NEW EVIDENCE ON THE STRUCTURE OF FOOD DEMAND IN CHINA: AN EASI DEMAND MODEL ESTIMATED VIA PANEL DATA TECHNIQUES

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Abstract: This study analyzes the structure of food demand in urban China based on the most recent household expenditure survey data. Consumer food preferences are represented by an Exact Affine Stone Index (EASI) demand model, which accounts for unobserved consumer heterogeneity and allows for arbitrary Engel curve shapes. Further, we account for unobserved province-level heterogeneity in food preferences via province fixed-effects. Our findings indicate that seafood, fruit, and vegetables are income and expenditure elastic, while commodities such as grains and eggs are less than unitary elastic.

Keywords: EASI demand, expenditure endogeneity, price endogeneity, food demand, urban China.

JEL Code: Q11, Q13, Q17.

Introduction

It has been well documented that food consumers in China have been undergoing significant changes in their food consumption patterns and food preferences. The general consensus is that consumers in China have become more dependent on animal products for protein, while substituting fine grains for coarse grains (e.g. Hovhannisyan and Gould 2011, 2014).

Considerable research effort has been devoted to this topic (e.g., Huang and Rozelle 1998; Gould and Villareal 2006; Hovhannisyan and Gould 2014). A great majority of these studies rely on the Almost Ideal demand System (AIDS) and various generalizations thereof, which has linear Engel curves for all goods (except for quadratic AIDS) and ignores unobserved consumer heterogeneity (Deaton and Muellbauer, 1980). Nevertheless, one has no good reasons to believe that Engel curves lack variety in shapes, or that observable variables account for all the variation in consumer preferences. Another major limitation of previous literature is that endogeneity of food prices has been ignored due mostly to limited data. This endogeneity is a result of agricultural commodity supply shifts caused by natural disasters and weather, shocks, rapid urbanization in China, etc., (e.g., Gilbert 2010; Stage et al.,2010).

We offer new evidence on the structure of food demand in China. This study has several distinguishing characteristics. First, we employ Exact Affine Stone Index (EASI) model of demand to represent consumer preferences. The EASI model not only shares all of the desirable properties of the AIDS model but also provides additional benefits. Specifically, it is not subject to the rank three limitation of Gorman (1981) and allows the Engel curves to take arbitrary shapes (Lewbel and Pendakur 2009). Further, the EASI accounts for unobserved consumer heterogeneity. This is especially important in welfare studies conducted on consumer-level since much of the demand variation is left unexplained. Second, we account for price and expenditure endogeneity using agricultural commodity supply shifters (such as the areas of agricultural lands in each province that has been irrigated, as well as the amount of fertilizer used in agricultural production (nitrogen and phosphate), total power of agricultural machinery (measured in kw), and the share of agricultural land affected by natural disasters such as flood and drought) as price instruments. Each of these factors has the potential to affect agricultural commodity prices through their effects on commodity stocks (Headey and Fan, 2008). Third, we extend the panel data estimation techniques to the estimation of the EASI model using province-level data on the consumption of seven food categories covering 30 provinces in China over 2003-2012 (National Bureau of Statistics of China). This fixed-effects estimator allows one to capture the vast differences in consumption patterns and food preferences across the various provinces.

Conceptual Model

The EASI Demand Specification

We modify the EASI incomplete demand specification to account for province fixed effects as follows:

(1) $$w_{it} = \sum_{r=1}^{R} \mu_r D_r + \sum_{j=1}^{N} \alpha_{ij} \log\left(p_{jt}\right) + \sum_{k=1}^{K} \beta_{ik} y_t^k + \sum_{l=1}^{L} \gamma_{il} z_{tl} + u_{it},\ \forall i, j = 1, \ldots, N;\ t = 1,\ \ldots,\ T.$$

where w_{it} is the budget share of the i^{th} commodity in year *t*, D_r represent province fixed-effects, p_{jt} is the price of the j^{th} commodity, *K* is highest order of polynomial in y_t, which is to be determined empirically[1], *L* is the number of exogenous demand shifters, z_{tl} is the l^{th} demand

[1] This polynomial function can be of any order, thus allowing the Engel curves to take any arbitrary shape (Lewbel and Pendakur, 2009)

shifter such as consumer income, household size, level of educational attainment, household age composition, etc., with z_{t1} being a constant, $\mu_r, \alpha_{ij}, \gamma_{il}, \beta_{ik}$ are parameters, and u_{it} is the residual.

