Staff Paper P13-5 **November 2013**

Staff Paper Series

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Vardges Hovhannisyan and Marin Bozic

Department of APPLIED ECONOMICS

College of Food, Agricultural and Natural Resource Sciences

UNIVERSITY OF MINNESOTA

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Vardges Hovhannisyan and Marin Bozic

Vardges Hovhannisyan is a Research Associate and Marin Bozic is Assistant Professor in the Department of Applied Economics, University of Minnesota.

ON PRICE ENDOGENEITY IN THE ANALYSIS OF FOOD DEMAND IN CHINA

Abstract: Price endogeneity has been ignored in previous analyses of food demand in China. We exploit farm price data collected from the China National Bureau of Statistics to account for price endogeneity using reduced form price equations. 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 substantial upward biased estimates of future food demand in China.

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

1. Introduction

With only eight percent of the world's arable land and close to a quarter of 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 has surpassed the U.S. in 2011 to become the top importer of agricultural goods (WTO, 2013). From 2005 to 2012, U.S. soybean exports to China nearly tripled, from 9.4 to 26.2 million metric tons which represents an increase to more than 60% of U.S. soybean exports and 30% of the soybean harvest (USDA 2013a; USDA 2013b).

In the light of these facts, 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. Fan, Cramer, and Wailes 1994; Huang and Rozelle 1998; Gould and Villareal 2006; Hovhannisyan and Gould 2011, 2013). A common characteristic of all these studies is that they ignore potential food price endogeneity. This has been driven mainly by the lack of data on food production costs that could be used to model food supply. In this study we use farm-level price data to account for food price endogeneity. Specifically, we incorporate reduced-form food supply relations into a structural framework of food demand, where farm prices play a crucial role in demand identification. We also account for total expenditure endogeneity as suggested by LaFrance (1991) and Thompson (2004). This is accomplished by including an expenditure reduced-form equation in our food demand system that incorporates provincial household demographic characteristics as determinants. We apply our method to the analysis of the structure of food demand in urban China using annual provincial-level panel data over the 2003-2009 period. Our findings provide strong statistical evidence of price and expenditure endogeneity

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

We find that ignoring price endogeneity results in significant upward bias in uncompensated own-price and income elasticities. For example, income elasticities for vegetables and fruit are overstated by 103.3 and 107.9 %, and own-price elasticities for seafood and fats are overstated by 53.9 and 79.5 %, respectively. The impact of these biases on long-term projection of food consumption is striking. Using the OECD projected income for China in the years 2020 and 2050, and the sets of income elasticities obtained under our two model specifications, we find that ignoring price endogeneity overstates meat, vegetable and grain consumption by \$129.7, \$66.8 and \$49.9 billion in 2020, and by \$1.1, \$0.6, \$0.4 trillion 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, with the size of the bias up to \$139.1 billion.

The paper proceeds as follows: Section 2 describes the methodological contributions of the study and provides an overview of our structural model. In Section 3 we provide a brief description of data underlying the analysis. This is followed by Section 4, which summarizes our econometric results. We discuss implications of our results for the assessment of future food demand in China in Section 5.

2. Methodology

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

2.1. The GQAIDS Demand Specification

The Almost Ideal Demand Systems (AIDS) specification of Deaton and Muellbauer (1980) has been a commonly used model in analysis of food demand. The original reason for adoption is that these systems offer the flexibility of a first-order approximation to an arbitrary demand system derived from the consumer utility maximization. We base the current analysis on the GQAIDS 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, and X total food expenditures. Assume we have the following indirect utility function (V) with underlying price independent logarithmic preferences (Bollino, 1987; Banks et al., 1997; Hovhannisyan and Gould, 2011):

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

where s is supernumerary expenditures ($s = X - \sum_i t_i \, p_i$) with t_i representing *pre-committed* demand (i.e., independent of expenditure and price effects), $\ln(P)$ and $b(p)$ are price indices where $\ln(P) = \alpha_0 + \sum_j \alpha_j \ln(p_j) + 0.5 \sum_i \sum_j \gamma_{ij} \ln(p_j)\ln(p_i)$ and $b(p) = \prod p_k^{\beta_k}$, respectively, $\lambda(\mathrm{p}) = \sum_i \lambda_i \ln(\mathrm{p}_i)$ is homogenous 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 (1):

$$(2) \qquad w_{ijt} = t_i \frac{p_{ijt}}{X_{jt}} + \frac{s_{jt}}{X_{jt}} \left\{ \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln(p_{ijt}) + \beta_i \ln\left(\frac{s_{jt}}{P_{ijt}}\right) + \frac{\lambda_i}{b(p_{ijt})} \left[\ln\left(\frac{s_{jt}}{P_{ijt}}\right) \right]^2 \right\} + u_{ijt}$$

where w_{ijt} is the budget share of product i (i.e., $p_{ijt}q_{ijt} / X_{jt}$) in province j at time t, and u_{ijt} represents unobserved demand shifters with certain statistical properties discussed later on.

