STRUCTURAL CHANGE IN CHINESE FOOD PREFERENCES

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Abstract

The article tests for structural food preference change in urban China using province-level panel data from 2002 to 2010. We employ the Generalized Quadratic Almost Ideal Demand System to represent consumer preferences and estimate demand for seven food groups in a dynamic setting. This relaxes many of the restrictions on the demand models used in the literature on structural preference change. Our findings suggest that Chinese food preferences are continuing to evolve.

Keywords: Food preference, structural change, dynamic GQAIDS model, food demand in China.

1 Introduction

It has been well documented in many studies that Chinese consumers have undergone major changes in their food consumption patterns in the face of vast changes relating to their economic and demographic circumstances (e.g. Hsu et al. 2001; Ma et al. 2006; Hovhannisyan and Gould 2011). China has been a vibrant market with a great potential to continue its remarkable growth that will have major implications for further developments in food preferences. Given the crucial role China plays globally, it is important not only to quantify the recent changes in various demand components but also the relative importance of economic and non-economic factors in shaping these preferences. From the policy perspective, though, it is essential to to get a sense for whether the observed changes in the pattern of Chinese food consumption are reflective of structural shifts in food preferences or just the fact of consumers responding to variations in economic factors under stable preferences (Dong and Fuller 2010).

Preference changes may be either demand driven (e.g. changing demographic composition or consumers responding to health information) or supply driven (e.g. marketing campaigns designed by suppliers to affect consumer preferences). The literature on consumer preference change comprises both parametric and non-parametric methods. The latter approach largely consists in testing data for consistency with axioms of revealed preference (i.e., the generalized axiom of revealed preference, the strong axiom of revealed preference and the weak axiom of revealed preference), homotheticity of preferences and weak separability (Varian 1982). Specifically, a finding of data being consistent with these axioms has been interpreted as an evidence of stable preferences. Similarly, data not supportive of revealed preferences may point towards potential preference change. Alston and Chalfant (1992) present an excellent review of this approach and illustrate the relevant details in an application to the Australian meat demand. Dong and Fuller (2010) apply this framework to the Chinese market and find that food preferences underwent some transition from traditional to western diets following the early reforms at the beginning of 1980s. It deserves mentioning that studies using the non-parametric method rarely find data inconsistency with the above axioms especially when time-series data are used in the analysis (Okrent and Alston 2011).

The parametric approach, on the other hand, relied upon specifying certain functional forms of demand models and testing for changes in structural parameters of the system. Blanciforti, Green and King (1986), for example, use a Linear Approximate Almost Ideal Demand System (LA-AIDS) to test for consistency of this demand specification with economic restrictions of homogeneity, symmetry and negativity. Similar to the non-parametric approach, they interpret the non-compliance of demand equations with these restrictions as possible preference change. In contrast, Chavas (1983), Eales and Unnevehr (1988) apply a Chow test to examine stability of demand parameters. Alternatively, one may include a dummy shift variable in the intercept to allow for parameter dependence on time, however this approach may not reveal the true sources of the change (Okrent and Alston 2011).

The major goal of the research in this article is to examine possible preference change in urban China using province-level panel data based on annual household expenditure surveys from 2002 to 2010. We rely upon the parametric approach for the demand analysis given the low power of the non-parametric method as discussed above. However, unlike most studies in this line of literature we explicitly model potential structural change in the empirical framework following studies by Ohtani and Katayama (1986) and Moschini and Meilke (1989). More specifically, we incorporate a time transition function into the demand model that allows for possible changes in the demand structure accounted for by various factors on the demand side.

