Revealing the fundamental parameters of a food demand system using estimated elasticities

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Selected Paper prepared for presentation at the 2022 Agricultural & Applied Economics Association Annual Meeting, Anaheim, CA; July 31-August 2

This material is based upon work supported by the U.S. Department of Agriculture, Office of the Chief Economist, under Agreement #58-0111-20-016, and the USDA National Institute of Food and Agriculture, Hatch project number MO-C1537173. Any opinion, findings, conclusions, or recommendations expressed in this publication are those of the authors and do not necessarily reflect the view of the U.S. Department of Agriculture nor the University of Missouri.

1. Introduction

The Almost Ideal Demand System (AIDS) of Deaton and Muellbauer (1980) created a new approach to demand analysis. Indeed, their work led to numerous studies that examined consumer food demand theory and estimated elasticity using some form of this system since the mid-1980s. Refinements to their original work developed advanced demand systems, argued for alternative estimation methods, and suggested new ways to calculate elasticities for each model. With these new tools for applied economics, the estimation of demand elasticities has been the subject of numerous empirical studies.

Surveys of these studies recognize that the elasticity estimates for the same or similar food products differ significantly between studies and even over time (see Okrent and Alston (2011) for an overview of food demand estimation in the U.S.). Oftentimes, the literature does not provide the elasticities that can be properly used for research that informs policymakers and other decision makers. For example, an analysis of the impact of higher beef prices on consumer welfare requires a matrix of Hicksian (compensated) own- and cross-price elasticities (Dong et al., 2022). Numerous meta-analyses have attempted to synthesize elasticities from past studies (Chen et al., 2015; Cornelsen et al., 2016; Colen et al., 2018; Gallet, 2010; Gallet, 2007; Nelson, 2013; Ogundari and Abdulai, 2013; Zhou et al., 2020). We detect an inconsistency: while the majority of elasticity estimates are from a demand system with its underlying microeconomic basis, meta-analysis, unfortunately, is not related directly to economic theory.

The typical demand elasticity meta-analysis in economics normally applies linear regression models with elasticities as dependent variable, and study's sample and empirical model characteristics among the explanatory variables. The year of the database or of the study might also be used in the regression to reflect trends in income, prices, or other factors that influence elasticities over time. The specification of the model is based on the features of each study and most of the variables are categorical variables. These categorical variables might include an indicator for the underlying theoretical basis of demand, including whether or what type of a demand system is used. Despite the implicit or explicit reference to how demand theory, income, and market conditions affect elasticities, the usual meta-analysis uses only indirect measures like trends and categorical variables to capture these effects. Despite the fact that some important share of the elasticities taken from the literature are from a theoretical demand system, the usual meta-analysis imposes no theoretical constraints and is instead mostly driven by statistical considerations of significance and fit.

Meta-analysis to find demand elasticities might not support applied economics and could be inconsistent with the economic science used in many of the studies from which observations are drawn. Market analysis depends on elasticities that are at least downward-sloping and have non-zero cross-price effects that are also symmetric. But meta-analysis tends to focus on own-price and income elasticities and permit any outcome by way of sign or relative size of effect, meaning an upward sloping demand curve can still be accepted. Welfare analysis of policy options or market shocks depends on well-behaved demands, but typical meta-analysis might not impose symmetry, adding up, or other theoretical demand constraints that are derived from microeconomics. Thus, in a sense, there is an inconsistency between a statistics-driven approach and the demand theory underlying many of the studies from which observations are drawn.

In this study, we estimate U.S. food demand based on a modified meta-analysis. Instead of the traditional meta-analysis methods, we impose an underlying demand system. We fit an economic demand system by relating the elasticities from the literature as dependent variable to the market data using demand system elasticity formulas and estimate the fundamental demand system parameters. There are several demand systems that we can apply such as AIDS, Quadratic AIDS (QUAIDS), Rotterdam, or an incomplete demand system (LinQuad). We choose the Quadratic Almost Ideal Demand System (QUAIDS) to allow for nonlinear expenditure effects (Banks et al., 1997).

