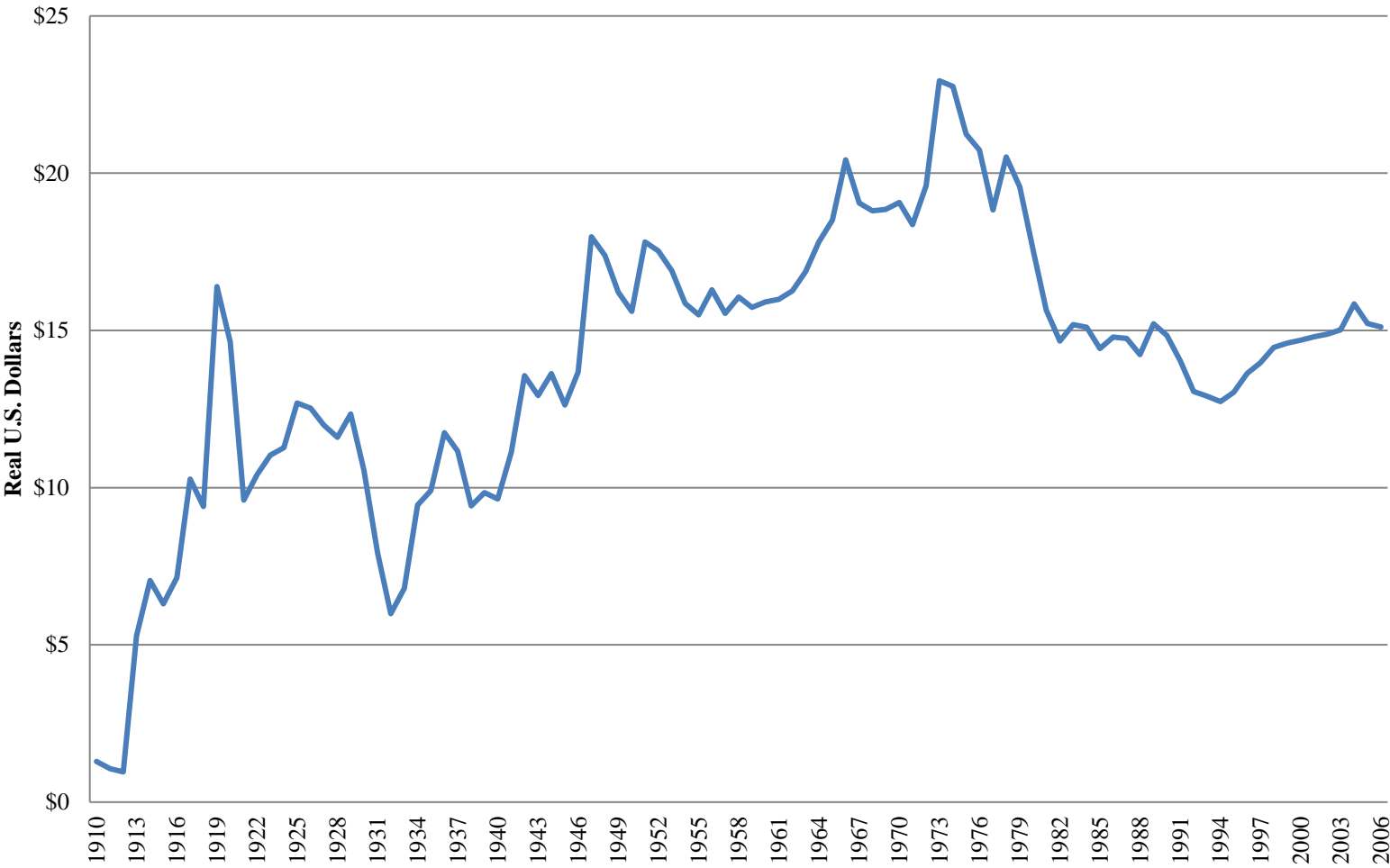


Figure 7. Comparison of Taste Expenditures across Estimation Techniques

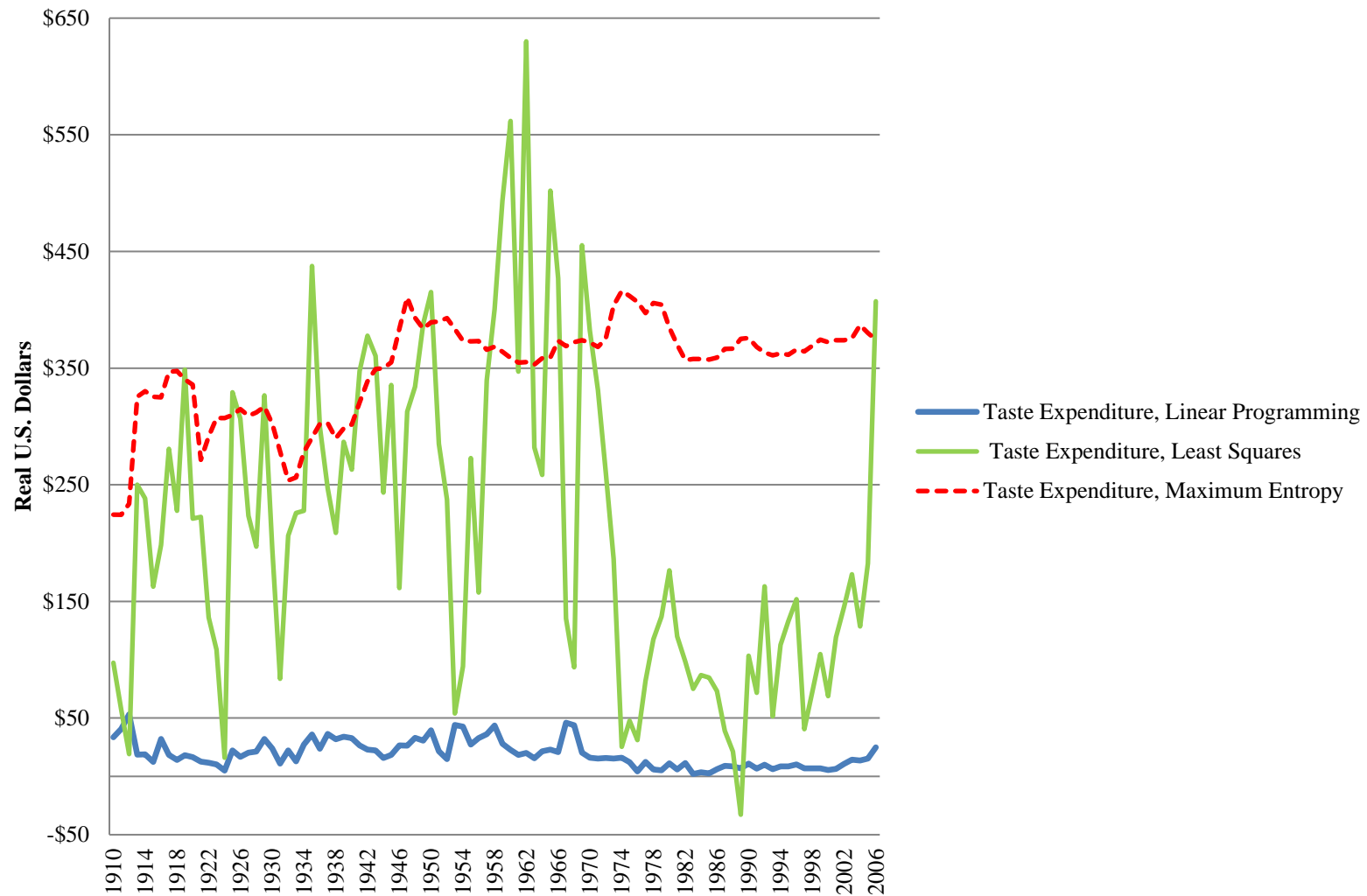


Figure 8. Comparison of Nutrition Expenditures across Estimation Techniques

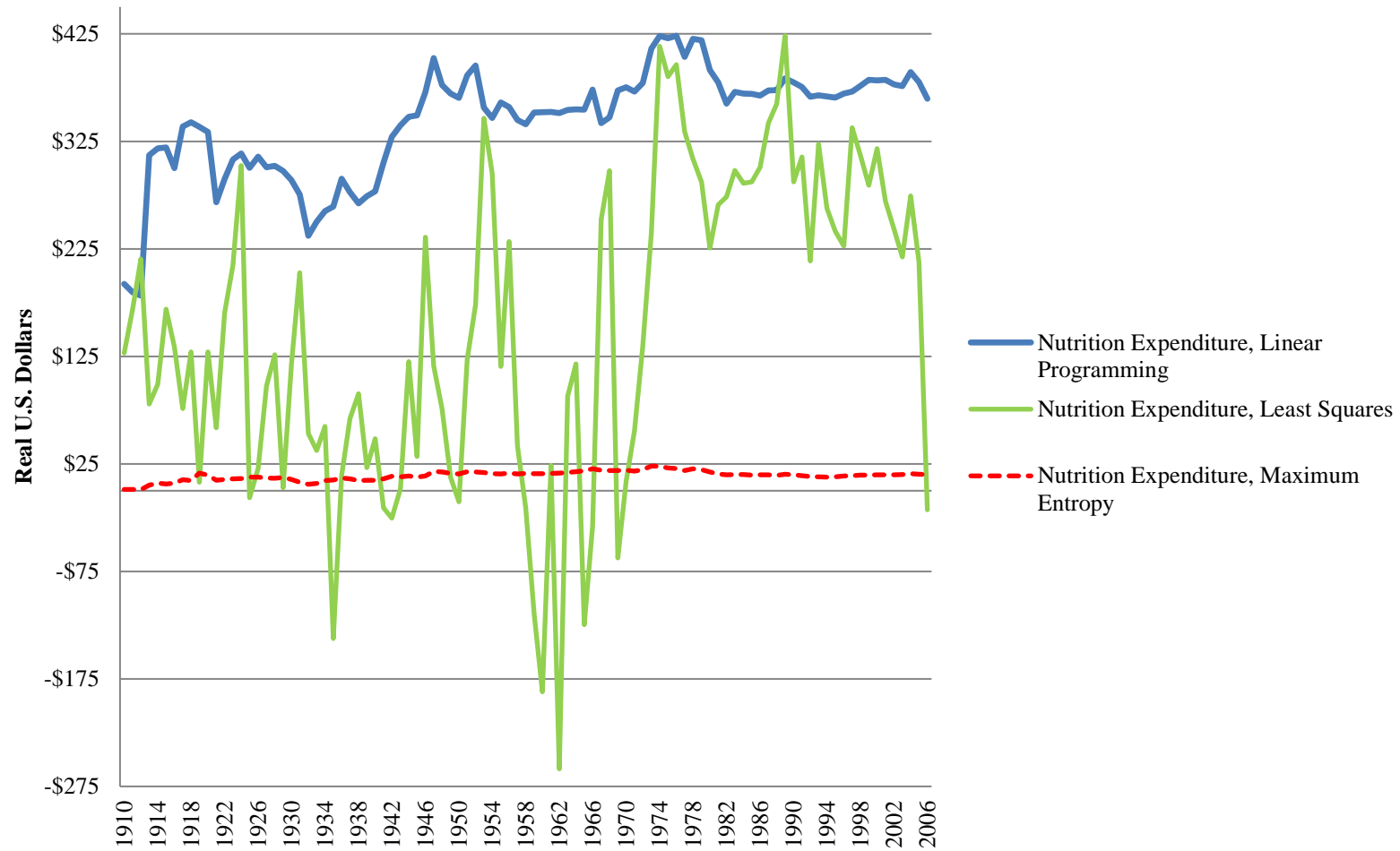


Figure 9. Nutrient Expenditures for Calories, Protein, Fat, and Cholesterol using Maximum Entropy,

