Determinants of municipal-level household food waste

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Determinants of municipal-level household food waste

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Abstract

Using time series data on municipal-level household food scrap drawn from a city-wide food scrap recycling program from 2007m1 to 2018m8, we proxy the household food wastage rate (FWR) by the edible-to-inedible food scrap ratio and then apply both linear and semiparametric varying-coefficient cointegration tests to examine the municipal-level long-run relationship between socioeconomic factors and household FWR. The linear model shows that food price, old-age population share, and average household size are positively related to FWR, whereas working-age population share is negatively related to FWR. Consistent with the environmental Kuznets curve hypothesis, the varying-coefficient model further reveals that the direct relationship between income and FWR is inverted-U shaped. Moreover, income alters the relationship between socioeconomic factors and FWR. The FWR-increasing effect of population aging (food price) likely aggravates (diminishes) with economic growth. With these in mind, for policymakers trying to reduce food waste, the steady increases in food price and old-age share pose challenges, whereas the declining trend in average household size brings relief. Given the results, one way to reduce food waste is subsidizing both the design of smart packaging and the development of semi-prepared convenience food with flexible portion sizes and portion sizes suitable for older adults.

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I. INTRODUCTION

Will food waste continue to grow as it has in the past few decades? Do higher income and food prices as well as increasing proportions of older people and single-person households introduce new challenges for municipalities to tackle the changing conditions of food waste management? The objective of this paper is threefold. First, it proposes a proxy for municipal household food wastage rate (FWR). Second, it tests for the existence of a long-run equilibrium relationship between socioeconomic factors and FWR. As suggested in Schanes et al. (2018) and the micro-level qualitative studies to be reviewed below, wasting food is a habitual behavior that requires interdisciplinary efforts. Thus, the consequence of the socioeconomic evolution on FWR is essentially a long-run concept. Regarding time series variables, the idea of cointegration is identical to the existence of a long-run equilibrium toward which an economy converges over time. Given that the consequence of socioeconomic change on food waste behavior is essentially a long-run notion, we apply the autoregressive distributed lag (ARDL) bounds cointegration test to monthly time series data at the municipal level over the period 2007m1 to 2018m8 to examine whether socioeconomic variables and FWR are cointegrated. Third, this paper examines whether the long-run relationship changes across different average wage levels. A long-run projection of municipal household FWR depends heavily on the correct identification of the long-run relationship between FWR and its determinants. Since income can fluctuate substantially over time, another piece of information necessary to project FWR in the long term is how income affects household FWR by altering the relationship between FWR and its determinants. In order to assess the presence of an inverted-U shaped environmental Kuznets curve (EKC) for FWR, i.e., to examine whether socioeconomic variables matter differently at different income levels, we apply a flexible semiparametric varying-coefficient cointegration (VCC) test to the data. The semiparametric model takes the form of a varying-coefficient specification in which the parameters for the regressors are specified as unknown smooth functions of income. The VCC coefficient function estimates are data-driven, permitting the influence of income and the other regressors on municipal household FWR to vary with income in an unprespecified way.

Food waste refers to the discarding or non-food use of food that is safe and nutritious for human consumption (FAO, 2019). Food wastage rate (FWR), defined as the ratio of edible food discarded to the sum of edible food utilized and discarded, is important to study because reducing FWR is useful not only for food security of the poor, but also for resource efficiency and sustainability. Agricultural production, fertilizer production, fuel use, and agriculture-induced change in land use account for 30% of global greenhouse gas emissions (Bellarby et al., 2008). Wasting food means the wanton wasted of the greenhouse emissions generated during the course of food production, distribution, storing and cooking (Garnett, 2011). On top of that, food waste is associated with deforestation, global warming, and water shortage (Graham-Rowe et al., 2014; Tonini et al., 2018; Martinez-Sanchez et al., 2016). Goal 12 of Sustainable Development Goals (SDGs) - ensuring sustainable consumption and production patterns - targets halving per capita food waste at the retail and consumer level by 2030. Compared to production, distribution, and retailing, consumption is the stage of the food supply chain that generates the most food waste (Aschemann-Witzel et al., 2015; Aschemann-Witzel, 2016). In light of this, our analysis focuses on household food waste at the macro-level.

The rest of the paper is structured as follows. Section 2 describes the food scrap collection program in Taipei, Taiwan. Section 3 presents the data and estimation strategy. Section 4 outlines the results. Section 5 concludes the paper with policy implications.

II. BACKGROUND

A. Food Scrap Collection Program In Taipei

Our time series analysis is made possible by the availability of nearly 11 years of monthly data on municipal-level edible and inedible household food scraps generated by a city-wide food scrap recycle program. Food scrap accounts for 30-40% of Taipei's total household waste (Taipei City Government 2018). Due to its high population density, minimizing landfill use and reducing dioxin emission from incinerators are particularly important to the metropolis. On December 26, 2003, the Taipei City Department of Environmental Protection implemented four municipal programs - "mandatory waste sorting", "food scrap recycling", "pay-as-you-throw", and "keep waste off ground" – in which all residents are responsible for sorting the waste they generate and taking it to a recycling truck at a designated time at a nearby designated collection spot by themselves. Residents are required to sort their waste into four categories: general refuse, recyclable, edible and inedible food scrap. Edible food scrap refers to cooked food waste that is fed to pigs, whereas inedible food scrap refers to raw food scrap that is composted. Residents pay for the disposal of general refuse on a "per-bag" basis and can be charged high penalties for randomly leaving waste on the ground. On the other hand, handing over properly sorted recyclables and edible and inedible food scraps to the recycling truck is free. This creates strong economic incentives to separate recyclables and food scraps from general refuses. The "keep waste off ground" policy is essentially a "save time-as-you-prevent" scheme. Unlike other waste collection methods such as community bin or curbside pick-up, the waste collection program in Taipei requires residents to set aside time to wait for the arrival of the recycling truck. This provides a nonmonetary incentive for residents to cut down on waste.