In doing so, we conduct our research in four steps. The first step is to build the database of published elasticity estimates. We start with the Economic Research Service (ERS)'s Commodity and Food Elasticities database and add other empirical studies on demand elasticities in Google Scholar and the AgEcon Search database. Second, we collect additional information necessary for estimation. The elasticity formula derived from the QUAIDS requires price and total expenditure share data. We collect price index and food at home expenditure data from the Bureau of Labor Statistic (BLS). We relate these additional data to the studies' elasticities using the midpoint of each study's data. Third, we estimate the fundamental parameters of the demand system. Like other meta-analysis, the elasticities of past studies are our dependent variables, but unlike past approaches, we use the QUAIDS demand elasticity formulas that combine fundamental demand parameters and market data as our equations. We choose the best fundamental demand parameters that minimize the sum of squared residuals of a nonlinear least squares regression. Finally, we show own-price, cross-price, and expenditure elasticities calculated from the fitted fundamental parameters.

We should stress that our method is the opposite of the common statistics-driven approach to meta-analysis, not necessarily a better option in all cases. We see a trade-off: whereas past demand meta-analysis has been able to exploit a vast literature and generate statistically validated results with limited economic theory, our approach relies on the vast applied demand theory literature and generates economically validated results that could have less statistical basis. It is a future research question to improve the statistical validity of our method without disregarding economic theory. At present, however, our goal is to develop our approach and apply the method to the case of U.S. food demand.

Results will be of wide interest. First, there is the practical value to applied economists who assess market and welfare impacts of policy interventions or market shocks, namely the elasticities to use. By including theoretical demand system properties in our meta-analysis, we will be able to deliver consensus values for elasticities that are consistent with microeconomic theory and perhaps more reliable inputs into applied economics. For example, if we impose symmetry, adding up, and other constraints, then our elasticities will be consistent with demand curves that are associated with a well-behaved utility function and consequently can support welfare analysis, in contrast to the output of past meta-analyses. Second, economists should welcome our extension beyond statistics-driven meta-analysis to an approach that draws on the same economic theory that was used in the vast majority of past demand studies.

The remainder of this paper is organized as follows. Section 2 presents the model specification and theoretical restrictions used for the meta-analysis. In section 3 we provide the summary statistics of the meta dataset depending on commodity types and study characteristics. Section 4 provides the empirical result and section 5 concludes.

2. Method

We estimate the fundamental demand parameters of the QUAIDS model for major food groups by using the published elasticities as observations and real market data as independent variables. The observed expenditure of good *i* in study s (ε_{is}) and uncompensated (Marshallian) price elasticity of good *i* with respect to price *j* in study s (ε_{ijs}) in the QUAIDS model are defined as follows.

$$(1)\ \varepsilon_{is} = 1 + \left[\beta_i + \frac{2\lambda_i}{b(\boldsymbol{p})}\left\{\ln\left(\frac{m_s}{\alpha(\boldsymbol{p})}\right)\right\}\right]/w_{is}$$

$$(2)\ \varepsilon_{ijs} = -\delta_{ij} + \left[\gamma_{ij} - \left[\beta_i + \frac{2\lambda_i}{b(\boldsymbol{p})}\left\{\ln\left(\frac{m_s}{\alpha(\boldsymbol{p})}\right)\right\}\right]\{\alpha_j + \textstyle\sum_{k=1}^{8}\gamma_{jk}\ln(p_{ks})\}\right]/w_{is}$$

where (3) $$\ln a(\boldsymbol{p}) = \alpha_o + \textstyle\sum_{i=1}^{8}\alpha_i \ln p_{is} + \frac{1}{2}\sum_{i=1}^{8}\sum_{j=1}^{8}\gamma_{ij}\ln(p_{is})\ln(p_{js})$$

and (4) $$b(\boldsymbol{p}) = \textstyle\prod_{i=1}^{8} p_{is}{}^{\beta_i}$$

Subscripts $i, j,$ and k index goods and s indexes the observed studies in our dataset. The market data enter into this equation in the form of prices p, total food at home expenditure m, and budget shares w. Prices matter: p_s indicates the price index of each commodity in the time period corresponding to the midpoint year of the study's data. Similarly, m_s indicates total food at home expenditures on the commodities at the midpoint year of the study's data, and w_{is} is the food at home expenditure share of good i at the midpoint of the study's data. Consistent with the theory underlying the QUAIDS, $a(\boldsymbol{p})$ and $b(\boldsymbol{p})$ are the price indices with $\boldsymbol{p}$ being the N-vector of prices. The Kronecker delta, δ_{ij}, is equal to 1 for the own-price elasticity $(i = j)$ and equal to zero for the cross-price elasticity $(i \neq j)$. We estimate the optimized fundamental parameters β, λ, γ and α that minimize the sum of squared errors between the observed elasticities and predicted values.