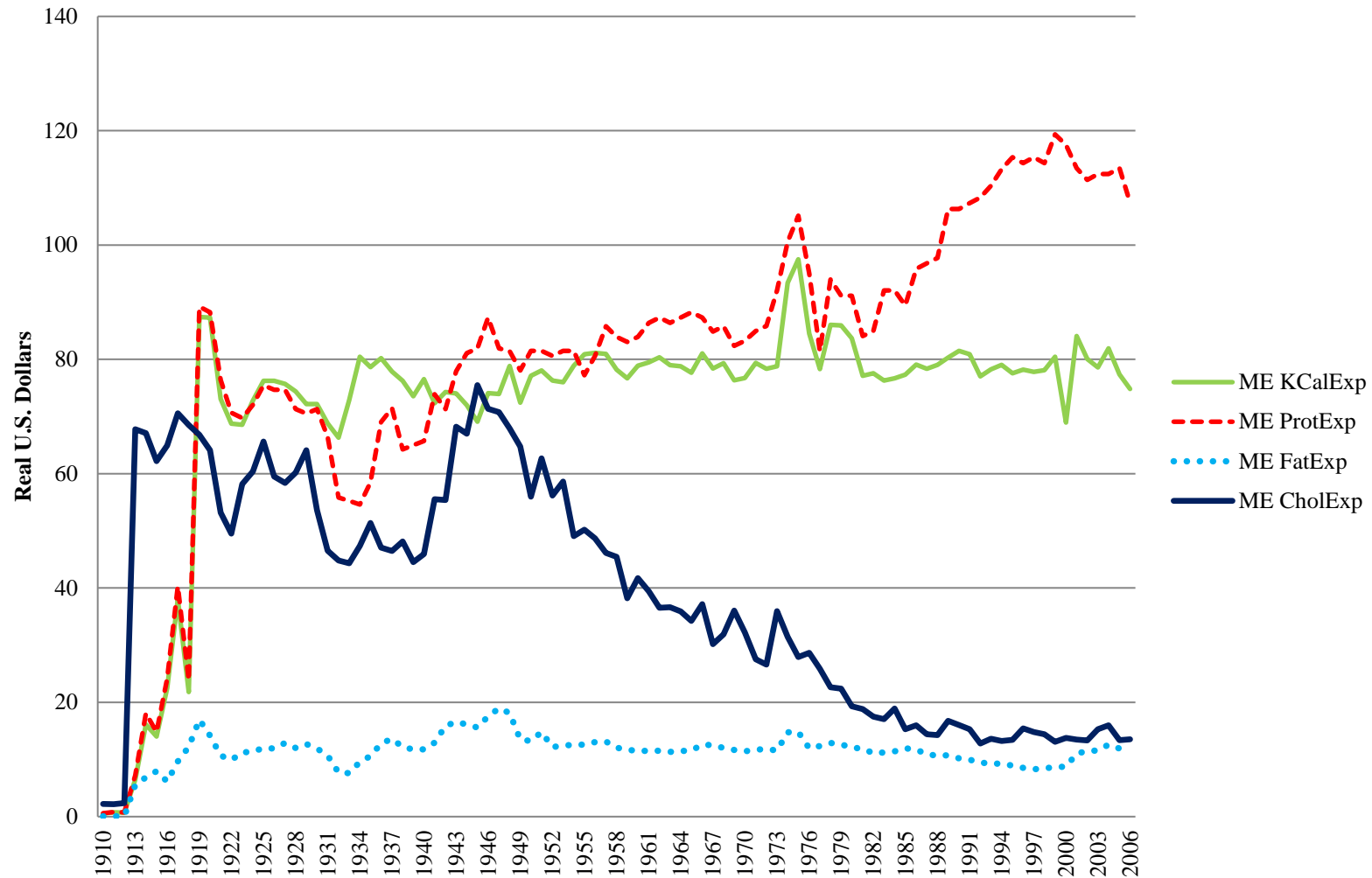


Figure 10. Comparison of Calorie Expenditure across Estimation Techniques

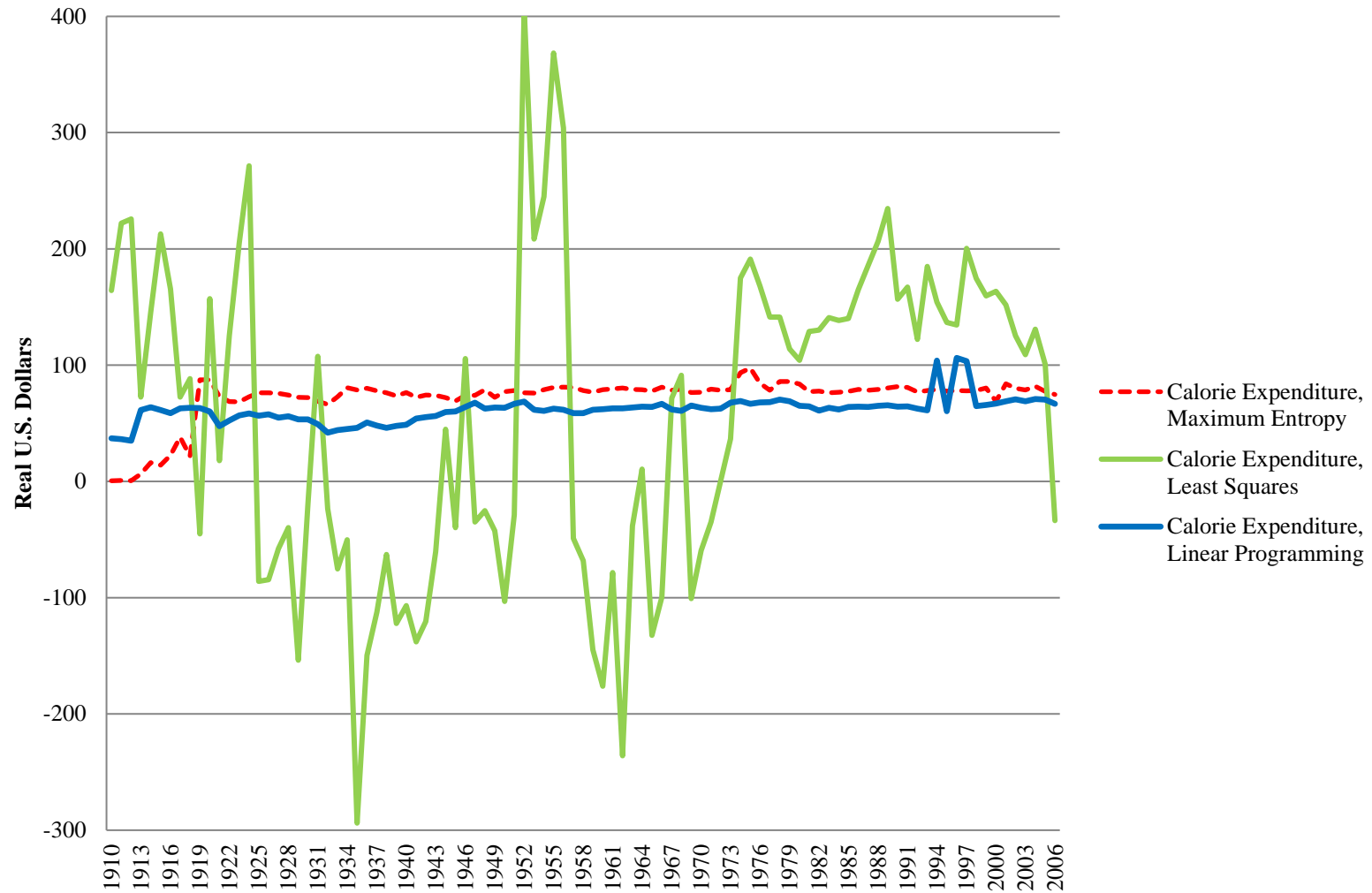


Figure 10. Comparison of Calorie Expenditure across Estimation Techniques

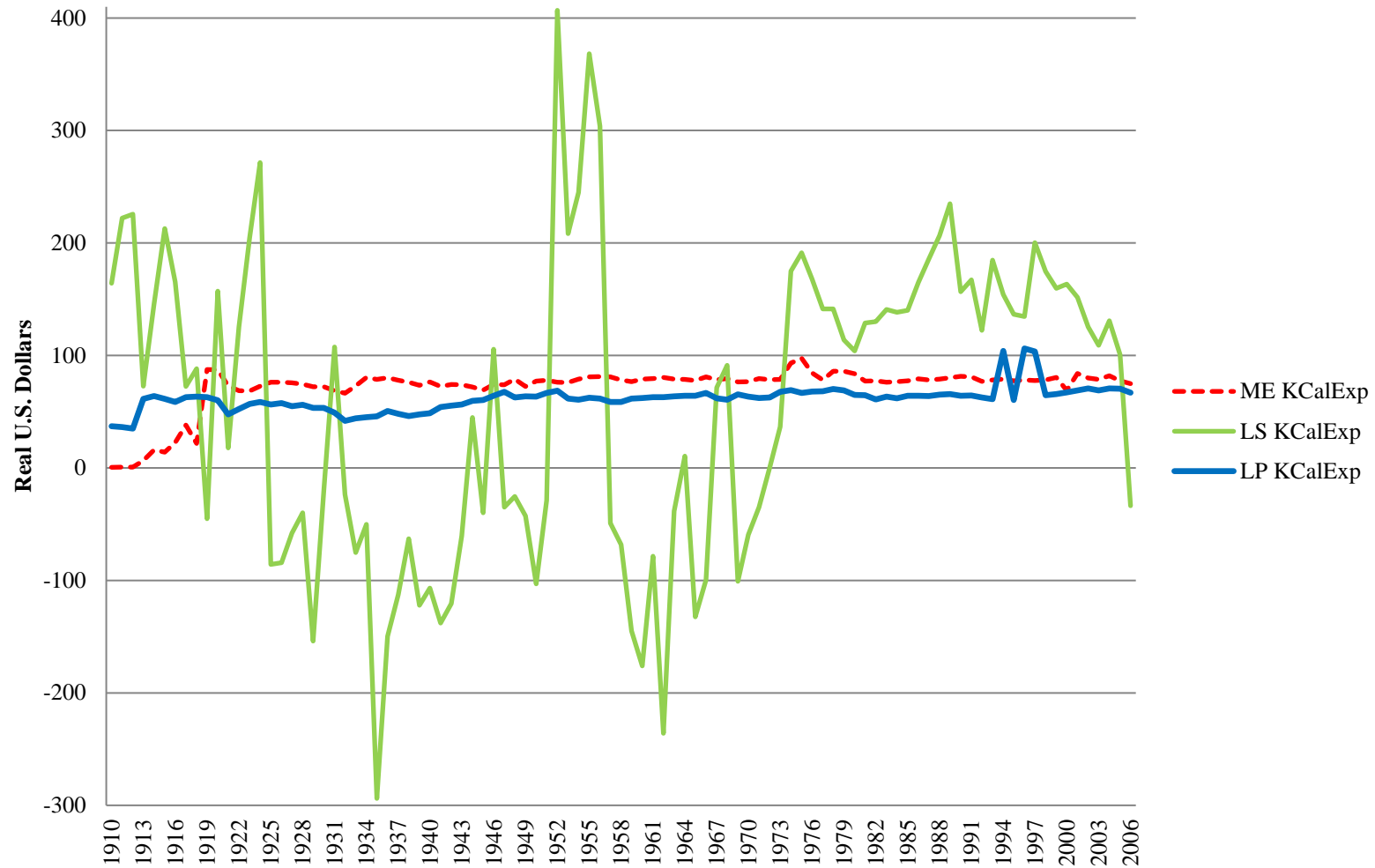


Figure 11. Comparison of Protein Expenditure across Estimation Techniques

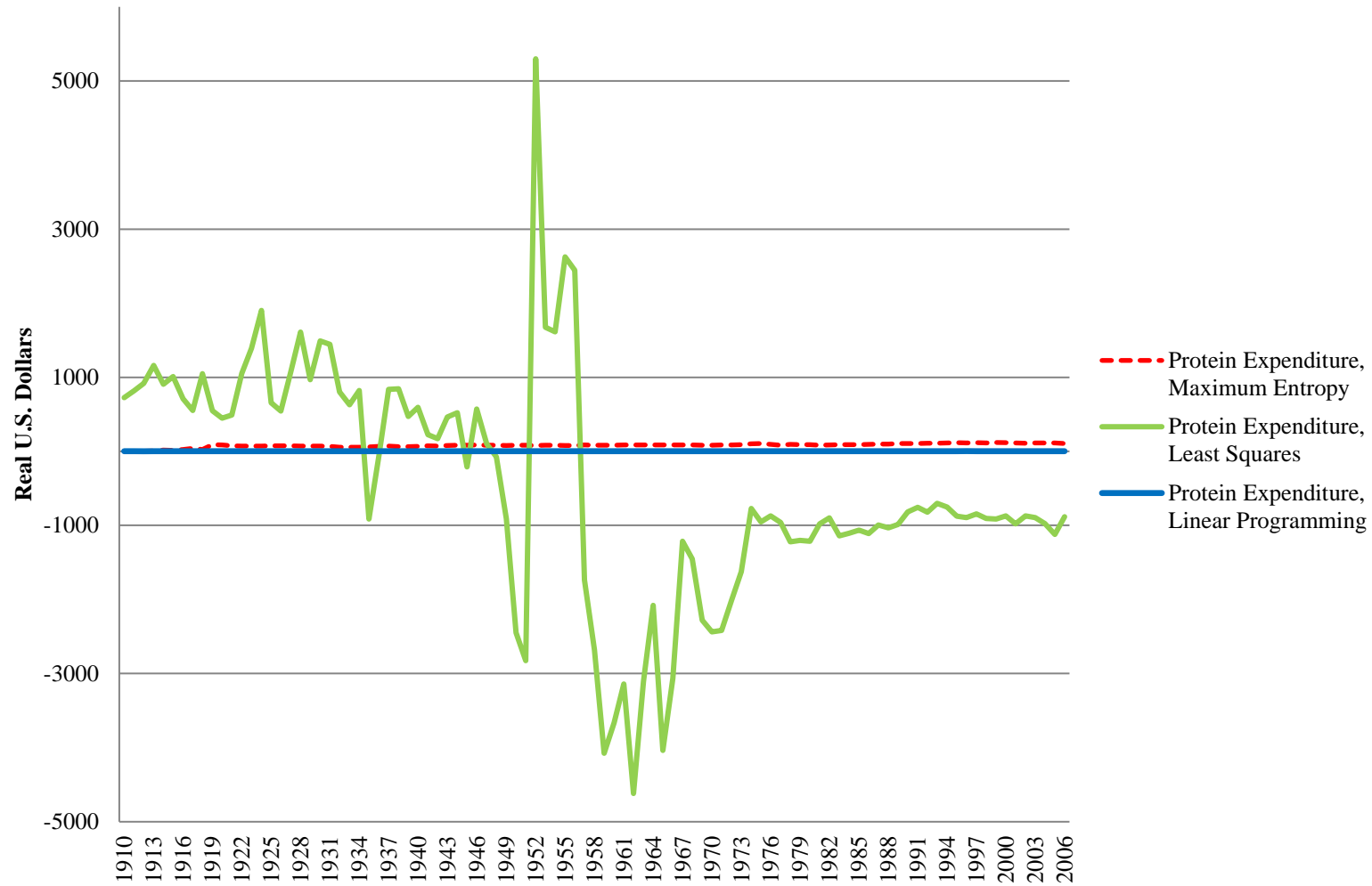


Figure 12. Comparison of Fat Expenditure across Estimation Techniques