B. Conceptual Framework

The economics literature has highlighted a number of socioeconomic factors that may influence the decision to discard food. Building on Becker's (1965) household production model in which households allocate time between home production and labor market, Lusk and Ellison (2017) demonstrated that the decision to discard food can be the result of rational optimization under the conditions of food price, opportunity costs of time (wage income), and productivity of meal planning and preparation time. Additionally, consumer demand theories point to nonlinearity and parameter heterogeneity for the effect of these variables on municipal FWR. In particular, the Quadratic Almost Ideal Demand System (QUAIDS) where the quantity demanded for a good is allowed to be nonlinearly related to income (Banks et al. 1997; Khanal et al., 2016) implies that a good can be a luxury when income is low but a necessity or inferior when income is high. Gale and Huang (2007), Yu and Abler (2009), and Abler (2010) empirically showed that the income elasticity of the demand for food quality is significantly positive. Merellay and Santabárbara (2017) found evidence of a positive link between importer income and quality of imports. If high-quality foods have a lower wastage rate owing to their superior flavor, freshness or ease of preparation, then one might expect the municipal FWR to depend on the composition of food consumption across high- and low-quality products. With these in mind, changes in income may result in compositional changes in food demand that lead to a nonlinear relationship between income and municipal FWR. At low income levels, a rise in income may lead households to purchase more low-quality foods that can be bought in large quantity. Conversely, at higher levels of income, low-quality foods become inferior, whereas high-quality foods that people would utilize more fully, become necessities or luxuries. In light of these, one might expect the change in the composition of food expenditure across high- and low-quality foods as income rises will yield an inverted-U relationship between income and municipal FWR.

Regarding the link between food price and FWR, Hamilton and Richards (2019) provided a useful theoretical framework assuming that a higher food utilization rate requires more meal planning efforts, which enter utility negatively. As such, food utilization effort is positively related to the quantity of food purchased. Thus, Hamilton and Richards (2019) showed that a rise in the price of food improves food utilization among price-inelastic households, yet impedes food utilization in price-elastic households. If the demand for food is price-elastic in the majority of households, then municipal FWR must go up as food price rises - an implication that runs counter to conventional wisdom. In light of the finding in Abler (2010) and Seale and Regmi (2006) that there is a tendency for both the income elasticity and the absolute value of the own-price elasticity of food demand to decline as income increases, it is desirable to incorporate nonlinearity and parameter heterogeneity when examining the long-run relationship among income, food price, and municipal FWR.

Aside from income and prices, demographic transition may also alter a municipality's long-run level of FWR. As in many advanced economies, average household size has been on a downward trend in Taipei. Crossley and Lu (2018) outlined a mechanism through which returns to scale in the time input to home production may lead large households to substitute towards foods that are cheaper but more time intensive. Based on Canadian food expenditure and time use data, they found that larger households' baskets have fewer ready-to-eat foods yet more foods that require preparation time and that per capita food preparation time is higher for larger households. As will be described below, food scrap disposal in Taipei costs time, because it requires residents to meet their local recycling truck at a designated time. Therefore, one might expect single-person households to exhibit a lower FWR. Moreover, divergence in food preferences may arise as household size increases, thereby exacerbating FWR (Parizeau et al., 2015; Neff et al., 2015). For these reasons, we include average household size as a long-run forcing variable for municipal household FWR.

Another demographic variable that has witnessed a downward trend in Taipei is working-age share. On the one hand, the higher opportunity cost of time for the working-age population might lead them to spend less on meal planning and thereby waste more than the rest of the population. On the other hand, if working-age people are more competent in meal planning or have stronger environmental awareness, then one would expect the working-age population share to have a tempering effect on FWR.

A common implication of the above insights from economic theories is that there are nonlinearity and parameter heterogeneity induced by a person's current level of income, because the above analytical frameworks predict that the existing level of income matters for the effects of income, food price, and working-age population share on municipal FWR. Of course, the relationship between socioeconomic factors and municipal FWR and whether the relationship varies across levels of income are ultimately empirical matters.

C. Prior Empirical Studies

The empirical literature so far has documented evidence using cross-sectional data collected at the micro-level. In a qualitative study based on semi-structured interviews with 15 UK household food purchasers, Graham-Rowe et al. (2014) identified three major motives for minimizing food waste: (1) waste concerns; (2) doing the 'right' thing; and (3) food management skills. Results from a literature review and expert interviews by Aschemann-Witzel et al. (2015) revealed that the level of food waste is affected by marketing, consumers' food preparation skills, and trade-off between priorities. A study of 68 households in Guelph, Canada suggests that food awareness, waste awareness, family lifestyles, and convenience lifestyles substantially affect household food wasting behaviors (Parizeau et al., 2015). Based on a survey of 928 UK residents, Mallinson et al. (2016) found that household size, packaging format, and price-awareness all exert significant influence on food waste behaviors. By applying linear regression to data collected from an online survey, Schmidt and Matthies (2018) revealed that consumption practices that prevent food waste are significant determinants of dairy and bakery product wastage. Our work is most related to Setti et al. (2016), who used survey data on 1,403 individuals in 2013 to show that Italian consumers in the middle-income brackets waste food more frequently than those in the lower and higher income brackets do, meaning that the relationship between income and food waste frequency is described by an inverted U-shaped household food waste Kuznets curve (FWKC).

There are two limitations in the existing studies on household food waste behavior. First, as suggested in the above micro-level studies, food wasting is a habitual behavior. Thus, the consequence of socioeconomic development on household FWR is essentially a long-run concept that can be better understood using time series data. Moreover, given the large disparity in socioeconomic characteristics across individual households, a municipality's trajectory as its income increases over time may not be correctly inferred from the pattern uncovered from a group of households at different levels of income at a point in time. Second, previous studies do not consider nonlinearity and parameter heterogeneity induced by income, which is crucial for adjusting policies according to changing times.

