Asymmetric Intra-household Allocation of Calories in China: Implication for Demographic Bias and the Need for Demographic Targeting

Satoru Shimokawa

Hong Kong University of Science and Technology

Division of Social Science

Clear Water Bay, Kowloon

Hong Kong

Tel: +852-2358-7836

E-mail: sosatoru@ust.hk

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Abstract

This article questions the assumption of symmetric consumption behavior in the conventional analysis of intra-household calorie allocation. It proposes a framework that takes into account asymmetric consumption behavior due to liquidity constraints or loss aversion. Using panel data from China, we find that intra-household calorie allocation responds asymmetrically to expected declines and increases in household food availability, which is qualitatively consistent with the liquidity constraint model. Clarifying such asymmetric responses enables us to relate calorie elasticity estimates to the status of demographic groups within a household without requiring a full interpretation of the ordering of the estimates across demographic groups. Results also show that by ignoring such asymmetric responses, conventional analysis can underestimate demographic differences in calorie elasticity estimates and provide misleading implications about the need for demographic targeting in nutrition programs.

Understanding how a household allocates calories across its members (so-called intra-household calorie allocation) is critical for designing policies to improve the nutrition of over 800 million undernourished people in the world because most of the calories for these people are obtained through intra-household calorie allocation. While previous studies commonly assume symmetric consumption behavior in the analysis of intra-household calorie allocation (the so-called symmetric framework), this article questions the symmetric framework and examines whether intra-household calorie allocation responds asymmetrically to expected declines and increases in household food availability. Such asymmetric responses can be reasonably predicted from a considerable literature exploiting a liquidity constraint or loss aversion for explaining asymmetry in savings and consumption (Altonji and Siow 1987; Bowman et al. 1999, Tversky and Kahneman 1991; Shea 1995a; Shea 1995b).

Clarifying such asymmetry in intra-household calorie allocation can lead to different implications from the symmetric framework in terms of demographic bias in calorie allocation and the need for demographic targeting to improve the nutrition of a deprived group. For example, such demographic bias may actually exist even when the symmetric framework fails to find significant demographic bias, and such demographic targeting may not be required even when the symmetric framework finds significant demographic bias. Key parameters in addressing these issues are the elasticities of calorie demand with respect to income, prices, and food availability (hereafter, the elasticities are collectively referred to as "calorie elasticity"). Most previous studies estimate calorie elasticities with respect to income and prices because income and prices affect the food purchasing power of a household (see Strauss and Thomas (1995) for a survey of such studies). Additionally, some studies more directly estimate calorie elasticities with respect to household food availability because changes in income and prices may not properly measure changes in food consumption due to both consumption smoothing and Engel's law (Mangyo 2008).

However, regardless of the type of calorie elasticity, existing studies rarely examine the nature of asymmetric consumption behavior underlying calorie demand and intra-household calorie allocation. Our review of recent studies in addition to the review of 43 studies in Strauss and Thomas (1995) and Bouis (1994) indicate that all previous studies, except for Behrman et al. (1997), commonly assume that caloric intake (or consumption) responds symmetrically to declines and increases in income, prices, or food availability. Behrman et al. (1997) take into account the sequential nature of agricultural production and show that farmers' income-calorie relationships differ between planting and harvest stages in Pakistan. Although their analytical framework is still based on symmetric consumption behavior, their findings imply that household calorie demand can respond asymmetrically to expected declines and increases in income. On the other hand, they examine the income-calorie relationships only at the household level and do not examine intra-household calorie allocation. In this article, we build on the essential institution of Mangyo (2008), but extend and modify his model to build a framework that can be systematically applied to examining the potential asymmetry in intra-household calorie allocation.

We first theoretically demonstrate that the manner of intra-household calorie allocation may differ between when household food availability is expected to decline and when it is expected to increase by exploiting both the liquidity constraint model and the loss aversion model. We then derive testable predictions about how asymmetrically the household allocates calories across its members in response to expected declines and increases if one of the theoretical models is true. Second, we estimate the elasticity of individual caloric intake with respect to both actual and expected changes in calorie consumption per household member for each of six demographic groups (boys, girls, prime-age men, prime-age women, elderly men, and elderly women). Here, calorie consumption per household member is a measure of household food availability. The elasticity estimates with respect to expected changes in household food availability are used to test our theoretical predictions, while those with respect to actual changes in household food availability are used to make a direct comparison with previous findings. We also examine demographic differences in the elasticity estimates. For the empirical analysis, we use data from the China Health and Nutrition Survey (CHNS) during 1991-2000.

This article offers three important advantages over previous studies, including

Mangyo (2008). First, our asymmetric framework sheds light on a potential bias in calorie elasticity estimates obtained under the symmetric framework, which can be induced by the potential asymmetry in calorie elasticity (hereafter referred to as "asymmetry bias"). Examining such an issue is particularly interesting for the case of China because such bias may deliver a potential explanation for the puzzling observations of gender bias in China. Previous studies on China have consistently failed to find significant gender bias in food consumption and other treatments (e.g., Gong et al. 2005; Lee 2007) even though some studies find significant gender bias in health outcomes such as mortality and sex ratios (e.g., Klasen and Wink 2003). These findings have been recognized as an important puzzle (Deaton 1989; Case and Deaton 2003). This article reconsiders these puzzling observations by examining whether controlling the asymmetry bias in calorie elasticity leads us to find significant gender bias in the elasticity.

Second, our asymmetric framework provides a new approach to connecting calorie elasticity estimates and the status of demographic groups within a household. In most previous studies, such status is commonly related to the ordering of calorie elasticity estimates across demographic groups. However, Mangyo (2008) shows that the relationship between the status and the ordering is somewhat ambiguous under the symmetric framework. Thus, our asymmetric framework tackles the issue from a different aspect by specifying which theoretical framework is potentially consistent with the observed asymmetry in calorie elasticity estimates. Our framework provides testable predictions of the asymmetry in calorie elasticity, and the predictions are independent of the ordering of calorie elasticity across demographic groups. Thus, if the observed asymmetry is potentially consistent with a certain theoretical framework, the framework can be used to derive implications about the status of demographic groups.

Lastly, our asymmetric framework provides clearer implications about the need and the effect of demographic targeting for improving or protecting the caloric intake of a deprived group. The need for such targeting is often justified by showing how unequally foods are allocated across demographic groups when food availability decreases due to certain negative shocks. In contrast, the effect of such targeting depends on how foods are allocated across demographic groups when food availability increases due to certain public interventions. Thus, discussing the need and the effect of such targeting often relates to a gap in the direction of changes in food availability. Such a gap is allowable only if a household responds to declines and increases in food availability in the same way. However, if a household responds to declines and increases in food availability in a different way, such a gap may cause confusion over the need and the effect of demographic targeting. Using our asymmetric framework, we can avoid such a confusion, which is overlooked in the symmetric framework.

The following sections describe a conceptual framework, the estimation strategy, the data, the estimation results, and provide conclusions.

Conceptual Framework

To clarify theoretical implications of empirical findings, we first develop a simple two-period household utility model that contains one primary member with higher earnings potential and one dependent member with lower earnings potential. Households follow a two-stage utility maximization assuming that household utility is time-separable and homothetically separable in each time period in household member partition.