We contribute to the literature of structural change by using the Generalized Quadratic Almost Ideal Demand System (GQAIDS) to model consumer food preferences (Deaton and Muellbauer 1980; Bollino 1989; Banks et al. 1993). The choice of a particular functional form may prove essential to the parametric approach for structural change. Therefore the flexibility and generality offered by the GQAIDS as opposed to its nested models can not be underestimated in this analytic framework. Previous studies, in contrast, have relied upon demand structures that may be restrictive in the empirical demand analysis. Ohtani and Katayama (1986), for example, use an ad hoc linear demand specification, whereas many other studies employ a Linear Approximate AIDS (LA-AIDS) model of demand motivated in part by empirical convenience (see, for example, Moschini and Meilke 1986; Dong and Fuller 2010). Our use of the GQAIDS specification allows for possible pre-committed demand components and relaxes the assumption of linear relationship between the logarithm of total expenditures and the respective budget shares. Furthermore, it incorporates the nonlinear translog price index, whereas the LA-AIDS model builds up on its linear approximation, namely the Stone price index (SI).[1] Exclusion of certain demand factors from the empirical analysis may result in misspecification bias since their effects may be ascribed to included demand factors (Tonsor and Marsh 2007).

Our empirical findings show that the GQAIDS outperforms its nested models. Furthermore, basing our analysis of the structural change on this specification we find that food preferences in urban China may have undergone structural changes that lasted from 2004 to 2009. Finally, given our limited time period, we compute the estimates of economic effects before and after the structural change and offer a discussion on the directions it has taken.

The article is organized as follows. Section 2 presents the theoretical specification of the GQAIDS demand model along with a test on the structural change in consumer food preferences. Section 3 provides a summary of the panel data underlying the study followed by the discussion of the results from the empir-

[1] The use of the SI is recommended in situations where prices are correlated, so that SI provides somewhat accurate approximation to the nonlinear price index.

ical analysis. Major conclusions emerging from the article find their reflection in Section 4. We further offer some suggestions that will benefit future work. Finally, uncompensated and expenditure elasticity estimates are reported in the Appendix.

2 Methodology

This section is used to provide an overview of the methodology used in this study. More specifically, we derive the GQAIDS model assuming food preferences are of the respective form. Given our use of the panel data, we next discuss some important issues concerning the time-series aspect of the empirical analysis. Lastly, we present an analytical framework that is used to test for possible structural changes in consumer preferences.

2.1 Demand

With p_i , q_i and t_i denoting the price, quantity and pre-committed demand[2] for the i^{th} food, respectively, and $X = \sum_i p_i q_i$ being the total expenditures on a group of food commodities in question, let $s = X - \sum t_i p_i$ represent the supernumerary expenditures that are determined by economic factors. Similarly, $\sum t_i p_i$ is the total pre-committed expenditure that a typical household spends independent of their income level and food prices. The GQAIDS demand system is then developed assuming consumer food preferences are characterized by the following indirect utility function (Hovhannisyan and Gould 2011):

[2] Pre-committed quantities represent the part of demand that is independent of income and price effects.

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

where $\frac{s}{P}$ is the supernumerary expenditures deflated by a translog nonlinear price index, with the latter given by $ln(P) = \alpha_0 + \sum \alpha_k ln(p_k) + 0.5 \sum \sum \gamma_{ij} ln(p_i) ln(p_j)$. In addition, $b(p) = \prod p_j^{\beta_j}$ is a Cobb-Douglas price index, $\lambda(p) = \sum \lambda_i ln(p_i)$ is a function that is homogenous of degree zero in prices, such that $\sum \lambda_i = 0$, and α_j, β_j, γ_{ij} are structural parameters to be estimated.

Using this behavioral setup, we derive the Marshallian demand functions using Roy's identity. Multiplying both sides of these quantity demands by the respective $\frac{p_i}{m}$ ratios yields the Marshallian budget share equations the stochastic formulation of which are presented below:

$$w_{it} = t_i \frac{p_{it}}{X} + \frac{s}{X} \left\{ \alpha_{it} + \sum \gamma_{ik} ln(p_{it}) + \beta_i ln\left(\frac{s}{P}\right) + \frac{\lambda_i}{b(p)} \left[ln\left(\frac{s}{P}\right) \right]^2 \right\} + u_{it} \quad (2)$$

where t_i is the pre-committed quantity for product i, λ_i captures nonlinear Engel curve effects on the respective budget shares, and u_{it} represents unobserved demand shifters whose statistical properties are discussed later on.