Despite that measuring and projecting municipal household FWR are crucial for formulating policy, we have not seen any study that address this issue. The main reason for this gap lies with the lack of a reliable measure of FWR as well as the required time series data. In general, there is no observable time series data on the quantities of food purchased, utilized, and discarded by households at the macro-level. Consequently, measuring macro-level household FWR and identifying its long-run determinants have been a challenging task.

We depart from previous studies that limit their focus to household-level cross-sectional data on the amount of food waste. Instead of this focus on how differences in income and demographic characteristics across households lead to cross-sectional differences in the amount of food waste, we highlight how variations in average wage income, price, population age structure and average household size across time affect a municipality's long-run household FWR. Furthermore, we deepen existing studies by considering nonlinearity and parameter heterogeneity across income levels.

A municipality's FWR trajectory as its income changes over time may not be correctly inferred from the pattern identified from a group of households at different income levels at a point in time. Survey and interview data collected at a point in time are unable to measure changes over time in the population. Time series analyses of municipal-level data complement survey-based research, as they help researchers to analyze trends, identify associations, and predict future. Motivated by Lusk and Ellison's (2017) household production model, Setti et al.'s (2016) FWKC hypothesis, and the factors identified by the aforementioned survey-based studies, our paper aims to test for the existence of a long-run level relationship among the extent of household food waste and food price, real wage, and food management skill in the city of Taipei over the period 2007m1 to 2018m8 using the ARDL bounds testing procedure and the semiparametric VCC test.

This paper contributes to the literature on the determinants of household food waste in two ways. First, this analysis allows policymakers to project changes in FWR that could be expected if the level of a particular municipal socio-demographic characteristic, for example, the share of working-age population, changes. To the best of our knowledge, we provide the first estimates of the long-run relationship between municipal FWR and its determinants within a cointegrated time series setting. Second, this paper tests the EKC hypothesis via a semiparametric VCC test, therefore mitigating the potential functional form misspecification. Unlike conventional tests of the EKC hypothesis, which typically model the logarithm of an indicator of environmental degradation as a quadratic function of the logarithm of income, the semiparametric varying-coefficient model allows the dependent variable to vary smoothly with the income level in an unspecified way.

III. DATA

Data availability and the economic theory of Lusk and Ellison (2017) guide us to formulate the following double log empirical model so that in equilibrium FWR, as measured by the edible-to-inedible food scrap ratio (W), depends on the opportunity cost of time, as measured by real wage (R), the market price for raw food ingredients (P), productivity in meal preparation, as gauged by the share of population aged 15 to 64 (M), the share of population aged 65 or older (O), household size (S), and food composition and storage condition, as proxied by average temperature, average humidity, number of rainy days, precipitation, and hours of sunlight ($E^l, l = 1, \ldots, 5$).

$$y_t = a_0 + \sum_{j=1}^{k} a_j x_{j,t} + \varepsilon_t, \tag{1}$$

where y_t represents the log of the edible-to-inedible food scrap ratio (lnW_t), and $x_{j,t}, j = 1, \ldots, k$ represents the log for the k determinants of the long-run equilibrium level of the dependent variable y. The coefficients in equation (1), a_js, are the elasticity of the ratio of edible to inedible food scraps with respect to the j^{th} explanatory variable.

The justification for proxying FWR by the ratio of edible-to-inedible food scraps is as follows. We define FWR as the ratio of edible food scrap (ED) to the sum of edible food scrap (ED) and food eaten (EN):

$$FWR = ED/(ED + EN). \tag{2}$$

While data on ED and inedible food scraps (IE) are publicly available, data on EN are not. To come up with an operational definition of food waste, we assume that the ratio of inedible food scraps to the sum of edible food scraps and food eaten is constant over time, i.e., $(IE/(ED + EN)) = c$. With the aid of this assumption, FWR can be measured up to a scale: $FWR = c \times (ED/IE)$. Given this, the log of the ratio of edible to inedible food scrap - $\mathrm{lnW} = \ln(ED/IE)$ - serves as our dependent variable.

This analysis is based on a unique set of time series data on edible and inedible food scraps. As noted above, Taipei started to collect and recycle household food scraps in 2003, mandating residents to separate kitchen waste into two groups - those for composting and those for feeding pigs - and to carry the sorted food scraps along with other recyclables to the recycling truck at the designated time at the designated sidewalks nearby their residence each evening. We measure IE using per capita daily food scraps collected for compost - residues to be fermented and then used as fertilizer, including peels, shells, cores, bones, tea leaves, and coffee grounds. To measure ED, we resort to per capita daily kitchen scraps to be steamed and then used as pig feed, also called non-compostable food scrap. Non-compostable food scraps are mainly digestible scraps discarded due to over-purchasing or over-preparing. Both ED and IE are measured in kilograms. The amounts of edible and inedible household food scraps collected are made publicly available on a monthly basis. As of October 2018, the city collects 4,865.84 tons of compostable food waste and 317.35 tons of non-compostable food waste per month. Spread over a month, this amounts to about 0.06 and 0.004 kilograms per resident per day. Over time, the separation of food scraps from other types of recyclables and the separation of edible from non-edible food scraps have become common practice in Taipei.

As for the regressors, $\ln R$ denotes the log of real average monthly wage, which is calculated as average nominal wage divided by the consumer price index (CPI) and then multiplied by 100; $\ln P$ represents the log of CPI for food; $\ln M$, $\ln O$, and $\ln U$ denote the log of the percentage of population aged 15 to 64 years, 65 years or older, and 15 years or younger, respectively, while $\ln S$ denotes the log of the average number of persons residing in a housing unit. All the variables are available on a monthly basis from Taipei's PC-AXIS database.[1] To ensure that the results are not driven by changes in the compliance and enforcement of the food scrap recycling program in its beginning stage, we exclude data from the first four years of the program. The sample period is 2007m1 to 2018m8.

