On Price Endogeneity in the Analysis of Food Demand in China

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Abstract: Price endogeneity has been ignored in previous analyses of food demand in China. We examine agricultural input price data from the China National Bureau of Statistics and use reduced-form price equations to account for price endogeneity in this setting. Applying our unique econometric approach to the analysis of provincial-level food demand in China, we find strong statistical evidence of price endogeneity. Models that ignore price endogeneity result in substantially biased elasticities and misleading estimates of future food demand in China.

Keywords: Consumer welfare, expenditure endogeneity, food demand in China, Generalized Quadratic AIDS, price endogeneity.

JEL Code: Q11, Q13, Q17.

Introduction

With only eight percent of the world's arable land and close to a quarter of the world's population, China faces increasing difficulties in meeting rising domestic demand for food (World Bank 2013). A net exporter of agricultural products in 2002, China surpassed the United States in 2011 to become the top importer of agricultural goods (World Trade Organization 2013). From 2005 to 2013, US soybean exports to China nearly tripled, from 9.4 to 24.6 million metric tons. This increase includes more than 60% of US soybean exports and 30% of the soybean harvest (US Department of Agriculture 2014a, 2014b). Thus, it is important to understand the structure and determinants of food demand in China.

Considerable research effort has been devoted to this topic (e.g., Shenggen, Cramer, and Wailes 1994; Huang and Rozelle 1998; Gould and Villareal 2006; Hovhannisyan and Gould 2011, 2014). However, these studies ignore potential food price endogeneity, mainly because of a lack of data on food production costs that could be used to model food supply. In this study, we use agricultural input price data to account for food price endogeneity. Specifically, we incorporate reduced-form price equations into a structural framework of food demand. To do this, we use information on agricultural input prices and disaster-affected areas to identify demand. We also account for total expenditure endogeneity, as suggested by LaFrance (1991) and Thompson (2004). We include an expenditure reduced-form equation in our food demand system that incorporates consumer disposable income and consumer price index (CPI) as determinants. We then analyze the structure of food demand in urban China by using annual, provincial-level, panel data from 2003 to 2009. Our findings provide strong statistical evidence of price and expenditure endogeneity.

Estimates of price and income elasticities in food demand are commonly used in a wide range of economic analyses. These include formal computation models of world agricultural markets (e.g., Valenzuela et al. 2007), analyses of trade and fiscal policies (Clarete and Whalley 1988; Kehoe and Serra-Puche 1983), an investigation of the relationship between agricultural activity and energy use (Hertel and Beckman 2011), a projection of global food demand (Yu et al. 2004), and a study of population growth and economic development effects on global food production and consumption (Schneider et al. 2011). Dhar, Chavas, and Gould (2003) argue that elasticity estimates obtained from models that ignore food price endogeneity are likely to be biased, resulting in erroneous policy advice and biased forecasts of future demand for food.

Our results reveal that ignoring price endogeneity results in substantial biases in price and expenditure elasticity estimates. We use projected prices and income from the Organisation for Economic Co-operation and Development (OECD) to forecast the magnitude and price responsiveness of food demand in China (OECD 2013). We find sizeable differences in projections between model specifications that include price and expenditure endogeneity and models that ignore endogeneity. Using a counter-factual simulation analysis, we demonstrate that including price endogeneity can substantially alter estimates of the impact of various price-change scenarios on consumer welfare.

The article proceeds as follows. Section 2 describes the methodological contributions of the study and provides an overview of our structural model. Section 3 provides a brief description of the data underlying the analysis. Section 4 summarizes our econometric results. Section 5 summarizes the implications of our results in assessing future food demand in China.

Methodology

In this section, we discuss the Generalized Quadratic Almost Ideal Demand System (GQUAIDS) specification that supports our study. We also present a reduced-form approach to modeling food supply and expenditures. This model includes both food price and expenditure endogeneity. Finally, we briefly discuss econometric issues that may arise from the time-series aspect of our panel data, and we provide test procedures for modeling diagnostics and evaluating price and expenditure endogeneity.

The GQUAIDS Demand Specification

The Almost Ideal Demand System (AIDS) specification of Deaton and Muellbauer (1980) has been a commonly used model for analyzing food demand. This model offers the flexibility of a first-order approximation to an arbitrary demand system, which is derived from the consumer utility maximization. We base the current analysis on the GQUAIDS model, given that it nests alternative AIDS-based specifications. Let p_i and q_i denote the price and quantity of the i^{th} food, respectively, and let X be total food expenditures. Assume that we have the following indirect utility function (V) with underlying price-independent logarithmic preferences (Bollino 1987; Banks, Blundell, and Lewbel 1997; Hovhannisyan and Gould 2011):

$$\ln V = \left[\left(\frac{\ln(s) - \ln(P)}{b(p)} \right)^{-1} + \lambda(p) \right]^{-1} \qquad (0)$$

where s is supernumerary expenditures ($s = X - \sum_i c_i p_i$), with c_i representing *pre-committed* demand (i.e., independent of expenditure and price effects); *P* is a price index, with $\ln(P) = \alpha_0 + \sum_j \alpha_j \ln(p_j) + 0.5\sum_i \sum_j \gamma_{ij} \ln(p_j)\ln(p_i)$; $b(p) = \prod p_k^{\beta_k}$ is a price aggregator; $\lambda(p) = \sum_i \lambda_i \ln(p_i)$ is homogeneous of degree zero in prices, with $\sum_i \lambda_i = 0$; and $\alpha, \beta, \gamma, \lambda$ are unknown utility function parameters.

We derive an uncompensated demand system by applying Roy's identity to (0):

(1) $$w_i = c_i \frac{p_i}{X} + \frac{s}{X}\left\{\alpha_i + \sum_{k=1}^{n} \gamma_{ik} \ln(p_k) + \beta_i \ln\left(\frac{s}{P}\right) + \frac{\lambda_i}{b(p)}\left[\ln\left(\frac{s}{P}\right)\right]^2\right\}$$

where w_i is the budget share of product i (i.e., $p_i q_i / X$).