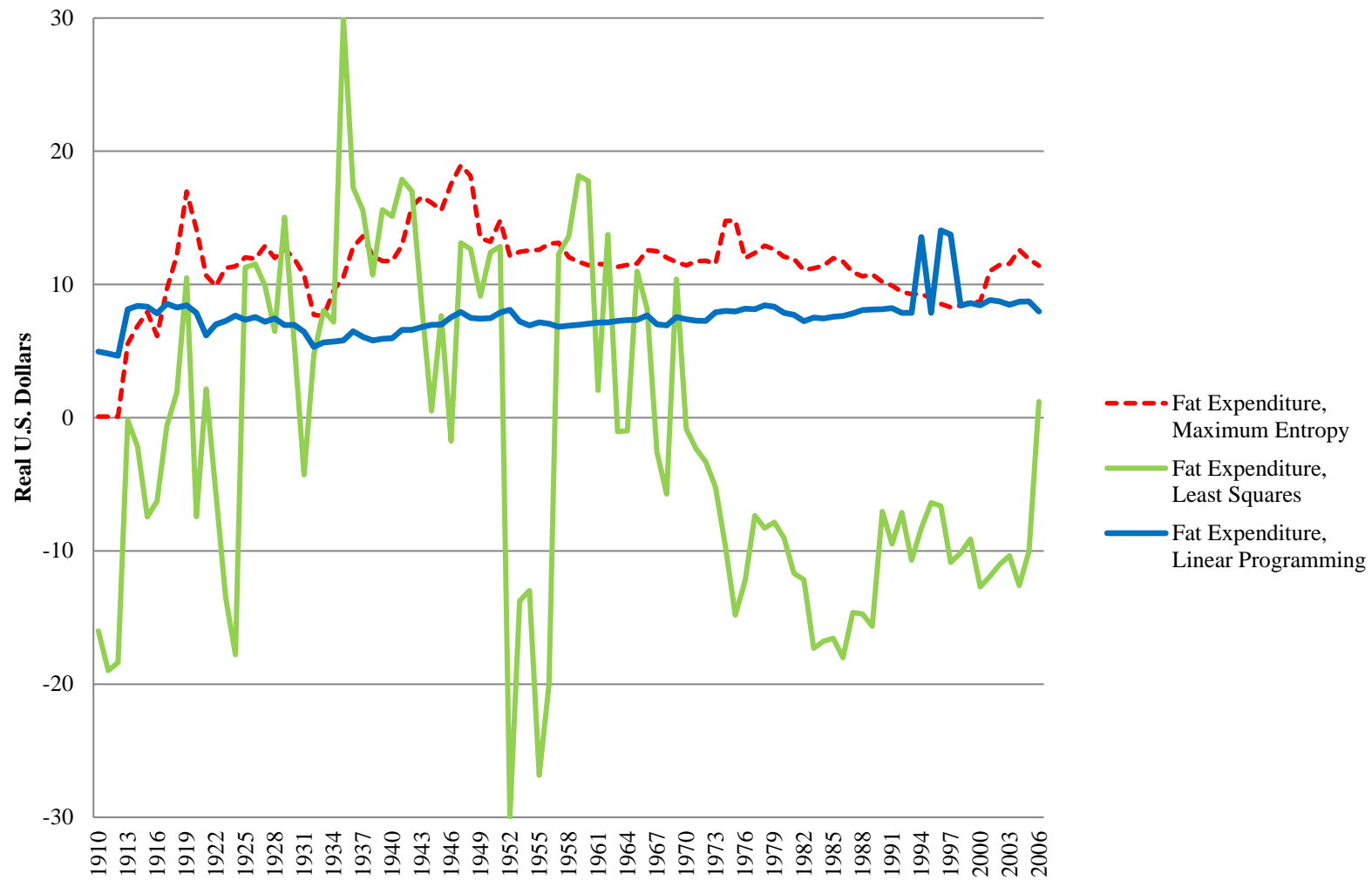
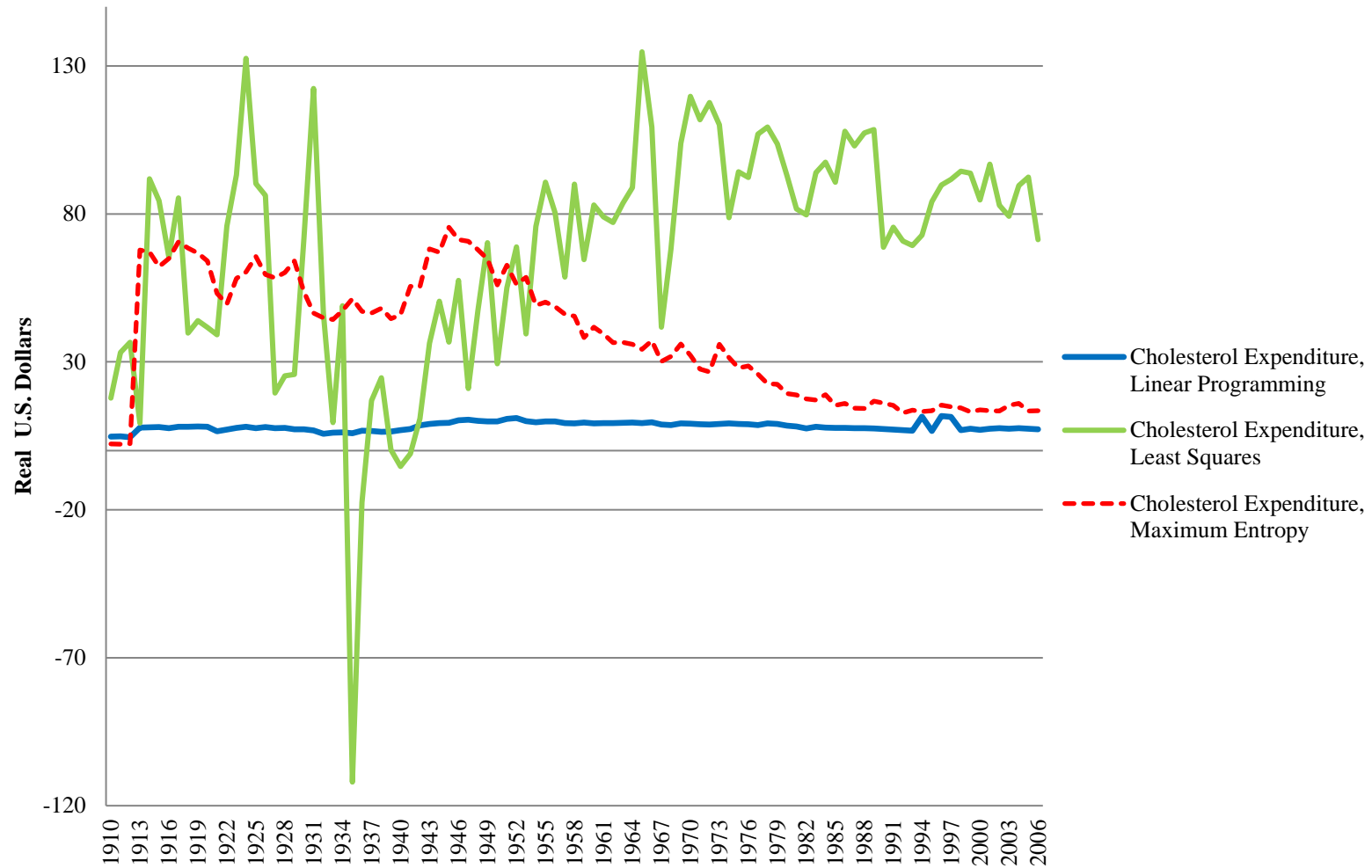
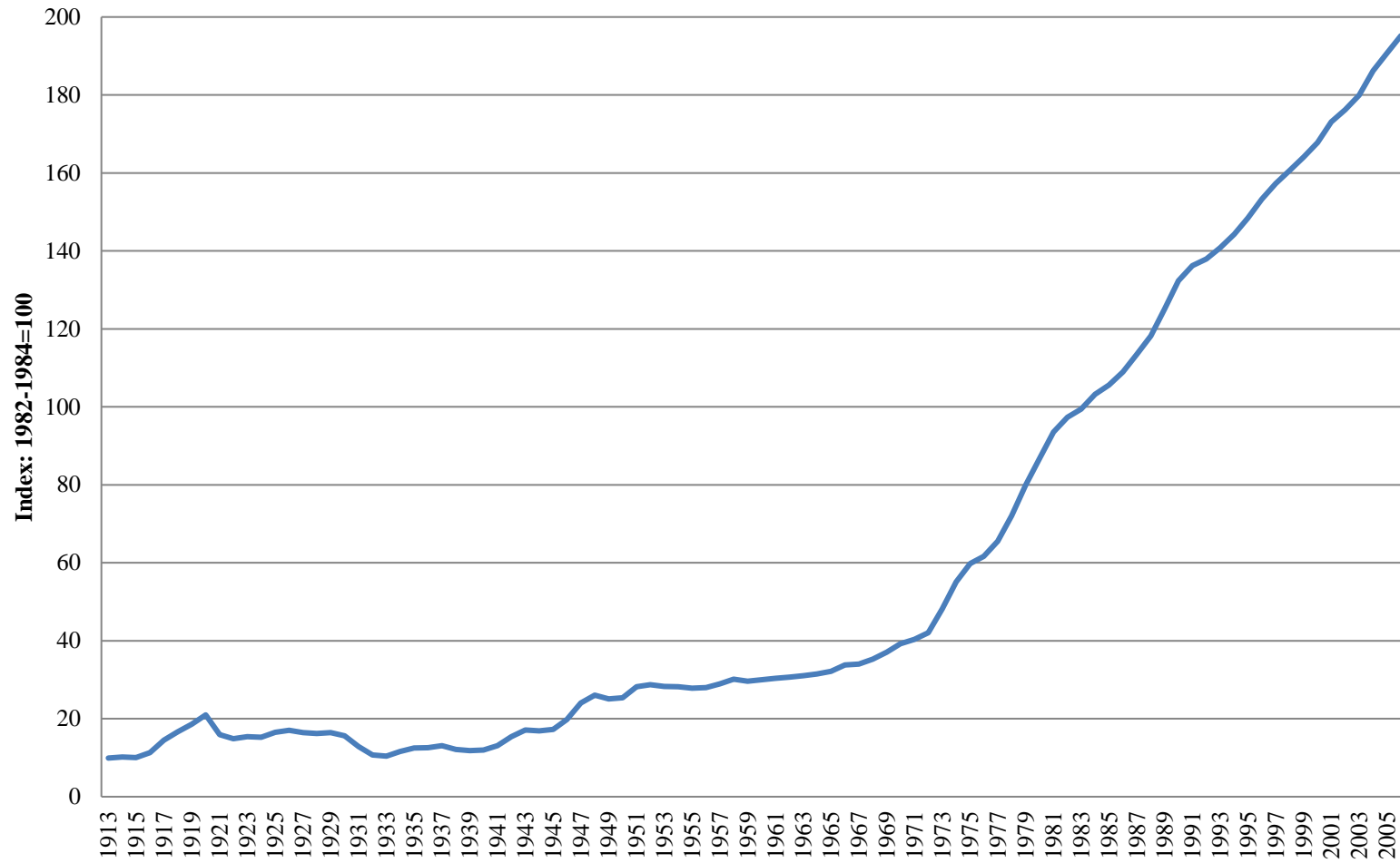


Figure 13. Comparison of Cholesterol Expenditure across Estimation Techniques



**Figure 14. Consumer Price Index for all Urban Consumers:
Food Price Index**



(Federal Reserve Economic Data 2014)

TABLES

Table 1. Food Items Used in Estimation

1. Milk
2. Butter
3. Cheese
4. Frozen Dairy (Ice Cream)