The QUAIDS model derivation leads to parameter constraints based on microeconomic theory. A great many of the elasticities we use are based on demand systems, most of which impose these constraints. Similarly, we additionally impose these theoretical restrictions

(5) $\gamma_{ij} = \gamma_{ji}$,

(6) $\sum_{j=1}^{n} \gamma_{ij} = 0$,

(7) $\sum_{i=1}^{n} \gamma_{ij} = 0$,

(8) $\sum_{i=1}^{n} \alpha_i = 1$,

(9) $\sum_{i=1}^{n} \beta_i = 0$, and

(10) $\sum_{i=1}^{n} \lambda_i = 0$.

Our results will consequently have the same microeconomic foundations as the source studies and, moreover, facilitate the same uses to which those past studies' elasticities can be put.

3. Data

3.1. Elasticities

For the left-hand side variable, we create a database comprising published elasticity estimates. We use the Commodity and Food Elasticities database from the Economic Research

Service (ERS) of the U.S. Department of Agriculture (USDA). This database includes Marshallian price and income elasticities. Additionally, we search for recent empirical studies estimating U.S. food demand elasticities on Google Scholar and the AgEcon Search database. Finally, we have a total of 42 studies that have been published from 1984 to 2022 (a full list of study is provided in the Supplement). Elasticities estimated from these studies are based on different demand representations, statistical strategies, and consumer data. In some cases, a demand system was applied for all goods purchased by a household or in other cases, for a narrowly-defined, disaggregated group of particular food products such as tomato sauces or meats.

We take some steps before estimation to render elasticities comparable. Some elasticities are conditional on group expenditures while the others are conditional on total expenditures or income. This is clearly an important consideration for so-called income elasticities. If a study uses a demand system and generates elasticities of product demand with respect to group expenditures, then these results might be far from income elasticities. However, conditionality also matters for price elasticities; price elasticities for product demand can be different if group expenditure is constant versus if it is endogenous. These risks are not new and there are strategies to address them (for examples, see Carpentier and Goymard (2001) and Thompson (2004)).

Therefore, we undertake three data conversion steps by Chen et al. (2016). The first step is to derive Marshallian elasticities from studies only reporting Hicksian elasticities using the Slutsky equation. The second step is to convert elasticities conditional on group expenditure to elasticities with respect to total income elasticities based on procedures of Carpentier and

Guyomard (2001).[1] The last step is to make the same aggregation level of each commodity as we have many disaggregated items. We use the generalized composite commodity theorem proposed by Lewbel (1996).

Table 1 represents summary statistics of our elasticity database for the most studied food groups, namely 1) Alcoholic beverages, 2) (Non-alcoholic) beverages, 3) Fats and oils, 4) Fruits and vegetables, 5) Grains, 6) Milk and dairy, 7) Protein foods, and 8) Sugars. Here, we report only own-price and income elasticities. We should stress that the literature suggests a focus on these demand indicators; there is a deficit of cross-price elasticity estimates. Given the QUAIDS demand elasticity formulas, however, all fundamental demand parameters appear in all elasticity equations, so our approach is able to generate consistent cross-price effects despite the limitation.

Protein food (beef, pork, poultry, seafood, and eggs) demand is a popular topic, accounting for 36% of the own-price elasticities and 36% of all demand elasticities. These shares are more than twice as much as the shares of the next most studied group, namely fruits and vegetables. Alcoholic beverages are unpopular, by these measures. Data periods of studies hint at a story of applied demand analysis. The surge in demand system estimation in the wake of the innovation of Deaton and Muellbauer (1980) and related work might be the reason for the many datasets with a center point in the 1970s or 1980s. The recent surge in point-of-sale data could be the reason for the second surge with databases centered on 2000s data.

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[1] In our database, there are elasticities conditional on different group expenditure terms, including meat, fresh fruit and vegetable, sugar, dairy, at-home nonalcoholic beverage, beverage, and oils and fats expenditure. We only convert these elasticities that are conditional on expenditure on a subset of foods. But we do not convert elasticities conditional on food at home expenditure to income.

