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"Explaining the Shift from Preserved to Fresh Vegetable Consumption"

Abstract

After falling through the 1970s and 80's, the share of vegetables consumed fresh rather than preserved has risen steadily from 47 percent to 57 percent between 1991 and 2009. While trade liberalization and cost shifts are likely to have played some significant role in this shift, rising incomes have also allowed consumers to substitute towards higher value fresh products. To estimate the role income growth in explaining this shift, we use household panel data for 25 fresh and preserved vegetable commodities to estimate a disaggregated censored EASI demand system with non-linear Engel curves to consider what share of fresh consumption growth is attributable to income growth as opposed to price shifts. In general, we find that our estimated incomes elasticities are significantly smaller for preserved vegetables on a commodity by commodity basis implying that fresh goods will represent a large share of consumer expenditure as incomes grow over time.

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I. Introduction

The development and widespread adoption of flash freezing, mechanical refrigeration, and home electrification in the first half of the 20th century established the modern infrastructure associated with the preservation of fresh vegetables. For 60 years or more, preservation (i.e. canning, freezing and dehydration) has allowed the consumption and harvest of many vegetables to become temporally unlinked. With the rise of frozen foods companies such as Birdseye and Green Giant, the share of U.S. vegetables consumed fresh fell in the post-War II Era. However, as Figure 1 shows, after falling through the 1970s and 80's, the fresh share rose steadily from 47 percent in 1991 to 57 percent in 2009. This reversal likely stems from several economic causal factors including improved supply chain logistics in shipping fresh foods, tariff reductions, and increased trade access, especially tropical and out-of-season fresh items. Income effects, the focus of our study, have also allowed consumers to substitute away from low-quality preserved vegetables and towards higher-quality, more-convenient fresh products. And, as indicated by Figure 2, per capita consumption of vegetables has increased generally since the 1970s, a shift primarily emerging from increased fresh consumption.

II.a History of Preservation

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There are three primary methods for the extended preservation of fresh vegetables– dehydration, canning (including pickling) and freezing. Dehydration, whose practice predates modern history and requires little specialized technology aside from salt, prevents microbial formation by removing moisture from the food. Dehydration has been primarily used with aromatic vegetables - spices (i.e. oregano, basil, red pepper), tomatoes, and onions – and staple legumes (i.e. black beans, kidney beans). Historically, canning involved pickling which prevents microbial reproduction by submerging the food in acidic or saline solutions. Pickling, which significantly changes the taste and texture of food items, primarily occurs with cabbage, cucumbers and other melons. Modern canning essentially heat pasteurizes food before sealing it in an airtight jar or steel can, a process that changes the texture of the food significantly.

The flash freezing process was developed by Clarence Birdseye and was originally directed toward preserving very perishable fish (Kurlansky, 2009). Throughout the 1800s, food was preserved with natural ice harvested in winter from frozen freshwater sources through the colder areas of the United States and transportation innovations (engine driven railways and boats) heighten the demand for ways to preserve foods in transit. While mechanical refrigeration (refrigerators powered by electricity) had been employed by Pullman with great success in shipping meat in railcars, the freezing process damaged the taste and texture of vegetables by making them limp and mushy and limited its appeal. Birdseye, while working as a fur trader in New Foundland, noted that Native American Inuit people could preserve the quality of fish by freezing them quickly at the very low ambient temperatures. Because ice crystals are smaller when they form faster, the flash-freezing, process (as Birdseye's process came to be called) did not damage cell walls of vegetables and fish and largely preserved their important food texture properties. Despite these advantages, the adoption of frozen foods was not immediate as the technology required both stores and consumers to have mechanical refrigerators and electrical access.

II.b Market Trends for Fresh Products

Concerns over nutrition and obesity create an ongoing interest in understanding the drivers of consumption of various food items. Understanding the specific factors driving vegetable demand has been of substantial concern since the USDA revamped the food pyramid, adjusted school lunch programs to encourage vegetable consumption and undertaken various program to promote vegetable consumption.

Promotion of vegetable consumption is often linked to encouraging its consumption in a fresh and unprocessed state. For instance, various groups promote farmers markets and the promotion of locally procured as a way to encourage its consumption (Pollan, 2008). Recently, a Union of Concerned Scientists argued that by encouraging the production of fruits and vegetables and, specifically, the availability of fresh, locally grown produce, national welfare might increase by as much as $11 Trillion (Union of Concerned Scientisits, 2013)[1].

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While the potential health benefit of eating equal volumes of vegetables in fresh versus preserved states is a matter of debate, the shift away from preserved vegetables is noteworthy and, apart from preference changes, likely stems from the following causes:

- reduced tariffs with key trade partners lowering prices,
- increased access to foreign imports owing to the relaxation of sanitary and phytosanitary restrictions,
- greater north-south trade facilitating out-of-season availability of fresh vegetables,
- innovations in international shipping that have facilitated the fresh vegetable trade,
- and rising consumer incomes.

Identifying the specific causal roles of trade liberalization is vexing because liberalization often reduces the costs of both fresh and preserved vegetables. However, as these changes are largely captured by price effects in equilibrium they are largely controlled for in our model,

[1]About 73 percent of 2013 U.S. GDP!

which allows us to focus more narrowly on disparate income effects between fresh and preserved vegetables.

I.c Demand Modeling Approach

Numerous studies have estimated how the demand for vegetables depends on income using a various dataset and specifications. However, we know of no study that specifically contrasts fresh and frozen vegetable consumption on a disaggregated basis while controlling for cross commodity interactions generally. Moreover, many previous demand studies impose a priori restriction on how demand responds to income changes and how zero consumption levels are treated. Using a novel dataset and several newly developed modeling techniques, we use a large rich panel dataset on household consumption to estimate income effects in more flexible form than that considered in many previous studies and, following the work of Zhen et al. (2011), employ several methodological innovations that accommodate the large number of goods, many of which consumers only purchased occasionally.

Our first two innovations address the construction of price indexes and the fact that Homescan data only includes the prices of goods actually purchased by the consumer. First, to infer the price of goods not purchased, we run a regression of prices paid for that good by other consumers in the same market and time to generate estimated prices. Second, to aggregate the prices of the various sub-products with a commodity group, we construct a Fisher Ideal Price Index for each household for each commodity using our estimated prices for each UPC for the sub-products. This price index represents a second order approximation to the ratio of the cost function of obtaining, alternatively, the utility level provided at the index quantity and price and that same utility level at the index quantity and the observed current prices (Diewert, 1976). We substitute this price index directly into the demand system as it represents the cost expenditure required to obtain the optimal utility possible under the index prices when now faced with the (higher or lower) current prices. We use the average price and quantity as the index.

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Other innovations involve demand estimation. Third, expenditures on vegetables are unlikely to be income separable from other expenditures. Subsequently, we include a numeraire good constructed from the regional CPI within the demand system using the method of LaFrance and Hanemann (1989). Fourth, to account for zero consumption of some of the commodities within a period, we use as Tobit model of demand where the consumption decision is considered as two simultaneous steps – the decision to purchase a specific commodity, followed by the decision on how much expenditure to allocate to the commodity. Fifth, being especially concerned about the role of income, we estimate the EASI demand system. Unlike some commonly used demand systems, the EASI (Exact Affine Stone Index) Marshallian Implicit Demand Model can incorporate Engle curves of any arbitrary flexibility (Lewbel and Pendakur, 2009).

As relatively little research informs the basic demand patterns for fresh and preserved vegetables on a disaggregated basis, we will discuss our results in terms of estimate price and income effects and relate them to potential policy applications. For instance, the extent to which a price increase causes intra-commodity (fresh broccoli to frozen broccoli) and inter-commodity (fresh broccoli to asparagus) substitution has been largely unaddressed within demand studies. Income-wise, more fresh consumption may tilt the distribution of the food dollar between processors and farms or imports and domestic goods (depending on the product and seasons). Nutritionally, fresh vegetables may impart some nutritional benefits to the extent they are preserved with less salt or sugar. Environmentally, fresh products may require less packaging and pre-processing energy but also involve greater home waste, more frequent store travel and larger refrigeration demands at all stages. Food-safety wise, the differential treatment of some fresh and preserved goods under the Food Safety Modernization Act of 2011 may generate compliance costs that shift consumption patterns predictably and change certain food safety outcomes.

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II. Description of Data

II.a Homescan Data

We use Homescan data from AC Nielsen in our model. In this data, households log their purchases of food items from grocery or convenience stores using scanners provided by Nielsen or by manually logging their purchases. The data links the scanned or logged purchases to retail prices from the nearby retail outlets. Most prices are automatically recovered from store prices through the Universal Product Code (UPC) or Stock Keeping Unit (SKU) number, but in cases where they are absent, prices are manually recorded from receipts. Einav et al(2008) and Einav et al(2010) provides a detailed description of the price recording process and an analysis of potential recording error.

