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AN EMPIRICAL ANALYSIS OF WELFARE CONSEQUENCES OF RISING FOOD PRICES IN URBAN CHINA: THE EASI APPROACH

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Abstract: The recent rise in food prices in China triggered by global commodity price spikes led to growing welfare concerns among economists and policymakers. While evidence suggests the Chinese government was successful in preventing major upswings in food prices, the true impact on consumer welfare remains unknown. This study examines consumer welfare consequences of food price increases in China based on the Fixed-Effects Exact Affine Stone Index (FE-EASI) demand model that accounts for unobserved consumer and provincial heterogeneity estimated on nationally representative provincial-level panel data. The effects of actual price changes as well as two policy initiatives are evaluated. The major findings indicate that urban wages outpaced food prices, and consumer welfare loss has been moderate as a fraction of food expenditures. The results of policy analysis indicate that government subsidies overcompensated the negative effects of price increases for the relatively less affluent households. Finally, a counterfactual analysis is utilized to illustrate the empirical superiority of the EASI over the QUAIDS system commonly used in previous welfare analyses.

Keywords: Consumer welfare, food demand in China, food prices, EASI demand model, unobserved preference heterogeneity.

JEL Code: D11, D12.

1. Introduction

Increased volatility in global commodity markets and rising food prices are fueling ongoing policy debates regarding the potential consumer welfare implications (Piesse and Thirtle 2009; Cudjoe et al. 2010; Heady 2011). The growing concerns about the next world food crisis have motivated a large body of literature focused on welfare analysis and policy evaluation in the context of developing and emerging economies where the food security of billions of people and the economic and political stability are at stake (Jensen and Miller 2008; Yang et al. 2008; Gilbert 2010; Attanasio et al. 2013; Ferreira et al. 2013). Recent evidence from Mexico shows that as expected, all net food consumers suffered from rising food prices, however the adverse effects were borne disproportionately by the poor (Attanasio et al. 2013). In contrast, a study conducted on Brazil by Ferreira et al. (2013) found that middle-income consumers bore the brunt of higher food prices, while the lower income classes were relatively less affected due to differing effect on wage dynamics across income categories (Ferreira et al. 2013). In a similar study with a broader geographic coverage, Ivanic and Martin (2008) found that income increases can smoothen the unfavorable impacts of increased food prices, especially in countries where wages trace food prices more closely (Ivanic and Martin 2008). Furthermore, studies on China have shown that the targeted policy initiatives can mitigate the effects of growing global food prices on population's food consumption and consumer welfare in general (Jensen and Miller 2008; Yang et al. 2008; Abbott 2010). Thus, the need for detailed analysis of welfare consequences of global commodity price rise and related policy interventions is well recognized by the researchers and policy makers. There is also a recognition that the ability to move the policy debate forward is largely driven by the accuracy and robustness of the models used to estimate the underlying consumer demand systems.

The AIDS model of Deaton and Muellbauer (1980) and its variations have been workhorse models in applied consumer demand analysis for around three decades. Despite their appeal and popularity, the AIDS and other similar models are not without limitations. Specifically, they are subject to Gorman's (1981) rank restrictions and cannot account for higher order curvilinear effects beyond quadratic. Further, these previous models are not flexible enough to recognize unobserved consumer heterogeneity. This can result in biased elasticity estimates under certain conditions, which could potentially lead to distorted policy outcomes. Recently, the Exact Affine Stone Index (EASI) demand specification was proposed by Lewbel and Pendakur (2009) as a more refined approach to applied consumer demand analysis. The advantages of EASI demand specification is that it directly addresses the fundamental shortcomings of the AIDS models by allowing for arbitrarily complex Engel curves where the slope of the curve is determined by the data, and provides sufficient flexibility for recognizing unobserved consumer heterogeneity. The latter is especially important for welfare and policy analyses conducted on disaggregate consumer-level data (Zhen et al. 2013).

This study applies the EASI demand specification to the empirical examination of welfare effects of food price dynamics and related policy interventions in urban China. Specifically, it uses nationally representative provincial-level panel data to achieve following three research objectives: (*i*) estimate consumer food demand structure by properly accounting for provincial heterogeneity and the price and expenditure endogeneity, (*ii*) analyze the welfare effects of increased food prices, and (*iii*) evaluate the effectiveness of two policy initiatives designed to mitigate the negative welfare impacts. China provides a particularly interesting empirical context because of the important role it plays in global agri-food systems (Hovhannisyan and Gould 2011). Following market liberalization and policy reforms initiated in 1979, China has become one of the fastest growing economies in the world ultimately surpassing the US in 2014 as the world's largest economy when measured by purchasing power parity-based GDP (World Bank 2016). With the recent shifts in food prices there are growing concerns among policy makers about the welfare dynamics of Chinese consumers and the likely spillover effects of related policy interventions that could be transmitted into other economies through global agri-food trade channels (Jensen and Miller 2008; Yang et al. 2008; Gilbert 2010; Attanasio et al. 2013). This paper aims to inform these policy concerns by providing methodological and empirical contribution to the literature.

From the methodological perspective, this paper extends the EASI system to account for price and expenditure endogeneity by exploiting province-level agricultural commodity supply shifters such as agricultural land affected by natural calamities (flood, drought, windstorm, and hail), per capita agricultural land, farm productive fixed assets, etc. This is a particularly valuable enhancement as there is evidence in the literature that omitting the supply side of the agricultural commodity price formation mechanism can lead to biased forecasts of future food demand (Hovhannisyan and Bozic 2017). Further, a fixed-effects EASI (FE-EASI) model is introduced to address potential omitted variable bias brought by unobserved provincial heterogeneity. In the case of China, such heterogeneity can arise from the socio-cultural and other dimensions of diversity across provinces, which have been shown to have a significant impact on consumer food preferences.

From the empirical perspective, this study evaluates the effectiveness of two policy initiatives designed to mitigate the unfavorable impact of food price increases, namely: (*i*) the Minimum Living Standard Assistance (MLSA) program launched by the Chinese government with the goal of alleviating urban poverty, and (*ii*) a government price subsidy amounting to 5% of new prices reflecting price rise. The findings emerging from this study indicate that despite the steady rise in food commodity prices, consumer welfare loss relative to consumer food expenditures has been moderate. Further, the urban wages are shown to have outpaced the increase in food prices in the study period, which can lead to welfare improvement in urban China. The results of policy analysis indicate that government subsidies overcompensate the negative effects of price increases for the relatively less affluent households. To complete the analysis, we evaluate the Quadratic AIDS (QUAIDS) model relative to the EASI specification. Specifically, counterfactual simulations are performed to examine the differential effects on projected food consumption and consumer welfare changes of the EASI and the QUAIDS models. The results complement and enhance the findings of previous studies in this area of literature and highlight the advantages of new and refined demand modeling approaches in informing food policy decisions.

The rest of the paper is organized as follows: Section 2 presents the methods including an overview of the EASI demand specification, a strategy for addressing endogeneity issues, and an analytical framework for the evaluation of consumer welfare impacts. Section 3 describes the data and variables. Section 4 presents the empirical results followed by the discussion of policy implications in Section 5. Section 6 concludes.