Table 1. Summary statistics of the meta-analysis dataset

	Own-price elasticity				**Income and FAH expenditure elasticity**			
	Number	**Share**	**Mean**	**SD**	**Number**	**Share**	**Mean**	**SD**
Total	148	100%	-0.637	0.482	157	100%	0.441	0.372
Food Commodities								
Alcoholic beverages	3	2%	-0.794	0.329	3	2%	0.518	0.208
Beverages	15	10%	-0.793	0.562	15	10%	0.526	0.401
Fats and oils	14	9%	-0.507	0.455	15	10%	0.535	0.512
Fruits and vegetables	21	14%	-0.740	0.572	22	14%	0.536	0.422
Grains	15	10%	-0.614	0.428	16	10%	0.498	0.435
Milk and dairy	17	11%	-0.644	0.521	18	11%	0.483	0.369
Protein foods	53	36%	-0.534	0.376	57	36%	0.599	0.433
Sugars	10	7%	-0.897	0.659	11	7%	0.348	0.541
Functional forms								
AIDS and Variants	35	24%	-0.576	0.598	41	26%	0.574	0.516
Rotterdam	19	13%	-0.464	0.158	19	12%	0.373	0.381
Translog	6	4%	-0.673	0.368	10	6%	0.722	0.256
LES	8	5%	-0.227	0.256	8	5%	0.230	0.337
EASI demand	50	34%	-0.951	0.402	50	32%	0.717	0.369
NBR	7	5%	-0.649	0.230	7	4%	0.525	0.291
GODDS	8	5%	-0.535	0.337	8	5%	0.088	0.105
CBS	1	1%	-0.400	.	1	1%	0.640	.
S-Branch	1	1%	-1.232	.	1	1%	1.184	.
Double log	8	5%	-0.140	0.208	7	4%	0.251	0.171
Florida-Slutsky	5	3%	-0.068	0.024	5	3%	0.084	0.030
Midpoint year								
1960s	13	9%	-0.306	0.231	13	8%	0.251	0.267
1970s	20	14%	-0.419	0.370	25	16%	0.465	0.366
1980s	26	18%	-0.568	0.452	30	19%	0.699	0.319
1990s	13	9%	-0.356	0.258	13	8%	0.428	0.714
2000s	65	44%	-0.765	0.490	65	41%	0.577	0.446
2010s	11	7%	-1.163	0.448	11	7%	0.453	0.291

Note: FAH = Food at home, LES=Linear Expenditure System; EASI = Exact Affine Stone Index; S-Branch = Brown and Heien's S-branch system; GODDS = Generalized Ordinary Differential Demand System; NBR = National Bureau of Research; CBS= Central Bureau of Statistics model; Midpoint year = Midpoint year of the study's data.

Demand systems dominate this literature – indeed, this is a key motivation for our approach. Broadly speaking, more than 90% of elasticities are based on a demand system. AIDS or variants of that model account for a large portion. Thus, the vast majority of elasticities in the literature are based on economic theory and our imposition of the same underlying concepts is a continuation of these methods.

3.2. Market data

The elasticity formula derived from the demand system requires prices (p), expenditure shares (w), and total food at home expenditure (m). At present, we collect Consumer Price Index data and total food-at-home (FAH) expenditures for each food group from the Bureau of Labor Statistic (BLS) and only use historical market data corresponding to the midpoint of each study's data. The total FAH expenditures represent total expenditures of all household units in the BLS Diary Survey sample, which is a component of the Consumer Expenditure Survey (CES), and are calculated as the sum of the expenditures for eight food groups in a given year. The expenditure share for each food group is calculated accordingly (Table 2). A key point here is how we define expenditure shares and, implicitly, expenditure. We use FAH expenditure; we do not use total consumer expenditure, total household income, or some other measure that might be more fully appropriate if we seek an income elasticity. We understand that a researcher might have a reason to seek either an elasticity with respect to FAH expenditure or an elasticity with respect to income, but we do not attempt to broaden the assessment. At present, we only generate elasticities with respect to FAH expenditure. Future research may consider adding food-away-from-home (FAFH) to acquire a more accurate measure of total food expenditure, though this approach presents another challenge of converting elasticities from studies that ignore FAFH in their estimation.