The demand functions represented by (1) satisfy the Engel aggregation and Slutsky symmetry restrictions. They are homogeneous of degree zero in prices and expenditures, with the following restrictions:

(2) $$\sum_i \alpha_i = 1,\ \sum_i \beta_i = 0, \sum_i \gamma_{ij} = 0,\ \forall j = 1,...,n, \quad \text{and} \quad \gamma_{ij} = \gamma_{ji},\ \forall j \neq i$$

Various demand specifications can be obtained from the GQUAIDS framework through respective parameter restrictions. The AIDS model is obtained via the joint restrictions $\lambda_i = 0,\ c_i = 0, \forall i = 1,...,n$. The Generalized AIDS (GAIDS) model, originally developed by Bollino (1987), is obtained using the assumption $\lambda_i = 0, \forall i = 1,...,n$. Finally, the Quadratic AIDS (QUAIDS) specification is obtained via the joint restrictions $c_i = 0, \forall i = 1,...,n$.[1]

Price and Expenditure Endogeneity in Demand Analyses

We believe prices are correlated with the error terms in food demand equations. Therefore, prices are endogenous, because price changes are driven not only by demand factors but also by supply shifters, such as the agricultural input prices that underlie production costs. Consumer preferences can be sufficiently represented so that the remaining error term in a full-system demand equation (i.e., one that contains both demand and supply functions) is white noise. Even in this case, however, omitting the supply side of the price formation mechanism results in this demand error also reflecting supply-driven price variation, which leads to endogeneity bias, since price is correlated with the demand error term.

The resulting parameter estimates and economic effects will likely cause erroneous policy advice and biased forecasts of future food demand (Dhar, Chavas, and Gould 2003). If there is no supply allowance in the empirical model, for example, beef herd liquidations that are caused by feed price spikes may appear as a structural change in demand. Similarly, production efficiency gains that lead to outward supply shifts can be attributed to demand expansion, irrespective of price and expenditure (Eales and Unnevehr 1993). Furthermore, food prices should be considered endogenous, with no regard to the level of aggregation at which the analyses are performed. Specifically, even in extremely disaggregated analyses, consumer responsiveness to supplier promotional actions establishes price endogeneity. However, the problem may be more pervasive at the macro-level analyses, such as the current study.

To disentangle the impacts of simultaneous supply and demand shifts on equilibrium food prices and quantities, we rely on instrumental variables. One way to accomplish this is to include reduced-form price equations for each food commodity, which relate food prices to these exogenous supply shifters. In practice, finding relevant and valid instruments has been challenging, thus common practice has been to rely on the exogenous price assumption in empirical food demand studies in China.

In this study, we use agricultural input prices that have been commonly held as classic instruments. While input prices are correlated with food prices, they are unlikely to be correlated with unobserved demand determinants, such as consumer mood or the impacts of unobserved promotional activities. Additionally, we supplement our instruments with a variable that reflects disaster-affected areas in China. This variable is constructed as the share of land affected by drought or flood in the respective provinces in a given year. This essentially represents unpredictable supply shocks that are excluded from the demand equation and uncorrelated with the demand error term. 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) $$\ln\left(p_i\right) = \kappa_{i1} + \sum_{j=2}^{10} \kappa_{ij} \ln\left(p_j^{Input}\right) + \kappa_{i11} Dis + \iota_i, \quad \forall i = 1, \ldots, n$$

where p_j^{Input} comprises prices for eight agricultural inputs in China (see data description for details on the inputs used in the analysis); $\kappa_{ij}, j = 1,..,10$ are parameters that represent the marginal and separate impact of each of these input prices on food prices; *Dis* is the share of disaster-affected areas across provinces in the sample period; and ι_i represents unobserved supply shocks, with statistical properties specified in the empirical discussion.

The standard instrumental variable approach is not applicable in nonlinear, simultaneous-equation systems, like the one in our study. Therefore, we use an alternative approach by adopting a full information maximum likelihood (FIML) estimation procedure that accounts for the true nature of simultaneity between supply and demand (e.g., Kadiyali, Vilcussim, and Chintagunta 1996).[2] The FIML estimator is the maximum likelihood counterpart of the three-stage least squares (3SLS), which represents the generalized method of moments (GMM) estimator applied to a system of simultaneous equations. Like 3SLS, the FIML estimator is asymptotically consistent without the normality assumption (Amemiya 1985, pp. 232–233). Additionally, the FIML and 3SLS estimators are asymptotically equivalent in linear equation systems, however nonlinear FIML is more efficient than nonlinear 3SLS (Hayashi 2000, pp. 534–535). Finally, FIML has the invariance property in finite samples (i.e., the FIML estimator is invariant to re-parameterization), while the 3SLS and GMM estimators lack this property (Hayashi 2000, pp. 452–453).

Expenditure endogeneity is another issue that arises in systems like the one we used. Specifically, total food expenditure (X) is defined as the sum of expenditures on individual food commodities in our system $\left(p_i q_i\right)$. Commodity-specific expenditures, expressed as budget shares (i.e., $w_i = p_i q_i / X$) are left-hand side variables in the expenditure share equations (i.e., they are assumed endogenous). It therefore appears that expenditure shares that constitute explained variables (w_i) and total expenditures (X) that represent an explanatory variable in each of the demand/share equations are jointly determined in our system (1) and are thus jointly endogenous (e.g., Attfield 1985).

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 thereof:

(4) $$\ln(X_j) = \varphi_1 + \varphi_2 \ln(\mathrm{I}_j) + \varphi_3 \ln(CPI) + \tau_j, \quad \forall\, j = 1, \ldots, M$$

where I_j is per capita average annual income in province j, CPI is consumer price index that does not vary across provinces, τ_j represents unobserved expenditure determinants whose statistical properties are presented in the empirical framework, and M is the number of provinces. This approach accounts for the effects of price changes for products outside the system (φ_3), as well as effects of consumer income (φ_2) on the food demand system (Thompson 2004).

In constructing the reduced-form expenditure equation (4), we build on previous literature (e.g., Blundell and Robin 2000; Dhar, Chavas, and Gould 2003; Thompson 2004). Consumer income emerges as an important determinant for expenditure. Furthermore, it is unlikely for income to be correlated with the demand error term that comprises unobserved consumer tastes among other things. We also use the CPI to account for the impacts of other prices on food expenditures. Unlike previous studies (e.g., Blundell and Robin 2000), we do not include the price index P in equation (5), because this may violate the homogeneity of degree zero of total real consumption demand in prices and money income (i.e., money illusion). Finally, the functional form of the expenditure equation facilitates the estimation of income elasticities. Specifically, income elasticity of demand (η_i^I) can be represented as:

$$\eta_i^I = \frac{\partial \ln(q_i)}{\partial \ln(X)} \frac{\partial \ln(X)}{\partial \ln(I)} = \xi_i \varphi_2$$

where $\varphi_2 = \frac{\partial \ln(X)}{\partial \ln(I)}$ is the expenditure income elasticity, and $\xi_i = \frac{\partial \ln(q_i)}{\partial \ln(X)}$ is the demand expenditure elasticity.

