EFFECTS OF URBANIZATION ON FOOD DEMAND IN CHINA

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Abstract: Urbanization in China has been on a steady rise recently, which has contributed to the changing consumer food preferences and consumption patterns. This carries significant implications for food security in China and the global food trade, given the role China plays on global food markets. This study investigates the effects of urbanization on food demand in China by developing a structural framework that incorporates urbanization into a theory-plausible demand system. It also considers the effects of urbanization-induced loss of agricultural land and deteriorating soil quality on food supply. Modeling the demand and supply components simultaneously allows us to undertake equilibrium analysis to determine prices. Based on the urbanization elasticities derived and estimated in this study, our findings indicate that urbanization has reduced demand for grains and fats, while increasing demand for meats, seafood, fruit, vegetables and eggs.

Keywords: Consumer food preference, EASI demand model, structural change, urbanization.

JEL Code: D11, D12.

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Introduction

Rising incomes and population growth in the second half of the 20th century are considered some of the most significant factors contributing to the global food consumption growth. New evidence also indicates the importance of demographic changes such as the increased urbanization in shaping consumer food preferences and food consumption dynamics. Defined as the proportion of the total population residing in urban areas, urbanization is observed to go hand-in-hand with economic development. Developing countries, in particular, have undergone rapid urbanization, which has brought dramatic changes to consumer food preferences (Huang and David 1993; Regmi and Dyck 2001). This is especially true for China, which went through the largest rural-urban migration in human history following the economic reforms of 1978 (Zhang and Shunfeng 2003). As a result, urbanization in China has increased from 17.9% to 54.8% over the period 1978-2014 with some administrative divisions such as Beijing (86.3%) reaching even higher urbanization rates (NBSC 2015). According to the United Nations Population Division (2012), this trend will continue into the future, and the share of urban population in China will exceed 60% by 2020.

Evidence suggests that urbanization can affect consumer food demand in a variety of ways, which may come from changes in, for example, consumer lifestyles, food tastes, preferences, and food availability. This can also be a result of higher incomes in cities, where better job opportunities and an increasing number of working women generate a larger demand for fast food and convenience food (Kennedy and Reardon 1994). An even more dramatic change has been the compositional shift in the traditional diets, when food diets become more varied because of the increased availability and a better variety of food products that urban markets have to offer (Regmi and Dyck 2001). Urbanization can also affect consumption patterns through its effects on agricultural land, food supply and prices, which has received scant attention in the literature. For example, accelerated urbanization in China has led to the loss of agricultural land, which can reduce food supply and cause higher food prices, *ceteris paribus* (Stage, Stage, and McGranahan 2010). Further, rapid urbanization has been found to affect agricultural commodity supply through its effects on soil quality (Angel et al. 2005). This supply-side impact can confound the effects of urbanization on food demand, and can result in simultaneity bias in estimated demand coefficients and unreliable future food demand forecasts.

Despite the importance of urbanization in shaping consumer preferences, nonetheless, there is a lack of scientific evidence as to the contribution of urbanization to the changing food diets in China. Huang and David (1993) was the first to examine the urbanization impact on the demand for three cereal grains using national-level annual aggregate time series data from several Asian countries. However, in the last two decades, urban diet has changed considerably from cereal grains to incorporate fruit and vegetables, meat, seafood, and dairy products. Hence, there is a need to study these recent trends in urban diet composition and consumption patterns.

The major objective of the current study is to investigate the effects of urbanization on food demand in China by addressing the fundamental issues not examined in previous studies. Its contributions are manifold. First, we develop a theoretical model by incorporating urbanization into an Exact Affine Stone Index (EASI) system of Lewbel and Pendakur (2009) to assess the changes in consumer food preferences brought by urbanization. We base our analytical framework on the EASI system because of its ability to account for unobserved consumer heterogeneity and to allow for arbitrary complex Engel curves (Lewbel and Pendakur 2009). *Urbanization elasticities* derived from this structural model can be very useful in designing effective government food policies. Second, we empirically examine the effects of urbanization on food demand and consumer preferences in China by applying our model to the most recent provincial-level panel data on consumer food expenditures provided by the National Bureau of Statistics of China (NBSC 2005-2012). In contrast to the previous literature, this allows us to account for unobserved provincial heterogeneity such as socio-cultural idiosyncrasies and differences in food-related customs, which can have profound effects on consumer food tastes and preferences, whereas national-level analyses will likely confound the urbanization effects (Anderson 1988; Ma 2015). Third, our empirical framework recognizes potential food supply and price response to the increased urbanization in China resulting from the loss of agricultural land and deteriorating soil quality (Angel et al. 2005; Stage, Stage, and McGranahan 2010). Previous literature overlooks this source of price endogeneity, which impacts demand estimates and renders future demand forecasts inaccurate. These unreliable estimates will ultimately misguide the production plans and economic well-being of Chinese producers and its trading partners, given the sheer size of the Chinese economy and its increasingly important role on the global food markets.

Our results indicate that urbanization has a significant role in shaping consumer food preferences in China. Specifically, urbanization has resulted in an increase in demand for meats, seafood, vegetables, fruit and eggs, while reducing demand for grains and fats. In addition, omitting urbanization from food demand analyses is found to generate imprecise economic effects. Given the vast differences across the Chinese provinces in terms of urbanization rates and levels, demographic, socio-cultural and other idiosyncrasies, we further calculate urbanization elasticities for each province and food commodity under study.

A Structural Framework for the Analysis of Urbanization Effects on Food Demand

We develop a structural framework for the analysis of urbanization outcomes by incorporating urbanization into the EASI demand system of Lewbel and Pendakur (2009). This allows us to account for structural changes in consumer food preferences with urbanization being the underlying driving force. In addition, we supplement this analytical framework with reduced-form price equations to also account for the impact of urbanization-induced loss of agricultural land and deteriorating soil quality on food supply and prices. This approach corrects for the simultaneity bias in prices brought by commodity supply shifters (Hovhannisyan and Bozic 2016) and structural changes such as urbanization.

Our choice of the EASI model as a basis for deriving our structural framework reflects the superiority of the EASI over other popular demand models such as the Almost Ideal Demand System (AIDS) of Deaton and Muellbauer (1980) and its variants. Specifically, the EASI specification accounts for unobserved consumer heterogeneity and allows for arbitrary Engel curves while retaining the desirable features of the previous models (Pendakur 2008; Zhen et al. 2013). Let w_{rit} denote the budget share of commodity *i* in province *r* in year *t*; p_{rit} be the price of commodity *i* in province *r* in year *t*; y_{rt} be real food expenditures in province *r* in year *t*; *L* be the highest order of polynomial in real expenditures; D_r be a dummy variable for province *r* to capture the unobserved provincial heterogeneity; *N* and *R* represent the number of commodities and provinces, respectively; u_{rit} denote unobserved share determinants; and $\lambda_{i0}, \gamma_{ir}, \beta_{il}$, and α_{ij} be parameters. The EASI system is then specified by the following functional form

(1)
$$w_{rit} = \lambda_{i0} + \sum_{r=1}^{R} \gamma_{ir} D_r + \sum_{l=1}^{L} \beta_{il} y_{rt}^{l} + \sum_{j=1}^{N} \alpha_{ij} \log\left(p_{rjt}\right) + u_{rit},$$
$$\forall r = 1, ..., R;\ l = 1, ..., L;\ i, j = 1, ..., N; t = 1,\ ...,\ T.$$

The demand system in equation (1) satisfies the following theoretical restrictions of aggregation and symmetry

(2)
$$\sum_i \lambda_{i0} = 1, \sum_i \gamma_{ir} = 0\ \sum_i \beta_{il} = 0, \sum_i \alpha_{ij} = 0,\ \forall j = 1, ..., n, \quad \text{and} \quad \alpha_{ij} = \alpha_{ji},\ \forall j \neq i$$

Following Pendakur (2008) and Zhen et al. (2013), we specify Stone price-deflated real expenditures $y_{rt} = \log(x_{rt}) - \sum_{j=1}^{N} w_{rjt} \log(p_{rjt})$, where x_{rt} represents nominal food expenditures in province *r* in year *t*. This results in a linear approximate EASI model, the purpose of which is to simplify empirical demand analysis already complicated by the inclusion of a large number of provincial fixed-effects. Unlike the linear approximate AIDS model, where the Stone price index is only an approximation to the true expenditure deflator, in the EASI system it is the correct deflator of food expenditures by its very design (Zhen et al. 2013). Importantly, the linear EASI specification has been found to yield almost identical results to those of the nonlinear specifications (Lewbel and Pendakur 2009).