We further impose the following aggregation, homogeneity and symmetry restrictions on the system of equations given by (2) to assure consistency with the neoclassical demand theory:

$$\sum \alpha_k = 1, \sum \beta_i = \sum \lambda_j = \sum \gamma_{mn} = 0, \gamma_{ij} = \gamma_{ji}, \forall i \neq j \quad (3)$$

As already mentioned, of the alternative AIDS specifications the GQAIDS offers the most general structure. For example, the nonlinear AIDS specification is obtained from the GQAIDS through the joint restrictions of: $\lambda_i = 0$, $t_i = 0$, $\forall i$, while imposing $\lambda_i = 0$, $\forall i$ and $t_i = 0$, $\forall i$ separately results in the Generalized

AIDS (GAIDS) and Quadratic AIDS (QAIDS) demand systems, respectively.

An important consideration in studies using time-series data is autocorrelation. Arguably, it may be reflective of incorrect functional form for the model of interest (Alston and Chalfant 1991) or, alternatively, it may be caused by model misspecification resulting from the exclusion of some relevant dynamic effects (Blanciforti, Green and King 1986).

Unlike many studies that estimate the first difference forms of the original models, we assume that budget share error terms are distributed with mean zero and have a variance-covariance matrix exhibiting an AR(1) error structure:[3]

$$u_{it} = \rho u_{it-1} + \varepsilon_{it} \tag{4}$$

where ρ is the autocorrelation coefficient, u_{it-1} is unobservable demand shifter lagged by one period, and ε_{it} is a random error.

To incorporate ε that possesses desirable properties into the demand equations, we multiply one period lagged equations in (2) by ρ and subtract it from (2) as shown below:

$$w_{it} = \rho w_{it-1} + t_i \frac{p_{it}}{X} + \frac{s}{X} \left\{ \alpha_i + \sum \gamma_{ik} ln(p_{kt}) + \beta_i ln\left(\frac{s}{P}\right) + \frac{\lambda_i}{b(p)} \left[\left(\frac{s}{P}\right)\right]^2 \right\} -$$

$$\rho \left\{ t_i \frac{p_{it-1}}{X^*} + \frac{s^*}{X^*} \left\{ \alpha_i + \sum \gamma_{ik} ln(p_{kt-1}) + \beta_i ln\left(\frac{s^*}{P^*}\right) + \frac{\lambda_i}{b^*(p)} \left[ln\left(\frac{s^*}{P^*}\right)\right]^2 \right\}\right\} + \varepsilon_{it} \tag{5}$$

where s^*, X^*, $ln(P^*)$, $b^*(p)$ are one period lagged counterparts of the previously defined variables/functions.

We estimate the food demand system in urban China using equation (5) with respective theoretical restrictions provided by (3). Importantly, we impose the

[3]Put simply, instead of restricting ρ to be one, as in the first difference approach, we estimate it.

same ρ on each equation which is required by the expenditure adding-up property (Berndt and Savin 1975). Given the importance of the demand specification in the structural change literature, we use the Bewley likelihood ratio test for selecting a particular model. It is given by $B_{LLR} = 2\left(LL^{U} - LL^{R}\right)\left(\frac{E\,N^{S} - N^{p}}{E\,N^{S}}\right)$, where $LL^{U,R}$ is the optimal log-likelihood value from the unrestricted and restricted models, respectively, E is the number of equations estimated, N^{S} is the sample size, and $N^{p}$is the number of parameters in the unrestricted model (Bewley 1986). With the standard assumptions, B_{LLR} test statistic can be shown to follow a χ^2 distribution with degrees of freedom equal to the number of additional parameters in the unrestricted model.