2. Methods

2.1. The EASI Demand Specification

Models such as the Linear Approximate-AIDS, the Generalized AIDS (Bollino 1987), and the Quadratic AIDS (Banks et al. 1997) have been popular in Chinese consumer behavior studies. Some of the well-known applications include Fan et al. (1995), Huang and Rozelle (1998), Gould and Villarreal (2006), Gale and Huang (2007). What makes these models particularly appealing is that they are theory-consistent, *i.e.*, they satisfy budget constraints and the axioms of order, aggregate over consumers without invoking parallel linear Engel curves, and are relatively simple to estimate. However, despite their attractive features, they have number of important restrictions and are not flexible enough for recognizing unobserved consumer heterogeneity. These limitations have become a source of concern for policy makers and highlighted a need for more robust demand modeling approaches. The EASI demand specification proposed by Lewbel and Pendakur (2009) offers a more refined approach to applied consumer demand analysis.

This paper utilizes the EASI demand specification and extends it further to account for province-level unobserved consumer preference heterogeneity in China as follows:

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

where w_{rit} is the budget share of commodity i in province r in year t; N is the number of commodities analyzed and R is the number of provinces; p_{rjt} denotes the price of commodity j in province r in year t; y_{rt} is consumer real food expenditures in province r in year t; L is the highest order of polynomial in real expenditures; D_r is a dummy variable for province r that is used to account for unobserved provincial heterogeneity; u_{rit} represents unobserved expenditure share determinants; and $\alpha_{i0}, \alpha_{ij}, \beta_{il}, \gamma_{ir}$ are parameters.

To simplify analyses already complicated by the incorporation of a large number of province fixed-effects, and a system of reduced-form price equations to be discussed below, we employ an approximate EASI model provided by Lewbel and Pendakur (2009). Specifically, y_{rt} is represented as Stone price-deflated real expenditures provided below:

(2) $$y_{rt} = \log\left(x_{rt}\right) - \Sigma_{j=1}^{N} w_{rjt} \log\left(p_{rjt}\right),$$

It should be noted that in the nonlinear variants of the EASI model, y_{rt} is the affine transformation of the Stone price-deflated real expenditures. Importantly, though, the Stone price is the correct deflator of food expenditures by the very design of the EASI system. This is in contrast to the linear approximate AIDS demand specification, where the Stone price index is only an approximation to the true expenditure deflator (Zhen et al 2013). Moreover, the linear approximate EASI and its nonlinear variants have been found to yield very similar results based on a number of different datasets (e.g., Lewbel and Pendakur 2009).

2.2. Endogeneity Issues and Identification Strategy in the EASI Model

By design, the EASI model is plagued by endogeneity of real expenditures (y_{rt}), the reason being that budget shares also appear on the right-hand side of the share equations, as can be seen from equation (2). Nevertheless, empirical findings from Pendakur and Lewbel (2009), Zhen et al. (2013), and similar studies confirm that this source of endogeneity is not very important from a numerical perspective. A second source of endogeneity of real expenditures in incomplete demand systems stems from the endogeneity of food expenditures; specifically, from expenditure shares and total expenditures being determined simultaneously (Dhar, Chavas and Gould 2003).

Price endogeneity is another form of endogeneity typically present in demand analysis (e.g., Dhar et al. 2003; Zhen et al. 2013). In our empirical setting, price endogeneity may be caused by the omission of important demand-side price determinants such as cultural characteristics, food customs, and other unsuspected factors that typically cannot be quantified, and which are correlated with the included covariates such as food expenditures. Additionally, price endogeneity may be a result of food supply and demand being determined simultaneously, when the supply side of the price formation mechanism is ignored. This has been found to be particularly important when analyzing food demand in China (Hovhannisyan and Bozic 2017). The underlying reason is that agricultural production fluctuations in China, which are mostly induced by abrupt weather changes and natural disasters, constitute the single most important source of agricultural commodity price volatility (Jianguo 1996; Headey and Fan 2008; Gilbert 2010; Guojiang 2010; Lu et al. 2014). As regards the direction of the price endogeneity bias, simultaneity typically leads to an upward bias in estimated price coefficients, whereas omitted variables bring about a reverse effect in linear models.

Correcting for Omitted Variable Bias through Province-Level Fixed-Effects

This study addresses potential omitted variable-induced price endogeneity by introducing province fixed-effects into the EASI model. Province-level fixed-effects allow us to account for time-invariant unobserved province heterogeneity reflecting the socio-cultural and other dimensions of diversity across Chinese provinces, which have been documented to have a significant impact on consumer food preferences (Anderson 1988; Ma 2015).

Consumer food choices and dietary habits are influenced by variety of factors including economic and demographic (e.g. cost, income, access, education, cooking skills, and time) as well as socio-cultural (e.g. ethnicity, religion, attitudes, and beliefs) (Asp 1999). While the factors in the first group are relatively easy to capture and quantify in economic analysis, it is not always possible to fully account for the influence of socio-cultural factors on food demand. This can become a serious empirical shortcoming when analyzing consumer demand in a country such as China with vast ethnic and cultural diversity across regions (Anderson 1988; Harrell 2013). For example, the food choices in northern region of china including Inner Mongolia and neighboring provinces are dominated by dairy, red meat, and wheat due to the influence of Mongolian ethnic traditions, while in the northwest provinces of Xinjiang and Qinghai the diets are influenced by the traditions of Muslim minorities. In contrast, in the southern provinces of

Yunnan, Guizhou, and Guangxi the food choices are dominated by rice, fruits, and vegetables influenced by southern minority food traditions, while the eastern China cuisine is known for the abundance of seafood (Anderson 1988). These food preferences driven by socio-cultural factors are deeply rooted and are slow to change over time. This study captures the time-invariant province-level heterogeneity by incorporating province fixed-effects into the EASI model and utilizing the longest and most recent provincial panel data on Chinese consumer food expenditures. While this approach does not capture potential time-variant province level differences, it provides a valuable improvement over the previous literature by having the province-level fixed effects accounted for in the results.

Correcting for Simultaneity Bias

This paper also corrects for simultaneity bias by extending the EASI system to incorporate reduced-form price equations that relate food prices to exogenous supply shifters (see Dhar et al. (2003) for more details on this approach). It is worth noting that finding proper price instruments remains a daunting task in practice, given limited data. Therefore, many empirical studies rely on Hausman-type of instruments, where prices from neighboring markets are used to identify price effects on demand (Hausman 1997). Identification in this setting rests on the assumption that prices from these adjacent markets reflect supply shocks only (see for example, Zhen et al. 2013). Nevertheless, this approach becomes invalid in empirical settings where nation-wide advertising campaigns induce positive demand shocks across various markets. This issue is sidestepped in the approach offered by Dhar, Chavas, and Gould (2003). Specifically, the simultaneity bias is addressed through the inclusion of reduced-form price equations. We are able to use this approach by utilizing the most recent and the longest panel data on agricultural commodity supply shifters as shown below:

(3) $$\ln\left(p_{rit}\right) = \gamma_{i0} + \sum_{k=1}^{7} \gamma_{ik} Ins_{rkt} + \xi_{rit}, \quad \forall i = 1,...,7;\ r = 1,...,29; t = 1,...,10.$$

where Ins_{rkt} represents supply shifters, namely areas in province r in year t that are affected by flood, drought, windstorm and hail, per capita agricultural land, total power of large and medium agricultural machinery, and other productive fixed assets owned by farm producers in China, ξ_{rit} is the residual of the i^{th} reduced-form price equation, and γ_{i0}, γ_{ik} are parameters.

An instrument for real expenditures y_{rt} is constructed as follows:

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

where $\tilde{y}_{rt}$ is the instrument for y_{rt}, $\tilde{x}_{rt}$ is per capita average provincial income, $\bar{w}_j$ is average provincial budget share of commodity j, and p_{rjt} represent agricultural commodity supply shifters used to instrument for p_{rjt}.While this approach is similar to the one utilized by Pendakur (2008) and Zhen et al. (2013), unlike these studies, the current study employs exogenous commodity supply shifters in lieu of Hausman-type instruments. Additionally, the expenditure endogeneity is addressed using data on per capita income.