First Stage: Inter-temporal Allocation

First, a household maximizes the two-period household utility U = u(c_1; A)+E_1[u(c_2; A)] subject to an inter-temporal budget constraint $p_1 c_1 + c_2 = y_0 + W_1 c_1 + W_2 c_2$, where c_t is caloric intake at time t; A is a taste shifter; p_1 is a price of calorie at time 1 relative to time 2; y_0 is the initial non-labor wealth; W_t is a wage indicator at time t and a linearly homogeneous aggregator function of the form $W_t(w_{pt}, w_{dt})$ where w_{pt} and w_{dt} are wage rates for a primary member and for a dependent member at time t, respectively. The household production function is assumed to be linear and separable. While W_1 is assumed predetermined, W_2 is assumed to follow the stochastic process, $W_2 = W_1 + v_2$, where v_2 is stochastic and a source of income uncertainty. We assume that the household observes W_2 at the beginning of time 2. Then, from the budget constraint and the state equation, c_2 can be expressed as $c_2 = \frac{(y_0+(W_1-p_1)c_1)}{(1-W_1-v_2)}$. Thus, the maximization problem for the households is

$$\max_{c_1}\{u(c_1; A) + E_1[u((y_0 + (W_1 - p_1)c_1)/(1 - W_1 - v_2); A) \mid p_1, W_1, v_2]\}. \qquad (1)$$

In conventional settings, a utility function is assumed to be strictly concave and differentiable with $u'(0) = +\infty$ and $u''(.) < 0$, and there is no liquidity constraint. Then, the first order condition (FOC) is $u'(c_1; A) = -E[\frac{(W_1-p_1)}{(1-W_1-v_2)} u'(\frac{y_0+(W_1-p_1)c_1}{(1-W_1-v_2)}; A)]$, and thus the optimal caloric intake at time 1 can be expressed as $c_1^* = c_1^*(\frac{(W_1-p_1)}{(1-W_1-v_2)}, y_0; A)$. Once c_1^* is determined, c_2^* is also uniquely determined as shown above. Because c_1^* is a unique solution regardless of the direction of expected changes in income, the household caloric intake responds symmetrically to expected declines and increases in income.

We can also describe how caloric intake may respond asymmetrically to income changes by exploiting the framework of a liquidity constraint or loss aversion. Problem (1) can be modified to incorporate a liquidity constraint by assuming that borrowing is prohibited at time 1 – i.e., we have the additional budget constraint $p_1c_1 \leq y_0 + W_1c_1$. If the budget constraint is binding, c_1^* is $c_1^* = \frac{y_0}{(p_1-W_1)}$. Otherwise, c_1^* is identical to the solution in the conventional case. Thus, the solution can be written in a general form $c_1^* = c_1^*(y_0,\ p_1,\ W_1,\ v_2;\ A)$. In this liquidity constraint model, households are not allowed to borrow money or food for expected income increases, but they can save money or food for expected income declines. Thus, changes in the optimal caloric intake between two time periods should be larger for expected increases than for expected declines; thus caloric intake should respond more elastically to expected increases than to expected declines.

Problem (1) can also be modified to incorporate loss aversion by assuming that u(.) shares the properties of the Kahneman-Tversky (KT) value function around zero (Kahneman and Tversky 1979; Tversky and Kahneman 1991). That is, a household has reference-dependent preferences so that the household feels stronger about avoiding a loss of one unit than making a gain of one unit (loss aversion), and the marginal valuation of another unit of the outcomes decreases as the distance from the reference point increases (diminishing sensitivity). Following the framework in Bowman et al. (1999), we define $u(.) = l(r_t) + m(c_t - r_t)$, where l(.) is the reference utility, m(.) is a gain-loss utility function (m(0) = 0, m'(x) > 0, m''(x) < 0 if x > 0, m''(x) > 0 if x < 0, and m(y)+m(-y) < m(x)+m(-x) if y > x > 0), and r_t is a nutrient reference point at time t. u(.) is assumed continuous, have a bounded slope, and twice differentiable except for when c = r (see, p156-159 in Bowman et al. 1999 for more detailed assumptions). While the first-period reference point r_1 is assumed to be predetermined, the second-period reference point r_2 is determined by r_1, and c_1, $r_2 \equiv (1-\alpha)r_1 + \alpha\, c_1$ where $\alpha \in [0,1]$ measures the speed at which the r changes in response to c_1. Then, the FOC is $m'(c_1 - r_1) = -E\left[\alpha \cdot l'\left((1-\alpha)r_1 + \alpha c_1\right) + \left(\frac{(W_1 - p_1)}{(1-W_1-v_2)} - \alpha\right) \quad m'\left(\frac{y_0 + (W_1 - p_1)c_1}{(1-W_1-v_2)} - \left((1-\alpha)r_1 + \alpha c_1\right)\right)\right]$ and the optimal solution can be expressed as $c_1^* = c_1^*(y_0, p_1, W_1, v_2, r_1, \alpha; A)$. Among a wide range of potential cases in the loss aversion model, the most important case is that when there is enough uncertainty (i.e., $P[Y \geq r_1] \geq \frac{2\alpha}{1+\alpha}$ and $P[Y \geq 0.5r_1] = 1$ where $Y = \frac{y_0 + W_1 c_1 + W_2 c_2}{2}$), the household resists lowering consumption in response to expected income declines. Neither the conventional nor the liquidity constraint models explain such behavior. In this case, changes in the optimal caloric intake between two time periods could be larger for expected declines than for expected increases; thus caloric intake could respond more elastically to expected declines than to expected increases.

Second Stage: Intra-household Allocation

Second, the household decides how to allocate the predetermined c_t^* between household members at each time period by maximizing $U_t(c_{pt}, c_{dt})$, where c_{pt} and c_{dt} are caloric intake of the primary member (p) and the dependent member (d) at time t, respectively. Because $c_t^* = c_{pt} + c_{dt}$, the second-stage optimization problem can be defined as:

$$\max_{c_{pt}} U_t = u(c_{pt}; A) + \beta\, u(c_t^* - c_{pt}; A), \text{ subject to } p_t c_t^* \leq y_t + w_{pt} c_{pt} + w_{dt}(c_t^* - c_{pt}), \qquad (2)$$

where $\beta \in (0,1)$ represents member preference; y_t is non-labor wealth at time t; w_{pt} and w_{dt} are wage rates for a primary and a dependent member at time t, respectively; and u(.) has the same functional form to the household utility function. We assume $w_{pt} > w_{dt}$ and that the household observes w_{p2} and w_{d2} at the beginning of time 2. In this setting, the inequality between c_{pt}^* and c_{dt}^* is sensitive to the shape of the utility function (i.e., relative risk aversion with respect to c_t); and either direction of inequality is plausible in all three models presented above (Mangyo 2008). Thus, examining differences in income elasticity of caloric intake between the primary and the dependent members is rather an empirical question.