The standard approach to obtaining standard errors of income elasticities (η_i^I) is based on an independence assumption between ξ_i and φ_2, which may be overly restrictive in practice (e.g., Chern et al. 2004). We compute the standard errors of income elasticities (η_i^I) via the delta method, allowing for unrestricted covariance between ξ_i and φ_2.

Test Procedure for Evaluating Price and Expenditure Endogeneity

Following LaFrance (1993), we adopt the Durbin, Wu, and Hausman (DWH) test procedure to evaluate price and expenditure endogeneity. This procedure includes evaluating the statistical difference between parameter estimates that are obtained under the exogenous and endogenous regimes. The null hypothesis is that the parameter estimates are consistent, without accounting for endogeneity. The DWH test statistic (Λ_{DWH}) is computed as follows:

(5) $$\Lambda_{DWH} = \left(\Gamma_{Exog} - \Gamma_{Endog}\right)\left[\Sigma_{Exog} - \Sigma_{Endog}\right]^{-1}\left(\Gamma_{Exog} - \Gamma_{Endog}\right)$$

where Γ_{Exog} and Γ_{Endog} represent parameter estimates from the exogenous and endogenous regimes, and Σ_{Exog}, and Σ_{Endog} are the corresponding parameter covariance matrices, respectively. Under the null hypothesis, Λ_{DWH} is distributed asymptotically as $\chi^2(K)$, where K is the number of endogenous variables in the model.

The GQUAIDS Elasticities and Consumer Welfare Evaluation Method

Elasticity estimates from the GQUAIDS model form the basis for evaluating how changes in economic factors, such as food prices, affect Chinese consumer welfare. We compute uncompensated $\left(\varepsilon_{ij}{}^{M}\right)$, compensated $\left(\varepsilon_{ij}{}^{H}\right)$, and expenditure $\left(\xi_i\right)$ elasticity estimates via the following formulas, provided by Hovhannisyan and Gould (2011):

$$\xi_i = 1 + \frac{1}{w_i}\left[\beta_i + \frac{2\lambda_i}{b(p)}L - M_i + \frac{\sum t_k p_k}{X}\left(A_i + \beta_i L + \frac{\lambda_i}{b(p)}L^2\right)\right] \tag{6}$$

$$\begin{aligned} \varepsilon_{ij}^{M} = {} & \frac{1}{w_i}\left[\delta_{ij}M_i - M_j\left(A_i + \beta_i L + \frac{\lambda_i}{b(p)}L^2\right) + \right. \\ & \left. \frac{s}{X}\left(\gamma_{ij} - \beta_i\left(A_j + S_j\right) - \frac{\lambda_i \beta_j}{\prod p_k^{\beta_k}}L^2 - 2\frac{\lambda_i}{b(p)}\left(S_j L + A_j\left[\ln(\mathrm{s}) + 2\ln(\mathrm{P})\right]\right)\right)\right] \end{aligned} \tag{7}$$

$$\varepsilon_{ij}^{H} = \varepsilon_{ij}^{M} + \xi_i w_j \tag{8}$$

where δ_{ij} is the Kronecker delta (i.e., $\delta_{ij} = 1, \forall i = j$, $\delta_{ij} = 0, \forall i \neq j$, $A_i = \alpha_i + \sum \gamma_{ij} \ln\left(p_j\right)$, $L = \ln\left(s\right) - \ln\left(P\right)$, $M_i = \frac{t_i p_i}{X}$, and $S_i = \frac{t_i p_i}{s}$).

We base our evaluation of welfare impacts of price changes on the Hicksian compensating variation (CV), because it compensates for the assumption of constant marginal utility of income in uncompensated demand models. Let $E(p,u)$ denote the minimum expenditure necessary to obtain utility u at a given price vector p. Furthermore, denote an initial price level, utility level, and new price vector by p_0, u_0, and p_1, respectively. The CV approach measures the change in consumer expenditure necessary to compensate consumers for a given price change, such that utility remains intact (Huang 1993):

$$(8) \qquad CV = E\left(p_1, u_0\right) - E\left(p_0, u_0\right) = p_1 q^h\left(p_1, u_0\right) - p_0 q_0\left(p_0, u_0\right)$$

where $q^h\left(p_1, u_0\right)$ is the compensated (Hicksian) demand, evaluated at a price p_1 and initial utility level u_0. A positive CV estimate indicates welfare loss, as the initial utility level can only be achieved at a higher cost, while a negative CV implies welfare gain.

To obtain an estimable version of equation (10), we modify this equation using a vector of compensated quantity changes $dq^h = q^h\left(p_1, u_0\right) - q_0\left(p_0, u_0\right)$ as follows:

$$(9) \qquad CV = p_1 dq^h + dp\, q_0\left(p_0, \mu_0\right)$$

where $dp = p_1 - p_0$ is a vector of price changes, and dq^h is computed via (12):

$$(10) \quad \frac{dq_i^h}{q_i} = \sum_j \varepsilon_{ij}^H \left(\frac{dp_j}{p_j}\right)$$

where (ε_{ij}^H) represents the compensated elasticity calculated in equation (9).

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 2009 (China

Statistical Yearbooks, 2003–2009). 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.[3] Dong and Fuller (2010) provide more details on the sampling procedure and data collection for this analysis.

We use per capita expenditure and food price index 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. We use price index rather than level data because province-level price data are not included in our sample period. Furthermore, we exploit agricultural input price data to account for price endogeneity via construction of reduced-form price equations, as previously discussed. Specifically, we use price indices for forage, commodity animal products, semi-mechanized farm tools, mechanized farm machinery, chemical fertilizer, pesticides, machinery oil, and other means of agricultural production. Agricultural input prices have been commonly held as classic instruments, assuming that input prices are correlated with food prices and are unlikely to correlate with unobserved demand determinants. Additionally, we supplement our instruments with the land share that is affected by drought or flood in the respective provinces in a given year. This essentially represents unpredictable supply shocks that are excluded from the demand equation and uncorrelated with the demand error term. Finally, we use province-level, per capita, household income data and a CPI estimate 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.