2.3. An Analytical Framework for the Evaluation of Consumer Welfare Impacts

Consumer welfare impact of food price change is assessed via the Hicksian compensating variation (CV), given that the latter remains the most widely used welfare analysis tool. Let $E(p,u)$ denote the minimum expenditure necessary to obtain utility u at a given price vector p with p_0 and p_1 representing original and new price vectors, respectively, and u_0 denote utility from food consumption. The CV estimate reflects the adjustment in consumer income needed to leave the consumer unaffected by a price change and is measured as follows:

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

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

To develop an empirically tractable version of equation (5), we revise it based on a vector of compensated quantity changes $dq^h = q^h\left(p_1, u_0\right) - q_0\left(p_0, u_0\right)$ as shown below:

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

where $dp = p_1 - p_0$ is a vector of price changes, and dq^h is calculated by the following equation:

(7) $$\frac{dq^h}{q} = \sum e^H\left(\frac{dp}{p}\right)$$

where (e^H) represents the compensated (Hicksian) elasticity.

3. Data and Construction of Variables

The panel data used in this study cover the period from 2003 to 2012 and constitute the most recent and the longest province level panel data on Chinese consumer food expenditures (NBSC, China Statistical Yearbooks 2003–2012). The data were obtained from the National Bureau of Statistics of China (NBSC) and include detailed information on household food expenditures, unit prices, household socio-demographic characteristics, and agricultural commodity supply shifters. The NBSC collects data from representative urban households annually as part of the Chinese Urban Household Income and Expenditure Survey. The survey is conducted using a two-stage stratified systematic random sampling method, where a third of households are dropped each period and replaced with a fresh sample of equal size based on a rotating-sample design. The collected data are then aggregated by the NBSC to province level.

The population of inference for this study includes urban consumers in all provinces of China excluding Tibet.[1] The study is confined to urban population because of limited food consumption data for rural areas, and in order to avoid potential identification issues resulting from home-based food production in rural China (Gould and Villarreal 2006). The analysis centers on seven most commonly used food commodity groups categorized as meats (*i.e.,* beef, lamb, poultry, pork, and other meats), seafood, vegetables, fruit, grains, eggs, and fats and oils. Categorizing commodities in this way results in a 2,100 total number of observations for the EASI demand system. The descriptive statistics presented in Table 1 show that meats are the most popular category accounting for the largest share (34%) in food expenditure followed by vegetables (17.6%), grains (15.1%), fruit (14.0%), and seafood (9.9%). Traditionally, seafood has been more popular in coastal provinces of China, however, in recent years there has been a strong rise in seafood demand across China in general. This is particularly the case with luxury seafood consumption, which is believed to be driven by factors such as conspicuous consumption and social status, the increased popularity of Southern Chinese cuisine, and cultural

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[1] Sampled provincial-level administrative divisions are: Anhui, Beijing, Chongqing, Fujian, Gansu, Guangdong, Guangxi, Guizhou, Hainan, Hebei, Heilongjiang, Henan, Hubei, Hunan, Inner Mongolia, Jiangsu, Jiangxi, Jilin, Liaoning, Ningxia, Qinghai, Shaanxi, Shandong, Shanghai, Shanxi, Sichuan, Tianjin, Xinjiang, Yunnan, and Zhejiang. Tibet was excluded due to limited data availability.

beliefs and norms related to traditional Chinese medicine (Fabinyi 2012). Nevertheless, the meats remain the most expensive food group (22.8 Yuan/kg), followed by seafood (19.1 Yuan/kg), and fats and oils (10.9 Yuan/kg). Interestingly, the variability in food prices is comparable across categories and is ranging from 23% for fats and oils to 43% for seafood. Table 1 also summarizes the agricultural commodity supply shifters underlying our reduced-form price equations. Agricultural production in China is very vulnerable to drought, flood, and windstorms and hail. Specifically, on average 9.3% of the arable land in China is affected by drought (334,400 ha per province), while 4.8% is subject to flood (175,000 ha per province) annually. Windstorms and hail, on the other hand, cause relatively milder damage affecting only 1.8% of the agricultural land. As can be seen from the respective coefficients of variation (CV), natural calamities vary greatly from one province to another (the CV is estimated at 137-157%). These variables constitute a reliable set of price instruments from the identification perspective, since it has been documented that the supply shocks induced by abrupt weather changes and natural disasters are the most important sources of price variability in Chinese agriculture (Gilbert 2010). The set of instruments is further supplemented by the variables on per capita agricultural land, farm productive fixed assets, irrigated agricultural land, and total power of large and medium agricultural machinery.

4. Empirical Results

4.1. Estimation Results from the EASI Model

The EASI demand system is estimated through the Full Information Maximum Likelihood (FIML) procedure. The procedure involves estimating a full EASI model that incorporates reduced-form price and expenditure equations provided by (3) and (4), respectively, into the demand system in (1). This allows accounting for price endogeneity induced by both simultaneity and omitted variables, and further addresses expenditure endogeneity. Several EASI specifications are estimated via the GAUSSX programming module of the GAUSS software system with allowance being made for contemporaneous correlation across the stochastic terms of the system of equations (GAUSS optimization algorithm is utilized for the model estimations and heteroskedasticity-consistent standard errors are obtained via the ROBUST option). Specifically, to determine the proper specification for the EASI system, the full system comprising equations (1), (3), and (4) is estimated with the demand system allowing for different polynomial structures. The degree of polynomial function is increased one at a time starting at L=1, and the Bewley likelihood ratio (B_{LR}) test procedure is adopted to evaluate the incremental change in the explanatory power of these more general models. The results indicate that at L=4 the EASI system provides the best fit of the data, and adding one more degree of income polynomial does not considerably enhance the explanatory power of the model (the respective p-value associated with the B_{LR} test statistic is 0.27 (Bewley 1986)).[2] Interestingly, many previous studies find that L=5 offers the most optimal polynomial structure in the EASI model (see for example, Lewbel and Pendakur 2009; Zhen et al. 2013). Based on the results of model diagnostics, the *quartic* EASI model is deemed as the most preferred specification for the use in further analysis.

Based on the statistical evidence from the Durbin-Wu-Hausman test, food prices and expenditures are found to be endogenous (Dhar, Chavas, and Gould 2003). Further evidence

[2] It deserves noting that L should be less R, i.e., the number of demand equations, from the convergence perspective (Pendakur 2008).

from a first stage F-test confirms that the set of price instruments used in the analysis are relevant (the associated p-value<0.00). Finally, the B_{LR} test for the joint significance of the province fixed-effects indicates that the unobserved provincial heterogeneity significantly enhances the explanatory power of the EASI system. Table 2 displays the demand estimates from the full model accounting for provincial heterogeneity as well as the price and expenditure endogeneity. The majority of coefficients are statistically significant at standard significance levels and have expected signs. For example, β_{i0} which can be interpreted as subsistence budget shares, are estimated to be positive and significant, and fall in a range 0.01-0.25.

Table 3 presents parameters estimates from the reduced-form price equations. The results are consistent with economic theory predictions indicating the positive effect of adverse weather events such as flood, wind, and hail on the prices of fruits, vegetables, and grains. The estimated effect of irrigation is also in the expected direction and is negative for prices of all categories except seafood. The results also indicate that the per capita agricultural land has a negative impact on prices of vegetables, fats and oils, and a positive estimated effect on grain prices. One scenario consistent with this finding may be that per capita agricultural land expansion happened concurrently with reallocation of land from grain to another crop production.