Table 2. Summary statistics of historical market data

Variable	Description	Mean	SD	Min	Max
P_1	Consumer Price index of alcoholic beverages	132.6	44.0	74.8	205.5
P_2	Consumer Price index of beverages	107.2	46.6	21.1	170.8
P_3	Consumer Price index of fats and oils	147.7	28.2	121.2	229.6
P_4	Consumer Price index of fruit and vegetables	159.8	86.8	31.5	300.9
P_5	Consumer Price index of grains	174.0	42.9	132.4	276.5
P_6	Consumer Price index of milk and dairy	149.9	34.5	115.6	225.3
P_7	Consumer Price index of protein foods	131.4	60.3	39.1	253.0
P_8	Consumer Price index of sugars	145.2	27.6	119.4	220.2
w_1	Expenditure share for alcoholic beverages	0.088	0.005	0.081	0.093
w_2	Expenditure share for beverages	0.093	0.004	0.087	0.107
w_3	Expenditure share for fats and oils	0.029	0.000	0.029	0.030
w_4	Expenditure share for fruit and vegetables	0.174	0.022	0.149	0.219
w_5	Expenditure share for grains	0.145	0.013	0.128	0.162
w_6	Expenditure share for milk and dairy	0.126	0.005	0.119	0.134
w_7	Expenditure share for protein foods	0.306	0.034	0.246	0.343
w_8	Expenditure share for sugars	0.041	0.001	0.039	0.042
m	Calculated food at home expenditure (weekly, $)	633,392	256,855	341,457	924,285

Note: This table represents average values for the entire sample period, but elasticity estimation presented later uses the data for the median year of the sub-sample of each original study. Thus, in our meta-analysis we use market data that corresponds to the data used for the original elasticity estimation.

4. Results

We estimate equations 1 and 2 subject to an additive error using nonlinear least squares. Equations 3 and 4 are substituted into these equations so all cross-effects and related fundamental parameters of demand are explicitly represented. We apply all constraints of equations 5-10 on the fundamental parameters. We choose the parameter values that minimize squared errors. Parameter results demonstrate that we correctly impose QUAIDS symmetry and adding up (Table 3).

A noteworthy assumption of our equations is that studies estimating partial items ignore the cross effect and they have non-zero effects. There are several studies that only report partial items by estimating one or two items, not estimating the all eight groups of goods. As our demand system has eight elements in the group, all studies should have cross-price effects explicitly or implicitly. One alternative would be to impose a value of zero for all omitted cross-effects in past studies. This assumption might be consistent with the view that those cross-effects were omitted because researchers thought they were approximately zero. However, we do not make this assumption. Instead, we treat cross-effects as omitted but not necessarily zero. Thus, we use all data available from our literature review without imposing zero for omitted values. Of course, this is an empirical question, in the end. If it were the case that a cross-effect omitted from one or more studies really is quite close to zero, then we expect that the studies that include that cross-effect should estimate a value close to zero and, in that case, our results should generate a similarly small effect without having to impose the value *a priori*.

Table 3. Fundamental parameters estimated from observed studies

	$i = 1$	$i = 2$	$i = 3$	$i = 4$	$i = 5$	$i = 6$	$i = 7$	$i = 8$
α_i	-0.155 (0.343)	-0.103 (0.214)	0.199 (0.190)	0.341* (0.206)	-0.203 (0.247)	-0.074 (0.203)	0.365 (0.228)	0.632
β_i	-0.109 (0.151)	0.326*** (0.099)	-0.044 (0.031)	-0.283*** (0.084)	0.127 (0.114)	0.338*** (0.103)	-0.209 (0.128)	-0.148
λ_i	0.011 (0.016)	-0.018 (0.025)	0.002 (0.003)	0.016 (0.024)	-0.007 (0.013)	-0.020 (0.031)	0.010 (0.016)	0.007
γ_{i1}	-0.002 (0.030)	-0.003 (0.016)	0.002 (0.008)	0.004 (0.019)	-0.016 (0.019)	-0.012 (0.017)	0.019 (0.022)	0.008
γ_{i2}	-0.003 (0.016)	0.021** (0.010)	0.001 (0.006)	0.007 (0.014)	-0.004 (0.013)	-0.001 (0.013)	-0.025** (0.015)	0.004
γ_{i3}	0.002 (0.008)	0.001 (0.006)	0.012*** (0.004)	-0.005 (0.006)	-0.001 (0.006)	0.005 (0.005)	-0.007 (0.006)	-0.006
γ_{i4}	0.004 (0.019)	0.007 (0.014)	-0.005 (0.006)	0.048*** (0.015)	-0.003 (0.014)	-0.013 (0.013)	-0.035** (0.016)	-0.002
γ_{i5}	-0.016 (0.019)	-0.004 (0.013)	-0.001 (0.006)	-0.003 (0.014)	0.056*** (0.015)	-0.007 (0.012)	-0.029* (0.015)	0.004
γ_{i6}	-0.012 (0.017)	-0.001 (0.013)	0.005 (0.005)	-0.013 (0.013)	-0.007 (0.012)	0.043*** (0.013)	-0.014 (0.014)	-0.001
γ_{i7}	0.019 (0.022)	-0.025 (0.015)	-0.007 (0.006)	-0.035 (0.016)	-0.029 (0.015)	-0.014 (0.014)	0.102*** (0.018)	-0.012
γ_{i8}	0.008	0.004	-0.006	-0.002	0.004	-0.001	-0.012	0.005