The demand functions represented by (2) satisfy Engel aggregation, Slutsky symmetry restrictions, and are homogenous of degree zero in prices and expenditures with the imposition of the following restrictions:

$$(3) \qquad \sum_i \alpha_i = 1,\ \sum_i \beta_i = 0, \sum_i \gamma_{ij} = 0,\ \forall j = 1,...,n, \text{and}\ \gamma_{ij} = \gamma_{ji},\ \forall j \neq i$$

Various demand specifications can be obtained from the GQAIDS framework through respective parameter restrictions. The AIDS model is obtained via the joint restrictions of: $\lambda_i = 0,\ t_i = 0, \forall i = 1,...,n$. The Generalized AIDS (GAIDS) originally developed by Bollino (1997) is obtained by the assumption that $\lambda_i = 0, \forall i = 1,...,n$. The Quadratic AIDS (QAIDS) specification is obtained from the restriction that $t_i = 0, \forall i = 1,...,n$.[1]

2.2. Price and Expenditure Endogeneity in Demand Analyses

Food demand models that do not include determinants of food supply implicitly assume price changes are exogenous. In such models, the identification of demand parameters rests on the assumption that all observed price variations are due to unobserved supply shocks. However, it is unlikely that consumer behavior can be completely captured using only observed determinants of demand. Therefore, observed price shocks are likely due to both demand and supply shocks. Unless supply functions are properly modeled, it is not possible to identify the source of a price shock. This results in an endogeneity bias. Elasticity estimates obtained from models that ignore food price endogeneity will likely lead to erroneous policy advices and biased forecasts of future food demand (Dhar, Chavas and Gould, 2003). Furthermore, it deserves noting that food prices should be considered endogenous with no regard to the level of aggregation at which the analyses are performed. Specifically, even at a very disaggregate-level analysis, consumer responsiveness to supplier promotional actions sets up price endogeneity. However, the problem may be more pervasive at the macro-level analyses, such as the current study (Dhar, Chavas and Gould, 2003).

To account for price endogeneity, we incorporate the procedure outlined by Dhar, Chavas and Gould (2003), where a reduced-form price equation is incorporated into the GQAIDS demand system:

$$p_{ijt} = \kappa_{i1} + \kappa_{i2} T_{it} + \kappa_{i3} q_{ijt} + \kappa_{i4} p_{ijt}^F + \iota_{ijt} \tag{4}$$

where T_{it} captures time trend in commodity price, q_{ijt} and p_{ijt}^F are the quantity and farm price of commodity i in province j in time period t, $\kappa_{im}, m = 1,..,4$ are parameters, and ι_{ijt} represents unobserved supply shocks with statistical properties specified in the empirical discussion. Identifying supply shifters that are inherently exogenous to the unobserved demand determinants is a crucial task in empirical demand studies. This is especially true for the developing world and particularly China, provided that province and commodity-level cost data are usually unobserved. The lack of cost data underlies the motivation behind the Hausman and Taylor's (1981) approach to treating price endogeneity. In their analysis, they use prices from neighboring geographic districts as the instruments for prices in a given city-market. Their approach for accounting price endogeneity rests on a key assumption that the neighboring regions have the same cost specification, while demand idiosyncrasies are independent across markets. Nevertheless, prices may also reflect demand shocks that are common across markets, and thus are not valid instruments.

We use an alternative approach by adopting a full information maximum likelihood (FIML) estimation procedure to account for the true nature of simultaneity between supply and demand (e.g., Kadiyali, Vilcussim, and Chintagunta, 1996).[2] The efficiency and consistency of parameter estimates in the FIML framework are immune to the choice of instruments. This is unlike the standard instrumental variable approach, where the choice of instruments is not an easy task in non-linear demand systems, such as the GQAIDS model used here (Hayashi, p. 482).

An important consideration in empirical food demand analysis is whether total food expenditure is endogenous to the food purchase process. Given our focus on a group of food commodities, under the separability assumption, food expenditures are endogenous since, unlike income, expenditures are determined along with food quantities/prices (LaFrance, 1991). A number of previous food demand analyses provide empirical evidence for expenditure endogeneity (e.g., Dhar et al., 2003; Thompson, 2004; Hovhannisyan and Gould, 2011). We accommodate expenditure endogeneity via the following reduced-form equation:

(5) $$\log\left(X_{jt}\right) = \varphi_1 + \varphi_2 \log\left(\mathrm{I}_{jt}\right) + \varphi_3 HS_{jt} + \varphi_4 CPI_{jt} + \tau_{jt}$$

where I_{jt} is per-capita average annual income, HS_{jt} is average household size, CPI_{jt} is consumer price index in province j in year t, and τ_{jt} represents unobserved determinants of total expenditures whose statistical properties are presented in the empirical framework.