Price and expenditure elasticities are calculated using formulas derived by Zhen et al. (2013). Table 4 presents the Marshallian price (ε^M), and expenditure elasticity estimates (e_i) evaluated at sample mean values. All own-price elasticity estimates appear to be consistent with theory and are statistically significant. Further, own price elasticities are less than unitary elastic for all commodities except for seafood (-1.13) and fats/oils (-1.21). This may be reflective of consumer price reaction to changing composition of seafood consumption in China with more luxury seafood finding its way into household consumption (Fabinyi 2012). In the same vein, China has been increasing imports of fats and oils that are refined into consumer oil products, which tend to be more expensive than their domestically produced counterparts (Gale et al. 2015). More importantly, with the development of modern food supply chains offering wider choices of food products and greater substitution possibilities, Chinese consumer demand may have become more price elastic (Chen et al. 2015).

Expenditure elasticities are estimated to be considerably elastic for seafood (1.87), vegetables (1.22), and fruit (1.49), while being inelastic for meats (0.74), grains (0.64), eggs (0.72), and fats and oils (0.30). These results are reflective of some of the recently observed dietary changes in China with increasingly affluent consumers leaning more toward broader diets incorporating more seafood and convenience food at the expense of traditional staples such as rice, wheat, and pork (Villasante 2013; Gale 2003). The finding of elastic expenditure elasticity for seafood is consistent with the findings of Dong and Fuller (2010) and other similar studies. It is interesting to note, however, that while expenditure share of seafood is expected to rise with income, eventually it declines beyond a certain income threshold, as can be seen in Figure 1.

The findings on the estimated expenditure elasticity of grain are in stark contrast to findings in many previous studies. For example, Walker (2010) finds that expenditure elasticity of grain is than unitary elastic, which does not seem to be consistent with recently observed food consumption trends in China. In the same vein, Hovhannisyan and Gould (2014) report that grain is expenditure-elastic both in pre- (1.07) and post-structural change period (1.04). Similar findings are also reported in Liu and Chern (2001), Zhang and Wang (2003), and Yu and Abler (2009). This difference in major findings may be attributed to various reasons including the differences in data (geographic coverage, sample period, aggregation level, etc.) and differences in methodology. The latter is more likely since all of the previous studies rely on demand models that ignore unobserved consumer and provincial heterogeneities, impose restrictive Engel curves, and do not address price endogeneity. Following Dhar et al. (2003), this paper demonstrates that ignoring unobserved provincial diversity and/or price endogeneity can induce sizable biases in price and expenditure effects. This finding is illustrated in Table A.1.

4.2. Consumer Welfare Analysis

As can be observed from Figure 1 (panel a), over the study period, prices have increased substantially for all commodities in question. Specifically, fats/oils and egg prices rose by 74.8% and 88.5%, respectively, while meat, seafood, vegetable, fruit, and grain prices more than doubled. However, this growth pattern has not always been smooth for all food categories under study. For example, meat and fats/oils prices increased sharply before the global economic downturn towards the end of 2008, while declining in the year leading up to 2010. Grain prices, on the other hand, continued a moderate growth up until 2009 and accelerated thereafter. Many of these domestic food price increases were ascribed to the buoyant global commodity prices brought by higher grain prices. The latter in turn was a result of increasing demand for grains on the part of the biofuel industry, as well as global shortage of major grains driven by unfavorable growing-season climate in major grain producing countries such as Australia and Canada (Jensen and Miller, 2008). However, rising food commodity prices do not appear to have reduced consumer welfare in urban China as food price increases have gone hand-in-hand with a dramatic improvement in urban wages; moreover, wages outpaced food prices in the entire sample period (Figure 1, panel b). As a result, relative food prices have declined for all the commodities under study with the rate ranging from 32.7% for meats to 48.5% for fats/oil over 2003-2012.

To evaluate the effects of rising food prices on consumer welfare in China, we further calculate CV values that provide a direct measure of welfare change based on the structural parameter and Hicksian elasticity estimates obtained from the EASI system. Specifically, CV is computed for actual price changes, as well as two hypothetical scenarios of uniform increases in all food items by 15% and 25%. Our results indicate that CV is positive and on a rise for all price scenarios, implying a welfare loss, with the estimates falling in the ranges 197-442 and 328-736 Chinese Yuans for a 15% and 25% uniform price increase scenarios (Figure 2, panel a).[3] However, the effects on consumer welfare of actual price increases in the sample period are found to be in the range 10-282 Yuan demonstrating a considerably volatile pattern. This may be reflective of consumers substituting toward relatively more affordable food commodities, given that the stabilizing policy responses by the Chinese government helped mitigate the effects of global food price spikes on a number of food commodities (Yang et al. 2008). In addition, we compute mean welfare loss relative to actual food expenditures for a more realistic assessment of the true welfare consequences of food price dynamics. Figure 2 (panel b) reveals that these relative consumer welfare effects have been relatively stable for the two hypothetical price change scenarios with the impact magnitude fluctuating within the respective ranges of 12.0-13.6% and 20.0-23.7%. In contrast, actual welfare change manifests a wider variation extending from 0.6 to 13.0%, which mimics the absolute welfare change measured in Yuans. Given the considerable regional heterogeneity in terms of both food customs and culture on the one hand, and consumer income and food expenditures on the other, we also obtain provincial-level mean

[3] The US Dollar to Chinese Yuan Exchange Rate was at a level of 6-8 over our sample period.

CV values. These estimates are presented in Figure 3 for the actual as well as hypothetical price change scenarios. As it appears, Beijing, Shanghai and other provinces with a similar degree of high urbanization bore the brunt of unfavorable price dynamics while relatively less urbanized provinces such as Anhui and Gansu were less affected due in part to greater food availability.

5. **Policy Implications**

5.1. *Evaluating the Effectiveness of MLSA and a Price Subsidy*

To further illustrate the value of our empirical findings in informing policy decisions, we evaluate the effectiveness of two policies designed to mitigate the unfavorable impact of food price increases, namely: (*i*) the Minimum Living Standard Assistance (MLSA) program launched by the Chinese government with the goal of alleviating urban poverty, and (*ii*) a government price subsidy amounting to 5% of new prices reflecting price rise. The distribution of welfare losses measured as a fraction of total food expenditures are provided in Table 5. The first column presents relative welfare loss resulting from actual price increases in the sample period, which extends from 0.23% to 14.50%. The second column shows welfare loss after MLSA lump-sum transfers to urban households are taken into account (based on the actual per capita MLSA subsidies reported in Wu and Ramesh (2014)). Specifically, the respective welfare impact distribution is estimated to fall in the range -1.41%-13.45%, indicating that government subsidies overcompensate the negative effects of price increases for the relatively less affluent households. As can be seen from the third column, a 5% price subsidy appears to be a more effective policy measure from the welfare enhancement perspective vis-à-vis the MLSA program with the welfare impact distribution extending from -4.37% for the 5^{th} percentile to -9.60% for the 95^{th} percentile.

To summarize, the above findings indicate that larger negative welfare consequences of rising global food prices brought by increasing energy prices and production shortfalls in major commodity supplying countries were avoided in China due in no small part to the adequate and timely policy decisions (Yang et al. 2008). Specifically, government responses such as drawing down commodity stocks and restricting major grain exports utilized by the Chinese government to counter global food price spikes proved to be viable policy measures in restraining domestic food price increases, which lessened potential adverse welfare consequences. Government subsidy programs such as the MLSA helped further mitigate the negative effects of food price increases.