To simplify the analysis already complicated by the incorporation of province fixed-effects and the endogeneity of food prices and total expenditure, we estimate the demand system in (1) as an approximate EASI model, where y_t is specified as the Stone price-deflated real income provided in what follows:

(2) $$y_t = \log(x_t) - \sum_{j=1}^{N} w_{jt} \log(p_{jt}),$$

where x_t is consumer total expenditure on the group of seven food products in the analysis.

It should be mentioned that in the fully nonlinear EASI model, y_t is the affine transformation of the stone price-deflated real expenditures. This is in contrast to the Stone price index underlying the linear approximate AIDS demand specification, where it represents an approximation to the true expenditure deflator. More specifically, by construction, the Stone price in the EASI demand system is the correct and exact deflator of food expenditures. Further, Lewbel and Pendakur (2009) find that the linear approximate EASI and full nonlinear EASI models generate virtually identical parameter estimates. For the details concerning the derivation of the EASI demand model see Lewbel and Pendakur (2009), and Zhen et al. (2013).

Endogeneity Issues in the EASI Model

Several potential sources of endogeneity are present in the EASI demand model. First and foremost, y_t contains the budget shares w_{it} by design as can be seen from (2). Hence, total expenditures (y_t) and its polynomials of various order are endogenous. Second, and more importantly, food prices are endogenous in our empirical framework. This is due to the simultaneous determination of the budget shares and food prices, omitted variables, or measurement errors. While our use the fixed-effects panel data technique accounts for unobserved province heterogeneity, and at the very least mitigates the omitted variable bias, price endogeneity resulting from the supply-induced price shocks are still present in a given empirical demand analysis. Specifically, supply shocks and especially the ones brought about by weather shocks and natural disasters constitute the most important source of price variability in agriculture (Gilbert, 2010). Evidence suggests that agricultural production fluctuations in China is a significant factor underlying agricultural commodity price volatility (Luo Jianguo, 1996; Cheng Guojiang, 2010; Jie Lu et al., 2014). Therefore, ignoring this source of price variation will bias the demand estimates and result in erroneous policy implications.

Identification Strategy

We utilize two distinct sets of instruments to account for price endogeneity, which were obtained from the National Bureau of Statistics of China (NBSC, 2003-2012). Specifically, the first set includes the areas of agricultural lands in each province that has been irrigated, as well as the amount of fertilizer used in agricultural production (nitrogen and phosphate), total power of agricultural machinery (measured in kw), and the share of agricultural land affected by natural disasters such as flood and drought. Each of these factors has the potential to affect agricultural commodity prices that underlie our analysis through their effects on commodity stocks (Headey and Fan, 2008). For example, irrigation combined with fertilizer use in such a way to minimize pests will boost agricultural productivity and result in lower agricultural commodity prices, ceteris paribus. In a similar vein, natural disasters and extreme weather destroy crops, which leads to higher food prices, other things equal. This essentially represents unpredictable supply shocks that are excluded from demand equations and are uncorrelated with the demand error term. What makes these variables valid instruments is the absence of a feedback effect from commodity prices (certainly not for natural events). Further, even if irrigation, fertilizer use, and the total power of agricultural machinery, etc., were to respond to agricultural commodity price variations, this response will not happen instantaneously due in no small part to information lags and the nature of agricultural production.