This approach allows for the accounting of the effects of changes in prices of products outside the system (φ_4), as well as those of consumer income (φ_2) and household size (φ_3) on the food demand system (Thompson, 2004).

Our choice of the expenditure function in equation (5) is motivated by the fact that it facilitates 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 independence assumption between ξ_i and φ_2, which may be overly restrictive in practice (e.g., Chern et al., 2004). We, therefore, compute the standard errors of income elasticities (η_i^I) via the delta method allowing for unrestricted covariance between ξ_i and φ_2.

2.3. 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 consists in evaluating the statistical difference between parameter estimates 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:

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

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

2.4. The GQAIDS Elasticities and Consumer Welfare Evaluation Procedure

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

$$\xi_i = 1 + \frac{1}{w_i}\left[\beta_i + \frac{2\lambda_i}{b(p)}L^2 - M_i + \frac{\sum t_k p_k}{X}\left(A_i + \beta_i L + \frac{\lambda_i}{b(p)}L^2\right)\right] \tag{7}$$

$$\begin{aligned}\varepsilon_{ij}^{M} &= \frac{1}{w_i}\left[\delta_{ij}M_i - M_j\left(A_i + \beta_i L + \frac{\lambda_i}{b(p)}L^2\right) + \right. \\ &\left.\frac{s}{X}\left(\gamma_{ij} - \beta_i\left(A_j + S_j\right) - \frac{\lambda_i\beta_j}{\prod p_k^{\beta_k}}L^2 - 2\frac{\lambda_i}{b(p)}\left(S_j L + A_j\left[\ln(\mathrm{s}) + \ln(\mathrm{P})\right]\right)\right)\right]\end{aligned} \tag{8}$$

$$\varepsilon_{ij}^{H} = \varepsilon_{ij}^{M} + \xi_i w_j \tag{9}$$

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

The welfare impacts discussed below are based on the Hicksian compensating variation (CV), which avoids the assumption of constant marginal utility of income encountered in uncompensated demand models. Let $E(p,u)$ denote the minimum expenditure necessary to obtain utility u at a given price vector, p. Furthermore, assume that the initial price and utility levels are represented by p_0 and u_0, respectively, and p_1 is a new price vector. The CV is used to measure the change in consumer expenditure necessary to compensate consumers for a given price change, such that utility remains at the initial level, u_0 (Huang, 1993):

(10) $$CV = E(p_1, u_0) - E(p_0, u_0) = p_1 q^h(p_1, u_0) - p_0 q_0(p_0, u_0)$$

where $q^h(p_1, u_0)$ is compensated (Hicksian) demand evaluated at a given price vector p_1 and initial utility level, u_0. A positive CV estimate indicates a decline in consumer welfare, as the initial utility level can now be achieved only at higher cost, while a negative CV estimate is indicative of welfare gain.

Let $dp = p_1 - p_0$ be a vector of price changes and $dq^h = q^h(p_1, u_0) - q_0(p_0, u_0)$ be a vector of compensated quantity changes. Substituting the above into (10) yields the following expression for the CV:

(11) $$CV = p_1 dq^h + dp\, q_0(p_0, \mu_0)$$

Finally, we estimate the impacts on compensated quantities (dq^h) using estimated compensated elasticities (ε_{ij}^H) provided by (9); which is subsequently used to compute the CV via (11):

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

3. Description of Province-Level Panel Data

We base our study on annual expenditure survey data obtained from the China National Bureau of Statistics (CNBS). We limit our focus to 30 geographic divisions in urban China, to sidestep potential identification issues stemming from home production of food in rural China.[3] Our sample period extends from 2003 to 2009 (Chinese Urban Household Income and Expenditure

Survey, China Statistical Yearbooks, 2003-2009). Dong and Fuller (2010) provide more details on the sampling procedure and data collection concerning the data used in this analysis.

We use separate per capita expenditure values for the food groupings used in our demand system and associated food type-specific price indices. We exploit farm price index data to account for price endogeneity via construction of reduced-form supply relations as discussed earlier. Moreover, we control for expenditure endogeneity utilizing provincial-level data on per capita household income, household size and CPI.

The descriptive statistics of the main variables used in this analysis are presented in Table 1. Per capita expenditures on various meat types (i.e., beef, lamb, poultry, pork and other) account for 34.3 % of the total group expenditures over the study period, which is followed by expenditures on vegetables (17.2 %), grains (14.4 %), and fruit (13.2 %). As documented in other similar studies [see for example, Hovhannisyan and Gould (2011)], seafood is an important part of modern Chinese diet (11.2 %). There is a large variation in seafood consumption across districts with coastal area communities consuming seafood in larger amounts.