Homescan data divides consumption into product modules representing broad consumption types found in grocery stores. The portion of our panel that contains data on fresh and frozen vegetables includes dry goods, frozen goods and random weight modules which roughly correspond to canned, frozen and fresh goods. Table 2 provides statistics on the demographic composition of the panel. The relevant portion of the panel covers approximately 9,000 households in 52 markets and 9 remaining areas of the United States between 2002 and 2006.

While the underlying data is recorded on a daily basis, we aggregated to the monthly level. The average length of participation in the panel is 32 months. Demographic data of the panelists is contrasted with available average demographic information of U.S. households.

Initially, we aggregate commodities across 45 commodity groups. However, the sparseness observations of certain commodity groups led us to further aggregate the goods into 23 distinct commodity groups, 1 other fresh aggregate, and 1 other preserved aggregate for a total of 25 total goods in the demand system. Aggregations were based on unique identifiers within the dataset includes UPC codes for items within the dry goods and frozen goods product modules and which the SKUs within the random weight product module. Table 2 provides the number of identified for each good, average total expenditures across households, and the average likelihood a commodity is purchased in a given month.

II.b Forming Price and Expenditure Aggregates

Individual product identifiers differ across product modules. Dry goods and frozen goods are typically uniform in terms of weights, levels of processing and product characteristics. Examples include a can of corn or a bag of salad. With random weight goods, product weights are determined by the size of the good purchased and, therefore, random. The data accounts for accounts for significant quality or processing distinctions. Pre-cut celery has a higher price by weight than whole celery but this merely represents its large edible portion. Goods may nonetheless vary size and quality in ways that are unobservable to us as researchers.

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II.c Estimating Missing Prices

Within our dataset, prices are only observed for goods when consumers make a purchase. As indicated by Table 3, consumers generally only purchase 5 different vegetable commodities each month or 20% of commodities considered. Prices are missing when consumers do not purchase any uniquely identified good in a product category. If a consumer does not purchased any product within the commodity category in a given month, then the price of that is commodity is missing and this may occur for two reasons. First, the consumer simply chooses not to purchase an available product as part of the consumer optimization process. In this case, missing prices can be estimated using some unbiased measure and re-inserted into the demand system as if they were actual prices. We employ this method and provide details on our estimation method in the Appendix.

Alternatively, the product is unavailable to the consumer and cannot be purchased at any price. In this case, economists occasionally address this problem with demand system estimation by estimating a virtual or choke price as the theoretical price index that makes the consumers demand for the good exactly equal to zero. Lee and Pitt (1986) show that the conjectured virtual price can be solved for as an analytical solution from the other demand system parameters, reinserted into the demand function when the price of that good is missing, and used to estimate the demand system parameters generally. While several authors have adapted this method directly (Phaneuf, et al., 2000, Yue and Beghin, 2009), the computational requirements for solving demand systems with many goods often makes this method prohibitive (Millimet and Tchernis, 2008).

Besides obvious concerns about tractability, we dismiss unavailability as a reason for missing prices for three reasons. First, our specific demand model involves many goods identified for each of our commodity categories. If any of the individual goods are available then the model remains theoretically consistent. Second, our data incorporates the fact that consumers can purchase from multiple grocery outlets. Even if a single store has limited offerings, it remains available if consumers can purchase it somewhere reasonable close by. Third, in recent years, many fresh produce items have become available out-of-season and preserved produce items are typically available year round.

II.d Constructing Price Indices

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While a naive demand system might aggregate goods by total weight (i.e. total ounces of celery purchased) and then construct an average price for the commodity based on the weights of the good purchased, this method assumes that all goods in a commodity group are prefect substitutes. Instead, we use a Fischer Ideal Price Index (FIPI) to account for utility differences among the various goods in a commodity group[2]. The FIPI develops a sub-utility structure for consuming goods within the commodity category based on the expenditure shares of the respective goods.

Diewert (1976) showed that the FIPI can represent a ratio of cost functions following the translog cost function and parameterized by reference prices and quantities (p_{k0} and q_{k0}, respectively). As Christensen, Jorgensen and Lau (1973) had previously shown to be second order approximation of an arbitrary twice continuously differentiable linear homogenous

[2] As our demand estimation does not require that we form any aggregates of weight as long as the underlying characteristics of the products within the identifiers are stable. However, for purposes of later analysis on nutrition outcomes, we developed multipliers to standardize the comparable edible weights of products based previous work of Stewart (2011). Our size adjustment factors are specifically obtained from USDA's *Food Yields Summarized by Different Stages of Preparation (Need Reference)*.

function, the FIPI can similarly be interpreted as the ratio of two cost function sharing these properties consistent with utility theory. Intuitively, our p_{jht} then represents the cost of utility at the current prices (of the *k* products in commodity *j*) relative to the cost of utility at the reference prices.

The equation for the Fischer Ideal Price Index (FIPI) is:

$$p_{jht} = p_{jht}(p_{kht}, q_{kht}, p_{k0}, q_{k0}) = \sqrt{\frac{\sum_k p_{kht} q_{k0}}{\sum_k p_{k0} q_{k0}} \frac{\sum_k p_{kht} q_{kht}}{\sum_k p_{k0} q_{kht}}} \quad (1)$$

For each of the *j* product categories, the reference quantities (q_{k0}) used to parameterize the FIPI are the average quantity purchased (across the *h* households and *t* monthly time periods) of each of the *k* sub-products in commodity *j*. These values, which include zero values in the months that the consumers did not make a purchase, are given in Table 1. When consumption is zero for all *k* sub-products (q_{kht}), the $\sum_k p_{k0} q_{kht}$ and $\sum_k p_{kht} q_{kht}$ terms are both potentially zero as well. For these observations, we use equation (2):

$$p_{jht} = p_{jht}(p_{kht}, p_{k0}, q_{k0} | q_{kht} = 0) = \sqrt{\frac{\sum_k p_{kht} q_{k0}}{\sum_k p_{k0} q_{k0}} \frac{\sum p_{kht}}{\sum p_{k0}}} \quad (2)$$

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II.e Income Separability and the Construction of the Numeraire Good

As outlined in LaFrance and Haneman (1989), we construct a numeraire good from our measure of income and the CPI. The numeraire good represents all other purchases that may be made with consumer income and numeraire good expenditure is simply the consumer's remaining (monthly) income once total vegetable expenditures have been subtracted. Budget shares for each commodity and the numeraire good can be calculated (w_j) by dividing by income and used, in conjunction with the commodity price indexes (*PI*) to calculate an aggregate price index (P_{INDEX}) as:

$$P_{INDEX} = \sum_j w_j \, PI_j. \quad (3)$$

The price of the numeraire good (indexed as J) is then:

$$PI_{J\,(numeraire)} = \left(P_{INDEX} - \sum_J^{J-1} w_j PI_j \right) / w_J. \quad (4)$$

A commonly used price index is the Consumer Price Index (CPI) of the Bureau of Labor Statistics which is calculated regionally. Zhen et al (2012), however, notes that the regionally calculated

CPI must be adjusted to allow for comparison across markets because the figure is independently calibrated to 100 in their respective regions. In a similar manner, we adjust our monthly regional CPI measures using quarterly prices from the Consumer Expenditure Survey of the Council for Community and Economic Research.

II.f Accounting for Price Endogeneity

At the commodity level, the diffuse production (consistent with a high degree of competition) and long production lags associated with vegetable supply provide some assurance that supplies are exogenously determined and define the price variation which identifies the demand relationships. Because our data is recorded at the household, rather than the national level, however, the possibility of endogenous prices arises if supplies are re-directed regionally in response to demand factors. If prices are exogenous, then estimation can proceed with their direct inclusion in the demand system.

If prices are endogenous, then the endogeneity must be accounted for either through instrumentation or through some other control method. Often lagged prices are used as instruments for current prices. Alternatively, in studying breakfast cereals where market power is strongly suspected to exist, Hausman (1996) instruments for individual price by using the prices in nearby markets. Bresnahan (1997) questions whether this instrumentation method is appropriate if regional promotions have demand effect that spill across market boundaries. In related work, Nevo (Nevo, 2000) uses cost shifters (in addition to neighboring market prices) as price instruments. In both Nevo's and Hausman's applications, market power is strongly suspect a priori.