α_0	Standard error	Mean Squared Error	R^2	$Adj\ R^2$	Obs
0.00000188	0.42	0.15	0.49	0.48	575

Note 1: Groups are alcoholic beverages (1), beverages (2), fats and oils (3), fruits and vegetables (4), grains (5), milk and dairy (6), protein foods (7), and sugars (8).
Note 2: Standard errors appear in parentheses where available. No standard error is provided in those cases where a parameter is constrained to be a function of other parameters.
Note 3: P-values are estimated under the assumption that errors are normally distributed. *** denotes significance at p < 1%. ** denotes significance at p < 5%. * denotes significance at p < 10%.

Price and income elasticities are calculated using these consensus fundamental demand parameters (Table 4). Midpoint or average values of price and FAH expenditure data from three periods, 1990, 2010, and 2016-2020, are used for comparison. As expected, all own-price elasticities are negative with magnitudes relatively comparable to the averages for these food groups compiled in Jeon et al. (2022). All elasticities with respect to food group expenditure are positive with alcoholic beverages tending to be most elastic, followed by fruits and vegetables. Cross-price effects tend to be relatively small compared to own-price effects for most goods. The signs of cross-price elasticities tend to be consistent across different time periods (or in other words, different levels of prices and FAH expenditures). Alcoholic beverages have been found to be more elastic with respect to expenditure, by some definition, than some other foods (Huang, 1985; Gallet et al., 1998; Okrent and Alston, 2011). As the elasticities are based on data for periods when food consumption of most of the U.S. population far exceeded the threshold for mere survival, spending more on the FAH group as a whole would mean buying more expensive food items, among them alcoholic beverages. However, we acknowledge that the magnitude of elasticities for alcoholic beverages revealed in Table 4 warrant further investigation.

Table 4. Estimated price and expenditure elasticities

1990

Own- and cross-price elasticities

Quantity	ALC	BEV	FATS	FR/VG	GR	MK	PT	SG	EXP
ALC	-0.85	0.07	-0.19	-0.33	0.00	-0.07	-0.14	-0.53	2.09
BEV	-0.05	-0.78	0.02	0.10	-0.06	-0.01	-0.24	0.09	0.93
FATS	0.01	-0.02	-0.52	-0.04	-0.12	0.14	-0.10	0.00	0.63
FR/VG	0.03	0.04	-0.04	-0.75	-0.01	-0.07	-0.21	-0.03	1.04
GR	-0.10	-0.03	0.00	-0.01	-0.66	-0.05	-0.17	0.04	0.97
MK	-0.11	-0.02	0.06	-0.06	-0.08	-0.67	-0.06	0.06	0.88
PT	0.04	-0.10	0.00	-0.08	-0.12	-0.06	-0.61	0.03	0.88
SG	0.13	0.07	-0.08	0.08	0.02	-0.06	-0.15	-0.91	0.64

2010

Own- and cross-price elasticities

Quantity	ALC	BEV	FATS	FR/VG	GR	MK	PT	SG	EXP
ALC	-0.83	0.09	-0.22	-0.39	0.03	-0.05	-0.20	-0.61	2.25
BEV	-0.08	-0.83	0.06	0.16	-0.09	-0.03	-0.14	0.20	0.72
FATS	0.02	-0.01	-0.58	-0.06	-0.09	0.14	-0.12	-0.05	0.73
FR/VG	0.04	0.04	-0.05	-0.82	0.01	-0.05	-0.20	-0.08	1.12
GR	-0.11	-0.03	0.01	0.01	-0.66	-0.05	-0.15	0.07	0.91
MK	-0.15	-0.04	0.11	0.01	-0.12	-0.67	0.00	0.18	0.67
PT	0.06	-0.11	-0.01	-0.11	-0.13	-0.06	-0.55	0.01	0.91
SG	0.17	0.09	-0.13	0.01	0.07	-0.05	-0.23	-1.04	0.86