2.2 A Parametric Test for Structural Change

To model potential structural change in preferences we use the gradual switching regression framework proposed by Ohtani and Katayama (1986). More specifically, we incorporate a time transition function into the demand model with this function specified as follows:

$$
\begin{aligned}
h_t &= 0, && for\, t = 1,\, ...,\, \tau_1, \\
h_t &= \frac{(t-\tau_1)}{(t-\tau_2)} && for\, t = \tau_1 + 1,\, ...,\, \tau_2 - 1, \\
h_t &= 1 && for\, t = \tau_2,\, ...,\, T,
\end{aligned}
\tag{6}
$$

where τ_1 is the end of the first regime and τ_2 is the starting point of the second regime, with $\tau_1 < \tau_2$.

Following this logic, the period between $\tau_1$and τ_2 may be interpreted as a transition path. Importantly, a finding of $\tau_1 + 1 = \tau_2$ signifies an abrupt change while $\tau_1 + 1 < \tau_2$ is suggestive of gradual transition.

Our empirical analysis builds up on the following dynamic specification of the GQAIDS model that includes the above time transition functions:

$$w_{it} = \rho w_{it-1} + t_i^h \frac{p_{it}}{X} + \frac{s}{X} \left\{ \alpha_i^h + \sum \gamma_{ik}^h ln(p_{kt}) + \beta_i^h ln\left(\frac{s^h}{P^h}\right) + \frac{\lambda_i^h}{b(p)^h}\left[\left(\frac{s^h}{P^h}\right)\right]^2 \right\} -$$

$$\rho \left\{ t_i^h \frac{p_{it-1}}{X^*} + \frac{s^*}{X^*} \left\{ \alpha_i^h + \sum \gamma_{ik}^h ln(p_{kt-1}) + \beta_i^h ln\left(\frac{s^*}{P^*}\right) + \frac{\lambda_i^h}{b^*(p)}\left[ln\left(\frac{s^*}{P^*}\right)\right]^2 \right\}\right\} + \varepsilon_{it} \tag{7}$$

where $t_i^h = t_i + \delta_i h_t$, $\alpha_i^h = \alpha_i + \eta_i h_t$, $\gamma_{ik}^h = \gamma_{ik} + \varphi_{ik} h_t$, $\beta_i^h = \beta_i + \mu_i h_t$, $\lambda_i^h = \lambda_i + \phi_i h_t$.

Unlike the studies using the LA-AIDS model, our use of nonlinear specifications requires further adjustments in the respective nonlinear price indices as follows: $ln(P)^h = \alpha_0 + \sum \alpha_k^h ln(p_k) + \frac{1}{2}\sum\sum \gamma_{ij}^h ln(p_i) ln(p_j)$, $b(p)^h = \prod p_j^{\beta_j^h}$, and s^*, X^*, $ln(P^*)$, $b^*(p)$ are one period lagged counterparts of the respective variables/functions, as before. Moreover, to preserve the theoretical properties of the model, additional restrictions of the form $\sum \delta_i = \sum \eta_i = \sum \varphi_{ik} = \sum \mu_i = \sum \phi_i = 0$ and $\varphi_{ik} = \varphi_{ki}$ are imposed.

From the parameter estimates, we also calculate uncompensated (ε_{ij}^M), compensated (ε_{ij}^H) and expenditure (ξ_i) elasticities using the respective formulas provided by Hovhannisyan and Gould (2011):

$$\xi_i = 1 + \frac{1}{w_i}\left[\beta_i^h + \frac{2\lambda_i^h}{b(p)^h}L^2 - M_i + \frac{\sum t_i^h p_i}{X}\left(A_i + \beta_i L + \frac{\lambda_i^h}{b(p)^h}L^2\right)\right] \tag{8}$$

$$\varepsilon_{ij}^M = \frac{1}{w_i}\left\{\delta_{ij} M_i - M_j \left[A_i + \beta_i L + \tfrac{\lambda_i}{b(p)^h}L^2\right] \quad + \right.$$

$$\left.\frac{s}{X}\left[\gamma_{ij}^h - \beta_i^h\left[A_j + S_j\right] - \frac{\lambda_i^h \beta_j^h}{exp(\sum \beta_k^h ln(p_k))}L^2 - \frac{2\lambda_i^h}{b(p)^h}\left[S_j L + A_j\left[ln(s)^h + 2P^h\right]\right]\right]\right\} \tag{9}$$

$$\varepsilon_{ij}^{H} = \varepsilon_{ij}^{M} + \xi_i w_j \tag{10}$$

where $A_i = \alpha_i^h + \sum \gamma_{ij}^h ln\,(p_j)$, $L = ln\left(\frac{s^h}{P}\right)$, $M_i = \frac{t_i^h p_i}{X}$, $S_i = \frac{t_i^h p_i}{s^h}$ and δ_{ij} is the Kronecker delta.