5. Other Dairy (Canned and Dry Milk)
6. Beef
7. Pork
8. Other Red Meat
9. Fish
10. Poultry
11. Fresh Citrus Fruit
12. Fresh Non-citrus Fruit
13. Fresh Vegetables
14. Potatoes
15. Processed Fruit
16. Processed Vegetables
17. Fats and Oils
18. Eggs
19. Cereals
20. Sugars and Caloric Sweeteners
21. Coffee, Tea and Cocoa

Table 2. Nutrients Used in Estimation

Nutrient	Unit of Measurement
1. Food Energy	kilocalorie (kcal)
2. Protein	gram (g.)
3. Fats	gram (g.)
4. Cholesterol	milligram (mg.)
5. Vitamin A	IU
6. Vitamin B12	milligram (mg.)
7. Vitamin B6	milligram (mg.)
8. Vitamin C	milligram (mg.)
9. Niacin	milligram (mg.)
10. Riboflavin	milligram (mg.)
11. Thiamin	milligram (mg.)
12. Calcium	milligram (mg.)
13. Iron	milligram (mg.)
14. Magnesium	milligram (mg.)
15. Phosphorous	milligram (mg.)
16. Potassium	milligram (mg.)
17. Sodium	milligram (mg.)
18. Zinc	milligram (mg.)