Table 1 shows that food commodity prices have comparable volatility, relative to the agricultural input prices in our sample. Specifically, the coefficient of variation (i.e., the ratio of the standard deviation to the mean) ranges from 6.5 for the fats and oils price to 15.3 for the seafood price. In the meantime, the coefficient of variation for the agricultural input price indices varies from as low as 4.4 for mechanized farm machinery to 22.1 for commodity animal products.

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.

Applying the Food Demand System to Urban China

In this section, first we provide an overview of an econometric issue encountered in time-series analysis and offer an empirical model that addresses this issue. Next, we discuss the results from our empirical model, and evaluate the endogeneity bias.

Econometric Issues

Given the time-series aspect of our panel data, we must account for potential autocorrelation in the error terms of both the demand and the reduced-form equations. Autocorrelation may be attributed to model misspecification, which usually results from ignoring dynamic aspects of the data-generating process (Blanciforti, Green, and King 1986) or from incorrect functional forms (Alston and Chalfant 1991). The common approach to correct autocorrelation has been to use first difference forms of the original models. This approach is tantamount to imposing a diagonal variance-covariance matrix, with the diagonal elements (i.e., autocorrelation coefficient ρ) fixed at one (Gao and Shonkwiler 1993; Dong and Fuller 2010). In contrast, we consider several autocorrelation structures and estimate ρ by assuming that the variance-covariance matrix exhibits an AR(1) process:

$$(11) \qquad \begin{pmatrix} u_{jt} \\ \iota_{jt} \\ \tau_{jt} \end{pmatrix} = \begin{pmatrix} \rho_1 u_{jt-1} \\ \rho_2 \iota_{jt-1} \\ \rho_3 \tau_{jt-1} \end{pmatrix} + \begin{pmatrix} u_{jt}^o \\ \iota_{jt}^o \\ \tau_{jt}^o \end{pmatrix}$$

where $\left(u_{jt-1}, \iota_{jt-1}, \tau_{jt-1}\right)^T$ represents unobserved demand, price, and expenditure shifters, respectively lagged by one period, and where $\left(u_{jt}^o, \iota_{jt}^o, \tau_{jt}^o\right)^T$ are independent and identically distributed shocks.

Following Piggott and Marsh (2004), we explore a series of autocorrelation structures of the demand system. Specifically, we consider the following autocorrelation structures represented by the R matrix:[4] (i) a full R matrix where $R_{ij} \neq 0, \forall i, j = 1, ..., N^E$ and N^E is the number of equations, (ii) a diagonal R matrix with identical diagonal and zero off-diagonal elements, and (iii) $R = 0$ (i.e., no autocorrelation). As illustrated in the literature, we do not identify the full R matrix for our demand system. Therefore, we use the Berndt and Savin (1975) approach to evaluate the $\overline{R}^*$ matrix that comprises the first n-1 rows of the $\overline{R}$ matrix (with respective elements given as $\overline{R}_{ij} = R_{ij} - R_{ik}, \forall i = 1,...,N^E, k = 1,...,n,$ and $\forall j = 1,...,N^E - 1$). To this end, we test for the joint significance of the R_{ij} elements, rather than computing the individual coefficients.

Our full model comprises the following: budget share (**Error! Reference source not found.**), reduced-form price (**Error! Reference source not found.**), and expenditure equations (**Error! Reference source not found.**):

$$w_{ijt} = \rho_1 w_{ijt-1} + c_i \frac{p_{ijt}}{X_{jt}} + \frac{s_{jt}}{X_{jt}} \left\{ \alpha_i + \sum_{k=1}^{n} \gamma_{ik} \ln(p_{kjt}) + \beta_i \ln\left(\frac{s_{jt}}{P}\right) + \frac{\lambda_i}{b(p)} \left[\ln\left(\frac{s_{jt}}{P}\right) \right]^2 \right\} - \rho_1 \left[c_i \frac{p_{ijt-1}}{X_{jt-1}} + \frac{s_{jt-1}}{X_{jt-1}} \left\{ \alpha_i + \sum_{k=1}^{n} \gamma_{ik} \ln(p_{kjt-1}) + \beta_i \ln\left(\frac{s_{jt-1}}{P^*}\right) + \frac{\lambda_i}{b(p)^*} \left[\ln\left(\frac{s_{jt-1}}{P^*}\right) \right]^2 \right\} \right] + u_{ijt}^o \tag{12}$$

$$\ln\left(p_{ijt}\right) = \rho_2 \ln\left(p_{ijt-1}\right) + \kappa_{i1} + \sum_{m=2}^{10} \kappa_{im} \ln\left(p_{mjt}^{Input}\right) + \kappa_{i11} Dis_{jt} - \rho_2 \left[\kappa_{i1} + \sum_{m=2}^{10} \kappa_{im} \ln\left(p_{mjt-1}^{Input}\right) + \kappa_{i11} Dis_{jt-1} \right] + \iota_{ijt}^o \tag{13}$$

$$\ln\left(X_{jt}\right) = \rho_3 \ln\left(X_{jt-1}\right) + \varphi_1 + \varphi_2 \ln\left(\mathrm{I}_{jt}\right) + \varphi_3 \ln\left(CPI_t\right) - \rho_3 \left[\varphi_1 + \varphi_2 \ln\left(\mathrm{I}_{jt-1}\right) + \varphi_3 \ln\left(CPI_{t-1}\right) \right] + \tau_{jt}^o \tag{14}$$

where i, j, and t represent the commodity, province, and year, respectively, and P^*, $b(p)^*$ are one-period lagged counterparts of the original price index P and price aggregator $b(p)$, respectively.

Estimated Structure of Food Demand in Urban China

A series of demand specifications are estimated via the GAUSSX programming module of the GAUSS software system. We allow for contemporaneous correlation across the stochastic terms of all equations. Given the nonlinear nature of the equations in (14), we estimate the demand system via the FIML method with BHHH 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 (table 2).[5] The procedure outcomes indicate that the GAIDS models do not enhance the explanatory power of the AIDS specification significantly, either when autocorrelation is ignored or when it is accommodated (the same is true for the GQUAIDS and QUAIDS specifications). In other words, the empirical evidence from our study does not support pre-committed quantities (c_i) in urban China. On the other hand, Engel curves are found to be nonlinear (i.e., budget shares are quadratic in the logarithm of total expenditure). These results are inconsistent with similar studies, such as Hovhannisyan and Gould (2011). However, they use household-level data from only three Chinese provinces, while we rely on provincial-level aggregate data from almost all of urban China. Given these results from the model diagnostics, we base our further analysis on the QUAIDS specification.