In summary, three testable implications can be derived. Let λ^+ and λ^- reflect the response of caloric intake to expected income increases and declines, respectively –

i.e., $\frac{(c_2^* - c_1^*)}{E[\Delta I]}$ represents λ^+ if $E[\Delta I] \geq 0$ and λ^- if $E[\Delta I] < 0$, where $\Delta I = v_2 c_2^* + W_1(c_2^* - c_1^*)$. Then, first, if $\lambda^+ = \lambda^-$ for all household members, the results are consistent with the conventional symmetric model. Second, if $\lambda^+ \geq \lambda^-$ for all household members and $\lambda^+ > \lambda^-$ for some household members, the results are consistent with the liquidity constraint model. Third, if $\lambda^+ \leq \lambda^-$ for all household members and $\lambda^+ < \lambda^-$ for some household members, the results are consistent with the loss aversion model. For other cases, theoretical implications are inconclusive.

Estimation Strategy

We employ a reduced form approach[1] to estimate the average response of individual caloric intake to expected changes in income for calorie consumption (i.e., elasticity forms of λ^+ and λ^-) for each of six demographic groups: boys (between 2-17 y), girls, prime-age men (between 18-60 y), prime-age women, elderly men (over 60 y), and elderly women. As a measure of changes in income for calorie consumption (i.e., ΔI), we use changes in calorie consumption per household member[2] rather than changes in income or food expenditure per household member due to two reasons. First, expenditure data are not collected in the CHNS survey. Second, although total household income are available in the CHNS, changes in total household income may not properly measure changes in household food expenditure because of both consumption smoothing and Engel's law.

The basic estimating equation for individual *i* in household *h* in community *v* between times t–1 and t is

$$\Delta\ln(\mathrm{N_{ihvt}}) = \alpha + \lambda\,\Delta\ln\left(\widehat{\mathrm{Y}}_{\mathrm{hvt}}\right) + \alpha_{\mathrm{X}}\Delta\mathrm{X_{ihvt}} + \Delta\mu_{\mathrm{it}} + \Delta\mu_{\mathrm{ht}} + \Delta\mu_{\mathrm{vt}} + +\Delta\nu_{\mathrm{ihvt}} \qquad (3)$$

where $\Delta\ln(\mathrm{N_{ihvt}})$ is a change in log caloric intake for individual *i* between t–1 and t; $\Delta\ln\left(\widehat{\mathrm{Y}}_{\mathrm{hvt}}\right)$ is an expected change in log calorie consumption per household member for household *h* between t–1 and t; $\Delta\mathrm{X_{ihvt}}$ is a vector of changes in other time-variant individual-, household- and community-level characteristics between t–1 and t; $\Delta\mu_{\mathrm{it}}$, $\Delta\mu_{\mathrm{ht}}$ and $\Delta\mu_{\mathrm{vt}}$ reflect changes in the unobserved time-variant nutrient requirements specific for individual, household and community, respectively; and $\Delta\nu_{\mathrm{ihvt}}$ is the remaining error.

In equation (3), time-invariant unobserved factors are eliminated by differencing across years within the same individual. To control remaining unobserved time-variant effects, we use several proxies: gender and age dummies ($\mathrm{A_{it}}$) for the unobserved individual-specific nutrient requirement $\Delta\mu_{\mathrm{it}}$; household head characteristics and household demography ($\mathrm{S_{ht}}$) for the unobserved household-specific nutrient requirement $\Delta\mu_{\mathrm{ht}}$; and location dummies of residence ($\mathrm{R_{vt}}$) for the unobserved community-specific nutrient requirement $\Delta\mu_{\mathrm{vt}}$. Because gender and age are controlled, caloric intake $\mathrm{N_{ihvt}}$ need not be normalized using the age- and gender-specific calorie requirements. Then, equation (3) can be rewritten as

$$\Delta\ln(\mathrm{N_{ihvt}}) = \alpha + \lambda\,\Delta\ln\left(\widehat{\mathrm{Y}}_{\mathrm{hvt}}\right) + \alpha_{\mathrm{X}}\Delta\mathrm{X_{ihvt}} + \alpha_{\mathrm{A}}\mathrm{A_{it}} + \alpha_{\mathrm{S}}\mathrm{S_{ht}} + \alpha_{\mathrm{R}}\mathrm{R_{vt}} + +\Delta\nu_{\mathrm{ihvt}} \qquad (4)$$

To introduce asymmetric consumption behavior into equation (4), we employ a framework similar to that in Bowman et al. (1999) as follows

$$\Delta\ln(N_{ihvt}) = \alpha + \lambda^{+}(POS_{ht})\Delta\ln(\widehat{Y}_{hvt}) + \lambda^{-}(NEG_{ht})\Delta\ln(\widehat{Y}_{hvt}) + \alpha_X \Delta X_{ihvt} \quad (5)$$

$$+\alpha_A A_{it} + \alpha_S S_{ht} + \alpha_R R_{vt} + +\Delta\nu_{ihvt}$$

where POS_{ht} is a dummy variable for household *h* in which expected calorie consumption per household member increases between t–1 and t, and NEG_{ht} is a dummy variable for household *h* in which expected calorie consumption per household member decreases between t–1 and t. Thus, $\lambda^{+}$and λ^{-} in equation (5) measure the response of individual caloric intake to expected increases and declines in calorie consumption per household member, respectively. Hereafter, equations (4) and (5) are referred to as expected models.

$\Delta\ln(\widehat{Y}_{hvt})$ in the expected models is projected using information available at t–1 as follows

$$\Delta\ln(Y_{hvt}) = \beta + \beta_Y \Delta\ln(Y_{hv(t-1)}) + \beta_G \Delta G_{hv(t-1)} + \beta_S S_{h(t-1)} + \beta_R R_{v(t-1)} + \Delta\tau_{hvt}, \quad (6)$$

where $\Delta\ln(Y_{hv(t-1)})$ is a change in calorie consumption per household member between t–2 and t–1; and $\Delta G_{hv(t-1)}$ is a vector of changes in exogenous variables that affect household calorie requirements between t–2 and t–1. $S_{h(t-1)}$ and $R_{v(t-1)}$, the same sets of proxies in equation (5) at t-1, are included to capture the unobserved time-variant household- and community-specific characteristics that affect calorie consumption at t–1. $\Delta\tau_{hvt}$ is the remaining error. Then, we use the fitted value of equation (6) as a measure of

$\Delta\ln(\hat{Y}_{hvt})$. To clarify the effect of this procedure, we also estimate equations (4) and (5) replacing $\Delta\ln(\hat{Y}_{hvt})$ with actual changes in calorie consumption per household member $\Delta\ln(Y_{hvt})$. Hereafter, the models using $\Delta\ln(Y_{hvt})$ are referred to as basic models.