As regards the commodity price indices, the most volatile pattern over the period in question is manifested by meats, seafood, and eggs, with the respective coefficients of variation (COV) being 15.34, 13.04, and 9.10. Average farm price indices, on the other hand, also demonstrate a rather volatile pattern, with those for fats and oils, meats, and eggs equaling 17.52, 12.57, and 10.93, respectively.

Urban China manifests a large heterogeneity in terms of consumer income, with the coastal provinces and cities having relatively high income levels compared to their inland counterparts. For example, in 2003 per-capita income in Ningxia province was only 6,530.5 Yuan as opposed to 14,867.5 Yuan in Shanghai. The less wealthy provinces also happen to have larger household size. For instance, in year 2004, the average household size in Hainan was 4.16 people, compared to only 2.79 people in Beijing.

4. Application of the Food Demand System to Urban China

4.1. Econometric Issues

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

$$\begin{pmatrix} u_{it} \\ \iota_{it} \\ \tau_{it} \end{pmatrix} = \rho \begin{pmatrix} u_{it-1} \\ \iota_{it-1} \\ \tau_{it-1} \end{pmatrix} + \begin{pmatrix} u_{it}^{o} \\ \iota_{it}^{o} \\ \tau_{it}^{o} \end{pmatrix} \tag{13}$$

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

We consider the following autocorrelation structures represented by the R matrix:[4] (i) a full R matrix with $R_{ij} \neq 0, \forall i, j = 1,\ldots, N^E$ 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 previous literature, the full R matrix is not identified for our demand system. We, therefore, embrace the Berndt and Savin (1975) approach to evaluating the $\overline{R}^*$ matrix that comprises the first n-1 rows of the $\overline{R}$ matrix (with respective elements given as $\overline{R}_{ij} = R_{ij} - R_{in}, \forall i = 1,..., N^E$ 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 (14), reduced-form price (15), and expenditure equations (16):

$$
\begin{aligned}
w_{ijt} = {} & \rho w_{ijt-1} + t_i \frac{p_{ijt}}{X_{jt}} + \frac{s_{jt}}{X_{jt}} \left\{ \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln(p_{ijt}) + \beta_i \ln\left(\frac{s_{jt}}{P_{ijt}}\right) + \frac{\lambda_i}{b(p_{ijt})} \left[\ln\left(\frac{s_{jt}}{P_{ijt}}\right) \right]^2 \right\} - \\
& \rho \left[t_i \frac{p_{ijt-1}}{X_{jt-1}} + \frac{s_{jt-1}}{X_{jt-1}} \left\{ \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln(p_{ijt-1}) + \beta_i \ln\left(\frac{s_{jt-1}}{P_{ijt-1}}\right) + \frac{\lambda_i}{b(p_{ijt-1})} \left[\ln\left(\frac{s_{jt-1}}{P_{ijt-1}}\right) \right]^2 \right\} \right] + u_{ijt}^o
\end{aligned}
\tag{14}
$$

$$
\begin{aligned}
p_{ijt} = {} & \rho p_{ijt-1} + \kappa_{i1} + \kappa_{i2} T_{it} + \kappa_{i3} q_{ijt} + \kappa_{i4} p_{ijt}^F \\
& - \rho \left[\kappa_{i1} + \kappa_{i2} T_{it-1} + \kappa_{i3} q_{ijt-1} + \kappa_{i4} p_{ijt-1}^F \right] + \iota_{ijt}^o
\end{aligned}
\tag{15}
$$

$$
\begin{aligned}
\log\left(X_{jt}\right) = {} & \rho \log\left(X_{jt-1}\right) + \varphi_1 + \varphi_2 \log\left(\mathrm{I}_{jt}\right) + \varphi_3 HS_{jt} + \varphi_4 CPI_{jt} \\
& - \rho \left[\varphi_1 + \varphi_2 \log\left(\mathrm{I}_{jt-1}\right) + \varphi_3 HS_{jt-1} + \varphi_4 CPI_{jt-1} \right] + \tau_{jt}^o
\end{aligned}
\tag{16}
$$

4.2. 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 perform model comparisons via the Bewley likelihood ratio (B_{LR}) test procedure.[5] The outcomes from this procedure indicate that the GQAIDS provides the best fit of the data (Table 2). We find empirical support for pre-committed quantities (t_i) in urban China, and Engel curves are found to be nonlinear (i.e., budget shares are nonlinear functions of the logarithm of total expenditure). These results are consistent with previous literature (e.g., Hovhannisyan and Gould, 2011). We base our further analysis on the GQAIDS model, given its empirical superiority over the more restrictive specifications.