5.2. EASI vs. QUAIDS Model: A Comparative Analysis

Given the popularity of the QUAIDS model in previous welfare analysis (see for example Attanasio et al. 2013), as a final exercise, we evaluate its performance relative to the EASI specification based on a number of different criteria as discussed below.

AIC and Corrected AIC for Model Diagnostics Tests

First, we perform an Akaike Information Criterion (AIC) test procedure for model diagnostics along with a corrected AIC (AICc) that accounts for a small sample size, given the non-nested nature of the models in question. Table 6 presents the model diagnostics summary. The test statistic values are estimated to be lower for the EASI model under a variety of model assumptions regarding price and expenditure endogeneity, as well as unobserved provincial heterogeneity, which demonstrates the empirical superiority of the EASI over the QUAIDS specification.[4]

Restricted Curvilinearity of the QUAIDS Engel Curves

Second, an important area where the EASI specification provides a clear advantage over the QUAIDS is the modelling of the Engel curves. Specifically, while the QUAIDS model can only provide a quadratic approximation to the actual Engel curves, the EASI system allows for a more flexible structure with the data determining the shape of these curves as is illustrated in Figure 4. For example, Chinese consumers in Beijing municipality are found to have quartic Engel curves (i.e., fourth degree polynomial function) for seafood, fruit, grains, and eggs, which the QUAIDS model is incapable of capturing.

Bias in the QUAIDS Elasticity Estimates

Third, we evaluate the bias in the QUAIDS elasticities as a percentage difference from the EASI elasticities. As shown in Table 7, the expenditure elasticity bias falls in a range 13.8-72.5%, while those for the Marshallian elasticities can reach up to a factor of 37. These biases in the elasticity measures can lead to sizable distortions in public policies, given the sheer size of the economy, where even small inaccuracies magnify the prediction errors in policy outcomes.

Simulating the Effects of the QUAIDS Elasticity Bias on Food Consumption Projections and Consumer Welfare

[4] See Snipes and Taylor (2014) for details concerning the calculation and the interpretation of the AIC and the AICc test statistics.

Fourth, we perform a number of counterfactual exercises to evaluate the effects of using the QUAIDS model on food consumption projections and the estimates of consumer welfare impacts. Based on the OECD-projected prices in 2020, our findings indicate that the QUAIDS-induced elasticity bias overestimates the reduction in meat consumption by $12.2 billion, while underestimating the decrease in seafood, grain, and fats/oils consumption by $171.9, $69.1, and $370.2 billion, respectively (OECD, 2013). Next, using the OECD-projected income for China for 2020, we find that QUAIDS based projections overstate meat, grain, egg, and fats/oils consumption by $87.3, $114.8, $12.7, and $57.7 billion, while understating seafood, vegetable, and fruit consumption by $157.9, $77.3, and $78.8 billion, respectively. The magnitude of the bias is even more striking for 2050 food consumption projections. Specifically, meat grain, egg, and fats/oils consumption projections are found to be overstated by $340.5, $447.8, $49.7, and $225.1 billion, respectively, while seafood, vegetable, and fruit consumption forecasts are understated by $616.0, $301.6, and $307.2 billion, respectively. Finally, we perform a counter-factual simulation exercise to evaluate the effects on consumer welfare of the bias in the QUAIDS elasticities. As can be seen from Table 8, under the hypothetical price change scenario 7 (*i.e.*, a subset of commodities undergoes a 50% price increase and the remaining subset undergoes a 50% price decrease) consumer welfare changes are underestimated by $389.2 billion, while in the scenario 8 (*i.e.*, reverse of the scenario 7) consumer welfare changes are overestimated by $258.4 billion.

6. Conclusions

This study extends the recent advances in consumer theory to the empirical examination of welfare effects in urban China following the recent rise in food prices. Specifically, consumer welfare consequences were evaluated based on the Fixed-Effects Exact Affine Stone Index (FE-

EASI) demand model that allows for flexible Engel curves and accounts for both unobserved consumer and province heterogeneity. Our findings indicate that despite the steady rise in food commodity prices, consumer welfare loss relative to consumer food expenditures has been moderate. Further, urban wages are shown to have outpaced the increase in food prices in the study period, which can lead to welfare improvement in urban China. These findings provide a testament to the effective government policies in curbing and mitigating the negative effects on consumer welfare of rising food prices brought by a global commodity price surge. Given the popularity of the Quadratic AIDS (QUAIDS) model in the previous literature, we further evaluate its performance relative to the EASI specification. The results of counterfactual simulations reveal the differential effects on projected food consumption and consumer welfare changes of the EASI and the QUAIDS models, which highlights the bias in elasticity estimates that could potentially lead to distorted policy outcomes in agricultural trade and foreign direct investment. These results complement and enhance the findings of previous studies in this area of literature and highlight the need to develop better models that help improve our understanding of the factors shaping food preferences in China. Ultimately, this can provide a more reliable basis for agricultural policy, trade, and foreign direct investment decisions the importance of which has long been recognized by governments and the global agribusiness industry decision makers alike.

Future work would benefit substantially from a more complete analysis of the welfare effects of food price changes that also considers rural consumers. Because of limited nationally representative data on food consumption in rural China, this remains an overlooked area. Finally, extending welfare analyses to household-level data as such data become readily available would make the accurate evaluation of price change effects across the various social classes possible.

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Table 1. Descriptive Statistics for Food Expenditures, Prices, Budget Shares, and Agricultural Commodity Supply Shifters

Variable	Mean	STD	Variable	Mean	STD
Expenditure (Yuan/person)			*Disaster-affected area (1,000 ha)*		
Meats	745.7	331.0	*Flood*	175.2	274.5
Seafood	239.6	224.6	*Drought*	334.4	449.1
Vegetables	377.6	135.9	*Windstorm and hail*	63.4	86.9
Fruits	301.1	129.8	Irrigated area (10,000 ha)	192.2	142.1
Grains	311.2	94.5	Total power of large and medium agricultural machinery (100,000 kw)	89.3	131.5
Eggs	81.6	28.8	Productive fixed assets of rural households (1,000 Yuan/person)	9.9	5.9
Fats and oils	116.6	39.6	Per capita agricultural land (ha/person)	2.4	2.5
Agricultural Commodity Price			**Budget Share (%)**		
Meats	22.8	6.6	Meats	33.9	5.3
Seafood	19.1	8.2	Seafood	9.9	6.4
Vegetables	3.1	1.1	Vegetables	17.6	2.4
Fruit	4.7	1.6	Fruit	14.0	3.1
Grains	3.7	0.9	Grains	15.1	3.5
Eggs	8.5	2.3	Eggs	4.0	1.3
Fats and oils	10.9	2.5	Fats and oils	5.6	1.4
Income (1,000 Yuan/person)	14.3	6.6			