To incorporate structural food preference change into the EASI system to reflect the role of urbanization in shaping tastes and preferences, we generalize the EASI model in equation (1) to

$$w_{rit} = \left(\lambda_{i0} + \lambda_{i0}^{u} Urb_{rt}\right) + \sum_{r=1}^{R} \gamma_{ir} D_r + \sum_{l=1}^{L} \left(\beta_{il} + \beta_{il}^{u} Urb_{rt}\right) y_{rt}^{l} + \sum_{j=1}^{N} \left(\alpha_{ij} + \alpha_{ij}^{u} Urb_{rt}\right) \log\left(p_{rjt}\right) + \varepsilon_{rit}, \quad (3)$$

$$\forall r = 1,...,R;\ l = 1,...,L;\ i, j = 1,...,N; t = 1,\ ...,\ T.$$

where Urb_{rt} is the urbanization rate measured as a ratio of urban population to total population in province *r* in year *t*, λ_{i0}^{u}, β_{il}^{u}, and α_{ij}^{u} are parameters, and ε_{rit} is the disturbance term. Here λ_{i0}^{u} accounts for the urbanization-induced shift in intercept, and β_{il}^{u} and α_{ij}^{u} measure the changes in the impact of real income and prices on expenditure shares, respectively, brought about by urbanization. Theoretical restrictions of adding-up require $\sum_i \lambda_{i0}^{u} = 0$, $\sum_i \beta_{il}^{u} = 0$, and $\sum_i \alpha_{ij}^{u} = 0$. Additionally, the standard EASI system (1) can be obtained from the generalized demand model in equation (3) via the imposition of the joint restriction of $\lambda_{i0}^{u} = 0, \beta_{il}^{u} = 0,$ and $\alpha_{ij}^{u} = 0,\ \forall\, l = 1,..., L,\ \forall\, i,\ j = 1,..., N.$

Our model allows urbanization to shift the demand intercepts and alter the income coefficients in a linear manner as in Huang and David (1993). However, in the latter study, the urbanization-induced differential effects of prices on expenditure shares is ignored.[1] Given the fact that urban markets offer a greater variety of food products and thus more substitutes to choose from, we expect that urbanization also affects price coefficients in demand equations. This effect is accounted for through the introduction of the parameters $\alpha_{ij}^{u}, \forall i,\ j = 1,..., N$, which capture the urbanization-driven change in price coefficients. An even bigger limitation of the previous literature is the omission of the effects of urbanization on food supply and prices that can result from reduced agricultural land and deteriorated soil quality. This is particularly important in China, where swift urbanization has been documented to have reduced agricultural land tremendously, the ultimate consequence of which is diminished agricultural commodity supply and higher food prices, *ceteris paribus* (Stage, Stage, and McGranahan 2010). Further, urbanization is most often

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[1] The current study improves on the previous literature, and particularly Huang and David (1993) in other important ways as well. For example, our EASI-based framework allows for unobserved consumer heterogeneity and arbitrary Engel curves unlike the linear approximate AIDS model underlying the previous studies; we conduct the analysis at a more disaggregate-level and account for unobserved provincial heterogeneity; we examine the effects of urbanization on a more inclusive group of food commodities; and finally, we use actual consumption data, whereas some of the previous studies relied on national-level supply-utilization balance sheets.

linked to economic growth, and, consequently, increased environmental degradation. In China, the effects of environmental degradation on soil quality has been found to be more important than the loss of arable land to urbanization (Angel et al. 2005). Hence, it is imperative to also account for this urbanization-induced supply-side variation in food prices, to fully capture the urbanization outcomes. Toward this goal, we adopt a procedure offered by Dhar, Chavas, and Gould (2003) to supplement our structural framework in (3) by including reduced-form price equations, which relate food prices to urbanization and other exogenous agricultural commodity supply shifters

(4) $$\ln\left(p_{irt}\right) = \psi_{i0} + \psi_{i1}\ln\left(Urb_{rt}\right) + \sum_{k=2}^{K}\psi_{ik}\ln\left(Z_{krt}\right) + \zeta_{it}, \quad \forall i, j = 1,...,N, \ r = 1,...,R, \ t = 1,...,\mathrm{T}.$$

where Z_{krt} denotes other commodity supply shifters such as the share of agricultural land affected by flood, drought, wind and hail, and per capita land used in agricultural production in province *r* in year *t*; $\psi_{iq}, \forall q = 0,...,K$ are parameters; and ζ_{it} represents unobserved supply-side determinants of the i^{th} food commodity price. This empirical framework corrects for the simultaneity bias in price coefficients that can result from price endogeneity.[2]

Expenditure, Price, and Urbanization Elasticities

We derive expenditure and price elasticity formulas from the generalized EASI demand system (3) by following Banks, Blundell, and Lewbel (1997) and Zhen et al. (2013). Specifically, the expenditure elasticities are

(5) $$E = \left(diag\left(W\right)\right)^{-1}\left[\left(I_N + BP'\right)^{-1}B\right] + 1_N,$$

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[2] Hovhannisyan and Bozic (2016) provide more details regarding the price endogeneity in empirical demand models resulting from the omission of the supply side of the market.

where $E=\left(e_1,e_2,...,e_N\right)$ is the $(N \text{ x } 1)$ expenditure elasticity vector, *W* is the (*N* x 1) vector of observed commodity budget shares, *B* is a (*N* x 1) vector with its i^{th} element represented by $\sum_{l=1}^{L}\left(\beta_{il}+\beta_{il}^{u}Urb_{rt}\right)ly^{l-1}$, *P* is the $(N \text{ x } 1)$ vector of log prices, and 1_N is a $(N \text{ x } 1)$ vector of ones.

Next, the Hicksian elasticities of demand are

(6) $$e_{ij}^{H}=\frac{\left(\alpha_{ij}+\alpha_{ij}^{u}Urb_{rt}\right)}{w_i}+w_j-\delta_{ij},\ \ \forall\, i,\, j=1,...,N,$$

where e_{ij}^{H} is the Hicksian elasticity of demand for commodity *i* with respect to the price of commodity *j* ; and δ_{ij} is the Kronecker delta that equals 1 if $i = j$, and 0 otherwise. Using the Hicksian $\left(e_{ij}^{H}\right)$ and expenditure elasticity $\left(e_i\right)$ formulas, we obtain the Marshallian price elasticities $\left(e_{ij}^{M}\right)$ via the Slutsky equation $e_{ij}^{M}=e_{ij}^{H}-w_j\,\mathrm{e}_i$.