The full model, comprising demand (14), price (15) and expenditure functions (16) is estimated under theoretical restrictions (3). We further allow for cross-equation contemporaneous correlation and embrace AR (1) error structure with three autocorrelation structures (R) estimated as discussed above. The B_{LR} 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 statistically insignificant ($p - value < 0.01$).

Estimation results from the full model with the underlying diagonal R matrix are presented in Tables 3 and 4. The model provides a good fit of the data with the vast majority of the 90 parameters being statistically significant at standard significance levels. This is further supported by the outcome of the overall significance test ($p - value < 0.01$). The autocorrelation coefficient is very close to 1 (i.e., $\rho = 0.99$), which is consistent with findings from Hovhannisyan and Gould (2013) which used a similar dataset for food demand estimation.

A majority of the coefficients in the price and expenditure equations are significant and of expected sign. For example, the amount of food commodities available in markets affect food price adversely. We also estimate an overall positive trend in food prices that may be a result of rising incomes in urban China. Importantly, farm prices are found to have a positive significant impact on food prices for seafood, fruit, eggs, and fats, while the coefficient is insignificant for the rest of the commodities.

Income has a positive significant impact on expenditures, with an estimated income elasticity of total food expenditures (i.e., φ_2) to be 0.179, which is also statistically significant . Household size appears to not be an important consideration when deciding on food expenditures. This may be on the account of little variation in the household size in China in as a result of one child requirement. Finally, CPI has an adverse effect on expenditures; which implies that consumers respond to price increases by cutting back on purchase amounts that more than compensate the price effect.

Uncompensated (ε^M), compensated price (ε^H), expenditure elasticities (ξ), and income elasticities (η^I) are computed via equations (7)--(9) and the respective estimates are presented in Tables 5 and 6. In general, estimates are statistically significant. Uncompensated own-price elasticities are more than unitary elastic ranging from -1.919 for seafood to -1.080 for fats and oils. Expenditure elasticity is the highest for seafood (1.235), followed by meats (1.053). Vegetables and fruit have an identical estimate (0.969), and eggs are found to have the lowest expenditure elasticity (0.806). Income elasticities fall in the range of 0.144 to 0.221, 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 performed 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 endogeneity, expenditure endogeneity, and joint price and expenditure endogeneity given a $p-value < 0.01$ for all three tests. These findings are in accord with results from Dhar, Chavas, and Gould (2003) in the analysis of U.S. beverage consumption, Thompson (2004) in a study of Japanese meat consumption, and Hovhannisyan and Gould (2011) in an examination of food demand in China.

Quantifying Price Endogeneity Bias

The present study is the first attempt at documenting price endogeneity in Chinese food demand analyses stemming from supply and demand simultaneity, while expenditure endogeneity has received due attention in the previous literature. Therefore, in what follows, we concentrate on the price endogeneity bias. We quantify the bias in economic effects using a formula offered by LaFrance (1993). More specifically, we compute absolute percentage difference between the respective sets of elasticity estimates under exogenous and endogenous price regimes as follows:

(17) $$\Delta_{EL} = \frac{100\left|\varsigma^{Exog} - \varsigma^{Endog}\right|}{0.5\left|\varsigma^{Exog} + \varsigma^{Endog}\right|}$$

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 an empirical evidence of price endogeneity carrying a significant impact on elasticity estimates (Table 7).[6] Overall, price endogeneity is found to cause an upward bias in estimates of uncompensated and compensated own-price, as well as expenditure and income elasticities. For example, the size of the bias in uncompensated own-price elasticities ranges from 28.7 % for vegetables to 79.5 % for fats and oils. Importantly, this magnitude is found to be appreciably higher in income elasticities that extend from 64.6 % for fats to 107.9 % for fruit. It should also be mentioned that as regards the magnitude the resulting cross-price elasticities are affected the most by the price endogeneity. For example, the cross-price elasticity between fats and seafood changes by a factor of 11, when price endogeneity is taken into account.

In this study, we also use counter-factual simulation analysis based on our elasticity estimates as presented in section (2.4), to identify the bias in the estimated impact of possible price change scenarios on consumer welfare as represented by CV values calculated using both sets of parameters (Table 8). We find a large difference in the implied welfare change for the majority of eight scenarios considered. Ignoring price endogeneity tends to understate the impact of rising food prices on consumer welfare while overstating the impact of declining food prices. The magnitude of the price endogeneity bias in estimated welfare change reaches up to $139.1 billion for the eight price change scenarios considered. It should be noted, nevertheless, that this simulation exercise should not be considered a complete policy analysis. It rather represents a demonstrative tool to delineate the importance of modeling assumptions such as price exogeneity to implications and predictions of the model.