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In our specific application, market power is of less concern owing to the factors already mentioned regarding commodity demand and because the commodities themselves are collections of disparate goods with several manufacturers and sellers. If regional promotion schemes impact aggregate prices of a commodity in a region, that affect would be capture by the inclusion of the average price of the commodity in the region as a demand shifter within the demographic variables. We implement this estimation method in the mean price coefficients model, along with the IV model and a base model which excludes any correction for price endogeneity.

II.g The Censored EASI Demand System

Because income effects are of key interest in our application, we are especially interested in maintaining flexibility in how income affects demand. Many commonly employed demand systems such as the AI and TL demand system restrict the shape of derived Engel curves to be linear. While several authors have modified these models to incorporate greater flexibility, the EASI demand systems derived by Lewbel (2009) allows for any arbitrary shaped Engel curve to be specified using higher-order polynomials while maintaining many of the desirable properties associated with the well-established AI and TL demand system.

The EASI demand system is derived from a utility-theoretic cost function where budget share depend on prices (*p*), real income (*y*) and demographic variables (*z*). It is described in detail in Lewbel and Pendakur (2009). Suppressing the time and household ID variables, estimated share equations are derived as:

$$w_j = \sum_r b_{rj}\, y^r + \sum_l \left(C_{lj} z_l + D_{lj} z_l y \right) + \sum_l \sum_k A_{lkj}\, z_l p_k + \sum_k B_{kj}\, p_k y + \varepsilon_j \qquad (5)$$

where *j* and *k* both index the commodity; *r* indexes the higher income effects; and *l* indexes the demographics. In this specification, the estimated b_{rj} and C_{lj} terms can loosely be interpreted as individually capturing income and demographic effects, including higher order polynomial income effects that allow for flexible Engel curves. The D_{lj} terms capture potential interaction effects between income and demographics. The A_{lkj} and B_{kj} terms capture price effects and their interactions with demographic variables and income. As with the familiar AI and TL demand systems, homogeneity, symmetry and adding-up (aggregation) restrictions can be imposed.

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In an uncensored demand system, the Hicksian elasticity of demand $\left(h_{ij}\right)$ is given as:

$$h_{ij} = \frac{a_{ij}}{w_j} + w_j - \delta_{ij} \qquad (6)$$

where $\delta_{ij} = 1$ if $i = j$, and 0 otherwise. The $J \times 1$ vector of income elasticities was calculated as:

$$E = \left(diag(W)\right)^{-1} \left[\left(I_J + BP' \right) B \right] + 1_J \qquad (7)$$

where W is the $J \times 1$ vector of observed budget shares, B is a $J \times 1$ vector whose i[th] element equals $\sum_{r=1}^{L} r b_{ir} y^{r-1}$, P is the $J \times 1$ vector of prices, and 1_J is a $J \times 1$ vector of ones. The Marshallian prices elasticity $\left(e_{ij}\right)$ is recovered from the Slutsky equation $e_{ij} = h_{ij} - w_j e_i$ where e_i is the income elasticity obtained from (7).

When demand is censored at zero, meaningful elasticity estimates cannot be obtained at zero demands. One solution is to calculate expected elasticities by replacing W with conditional means of observed budget shares and substituting marginal effects of log prices and real income polynomials on these conditional means for a_{ij} and b_{ir} in equations (6) and (7). We calculated expected price and expenditure elasticities at all observations. The standard error for each point was generated by taking 100 random draws from a multivariate normal distribution with the mean vector and variance-covariance matrix set to their estimated values (Krinsky and Robb, 1986).

III. Empirical Results

III.a Model Specification

To consider potentially endogenous prices, we estimate the demand models in three separate ways. First, we estimate a base model that does not control for price endogeneity. Second, we estimate a mean coefficients model which controls for price endogeneity by including the average price of each good on a household-by-household basis as a demand shifter. With the inclusion of this term, the price variation is still present in our data via aggregate price shifts across households (on a good by good basis) or through seasonal or idiosyncratic reasons, but any endogeneity of price that is specific to the consumer (for example, if retails charge wealthier consumers higher prices) is controlled for. Third, we estimate the demand system using an instrumental variables estimator in the manner discussed by Hausman (1997)and Nevo (2001).

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III.a.i Incorporating Higher Order Income Effects

In our initial results, we ignore demographic interactions and higher-order income effects owing to the time required to run multiple versions of the model and perform specification. In the current estimates of each model, price effects are assumed to be linear.

III.a.ii The Choice of Price Instruments

We use the Hausman method of instrumenting prices in a given market using prices in neighboring geographic markets. There are potentially many ways to create these instruments. We compare three potential instruments – the average of all prices in neighboring markets weighted by the inverse of distance, the same average of all prices weighted by inverse squared distance, the average prices in the closest market, the average price in the closest three markets. We estimate a regression of the price based on the proposed instrument for each of commodities. Based on the sum of the R^2 values across the equations, we use the average price weighted by the inverse square of the distance while noting that that this measure does not change appreciable across the methods.

III.a.iii Testing the Significance of Mean Coefficients

The mean coefficients model nests the base model. If the coefficients for the mean prices are significant, then the base model is rejected in favor of the mean coefficients model. In later versions of this paper, we will test for this using a simple t-test.

III.a.iv Comparing the IV and Base Models

The base model assumes that prices are exogenous while the IV model instruments for them. If prices are exogenous, then its estimates are unbiased and the model is more efficient than the IV model. The Wu-Hausman test will be applied to later versions of this model to test for the erogeneity of prices.

III.b Model Parameter Estimates

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Reporting and interpreting the model parameter estimates in a concise way is challenging owing to the large number of parameters in demand systems with cross commodity price effects. In general, most flexible demand systems including the AI, TL and EASI demand systems require at least $n - 1 + \big(n(n-1)\big)/2$ parameters to estimate income and price effects respectively. In our case where n is 26, this amounts to 350 parameters, and obviously, including demographics, higher order income effects and interacted income effects increases this figure further. In all, our base model includes 675 parameters while the mean coefficients mode includes 1300. Later versions of this paper will include an electronic appendix that reports the individual parameters estimates and the covariance matrices for each model.

III.B.i Base Model

Table 4 provides the price and income elasticities estimated from the base model. Later versions of this paper will discuss fit statistics in greater detail as well as provided detailed Engel curves that are associated with the inclusion of higher-order income effects.
In general, the model indicates that fresh vegetables have larger income elasticity than preserved vegetables for goods in which we made a direct comparison in our estimation. Specifically, the estimated income elasticities for fresh broccoli, corn, green beans and

mushrooms are: 0.77, 0.81, 0.83, and 0.80 respectively. At the same time, the income elasticities for these same goods in their preserved state are: 0.44, 0.43, 0.32, and 0.65. In short, preserved goods have a much smaller income elasticity than fresh goods. As incomes grow over time, consumers are likely to substitute from the preserved to the fresh forms of these commodities[3].

With the exception of preserved mushrooms and fresh zucchini, the signs of price elasticities were as expected. Because this demand system is less aggregated than many demand systems that consider the demand for vegetables collectively as a commodity class, we would expect our demand system to predict demand curves with more elastic demand. Of our 25 vegetable commodities, 21 have elastic demands when estimated at the mean price.

III.B.ii Mean Coefficients Model

Table 5 provides the price and income elasticities estimated from the mean coefficients model. Again, later versions of the paper will provide greater detail on the income effects by incorporating more flexible modeling. In general, however, the predicted income elasticities from the mean coefficients model display a similar patter to those of the base model. The income elasticities for fresh broccoli, corn, green beans and mushrooms are: 0.47, 0.78, 0.60, and 0.64 respectively. At the same time, the income elasticities for these same goods in their preserved state are: 0.30, 0.34, 0.22, and 0.55. Again, as consumer incomes grow a large share of added expenditure moves to fresh rather than preserved consumption. Again, as with the base model, 21 of 25 commodities have elastic demands when estimated at the mean price.

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III.B.iii Instrumental Variables Model

Later versions of this paper will provide estimates based on the instrumental variables model

<u>IV.</u> Conclusion

While preservation innovations of the mid-20th century allowed consumers to have a greater variety of vegetables out of season, it also lead to a lower share of consumption being fresh[4]. In considering the factors that have reversed that trend and driven consumers to increasingly purchase fresh vegetables, we specifically examine the role of income.

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[3] For the two aggregates, this finding does not hold for either the base or the mean coefficients version of this model. It is important to recognize however, that those two classes of goods do not necessarily overlap.

[4] Unfortunately, no lengthy time series data can confirm the generally understood notion that the share of vegetables consumed as preserved rose between 1945 and 1970.