Finally, we derive urbanization elasticities from the generalized EASI system in (3) to analyze the importance of urbanization in shaping consumer food preferences[3]

(7) $$e_{ij}^{Urb}=\frac{Urb_{rt}}{w_i}\left(\lambda_{i0}^{u}+\sum_{l=1}\beta_{il}^{u}y^{l}+\sum_{k=1}\alpha_{ik}^{u}\log\left(p_{rjt}\right)\right)$$

where e_{ij}^{Urb} is the urbanization elasticity of demand for commodity *i* with respect to the price of commodity *j*.

Data

[3] Details concerning the elasticity derivations are available upon request.

The current study utilizes provincial-level panel data collected by the NBSC, which contain household food expenditure surveys over the period 2005-2012. The data contain unit prices, annual average household expenditures for seven widely consumed food commodity aggregates across 30 provinces/administrative divisions/cities, and consumer demographics.[4] The seven food categories analyzed include meats (i.e., beef, lamb, poultry, pork, etc.), seafood, vegetables, fruit, grains, eggs, and fats/oils. A total of 1,680 observations are used in the empirical demand analysis. Dong and Fuller (2010), and Hovhannisyan and Bozic (2016) provide more details concerning the data collection and aggregation methods used by the NBSC.

Table 1 provides the descriptive statistics of the major variables underlying our structural model. Meats command the highest per capita expenditures (810.7 Yuans) of the included commodities with an average budget share of 34.0%. This is followed by vegetables (411.6 Yuans or 17.7% budget share), grains (334.8 Yuans or 14.9% share), fruit (330.9 Yuans or 14.2% share), seafood (257.5 Yuans or 9.8% share), fats/oils (125.2 Yuans or 5.5% share), and eggs (86.8 Yuans or 3.9% share). As it appears, grains still constitute an important part of the urban Chinese diet despite the rapid decline in the coarse grain consumption recently (Zhai et al. 2014). Further, seafood that has been traditionally consumed in coastal provinces, recently has

[4] Sampled provincial-level administrative divisions include: 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 was excluded due to limited data on urbanization.

become more popular in the other parts of China despite its relatively high unit price of 20.3 Yuans/kg (Hovhannisyan and Gould 2011). Finally, rising consumer incomes coupled with changing consumer lifestyles and urbanization-induced structural preference changes brought compositional shifts in traditional Chinese food diets resulting in a sharp increase in meat consumption (Liu et al. 2009).

We supplement the household food expenditure panel information with data on urbanization, as well as other agricultural commodity supply shifters such the portion of agricultural land affected by natural calamities, and per capita land available for agricultural production. As can be seen from Table 1, average urbanization rate in China is 50% with the rate manifesting wide variations across the 29 provinces/administrative divisions in our sample. For example, more than 70% of the population in Yunnan still reside in rural areas, whereas Beijing residents are located predominantly in urban cities (almost 90% of the population). Figure 1 offers a closer look at the urbanization dynamics in three provinces (i.e., Beijing, Zhejiang, and Yunnan) representing highly, moderately, and lowly urbanized administrative divisions. One common trend underlying these graphs is that in the 21st century urbanization has been on a steady rise in all three types of provinces, however urbanization rate has been slowing down in highly-urbanized provinces such as Beijing. According to Regmi and Dyck (2001), lowly-urbanized (e.g., Yunnan) and moderately-urbanized (e.g., Zhejiang) provinces will likely undergo more pronounced changes in food diets vis-a-vis the highly-urbanized provinces / administrative divisions such as Beijing.

Empirical Analysis and Results

We base our empirical analysis on the structural framework that incorporates the generalized EASI demand system (3) and the reduced-form price equations in (4) capturing the supply-side effects of urbanization and other shifters on food prices. This structural framework is estimated using a Full Information Maximum Likelihood (FIML) procedure that takes account of theoretical demand restrictions and a demand equation is dropped to avoid singularity problem. An important benefit of the FIML is its ability to account for the true simultaneity of food supply and demand in determining food prices (Hayashi 2000). The estimation results are invariant to the choice of the demand equation excluded from the estimation. The parameter estimates from this omitted equation are recovered from the theoretical restrictions imposed on the model.

The proper polynomial structure for our generalized EASI demand system is an empirical question, which we examine using a series of diagnostics tests based on the LR test procedure (Pendakur 2008). Our findings indicate that the demand system with a cubic polynomial structure fits our data best, and the quartic and higher order polynomial structures (L>=4) do not provide significant improvement over this specification. An important implication of this finding is that the Quadratic AIDS and other similar AIDS specifications are restrictive for this type of analysis because of the inability of these previous models to account for nonlinear Engel curves beyond quadratic curvilinearity.

We incorporate provincial fixed-effects into the demand system (3) to account for unobserved provincial heterogeneity such as food customs, cooking traditions, and cultural idiosyncrasies that vary across provinces while being fairly constant for each province over time and can influence food consumption in non-trivial ways (Anderson 1988; Ma 2015). In addition, our empirical framework accounts for simultaneity bias in the estimated price coefficients as discussed above. Finally, we account for the endogeneity of real expenditures y_{rt} by constructing expenditure instruments as follows

(8) $$\tilde{y}_{rt} \equiv \log\left(\tilde{x}_{rt}\right) - \sum_{j=1}^{N} \overline{w}_j \log\left(p_{rjt}\right)$$

where $\tilde{y}_{rt}$ is the instrument for y_{rt}, $\tilde{x}_{rt}$ is per capita average provincial income, $\overline{w}_j$ is average provincial budget share of commodity *j*, and p_{rjt} represent urbanization and other supply shifters such as natural calamity-affected agricultural land used in (4) to instrument for p_{rjt}. While very similar to an approach offered by Zhen et al. (2013), equation (8) exploits exogenous variation in commodity supply shifters. In contrast, Zhen et al. (2013) rely on Hausman-type price instruments, which can be problematic in our model; for example, when the effect on food demand of various marketing campaigns extends to more than one market (Hausman 1997). Durbin-Wu-Housman test outcome indicates that food prices and expenditures are endogenous (Dhar, Chavas, and Gould 2003). Using a first stage F-test, we further find that urbanization and other supply shifters utilized in this study are important food price determinants, or equivalently, our price instruments meet the relevance requirement (the associated *p*-value<0.00).

Tables 2-3 present the parameter estimates from our generalized EASI demand system and the estimated impact of urbanization on the price and income coefficients, respectively. Using the LR test procedure, we find that our structural framework provides a good fit of the data with the respective *p*-value < 0.00. Moreover, the LR test for the joint significance of the provincial fixed-effects indicates that the unobserved provincial heterogeneity has considerable influence on food budget shares (Table 2, lower part). The majority of coefficients in Tables 2-3 are statistically significant at standard significance-levels and have expected signs. For example, λ_{i0} which can be interpreted as subsistence budget shares, are estimated to be positive and significant, and fall in the range 0.02-0.26. Real expenditure coefficients β_{i1}, on the other hand, are estimated to be positive for seafood and vegetables, and negative for fats and oil with the majority of β_{i2} and β_{i3} coefficients being statistically significant. This is a testament to the highly nonlinear Engel curves, which cannot be represented by more restrictive models such as the Quadratic AIDS that can only account for quadratic Engel curves. Table 3 reveals that urbanization affects consumer food preferences for many commodities by altering both real income and price coefficients. For example, β_{i1}^{u} coefficients indicate that urbanization has contributed to the increase in demand for seafood and to the decline in demand for grains with the effect being non-linear, given the statistically significant β_{i2}^{u} coefficients. The LR test procedure further certifies that urbanization has significant effects on consumption patterns of the food commodities under study (Table 3, lower part). This implies that the previous empirical demand studies overlooking the urbanization-driven changes suffer from a specification bias that can generate inaccurate economic effects and unreliable food demand and trade forecasts.