Following Piggott et al. (1996) and Piggott and Marsh (2004), we perform a series of B_{LR} test procedures to identify the autocorrelation structure that provides the best fit of the data. The test outcomes provide evidence of autocorrelation in the model, as we reject the null hypothesis that $R = 0$. Nevertheless, the difference between the specification with no restrictions on R (i.e., $R_{ij} \neq 0, \forall i, j = 1,...,N^E$) and the diagonal R as provided in (ii) (i.e., $R_{ij} = d, \forall i = j,$ and $R_{ij} = 0, \forall i \neq j$) is not statistically significant. Therefore, we estimate the full model as provided in equations (14) and (15) under the theoretical restrictions given by equation (2), where allowance is made for contemporaneous correlation.

Tables 3 and 4 show the estimation results from the full model. The model provides a good fit of the data. The vast majority of the 125 parameters are statistically significant at standard significance levels. The overall significance test ($p-value < 0.01$) further supports the outcome. The autocorrelation coefficients for the demand and expenditure equations are 0.968 and 0.989, respectively, which is somewhat similar to findings from Hovhannisyan and Gould (2014), for which they used a similar dataset for food demand estimation. Unlike these estimates, the autocorrelation coefficient for the reduced-form price equation is negative and statistically significant (-0.274).

A majority of coefficients in the price and expenditure equations are also significant and of the expected sign. We perform several tests of the relevance of our instruments (F-test for the first stage). Unlike other studies that report single-equation F-test outcomes for the reduced-form price equations, we perform a variety of F-tests that are developed for the reduced-form equations as a system. Our findings provide strong empirical evidence of the relevance of our instruments, irrespective of the type of the F-test conducted (i.e., respective *p-values*<0.01), such as Berndt F-test, Judge F-test, McElroy F-test, Dhrymes t-test, and Greene t-test (Berndt 1991; Judge et al. 1985; McElroy 1977; Dhrymes 1974; Greene 1993).

A rise in income is estimated to affect food expenditures favorably (i.e., according to the Engle 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_2) is estimated to be 0.3, 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).

We experiment with the reduced-form expenditure function by including a series of control variables, such as household size, time trend, and provincial dummy variables, but none of these variables were found to be statistically significant. This might be caused by high correlation between the time trend and CPI, assuming that CPI does not vary across provinces and, thus, is only reflective of the time change. Similarly, income and household size are inversely related in our sample, where less affluent households tend to be larger, relative to more wealthy households. We also find that food expenditures do not increase in the face of inflation, with the latter measured by CPI. Our interpretation of these findings is that consumer income, combined with the price index, represents some of the key determinants of consumer food expenditures. Our findings for the reduced-form price equations offer mixed evidence of the impacts of agricultural input prices on food commodity prices. Finally, the average impacts of exogenous food price determinants excluded from the reduced-form price equations are positive across all commodities, except for vegetables.

Uncompensated price (ε^M), compensated price (ε^H), expenditure (ξ), and income elasticities (η^I) are computed via equations (6)–(8). Tables 5 and 6 present the respective estimates. In general, estimates are statistically significant. Uncompensated own-price elasticities are more than unitary elastic for seafood (-1.144), meats (-1.038), and vegetables (-1.021), while the respective estimates for fruits, grains, eggs, and fats and oils are -0.985, -0.836, -0.966, and -0.654. Expenditure elasticity is the highest for fats and oils (1.084). Vegetables and meats have almost identical estimates (1.035 and 1.032, respectively). The expenditure elasticity for eggs is nearly unitary elastic (1.024), followed by fruits and seafood (0.969 and 0.953, respectively), and grains (0.908). Income elasticities fall in the range of 0.272 to 0.325 and are proportional to the expenditure elasticity, with φ_2 representing the proportionality factor.

Price and Expenditure Endogeneity Test Outcomes

Using the DWH test procedure, we perform separate tests for price endogeneity, expenditure endogeneity, and both price and expenditure endogeneity. The test outcomes provide ample support for rejecting the null hypothesis of price exogeneity, expenditure exogeneity, and joint price and expenditure exogeneity, given a $p-value < 0.01$ for all three tests. These findings concur with Dhar, Chavas, and Gould's (2003) analysis of US beverage consumption, with Thompson's (2004) study of Japanese meat consumption, and with Hovhannisyan and Gould's (2011) examination of food demand in China.

Quantifying Price Endogeneity Bias

The present study is the first attempt to document price endogeneity in Chinese food demand analyses, stemming from supply and demand simultaneity. Expenditure endogeneity has received due attention in the literature. We quantify the bias in economic effects by determining the percentage difference between the respective sets of elasticity estimates under exogenous and endogenous price regimes, as follows:

$$\Delta_{EL} = \frac{100\left(\varsigma^{Exog} - \varsigma^{Endog}\right)}{\varsigma^{Exog}} \tag{15}$$

where ς^{Exog}, ς^{Endog} are elasticity estimates from models with exogenous and endogenous prices, respectively, and $\varsigma \equiv \left[\varepsilon^{M}, \varepsilon^{H}, \xi\right]^{T}$.

Estimates of Δ_{EL} present empirical evidence that price endogeneity significantly impacts price elasticity estimates (Table 7).[6] Price endogeneity is found to cause an upward bias in all estimates of uncompensated and compensated own-price elasticities, with the size of the bias reaching 48% for fats and oils and 28.7% for meats, for compensated own-price elasticity. Overall, the magnitude of bias in compensated and uncompensated own-price elasticity estimates are very close across commodities. The largest bias is found in the cross-price elasticity between meats and fats and oils, with the estimate changing by a factor of 106 when accounting for endogeneity issues in the demand system. We also find that the bias in expenditure elasticity estimates is smaller, as compared to uncompensated and compensated elasticities, and that the direction of the bias varies by commodities. For example, ignoring endogeneity underestimates expenditure elasticity estimates by 6.5% and 5% for fruits and vegetables, respectively, while it overstates the estimates for fats/oils and meats by 5.2% and 4.2%, respectively.