As a final exercise we evaluate the impact of bias in income elasticities on long-term projections of consumption of different food commodities in China. Using the OECD projected income for China in the years 2020 and 2050, and the sets of income elasticities obtained under our two model specifications, we find that ignoring price endogeneity overstates meat, vegetable and grain consumption by $129.7, $66.8 and $49.9 billion in 2020, and by $1.1, $0.6, $0.4 trillion in 2050, respectively. The major finding emerging from this study is that using conventional methods to studying 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.

5. Conclusions

Given China's importance for world agricultural trade, considerable research efforts has been devoted to understanding the structure and dynamics of food demand in China. However, previous literature on food demand in China suffered from significant flaws. Specifically, price endogeneity has long been ignored driven by 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 farm 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 identification of demand. We further account for expenditure endogeneity, which remains an important issue in empirical demand studies. This is achieved by including an expenditure reduced-form equation, where use is made of household demographic characteristics.

We apply our method to the analysis of the structure of food demand in urban China based on province-level panel data. 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 upward bias in uncompensated own-price and income elasticities. For example, income elasticities for vegetables and fruit are overstated by 103.3 and 107.9 %, and own-price elasticities for seafood and fats are overstated by 53.9 and 79.5 %, respectively. The impact of bias on long-term projection of food consumption is considerable. Using the OECD projected income for China in the years 2020 and 2060, and the sets of income elasticities obtained under our two model specifications, we find that ignoring price endogeneity overstates meat, vegetable and grain consumption by \$129.7, \$66.8 and \$49.9 billion in 2020, and by \$1.1, \$0.6, \$0.4 trillion 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, with the size of the bias up to $139.1 billion.

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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
Fruit	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	105.0	36.7	43.5	232.2
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	108.1	16.6	74.0	147.5
Farm Price Index (%)				
Meats	108.4	13.6	80.5	143.9
Seafood	105.6	8.6	75.9	158.7
Vegetables	107.7	8.0	73.7	145.3
Fruit	104.3	9.4	65.6	128.2
Grains	108.0	10.8	90.0	184.3
Eggs	107.3	11.7	87.4	227.6
Fats	109.9	19.3	74.2	296.9
Per capita Income (1000 Yuan)	11.9	4.4	6.5	28.8
Household size	3.3	0.3	2.5	4.2

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
(i)	**No pre-committed quantities** ($t_j = 0, \forall j = 1,...,n$), i.e., GQAIDS and QAIDS are equivalent	1734	7	<0.01
(ii)	**Linear Engel curves in logarithmic expenditures** ($\lambda_j = 0, \forall j = 1,...,n$), i.e., GQAIDS and GAIDS are equivalent	2341	7	<0.01
(iii)	**No pre-committed quantities and linear Engel Curves in log expenditures** ($t_j = \lambda_j = 0, \forall j = 1,...,n$), i.e., GQAIDS and AIDS are equivalent	5668	14	<0.01
(iv)	**No pre-committed quantities, linear Engel Curves in log expenditures and Stone Price Index** ($t_j = \lambda_j = 0, \forall j = 1,...,n$), i.e., GQAIDS and LA/AIDS are equivalent	10,352	35	<0.01

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

Parameter	Meats	Seafood	Vegetables	Fruit	Grains	Eggs	Fats
t_i	**-0.008**	0.003	0.000	0.000	**0.003**	**0.003**	**-0.499**
	(0.003)	*(0.003)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.198)*
λ_i	**-0.030**	**0.024**	**0.013**	-0.001	**0.005**	-0.001	**-0.010**
	(0.014)	*(0.012)*	*(0.006)*	*(0.005)*	*(0.002)*	*(0.002)*	*(0.001)*
α_i	**-0.020**	0.014	**0.015**	-0.004	0.001	-0.002	**0.996**
	(0.010)	*(0.009)*	*(0.007)*	*(0.004)*	*(0.003)*	*(0.002)*	*(0.180)*
β_i	**-0.061**	**0.051**	**0.026**	-0.004	0.007	0.000	-0.018
	(0.021)	*(0.017)*	*(0.013)*	*(0.011)*	*(0.008)*	*(0.005)*	*(0.164)*
γ meats	**-0.014**	**0.008**	**0.008**	**0.002**	0.001	0.001	-0.007
	(0.007)	*(0.003)*	*(0.003)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.004)*
γ seafood		**-0.026**	**0.002**	**0.004**	**0.004**	**0.001**	**0.007**
		(0.008)	*(0.001)*	*(0.001)*	*(0.001)*	*(0.000)*	*(0.003)*
γ vegetables			**-0.013**	0.000	**0.002**	0.001	-0.001
			(0.005)	*(0.001)*	*(0.001)*	*(0.001)*	*(0.002)*
γ fruit				**-0.011**	0.001	**0.001**	0.002
				(0.004)	*(0.001)*	*(0.000)*	*(0.002)*
γ grains					**-0.009**	0.001	0.000
					(0.003)	*(0.001)*	*(0.001)*
γ eggs						**-0.006**	0.001
						(0.002)	*(0.001)*
γ fats							-0.003
							(0.754)
ρ							**0.998**
							(0.001)

Note: The numbers in parenthesis and italicized are the estimated parameter standard errors. Values in bold identify elasticity estimates statistically different from 0 at the 0.05 or lower significance levels.