Table 3. Summary Statistics of Observed Nutrient Consumption

Nutrient per Day	Mean	Std. Dev.	Min	Max
Kcal/day	3334.021	220.2681	3000	3900
Protein g/day	96.90722	6.692786	86	111
Fat g/day	138.6804	15.25174	112	181
Vitamin A IU/day	7395.361	1575.714	430	9910
Vitamin B6 mg/day	2.004124	0.20203	1.7	2.4
Thiamin mg/day	2.019588	0.550878	1.3	3
Riboflavin mg/day	2.350515	0.41057	1.7	3
Vitamin B12 mg/day	8.227835	0.608403	6.9	9.5
Zinc mg/day	12.98454	1.388895	11.1	15.7
Iron mg/day	16.2701	3.788996	12.2	23.4
Niacin mg/day	22.38144	5.788716	15	32
Vitamin C mg/day	98.23711	13.53604	77	122
Magnesium mg/day	358.4536	24.21003	320	400
Cholesterol mg/day	444.8454	32.63157	390	530
Calcium mg/day	902.7835	82.06631	690	1070
Sodium mg/day	1106.186	139.5188	810	1270
Phosphorus mg/day	1547.216	92.02289	1410	1720
Potassium mg/day	3595.258	148.2403	3320	4090

Table 4. Summary Statistics of Food Consumption

Food in Pounds per Day	Mean	Std. Dev.	Min	Max
Milk lb/day	0.78593	0.11648	0.57614	1.04329
Butter lb/day	0.02721	0.01529	0.01123	0.05096
Cheese lb/day	0.04231	0.02718	0.01205	0.09737
Frozen Dairy lb/day	0.05638	0.02335	0.00986	0.08192
Other Dairy lb/day	0.04951	0.01706	0.01781	0.08959
Beef lb/day	0.18009	0.0355	0.11753	0.26685
Pork lb/day	0.1575	0.01837	0.11808	0.20274
Other Red Meat lb/day	0.03619	0.00804	0.02027	0.05342
Fish lb/day	0.03299	0.00562	0.02192	0.0454
Poultry lb/day	0.12257	0.08897	0.03973	0.3246
Fresh Citrus Fruit lb/day	0.08292	0.02973	0.04164	0.17041
Fresh Non-Citrus Fruit lb/day	0.20389	0.05487	0.12301	0.34219
Fresh Veggies lb/day	0.25251	0.04972	0.15342	0.36803
Potatoes lb/day	0.34581	0.07308	0.26986	0.56603
Processed Fruit lb/day	0.12906	0.07831	0.01863	0.24268
Processed Veggies lb/day	0.15346	0.0482	0.05342	0.21014
Fats and Oils lb/day	0.12224	0.04529	0.06082	0.2326
Eggs lb/day	0.10409	0.01483	0.08082	0.13479
Cereals lb/day	0.51053	0.11611	0.36356	0.79315
Sugars and Sweeteners lb/day	0.31945	0.05287	0.22603	0.43479
Coffee, Tea and Cocoa lb/day	0.03779	0.00628	0.02493	0.05699

Table 5. Summary Statistics of Demographic Variables

Demographic Variables	Mean	Std. Dev.	Min	Max
Average Family Size	3.657071	0.424834	3.13	4.54
Population Proportion under 15	0.265101	0.039958	0.201032	0.320549
Population Proportion 15-54	0.564275	0.025035	0.509526	0.60138
Population Proportion Black	0.109896	0.012013	0.097	0.1353
Population Proportion White	0.872775	0.028183	0.8127	0.898
Population Proportion Other	0.017327	0.016364	0.004	0.052
Per Capita Disposable Income	2668.5	1435.802	808.0357	5524.186
Unemployment	0.066869	0.046275	0.012	0.249

Table 6. Coefficients for Demographic Variables Relating to Nutrient Shadow Prices

		Young Population	Middle-aged Population	Black Population	White Population	Real Per Capita Income	Average Family Size	Labeling of Nutrition Facts	Social Security Act	Food Stamps Program Nationwide	Mandatory Pasteurization of Milk	WWII	Post-WWII	Real Per Capita Income, Squared
Calorie Shadow Prices	LP	0	0	0	0	+	0	+	0	+	0	0	0	-
	LS	0	0	0	0	0	0	0	-	+	0	+	+	0
	ME	0	-	-	-	+	0	0	+	+	0	-	-	0
Protein Shadow Prices	LP	0		-	0	+	+	+	0	+	0	0	0	-
	LS	+	+	0	0	0	-	0	-	0	0	0	0	+
	ME	+	0	-	-	+	-	0	0	0	+	-	0	+
Fat Shadow Prices	LP	+	+	-	-	+	0	+	0	+	0	0	0	-
	LS	0	0	-	-	0	0	0	+	0	0	-	-	0
	ME	+	+	-	0	+	0	0	0	0	+	0	0	0
Calcium Shadow Prices	LP	+	+	0	+	+	0	+	0	+	+	+	+	-
	LS	-	-	0	+	0	0	+	-	0	0	0	0	0
	ME	0	-	+	+	0	0	+	0	0	0	+	0	0

Table 7. Coefficients for Demographic Variables Relating to Food Tastes

		Young Population	Middle-aged Population	Black Population	White Population	Real Per Capita Income	Average Family Size	Unemployment	Mandatory Pasteurization of Milk	Labeling of Nutrition Facts	Social Security Act	Food Stamps Program Nationwide	WIC Nationwide	WWII	Post-WWII	Real Per Capita Income, Squared
Milk Taste Value	ME	0	0	+	+	0	0	-	0	+	+	+	-	0	0	+
	LS	-	0	0	0	0	+	+	+	+	+	-	0	0	0	0
Beef Taste Value	ME	0	0	+	+	0	0	0	0	+	0	0	-	0	+	0
	LS	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0
Poultry Taste Value	ME	+	+	0	+	-	0	-	0	+	+	0	0	+	+	+
	LS	0	0	0	0	0	+	+	0	0	+	-	0	0	-	0
Processed Non-Citrus Fruit Taste Value	ME	-	-	-	-	0	0	0	0	0	0	+	0	0	-	+
	LS	-	-	0	0	0	+	0	0	0	+	-	0	0	0	0
Sugar and Sweetener Taste Value	ME	+	+	0	0	0	0	0	0	0	+	+	0	0	0	0
	LS	0	-	0	0	0	0	+	0	0	0	-	0	-	-	-
Coffee Taste Value	ME	0	0	-	+	0	-	0	-	0	-	+	+	0	0	+
	LS	-	-	0	-	0	+	+	+	0	+	-	0	0	-	0

Table 8. Effects on Taste Share of Food Expenditure⁴

Independent Variables	LP		LS		ME	
Average Family Size	-0.120*	(-1.9)	1.419**	(2.06)	-0.032***	(-3.48)
Age 54 and Older	0.978	(1.07)	24.410**	(2.45)	-0.450***	(-3.38)
Black	15.267***	(5.62)	-27.423	(-0.93)	3.191***	(8.08)
Other	-8.130***	(-3.01)	15.453	(0.53)	-0.204	(-0.52)
Real Disposable Income	0.000***	(-3.83)	0.000	(-1.14)	-0.00003***	(-5.82)
Unemployment	-0.250*	(-1.94)	0.232	(0.17)	-0.002	(-0.1)
WWII and After (1942)	-0.041	(-1.64)	0.071	(0.26)	0.010***	(2.85)
WIC Goes National (1975)	-0.033	(-1.41)	-0.227	(-0.88)	0.000	(-0.04)
Constant	-0.863***	(-2.71)	-5.085	(-1.47)	0.871***	(18.86)

⁴ Statistical significance is denoted by * at the 10% level, ** at the 5% level, and *** at the 1% level. T-statistics are in parentheses next to the coefficient.