Table 4 presents the estimation results from the reduced-form price equations. Specifically, flood and wind/hail are found to affect commodity prices positively, except for seafood and eggs. This is most likely due to the diminished agricultural commodity stock resulting from the adverse weather shocks. Though drought has resulted in lower grain and vegetable prices. These effects appear to be considerably smaller in magnitude vis-à-vis the flood effects. It is worth pointing out that grains are predominantly grown in North China Plain which is very vulnerable to persistent rainfall and flooding, whereas East China is the most drought-prone region. Additionally, the effects of drought largely depend on its severity and the impact thereof on commodity yields. Most importantly, we find that the supply-side effect of urbanization on food prices has been positive for all commodities with the exception of eggs. This is consistent with fact that increased urbanization reduces land availability for agricultural production, which in turn brings diminished food commodity supply, and consequently, higher food prices.

Table 5 presents the Marshallian price (e^M), expenditure (e_i), and urbanization elasticity (e^U) estimates evaluated at the sample mean values.[5] All own-price elasticity estimates appear to be consistent with theory and are statistically significant. Urbanization elasticities, which measure the percentage change in demand caused by a percent change in the urbanization rate, are estimated to be positive and statistically significant for meats (0.052), seafood (0.061), vegetables (0.015), fruit (0.263), and eggs (0.011), whereas the elasticities for grains (-0.315) and fats (-0.310) are found to be negative and significant. These results are consistent with the qualitative predictions from Hsu, Chern, and Gale (2001), Regmi and Dyck (2001) and other descriptive studies investigating urbanization-driven food consumption changes. Specifically, improved food accessibility and availability (*i.e*., modern supermarkets offering a wide range of food items tend to locate in urban areas), ownership of refrigerators, and overall better living standards that urban markets have to offer can boost the consumption of poultry, fish, and eggs. Further, the average rural resident's intake of energy-rich carbohydrates, and first of all cereal grains, exceeds that of urban dwellers despite the fact that coarse grains that are most popular in rural China are partially replaced by refined grains in cities (Huang and David 1993; Hsu, Chern, and Gale 2001).

To examine the importance of urbanization, we further calculate the percentage difference between the elasticity estimates from the standard EASI model and the generalized demand system incorporating urbanization. Table A1 shows that ignoring urbanization can introduce significant biases into the Marshallian and Hicksian elasticity estimates. For example, the cross price elasticity between meats and seafood is underestimated by a factor of 12, the own price elasticity for grains

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[5] Hicksian elasticity estimates are not presented for limited space, but are available upon request.

is overestimated by 67.3%, and the own price elasticity for fruit is underestimated by 251.9%. It should be noted, however, that expenditure elasticities are not significantly impacted by urbanization.

It is important to recognize the fact that urbanization-caused changes in food diets are most pronounced before a country or a region reaches a certain level of urbanization (Regmi and Dyck 2001). In other words, urbanization will not likely bring dramatic changes to food preferences and consumer demand once provinces achieve an economic development threshold or advanced urbanization. Given the vast differences in urbanization levels and rates across the Chinese provinces (Figure 1), we calculate the urbanization elasticities for the seven commodities under study across all 29 provinces. Figures 2-5 present these elasticities for meats and seafood, vegetables and fruit, grains, and eggs and fats/oils. There appears to be considerable province-level heterogeneity in the elasticity estimates not only in terms of the magnitude but also the direction of the effect. For example, urbanization elasticities of demand for meats are positive for all provinces except for Shanghai, Fujian, and Zhejiang, which are also three neighboring provinces/cities along the south-eastern coast (Figure 2). One possible reason for this finding may be the fact that consumers in these administrative divisions have been substituting seafood for meats, given the increased availability of seafood in the coastal provinces (Figure 2). Further, urbanization elasticities for grains and fats/oils vary greatly in magnitude despite them being negative across all provinces (Figures 4 and 5, respectively). Therefore, it is important to take these provincial-level differential effects of urbanization into account when evaluating the impact of urbanization on food commodity trade and designing agricultural and food policies.

Conclusions

Rapid urbanization along with income and population growth are considered to be some of the most important factors in the second half of the 20^{th} century to have shaped consumer food preferences in many parts of the world. This is particularly true for China in the recent decades, where the dramatic changes to traditional food diet have kept apace with the accelerated urbanization throughout the country.

The current study analyzes the impact of urbanization on consumer food preferences in China by developing a structural framework that incorporates urbanization into the Exact Affine Stone Index demand system. Our analytical framework provides a considerable improvement over the previous literature by utilizing the recent advances in consumer demand theory. Further, our empirical framework relies on an equilibrium analysis, which recognizes the effects of urbanization-induced loss of agricultural land and deteriorating soil quality on food supply and prices. Based on the urbanization elasticities derived in this study, we find that urbanization has reduced demand for grains and fats, while increasing demand for meats, seafood, fruit, vegetables, and eggs. The results emerging from this study can provide invaluable information for designing accurate and effective agricultural, food, and trade policies.

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Table 1. Descriptive Statistics for Food Expenditures, Prices, Income, and Budget Shares

Variable	Mean	STD	Min	Max
Expenditure (Yuan/Capita)				
Meats	810.7	331.4	280.6	2086.7
Seafood	257.5	235.4	36.8	1220.0
Vegetables	411.6	129.7	169.5	797.0
Fruits	330.9	126.4	144.1	772.9
Grains	334.8	90.2	192.9	699.8
Eggs	86.8	28.8	35.1	195.9
Fats and oils	125.2	38.9	43.5	266.6
Agricultural Commodity Price (Yuan/kg)				
Meats	24.6	6.1	14.1	41.3
Seafood	20.3	8.4	11.0	57.5
Vegetables	3.3	1.1	1.7	7.3
Fruit	5.0	1.5	2.3	9.9
Grains	3.9	0.8	2.6	6.4
Eggs	9.1	2.2	5.3	15.8
Fats and oils	11.4	2.4	6.7	17.0
Per capita Income (1,000 Yuan)	15.8	6.5	2.9	40.2
Budget Share (%)				
Meats	34.0	5.3	24.9	48.3
Seafood	9.8	6.3	3.1	27.1
Vegetables	17.7	2.4	12.7	24.4
Fruit	14.2	3.1	7.5	22.2
Grains	14.9	3.4	7.4	24.3
Eggs	3.9	1.2	1.4	6.9
Fats and oils	5.5	1.5	2.6	10.7
Agricultural Commodity Supply Shifters				
Urbanization rate (% of urban population in total)	50.0	14.3	26.9	89.0
Other Shifters				
Disaster-affected area (1,000 ha)				
Flood	175.2	274.5	0.1	2208.0
Drought	334.4	449.1	0.1	3133.0
Windstorm and hail	63.4	86.9	0.1	682.5
Irrigated area (10,000 ha)	192.2	142.1	16.8.	520.6
Total power of large and medium agricultural machinery (100,000 kw)	89.3	131.5	0.1	808.9
Per capita agricultural land (ha/person)	2.4	2.5	0.3	13.6