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

Table 2. Parameter Estimates from the EASI Expenditure Share Equations

Parameter	Meats	Seafood	Vegetables	Fruit	Grains	Eggs	Fats
Intercept (β_{i0})	**0.241**	**0.248**	**0.225**	**0.144**	**0.081**	**0.014**	**0.047**
	0.011	*0.007*	*0.005*	*0.008*	*0.006*	*0.003*	*0.005*
Real income (β_{i1})	**-0.088**	**0.080**	**0.067**	0.064	**-0.150**	-0.010	**-0.037**
	0.046	*0.029*	*0.032*	*0.060*	*0.059*	*0.021*	*0.014*
Real income (β_{i2})	-0.010	**-0.054**	-0.007	**-0.039**	0.035	**0.035**	**0.039**
	0.035	*0.018*	*0.015*	*0.021*	*0.019*	*0.006*	*0.005*
Real income (β_{i3})	**0.254**	0.015	**0.078**	**-0.177**	**-0.103**	-0.022	**-0.045**
	0.044	*0.038*	*0.047*	*0.040*	*0.032*	*0.015*	*0.023*
Real income (β_{i4})	**0.666**	**-0.237**	0.072	**-0.258**	-0.132	**-0.074**	**-0.136**
	0.271	*0.104*	*0.065*	*0.143*	*0.132*	*0.018*	*0.026*
Price (α_{1i}) meats	0.027	-0.005	**0.143**	-0.078	**-0.109**	**-0.044**	0.066
	0.035	*0.023*	*0.029*	*0.054*	*0.052*	*0.011*	*0.061*
Price (α_{2i}) seafood		-0.004	**-0.075**	**-0.024**	**0.071**	0.009	0.028
		0.018	*0.018*	*0.013*	*0.028*	*0.015*	*0.030*
Price (α_{3i}) veg			**0.117**	-0.035	0.013	0.020	**-0.083**
			0.055	*0.055*	*0.036*	*0.017*	*0.049*
Price (α_{4i}) fruits				0.039	**0.156**	-0.012	0.054
				0.066	*0.045*	*0.022*	*0.058*
Price (α_{5i}) grains					0.013	-0.011	-0.033
					0.071	*0.015*	*0.067*
Price (α_{6i}) eggs						0.002	**0.037**
						0.016	*0.015*
Price (α_{7i}) fats/oils							-0.070
							0.081
Province fixed-effects					Yes		
Price and expenditure endogeneity accounted for					Yes		

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

Table 3. Parameter Estimates from the Reduced-Form Price Equations

Commodity		Flood	Drought	Wind/hail	Irrigated land	Machinery	Land	Other fixed assets
Meats	(γ_{1k})	**-0.009**	0.001	**0.013**	**-0.067**	**0.091**	0.014	**0.076**
		0.006	*0.003*	*0.004*	*0.013*	*0.008*	*0.015*	*0.016*
Seafood	(γ_{2k})	**-0.026**	**-0.008**	-0.003	**0.033**	-0.006	**-0.117**	**0.127**
		0.007	*0.004*	*0.004*	*0.017*	*0.009*	*0.016*	*0.018*
Vegetables	(γ_{3k})	**0.019**	-0.004	0.001	**-0.045**	**0.043**	**-0.033**	-0.016
		0.006	*0.005*	*0.004*	*0.014*	*0.009*	*0.014*	*0.013*
Fruit	(γ_{4k})	**0.015**	0.005	**0.010**	**-0.090**	**0.044**	-0.015	0.025
		0.008	*0.006*	*0.005*	*0.017*	*0.010*	*0.013*	*0.016*
Grains	(γ_{5k})	0.004	-0.007	**0.004**	**-0.059**	**0.039**	**0.041**	**0.041**
		0.005	*0.005*	*0.001*	*0.013*	*0.008*	*0.015*	*0.013*
Eggs	(γ_{6k})	**0.037**	0.000	-0.002	**-0.067**	**0.031**	0.008	-0.019
		0.006	*0.006*	*0.006*	*0.016*	*0.010*	*0.015*	*0.015*
Fats/oils	(γ_{7k})	0.006	0.003	0.007	**-0.028**	**0.055**	**-0.057**	**0.080**
		0.005	*0.003*	*0.004*	*0.014*	*0.007*	*0.013*	*0.023*

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

Table 4. Marshallian Price and Expenditure Elasticity Estimates from the EASI system

Commodity	Meats	Seafood	Veg.	Fruits	Grains	Eggs	Fats/oils	Expenditure
Meats	**-0.83**	0.01	**0.47**	**-0.19**	**-0.28**	**-0.12**	**0.21**	**0.74**
	0.04	*0.02*	*0.02*	*0.02*	*0.03*	*0.01*	*0.03*	*0.03*
Seafood	**-0.35**	**-1.13**	**-0.91**	**-0.37**	**0.59**	**0.06**	**0.24**	**1.87**
	0.08	*0.09*	*0.05*	*0.06*	*0.07*	*0.03*	*0.12*	*0.07*
Vegetables	**0.74**	**-0.45**	**-0.95**	**-0.23**	0.04	**0.11**	**-0.48**	**1.22**
	0.05	*0.04*	*0.05*	*0.04*	*0.03*	*0.01*	*0.07*	*0.05*
Fruit	**-0.72**	**-0.22**	**-0.34**	**-0.79**	**0.33**	**-0.11**	**0.36**	**1.49**
	0.06	*0.05*	*0.05*	*0.06*	*0.05*	*0.02*	*0.09*	*0.05*
Grains	**-0.60**	**0.51**	**0.15**	**0.42**	**-0.86**	**-0.06**	**-0.20**	**0.64**
	0.05	*0.05*	*0.04*	*0.04*	*0.07*	*0.03*	*0.05*	*0.05*
Eggs	**-0.72**	**0.26**	**0.56**	**-0.27**	**-0.25**	**-0.95**	**0.95**	**0.72**
	0.01	*0.08*	*0.06*	*0.07*	*0.09*	*0.01*	*0.19*	*0.06*
Fats/oils	**0.42**	**0.57**	-0.35	0.07	**-0.49**	**0.69**	**-1.21**	**0.30**
	0.16	*0.21*	*0.21*	*0.21*	*0.13*	*0.13*	*0.01*	*0.09*

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

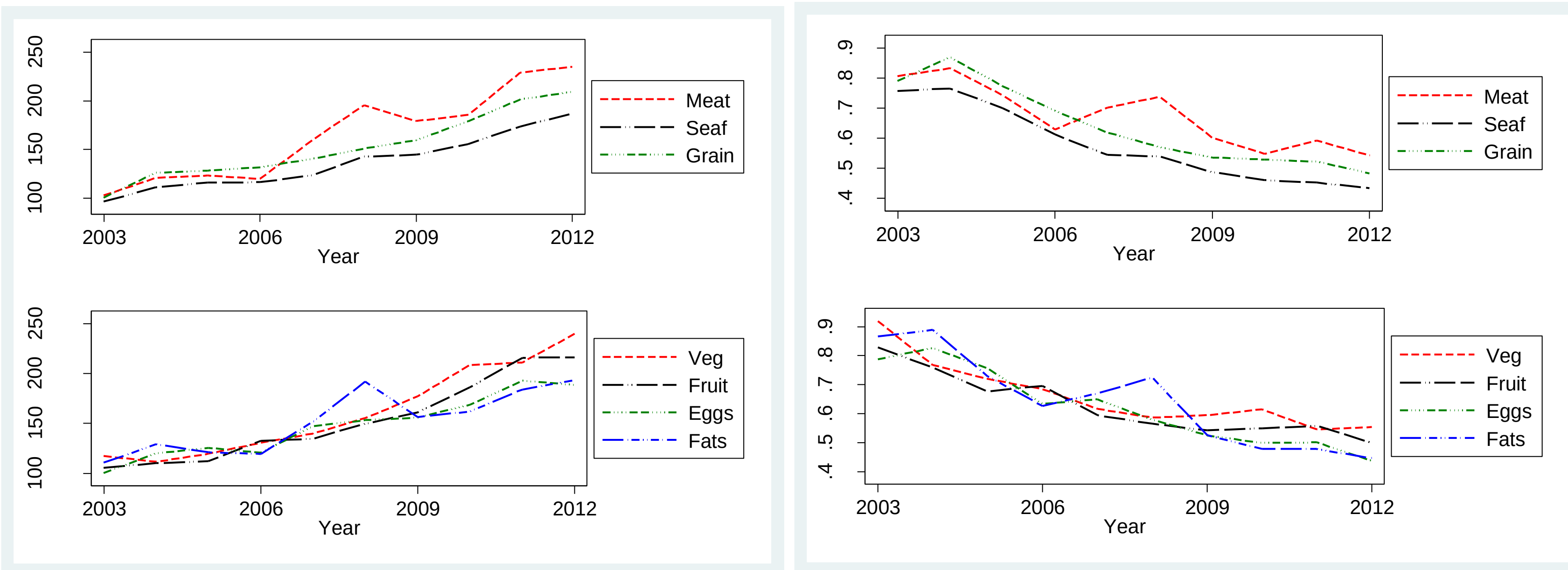

Figure 1.