Identification Issues

A key identification issue in specifying equations (4) and (5) is the potential endogeneity of $\Delta\ln(\hat{Y}_{hvt})$ that originates from the potential correlation between $\Delta\ln(Y_{hv(t-1)})$ in equation (6) and $\Delta\nu_{ihvt}$ because, for example, past calorie consumption may influence current unobserved dietary preference. To address the endogeneity issue, we incorporate instrumental variables (IV) estimation into the specification of equation (6) using two-stage least squares (2SLS). In the first stage, we specify the following equation:

$$\Delta\ln(Y_{hv(t-1)}) = \gamma + \gamma_G \Delta G_{hv(t-1)} + \gamma_Z Z_{hv(t-1)} + \gamma_S S_{h(t-1)} + \gamma_R R_{v(t-1)} + \Delta\varphi_{hv(t-1)}, \qquad (7)$$

where $\Delta G_{hv(t-1)}$ is the same set of exogenous variables used in equation (6); $Z_{hv(t-1)}$ is a set of instruments that are uncorrelated with $\Delta\tau_{hvt}$ and $\Delta\nu_{ihvt}$; $S_{h(t-1)}$ and $R_{v(t-1)}$ are the same sets of proxies used in equation (6); and $\Delta\varphi_{hv(t-1)}$ is the remaining error. In the second stage, $\Delta\ln(Y_{hvt})$ is predicted based on the first-stage result. Let $\Delta\ln(\tilde{Y}_{hvt})$ denote the predicted $\Delta\ln(Y_{hvt})$ in the IV estimation. Then, we specify equations (4) and (5) using $\Delta\ln(\tilde{Y}_{hvt})$ in place of $\Delta\ln(\hat{Y}_{hvt})$. Hereafter, the models using $\Delta\ln(\tilde{Y}_{hvt})$ are referred to as IV expected models.

We employ different sets of instruments $Z_{hv(t-1)}$ for urban and rural samples. For the urban sample, we exploit the disparities in the benefit of China's urban housing policy reform from in-kind housing allocation system (*danwei*) to a cash-based distribution system during 1978-1998; $Z_{hv(t-1)}$ includes an indicator of households with at least one public worker and an indicator of households that began owning their own residence during the reform period[3]. During the reform, the government provided rent subsidies only for urban households of employees who worked in central, budget funded work unit (mainly government organizations). These households were also allowed to purchase their residences at very favorable prices and low interest rates, which resulted in a much cheaper monthly housing cost. Moreover, the benefits of purchasing residences tend to favor higher-income households (Zhang 1999). Thus, including household members employed by the public sector and purchasing one's residence during the reform period may influence household calorie consumption through the reform's positive effect on household purchasing power. On the other hand, whether households include a public worker and purchase their residence during the reform period is expected to be determined as irrelevant to individual caloric intake in urban areas.

For the rural sample, we exploit the disparities in the effect of the government crop price among rural households in which at least one household member is engaged in farming; $Z_{hv(t-1)}$ includes an indicator of specialized farms and the government price of the crop that contributes most to their agricultural income. The government price is set by the Chinese government and affects household calorie consumption through its effect on agricultural income. Additionally, the effects of the government crop prices would be larger for specialized farms than other households. On the other hand, the government crop prices and the choice of farm types are expected to be determined as irrelevant to individual caloric intake.

Data

We use data from the first to the fifth waves of the China Health and Nutrition Survey (CHNS) from 1989-2000. Observations in 1989 and 2000 are used supplementarily to obtain consistent estimators in 1991, 1993, and 1997 – i.e., they are used for differencing time-variant variables and constructing lagged variables. The survey collects information on individuals' average daily caloric intake of three consecutive days, gender, age, employment status, education histories, household composition, and community-level characteristics.

Table 1 reports the summary statistics of the CHNS samples used in this article. We construct two separate samples, one urban and one rural, because we employ different sets of IVs. Also, because our key interest is calorie allocation among more than one household member, only multiple-person households are included in the samples. The rural sample becomes smaller than the urban sample because of the availability of the IVs. The potential effect of this sample selection is discussed in the results section. The validity of the IVs will be subjected to statistical tests in the following section.

Estimation Results

We are interested in the existence of asymmetry and demographic differences in the elasticity of individual caloric intake with respect to declines and increases in calorie consumption per household member. We employ three different estimation models (basic, expected, and IV expected models) to estimate the elasticity for each of six demographic groups. In all these estimations, the standard errors are robust to heteroskedasticity and are corrected for the nonindependence of observations from individuals observed more than once.

In estimating expected changes in calorie consumption per household member, which is used in the expected and IV expected models, the coefficients on lagged changes in calorie consumption per household member range from -0.686 to -0.495 and are statistically significant in all models; and the models explain 26.7 – 30.9% of the variance in actual changes in calorie consumption per household member. In the IV expected models, all IVs are statistically significant at the 10 percent level in the first-stage regressions (Partial F-statistics are 260.0 and 35.7); the hypotheses that the first-stage coefficients on all variables are jointly equal to zero are rejected at the one percent level. Also, the overidentification tests fail to reject the null hypotheses that the IVs are uncorrelated to the residual in equation (6) at the 10 percent level (Hansen J statistics are 5.97 [p-value: 0.12] and 2.73 [p-value: 0.43]). Moreover, the correlation coefficients between the second-stage fitted values and the residuals in equations (4) and (5) are insignificant (p-values range from 0.986 to 0.999 for the urban sample and from 0.980 to 0.999 for the rural sample). Although these test results do not fully guarantee the validity of the IVs, they at least leave the possibility that the IV estimation helps reducing endogeneity bias in calorie elasticity estimates.

Tables 2 and 3 present calorie elasticity estimates for the urban and rural samples, respectively (full results are available from the author upon request). Moreover, tables 4 and 5 summarize the sign and the statistical significance of pair-wise differences in calorie elasticity estimates across six demographic groups (i.e., the elasticity of a row group minus the elasticity of a column group) for the urban and rural sample, respectively. In the estimations, we control the following variables: log prices of major grain and pork in the community,[4] log household size, age dummies (twelve five-years-old categories between 6-79y, and over 80y [2-5y, 18-24y and 61-65y are excluded for the children, prime-age adults and the elderly, respectively]), proportions of demographic groups within households (2-5y, 6-11y, 12-17y, 18-24y, 25-59y, 60y+ for each gender [excluded category: males aged 25-59y]), characteristics of household heads (gender, age, and an indicator of secondary or higher education), seven province dummies, and year dummies.

The results in these tables provide at least four important implications about intra-household calorie allocation that are overlooked or examined minimally in the existing literature. First, our findings demonstrate that demographic differences in calorie elasticity estimates can be more significant by controlling the asymmetry bias. This phenomenon is particularly apparent in the results of expected and IV expected models for the rural sample (table 5). In the results, while all demographic differences are insignificant in the symmetric framework, we find significant differences across children, prime-age adults, and the elderly in the asymmetric framework. Moreover, in the basic models for the urban sample (table 4), we find more significant gender differences in calorie elasticity among children under the asymmetric framework than under the symmetric framework.

Second, our results show that the symmetric estimates may provide misleading implications about the need for demographic targeting. Our results demonstrate two cases. The first case is illustrated by the basic models for the urban sample (tables 2 and 4). The symmetric estimates show that the calorie elasticity of prime-age women is higher than that of prime-age men. Based on the symmetric estimates, we may be able to justify the need for programs targeting prime-age women. However, based on the corresponding asymmetric estimates, such targeting efforts may not be as critical as the symmetric estimates imply because the caloric intake of prime-age women increases more than that of prime-age men not only when food availability declines but also when food availability increases, regardless of targeting.[5] The second case is illustrated by the expected and IV expected models for the rural sample (table 5). The symmetric estimates demonstrate no significant demographic differences. In contrast, the corresponding asymmetric estimates imply that elderly women are treated worse than other demographic groups regardless of the direction of changes in food availability (tables 3 and 5). Thus, although the symmetric estimates provide no evidence of the need for demographic targeting, the asymmetric estimates indicate the need for programs targeting elderly women.