Figure 1 presents the trends in per capita edible, inedible food scrap and the edible-to-inedible food scrap ratio. As can be seen from Figure 1, since 2007m1, both per capita edible food scrap and the edible-to-inedible food scrap ratio have been continuously trending downward, while per capita inedible food scrap shows no clear trend, indicating that on a per capita basis Taipei residents are throwing away less and less edible food scraps, resulting in a lower and lower edible-to-inedible food scrap ratio over time.

Figure 2 presents the trends in population age structure. There is a clear rise (decline) in old (young)-age share over time. Working-age share first grows mildly between 2007 and 2012 and then declines rapidly. Figure 3 displays the trends in average household size, per capita real wage income, and CPI for food. The trends suggest that there has been a rapid decline (growth) in average household size (food price) for the entire study period. On the

[1] https://statdb.dbas.gov.taipei/pxweb2007-tp/dialog/statfile9.asp.

other hand, between 2007 and 2009 per capita real wage income fell gradually, and then rose slowly from 2013.

IV. Methodology

A. The ARDL Bounds Testing Procedure

In order to test for the presence of the equilibrium relationship given by equation (1), we first adopt the linear ARDL bounds testing procedure and then employ the VCC test to assess whether the bounds test results hold to more flexible modelling assumptions. We begin our empirical analysis by gauging the order of integration of the underlying variables. The augmented Dicky-Fuller test (ADF), Phillips-Perron (PP) test, and DF-GLS unit root test of Elliot et al. (1996) help us to make sure that none of the variables are integrated of order two or higher. After confirming that the dependent variables are a mixture of I(0) and I(1) variables, to test for the existence of the equilibrium relationship in equation (1) by the bounds test, we formulate the following ARDL $(p, q_1, \ldots, q_k)$ model, which allows the explanatory variable to affect the dependent variable with a lag:

$$y_t = \gamma_0 + \gamma_1 t + \sum_{i=1}^{p} \emptyset_i y_{t-i} + \sum_{j=1}^{k} \sum_{i=0}^{q_j} \theta_{ji}\, x_{j,t-i} + u_t. \tag{3}$$

The incorporation of time trend (t) in model (3) accounts for the steady increase in concern about food waste and in the consumption of semi-processed and convenience food, which take up a smaller inedible part than raw food inputs. Let Δ denote the first difference operator. Long-run equilibrium occurs when $\Delta y_t = 0, \Delta x_{j,t} = 0,$ and $u_t = 0.$ Thus, it can be shown that the effect of x_j on the equilibrium level of the dependent variable, also called the long-run coefficient, is $\beta_j = \sum_{i=0}^{q} \theta_{ji} / (1 - \sum_{i=1}^{p} \emptyset_i)$. To test the null of no cointegrating relationship between the variables, we reparameterize (3) into an unrestricted equilibrium correction model (ECM):

$$\Delta y_t = \gamma_0 + \gamma_1 t + \alpha y_{t-1} + \sum\nolimits_{j=1}^{k} \theta_j x_{j,t-1}$$
$$+ \sum\nolimits_{i=1}^{p-1} \varphi_{Y_i} \Delta y_{t-i} + \sum\nolimits_{j=1}^{k} \sum\nolimits_{i=1}^{q_j-1} \varphi_{X_{ji}} \Delta x_{j,t-i} + \sum\nolimits_{j=1}^{k} \omega_j \Delta x_{j,t} + u_t, \quad (4)$$

where $\alpha = -(1 - \sum_{i=1}^{p} \emptyset_i)$ and $\theta_j = \sum_{i=0}^{q_j} \theta_{ji}$.

The bounds test consists of two steps: an *F*-test and a *t*-test. There is statistical evidence for the presence of a long-run (cointegrating) relationship if the null hypothesis is rejected in both tests. Specifically, the first step involves estimating the unrestricted ECM in equation (4) by the OLS estimator and then calculating the *F*-statistic for testing the joint null hypothesis $H_0^F: \alpha = \theta_1 = \cdots = \theta_k = 0$ against the alternative hypothesis $H_A^F: (\alpha \neq 0) \cup (\theta_1 \neq 0) \cup \cdots \cup (\theta_k \neq 0)$.

If H_0^F is rejected, then one can proceed to the second step of the bounds test, which involves testing if the dependent variable is moving towards the estimated long-run equilibrium. Given that H_0^F is rejected, i.e., a linear combination of the underlying variables is stationary, the long-run relationship in model (1) is not a spurious regression. Banerjee et al. (1998) proposed an error correction mechanism test that is based upon the OLS coefficient on the lagged dependent variable in the unrestricted ECM. To this purpose, we reparameterize the unrestricted ECM into a restricted ECM:

$$\Delta y_t = \gamma_0 + \gamma_1 t + \alpha \left(y_{t-1} - \sum\nolimits_{j=1}^{k} \hat{\beta}_j x_{j,t-1} \right)$$
$$+ \sum\nolimits_{i=1}^{p-1} \varphi_{Y_i} \Delta y_{t-i} + \sum\nolimits_{j=1}^{k} \sum\nolimits_{i=1}^{q_j-1} \varphi_{X_{ji}} \Delta x_{j,t-i} + \sum\nolimits_{j=1}^{k} \omega_j \Delta x_{j,t} + u_t, \quad (5)$$

where $\hat{\beta}_j = -\frac{\hat{\theta}_j}{\hat{\alpha}}$ is calculated using the OLS estimates obtained from model (4). The term in the parenthesis is essentially the lagged error from the equilibrium relationship in model (1), also known as lagged equilibrium correction term (ECT_{t-1}). The lagged equilibrium correction term measures the deviation of the dependent variable from its equilibrium level in the previous period. The coefficient on ECT_{t-1}, α, is the speed of adjustment coefficient that measures how quickly the gap between the current and equilibrium levels of the dependent variable closes in one period. Put differently, α measures how fast the dependent variable returns to the long-run equilibrium value in one period of time. Unlike the error correction term, Δy_{t-i} and $\Delta x_{j,t-i}$ do not contain information about the long-run relationship; instead, they capture short-run effects from contemporaneous and lagged differences of the dependent and independent variables. The coefficients on lagged dependent and independent variables i.e., $\varphi_{Y_i}, \varphi_{X_{ji}}$, and ω_j, are thus called short-run coefficients.