Our preliminary results suggest that fresh vegetables have larger income elasticities than preserved vegetables. Subsequently, as consumer incomes grow over time, the share of income devoted to fresh vegetables grows faster than that of preserved vegetables. Despite the fact that are panels in only composed of a small subset (2002 to 2006) of the larger time period in which this larger shift occurred (1970 to 2012), the data seems to confirm that income growth is a major source of the consumption shift that this consumption shift can be analyzed on a good-by-good basis.

Similarly, this mode will be extended to estimate how the shifting consumption shares have arisen from improved trade access and increased productivity.   While both these factors will lower price, but the demand effects of prices falling are not uniform across goods.   Moreover, tariff reductions and improved trade access have been uneven with some heavily traded commodities such as asparagus from Peru, which were liberalized immediately in the early 1990s under the Andean Free Trade Agreement, while broccoli from Mexico saw gradual tariff reductions following the passage of NAFTA at about the same time.

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V.I Appendix

We estimate missing prices with the following equation:

$$p_{ijt} = \beta_0 + \beta_t * time_t + \beta_i * ID_i + \beta_j * SC_j + \beta_{j,t} * time_t * SC_j + \beta_{i,t} * ID_i * time_t \qquad \text{(A1)}$$

where *t* is a dummy variable for each time period (indexed by *t*), *SC* is the product subcategory (indexed by *j*) and *ID* is a dummy variable for each geographic market (indexed by *i*). The estimated prices were created automatically in SAS using the PROC GLMSELECT function with *time*, *ID* and *SC* as class variables.

In several instances, no consumer in a geographic region would purchase a specific subcategory of product in a given month. In these instances, SAS will not generate an estimate because the relevant $\beta_{i,t}$ or $\beta_{j,t}$ terms are unidentified. For these missing prices, we sequentially dropped the market ID interaction $(\beta_{i,t})$ and product subcategory interaction terms ($\beta_{i,t}$ and $\beta_{j,t}$), re-estimated the model, and used the predicted prices.

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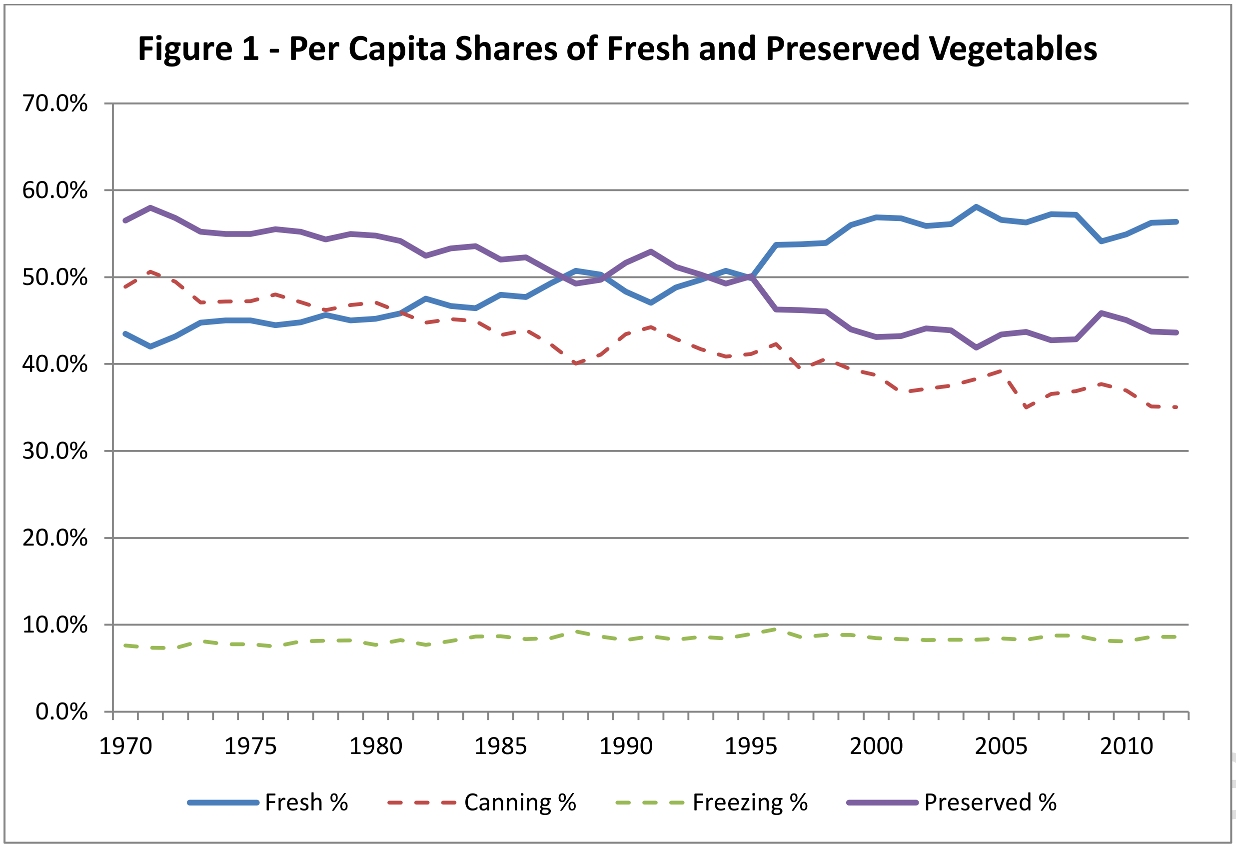
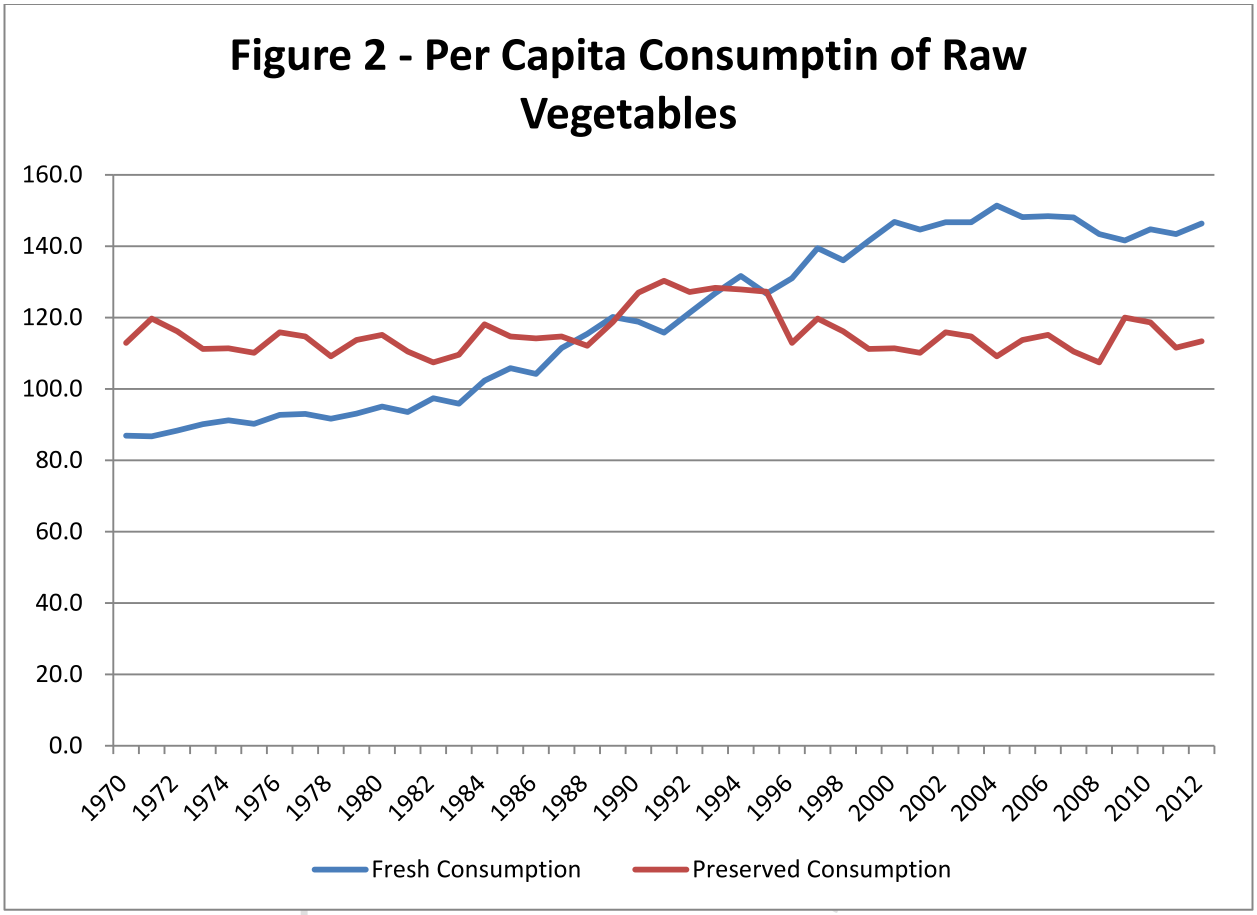