The impact of price and expenditure endogeneity bias on long-term projections of food consumption is striking. First, we use the OECD-projected price changes for China in 2020 and the sets of own-price uncompensated elasticity estimates from our two model specifications to evaluate the bias in projected consumption response. Specifically, prices for meats, seafood, grains, and fats/oils are expected to rise by 22%, 16%, 17%, and 6%, respectively, by the year 2020. These price increases are expected to cause a decrease in consumption of the respective food commodities. We find that models ignoring endogeneity understate this decline by $499.1, $215.3, $334.6, and $249.7 billion. As China further integrates itself into the global economy, these biased projections can profoundly affect world trade.[7]

Second, using the OECD-projected income for China in the years 2020 and 2050, we find that ignoring endogeneity, for example, overstates meat consumption by $27.7 billion in 2020 and by $108.2 billion in 2050, while understating fruit and vegetable consumption by $14.7 and $14.8 billion in 2020, and by $57.2 and $57.7 billion in 2050, respectively. As a final exercise, we use counter-factual simulation analysis to evaluate the impacts of hypothetical changes in a series of prices in our sample on consumer welfare. Our results indicate that ignoring endogeneity can substantially alter the welfare estimates, with the size of the bias reaching $79.2 billion (Table 8). Nevertheless, we acknowledge that this simulation exercise should not be considered a complete policy analysis. Rather, it represents a demonstrative tool to delineate the importance of modeling assumptions, such as price exogeneity, to implications and predictions of the model.

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, price endogeneity has long been ignored because of lack of data on the cost of food production that could be used to model food supply in China. Food prices, however, are endogenous due to simultaneity of food supply and demand.

We exploit agricultural input price data provided by the China National Bureau of Statistics to account for food price endogeneity. Specifically, we incorporate reduced-form food supply relations into the structural framework of demand, where farm prices play a crucial role in identifying demand. We further account for expenditure endogeneity, which is an important issue in empirical demand studies. We achieve this by including an expenditure reduced-form equation and using disposable income and CPI.

Using our method and province-level panel data, we analyze the structure of food demand in urban China. Our findings provide strong statistical evidence for price and expenditure endogeneity. Compared to the full model specification, we find that ignoring price endogeneity results in significant biases in uncompensated own-price and income elasticities. The impact of these biases on projection of food consumption is striking. Using the OECD-projected price changes for meats, seafood, grains, and fats/oils in

China in 2020, we find that ignoring price endogeneity understates the demand response to price changes by \$499.1, \$215.3, \$334.6, and \$249.7 billion, respectively. Furthermore, based on the OECD-projected income for China in the years 2020 and 2050, we find that ignoring endogeneity overstates meat consumption by \$27.7 billion in 2020 and by \$108.2 billion in 2050, while understating fruit and vegetable consumption by \$14.7 and \$14.8 billion in 2020, and by \$57.2 and \$57.7 billion in 2050, respectively. Finally, using counter-factual simulation analysis, we demonstrate that accounting for price endogeneity can substantially alter estimates of the impact of various price change scenarios on consumer welfare, by up to \$79.2 billion.

The major finding of this study is that using conventional methods to study consumer food preferences in China leads to erroneous policy implications. This is of utmost importance, given the sheer size of the Chinese economy and its role in the world market.

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

Variable	Mean	Std. Dev.	Min	Max
Expenditure (Yuan/Capita)				
Meats	628.5	250.4	251.8	1548.6
Seafood	205.4	186.5	36.4	954.0
Vegetables	314.1	89.7	156.0	571.1
Fruits	241.9	83.1	111.5	562.6
Grains	264.0	54.6	157.3	417.2
Eggs	71.9	22.3	25.8	139.0
Fats and oils	105.0	36.7	43.5	232.2
Commodity Price Index (%)				
Meats	109.6	14.3	86.7	142.0
Seafood	106.2	7.3	93.0	131.6
Vegetables	109.2	9.7	78.9	139.8
Fruit	107.0	6.9	94.3	125.3
Grains	107.4	8.2	96.7	139.6
Eggs	106.6	9.7	91.8	128.9
Fats and oils	108.1	16.6	74.0	147.5
Price Instruments				
Disaster-affected areas (%)	52.1	12.7	15.2	87.8
Agricultural Input Price Index (%)				
Forage	107.0	7.3	86.9	129.0
Commodity animal products	112.4	24.9	71.3	196.6
Semi-mechanized farm tools	102.9	4.6	94.7	130.4
Mechanized farm machinery	102.4	4.5	83.2	122.2
Chemical fertilizer	107.9	12.2	81.0	145.8
Pesticide	102.6	4.3	92.3	129.7
Machinery oil	107.8	6.9	85.8	123.5
Other means of agricultural production	104.6	6.5	85.9	130.3
Per capita Income (1000 Yuan)	11.9	4.4	6.5	28.8

Source: Chinese Urban Household Income and Expenditure Survey, China Statistical Yearbooks, 2003–2009.

Table 2. Summary of the Model Diagnostic Tests

	Hypothesis	B_{LR} value	df.	p-value
	No Autocorrelation			
(i)	**Food commodities are not consumed in pre-committed quantities** ($t_j = 0, \forall j = 1,...,n$), that is, GAIDS and AIDS are equivalent	6.1	7	0.53
(ii)	**Engel curves are linear in the logarithm of total expenditure** ($\lambda_j = 0, \forall j = 1,...,n$), that is, QUAIDS and AIDS are equivalent	31.7	7	<0.01
(iii)	**Linear AIDS model**, that is, AIDS and LA/AIDS are equivalent	1435.4	35	<0.01
	With Autocorrelation			
(iv)	**Food commodities are not consumed in pre-committed quantities** ($t_j = 0, \forall j = 1,...,n$), that is, GAIDS and AIDS are equivalent	9.4	7	0.23
(v)	**Engel curves are linear in the logarithm of total expenditure** ($\lambda_j = 0, \forall j = 1,...,n$), that is, QUAIDS and AIDS are equivalent	16.9	7	0.02
(vi)	**Linear AIDS model**, that is, AIDS and LA/AIDS are equivalent	1348.9	35	<0.01

Note: 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 model.