(a) Price indices over time (2003 is the base year)

(b) Price indices relative to urban wage index over time

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

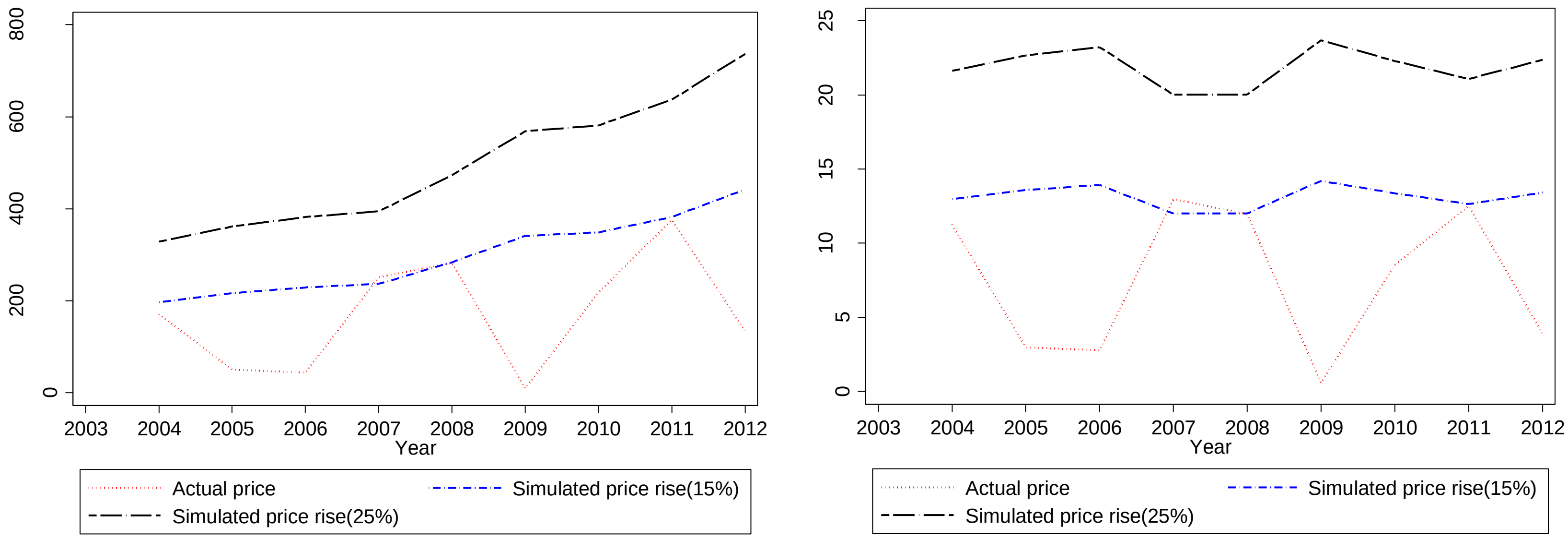

Figure 2.

(a) Mean welfare loss (Chinese Yuan) over time

(b) Mean welfare loss (% of total expenditures) over time

Note: Compensating variation is computed based on actual price changes, as well as two hypothetical price change scenarios

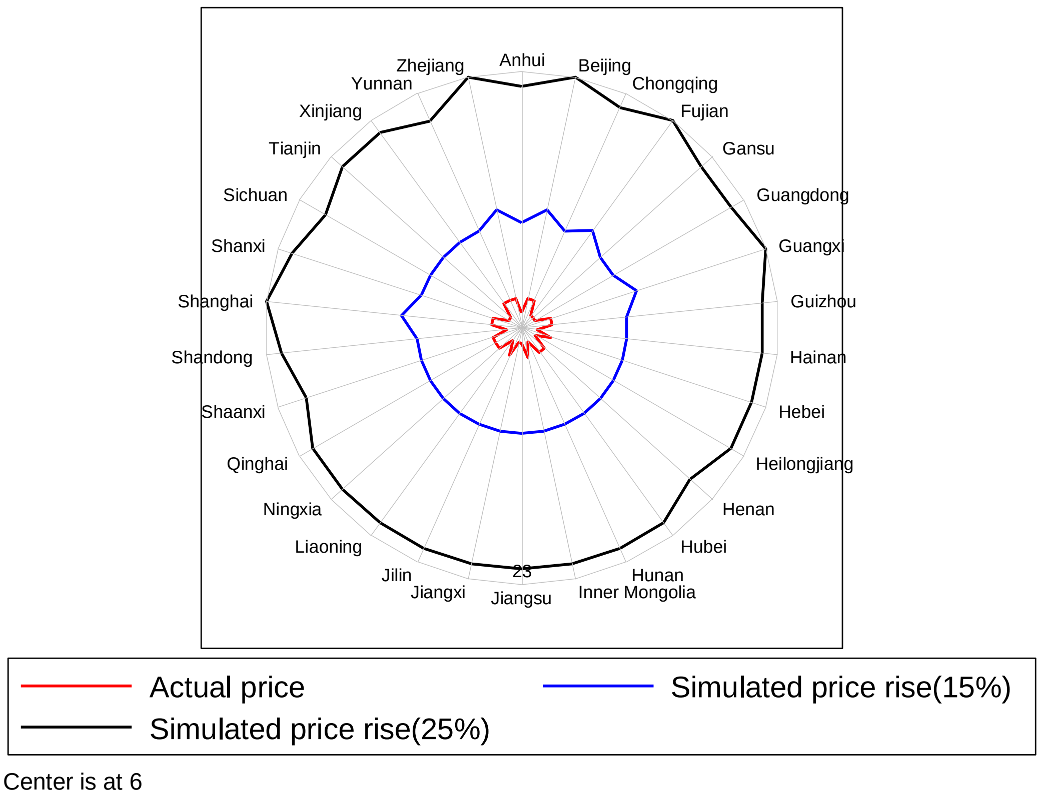

Figure 3. Mean welfare loss (% of food expenditure) by province

Note: Compensating variation is computed based on actual price changes, as well as two hypothetical price change scenarios.

Table 5. Distribution of Welfare Loss as a Fraction of Food Expenditures based on Actual Price Changes, 2003-2012.

Percentile of welfare losses	No policy	MLSA cash transfer	5% price subsidy
5th	0.23%	-1.41%	-4.37%
10th	1.47%	-0.10%	-3.27%
25th	2.91%	1.60%	-1.77%
50th	8.25%	6.82%	3.32%
Mean	7.51%	6.26%	2.75%
75th	11.89%	10.80%	7.13%
90th	13.46%	12.36%	8.74%
95th	14.50%	13.45%	9.60%

Note 1: Welfare effect is measured by Hicksian Compensating Variation, where a positive value indicates welfare loss.
Note 2: In addition to actual price changes (no policy), the effects on consumer welfare of two policy responses, namely Minimum Living Standard Assistance (MLSA) and 5% price subsidy, are evaluated.