Source: Economic Research Service Vegetable Yearbook (vegetables excluding melons)



Source: Economic Research Service Vegetable Yearbook (vegetables excluding melons)

Table 1 - Unconditional Average Monthly Expenditure and the Percentage of Monthly Expenditures that are Zero

Commodity	Variable	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	ALL	# of Comm. Ident.
Asparagus, Fresh	Uncond. Average	0.16	0.31	0.48	0.42	0.32	0.17	0.12	0.12	0.19	0.22	0.23	0.19	0.25	1
	% Zero Exp.	95.5%	90.3%	84.5%	86.6%	89.5%	94.9%	96.8%	96.7%	94.7%	92.9%	93.1%	94.5%	92.5%	
Broccolli, Fresh	Uncond. Average	0.41	0.35	0.37	0.36	0.36	0.32	0.31	0.31	0.34	0.37	0.35	0.36	0.35	10
	% Zero Exp.	80.2%	81.6%	80.8%	81.4%	81.2%	83.1%	83.8%	83.1%	82.8%	81.0%	82.2%	82.0%	81.9%	
Broccolli, Preserved	Uncond. Average	0.22	0.21	0.23	0.20	0.17	0.18	0.16	0.17	0.19	0.20	0.24	0.20	0.20	1
	% Zero Exp.	90.9%	91.2%	90.8%	91.8%	92.8%	92.7%	93.3%	92.7%	92.0%	91.8%	90.7%	91.6%	91.9%	
Cauliflower, Fresh	Uncond. Average	0.20	0.18	0.18	0.17	0.16	0.13	0.14	0.14	0.16	0.19	0.17	0.16	0.17	3
	% Zero Exp.	91.7%	92.3%	92.4%	92.3%	92.4%	94.4%	94.2%	93.7%	92.9%	91.1%	92.5%	93.2%	92.8%	
Celery Fresh	Uncond. Average	0.38	0.33	0.36	0.34	0.32	0.31	0.32	0.30	0.31	0.34	0.51	0.42	0.35	3
	% Zero Exp.	75.5%	77.8%	77.3%	78.4%	80.0%	80.0%	79.8%	80.3%	79.6%	78.2%	65.1%	72.5%	77.0%	
Corn, Fresh	Uncond. Average	0.03	0.03	0.06	0.18	0.45	0.35	0.48	0.42	0.21	0.06	0.03	0.02	0.19	2
	% Zero Exp.	98.5%	98.4%	96.8%	89.0%	76.5%	80.4%	75.8%	78.7%	87.7%	96.3%	98.2%	98.9%	89.6%	
Corn, Preserved	Uncond. Average	0.58	0.55	0.58	0.56	0.49	0.44	0.43	0.43	0.55	0.58	0.77	0.60	0.55	5
	% Zero Exp.	73.3%	75.3%	74.1%	75.2%	78.0%	79.7%	80.3%	80.2%	75.8%	74.2%	68.4%	73.6%	75.7%	
Cucumbers, Fresh	Uncond. Average	0.24	0.23	0.25	0.27	0.29	0.29	0.30	0.27	0.24	0.22	0.20	0.21	0.25	1
	% Zero Exp.	81.1%	81.4%	80.7%	78.8%	76.6%	76.6%	76.6%	78.3%	80.9%	82.2%	83.9%	82.9%	80.0%	
Green Beans, Fresh	Uncond. Average	0.12	0.11	0.13	0.13	0.12	0.13	0.15	0.15	0.13	0.11	0.15	0.14	0.13	2
	% Zero Exp.	93.6%	94.3%	92.6%	92.2%	92.8%	92.9%	91.4%	91.0%	92.2%	93.6%	92.7%	93.3%	92.7%	
Green Beans, Preserved	Uncond. Average	0.52	0.44	0.50	0.48	0.40	0.38	0.37	0.40	0.48	0.51	0.73	0.57	0.48	2
	% Zero Exp.	77.3%	79.1%	77.6%	78.7%	81.4%	82.7%	83.0%	82.2%	79.3%	77.6%	70.7%	75.9%	78.8%	
Iceberg Lettuce, Fresh	Uncond. Average	0.37	0.34	0.34	0.39	0.41	0.41	0.42	0.41	0.38	0.37	0.31	0.32	0.37	2
	% Zero Exp.	75.8%	76.7%	78.6%	75.2%	73.2%	73.2%	72.0%	72.2%	74.3%	75.3%	78.6%	78.8%	75.3%	
Other Lettuce, Fresh	Uncond. Average	0.15	0.14	0.17	0.16	0.16	0.16	0.16	0.15	0.14	0.13	0.12	0.13	0.15	2
	% Zero Exp.	91.4%	91.8%	91.2%	91.0%	91.0%	90.9%	90.5%	90.8%	91.6%	92.1%	92.8%	92.7%	91.5%	
Romaine Lettuce, Fresh	Uncond. Average	0.27	0.24	0.27	0.28	0.30	0.28	0.30	0.30	0.29	0.29	0.24	0.26	0.28	3
	% Zero Exp.	89.0%	89.9%	89.3%	88.9%	88.3%	88.4%	87.6%	88.0%	88.4%	88.7%	90.3%	90.1%	88.9%	
Mushrooms, Fresh	Uncond. Average	0.13	0.12	0.12	0.12	0.12	0.11	0.11	0.10	0.11	0.11	0.12	0.11	0.12	1
	% Zero Exp.	94.4%	94.6%	94.7%	94.6%	94.8%	94.9%	95.1%	95.3%	95.2%	95.4%	95.2%	95.5%	95.0%	
Mushrooms, Preserved	Uncond. Average	0.60	0.54	0.57	0.55	0.55	0.50	0.52	0.50	0.51	0.53	0.55	0.57	0.54	3
	% Zero Exp.	78.5%	79.6%	79.3%	80.3%	80.4%	81.4%	81.0%	81.4%	81.2%	80.4%	80.7%	80.4%	80.4%	
Onions, Fresh	Uncond. Average	0.82	0.75	0.79	0.78	0.90	0.80	0.85	0.83	0.81	0.79	0.86	0.81	0.82	3
	% Zero Exp.	55.1%	57.2%	56.0%	56.8%	54.7%	57.4%	55.6%	56.1%	56.3%	56.9%	54.9%	56.8%	56.2%	

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Table 1 - Unconditional Average Monthly Expenditure and the Percentage of Monthly Expenditures that are Zero (Continued)															
Commodity	Variable	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	ALL	# of Comm. Ident.
Peppers, Fresh	Uncond. Average	0.26	0.24	0.26	0.25	0.23	0.22	0.20	0.21	0.21	0.25	0.27	0.26	0.24	8
	% Zero Exp.	88.3%	89.3%	88.3%	89.2%	89.9%	90.5%	91.0%	90.6%	90.4%	89.3%	88.4%	88.9%	89.5%	
Potatoes, Fresh	Uncond. Average	2.46	2.22	2.51	2.27	2.25	2.13	2.13	2.16	2.28	2.37	2.45	2.47	2.31	5
	% Zero Exp.	40.0%	42.6%	39.2%	43.5%	44.5%	46.1%	47.0%	45.6%	42.8%	41.4%	41.3%	41.1%	42.9%	
Spinach, Fresh	Uncond. Average	0.18	0.17	0.20	0.17	0.17	0.16	0.15	0.15	0.13	0.13	0.13	0.14	0.16	2
	% Zero Exp.	93.0%	93.1%	92.5%	93.2%	93.4%	93.6%	94.1%	94.5%	94.8%	94.6%	95.0%	94.8%	93.9%	
Sprouts, Fresh	Uncond. Average	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	1
	% Zero Exp.	99.1%	99.2%	99.1%	99.3%	99.3%	99.4%	99.4%	99.4%	99.4%	99.4%	99.4%	99.4%	99.3%	
Tomatoes, Fresh	Uncond. Average	1.65	1.57	1.75	1.87	2.08	2.00	1.85	1.49	1.38	1.45	1.39	1.47	1.66	4
	% Zero Exp.	54.9%	52.8%	51.3%	48.6%	45.2%	45.0%	48.2%	56.9%	60.0%	60.5%	62.4%	60.4%	53.8%	
Yams, Fresh	Uncond. Average	0.19	0.19	0.23	0.21	0.15	0.13	0.13	0.13	0.18	0.23	0.51	0.32	0.22	2
	% Zero Exp.	89.9%	90.1%	88.3%	88.6%	92.2%	93.0%	93.4%	92.8%	90.5%	87.8%	77.3%	84.9%	89.1%	
Zucchini, Fresh	Uncond. Average	0.26	0.24	0.24	0.25	0.26	0.27	0.26	0.25	0.28	0.39	0.30	0.24	0.27	5
	% Zero Exp.	88.1%	89.0%	88.6%	88.0%	87.3%	86.5%	86.7%	88.1%	86.9%	84.4%	87.0%	89.7%	87.5%	
Other Veg, Fresh	Uncond. Average	0.35	0.32	0.42	0.29	0.29	0.27	0.28	0.28	0.29	0.33	0.32	0.32	0.31	
	% Zero Exp.	79.3%	80.7%	70.5%	82.1%	82.6%	83.3%	83.0%	83.2%	82.8%	81.6%	82.1%	81.8%	81.1%	
Other Veg, Pres.	Uncond. Average	1.69	1.49	1.56	1.49	1.26	1.16	1.19	1.19	1.38	1.57	2.22	1.95	1.51	
	% Zero Exp.	71.2%	73.5%	72.7%	73.8%	77.7%	78.6%	78.6%	78.6%	75.6%	72.1%	58.7%	66.0%	73.1%	
	Observations	24,483	24,259	25,042	24,845	24,829	24,241	24,336	24,234	24,190	24,436	24,848	23,503	293,246	