The restricted ECM demonstrates that the ARDL model is valuable for examining both the long-run relationship as well as the short-run dynamic interactions that do not affect the equilibrium. Theoretically, if the process is converging in the long run, then α will lie between -1 and 0. A negative and significant coefficient on ECT_{t-1} (α) provides evidence that the dependent variable converges towards its equilibrium level in the long-run. To test the null hypothesis that the dependent variable is not converging towards its equilibrium level in the long run, we perform a *t*-test of the single null hypothesis $H_0^t: \alpha = 0$ against $H_A^t: \alpha \neq 0$. Failure to reject H_0^t indicates that the relationship identified in the first part of the bounds test - i.e., the relationship found by rejecting H_0^F - is not sensible. By contrast, rejecting H_0^t represents compelling evidence of a level relationship between y_t and $x_{j,t}$s.

The bounds test for cointegration involves a comparison of the *F*-statistics against the critical value bounds, which are generated specifically for each sample size. Pesaran et al. (2001) provide two critical value bounds: the lower bound assumes that all the independent variables are I(0), and the upper bound assumes that the independent variables are I(1). For the F-test, the null is rejected if the test statistic exceeds the upper critical bound. An F-statistic less than the lower bound means that the null is not rejected. Regarding the t-test, the standard t-statistic on α in equation (5) can be compared to another set of upper and lower critical value bounds. If the absolute value of the t-statistic is greater than that of the upper bound, then a sensible long-run relationship exists. If the absolute value of the t-statistic is smaller than the lower bound, then there is no compelling evidence that the dependent variable is moving towards its long-run equilibrium, indicating that the relationship established by rejecting H_0^F does not make sense. If the absolute value of the t-statistic lies between the two bounds, then the test is inconclusive. Through stochastic simulations, Kripfganz and Schneider (2018) provide precise finite-sample and asymptotic critical values and approximate p-values for Pesaran et al.'s (2001) bounds testing procedure.[2]

B. Varying-coefficient Cointegration test

To uncover non-linearity and heterogeneities in the long-run relationship, we allow the cointegration coefficients to vary with the level of real wage. To this end, we explore the long-run relationship between food waste and its determinants using a semiparametric cointegration model developed by Cai et al. (2009) and Xiao (2009). The model, called the varying-coefficient model, allows the marginal effect of a non-stationary x-covariate on the non-stationary dependent variable y to depend on the level of a stationary state variate, say z, such that the cointegration coefficient is a smooth function of z. Li et al. (2015) offered an excellent application of the VCC model to test for the presence of purchasing power parity.

[2] These critical values can be implemented using Stata's ARDL command.

Allowing the cointegration coefficient to vary with a stationary state variable *x* leads to the following set-up:

$$y_t = \beta_0(z_t) + \beta_1(z_t)x_{1,t} + \beta_2(z_t)x_{2,t} + \beta_3(z_t)x_{3,t} + u_t, t = 1,2,\dots,n. \quad (6)$$

Note that model (6) includes fewer covariates than the ARDL model in model (3): one I(0) covariate and three I(1) covariates. One of the reasons is that the VCC model requires all variables except the state variable to be I(1) processes. Therefore, except for one (the log average real wage income) we exclude all other stationary covariates (the weather variables) from the VCC model. Another reason for including fewer covariates in the VCC model is that the semiparametric regression is a local modelling approach that uses only observations in a small neighborhood. The number of observations in a small neighborhood may be too small to provide good estimates of a large number of regression coefficients. For these reasons, we include three non-stationary covariates and one stationary covariate in the VCC model.

Let $x_t = \left(x_{1,t}\ \ x_{2,t}\ \ x_{3,t}\right)^T$, and let K be a kernel function chosen by the investigator, usually a probability density function symmetric about 0. According to Xiao (2009) and Li et al. (2015), the local constant estimator of the coefficient is given by:

$$\hat{\beta}(\mathrm{z}) = \left[\frac{1}{nh}\sum_{t=1}^{n} x_t x_t^T K\left(\frac{z_t - t}{h}\right)\right]^{-1} \left[\frac{1}{nh}\sum_{t=1}^{n} x_t y_t K\left(\frac{z_t - t}{h}\right)\right], \quad (7)$$

where $\hat{\beta}(z) = \left(\hat{\beta}_0(z), \hat{\beta}_1(z), \hat{\beta}_2(z), \hat{\beta}_3(z)\right)^t$, and h is the bandwidth controlling the smoothness of the resultant coefficient estimate. In this paper, we use the Gaussian kernel function defined as $K(u) = (2\pi)^{-1/2}e^{-u^2/2},\ u \in R$. See Cai et al. (2009) and Xiao (2009) for the consistency and also asymptotic normality of $\hat{\beta}(z)$. See also Xiao (2009) for an alternative estimating strategy based on local polynomials. Note that z plays two roles in determining *y*: a direct information variable and an indirect conditioning information variable. While the state variable z (in this analysis, real wage income) does not enter model (7) as an independent variable, the direct relationship between z and the dependent variable is described by the estimated intercept function $\hat{\beta}_0(z)$.