3 Empirical Framework

3.1 Data Underlying the Empirical Analysis

Data used in this study are obtained from annual expenditure surveys of urban Chinese households conducted by the China National Bureau of Statistics (CNBS).[4] To ensure representativeness, the CNBS applies a two-stage stratified systematic random sampling method. Each year a third of the household sample from the previous year is replaced by a new group based on a rotation-sampling technique (Dong and Fuller 2010). In addition, the CNBS has been increasing the sample size every year. [5]

For the analysis we use province-level aggregate annual data covering 31 provinces from 2002 to 2010, given that individual-level data are normally not available. The dataset includes per capita expenditures for various food commodity groups along with price indices from the respective provinces and years. Our use of the price indices instead of price level data is driven by the fact that price and quantity levels are unobserved at the province level. The food

[4] Chinese Urban Household Income and Expenditure Survey, China Statistical Yearbooks, 2002-2010.

[5] The focus of this study is on urban consumers in each province, to avoid identification issues related to home production of food commodities.

categories are defined into the following groups:beef, seafood, vegetables, fruit, grains, eggs, and fats.

Table 1 provides the descriptive statistics on price indices and food expenditures for the seven food commodity groups. It can be seen that the food categories included in the analysis comprise more than 56 percent of total food expenditures (i.e., both at home and away from home). Of these, beef is the most important food accounting for more than 34.0 percent of expenditures on the food items in question, which is followed by vegetables, grains and fruit with 17.5, 14.6, 13.3 percent shares, respectively. Notably, the recent years have seen seafood consumption in China gaining in importance, in the result of which it made up 11.9 percent of total expenditures on these food groups. As far as price movements, vegetables and beef have seen the steepest average increase over time with fats experiencing the most volatile prices in the entire period under study.

Table 1. Descriptive Statistics

	Mean	S.D.	Min	Max
Expenditure (Current Yuan)				
Food	3316.3	1163.0	1517.0	7777.0
Beef	641.2	263.6	225.2	1640.6
Seafood	205.0	192.1	35.4	999.6
Veg.	325.6	109.3	138.6	622.0
Fruit	247.2	94.1	99.5	646.3
Grain	272.0	72.5	145.2	614.7
Egg	71.6	23.4	25.7	158.8
Fats	103.5	37.1	37.6	232.2
Price Index (%)				

Beef	107.8	13.0	86.7	142.0
Seafood	105.2	7.3	91.3	131.6
Veg.	108.8	10.2	78.9	140.0
Fruit	107.3	7.3	88.6	125.3
Grain	106.8	8.0	94.7	139.6
Egg	106.2	8.7	91.8	129.0
Fats	106.5	14.9	74.0	148.0

Source: Chinese Urban Household Income and Expenditure Survey, China Statistical Yearbooks, 2002-2010.

3.2 Results from the Empirical Analysis

We employ the GAUSSX 4.0 module of the GAUSS software system to estimate the various specifications of the GQAIDS. The Newton Raphson and GAUSS optimization algorithms are used to compute the parameter estimates and the ROBUST option is used to obtain heteroskedasticity adjusted standard errors. We also allow for contemporaneous correlation across the equations in the system while allowing for a first-order autocorrelation in the unobservable shifter in each equation. This is a more general approach than the first difference estimation used by Gao and Shonkwiler (1993), Dong and Fuller (2010) and similar studies, given that the latter requires apriori knowledge of the autocorrelation parameter.