Table 2 - Demographic variables - Averages and Standard Deviations		
Variable	**Average**	**St Dev**
Months Households are in the Panel	32.36	17.45
Race - Hispanic (Caucasian is default)	0.07	0.25
Race - African American (Caucasian is default)	0.15	0.36
Race - Other than Caucasian, Hispanic or African Amer.)	0.06	0.23
Household Size	2.52	1.33
Number of Kids	0.52	1.33
Female College Education (1 if Yes)	0.36	0.47
Income	56,556	30,354

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Table 3 - Stats on Household Purchases		
Goods Purchased Per Period	Avg.	5.28
	Std.	2.05
Share of Goods Not Purchased	Avg.	0.80
	Std.	0.08
Expenditure per Household	Avg.	11.42
	Std.	7.33

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Table 4 - Income and Cross Commodity Elasticities (Base Model)

e(i,j)	1 (ASF)	2 (BRF)	3 (BRP)	4 (CFF)	5 (CLF)	6 (CNF)	7 (CNP)	8 (CUF)	9 (GBF)	10 (GBP)	11 (LIF)	12 (LOF)	13 (LRF)	14 (MUF)
1 (ASF)	-2.5448	-0.0983	0.0248	0.0099	-0.0143	0.0509	-0.0033	-0.0175	-0.0200	0.0322	0.0416	-0.0787	0.0211	-0.0406
2 (BRF)	-0.0790	-0.8729	0.0474	-0.1242	0.0554	-0.1482	0.0595	-0.1273	-0.0668	0.1499	-0.0198	0.0304	-0.1751	0.0041
3 (BRP)	0.0219	0.0522	-2.1676	-0.0305	-0.0339	-0.1406	0.2780	-0.0364	-0.0684	0.2055	0.0082	-0.0316	0.0159	-0.0998
4 (CFF)	0.0077	-0.1206	-0.0269	-1.7381	-0.0241	0.0904	0.1111	0.0891	0.0173	0.0595	-0.0493	-0.0388	-0.0863	0.0207
5 (CLF)	-0.0076	0.0368	-0.0204	-0.0165	-2.3015	0.1046	-0.0010	0.0504	0.1516	-0.0785	0.1641	-0.0502	0.0646	0.0031
6 (CNF)	0.0324	-0.1175	-0.1013	0.0738	0.1247	-1.0050	0.2059	0.0032	-0.6910	0.2199	0.0186	-0.0457	-0.2215	-0.0282
7 (CNP)	-0.0029	0.0642	0.2729	0.1235	-0.0017	0.2805	-3.9344	0.1122	0.1325	0.2111	0.1653	0.1608	0.0278	-0.0394
8 (CUF)	-0.0096	-0.0866	-0.0225	0.0624	0.0516	0.0028	0.0707	-1.8251	-0.1046	0.1312	0.0058	-0.0126	-0.1268	0.0416
9 (GBF)	-0.0126	-0.0525	-0.0488	0.0140	0.1793	-0.6851	0.0964	-0.1208	-1.2957	0.1916	0.0296	-0.1216	-0.2193	-0.0388
10 (GBP)	0.0270	0.1572	0.1958	0.0642	-0.1239	0.2909	0.2049	0.2021	0.2556	-3.7981	-0.0091	0.0635	0.1020	-0.0024
11 (LIF)	0.0233	-0.0139	0.0052	-0.0355	0.1726	0.0164	0.1069	0.0059	0.0263	-0.0061	-1.4887	0.0553	-0.0012	0.0311
12 (LOF)	-0.0479	0.0231	-0.0218	-0.0303	-0.0573	-0.0438	0.1129	-0.0141	-0.1173	0.0459	0.0600	-2.7169	0.0214	0.1614
13 (LRF)	0.0183	-0.1889	0.0156	-0.0958	0.1048	-0.3014	0.0277	-0.2010	-0.3011	0.1049	-0.0018	0.0304	-0.9771	-0.1235
14 (MUF)	-0.0353	0.0044	-0.0980	0.0231	0.0050	-0.0384	-0.0394	0.0661	-0.0534	-0.0025	0.0481	0.2300	-0.1238	-1.2137
15 (MUP)	-0.0168	0.0983	-0.0055	0.0024	0.1747	0.0237	0.1178	0.0645	0.1078	0.1930	0.1591	-0.0044	-0.0431	0.0542
16 (ONF)	-0.0052	0.1432	-0.0019	0.0662	-0.1024	0.0894	0.0257	0.2830	0.1603	0.2166	-0.0061	-0.1563	0.1543	0.0183
17 (PEF)	-0.0075	-0.0932	-0.0458	0.0386	-0.0096	-0.0167	0.2493	-0.0077	-0.0746	0.0689	0.1453	0.0050	-0.1358	-0.1582
18 (POF)	-0.0359	0.1326	0.1585	0.0041	0.3790	0.1554	0.4216	0.2676	0.0704	0.6074	0.1861	0.0107	0.1688	-0.0167
19 (SPF)	-0.0708	-0.0744	0.0312	-0.0593	0.0241	0.0027	0.0154	-0.0757	-0.1969	0.0243	-0.0359	-0.1009	0.0020	-0.1285
20 (SRF)	0.0196	-0.0204	-0.0085	0.0435	0.0644	-0.0456	0.0276	0.0173	-0.0325	0.0075	0.0440	0.0240	-0.0614	-0.0408
21 (TOF)	-0.1461	0.0002	0.0304	0.1655	0.4503	-0.3210	0.1253	-0.2873	0.1113	0.2568	-0.4980	-0.0255	-0.1459	0.1566
22 (YMF)	-0.0351	-0.0484	-0.1367	0.0365	-0.1982	0.4145	-0.1252	0.1756	0.1361	-0.1321	0.3278	0.1243	0.0325	-0.0133
23 (ZCF)	0.0275	-0.2966	0.0474	-0.0682	-0.2463	0.0915	0.0898	0.0241	-0.6509	-0.0509	-0.0215	-0.1061	-0.3003	-0.0227
24 (AGG_F)	-0.0661	-0.0076	0.0814	-0.0385	0.0302	0.0442	0.0805	0.0150	0.0170	0.0318	0.0000	0.0417	0.0594	0.0448
25 (AGG_P)	0.1253	0.1316	-0.1886	0.1360	-0.0024	0.1733	0.0674	0.1642	0.1458	-0.2669	0.0448	0.2196	0.1082	0.0933
26 (Numeraire)	1.8461	0.4833	1.5537	0.6342	0.8566	0.1115	1.1912	0.4557	1.5098	1.2740	0.4726	1.9453	0.9800	0.5384
Comp	10	12	12	16	14	16	21	16	13	19	16	13	13	12
Sub	15	13	13	9	11	9	4	9	12	6	9	12	12	13