We test the presence of a cointegration relationship by Xiao's (2009) *t*-test procedure. To this end, the regression residuals from model (6) are predicted by $\hat{u}_t = y_t - \hat{\beta}_0(z_t) - \hat{\beta}_1(z_t)x_{1,t} - \hat{\beta}_2(z_t)x_{2,t} - \hat{\beta}_3(z_t)x_{3,t}$. Note here under the null hypothesis that a cointegration relationship exists, and $E(u_t^2)$ is a finite constant. However, if u_t follows a unit root process $u_t = u_{t-1} + \epsilon_t$ with initial value 0, where ϵ_t is independently and identically distributed with mean zero and variance σ^2, then it is widely known that $E(u_t^2) = a + bt$. This suggests that one can test the presence of cointegration by testing whether the coefficient b of time trend variable t in the following linear model is zero:

$$\hat{u}_t^2 = a + bt + \epsilon_t. \tag{8}$$

Let $\hat{b}$ be the ordinary least square (OLS) estimate of b. The test statistic that serves to test the existence of a cointegrating relationship is then given by:

$$\tau_t = \hat{b}/\hat{s}(b). \tag{9}$$

Here, $b = \sqrt{\widehat{w}^2 / \sum_{t=1}^{n}(t-\bar{t})^2}$ with $\bar{t} = \sum_{t=1}^{n} t/n$, and $\widehat{w}^2$ is the consistent nonparametric estimator of the long-run variance of u_t^2 given by:

$$\widehat{w}^2 = \sum_{d=-M}^{M} k(d/M)c(d), \tag{10}$$

where $k(\cdot)$ is the lag window supported on $[-1,1]$ with $k(0) = 1$, $c(d) = \sum_{1 \le t, t+d \le n}(\hat{u}_t^2 - \sum_{j=1}^{n}\hat{u}_j^2 \ /n)\,(\hat{u}_{t+d}^2 - \sum_{j=1}^{n}\hat{u}_j^2 \ /n)$, M is the bandwidth parameter such that $M = M_n \to \infty$ and $M/n \to 0$ as $n \to 0$.

V. RESULTS

A. Parametric cointegration analysis

To test for the presence of a linear long-run relationship in (1), we begin by examining the stationarity of the variables. Table 1 reports the results from Augmented Dickey–Fuller (ADF), Philips-Perron (PP), and Elliot et al.'s (1996) (DF-GLS) unit root tests on the variables in levels and first differences. At least one of the three unit root tests suggests that the dependent variable (lnW_t) and four of the regressors - food price, share of population aged between 15 and 64, share of population aged 65 or older, and average household size ($\ln P_t$, $\ln M_t$, $\ln O_t$, and $\ln S_t$) - are non-stationary at level, but are stationary at first difference. On the other hand, as the null of unit root is rejected in almost all three tests, the rest of the regressors - the log of real wage ($\ln R_t$), temperature, humidity, number of rainy days, precipitation, hours of sunlight ($\ln E_t^l, l = 1, \dots, 5$) - can be regarded as stationary at level. Importantly, all the regressors have an order of integration that is less than two and are a mixture of I(0) and I(1) variables, thus necessitating the use of the ARDL bounds testing procedure. Because the unit root tests suggest that lnR_t and $\ln E_t^l, l = 1, \dots, 5$ can be regarded as stationary at level, in our estimation of the unrestricted ECM we treat these six variables as exogenous. In other words, we specify that average real wage and weather do not affect the long-run equilibrium level of FWR, but do affect its short-run fluctuations.

Identification of model (3) is based on the assumption that the lagged dependent variable, y_{t-1}, does not enter the equations for $\Delta x_{jt,}\ j = 1, \dots, k$. Since the population age structure is primarily determined in the past, and average household size is also primarily driven by past socio-demographic trends, the exclusion of the lagged level of FWR from the equations for the change in lnM_t, lnO_t, and lnS_t is justifiable. However, feedback from FWR to food price is likely. In what follows we shall formally test whether FWR is a long-run driving force of food price by the bounds test.

Rows 1 to 5 (6 to 7) of Table 2 present the results of the bounds test for univariate (multivariate) ARDL models. As can be seen from rows 1 to 4, both the F- and t-test statistics are more extreme than the upper bound of the critical value given by Pesaran et al. (2001) at the given level of significance. When we perform the bounds test by treating lnP as the dependent variable and lnW as the sole independent variable, we fail to reject the null hypothesis of no cointegrating relationship. Row 5 of Table 2 presents the result. Both the F- and t-test statistics are closer to zero than the critical values for I(0) variables, meaning that there is no feedback effect from lnW to lnP. The absence of feedback from FWR to food price, population age structure, and average household suggests that these variables can be interpreted as long-run forcing variables explaining lnW. As such, the unrestricted ECM in (4) is identified and can be consistently estimated by OLS.

Table 3 presents the estimated univariate restricted ECM when $lnP, lnM, lnO,$ and lnS are alternatively the sole forcing variable for lnW. The coefficient on the lagged equilibrium correction term is negative and significant in all five cases, supporting the existence of a long-run level relationship. The estimates of the long-run coefficient suggest that $lnP, lnO,$ and lnS enter the long-run equation significantly with a positive sign. On the other hand, lnM enters the long-run equation significantly with a negative sign. Specifically, the univariate ARDL model suggests that the long-run elasticity of the edible-to-inedible food scrap ratio with respect to food price, working-age share, old-age share, and average household size are 2.053, -5.275, 1.578, and 10.144, respectively.

Turning to multivariate ARDL models, row 6 of Table 2 reports the results of the bounds test for the multivariate ARDL model that includes *lnP*, *lnM*, and *lnS* as forcing variables. The *F*- and *t*-test statistics are both greater than the upper bound of the critical value given by Pesaran et al. (2001) at the 1% level, rejecting the null of no cointegrating relationship among the variables. Table 4 reports the coefficient estimates. The coefficient on the lagged error correction term is significantly negative, supporting the convergence towards a long-run relationship. The estimated long-run coefficients indicate that a 1% rise in food price (household size) increases the edible-to-inedible food scrap ratio by 1.227% (5.685%) in the long-run, whereas a 1% rise in the working-age share reduces the edible-to-inedible food scrap ratio by 2.358%. The positive coefficient estimate on lnP is inconsistent with the conventional wisdom and the prediction of Lusk and Ellison (2017) that a higher food price will lead people to waste less. This finding, however, aligns with the prediction of Hamilton and Richards (2019) that if the demand for food is indeed sufficiently price-elastic, then increases in food price reduce meal planning effort, thereby exacerbating FWR.