Third, the asymmetric framework provides useful information for relating calorie elasticity estimates to the status of demographic groups within a household. Our results indicate that the observed asymmetry in calorie elasticity estimates is potentially consistent with the liquidity constraint model. Moreover, if a household member is more significantly affected by the liquidity constraint, more calories for the member are saved for expected declines in food availability, and fewer calories are invested in the member for expected increases in food availability. Thus, such a member faces smaller elasticity with respect to expected declines and higher elasticity with respect to expected increases, i.e., more significant asymmetry in calorie elasticity. We can use this information to restrict potential relationships between calorie elasticity estimates and the status of demographic groups within the household.

There are mainly two competing hypotheses for interpreting the relationship between the calorie allocation and the status of demographic groups. The first hypothesis is that intra-household calorie allocation is driven by market incentives or gender preference. Under this hypothesis, members with higher earning potential such as prime-age adults or more-preferred members such as boys are treated better than other members, and being treated better indicates a stronger status within the household. The second hypothesis is that intra-household calorie allocation is determined by altruism toward physically or socially weaker members. Under this hypothesis, weaker members such as children and the elderly are treated better than stronger members such as prime-age adults due to altruism toward the weaker members, and being treated better indicates a weaker status within the household. On the other hand, regardless of which hypothesis is true, the calorie elasticity of a better-treated member becomes less significantly asymmetric under the liquidity constraint framework. Thus, by detecting which demographic group is treated better from the observed asymmetry in calorie elasticity estimates, we can predict which hypothesis is more appropriate to interpret calorie elasticity estimates.

In the urban sample, we find that the calorie elasticity of girls and prime-age adults is significantly asymmetric (table 2), which implies that these demographic groups are more significantly influenced by the constraint as compared to boys and the elderly. One potential interpretation is that prime-age adults allocate foods altruistically toward boys and the elderly in urban households. At the same time, the difference between boys and girls may be due to boy preference or market incentives such as the market return to boys' human capital. In the rural sample, by contrast, we find that the calorie elasticity of children and the elderly is significantly asymmetric, which implies that these demographic groups are more significantly influenced by the constraint as compared to prime-age adults. One potential interpretation is that foods are allocated based on market incentives such as earning potential in rural households, and the finding does not fit the hypothesis of altruism toward weaker members. It is also worth noting that the asymmetry in calorie elasticity is less significant among boys as compared to girls and the elderly. This might indicate the existence of market incentives or boy preference in rural households, although the difference between boys and girls is statistically insignificant.

Lastly, our results demonstrate significant differences in the manner of intra-household calorie allocation between urban and rural households. There are at least two potential explanations for the differences. First, it may be because of the relationship between caloric intake and productivity (i.e., production function) is different between the urban sample (households that include at least one public worker) and the rural sample (households that include at least one farmer). That is, the caloric intake of main earners (i.e., prime-age adults) is prioritized more greatly in the rural sample than in the urban sample because caloric intake is more critical for farming than for office work. Second, a different wealth (or consumption) level between urban and rural households may lead to a different relation of consumption and relative risk aversion. As Mangyo (2008) shows, calorie elasticities can be positively related to household members' status when their utilities exhibit decreasing relative risk aversion in consumption, and vice versa. Thus, if the difference in wealth level between rural and urban areas is large enough to change the relationship between consumption and relative risk aversion, the ordering of the elasticities across demographic groups could be different between rural and urban areas.

Conclusions

Our estimates, based on data from China during 1991-2000, suggest that taking into account asymmetric consumption behavior is critical for understanding demographic differences in the elasticity of individual caloric intake with respect to both actual and expected household food availability. This is because the elasticity estimates obtained under the symmetric framework tend to be biased downward when household food availability increases and biased upward when household food availability declines, which results in underestimating actual demographic differences in calorie elasticity. Moreover, our results show that the estimates obtained under the symmetric framework can underestimate gender differences among children in urban areas, which may partly explain why previous studies fail to find significant gender bias in intra-household calorie allocation in China.

In addition, our results demonstrate that the asymmetric framework proposed in this article can be a valuable addition to the toolkit of economists for examining the relationship between calorie elasticity estimates and the status of demographic groups within a household. The asymmetric framework enables us to relate calorie elasticity estimates to the status of demographic groups without requiring a full interpretation of the ordering of elasticity estimates across demographic groups, although such an interpretation is often required in previous studies and is shown to be somewhat ambiguous by Mangyo (2008). We use the information that the observed asymmetry in the elasticity estimates is potentially consistent with the liquidity constraint model – i.e., more significant asymmetry in the elasticity estimates indicates a larger influence of the constraint. As a result, we find that the caloric intake of girls and prime-age adults is more significantly influenced by the constraint as compared to boys and the elderly in urban areas. A potential interpretation is that prime-age adults altruistically allocate foods toward boys and the elderly in urban households, while food allocation based on the market return to boys' human capital or boy preference can also be consistent. In contrast, we find that the caloric intake of children and the elderly is more significantly influenced by the constraint as compared to prime-age adults in rural areas. A potential interpretation is that foods are allocated according to market incentives such as earning potential in rural households, and the findings do not fit the hypothesis of altruism toward children and the elderly.

From a policy perspective, our asymmetric framework can be a useful tool to evaluate the need for demographic targeting. Our results clarify two potential cases that the elasticity estimates obtained under the symmetric framework can provide misleading implications about the need. First, in urban areas, although the estimates of the basic symmetric models imply the need for programs targeting prime-age women, the estimates of the corresponding asymmetric models indicate that such targeting efforts may not be needed because the caloric intake of prime-age women increases more than that of prime-age men when food availability increases regardless of targeting (note that basic models examine the elasticity with respect to actual changes in food availability, and thus the liquidity constraint framework cannot be used to interpret the results). Second, in rural areas, although the estimates of the symmetric expected and IV expected models demonstrate no significant demographic differences and thus provide no support for the need for demographic targeting, the estimates of the corresponding asymmetric models demonstrate significant differences between elderly women and other demographic groups and indicate the need for programs targeting elderly women.

Lastly, the estimates of both symmetric and asymmetric models indicate that the manner of intra-household calorie allocation differs by rural/urban areas and wealth levels. The finding indicates that a broad stroke nutrition policy without any targeting effort may have different effects on the nutrition of recipients depending on their residence or wealth levels, which can even lead to undesirable results (e.g., remaining calorie deficiency and increasing obesity). Thus, if food is given to households by government programs, more targeted programs, which are differentiated by residence or wealth stratum, may be required.

End Notes

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[1] The reduced approach is based on the unified model. Although the unified model is very restrictive, available data do not permit testing more advanced models such as a bargaining model with a fixed structure against the maximization of unified preferences.

[2] Calorie consumption per household member is the sum of individual intake within a household, divided by household size.

[3] Households that started owning their residence during the reform period are predicted from the age of their residence and the change in form of obtaining their residence during the survey period (i.e., the change from renting to ownership).

[4] Major grains and pork are chosen because they are the two largest sources of calories in our CHNS sample. On average, 77.4% and 13.4% of total daily calorie intake are from grains and pork, respectively. We employ the community-level price of pork and a grain that is most commonly eaten in the community.