Table 3. Parameter Estimates with Endogenous Price and Expenditure Equations: Share Equations

Parameter	Meats	Seafood	Vegetables	Fruit	Grains	Eggs	Fats
α_i	**0.394**	**0.083**	**0.188**	**0.172**	**0.088**	-0.004	**0.079**
	(0.048)	*(0.018)*	*(0.028)*	*(0.034)*	*(0.020)*	*(0.009)*	*(0.017)*
β_i	**0.011**	**-0.005**	**0.006**	-0.004	**-0.014**	0.001	**0.005**
	(0.004)	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*	*(0.001)*	*(0.002)*
λ_i	-0.007	**0.012**	0.007	0.003	**-0.008**	0.000	**-0.006**
	(0.007)	*(0.005)*	*(0.006)*	*(0.005)*	*(0.005)*	*(0.001)*	*(0.003)*
γ meats	-0.009	-0.002	**0.009**	**0.010**	**-0.022**	**0.018**	-0.004
	(0.009)	*(0.005)*	*(0.005)*	*(0.005)*	*(0.005)*	*(0.003)*	*(0.007)*
γ seafood		**-0.015**	**0.010**	**-0.008**	**0.014**	**-0.010**	**0.010**
		(0.006)	*(0.004)*	*(0.004)*	*(0.005)*	*(0.002)*	*(0.004)*
γ vegetables			-0.002	-0.003	-0.005	0.002	**-0.010**
			(0.005)	*(0.004)*	*(0.004)*	*(0.001)*	*(0.005)*
γ fruits				0.001	-0.006	0.000	0.005
				(0.005)	*(0.004)*	*(0.002)*	*(0.004)*
γ grains					**0.024**	0.002	-0.007
					(0.006)	*(0.002)*	*(0.005)*
γ eggs						0.001	**-0.013**
						(0.003)	*(0.002)*
γ fats/oils							**0.021**
							(0.009)
Autocorrelation coefficient (ρ_1)					**0.968**		
					(0.005)		

Note: The italicized numbers in parenthesis 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 4. Parameter Estimates from the Full Model with Endogenous Price and Expenditure

Reduced-form Price Equations										
Food	Intercept (κ_{i1})	Input1 (κ_{i2})	Input2 (κ_{i3})	Input3 (κ_{i4})	Input4 (κ_{i5})	Input5 (κ_{i6})	Input6 (κ_{i7})	Input7 (κ_{i8})	Input8 (κ_{i9})	Disast. (κ_{i10})
Meats	**0.014**	0.032	**0.192**	0.049	0.024	0.051	-0.007	-0.068	-0.040	0.008
	(0.005)	*(0.059)*	*(0.018)*	*(0.073)*	*(0.088)*	*(0.046)*	*(0.057)*	*(0.057)*	*(0.054)*	*(0.010)*
Seafd.	**0.006**	**0.126**	**0.029**	0.003	-0.054	**0.353**	-0.016	**-0.158**	**-0.113**	-0.010
	(0.003)	*(0.065)*	*(0.017)*	*(0.081)*	*(0.096)*	*(0.049)*	*(0.087)*	*(0.057)*	*(0.059)*	*(0.011)*
Veg.	**-0.014**	**-0.259**	**-0.043**	0.000	**0.546**	-0.035	0.209	**-0.277**	0.088	0.009
	(0.004)	*(0.095)*	*(0.026)*	*(0.117)*	*(0.141)*	*(0.072)*	*(0.127)*	*(0.084)*	*(0.087)*	*(0.017)*
Fruits	0.002	-0.086	-0.019	0.116	**0.225**	-0.060	-0.018	**0.244**	-0.040	0.020
	(0.003)	*(0.076)*	*(0.021)*	*(0.094)*	*(0.112)*	*(0.057)*	*(0.095)*	*(0.067)*	*(0.069)*	*(0.013)*
Grains	**0.007**	**0.537**	-0.016	**-0.307**	**-0.218**	**0.117**	**-0.177**	-0.114	**-0.219**	**-0.037**
	(0.003)	*(0.080)*	*(0.022)*	*(0.099)*	*(0.118)*	*(0.060)*	*(0.107)*	*(0.070)*	*(0.073)*	*(0.014)*
Eggs	**0.014**	**0.232**	**0.134**	-0.104	**-0.299**	-0.071	-0.100	**-0.212**	-0.063	**-0.019**
	(0.003)	*(0.061)*	*(0.017)*	*(0.074)*	*(0.090)*	*(0.047)*	*(0.080)*	*(0.055)*	*(0.055)*	*(0.011)*
Fats/oils	0.006	0.205	**0.059**	0.150	-0.099	**0.131**	-0.013	**0.265**	**-0.204**	0.011
	(0.008)	*(0.089)*	*(0.027)*	*(0.049)*	*(0.133)*	*(0.069)*	*(0.079)*	*(0.086)*	*(0.081)*	*(0.015)*
		Autocorrelation coefficient (ρ_3)					**-0.274**			
							0.024			

LHS Variable	Expenditure Equation			
Log(Expenditure)	(ρ_2)	Intercept (κ_{i1})	Ln(Income)	Ln(CPI)
	0.989	**5.918**	**0.300**	-0.009

	(0.012)	*(0.948)*	*(0.107)*	*(0.046)*

Note: The italicized numbers in parenthesis 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 5. Uncompensated Price, Expenditure, and Income Elasticity Estimates from the Full Model with Endogenous Price and Expenditure