Regarding the short-run dynamics, the coefficient estimates on $\Delta\ln W_{t-1,}$, $\Delta\ln W_{t-2}$, $\Delta\ln S_t$, $\Delta\ln R_{t-1}$, $\Delta\ln E_{t-1}^2$,and $\Delta\ln E_{t-1}^5$ are significantly positive, whereas those on $\Delta\ln M_t$, $\Delta\ln E_{t-1}^1$, and $\Delta\ln E_t^2$ are significantly negative. It is worth noting from the signs of $\Delta\ln M_t$ and $\Delta\ln S_t$ that working-age share and household size have both long-run and short-run effects in the same direction, thus concuring with the prediction of Lusk et al. (2017) that a higher opportunity cost of time is associated with a higher edible-to-inedible food scrap ratio.

The above result is consistent over different specifications. When we replace working-age share with old-age share as an independent variable of the multivariate ARDL model, the result of the bounds test indicates that the null of no cointegrating relationship is decisively rejected (row 7 of Table 2). Table 5 shows that the estimated speed of adjustment from the multivariate ARDL model that includes lnP, lnO, and lnS as the forcing variables is -0.512 and statistically significant, implying that an error correction mechanism exists so that a positive gap from the long-run equilibrium has a negative impact on the growth rate of the edible-to-inedible food scrap ratio. The estimated long-run elasticity of lnW with respect to old-age share implies that a 1% increase in the share of population aged 65 years or older is associated with a statistically significant increase in the long-run level of the edible-to-inedible food scrap ratio by 0.723%.

The finding, in which a higher working-age share and smaller average household size are associated with a lower municipal FWR, whereas a higher old-age share is associated with a higher FWR, runs contrary to the observation on EU-27 residents in Secondi et al. (2015) that the older people become, the less likely they are to waste food. Our finding should be a consequence of the particular way in which the food scrap collection program is administered. As noted above, the food scrap recycling program in Taipei imposes a substantial time cost upon residents, requiring them to sort, store, and carry their food scrap to the designated collection spot at the designated time. Thus, people who have higher opportunity costs of time, i.e., working-age population, and those who have little scope to take advantage of increasing returns to scale in the time input to meal planning and food scrap recycling, i.e., single-person and small households, have greater incentive to minimize food waste. Under the "keep waste off ground" policy, if older people have a lower opportunity cost of time or are less competent in meal planning, then they may rather discard edible food than cultivate eco-conscious meal planning habits. This result suggests that the rapid growth in old-age share presents a challenge to food waste management.

B. Varying-coefficient Cointegration Analysis

We now turn to examining the nonlinearity and parameter heterogeneity in the long-run relationship between FWR and its determinants. To allow the cointegrating relationship to vary with income, we estimate the following varying-coefficient model:

$$lnW_t = \beta_0(lnR_t) + \beta_1(lnR_t)lnP_t + \beta_2(lnR_t)lnS_t + \beta_3(lnR_t)lnM_t + u_t. \quad (10)$$

Here, lnP_t, lnS_t, and lnM_t respectively correspond to $x_{i,t}$, $x_{2,t}$, and $x_{3,t}$, and lnR_t to z_t in (6).

Figure 4A presents the coefficient function estimates of equation (10). As can be seen from the upper left panel of Figure 4A, the profile shape of the intercept function $\beta_0(lnR_t)$ indicates that the direct relationship between income and the edible-to-inedible food scrap ratio is inverted-U shaped. For lnR below 11.2, lnW is largely a positive monotonic function of income. Beyond this threshold level of income, the extent of wastage declines as income increases.

The inverted-U shaped direct relationship between income and FWR can arise through two channels. First, changes in income may affect FWR through a composition effect (Setti et al., 2016). Growing income may aggravate food wastage at lower income levels, because at that stage people spend their increased income on cheaper but poor-quality food that gets easily discarded. At higher income levels, people can afford to replace a large quantity of low-quality food with a smaller quantity of high-quality food that could be utilized more fully. Consequently, as income grows beyond the threshold level of income at which people start to value quality over quantity, a further increase in income results in a decline in municipal FWR. Second, when income is lower, basic needs such as food and housing are prioritized over durables and recreation. A higher food price could force consumers to reduce or abandon their occasional consumption of durables and recreation. To maintain a given level of utility with reduced spending on durables and recreation, consumers may buy more food and waste more. At higher income levels, consumers no longer prioritize food over durables and recreation. Instead, they respond to higher food price by cutting back on food spending.

The upper right panel of Figure 4A shows the estimated coefficient function for lnP. As income increases, the elasticity of the edible-to-inedible food scrap ratio with respect to food price, $\beta_1(lnR_t)$, turns from positive to negative. While it runs counter to conventional wisdom, this finding aligns with a number of arguments. First, given that the food utilization rate and food purchase move in the same direction (Hamilton and Richards, 2019) and that the price elasticity of food demand diminishes as income increases (Abler, 2010), an increase in food price will lead to a larger fall in both food purchase and food utilization rate at lower income levels. Second, the profile shape of the long-run price elasticity of FWR may be the consequence of "quality shading" - that is, when income is low, food accounts for a larger share of the budget, and so consumers have a greater incentive to switch to cheaper but lower-quality substitutes, thereby raising FWR.

The lower left panel of Figure 4A presents the estimated coefficient function for lnS. Consistent with the estimation result from the multivariate ARDL model, lnM and lnS as forcing variables (Table 4), the long-run level of lnW is positively related to average household size throughout the range of income studied. This supports the argument in Crossley and Lu (2018) that if there exist returns to scale in home production, then per capita home production time should be greater in large households. Since, as described in the introduction that the disposal of food scraps in Taipei requires households to spend time on storing and separating their food scraps and meeting the recycling truck at the designated collection spot at the designated time, one might expect single-person households to have a stronger incentive to minimize food waste.