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

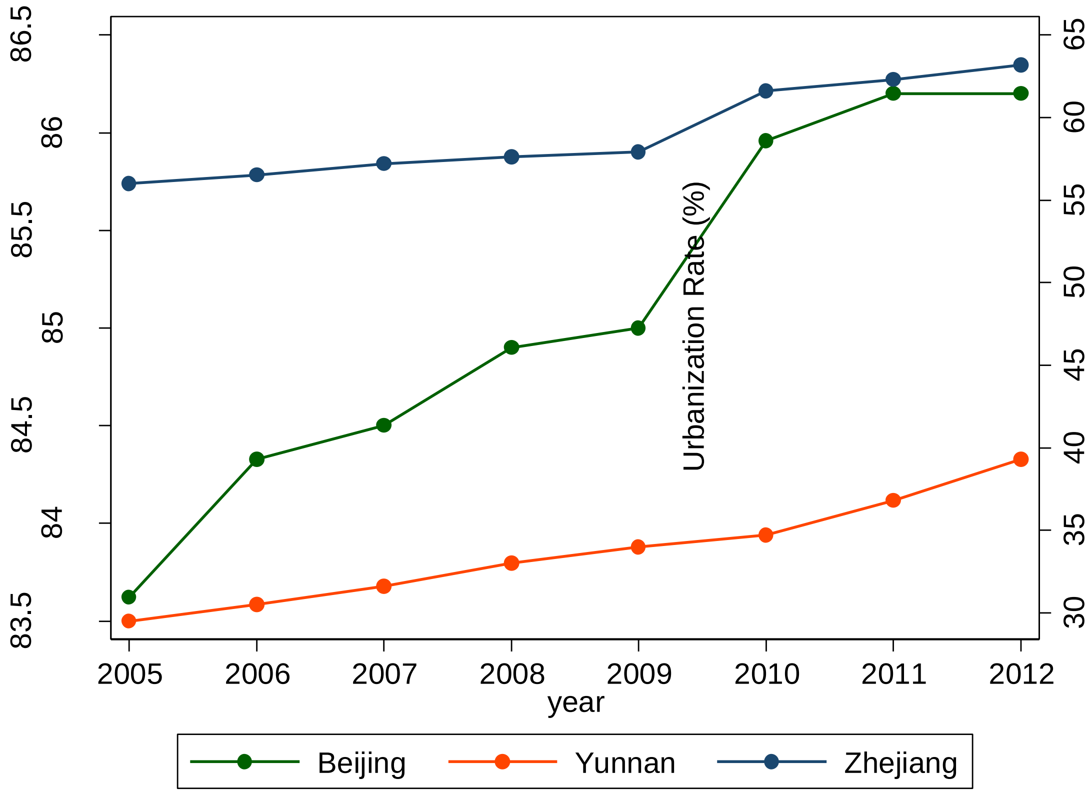

Figure 1. Urbanization Rates for Representative Highly-, Moderately, and Lowly-Urbanized Provinces in China, NBSC, 2005-2012.

Note: Beijing is measured on the left y-axis, and Yunnan and Zhejiang are measured on the right y-axis.

Table 2. Parameter Estimates from the EASI Expenditure Share Equations

Parameter	Meats	Seafood	Vegetable	Fruit	Grains	Eggs	Fats
Intercept (λ_{i0})	0.261 [a]	0.191 [a]	0.141 [a]	0.134 [a]	0.153 [a]	0.019 [a]	0.101 [a]
	(0.026)	*(0.019)*	*(0.021)*	*(0.025)*	*(0.025)*	*(0.008)*	*(0.005)*
Real income (β_{i1})	0.016	0.017 [a]	0.081 [a]	-0.080	0.060	-0.006	-0.088 [a]
	(0.070)	*(0.002)*	*(0.006)*	*(0.073)*	*(0.070)*	*(0.020)*	*(0.006)*
Real income (β_{i2})	-0.234 [a]	0.137 [a]	0.086	0.009	-0.164	0.022	0.143 [a]
	(0.122)	*(0.059)*	*(0.106)*	*(0.128)*	*(0.124)*	*(0.034)*	*(0.027)*
Real income (β_{i3})	0.166 [a]	-0.077 [a]	-0.070	0.001	0.090	-0.014 [a]	-0.096 [a]
	(0.074)	*(0.034)*	*(0.065)*	*(0.078)*	*(0.076)*	*(0.001)*	*(0.024)*
Price (α_{1i}) meats	-0.080 [a]	0.036 [a]	0.066 [a]	-0.114 [a]	-0.099 [a]	-0.024 [a]	0.216 [a]
	(0.021)	*(0.014)*	*(0.014)*	*(0.016)*	*(0.015)*	*(0.006)*	*(0.015)*
Price (α_{2i}) seafood		0.035 [c]	-0.177 [a]	0.026 [b]	0.061 [a]	0.032 [a]	-0.013
		(0.021)	*(0.012)*	*(0.013)*	*(0.014)*	*(0.007)*	*(0.011)*
Price (α_{3i}) veg			0.126 [a]	-0.040 [a]	0.031 [b]	-0.061 [a]	0.054 [a]
			(0.017)	*(0.015)*	*(0.014)*	*(0.005)*	*(0.012)*
Price (α_{4i}) fruits				0.138 [a]	-0.016	0.012 [b]	-0.006
				(0.022)	*(0.016)*	*(0.006)*	*(0.014)*
Price (α_{5i}) grains					0.105 [a]	-0.001	-0.081 [a]
					(0.021)	*(0.006)*	*(0.013)*
Price (α_{6i}) eggs						0.025 [a]	0.017 [a]
						(0.005)	*(0.004)*
Price (α_{7i}) fats							-0.186 [a]
							(0.006)

Null Hypothesis	Likelihood Ratio value	df.	*p*-value
Model does not fit the data	7,448.65	1	0.00
Provincial fixed-effects are not important	2,342.41	203	0.00
Price and expenditure are exogenous	2,582.21	49	0.00

Note 1: The standard errors are in parenthesis. [a, b, c] identify parameter estimates that are statistically different from 0 at the 0.01, 0.05, and 0.10 significance levels, respectively.

Table 3. Estimates of Parameters Representing the Effect of Urbanization on Food Demand

Parameter	Meats	Seafood	Vegetable	Fruit	Grains	Eggs	Fats
Intercept (λ^u_{i0})	0.004	0.006	0.011	0.063	-0.074 [a]	0.010	-0.019 [a]
	(0.053)	*0.042)*	*(0.043)*	*(0.053)*	*(0.030)*	*(0.017)*	*(0.003)*
Real income (β^u_{i1})	-0.109	0.196 [b]	0.129	0.001	-0.254 [b]	-0.025	0.061 [a]
	(0.130)	*(0.097)*	*(0.111)*	*(0.133)*	*(0.129)*	*(0.038)*	*(0.024)*
Real income (β^u_{i2})	0.431 [c]	-0.367 [b]	-0.385 [c]	0.210	0.419 [c]	-0.007	-0.301 [a]
	(0.244)	*(0.175)*	*(0.212)*	*(0.254)*	*(0.248)*	*(0.067)*	*(0.012)*
Real income (β^u_{i3})	-0.270 [c]	0.136	0.291 [b]	-0.183	-0.225	0.033	0.218 [a]
	(0.160)	*(0.115)*	*(0.139)*	*(0.167)*	*(0.163)*	*(0.044)*	*(0.034)*
Price (α^u_{1i}) meats	0.061	-0.112 [a]	-0.021	0.058	0.013	-0.029 [b]	0.031
	(0.054)	*(0.034)*	*(0.032)*	*(0.038)*	*(0.033)*	*(0.015)*	*(0.035)*
Price (α^u_{2i}) seafood		0.062	0.056 [a]	-0.042	0.020	-0.023	0.040 [c]
		(0.042)	*(0.026)*	*(0.031)*	*(0.028)*	*(0.015)*	*(0.024)*
Price (α^u_{3i}) veg			-0.042	0.003	-0.008	0.030 [a]	-0.018
			(0.036)	*(0.033)*	*(0.028)*	*(0.011)*	*(0.025)*
Price (α^u_{4i}) fruits				-0.081 [b]	0.056	-0.030 [a]	0.036
				(0.041)	*(0.030)*	*(0.013)*	*(0.030)*
Price (α^u_{5i}) grains					-0.046	0.007	-0.041
					(0.041)	*(0.011)*	*(0.028)*
Price (α^u_{6i}) eggs						0.032 [a]	0.014
						(0.012)	*(0.009)*
Price (α^u_{7i}) fats							-0.064 [a]
							(0.002)

Null Hypothesis	Likelihood Ratio value	df.	*p*-value
Urbanization has no effect on food demand	139.05	52	0.00

Note: The standard errors are in parenthesis. [a, b, c] identify parameter estimates that are statistically different from 0 at the 0.01, 0.05, and 0.10 significance levels, respectively.