Given the importance of a particular demand specification in the structural change analysis, we first estimate the system in (4) and perform model selection via the Bewley likelihood ratio test. Table 2 provides a summary of the test results. Evidently, the GQAIDS specification outperforms all the nested models, such as the AIDS, GAIDS, and QAIDS. This is in line with the findings from Hovhannisyan and Gould (2011), and manifests the importance of pre-committed quantities to Chinese food demand structure. This also means that the assumption of linear Engel curves, that has been extensively used in the literature, may not be characteristic of food preferences in urban China.

Table 2. Model Diagnostics

Hypothesis	B_{LLR}	df.	p-value
(a) GQAIDS vs. QAIDS (i.e., no pre-committed demand or $t_i = 0$, $\forall i = 1, ..., n$)	174.9	7	0.00
(b) GQAIDS vs. GAIDS (i.e., linear Engel curves or $\lambda_i = 0$, $\forall i = 1, ..., n$)	27.8	6	0.00
(c) GQAIDS vs. AIDS (i.e., no pre-committed demand and linear Engel curves or $\lambda_i = 0$, $t_i = 0\, \forall i = 1, ..., n$)	190.2	13	0.00

Source: Own calculations.

Given the results from model selection, we base the switching regression model on the GQAIDS specification to examine potential structural change in the food preferences. A total of 111 parameters are estimated, including those for structural change. Based on the optimal values of the respective likelihood functions we receive that the system with $\tau_1 = 2003$, $\tau_2 = 2009$ provides the best fit.

The estimation results are provided in Table 3. Importantly, the autocorrelation coefficient is statistically significant and different from one (0.98). This speaks to the dynamic effects being present in the demand structure. It also implies that the first differencing method widely used to account for dynamics may not be relevant in our situation (i.e., first difference method is equivalent to unit ρ in the original levels equation). Importantly, a majority of parameter estimates are statistically significant, including estimates for structural change. This in turn implies that demand parameters may have undergone structural change.

Table 3. Estimation Results

Parameter	Beef	Seafood	Veg.	Fruit	Grains	Eggs	Fats
t_i	0.043	-0.019	-0.021*	0.000	-0.020	-0.021*	0.104
	0.033	*0.027*	*0.007*	*0.012*	*0.030*	*0.010*	*0.339*
δ_i	-0.286	-0.075	0.071	-0.137	0.449*	0.163*	-2.111
	0.158	*0.143*	*0.065*	*0.103*	*0.193*	*0.066*	*2.489*
α_i	-0.192*	0.172*	0.304*	0.005	-0.155*	0.108*	0.758
	0.006	*0.007*	*0.011*	*0.007*	*0.010*	*0.001*	*0.692*
η_i	0.509	-0.620*	-1.511*	0.435*	0.422*	-0.722*	1.486
	0.759	*0.035*	*0.071*	*0.022*	*0.036*	*0.035*	*5.160*
β_i	-0.021*	0.011*	0.173*	-0.008	-0.109	-0.258	0.212
	0.002	*0.000*	*0.053*	*0.094*	*0.074*	*0.155*	*0.180*
μ_i	0.097	-0.065*	-2.282*	1.595*	0.503	-0.071	0.223
	0.094	*0.003*	*0.531*	*0.607*	*0.827*	*0.870*	*1.702*
λ_i	0.001*	-0.002*	-0.005*	0.002*	0.005*	-0.001	-0.000*
	0.000	*0.000*	*0.001*	*0.000*	*0.000*	*0.001*	*0.000*
ϕ_i	0.003	0.005*	0.025*	-0.020*	-0.020*	0.007*	-0.017*
	0.003	*0.001*	*0.001*	*0.001*	*0.002*	*0.000*	*0.001*
Beef							
γ_{ij}	0.006	0.000	-0.001	-0.025*	0.021	-0.007	0.006
	0.023	*0.008*	*0.009*	*0.012*	*0.011*	*0.004*	*0.019*
φ_{ij}	0.203	-0.015	-0.012	-0.031	-0.200*	0.048	0.007
	0.146	*0.030*	*0.028*	*0.035*	*0.091*	*0.026*	*0.045*
Seafood							