Appendix A, Estimated Shadow Prices Using Maximum Entropy

The Lagrangian for this problem is:

$$\begin{aligned}
 \mathcal{L} = & -\sum_{i=1}^I \int_0^{p_i} f_i(r) \ln f_i(r) dr - \sum_{j=1}^J \int_{-\tilde{\pi}_j}^{\tilde{\pi}_j} g_j(\pi) \ln g_j(\pi) d\pi + \sum_{i=1}^I \lambda_i \left[1 - \int_0^{p_i} f_i(r) dr \right] \\
 & + \sum_{j=1}^J \mu_j \left[1 - \int_{-\tilde{\pi}_j}^{\tilde{\pi}_j} g_j(\pi) d\pi \right] + \sum_{i=1}^I \lambda_i \left[p_i - \int_0^{p_i} r f_i(r) dr - \sum_{j=1}^J a_{ij} \int_{-\tilde{\pi}_j}^{\tilde{\pi}_j} \pi g_j(\pi) d\pi \right] \\
 (A1) \quad & = \sum_{i=1}^I \lambda_i + \sum_{j=1}^J \mu_j + \sum_{i=1}^I \lambda_i p_i - \sum_{i=1}^I \int_0^{p_i} [\ln f_i(r) + \lambda_i + \lambda_i r] f_i(r) dr \\
 & - \sum_{j=1}^J \int_{-\tilde{\pi}_j}^{\tilde{\pi}_j} [\ln g_j(\pi) + \mu_j + \sum_{i=1}^I \lambda_i a_{ij} \pi] g_j(\pi) d\pi.
 \end{aligned}$$

We obtain the following first-order conditions¹:

$$\begin{aligned}
 (A2) \quad & -\ln f_i(r) - \lambda_i - \lambda_i r - 1 = 0, \forall r \in [0, p_i], i = 1, \dots, I, \\
 & -\ln g_j(\pi) - \mu_j - \sum_{i=1}^I \lambda_i a_{ij} \pi - 1 = 0, \forall \pi \in [-\tilde{\pi}_j, \tilde{\pi}_j], j = 1, \dots, J,
 \end{aligned}$$

Simplifying equation (A2) into exponential form yields:

$$\begin{aligned}
 (A3) \quad & f_i(r) = e^{-(1+\lambda_i)} e^{-\gamma_i r}, \forall r \in [0, p_i], i = 1, \dots, I, \\
 & g_j(\pi) = e^{-(1+\mu_j)} e^{-\delta_j \pi}, \forall \pi \in [-\tilde{\pi}_j, \tilde{\pi}_j], j = 1, \dots, J
 \end{aligned}$$

where $\delta_j = \sum_{i=1}^I \gamma_i a_{ij}$, $j = 1, \dots, J$ is a convenient reduction in notation.

Using the constraints $1 = \int_0^{p_i} f_i(r) dr$ and $1 = \int_{-\tilde{\pi}_j}^{\tilde{\pi}_j} g_j(\pi) d\pi$ to clear $e^{-(1+\lambda_i)}$ and $e^{-(1+\mu_j)}$ out

of equations (A3), we start with the following taste shadow price density functions,

¹ It is known that problems such as equation (13), which are called isoperimetric calculus of variations problems (Clegg 1968), are solved by maximizing the Lagrangian point-wise with respect to each $f_i(r)$ and $g_j(\pi)$ for each (i, j) and all (r, π) in their respective supports (Seierstad and Sydsæter 1987).

$$1 = e^{-(1+\lambda_j)} \int_0^{p_i} e^{-\gamma_i r} dr = e^{-(1+\lambda_i)} \left[-\frac{1}{\gamma_i} e^{-\gamma_i r} \Big|_0^{p_i} \right] = e^{-(1+\lambda_i)} \left[-\frac{1}{\gamma_i} (e^{-\gamma_i p_i} - 1) \right], \text{ yielding}$$

$$e^{-(1+\lambda_j)} = \frac{\gamma_i}{1 - e^{-\gamma_i p_i}}, \text{ and further with the nutrient shadow density function,}$$

$$1 = e^{-(1+\mu_j)} \int_{-\tilde{\pi}_j}^{\tilde{\pi}_j} e^{-\delta_j \pi} d\pi = e^{-(1+\mu_i)} \left[-\frac{1}{\delta_j} e^{-\delta_j \pi} \Big|_{-\tilde{\pi}_j}^{\tilde{\pi}_j} \right] = e^{-(1+\mu_i)} \left[-\frac{1}{\delta_j} (e^{-\delta_j \pi_j} - e^{\delta_j \pi_j}) \right], \text{ yielding}$$

$$e^{-(1+\mu_i)} = \frac{\delta_j}{e^{\delta_j \tilde{\pi}_j} - e^{-\delta_j \tilde{\pi}_j}}. \text{ Plugging these statements into equation (A3), we arrive at the following:}$$

$$\begin{aligned} f_i(r) &= \frac{\gamma_i e^{-\gamma_i r}}{1 - e^{-\gamma_i p_i}}, \forall r \in [0, p_i], i = 1, \dots, I, \\ g_j(\pi) &= \frac{\delta_j e^{-\delta_j \pi}}{e^{\delta_j \tilde{\pi}_j} - e^{-\delta_j \tilde{\pi}_j}}, \forall \pi \in [-\tilde{\pi}_j, +\tilde{\pi}_j], \\ \delta_j &= \sum_{i=1}^I \gamma_i a_{ij}, j = 1, \dots, J. \end{aligned} \tag{A4}$$

From these equations, we use L'Hôpital's rule and integration by parts to find our expected value for each random variable, $E(\mathbf{R})$ and $E(\mathbf{II})$.

$$f_i(r) = \lim_{\gamma_i \rightarrow 0} \left(\frac{\gamma_i e^{-\gamma_i r}}{1 - e^{-\gamma_i p_i}} \right) = \frac{\lim_{\gamma_i \rightarrow 0} (1 - \gamma_i r) e^{-\gamma_i r}}{p_i \lim_{\gamma_i \rightarrow 0} e^{-\gamma_i p_i}} = \frac{1}{p_i}. \tag{A5}$$

This implies that $f_i(r) = \frac{1}{p_i}$, which is a uniform distribution over the support $[0, p_i]$. From this,

$\gamma_i = 0$ if and only if $E(\mathbf{R}) = \frac{1}{2} p_i$, and further that $\gamma_i > 0$ if and only if $E(\mathbf{R}) < \frac{1}{2} p_i$, and similarly that $\gamma_i < 0$ if and only if $E(\mathbf{R}) > \frac{1}{2} p_i$, depending on the sign of γ_i .