Table 4. Parameter Estimates from the Full Model with Endogenous Price and Expenditure

Commodity	**Commodity Supply Equations**			
	Intercept(κ_{i1})	Trend(κ_{i2})	Quantity(κ_{i3})	Farm Price(κ_{i4})
Meats	-0.036	0.359	**-0.104**	0.238
	(0.023)	*(0.224)*	*(0.004)*	*(0.213)*
Seafood	-0.008	0.086	**-0.152**	**0.280**
	(0.015)	*(0.146)*	*(0.010)*	*(0.129)*
Vegetables	**-0.058**	**0.576**	**-0.255**	0.175
	(0.027)	*(0.264)*	*(0.007)*	*(0.157)*
Fruit	-0.039	0.391	**-0.282**	**1.113**
	(0.021)	*(0.207)*	*(0.011)*	*(0.164)*
Grains	**-0.054**	**0.542**	**-0.342**	-0.066
	(0.026)	*(0.258)*	*(0.010)*	*(0.230)*
Eggs	**-0.056**	**0.557**	**-1.120**	**0.718**
	(0.029)	*(0.288)*	*(0.045)*	*(0.175)*
Fats	-0.016	0.163	**-0.690**	**0.359**
	(0.024)	*(0.240)*	*(0.031)*	*(0.124)*
Explained Variable	**Expenditure Equation**			
Log(Expenditure)	Intercept(φ_1)	Log(Income) (φ_2)	HH Size	CPI
	5.952	**0.179**	0.003	**-0.393**
	(2.252)	*(0.067)*	*(0.016)*	*(0.031)*

Note: The numbers in parenthesis and italicized are the estimated parameter standard errors. Values in bold identify elasticity estimates statistically different from 0 at the 0.05 or lower significance levels.

Table 5. Uncompensated Price, Expenditure, and Income Elasticity Estimates from the Full Model with Endogenous Price and Expenditure

	Meats	Seafood	Veg.	Fruit	Grains	Eggs	Fats	**Expend.**	**Income**
Meats	**-1.317**	**0.111**	**0.104**	**0.027**	**0.013**	**0.014**	-0.004	**1.053**	**0.188**
	(0.077)	*(0.031)*	*(0.029)*	*(0.009)*	*(0.005)*	*(0.005)*	*(0.019)*	*(0.023)*	*(0.072)*
Seafood	**0.371**	**-1.919**	**0.070**	**0.162**	**0.136**	**0.035**	**-0.090**	**1.235**	**0.221**
	(0.104)	*(0.319)*	*(0.034)*	*(0.050)*	*(0.042)*	*(0.010)*	*(0.044)*	*(0.049)*	*(0.084)*
Vegetables	**0.202**	**0.040**	**-1.309**	**0.009**	**0.037**	**0.030**	0.022	**0.969**	**0.173**
	(0.055)	*(0.020)*	*(0.099)*	*(0.005)*	*(0.012)*	*(0.009*	*(0.020)*	*(0.029)*	*(0.065)*
Fruit	**0.067**	**0.119**	**0.011**	**-1.329**	**0.032**	**0.031**	**0.100**	**0.969**	**0.173**
	(0.021)	*(0.037)*	*(0.006)*	*(0.113)*	*(0.010)*	*(0.009)*	*(0.020)*	*(0.032)*	*(0.065)*
Grains	**0.029**	**0.088**	**0.042**	**0.028**	**-1.123**	**0.023**	0.020	**0.893**	**0.160**
	(0.010)	*(0.028)*	*(0.014)*	*(0.008)*	*(0.076)*	*(0.007)*	*(0.016)*	*(0.025)*	*(0.060)*
Eggs	**0.117**	**0.083**	**0.127**	**0.100**	**0.084**	**-1.186**	**-0.130**	**0.806**	**0.144**
	(0.039)	*(0.025)*	*(0.038)*	*(0.030)*	*(0.025)*	*(0.178)*	*(0.039)*	*(0.045)*	*(0.055)*
Fats	0.288	0.249	**-0.026**	**0.156**	**-0.228**	**-0.229**	**-1.080**	**0.871**	**0.156**
	(0.209)	*(0.135)*	*(0.097)*	*(0.079)*	*(0.095)*	*(0.048)*	*(0.036)*	*(0.313)*	*(0.010)*

Note: The numbers in parenthesis and italicized are the estimated parameter standard error. Values in bold identify elasticity estimates statistically different from 0 at the 0.05 or lower significance levels.