[5] Here, we are talking about the results in basic models, and thus the interpretation of liquidity-constraint cannot be applied. That is, a higher elasticity for increases in food availability does not indicate that the member is more strictly restricted by the liquidity constraint.

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Table 1. Summary Statistics of Characteristics of Multiple-person Households in the China Health and Nutrition Survey, 1991-1997

		Urban sample		Rural sample	
Number of Households		581		638	
Number of Observations		2,520		2,373	
Variables		Mean	S.D.	Mean	S.D.
Dependent Variable					
ΔLn(individual calorie intake [kcal])		-0.014	0.401	0.000	0.409
Independent Variables					
ΔLn(calorie intake per household member [kcal])		-0.020	0.352	-0.008	0.356
	Dummy of increases (POS)	0.477	0.500	0.517	0.500
ΔExpected ln(calorie intake per household member [kcal])		-0.022	0.186	-0.010	0.197
	Dummy of increases (POS)	0.447	0.497	0.480	0.500
ΔIV Expected ln(calorie intake per household member [kcal])		-0.020	0.179	-0.009	0.152
	Dummy of increases (POS)	0.449	0.497	0.486	0.500
ΔLn(grain price [1989 yuan])		-0.108	0.330	-0.082	0.706
ΔLn(pork price [1989 yuan])		-0.162	0.502	-0.077	0.501
Household size [person]		3.817	1.352	4.275	1.376
Age dummies:	02-05 years old	0.040	0.195	0.025	0.156
	06-11 years old	0.139	0.346	0.169	0.374
	12-17 years old	0.062	0.241	0.089	0.285
	18-24 years old	0.060	0.237	0.050	0.218
	25-30 years old	0.107	0.309	0.064	0.244
	31-35 years old	0.118	0.323	0.081	0.273
	36-40 years old	0.136	0.343	0.094	0.292
	41-45 years old	0.114	0.318	0.114	0.318
	46-50 years old	0.065	0.247	0.094	0.292
	51-55 years old	0.047	0.212	0.081	0.273
	56-60 years old	0.035	0.185	0.061	0.239
	61-65 years old	0.034	0.182	0.037	0.189
	66-70 years old	0.022	0.146	0.022	0.146
	71-75 years old	0.012	0.108	0.008	0.089
	76-80 years old	0.006	0.079	0.007	0.082
	over 80 years old	0.003	0.045	0.003	0.054
Proportion of demographic groups within household:	Males aged 2-5 years old	0.037	0.089	0.029	0.079

	Females aged 2-5 years old	0.032	0.088	0.023	0.073
	Males aged 6-11 years old	0.074	0.127	0.086	0.131
	Females aged 6-11 years old	0.066	0.119	0.073	0.126
	Males aged 12-17 years old	0.051	0.111	0.067	0.122
	Females aged 12-17 years old	0.046	0.102	0.062	0.112
	Males aged 18-24 years old	0.042	0.106	0.060	0.118
	Females aged 18-24 years old	0.038	0.096	0.047	0.103
	Males aged 25-59 years old	0.261	0.116	0.241	0.120
	Females aged 25-59 years old	0.270	0.110	0.236	0.105
	Males over 60 years old	0.043	0.105	0.039	0.102
	Females over 60 years old	0.049	0.108	0.044	0.102
Household-head	Female	0.189	0.392	0.072	0.259
characteristics:	Age [years]	46.43	12.69	46.396	10.799
	Secondary or higher education	0.284	0.451	0.105	0.306
Province dummies:	Liaoning	0.123	0.328	0.020	0.139
	Jiangsu	0.099	0.299	0.089	0.285
	Shandong	0.020	0.139	0.124	0.330
	Henan	0.061	0.240	0.076	0.265
	Hubei	0.103	0.304	0.180	0.385
	Hunan	0.139	0.346	0.075	0.263
	Guanxi	0.225	0.418	0.206	0.405
	Guizhou	0.229	0.421	0.230	0.421
Year dummies:	Year 1991	0.217	0.412	-	-
	Year 1993	0.381	0.486	0.474	0.499
	Year 1997	0.402	0.490	0.526	0.499
Excluded Instruments					
Dummy of house ownership		0.695	0.479	-	-
Dummy of public workers		0.687	0.464	-	-
ΔLn(government. crop price)		-	-	0.222	1.090
Dummy of specialized farmers		-	-	0.121	0.327

Table 2. Elasticity Estimates of Individual Caloric Intake with respect to Calorie Consumption per Household Member by Demographic Group in Urban Areas in China

Dependent variable = individual calorie intake										
Demographic groups		**Basic** Coef. (p-value)		**Expected** Coef. (p-value)		**IV Expected** Coef. (p-value)		**Obs. Num.**	**F-statistics**	
Boys (2-17 years old)										
Symm		0.977	(0.00)	1.059	(0.00)	1.096	(0.00)	328	Basic:	41.6
	[95%CI]	*[0.897,*	*1.057]*	*[0.771,*	*1.347]*	*[0.798,*	*1.395]*		Exp:	5.8
									IV Exp:	5.8
Asymm	Positive	0.915	(0.00)	1.379	(0.00)	1.405	(0.00)	328	Basic:	43.3
	[95%CI]	*[0.724,*	*1.106]*	*[0.817,*	*1.941]*	*[0.802,*	*2.009]*		Exp:	6.0
	Negative	1.021	(0.00)	0.839	(0.00)	0.899	(0.00)		IV Exp:	6.0
	[95%CI]	*[0.922,*	*1.120]*	*[0.304,*	*1.373]*	*[0.359,*	*1.438]*			
	Pos. – Neg.	-0.106	(0.40)	0.540	(0.26)	0.507	(0.31)			
Girls (2-17 years old)										
Symm		0.835	(0.00)	0.794	(0.00)	0.819	(0.00)	278	Basic:	25.1
	[95%CI]	*[0.745,*	*0.924]*	*[0.535,*	*1.053]*	*[0.551,*	*1.087]*		Exp:	5.3
									IV Exp:	5.3
Asymm	Positive	1.032	(0.00)	1.250	(0.00)	1.284	(0.00)	278	Basic:	26.8
	[95%CI]	*[0.835,*	*1.229]*	*[0.748,*	*1.751]*	*[0.779,*	*1.789]*		Exp:	5.8
	Negative	0.742	(0.00)	0.487	(0.02)	0.502	(0.02)		IV Exp:	5.6
	[95%CI]	*[0.605,*	*0.878]*	*[0.075,*	*0.900]*	*[0.076,*	*0.928]*			
	Pos. – Neg.	0.291	(0.05)	0.762	(0.05)	0.782	(0.05)			
Prime-age Men (18-60 years old)										
Symm		0.947	(0.00)	1.009	(0.00)	1.044	(0.00)	826	Basic:	71.2
	[95%CI]	*[0.897,*	*0.998]*	*[0.862,*	*1.155]*	*[0.892,*	*1.195]*		Exp:	9.0
									IV Exp:	9.0
Asymm	Positive	0.880	(0.00)	1.234	(0.00)	1.274	(0.00)	826	Basic:	71.9
	[95%CI]	*[0.777,*	*0.982]*	*[1.003,*	*1.465]*	*[1.037,*	*1.512]*		Exp:	10.5
	Negative	1.004	(0.00)	0.793	(0.00)	0.819	(0.00)		IV Exp:	10.6
	[95%CI]	*[0.927,*	*1.082]*	*[0.521,*	*1.065]*	*[0.540,*	*1.098]*			
	Pos. – Neg.	-0.125	(0.11)	0.441	(0.04)	0.455	(0.04)			