Table 4. Parameter Estimates from the Reduced-Form Price Equations

Commodity		Intercept	Urban.	Flood	Drought	Wind/hail	Machinery	Land	Irrigated land
Meats	(ψ_{1k})	-0.080	0.151 [a]	-0.008	0.000	0.162 [a]	0.743 [a]	0.144 [a]	-0.249 [a]
		(0.048)	*(0.044)*	*(0.029)*	*(0.026)*	*(0.029)*	*(0.065)*	*(0.051)*	*(0.044)*
Seafood	(ψ_{2k})	0.337 [a]	0.222 [a]	-0.068 [a]	-0.041 [b]	0.013	-0.048	-0.138 [a]	0.072 [b]
		(0.036)	*(0.033)*	*(0.024)*	*(0.021)*	*(0.024)*	*(0.050)*	*(0.038)*	*(0.033)*
Vegetable	(ψ_{3k})	0.276 [a]	0.094 [b]	0.175 [a]	-0.087 [a]	-0.010	0.233 [a]	-0.120 [a]	-0.074 [c]
		(0.044)	*(0.039)*	*(0.033)*	*(0.029)*	*(0.031)*	*(0.058)*	*(0.045)*	*(0.040)*
Fruit	(ψ_{4k})	0.170 [a]	0.225 [a]	0.184 [a]	0.032	0.115 [a]	0.258 [a]	-0.071	-0.211 [a]
		(0.049)	*(0.042)*	*(0.040)*	*(0.035)*	*(0.038)*	*(0.066)*	*(0.049)*	*(0.045)*
Grains	(ψ_{5k})	0.032	0.242 [a]	0.169 [a]	-0.088 [b]	0.112 [b]	0.378 [a]	0.154 [a]	-0.265 [a]
		(0.060)	*(0.052)*	*(0.049)*	*(0.043)*	*(0.047)*	*(0.081)*	*(0.061)*	*(0.056)*
Eggs	(ψ_{6k})	0.531 [a]	-0.299 [a]	0.258 [a]	-0.133 [a]	-0.084 [b]	0.233 [a]	0.012	-0.186 [a]
		(0.056)	*(0.049)*	*(0.044)*	*(0.040)*	*(0.043)*	*(0.077)*	*(0.058)*	*(0.053)*
Fats/oils	(ψ_{7k})	0.233 [a]	-0.060	0.056 [b]	-0.029	0.097 [a]	0.572 [a]	-0.080	-0.111 [b]
		(0.050)	*(0.050)*	*(0.024)*	*(0.022)*	*(0.024)*	*(0.057)*	*(0.052)*	*(0.044)*

Note: The standard errors are in parenthesis. [a, b, c] identify parameter estimates that are statistically different from 0 at the 0.01, 0.05, and 0.10 significance levels, respectively.

Table 5. Marshallian Price, Expenditure, and Urbanization Elasticity Estimates from the EASI system

	Marshallian Elasticity $\left(e_{ij}^{M}\right)$							Expend.	Urban.
Commodity	Meats	Seafood	Veg.	Fruits	Grains	Eggs	Fats/oils	$\left(e_i\right)$	$\left(e_{ij}^{Urb}\right)$
Meats	-1.120 [a]	-0.004	0.197 [a]	-0.253 [a]	-0.257 [a]	-0.098 [a]	0.677 [a]	0.860 [a]	0.052 [a]
	(0.036)	*(0.025)*	*(0.022)*	*(0.027)*	*(0.026)*	*(0.011)*	*(0.024)*	*(0.023)*	*(0.021)*
Seafood	-0.308 [a]	-0.475 [a]	-1.726 [a]	0.005	0.592 [a]	0.215 [a]	-0.023	1.721 [a]	0.061 [b]
	(0.087)	*(0.144)*	*(0.075)*	*(0.084)*	*(0.087)*	*(0.050)*	*(0.058)*	*(0.342)*	*(0.030)*
Vegetable	0.131 [a]	-0.938 [a]	-0.481 [a]	-0.300 [a]	0.073 [a]	-0.302 [a]	0.235 [a]	1.581 [a]	0.015 [a]
	(0.043)	*(0.041)*	*(0.055)*	*(0.047)*	*(0.046)*	*(0.017)*	*(0.036)*	*(0.482)*	*(0.003)*
Fruit	-0.545 [a]	0.104 [c]	-0.215 [a]	-0.195 [b]	0.076	0.017	0.073	0.687 [a]	0.263 [a]
	(0.064)	*(0.058)*	*(0.058)*	*(0.091)*	*(0.067)*	*(0.024)*	*(0.053)*	*(0.216)*	*(0.007)*
Grains	-0.547 [a]	0.484 [a]	0.236 [a]	0.064	-0.370 [a]	0.021	-0.630 [a]	0.742 [a]	-0.315 [a]
	(0.059)	*(0.057)*	*(0.054)*	*(0.064)*	*(0.084)*	*(0.024)*	*(0.050)*	*(0.324)*	*(0.012)*
Eggs	-0.935 [a]	0.605 [a]	-1.293 [a]	0.007	0.029	-0.050	0.558 [a]	1.079 [a]	0.011 [a]
	(0.096)	*(0.127)*	*(0.077)*	*(0.088)*	*(0.093)*	*(0.008)*	*(0.059)*	*(0.361)*	*(0.004)*
Fats/oils	0.388 [a]	0.111	1.004 [a]	0.260 [c]	-0.611 [a]	0.426 [a]	-4.749 [a]	0.171 [a]	-0.310 [a]
	(0.147)	*(0.103)*	*(0.114)*	*(0.135)*	*(0.134)*	*(0.041)*	*(0.695)*	*(0.037)*	*(0.112)*

Note: The standard errors are in parenthesis. [a, b, c] identify parameter estimates that are statistically different from 0 at the 0.01, 0.05, and 0.10 significance levels, respectively.