γ_{ij}	0.005	0.001	0.004	-0.015	0.007*	-0.002
	0.011	*0.004*	*0.007*	*0.009*	*0.003*	*0.009*
φ_{ij}	0.105*	0.014	-0.038	0.012	-0.044*	-0.034
	0.047	*0.019*	*0.025*	*0.032*	*0.016*	*0.025*
Veg.						
γ_{ij}		0.003	0.009	-0.014*	-0.007*	0.009
		0.008	*0.006*	*0.007*	*0.003*	*0.008*
φ_{ij}		0.089	0.007	0.002	-0.006	-0.095*
		0.062	*0.017*	*0.034*	*0.008*	*0.032*
Fruit						
γ_{ij}			-0.010	0.011	0.004	0.006
			0.011	*0.008*	*0.004*	*0.009*
φ_{ij}			0.172	-0.045	0.002	-0.067*
			0.088	*0.036*	*0.013*	*0.021*
Grains						
γ_{ij}				0.030	-0.010*	-0.022
				0.015	*0.005*	*0.022*
φ_{ij}				0.114	0.018	0.100
				0.117	*0.014*	*0.058*
Eggs						
γ_{ij}					0.007	0.006
					0.006	*0.003*
φ_{ij}					0.033	-0.051*
					0.019	*0.023*
Fats						
γ_{ij}						-0.003

		1.048
φ_{ij}		0.140
		7.454
ρ	0.986*	
	0.008	

Note: * indicates statistical significance at the 5 % level. Standard errors appear in italic.

We further examine potential change in the impact of various demand factors via joint tests (Table 4). First we test for overall structural change and find sufficient empirical support for it. This is consistent with findings from Dong and Fuller (2010). Next, pre-committed demand components are found to have undergone structural change. As shown by Hovhannisyan and Gould (2011), pre-committed demand is more likely to change for relatively younger consumer groups with higher incomes, while older consumers with lower levels of educational attainment tend to stick with traditional Chinese food diet. Moreover, we find that the impact of expenditures and food prices have changed structurally along with nonlinear effects of Engel curves in the period of 2004 to 2009.

Table 4. Structural Change Test for the Impact of Demand Factors

Null hypothesis of	B_{LLR}	df.	p-value
No structural change in:			
All parameters (i.e.,$\delta_i = 0$, $\eta_i = 0$, $\varphi_{ik} = 0$, $\mu_i = 0$, $\phi_i = 0$,)	486.2	55	0.000
Pre-committed demand (i.e.,$\delta_i = 0$,)	28.9	7	0.012
Quadratic Engel curve parameter (i.e.,$\phi_i = 0$,)	16.3	6	0.000
Real expenditure parameters (i.e.,$\mu_i = 0$,)	70.3	6	0.000
Relative price parameters (i.e.,$\varphi_{ik} = 0$,)	310.5	28	0.000
AIDS intercept (i.e.,$\eta_i = 0$,)	56.6	6	0.000

Note: i, $k = 1, ..., n$.

Source: Own calculations.

Next, we evaluate elasticity measures at the mean data points using formulas in (8)-(10) and estimates of demand parameters (Table A1). Estimates of elasticities before structural change are obtained by setting $h_t = 0$ in equation (7) and using average data points over 2002 and 2003. In the same vein, after change estimates are computed using $h_t = 1$ and average data points over 2009 and 2010. The vast majority of the elasticity estimates are statistically significant at the standard significance levels. All own price uncompensated elasticities and expenditure effects except for fats are significant, consistent with theory and appear to be within a reasonable range as far as magnitude. It can also be seen that there has not been much change in elasticities in the recent years; which may be reflective of a fact that the sizable changes may have taken place in years following the major reforms in China (Dong and Fuller 2010).