Let us consider the case where $\gamma_i \neq 0$. We want to find $E(\mathbf{R})$. We know that

$$E(\mathbf{R}) = \int_0^{p_i} r f_i(r) dr = \int_0^{p_i} r \frac{\gamma_i e^{-\gamma_i r}}{1 - e^{-\gamma_i p_i}} dr. \tag{A6}$$

To solve equation (A6), we will integrate by parts, setting:

$$(A7) \quad u = r, \quad v = \frac{-e^{-\gamma_i r}}{1 - e^{-\gamma_i p_i}}, \quad u' = 1, \quad v' = \frac{\gamma_i r e^{-\gamma_i r}}{1 - e^{-\gamma_i p_i}}.$$

Now, we transform equation (A7) into:

$$(A8) \quad \begin{aligned} E(\mathbf{R}) &= -r \frac{e^{-\gamma_i r}}{1 - e^{-\gamma_i p_i}} \Big|_0^{p_i} - \int_0^{p_i} \frac{e^{-\gamma_i r}}{1 - e^{-\gamma_i p_i}} dr \\ &= -r \frac{e^{-\gamma_i r}}{1 - e^{-\gamma_i p_i}} \Big|_0^{p_i} - \frac{e^{-\gamma_i r}}{\gamma_i [1 - e^{-\gamma_i p_i}]} \Big|_0^{p_i} = -p_i \left[\frac{e^{-\gamma_i p_i}}{1 - e^{-\gamma_i p_i}} \right] + \frac{1}{\gamma_i} \\ &= p_i \left[\frac{1}{1 - e^{-\gamma_i p_i}} \right] + \frac{1}{\gamma_i}. \end{aligned}$$

Defining $\delta_j = \sum_{i=1}^I \gamma_i a_{ij}$, $j = 1, \dots, J$, we know that the Lagrange multipliers for the nutrient shadow prices, δ_j are determined by those of the taste attributes, γ_i . Accordingly, if and only if $\delta_j = 0$, then $E(\mathbf{II}) = 0$, if and only if $\delta_j > 0$, then $E(\mathbf{II}) < 0$, and similarly, if and only if $\delta_j < 0$, then $E(\mathbf{II}) > 0$, by the nature of Lagrangian multipliers. If $\gamma_i = 0, i = 1, \dots, I$, then $E(\mathbf{R}) = \frac{1}{2} p_i, i = 1, \dots, I$ and $E(\mathbf{II}) = 0, j = 1, \dots, J$. Thus, we know that we cannot have $\gamma_i = 0, i = 1, \dots, I$, since this would imply that $p_i = \frac{1}{2} p_i, i = 1, \dots, I$, which is a statement of contradiction. We obtain the expression of the mean $E(\mathbf{II}) \neq 0$ by integrating by parts our estimated function of equation (A4). Allow:

$$(A9) \quad u = \pi, \quad v = \frac{e^{-\delta_j \pi}}{e^{\delta_j \tilde{\pi}_j} - e^{-\delta_j \tilde{\pi}_j}}, \quad u' = 1, \quad v' = -\frac{\delta e^{-\delta_j \pi}}{e^{\delta_j \tilde{\pi}_j} - e^{-\delta_j \tilde{\pi}_j}}.$$

We obtain the following, recalling that $\delta_j = \sum_{i=1}^I \gamma_i a_{ij}$, $j = 1, \dots, J$:

$$\begin{aligned}
E(\boldsymbol{\Pi}) &= \int_{-\tilde{\pi}_i}^{\tilde{\pi}_i} \pi g_j(\pi) d\pi = \int_{-\tilde{\pi}_i}^{\tilde{\pi}_i} \pi \frac{\delta_j e^{-\delta_j \pi}}{e^{\delta_j \tilde{\pi}_j} - e^{-\delta_j \tilde{\pi}_j}} d\pi \\
&= -\pi \frac{e^{-\delta_j \pi}}{e^{\delta_j \tilde{\pi}_j} - e^{-\delta_j \tilde{\pi}_j}} \Big|_{-\tilde{\pi}_i}^{\tilde{\pi}_i} - \int_{-\tilde{\pi}_i}^{\tilde{\pi}_i} \frac{e^{-\delta_j \pi}}{e^{\delta_j \tilde{\pi}_j} - e^{-\delta_j \tilde{\pi}_j}} d\pi \\
&= -\tilde{\pi}_j \frac{e^{-\delta_j \tilde{\pi}_j}}{e^{\delta_j \tilde{\pi}_j} - e^{-\delta_j \tilde{\pi}_j}} - \tilde{\pi}_j \frac{e^{\delta_j \tilde{\pi}_j}}{e^{\delta_j \tilde{\pi}_j} - e^{-\delta_j \tilde{\pi}_j}} - \frac{1}{\delta_j} \left[\frac{e^{-\delta_j \tilde{\pi}_j}}{e^{\delta_j \tilde{\pi}_j} - e^{-\delta_j \tilde{\pi}_j}} \right]_{-\tilde{\pi}_i}^{\tilde{\pi}_i} \\
&= -\tilde{\pi}_j \frac{e^{-\delta_j \tilde{\pi}_j} + e^{\delta_j \tilde{\pi}_j}}{e^{\delta_j \tilde{\pi}_j} - e^{-\delta_j \tilde{\pi}_j}} - \frac{1}{\delta_j} \left[\frac{e^{-\delta_j \tilde{\pi}_j} - e^{\delta_j \tilde{\pi}_j}}{e^{\delta_j \tilde{\pi}_j} - e^{-\delta_j \tilde{\pi}_j}} \right] \\
&= -\tilde{\pi}_j \frac{e^{-\delta_j \tilde{\pi}_j} + e^{\delta_j \tilde{\pi}_j}}{e^{\delta_j \tilde{\pi}_j} - e^{-\delta_j \tilde{\pi}_j}} + \frac{1}{\delta_j} = \tilde{\pi}_j \left[\frac{1 + e^{2\delta_j \tilde{\pi}_j}}{1 - e^{2\delta_j \tilde{\pi}_j}} \right] + \frac{1}{\delta_j}
\end{aligned}
\tag{A10}$$

With these findings, we can substitute $\delta_j = \sum_{i=1}^I \gamma_i a_{ij}$ back into our hedonic price constraint from equation (10). The expected values are

$$\begin{aligned}
E(\mathbf{R}) &= p_i \frac{1}{1 - e^{-\gamma_i p_i}} + \frac{1}{\gamma_i} \\
E(\boldsymbol{\Pi}) &= \tilde{\pi}_j \left[\frac{1 + e^{2\delta_j \tilde{\pi}_j}}{1 - e^{2\delta_j \tilde{\pi}_j}} \right] + \frac{1}{\delta_j}
\end{aligned}
\tag{A11}$$

Substituting $\delta_j = \sum_{i=1}^I \gamma_i a_{ij}$ back into our hedonic price constraint from equation (10),

$\mathbf{p} = E(\mathbf{R}) + \mathbf{A}'E(\boldsymbol{\Pi})$, we obtain our price equation (13).

Appendix B, Seemingly Unrelated Regression

Beginning with the nutrient shadow prices as the dependent variables, consider a system of J seemingly unrelated equations, so that

$$(B1) \quad \pi_j = X_j \beta_j + \varepsilon_j, \quad j=1, \dots, 18,$$

where X_j is our matrix of independent variable vectors.² In matrix notation,

$$(B2) \quad X_j = \begin{bmatrix} X_1 & 0 & \dots & 0 \\ 0 & X_2 & \dots & 0 \\ & & \vdots & \\ 0 & 0 & \dots & X_{18} \end{bmatrix}.$$

Let $\Omega = \Sigma_j \otimes I$, where Σ_j is the $J \times J$ covariance matrix of disturbances, and \otimes is the Kronecker multiplier. The efficient GLS estimator is then:

$$(B3) \quad \hat{\beta} = [X' \Omega^{-1} X]^{-1} X' \Omega^{-1} \pi.$$

This SUR model has a similar form when estimating the food taste values as the dependent variables. In this case, we consider a system of I equations, such that:

$$(B4) \quad r_i = X_i \theta_i + \varepsilon_i, \quad i=1, \dots, 21.$$

Letting $\Psi = \Sigma_i \otimes I$, where Σ_i is the $I \times I$ covariance matrix of disturbances. The efficient GLS estimator is similarly:

$$(B5) \quad \hat{\theta} = [X' \Psi^{-1} X]^{-1} X' \Psi^{-1} r.$$

² Each of the variables in Equation (19) is a matrix of J vectors spanning the 97 years of estimates.