Price endogeneity may also be a result of structural changes in China and most importantly the increasing urbanization across the different provinces lately. Increasing urbanization may affect commodity prices in a variety of ways. For example, increasing urbanization occurs at the cost of the loss of agricultural land, which results in reduced agricultural commodity stock and higher food prices, ceteris paribus. (Stage et al., 2010). Further, urbanization is often linked to economic growth and, consequently, increased environmental degradation. More specifically, the impact of environmental degradation on soil quality in China is more important than the loss of arable land to urbanization (Angel et al., 2005). Finally, as has been documented in the previous literature (e.g., Hovhannisyan and Gould, 2011) consumers in urban China have been undergoing significant dietary changes by incorporating element of Western food diet into traditional Chinese food diet. Given the recent influx of rural migrant into urban areas, many of them get exposed to urban diets that are more reliant on animal products for protein, and fine grains in lieu of coarse grains. Therefore, ignoring this potential causal effect of urbanization on food prices may well introduce endogeneity into demand models. We supplement the instruments presented above by urbanization rate in China to account for the effect of the latter structural change on food prices. Our identification strategy is based on the premise that food prices have no effect on urbanization.

We account for price endogeneity via a procedure outlined by Dhar, Chavas, and Gould (2003), which incorporates reduced-form price equations into the demand system. These reduced-form price equations relate food prices to exogenous shifters:

(3) $$\ln\left(p_i\right)=\kappa_{i1}+\sum\nolimits_{j=2}^{7}\kappa_{ij}\ln\left(Instrument_j\right)+\iota_i,\quad \forall i=1,\ldots,N.$$

where $Instrument_j$ comprises price instruments as described above, and $\kappa_{ij},\ j=1,..7,$ are parameters.

To address the expenditure endogeneity resulting from the simultaneity of expenditure shares and total expenditures, we use a reduced-form expenditure equation that relates food expenditures to the exogenous shifters:

(4) $$\ln\left(X_{rt}\right)=\varphi_1+\varphi_2\ln\left(Income_{rt}\right)+\varphi_3 Trend_r+\sum\nolimits_{r=1}^{R}\phi_r D_r+\tau_j,\quad \forall\, r=1,\ldots,R;t=1,\ldots,T.$$

where I_j is per capita average annual income in province *r in year t*, D_r is province fixed-effects, $Trend_r$ accounts for time trend, and $\varphi_m,\phi_r,\forall m=1,\ldots,3,$ are parameters.

Description of Province-Level Panel Data

We base our study on annual expenditure survey data from the China National Bureau of Statistics. Specifically, we use data from the Chinese Urban Household Income and Expenditure Survey with our sample period extending from 2003 to 2012 (China Statistical Yearbooks, 2003–2012). We limit our focus to 30 geographic divisions in urban China to avoid potential demand identification issues caused by home-based food production in rural China.[1] Dong and Fuller (2010) provide more details on the sampling procedure and data collection for this analysis.

We use per capita expenditure and actual food price data for seven commodity groups, namely meats (i.e., beef, lamb, poultry, pork, and other meat), seafood, vegetables, fruits, grains, eggs, and fats and oils.[2] Our data contain 300 observations for each commodity. Further, we exploit data on agricultural commodity supply shifters presented above to account for price endogeneity via the construction of reduced-form price equations. Finally, we use provincial-level, per capita, household income data along with province dummies and time trend to account for expenditure endogeneity.

Table 1 presents the descriptive statistics of the main variables used in this analysis. Over the study period, the highest per capita expenditure is for meats (34%), followed by expenditures on vegetables (17%), grains (14%), fruits (13%), and seafood (11%). Seafood is an important part of the modern Chinese diet (Hovhannisyan and Gould 2011), with coastal communities consuming more seafood than do inland communities. Food commodity prices, on the other hand, have comparable volatility. Specifically, the coefficient of variation (i.e., the ratio of the standard deviation to the mean) ranges from 0.175 for grain price to 0.379 for the seafood price. Meanwhile, the coefficient of variation for the agricultural supply shifters varies from 0.244 for the share of disaster-affected areas to 1.021 for total power of agricultural machinery.