2016-2020

Own- and cross-price elasticities

Quantity	ALC	BEV	FATS	FR/VG	GR	MK	PT	SG	EXP
ALC	-0.84	0.09	-0.21	-0.36	0.03	-0.05	-0.20	-0.57	2.18
BEV	-0.07	-0.84	0.06	0.15	-0.09	-0.03	-0.13	0.19	0.73
FATS	0.02	-0.01	-0.55	-0.06	-0.10	0.14	-0.13	-0.05	0.71
FR/VG	0.04	0.04	-0.05	-0.83	0.01	-0.05	-0.20	-0.08	1.12
GR	-0.12	-0.04	0.01	0.01	-0.64	-0.06	-0.16	0.08	0.91
MK	-0.15	-0.05	0.11	0.01	-0.13	-0.66	0.01	0.18	0.65
PT	0.06	-0.11	-0.01	-0.11	-0.13	-0.06	-0.55	0.01	0.91
SG	0.17	0.09	-0.13	0.00	0.07	-0.05	-0.24	-1.05	0.86

Note: ALC = Alcoholic beverages, BEV = beverages, FATS = Fats and oils, FR/VG = Fruit and vegetable, GR = Grains, MK = Milk and dairy, PT = Protein food, SG= Sugars.

5. Conclusions

Food demand elasticities are critically important to applied economics, as evidenced by the vast literature focusing on the theory and application of finding their values. Demand response is critical for assessing how a policy change or market shock affects consumers and market outcomes more broadly. In a system of equations representing markets, demand inconsistencies such as lack of symmetry or adding up might lead to model failures that generate impossible outcomes or simply crash. Well-behaved demands are a necessary condition for welfare analysis, whereas inconsistent cross-effects of demand betray the famous requirement of a twice-differentiable utility function.

Demand meta-analysis prioritizes statistical validity over economic validity. This focus is certainly appropriate for many purposes, but not all and perhaps specifically not some of the key questions that applied economists need elasticities to answer. Without arguing that our way is better, we emphasize that our way is different. We do not follow the data to focus exclusively on own-price and income or expenditure effects, as many statistically driven studies must do. We do not approximate market or income influences with a trend term or categorical variables. We do not reduce the theoretical basis of past studies to a dummy variable.

We estimate elasticities of past studies using QUAIDS elasticity formula. As in past meta-analysis, the elasticities from past studies are our dependent variables, but the similarities largely stop at that point. Relevant market data are included explicitly, as required by the QUAIDS formula. We estimate the fundamental demand parameters of the QUAIDS elasticity formulas that minimize squared error relative to the elasticities of past studies. By imposing that structure and accompanying theoretical constraints, we maintain the same economic theory that supports the vast majority of the studies from which we draw our elasticity data.

Our approach is new and there are numerous possible considerations for extending or improving on our work. We assume QUAIDS and in that sense we have a degree of consistency with the many past demand studies that use this framework, but we could determine empirically which demand system to use. Moreover, although imposing a demand system and associated constraints is a common approach in demand analysis, we might test our constraints' statistical validity. We could revisit the definitions of the group, perhaps shifting to income elasticities instead of FAH expenditure elasticities or extending beyond the single-stage demand with aggregated groups of goods (protein, fruits and vegetables, for example) to a two-stage system with more narrowly defined goods (hamburger, egg, plant-based meat; spinach, apples, for example). Also, we might consider market data differentiation by data type, reflecting any systematic differences such as between point-of-sale and market data to give one example (Jeon et al., 2022), or using categorical variables correctly applied in the demand system framework.

We provide a new and potentially powerful approach to meta-analysis. We demonstrate the other, unobserved part of the trade-off that has been largely overlooked in the statistics-driven approach widely used. Without detracting from that method for its purposes, we emphasize an economics-driven approach that can be considered for other uses where the microeconomics of demand are among the criteria for assessing our work. While we see ways to extend beyond our innovation, we also see the potential that this could become a valuable tool for applied economists.

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