Table 6. Summary of the QUAIDS vs. EASI Demand Model Diagnostic Tests

Model	AIC	AICc
Exogenous price and expenditures		
No provincial effects		
QUAIDS	-1,537	-1,523
EASI	-2,491	-2,454
Provincial effects		
QUAIDS	-2,840	-2,801
EASI	-3,968	-3,886
Endogenous price and expenditures		
No provincial effects		
QUAIDS	-3,452	-3,329
EASI	-5,621	-5,523
Provincial effects		
QUAIDS	-5,896	-5,792
EASI	-8,024	-7,944

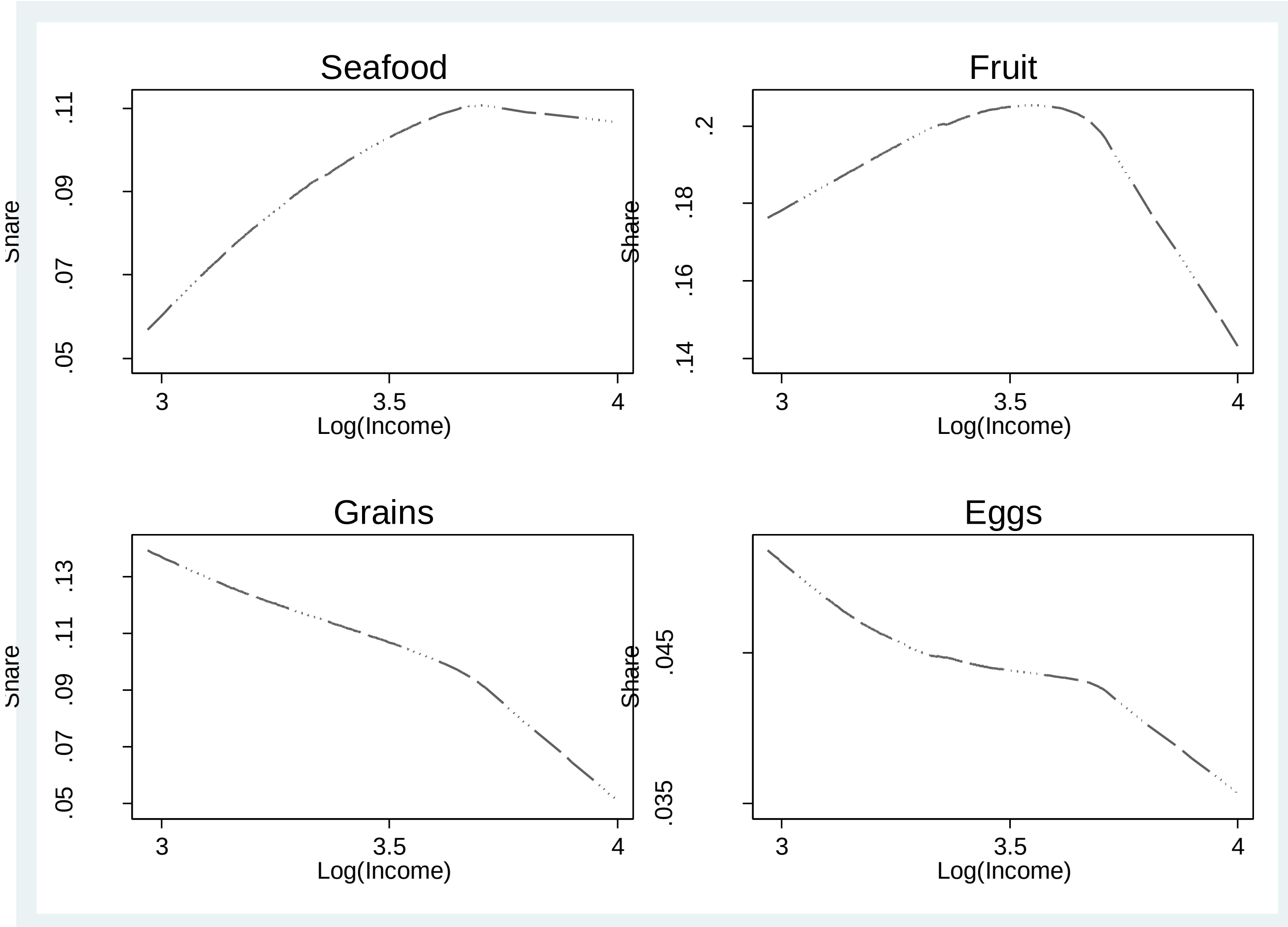

Figure 4. Estimated Engel curves for selected food commodities

Note: EASI demand model, unit prices, price and expenditure endogeneity corrected, L=4, Beijing.

Table 7. Percentage Difference between Marshallian and Expenditure Elasticity Estimates from the QUAIDS vs. EASI Models (%)

Commodity	Uncompensated Elasticity							
	Meats	Seafood	Veg.	Fruit	Grains	Eggs	Fats/oils	Expend.
Meats	3.4	444.8	-3033.3	392.3	-1350.8	437.1	325.8	13.8
Seafood	-324.2	-111.7	-1613.7	2761.9	223.9	56.4	367.0	-72.5
Vegetables	3083.9	-2414.0	-8.6	-733.3	372.1	208.4	687.5	-24.5
Fruit	1388.0	3766.7	-360.1	23.9	817.4	341.2	453.3	-29.2
Grains	-296.0	257.2	328.3	840.7	-25.3	8.0	240.8	47.0
Eggs	310.3	23.1	238.2	272.7	-4.2	-67.8	280.4	20.1
Fats/oils	173.3	529.5	235.9	136.8	215.6	282.6	-279.4	67.1

Note: The first column represents commodities with price change.

Table 8. Welfare Implications of the QUAIDS Hicksian Elasticity Bias under Different Price Change Scenarios

Commodity	**Price change scenario (%)**						
	1	2	3	4	5	6	7
Meats	+15	+25	+35	-40	+40	-50	+50
Seafood	-15	-25	-35	+40	-40	+50	-50
Vegetables	+15	+25	+35	-40	+40	-50	+50
Fruits	-15	-25	-35	+40	-40	+50	-50
Grains	+15	+25	+35	-40	+40	-50	+50
Eggs	-15	-25	-35	+40	-40	+50	-50
Fats and oils	+15	+25	+35	-40	+40	-50	+50
	1	2	3	4	5	6	7
Size of the bias ($ billion)	9.53	48.26	112.89	-259.54	154.93	-389.19	258.42

Note: Welfare consequences are evaluated based on the CV estimates.

Appendix

Table A.1. Percentage Difference between Elasticity Estimates from Models with and without Province Fixed-Effects (%)

Commodity	Uncompensated Elasticity							
	Meats	Seafood	Veg.	Fruit	Grains	Eggs	Fats/oils	Expend.
Meats	-24.8	-77.6	-113.4	-124.1	-103.9	-86.2	-69.7	-24.8
Seafood	-56.5	-209.7	-142.9	-82.0	114.2	-84.1	-127.6	-56.5
Vegetables	-35.8	-114.2	-4.3	-107.3	-10.7	-863.0	-282.4	-35.8
Fruit	-138.3	32.2	-128.0	-55.8	-80.0	-84.5	35.0	-138.3
Grains	-198.3	-83.0	-34.6	-66.3	-38.6	-60.0	-42.0	-198.3
Eggs	61.9	-79.9	6.4	-70.7	-61.4	-61.7	-244.8	61.9
Fats/oils	49.4	-111.3	363.0	13.2	-47.3	-169.9	-76.0	49.4

Note: The first column represents commodities with price change.