	Meats	Seafood	Veg.	Fruits	Grains	Eggs	Fats/oils	**Expend.**	**Income**
Meats	**-1.038**	-0.008	**0.020**	0.024	**-0.068**	**0.053**	-0.016	**1.032**	**0.310**
	(0.025)	*(0.015)*	*(0.006)*	*(0.015)*	*(0.015)*	*(0.009)*	*(0.024)*	*(0.012)*	*(0.003)*
Seafood	0.000	**-1.144**	**0.111**	**-0.068**	**0.147**	**-0.100**	0.101	**0.953**	**0.286**
	(0.051)	*(0.060)*	*(0.039)*	*(0.039)*	*(0.045)*	*(0.022)*	*(0.075)*	*(0.026)*	*(0.008)*
Veg.	0.037	**0.055**	**-1.021**	-0.025	**-0.031**	0.009	**-0.060**	**1.035**	**0.311**
	(0.027)	*(0.020)*	*(0.032)*	*(0.022)*	*(0.001)*	*(0.008)*	*(0.004)*	*(0.021)*	*(0.009)*
Fruits	**0.087**	**-0.054**	-0.019	**-0.985**	-0.040	0.003	**0.038**	**0.969**	**0.291**
	(0.037)	*(0.029)*	*(0.031)*	*(0.038)*	*(0.031)*	*(0.014)*	*(0.009)*	*(0.021)*	*(0.010)*
Grains	**-0.109**	**0.101**	-0.015	-0.022	**-0.836**	0.013	**-0.041**	**0.908**	**0.272**
	(0.034)	*(0.030)*	*(0.027)*	*(0.028)*	*(0.039)*	*(0.015)*	*(0.001)*	*(0.021)*	*(0.005)*
Eggs	**0.426**	**-0.242**	0.035	0.006	**0.047**	**-0.966**	**-0.328**	**1.024**	**0.307**
	(0.072)	*(0.052)*	*(0.038)*	*(0.046)*	*(0.014)*	*(0.062)*	*(0.145)*	*(0.023)*	*(0.003)*
Fats/oils	-0.108	**0.159**	**-0.185**	**0.066**	-0.132	-0.229	**-0.654**	**1.084**	**0.325**
	(0.135)	*(0.027)*	*(0.030)*	*(0.033)*	*(0.105)*	*(0.102)*	*(0.047)*	*(0.033)*	*(0.014)*

Note: The italicized numbers in parenthesis 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. The first column represents commodities with price change.

Table 6. Compensated Elasticity Estimates from the Full Model with Endogenous Price and Expenditure

	Meats	Seafood	Veg.	Fruits	Grains	Eggs	Fats/oils
Meats	**-0.689**	**0.095**	**0.200**	**0.163**	**0.089**	**0.096**	**0.045**
	(0.026)	*(0.015)*	*(0.015)*	*(0.015)*	*(0.016)*	*(0.009)*	*(0.024)*
Seafood	**0.323**	**-1.049**	**0.277**	0.061	**0.292**	**-0.060**	**0.157**
	(0.051)	*(0.061)*	*(0.036)*	*(0.039)*	*(0.046)*	*(0.022)*	*(0.075)*
Veg.	**0.387**	**0.159**	**-0.840**	**0.114**	**0.127**	**0.052**	0.001
	(0.028)	*(0.021)*	*(0.030)*	*(0.022)*	*(0.022)*	*(0.009)*	*(0.044)*
Fruits	**0.416**	0.043	**0.150**	**-0.855**	**0.108**	**0.043**	0.095
	(0.037)	*(0.029)*	*(0.028)*	*(0.038)*	*(0.032)*	*(0.014)*	*(0.059)*
Grains	**0.199**	**0.192**	**0.144**	**0.100**	**-0.698**	**0.050**	0.013
	(0.034)	*(0.030)*	*(0.025)*	*(0.028)*	*(0.040)*	*(0.015)*	*(0.041)*
Eggs	**0.772**	**-0.140**	**0.213**	**0.144**	**0.203**	**-0.924**	**-0.268**
	(0.072)	*(0.053)*	*(0.036)*	*(0.046)*	*(0.054)*	*(0.063)*	*(0.145)*
Fats/oils	**0.259**	**0.267**	0.004	0.212	0.033	**-0.185**	**-0.591**
	(0.135)	*(0.127)*	*(0.130)*	*(0.133)*	*(0.106)*	*(0.102)*	*(0.057)*

Note: The italicized numbers in parenthesis 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. The first column represents commodities with price change.

Table 7. Percentage Difference between Elasticity Estimates from Models with Exogenous vs. Endogenous Prices (%)

Commodity	Uncompensated Elasticity							
	Meats	Seaf.	Veg.	Fruit	Grains	Eggs	Fats/oils	Exp.
Meats	**-15.4**	77.4	140.2	135.6	10.1	-3.5	720.0	4.2
Seaf.	99.9	**-13.8**	-7.5	-154.7	-75.0	-32.6	-156.9	2.7
Veg.	154.9	3.5	**-7.7**	145.5	761.7	259.3	29.9	-5.0
Fruit	180.5	-225.5	122.5	**-22.7**	14.1	71.4	207.4	-6.5
Grains	-7.3	-64.4	159.8	29.6	**-6.6**	149.0	-65.4	-2.8
Eggs	-2.0	-33.3	235.8	82.2	148.5	**-14.5**	-6.2	-2.3
Fats/oils	-10670.0	-194.1	34.0	155.7	-23.7	-5.9	**-40.4**	5.2

Note: The first column represents commodities with price change.

Table 8. Estimated Welfare Bias When Price Endogeneity is Ignored under Various Price Scenarios

Commodity	**Price change scenario (%)**							
	1	2	3	4	5	6	7	8
Meats	+15	+20	+20	+50	+40	+50	+50	+100
Seafood	-15	+20	-20	-40	-40	-50	+50	+100
Vegetables	+15	-20	+20	+30	+40	+50	+50	+100
Fruits	-15	-20	-20	-40	-40	-50	+50	+100
Grains	+15	-20	+20	+20	+40	+50	+50	+100
Eggs	-15	+20	-20	-20	-40	-50	+50	+100
Fats and oils	+15	+20	+20	+40	+40	+50	+50	+100
	1	2	3	4	5	6	7	8
Size of the bias ($ billion)	13.5	14.9	20.0	57.5	55.6	79.2	-23.7	-63.3

Footnotes

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[1] Refer to Hovhannisyan and Gould (2011) for a more detailed treatment of the GQUAIDS demand model and associated price and expenditure elasticity formulas.

[2] Because of the non-linear nature of the GQUAIDS demand model, the instrumental variables approach is not applicable in our setting.

[3] 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 agricultural input prices are not observed for this province.

[4] See Piggott et al. (1996) for an excellent discussion of this approach.

[5] 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.

[6] We perform individual t-tests of difference to evaluate whether these differences are statistically significant. The results from this procedure provide strong evidence that these differences are significant.

[7] Foreign trade in China increased more than 5-fold from 2001 to 2012, reaching $155.7 billion, and its import dependence doubled. Oilseed imports are expected to increase by 40% in the near

future, accounting for around 59% of global trade in oilseeds. The expanding livestock sector will generate much higher demand for coarse grains, given the OECD projection that China will become the world's leading consumer of pork on a per capita basis by 2020.