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Table 4 - Income and Cross Commodity Elasticities (Base Model, Continued)													
e(i,j)	**15 (MUP)**	**16 (ONF)**	**17 (PEF)**	**18 (POF)**	**19 (SPF)**	**20 (SRF)**	**21 (TOF)**	**22 (YMF)**	**23 (ZCF)**	**24 (AGG_F)**	**25 (AGG_P)**	**26 (Num)**	**Inc. Elast**
1 (ASF)	0.1566	-0.0071	-0.0093	-0.0217	-0.0864	0.0756	-0.0865	-0.0447	0.0330	-0.1021	0.0469	0.0014	**0.9737**
2 (BRF)	-0.0133	0.1577	-0.0924	0.0647	-0.0730	-0.0631	0.0001	-0.0494	-0.2860	-0.0094	0.0395	0.0002	**0.7685**
3 (BRP)	-0.0227	-0.0024	-0.0501	0.0850	0.0337	-0.0289	0.0158	-0.1538	0.0503	0.1111	-0.0624	0.0007	**0.4393**
4 (CFF)	0.0448	0.0707	0.0372	0.0019	-0.0564	0.1306	0.0765	0.0363	-0.0639	-0.0464	0.0397	0.0002	**0.7433**
5 (CLF)	0.0933	-0.0749	-0.0063	0.1229	0.0157	0.1324	0.1425	-0.1347	-0.1578	0.0249	-0.0005	0.0001	**0.4525**
6 (CNF)	0.5384	0.0780	-0.0131	0.0601	0.0021	-0.1117	-0.1211	0.3361	0.0699	0.0435	0.0413	0.0000	**0.8066**
7 (CNP)	-0.0178	0.0305	0.2670	0.2220	0.0163	0.0922	0.0643	-0.1383	0.0935	0.1079	0.0218	0.0004	**0.4281**
8 (CUF)	0.0837	0.2119	-0.0052	0.0888	-0.0505	0.0364	-0.0931	0.1222	0.0158	0.0126	0.0336	0.0001	**0.7220**
9 (GBF)	-0.0052	0.1387	-0.0582	0.0270	-0.1517	-0.0789	0.0416	0.1094	-0.4932	0.0166	0.0344	0.0007	**0.8336**
10 (GBP)	0.0020	0.2498	0.0716	0.3106	0.0250	0.0244	0.1281	-0.1416	-0.0515	0.0414	-0.0841	0.0004	**0.3148**
11 (LIF)	0.0988	-0.0047	0.1007	0.0634	-0.0246	0.0951	-0.1658	0.2343	-0.0145	-0.0001	0.0094	-0.0001	**0.2232**
12 (LOF)	0.0160	-0.1305	0.0038	0.0039	-0.0751	0.0564	-0.0092	0.0964	-0.0776	0.0393	0.0500	0.0007	**0.5555**
13 (LRF)	0.1082	0.1832	-0.1452	0.0889	0.0021	-0.2048	-0.0749	0.0359	-0.3123	0.0795	0.0351	0.0006	**0.8617**
14 (MUF)	0.0373	0.0217	-0.1696	-0.0089	-0.1363	-0.1364	0.0805	-0.0147	-0.0237	0.0601	0.0303	0.0002	**0.8029**
15 (MUP)	0.0721	0.1700	-0.0758	0.1317	-0.0415	-0.0323	0.0787	0.1737	-0.1929	0.0559	0.0203	0.0004	**0.6522**
16 (ONF)	0.1721	-3.1910	0.0939	0.0879	0.0641	0.1264	0.1104	0.2909	0.0235	0.0859	0.0163	0.0000	**0.4543**
17 (PEF)	0.0946	0.1042	-1.7790	0.1274	-0.0073	-0.1563	0.0325	-0.0971	-0.0844	0.0432	0.0037	0.0004	**0.7619**
18 (POF)	-0.0028	0.1982	0.2589	-2.7929	0.2301	0.1404	0.2202	-0.0694	0.1069	0.2128	0.1153	-0.0004	**0.2783**
19 (SPF)	-0.0395	0.0719	-0.0074	0.1145	-1.7670	0.0074	0.0036	0.0220	-0.0599	0.0141	-0.0327	0.0008	**0.8775**
20 (SRF)	0.0499	0.0450	-0.0501	0.0221	0.0023	-1.1199	0.0054	-0.0013	0.0177	0.0250	-0.0006	0.0000	**0.6746**
21 (TOF)	-2.7235	0.2553	0.0678	0.2257	0.0074	0.0352	-1.7335	0.3394	0.0102	0.1141	0.0789	-0.0001	**0.5905**
22 (YMF)	0.1315	0.3130	-0.0942	-0.0332	0.0211	-0.0040	0.1579	-2.3781	-0.4992	0.0691	-0.0604	0.0007	**0.4944**
23 (ZCF)	-0.0651	0.0268	-0.0868	0.0541	-0.0610	0.0569	0.0050	-0.5295	1.4601	-0.0772	0.0268	-0.0004	**1.0078**
24 (AGG_F)	0.2297	0.0761	0.0345	0.0836	0.0112	0.0622	0.0437	0.0569	-0.0600	-2.5140	0.0323	0.0002	**0.5426**
25 (AGG_P)	-0.0360	0.0596	0.0121	0.1873	-0.1068	-0.0056	0.1249	-0.2056	0.0861	0.1336	-1.9226	0.0010	**0.6081**
26 (Num)	-0.0089	0.5038	0.9374	0.4184	1.3308	0.2018	0.3696	1.6197	-0.5968	0.9243	0.8868	-1.0030	**0.9949**
Comp	16	20	11	22	13	15	19	13	11	20	19	18	
Sub	9	5	14	3	12	10	6	12	14	5	6	7	

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Table 5 - Income and Cross Commodity Elasticities (Mean Coefficients Model)														
e(i,j)	**1 (ASF)**	**2 (BRF)**	**3 (BRP)**	**4 (CFF)**	**5 (CLF)**	**6 (CNF)**	**7 (CNP)**	**8 (CUF)**	**9 (GBF)**	**10 (GBP)**	**11 (LIF)**	**12 (LOF)**	**13 (LRF)**	**14 (MUF)**
1 (ASF)	-2.8722	-0.0937	0.0404	-0.0215	0.0225	0.0648	-0.0300	-0.0321	0.1040	0.0404	0.0310	-0.0288	0.0786	-0.0102
2 (BRF)	-0.0757	-0.7622	-0.0060	-0.1448	0.1085	-0.1238	0.0657	-0.0370	-0.0152	0.1040	-0.0719	0.0137	-0.1807	-0.0202
3 (BRP)	0.0369	-0.0069	-2.2622	0.0133	-0.0451	-0.0796	0.1974	-0.0318	0.0412	0.1119	0.0065	0.0779	-0.1146	-0.0271
4 (CFF)	-0.0168	-0.1403	0.0114	-2.4086	-0.0316	0.1132	0.1316	0.0733	0.0336	0.0527	0.0254	0.0295	-0.0843	0.0566
5 (CLF)	0.0123	0.0736	-0.0270	-0.0221	-2.4261	0.1194	0.0030	0.1123	0.0904	-0.0621	0.1416	-0.0167	0.0450	-0.0060
6 (CNF)	0.0422	-0.0997	-0.0566	0.0942	0.1416	-1.0902	0.2273	-0.1510	-0.6690	0.2252	-0.0925	-0.0612	-0.2367	-0.0414
7 (CNP)	-0.0268	0.0727	0.1930	0.1504	0.0048	0.3123	-4.1922	0.2648	0.1162	0.1040	0.2575	0.1824	-0.0320	0.0459
8 (CUF)	-0.0178	-0.0254	-0.0192	0.0519	0.1135	-0.1286	0.1641	-2.6135	-0.1285	0.1339	-0.0413	0.0043	-0.0818	-0.0210
9 (GBF)	0.0655	-0.0119	0.0284	0.0271	0.1039	-0.6478	0.0819	-0.1461	-1.5428	0.1295	-0.1217	-0.0988	-0.2261	-0.0610
10 (GBP)	0.0351	0.1117	0.1062	0.0585	-0.0983	0.3005	0.1009	0.2098	0.1784	-3.8130	0.0484	0.0489	0.0215	0.0191
11 (LIF)	0.0180	-0.0517	0.0042	0.0189	0.1499	-0.0826	0.1672	-0.0433	-0.1121	0.0323	-1.5083	0.0481	-0.0308	-0.0064
12 (LOF)	-0.0175	0.0103	0.0517	0.0228	-0.0184	-0.0571	0.1237	0.0047	-0.0951	0.0341	0.0502	-2.8203	0.0196	0.0033
13 (LRF)	0.0691	-0.1967	-0.1101	-0.0947	0.0721	-0.3197	-0.0314	-0.1298	-0.3154	0.0218	-0.0466	0.0285	-0.9104	-0.0689
14 (MUF)	-0.0089	-0.0218	-0.0258	0.0630	-0.0095	-0.0554	0.0447	-0.0331	-0.0843	0.0192	-0.0097	0.0048	-0.0683	-1.4783
15 (MUP)	-0.0221	0.0050	-0.0153	-0.0103	0.0861	0.0413	0.0558	0.1081	0.0263	0.0646	0.0127	0.0509	-0.0777	0.0389
16 (ONF)	0.0113	-0.0046	-0.0193	-0.0010	-0.0060	0.0024	0.1684	0.1059	0.0626	0.2429	0.0523	-0.0824	0.1110	0.0211
17 (PEF)	0.0066	-0.1601	-0.0812	0.0371	0.0500	-0.0500	0.2181	0.0009	-0.0442	-0.0630	0.0377	0.0608	-0.1693	-0.0340
18 (POF)	-0.0069	0.1312	0.0441	0.0399	0.3171	0.2889	0.4902	0.2884	0.1397	0.5772	0.2795	0.0105	0.1465	0.0503
19 (SPF)	-0.1313	-0.1024	-0.0208	-0.0672	0.0057	-0.0002	-0.0253	-0.0343	-0.1776	0.0091	-0.0388	-0.1164	-0.0106	-0.0926
20 (SRF)	-0.0120	-0.0104	-0.0184	-0.0233	0.0304	-0.0527	0.0637	0.0051	-0.0572	0.0476	0.0064	-0.0443	-0.0505	-0.0814
21 (TOF)	-0.1963	0.0751	-0.0251	0.1881	0.3439	-0.4325	0.1625	-0.3084	0.0346	0.2844	-0.3755	-0.0428	-0.1452	-0.0061
22 (YMF)	-0.0217	-0.0504	-0.1359	0.0376	-0.3666	0.5248	-0.0916	0.3212	0.0827	-0.2073	0.2684	0.0938	0.1766	-0.0201
23 (ZCF)	0.1207	-0.2438	-0.0050	-0.0873	-0.1529	0.0325	0.0379	-0.0087	-0.4413	-0.0647	0.0207	0.0162	-0.2417	-0.0235
24 (AGG_F)	-0.0917	-0.0685	0.0572	-0.0359	-0.0016	0.0792	0.0793	0.0477	0.0062	0.0504	0.0306	0.0335	0.0513	0.0341
25 (AGG_P)	0.1799	0.0206	-0.1682	0.1339	0.0274	0.1656	0.0372	0.1419	0.1662	-0.2327	0.0469	0.1925	-0.0661	0.0280
26 (Numeraire)	2.1774	1.0926	2.1712	1.5402	1.2701	0.3052	1.4290	1.4214	2.0095	1.9520	0.8964	2.1145	1.4126	1.0738
Comp	12	9	10	15	16	13	21	14	14	20	17	17	9	10
Sub	13	16	15	10	9	12	4	11	11	5	8	8	16	15