Table 2 [continued]

Prime-age Women (18-60 years old)										
Symm		1.020	(0.00)	1.049	(0.00)	1.086	(0.00)	878	Basic:	109.1
	[95%CI]	*[0.979,*	*1.060]*	*[0.885,*	*1.212]*	*[0.917,*	*1.254]*		Exp:	8.9
									IV Exp:	8.9
Asymm	Positive	1.027	(0.00)	1.270	(0.00)	1.306	(0.00)	878	Basic:	109.2
	[95%CI]	*[0.943,*	*1.111]*	*[0.996,*	*1.544]*	*[1.027,*	*1.585]*		Exp:	9.7
	Negative	1.014	(0.00)	0.843	(0.00)	0.879	(0.00)		IV Exp:	9.7
	[95%CI]	*[0.954,*	*1.074]*	*[0.523,*	*1.163]*	*[0.554,*	*1.204]*			
	Pos. – Neg.	0.013	(0.83)	0.428	(0.10)	0.427	(0.10)			
Elderly Men (over 60 years old)										
Symm		0.995	(0.00)	0.927	(0.00)	0.955	(0.00)	102	Basic:	33.9
	[95%CI]	*[0.860,*	*1.129]*	*[0.326,*	*1.528]*	*[0.333,*	*1.577]*		Exp:	11.9
									IV Exp:	11.9
Asymm	Positive	0.992	(0.00)	0.947	(0.04)	1.076	(0.02)	102	Basic:	32.5
	[95%CI]	*[0.771,*	*1.214]*	*[0.067,*	*1.827]*	*[0.213,*	*1.939]*		Exp:	11.5
	Negative	0.997	(0.00)	0.907	(0.06)	0.818	(0.11)		IV Exp:	11.4
	[95%CI]	*[0.794,*	*1.200]*	*[-0.039,*	*1.853]*	*-[0.191,*	*1.827]*			
	Pos. – Neg.	-0.005	(0.98)	0.040	(0.95)	0.258	(0.72)			
Elderly Women (over 60 years old)										
Symm		1.013	(0.00)	0.743	(0.02)	0.772	(0.02)	108	Basic:	12.4
	[95%CI]	*[0.799,*	*1.227]*	*[0.133,*	*1.352]*	*[0.144,*	*1.400]*		Exp:	5.2
									IV Exp:	5.2
Asymm	Positive	1.267	(0.00)	0.917	(0.03)	0.981	(0.02)	108	Basic:	13.8
	[95%CI]	*[0.855,*	*1.679]*	*[0.109,*	*1.725]*	*[0.162,*	*1.800]*		Exp:	4.9
	Negative	0.809	(0.00)	0.612	(0.22)	0.609	(0.24)		IV Exp:	5.0
	[95%CI]	*[0.459,*	*1.160]*	*[-0.369,*	*1.593]*	*-[0.417,*	*1.634]*			
	Pos. – Neg.	0.458	(0.17)	0.305	(0.66)	0.372	(0.60)			

Note: Control variables include log prices of major grain and pork in the community, log household size, age dummies, proportions of demographic groups within households, characteristics of household heads, province dummies, and year dummies.

Table 3. Elasticity Estimates of Individual Caloric Intake with respect to Calorie Consumption per Household Member by Demographic Group in Rural Areas in China

Dependent variable = individual calorie intake										
Demographic groups		**Basic** Coef.	(p-value)	**Expected** Coef.	(p-value)	**IV Expected** Coef.	(p-value)	**Obs. Num.**	**F-statistics**	
Boys (2-17 years old)										
Symm		0.998	(0.00)	1.032	(0.00)	0.746	(0.00)	378	Basic:	44.9
	[95%CI]	*[0.929,*	*1.066]*	*[0.679,*	*1.385]*	*[0.489,*	*1.002]*		Exp:	3.9
									IV Exp:	3.9
Asymm	Positive	0.989	(0.00)	1.340	(0.00)	0.982	(0.00)	378	Basic:	43.4
	[95%CI]	*[0.869,*	*1.109]*	*[0.839,*	*1.842]*	*[0.590,*	*1.374]*		Exp:	3.9
	Negative	1.009	(0.00)	0.455	(0.11)	0.332	(0.11)		IV Exp:	3.9
	[95%CI]	*[0.882,*	*1.137]*	*[-0.104,*	*1.015]*	*-[0.079,*	*0.743]*			
	Pos. – Neg.	-0.020	(0.85)	0.885	(0.04)	0.650	(0.06)			
Girls (2-17 years old)										
Symm		1.021	(0.00)	1.071	(0.00)	0.779	(0.00)	293	Basic:	33.6
	[95%CI]	*[0.934,*	*1.108]*	*[0.665,*	*1.477]*	*[0.483,*	*1.076]*		Exp:	3.6
									IV Exp:	3.6
Asymm	Positive	1.049	(0.00)	1.593	(0.00)	1.211	(0.00)	293	Basic:	33.7
	[95%CI]	*[0.923,*	*1.174]*	*[0.920,*	*2.265]*	*[0.698,*	*1.725]*		Exp:	3.8
	Negative	0.983	(0.00)	0.380	(0.31)	0.224	(0.42)		IV Exp:	3.9
	[95%CI]	*[0.814,*	*1.152]*	*[-0.355,*	*1.115]*	*-[0.317,*	*0.765]*			
	Pos. – Neg.	0.065	(0.59)	1.212	(0.06)	0.987	(0.04)			
Prime-age Men (18-60 years old)										
Symm		0.961	(0.00)	0.938	(0.00)	0.681	(0.00)	736	Basic:	80.8
	[95%CI]	*[0.906,*	*1.015]*	*[0.763,*	*1.113]*	*[0.554,*	*0.808]*		Exp:	7.5
									IV Exp:	7.5
Asymm	Positive	0.991	(0.00)	1.203	(0.00)	0.879	(0.00)	736	Basic:	80.3
	[95%CI]	*[0.868,*	*1.114]*	*[0.614,*	*1.791]*	*[0.418,*	*1.339]*		Exp:	7.6
	Negative	0.935	(0.00)	0.706	(0.01)	0.496	(0.02)		IV Exp:	7.7
	[95%CI]	*[0.874,*	*0.995]*	*[0.184,*	*1.227]*	*[0.069,*	*0.924]*			
	Pos. – Neg.	0.056	(0.48)	0.497	(0.36)	0.383	(0.38)			

Table 3 [continued]