Urban China manifests large heterogeneity in terms of consumer income, with relatively high income in the coastal provinces and cities, compared to their inland counterparts. For example, per capita income in Ningxia province was only 6,530 Yuan in 2003, as opposed to 14,867 Yuan in Shanghai. The less wealthy provinces also have larger households. For instance, the average household size in Hainan in 2004 was 4.16 people, compared to only 2.79 people in Beijing.

Empirical Results

Several EASI specifications are estimated via the GAUSSX programming module of the GAUSS software system. We allow for contemporaneous correlation across the stochastic terms of the demand equations. We estimate the demand system via the FIML method with DFP and GAUSS optimization algorithms. Furthermore, we use the ROBUST option to compute heteroskedasticity-consistent standard errors. We perform model comparisons via the Bewley likelihood ratio (B_{LR}) test procedure.[3] The procedure outcomes indicate that the EASI specification with cubic Engel curves provides the best fit of the data. Given these results from the model diagnostics, we base our further analysis on this particular EASI specification.

Tables 2 presents the estimation results from the full model. The model provides a good fit of the data. A great majority of the 125 parameters are statistically significant at standard significance levels. The overall significance test ($p-value < 0.01$) further supports this finding.

An increase in income is estimated to affect food expenditures favorably (i.e., according to the Engel's Law, expenditures grow in absolute term; however, they comprise a smaller share of the new income level). Our income elasticity of total food expenditures (i.e., φ_1) is estimated to be 0.34, which is also statistically significant. According to USDA projections, the average estimate for a group of developing countries is 0.4 (Meade, Muhammad, and Rada 2011). As regards China, its economy has been investment-driven with household consumption accounting for only 35 % of the GDP. This share is expected to grow to 45-50% by 2020 (Nielsen 2014).

Uncompensated price (ε^M), compensated price (ε^H), and expenditure (ξ) are computed via elasticity formulas provided by Zhen et al. (2013), and are reported in Tables 3 and 4.

Uncompensated own-price elasticity is found to be less than unitary elastic for all the commodities under study. The expenditure elasticity is more than unitary elastic for seafood (1.377), fruits (1.199), and vegetables (1.428), while the estimates for grains and eggs are found less than unitary elastic (0.618 and 0.347, respectively). As regards the expenditure elasticities, it might be surprising to find relatively high elasticity estimates given the level of aggregation of our data. This may be, for example due to seafood products increasing in popularity especially in urban areas in China that are usually more affluent relative to rural China (Hovhannisyan and Gould, 2011). Recent decades have also seen consumers becoming more reliant on animal products for protein with livestock accounting for more than 30% of total agricultural output sales in China in 2010 (Cao and Li, 2013). This could underlie the finding of expenditure elasticity for meats being close to unity (0.833). Recently, they have been incorporating more animal fats and oils into Chinese food diet. Importantly, Hovhannisyan and Gould (2011) show that expenditure elasticities vary considerably depending on the point of evaluation. For example, expenditure elasticities for different meats in 2003 are considerably higher than 1.00 when evaluated at Log (Expenditure) <5.00, whereas around 7.6 that happens to be the sample average these estimates tend to collapse to 1.00.

Conclusions

Given China's importance for world agricultural trade, considerable research efforts have been devoted to understanding the structure and dynamics of food demand in China. However, existing literature on food demand in China has significant flaws. Specifically, unobserved consumer heterogeneity has long been ignored because of lack of appropriate models. Further, Engel curves have been assumed to have certain shapes, which is restrictive from an empirical perspective.

This study analyzes the structure of food demand in urban China based on the most recent household expenditure survey data. Consumer food preferences are represented by an Exact Affine Stone Index (EASI) demand model, which accounts for unobserved consumer heterogeneity and allows for arbitrary Engel curve shapes. Further, we account for unobserved province-level heterogeneity in food preferences via province fixed-effects. Our findings indicate that seafood, fruit, and vegetables are income and expenditure elastic, while commodities such as grains and eggs are less than unitary elastic.