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

	Meats	Seafood	Veg.	Fruit	Grains	Eggs	Fats
Meats	**-0.961**	**0.216**	**0.288**	**0.168**	**0.173**	**0.058**	**0.058**
	(0.076)	*(0.031)*	*(0.028)*	*(0.009)*	*(0.006)*	*(0.005)*	*(0.019)*
Seafood	**0.789**	**-1.796**	**0.285**	**0.328**	**0.324**	**0.086**	-0.017
	(0.107)	*(0.318)*	*(0.035)*	*(0.051)*	*(0.043)*	*(0.011)*	*(0.044)*
Vegetables	**0.530**	**0.136**	**-1.139**	**0.139**	**0.185**	**0.070**	**0.079**
	(0.057)	*(0.020)*	*(0.098)*	*(0.006)*	*(0.013)*	*(0.009)*	*(0.020)*
Fruit	**0.395**	**0.216**	**0.181**	**-1.199**	**0.179**	**0.071**	**0.157**
	(0.025)	*(0.038)*	*(0.008)*	*(0.112)*	*(0.011)*	*(0.009)*	*(0.020)*
Grains	**0.331**	**0.177**	**0.198**	**0.148**	**-0.986**	**0.060**	**0.072**
	(0.014)	*(0.028)*	*(0.014)*	*(0.009)*	*(0.075)*	*(0.007)*	*(0.015)*
Eggs	**0.390**	**0.163**	**0.268**	**0.208**	**0.207**	**-1.153**	**-0.083**
	(0.042)	*(0.025)*	*(0.038)*	*(0.030)*	*(0.025)*	*(0.177)*	*(0.039)*
Fats	**0.583**	0.335	0.126	**0.273**	-0.095	**-0.193**	**-1.029**
	(0.391)	*(0.822)*	*(0.280)*	*(0.005)*	*(0.151)*	*(0.018)*	*(0.056)*

Note: The numbers in parenthesis and italicized are the estimated parameter standard error. Values in bold identify elasticity estimates statistically different from 0 at the 0.05 or lower significance levels.

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

Commodity	Uncompensated Elasticity								
	Meats	Seaf.	Veg.	Fruit	Grains	Eggs	Fats	Exp.	Income
Meats	41.1	502.4	389.2	902.0	273.0	88.3	144.7	0.7	95.2
Seafood	513.9	53.9	2.0	166.9	41.2	3493.0	11387.5	17.0	80.9
Vegetables	393.1	0.5	28.7	186.7	10.0	63.7	282.6	11.4	103.3
Fruit	880.9	164.6	173.8	36.2	945.9	18.8	1454.1	17.8	107.9
Grains	275.5	40.9	13.6	875.6	37.2	779.7	129.5	5.2	90.6
Eggs	88.5	2432.4	63.8	20.7	729.8	48.2	20.9	23.0	75.7
Fats	27.3	9.4	131.5	84.6	36.8	46.0	79.5	35.4	64.6

Commodity	Compensated Elasticity						
	Meats	Seaf	Veg.	Fruit	Grains	Eggs	Fats
Meats	61.4	115.0	61.8	49.9	74.3	32.9	40.2
Seafood	122.5	56.9	13.1	71.8	26.5	185.3	249.4
Vegetables	54.9	8.2	36.2	5.1	7.5	14.9	2092.8
Fruit	32.0	51.7	11.7	44.0	33.5	18.2	472.1
Grains	104.2	21.4	6.9	71.7	42.4	225.6	65.7
Eggs	28.5	303.4	40.7	0.3	327.7	49.0	38.9
Fats	31.3	15.6	282.6	61.2	38.7	55.3	82.1

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
Meat products	0	+20	+5	+5	-20	-30	-50	0
Fish	0	+20	+10	+5	-20	-30	-50	-50
Vegetables	0	+20	+15	+10	-20	-30	-50	0
Fruit	0	+20	+20	+10	-20	-30	-50	0
Grains	0	+20	+25	+15	-20	-30	-50	0
Eggs	0	+20	+30	+15	-20	-30	-50	+50
Fat and oil	+10	+20	+35	+20	-20	-30	-50	0
	1	2	3	4	5	6	7	8
Size of the bias ($ billion)	58.2	62.4	66.9	139.1	41.6	-54.6	-65.0	-122.9

Footnotes

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

[2] Due to the non-linear nature of the GQAIDS demand model, instrumental variables approach is inapplicable in our setting

[3] The cities, regions and provinces used in this study are Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang. Tibet is excluded from the analysis, given that farm prices are unobserved 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). $B_{LR} \sim \chi^2(g)$ distribution asymptotically, with degrees of freedom (g) equaling 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 a strong evidence of these differences being significant.