4 Conclusion

The article examines preference change in urban China using province-level panel data based on annual household expenditure surveys from the most recent years. Using a parametric approach with the underlying GQAIDS demand specification, we build a switching regression framework in line with a study by Ohtani and Katayama (1986). Empirical results from a system of seven food commodity groups estimated in a dynamic environment provide a strong evidence for structural changes in urban Chinese food preferences.

We acknowledge that our use of a dataset that omits years when the major reforms stated taking effect may be an important limitation (province-level data are only available for post 2000). Furthermore, data limitations do not allow us to account for potential endogeneity in total expenditures.

5 Appendix

Table A1. Elasticity Estimates before and after Structural Change

	Beef	Seaf.	Veg.	Fruit	Grain	Eggs	Fats
			Before structural change				
Beef	-0.895*	0.005*	-0.006*	-0.075*	0.028*	0.031*	0.048
	0.055	*0.001*	*0.001*	*0.009*	*0.004*	*0.004*	*0.029*
Seafood	0.019*	-1.130*	-0.020*	0.094*	-0.139*	-0.014*	-0.049
	0.002	*0.114*	*0.003*	*0.011*	*0.017*	*0.002*	*0.053*
Veg.	-0.012*	-0.011*	-1.064*	0.045*	-0.037*	-0.055*	0.004
	0.002	*0.002*	*0.027*	*0.006*	*0.005*	*0.007*	*0.042*
Fruit	-0.203*	0.084*	0.061*	-1.023*	0.017*	0.004*	-0.073
	0.025	*0.010*	*0.008*	*0.049*	*0.004*	*0.002*	*0.072*
Grain	0.064*	-0.101*	-0.042*	0.014*	-0.723*	-0.086*	-0.192*
	0.008	*0.013*	*0.005*	*0.002*	*0.101*	*0.011*	*0.056*
Eggs	0.235*	-0.015	-0.224*	0.005	-0.318*	-1.521*	-0.172
	0.033	*0.015*	*0.029*	*0.009*	*0.043*	*0.132*	*0.165*
Fats	-0.477	0.322	0.371*	0.140	-0.319	0.562*	-0.439
	0.450	*0.274*	*0.182*	*0.150*	*0.266*	*0.262*	*28.749*
Expend.	0.863*	1.239*	1.131*	1.133*	1.066*	2.010*	-0.160
	0.053	*0.115*	*0.028*	*0.054*	*0.098*	*0.137*	*0.715*
			After structural change				
Beef	-0.932*	0.004*	-0.006*	-0.074*	0.029*	0.029*	0.061
	0.029	*0.001*	*0.001*	*0.004*	*0.002*	*0.002*	*0.035*
Seafood	0.020*	-1.050*	-0.023*	0.104*	-0.160*	-0.013*	-0.089
	0.002	*0.074*	*0.002*	*0.006*	*0.009*	*0.001*	*0.062*
Veg.	-0.010*	-0.011*	-1.025*	0.040*	-0.033*	-0.050*	0.003

	0.001	*0.001*	*0.014*	*0.002*	*0.002*	*0.003*	*0.038*
Fruit	-0.181*	0.074*	0.056*	-1.025*	0.016*	0.001	-0.045
	0.011	*0.005*	*0.003*	*0.026*	*0.003*	*0.001*	*0.066*
Grain	0.065*	-0.102*	-0.041*	0.014*	-0.709*	-0.087*	-0.183*
	0.004	*0.006*	*0.002*	*0.001*	*0.057*	*0.005*	*0.054*
Eggs	0.253*	-0.009	-0.248*	-0.012	-0.358*	-1.462*	-0.362
	0.024	*0.015*	*0.017*	*0.009*	*0.027*	*0.078*	*0.329*
Fats	-0.313	0.199	0.308	0.178	-0.396	0.581*	-0.348
	0.355	*0.213*	*0.165*	*0.148*	*0.211*	*0.270*	*32.693*
Expend.	0.887*	1.211*	1.086*	1.105*	1.044*	2.197*	-0.209
	0.028	*0.075*	*0.015*	*0.030*	*0.057*	*0.097*	*0.741*

Note: * indicates significance at the 5 % level.

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