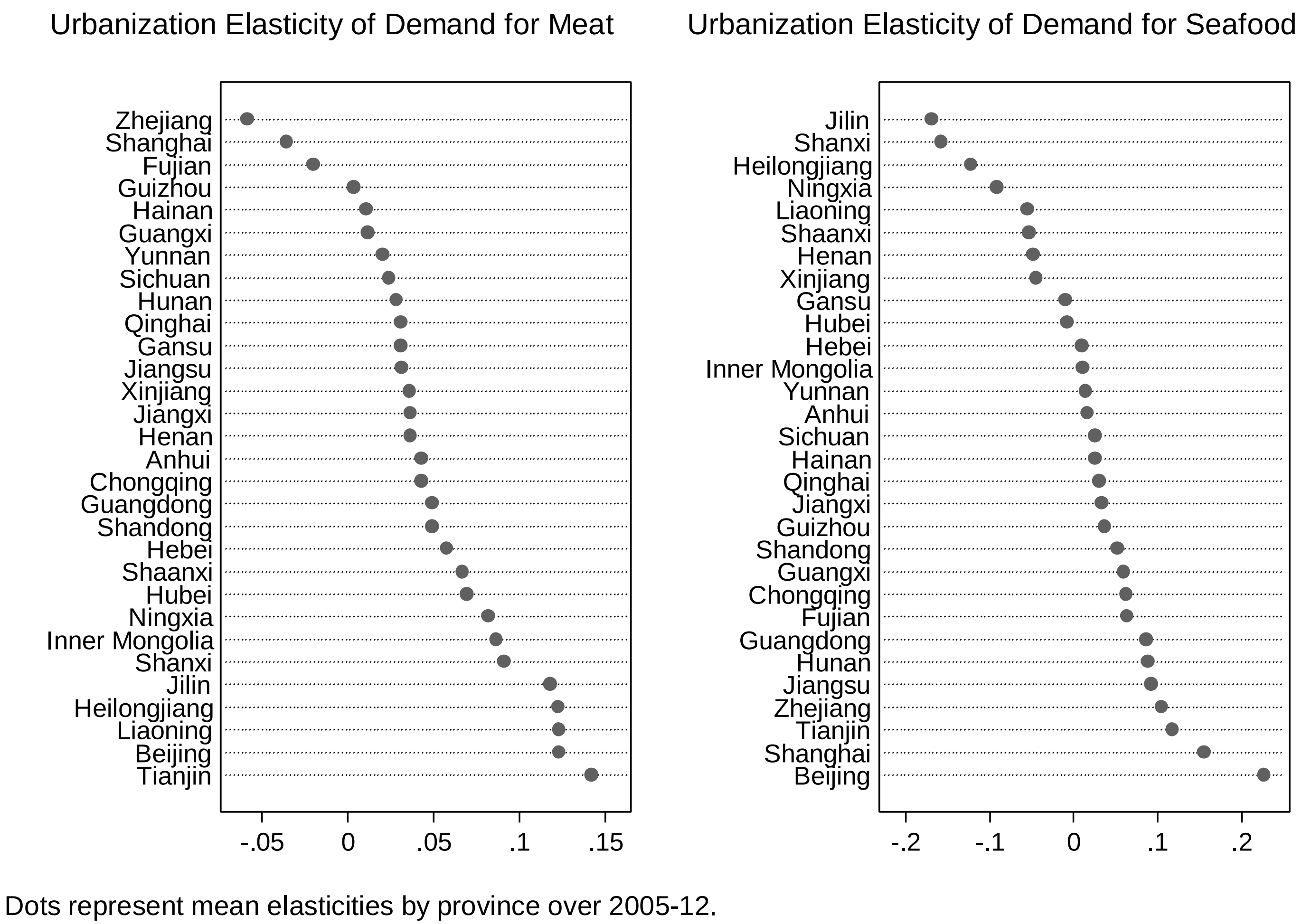

Figure 2. Urbanization elasticity of demand for meats and seafood

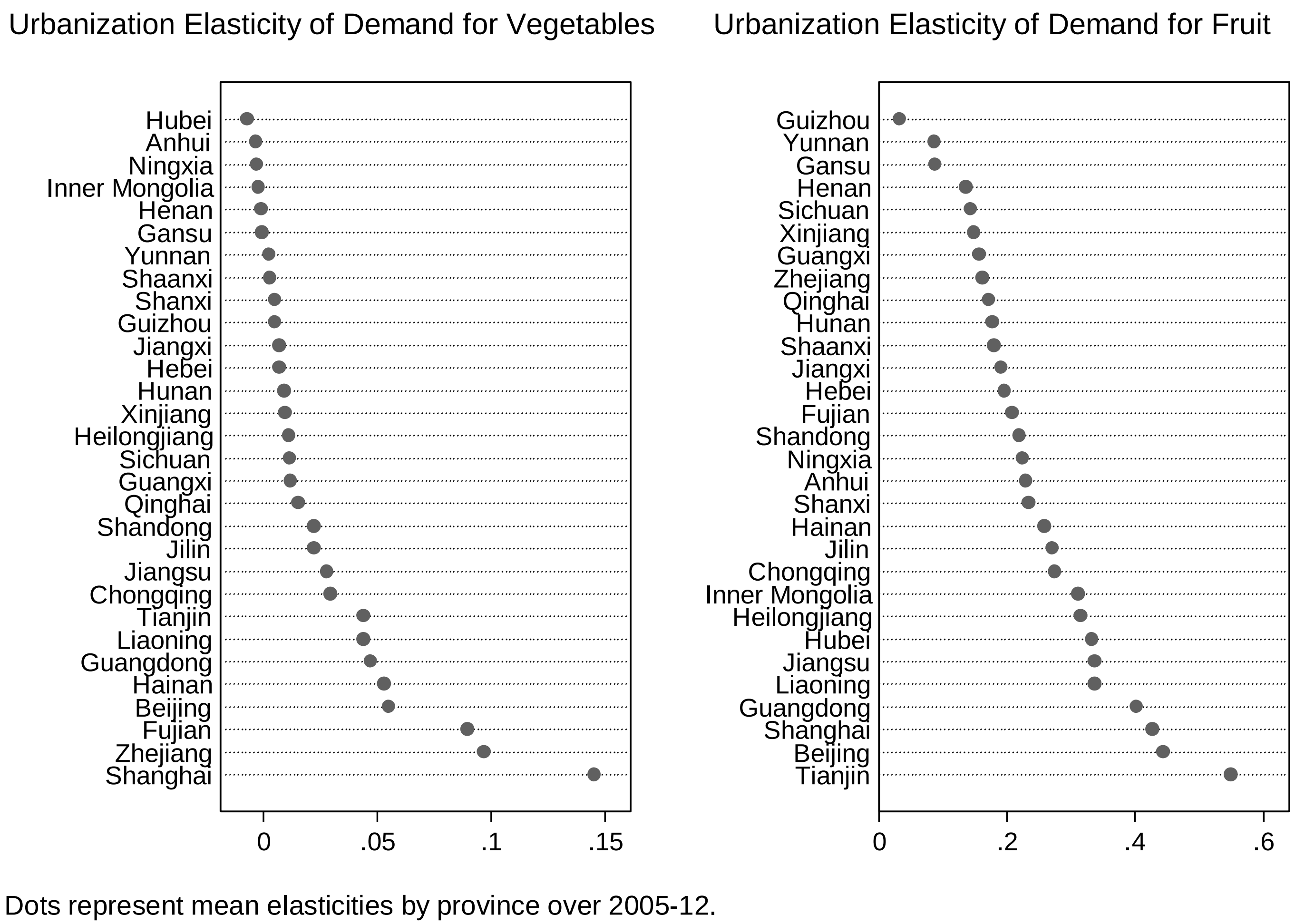

Figure 3. Urbanization elasticity of demand for vegetables and fruit

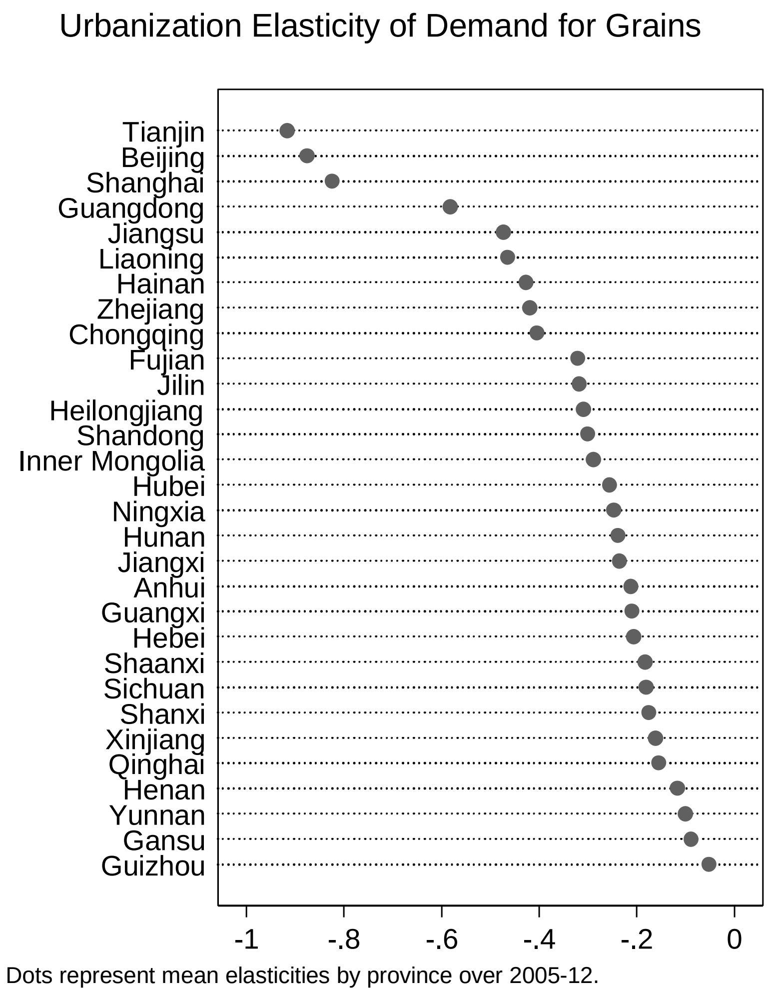

Figure 4. Urbanization elasticity of demand for grains

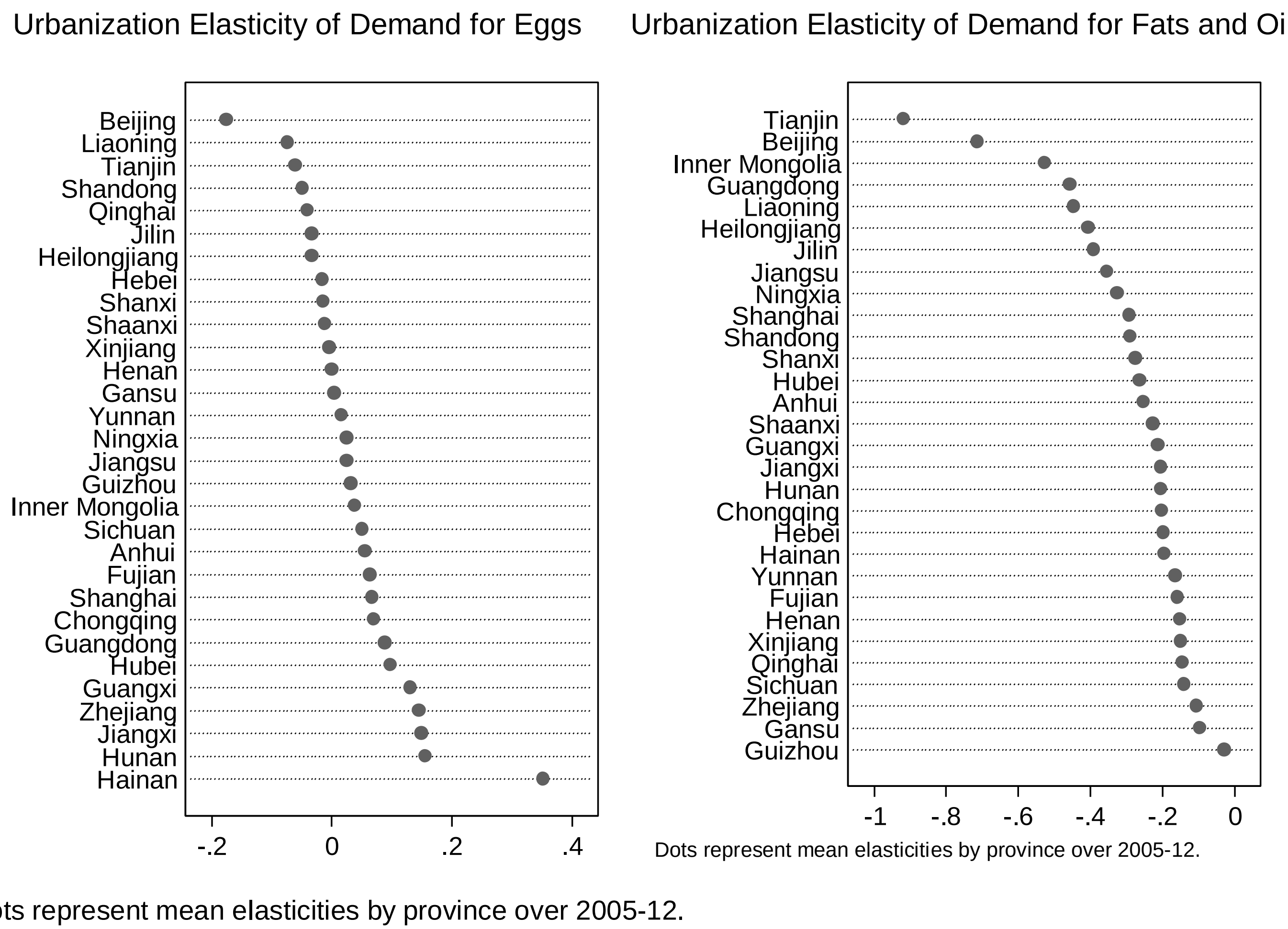

Figure 5. Urbanization elasticity of demand for eggs, and fats and oil

Appendix

Table A1. Percentage Difference between Elasticity Estimates from the Models with and without Urbanization (%)

Commodity	Uncompensated Elasticity							
	Meats	Seaf.	Veg.	Fruit	Grains	Eggs	Fats/oils	Expend.
Meats	1.3	106.0	-32.9	9.2	-125.6	53.4	-10.7	5.0