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Table 1. Descriptive Statistics of the Variables Used in the Analysis

Variable	Mean	STD	Min	Max	CV
Expenditure (Yuan/Capita)					
Meats	628.5	250.4	251.8	1548.6	0.398
Seafood	205.4	186.5	36.4	954.0	0.908
Vegetables	314.1	89.7	156.0	571.1	0.286
Fruits	241.9	83.1	111.5	562.6	0.344
Grains	264.0	54.6	157.3	417.2	0.207
Eggs	71.9	22.3	25.8	139.0	0.310
Fats and oils	105.0	36.7	43.5	232.2	0.350
Agricultural Commodity Price					
Meats	19.8	4.9	11.5	33.0	0.246
Seafood	17.0	6.4	8.8	42.1	0.379
Vegetables	2.6	0.7	1.4	5.9	0.284
Fruit	4.0	1.1	2.2	7.9	0.271
Grains	3.3	0.6	2.0	4.9	0.175
Eggs	7.6	1.9	4.4	12.9	0.244
Fats and oils	10.0	2.2	6.4	16.2	0.223
Price Instruments					
Disaster-affected areas (% of agricultural land)	52.1	12.7	15.2	87.8	0.244
Area of irrigated land (1,000 ha)	1,813.5	1398.0	153.7	5,033.0	0.771
Fertilizers (10,000 tons)					
Nitrogen	72.8	57.6	1.7	239.5	0.791
Phosphate	25.3	23.0	0.8	116.6	0.910
Total power of agricultural machinery (10,000 kw)	2,357.7	2,407.8	95.3	11,080.7	1.021
Urbanization rate (% of urban population)	51.7	12.4	15.2	82.9	0.239
Per capita Income (1000 Yuan)	11.9	4.4	6.5	28.8	0.370

Budget Share (%)					
Meats	33.9	5.3	24.9	48.4	0.157
Seafood	9.9	6.4	3.1	27.1	0.647
Vegetables	17.5	2.4	12.6	23.8	0.138
Fruit	13.5	2.9	7.5	22.3	0.212
Grains	15.3	3.6	8.1	24.5	0.238
Eggs	4.1	1.3	1.4	6.9	0.314
Fats and oils	5.9	1.4	1.9	7.5	0.242

Note: CV represents the coefficient of variation and is calculated as a ratio of the standard deviations to the respective mean.

Source: Chinese Urban Household Income and Expenditure Survey, China Statistical Yearbooks, 2003–2012.

Table 2. Parameter Estimates with Endogenous Price and Expenditure Equations: Share Equations

Parameter	Meats	Seafood	Vegetables	Fruit	Grains	Eggs	Fats
β_1	**0.354**	**0.140**	**0.101**	**0.184**	**0.171**	**0.050**	0.000
	0.004	*0.008*	*0.006*	*0.004*	*0.004*	*0.003*	*0.001*
β_2	**-0.053**	**0.035**	**0.070**	**0.026**	**-0.054**	**-0.024**	0.000
	0.012	*0.013*	*0.010*	*0.010*	*0.013*	*0.005*	*0.002*
β_3	0.067	0.065	0.052	**-0.094**	-0.051	**-0.038**	0.000
	0.053	*0.057*	*0.045*	*0.041*	*0.056*	*0.019*	*0.003*
α meats	**0.119**	**-0.081**	**-0.047**	**0.016**	0.000	-0.005	-0.002
	0.009	*0.006*	*0.006*	*0.006*	*0.007*	*0.004*	*0.008*
α seafood		**0.101**	**0.053**	**-0.041**	**-0.052**	**-0.023**	**0.044**
		0.011	*0.006*	*0.005*	*0.006*	*0.004*	*0.007*
α vegetables			**0.054**	**-0.018**	**-0.039**	**-0.014**	**0.011**
			0.006	*0.005*	*0.006*	*0.002*	*0.005*
α fruits				**0.079**	0.002	0.003	**-0.042**
				0.008	*0.006*	*0.003*	*0.006*
α grains					**0.121**	**0.019**	**-0.051**
					0.009	*0.004*	*0.007*
α eggs						**0.025**	-0.005
						0.004	*0.003*
α fats/oils							**0.044**
							0.003
Province fixed-effects						Yes	

Note: The italicized numbers are the estimated parameter standard errors.Values in bold identify elasticity estimates that are statistically different from 0 at or below the 0.05 significance level.