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Table 5 - Income and Cross Commodity Elasticities (Mean Coefficients Model, Continued)

e(i,j)	15 (MUP)	16 (ONF)	17 (PEF)	18 (POF)	19 (SPF)	20 (SRF)	21 (TOF)	22 (YMF)	23 (ZCF)	24 (AGG_F)	25 (AGG_P)	26 (Num)	Inc Elast
1 (ASF)	-0.0061	0.0152	0.0080	-0.0041	-0.1582	-0.0455	-0.1136	-0.0270	0.1502	-0.1408	0.0653	0.0014	**0.7482**
2 (BRF)	-0.0201	-0.0050	-0.1550	0.0626	-0.0997	-0.0318	0.0351	-0.0507	-0.2450	-0.0850	0.0060	0.0003	**0.4701**
3 (BRP)	-0.0235	-0.0238	-0.0890	0.0237	-0.0230	-0.0637	-0.0134	-0.1550	-0.0057	0.0804	-0.0559	0.0010	**0.3038**
4 (CFF)	0.0341	-0.0011	0.0348	0.0184	-0.0634	-0.0692	0.0851	0.0366	-0.0851	-0.0432	0.0380	0.0006	**0.4529**
5 (CLF)	0.0280	-0.0044	0.0329	0.1027	0.0038	0.0633	0.1092	-0.2507	-0.1044	-0.0014	0.0054	0.0002	**0.3251**
6 (CNF)	1.0738	0.0021	-0.0390	0.1111	-0.0002	-0.1302	-0.1630	0.4258	0.0263	0.0792	0.0391	0.0000	**0.7757**
7 (CNP)	-0.0229	0.2022	0.2337	0.2588	-0.0273	0.2162	0.0840	-0.1020	0.0422	0.1090	0.0120	0.0005	**0.3365**
8 (CUF)	0.0042	0.0788	0.0006	0.0944	-0.0229	0.0107	-0.0990	0.2219	-0.0060	0.0406	0.0285	0.0004	**0.4766**
9 (GBF)	-0.0145	0.0530	-0.0334	0.0520	-0.1349	-0.1368	0.0126	0.0650	-0.3461	0.0060	0.0380	0.0008	**0.6005**
10 (GBP)	-0.0084	0.2832	-0.0656	0.2959	0.0095	0.1568	0.1428	-0.2243	-0.0700	0.0672	-0.0734	0.0008	**0.2237**
11 (LIF)	0.0489	0.0407	0.0262	0.0958	-0.0272	0.0142	-0.1263	0.1943	0.0149	0.0273	0.0099	0.0000	**0.1154**
12 (LOF)	0.0278	-0.0672	0.0442	0.0037	-0.0851	-0.1019	-0.0151	0.0709	0.0122	0.0312	0.0423	0.0006	**0.3173**
13 (LRF)	0.0517	0.1310	-0.1784	0.0760	-0.0112	-0.1685	-0.0739	0.1935	-0.2644	0.0693	-0.0211	0.0007	**0.6720**
14 (MUF)	0.0620	0.0246	-0.0355	0.0258	-0.0973	-0.2692	-0.0032	-0.0218	-0.0255	0.0456	0.0088	0.0005	**0.6364**
15 (MUP)	0.0172	0.2290	-0.1462	0.1085	0.0016	-0.1158	0.0591	0.2070	-0.1424	0.0952	0.0179	0.0006	**0.5477**
16 (ONF)	0.0581	-3.6358	0.1017	0.0973	0.0900	0.0255	0.1466	0.2712	0.0885	0.1116	0.0340	0.0002	**0.2662**
17 (PEF)	0.0076	0.1139	-1.8375	0.1050	-0.0810	-0.0424	0.0507	-0.0893	-0.0685	0.0533	-0.0094	0.0006	**0.6658**
18 (POF)	0.0319	0.2212	0.2131	-2.7976	0.1519	0.2575	0.1786	-0.0502	0.0392	0.1861	0.1135	-0.0003	**0.1741**
19 (SPF)	-0.0707	0.1002	-0.0806	0.0744	-2.2086	-0.2038	0.0151	0.0400	-0.0095	-0.0241	-0.0288	0.0012	**0.6938**
20 (SRF)	0.0351	0.0090	-0.0134	0.0400	-0.0647	-1.4040	-0.0172	-0.0063	-0.0044	0.0245	0.0236	0.0002	**0.2025**
21 (TOF)	-2.5673	0.3403	0.1050	0.1823	0.0316	-0.1125	-1.7423	0.3376	0.1265	0.1628	0.0761	0.0001	**0.4509**
22 (YMF)	0.1766	0.2921	-0.0859	-0.0239	0.0387	-0.0190	0.1566	-2.6671	-0.3441	0.0769	-0.0887	0.0007	**0.3083**
23 (ZCF)	-0.1263	0.0955	-0.0660	0.0186	-0.0092	-0.0132	0.0588	-0.3447	0.6674	0.0170	0.0005	-0.0003	**0.9331**
24 (AGG_F)	0.1902	0.0976	0.0416	0.0715	-0.0189	0.0607	0.0613	0.0624	0.0138	-2.9022	0.0298	0.0004	**0.2453**
25 (AGG_P)	0.0014	0.1257	-0.0309	0.1846	-0.0957	0.2468	0.1212	-0.3041	0.0015	0.1263	-1.9973	0.0014	**0.5348**
26 (Num)	-0.0316	1.0341	1.3567	0.5691	2.2150	1.6925	0.6128	1.8756	-0.3918	1.5601	1.1621	-1.0064	**0.9940**
Comp	16	20	12	23	8	10	16	13	11	20	19	22	
Sub	9	5	13	2	17	15	9	12	14	5	6	3	

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