Prime-age Women (18-60 years old)										
Symm		0.982	(0.00)	1.003	(0.00)	0.729	(0.00)	752	Basic:	90.1
	[95%CI]	*[0.934,*	*1.029]*	*[0.849,*	*1.156]*	*[0.618,*	*0.841]*		Exp:	10.0
									IV Exp:	10.0
Asymm	Positive	1.058	(0.00)	0.987	(0.00)	0.708	(0.00)	752	Basic:	75.1
	[95%CI]	*[0.959,*	*1.156]*	*[0.380,*	*1.593]*	*[0.232,*	*1.183]*		Exp:	9.8
	Negative	0.919	(0.00)	1.018	(0.00)	0.752	(0.00)		IV Exp:	9.7
	[95%CI]	*[0.841,*	*0.997]*	*[0.452,*	*1.585]*	*[0.284,*	*1.219]*			
	Pos. – Neg.	0.139	(0.06)	-0.032	(0.96)	-0.044	(0.93)			
Elderly Men (over 60 years old)										
Symm		0.899	(0.00)	1.096	(0.00)	0.794	(0.00)	97	Basic:	35.4
	[95%CI]	*[0.775,*	*1.023]*	*[0.600,*	*1.593]*	*[0.428,*	*1.159]*		Exp:	5.5
									IV Exp:	5.5
Asymm	Positive	0.912	(0.00)	1.797	(0.00)	1.353	(0.00)	97	Basic:	35.7
	[95%CI]	*[0.649,*	*1.176]*	*[1.179,*	*2.416]*	*[0.869,*	*1.838]*		Exp:	8.0
	Negative	0.903	(0.00)	0.207	(0.71)	0.060	(0.89)		IV Exp:	7.7
	[95%CI]	*[0.692,*	*1.114]*	*[-0.887,*	*1.300]*	*-[0.816,*	*0.936]*			
	Pos. – Neg.	0.009	(0.97)	1.591	(0.03)	1.293	(0.03)			
Elderly Women (over 60 years old)										
Symm		0.927	(0.00)	1.172	(0.00)	0.850	(0.00)	117	Basic:	22.0
	[95%CI]	*[0.766,*	*1.088]*	*[0.587,*	*1.758]*	*[0.425,*	*1.274]*		Exp:	2.9
									IV Exp:	2.9
Asymm	Positive	0.897	(0.00)	1.926	(0.00)	1.434	(0.00)	117	Basic:	21.1
	[95%CI]	*[0.647,*	*1.148]*	*[0.973,*	*2.880]*	*[0.719,*	*2.150]*		Exp:	2.7
	Negative	0.952	(0.00)	0.357	(0.41)	0.188	(0.57)		IV Exp:	2.7
	[95%CI]	*[0.677,*	*1.228]*	*[-0.501,*	*1.216]*	*-[0.471,*	*0.846]*			
	Pos. – Neg.	-0.055	(0.80)	1.569	(0.03)	1.247	(0.03)			

Note: Control variables include log prices of major grain and pork in the community, log household size, age dummies, proportions of demographic groups within households, characteristics of household heads, province dummies, and year dummies.

Table 4. Significance of Pair-wise Differences in Calorie Elasticity Estimates across Demographic Groups in Urban Areas in China

	Asymmetric						Symmetric					
	B	G	PM	PW	EM	EW	B	G	PM	PW	EM	EW
Basic Models	The upper triangular matrix is for positive changes											
Boys (B)		0	0	0	0	0		-	-	-	-	-
Girls (G)	N*		P*	0	0	0	0		-	-	-	-
prime-age men (PM)	0	P*		N++	0	0	0	P+		-	-	-
prime-age women (PW)	0	P***	P**		0	0	P++	P**	P***		-	-
elderly men (EM)	0	P**	0	0		0	0	P*	P*	0		-
elderly women (EW)	0	P**	N+	0	0		P+	P*	P*	0	0	
	The lower triangular matrix is for negative changes											
Expected Models	The upper triangular matrix is for positive changes											
Boys (B)		0	0	0	0	0		-	-	-	-	-
Girls (G)	0		0	0	0	0	0		-	-	-	-
prime-age men (PM)	0	P+		0	0	0	0	P+		-	-	-
prime-age women (PW)	0	P+	0		0	0	0	P*	0		-	-
elderly men (EM)	0	0	0	0		0	0	0	0	0		-
elderly women (EW)	0	0	0	0	0		0	0	0	N+	0	
	The lower triangular matrix is for negative changes											
IV Expected Models	The upper triangular matrix is for positive changes											
Boys (B)		0	0	0	0	0		-	-	-	-	-
Girls (G)	0		0	0	0	0	N+		-	-	-	-
prime-age men (PM)	0	P+		0	0	0	0	P+		-	-	-
prime-age women (PW)	0	P+	0		0	0	0	P*	0		-	-
elderly men (EM)	0	0	0	0		0	0	0	0	0		-
elderly women (EW)	0	0	0	0	0		0	0	0	0	0	
	The lower triangular matrix is for negative changes											

Note (1) P and N indicates that "the elasticity of a row group minus the elasticity of a column group" is positive and negative, respectively.

(2) ***, **, *, ++, and + indicate that the difference in calorie elasticity estimates of the pair is statistically significant at the 1, 5, 10, 15, and 20% level, respectively. 0 indicates that the difference is insignificant even at the 20% level.

Table 5. Significance of Pair-wise Differences in Calorie Elasticity Estimates across Demographic Groups in Rural Areas in China

	Asymmetric						Symmetric					
	B	G	PM	PW	EM	EW	B	G	PM	PW	EM	EW
Basic Models	The upper triangular matrix is for positive changes											
Boys (B)		0	0	0	0	0		-	-	-	-	-
Girls (G)	0		0	0	0	0	0		-	-	-	-
prime-age men (PM)	N*	N*		0	0	P*	N***	N**		-	-	-
prime-age women (PW)	N**	N*	0		0	0	N**	N*	0		-	-
elderly men (EM)	0	0	N*	N*		0	0	0	N+	0		-
elderly women (EW)	N++	N++	0	0	P+		0	0	0	0	0	
	The lower triangular matrix is for negative changes											
Expected Models	The upper triangular matrix is for positive changes											
Boys (B)		0	0	0	0	N+		-	-	-	-	-
Girls (G)	0		0	P+	0	0	0		-	-	-	-
prime-age men (PM)	0	0		0	N+	N++	0	0		-	-	-
prime-age women (PW)	P+	P+	0		N*	N**	0	0	0		-	-
elderly men (EM)	0	0	0	N++		0	0	0	0	0		-
elderly women (EW)	0	0	0	N++	0		0	0	0	0	0	
	The lower triangular matrix is for negative changes											
IV Expected Models	The upper triangular matrix is for positive changes											
Boys (B)		0	0	0	0	N+		-	-	-	-	-
Girls (G)	0		0	P++	0	0	0		-	-	-	-
prime-age men (PM)	0	0		0	N+	N*	0	0		-	-	-
prime-age women (PW)	P+	P++	0		N*	N**	0	0	0		-	-
elderly men (EM)	0	0	0	N++		0	0	0	0	0		-
elderly women (EW)	0	0	0	N*	0		0	0	0	0	0	
	The lower triangular matrix is for negative changes											

Note (1) P and N indicates that "the elasticity of a row group minus the elasticity of a column group" is positive and negative, respectively.
(2) ***, **, *, ++, and + indicate that the difference in calorie elasticity estimates of the pair is statistically significant at the 1, 5, 10, 15, and 20% level, respectively. 0 indicates that the difference is insignificant even at the 20% level.