Table 3. Uncompensated Price and Expenditure Elasticity Estimates from the EASI demand specification

	Meats	Seafood	Veg.	Fruits	Grains	Eggs	Fats/oils	**Expend.**
Meats	**-0.593**	**-0.223**	**-0.109**	**0.072**	**0.025**	**-0.008**	0.004	**0.833**
Seafood	-0.952	**-0.012**	**0.469**	-0.471	**-0.586**	**-0.253**	0.427	**1.377**
Veg.	**-0.411**	0.258	**-0.771**	-0.162	**-0.284**	**-0.096**	**0.039**	**1.428**
Fruits	**0.050**	-0.315	-0.164	**-0.459**	-0.013	**0.013**	**-0.311**	**1.199**
Grains	**0.128**	**-0.308**	**-0.190**	0.069	**-0.143**	0.144	-0.318	**0.618**
Eggs	**0.099**	**-0.525**	**-0.235**	0.166	0.586	**-0.354**	**-0.083**	**0.347**
Fats/oils	**-0.032**	0.788	0.197	-0.746	-0.914	**-0.085**	**-0.209**	**0.990**

Note: Values in bold identify elasticity estimates that are statistically different from 0 at or below the 0.05 significance level. The first column represents commodities with price change.

Table 4. Uncompensated Price and Expenditure Elasticity Estimates from the EASI demand specification

	Meats	Seafood	Veg.	Fruits	Grains	Eggs	Fats/oils
Meats	**-0.311**	**-0.141**	**0.038**	**0.188**	**0.150**	**0.025**	0.051
Seafood	**-0.485**	**0.124**	**0.712**	**-0.279**	**-0.378**	-0.198	**0.504**
Veg.	**0.073**	0.398	**-0.519**	**0.038**	**-0.069**	**-0.039**	0.119
Fruits	0.456	**-0.197**	**0.048**	**-0.292**	**0.168**	**0.061**	-0.244
Grains	**0.338**	-0.247	**-0.081**	**0.156**	**-0.050**	**0.168**	**-0.284**
Eggs	**0.216**	**-0.490**	**-0.174**	**0.214**	**0.638**	**-0.340**	-0.063
Fats/oils	**0.307**	0.887	**0.373**	**-0.607**	**-0.763**	**-0.045**	**-0.153**

Note: Values in bold identify elasticity estimates that are statistically different from 0 at or below the 0.05 significance level. The first column represents commodities with price change.

Footnotes

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[1] The cities, regions, and provinces used in this study are: Anhui, Beijing, Chongqing, Fujian, Gansu, Guangdong, Guangxi, Guizhou, Hainan, Hebei, Heilongjiang, Henan, Hubei, Hunan, Inner Mongolia, Jiangsu, Jiangxi, Jilin, Liaoning, Ningxia, Qinghai, Shaanxi, Shandong, Shanghai, Shanxi, Sichuan, Tianjin, Xinjiang, Yunnan, and Zhejiang. Tibet is excluded from the analysis, given that supply shifters are not observed for this province.

[2] Combining categories and sub-categories of varying qualities into single commodities is a limitation of our empirical analysis, which we will address in our future research using more disaggregate data.

[3] The B_{LR} test statistic is given by $B_{LR} = 2(LL^U - LL^R)\left[(E * N^S - N^U) / E * N^S\right]$, where $LL^{U,R}$ is the optimal log-likelihood value from the unrestricted/restricted model, E is the number of equations, N^S represents the sample size, and N^U is the number of parameters in the unrestricted model (Bewley 1986). Asymptotically, $B_{LR} \sim \chi^2(g)$, where degrees of freedom (g) equals the difference in the number of estimated parameters under the restricted vs. unrestricted specification.