Seaf.	-1,203.4	21.8	-1.8	102.7	12.5	40.3	91.3	0.0
Veg.	-7.4	-4.0	-64.8	8.3	75.2	46.3	17.6	-14.6
Fruit	10.6	660.2	26.9	-251.9	67.2	74.7	219.6	7.4
Grains	-137.2	9.1	47.7	69.2	67.3	91.8	29.9	9.4
Eggs	50.9	37.7	48.7	96.4	96.9	86.6	65.6	0.5
Fats/oils	-9.8	135.0	10.9	436.8	30.7	63.6	-26.2	9.0
	Compensated Elasticity							
Meats	-0.1	50.6	-13.1	12.9	721.6	63.0	-9.5	
Seaf.	50.7	30.2	-2.2	-218.4	9.1	34.1	142.8	
Veg.	-13.1	-2.2	-323.6	42.7	38.3	52.7	10.8	
Fruit	12.8	-218.4	42.6	295.2	47.8	54.7	663.8	
Grains	720.2	9.1	38.3	47.8	74.3	82.5	31.0	
Eggs	63.0	34.1	52.7	54.6	82.5	97.5	63.3	
Fats/oils	-9.5	142.8	10.8	663.3	31.0	63.3	-26.3	

Note: The first column represents commodities with price change.