As can be seen from the lower right panel of Figure 4A, the coefficient on lnM appears to decline from positive to negative as income increases. Thus, compared with the linear ARDL model, which suggests that lnM is negatively related to lnW (Table 4), the VCC model further unveils that increases in the share of population that have higher opportunity costs of time do raise FWR, but only at low levels of opportunity costs of time. At lower income levels, food-away-from-home or ready-to-eat food are less affordable. Thus, a higher share of people who have less time on meal planning increases municipal FWR. However, at higher income levels, working-age people would probably choose to eat out or consume "ready-to-eat" food that comes in small portions in order to save time on food scrap recycling as mandated by the "keep waste off ground" policy.

To test the robustness of the results in Figure 4A, we replace working-age share with old-age share and present the coefficient function estimates in Figure 4B. The profile shape for the estimated smooth intercept and the coefficient function estimate on lnP and lnS are similar to their counterparts in Figure 4A. For lnR above 10.9, the estimated coefficient function for lnO is negative (positive). This suggests that population aging exacerbates FWR at high income levels.

VI. CONCLUSIONS

The purpose of this paper is to examine how socio-economic factors influence municipal FWR by using the linear ARDL model and the semiparametric VCC test to examine the cointegrating relationship between the variables. Based on monthly time series between 2007m1 and 2018m8 from a city-wide food scrap recycling program in Taipei that mandates all residents carry their food scrap to a designated collection spot at a designated time, we find in the long-run that higher food price, larger average household size, and higher old-age share lead to a higher municipal FWR, whereas higher working-age share contributes to a lower FWR. Stabilizing food prices can be an effective policy for reducing municipal food waste since food price has a statistically significantly positive effect on FWR. The "keep waste off ground" policy, which obligates residents to meet the recycling truck at the designated time, likely creates a stronger motivation for people who are more time constrained or less able to exploit the returns to scale in home production to prevent and reduce food waste.

The results from the more flexible VCC test further reveal that the cointegrating relationship between socioeconomic factors and municipal household FWR exhibits nonlinearity and parameter heterogeneity with respect to wage income. The result lends support to the FWKC hypothesis, whereby as wage income increases, municipal FWR first increases and then decreases. Aside from directly impacting FWR, wage income influences FWR by changing the effects of socioeconomic factors on FWR. As average wage income increases, the effects of food price and working-age share on FWR turn from positive to negative, whereas the impact of old-age share turns from negative to positive.

In upcoming decades, income and two FWR-increasing factors - population aging and food price - will presumably accelerate, whereas average household size - a FWR-decreasing factor - will presumably decline. As such, for policymakers targeting less food waste, the upward trends in food price and old-age share pose clear challenges, whereas the downward trend in average household size brings about a certain measure of relief. Moreover, the estimates from the varying-coefficient model indicate that the FWR-increasing effect of population aging (food price) likely aggravates (diminishes) with economic growth. Given the observed positive effect of old-age share on FWR and the trend toward an older population, the policy implication is that governments may be able to reduce food waste by subsidizing both the design of smart packaging and the development of semi-prepared convenience food with flexible portion sizes or portion sizes suitable for older adults. In order to raise food utilization, public authorities should be doing all they can to promote awareness campaigns at senior adults and large households about proper food storage, different notions of food quality, and eating robust rather than fragile food that is liable to spoilage. With the observed positive association between average household size and FWR, innovations that resolve the problems of over-purchase and one-dish-does-not-please-all can also help to reduce food waste.

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Table 1 Unit root tests

	ADF		PP		DF-GLS	
Variable	Level	First Difference	Level	First Difference	Level	First Difference
lnW	-4.001***	-7.670***	-4.378***	-9.397 ***	-1.945	-7.578***
lnR	-8.45***	-11.516***	-9.626***	-17.194***	-3.756***	-2.610*
lnP	-3.760**	-6.473***	-3.775**	-8.838***	-2.189	-4.050***
lnU	-2.746	-3.112*	-2.220	-8.532***	-0.978	-2.895*
lnO	0.545	-7.484***	-0.003	-21.555***	-0.259	-3.312**
lnM	-0.356	-3.959 ***	0.826	-6.308***	-0.460	-2.965*
lnS	-1.917	-6.756***	-2.187	-13.872***	-1.018	-4.474***
lntemperature	-3.708**	-6.890***	-5.089***	-7.046***	-1.166	-4.613***
lnhumidity	-7.930***	-17.544***	-8.034***	-20.136**	-5.552***	-9.124***
lnsunlight	-8.073***	-18.644***	-8.187***	-19.608***	-6.215***	-8.718***
lnprecipitation	-8.968***	-20.114***	-9.005***	-20.404***	-6.244***	-10.722***
lnrainyday	-11.541***	-20.114***	-11.537***	-27.458***	-5.670***	-12.501***

Notes: A trend is included in the regression. AIC is used to select the lag length and the maximum number of lags is set at six. *, **, and *** denote 10%, 5%, and 1% levels of significance, respectively.

Table 2 Bounds test for cointegrating relationship

Model	***F*-value (p-value, assuming all variables are I(1))**	***t*-value (p-value, assuming all variables are I(1))**	**Conclusion**
lnW=f(lnP)	4.924*(0.069)	-3.644**(0.049)	Reject H_0
lnW=f(lnM)	11.364***(0.000)	-5.828***(0.000)	Reject H_0
lnW=f(lnO)	5.205*(0.053)	-3.794**(0.034)	Reject H_0
lnW=f(lnS)	13.678***(0.000)	-6.377***(0.000)	Reject H_0
lnP=f(lnW)	4.128(0.142)	-3.321(0.1)	Do not reject H_0
lnW=f(lnP,lnM,lnS)	9.220***	-6.680***	Reject H_0
lnW=f(lnP,lnO,lnS)	9.418***	-6.741***	Reject H_0

H_0: No level relationship. The Pesaran et al. (2001) critical values for the equilibrium correction model with unrestricted intercepts and restricted trends (Case IV) are from Kripfganz and Schneider's (2018) STATA package ARDL. The order of the ARDL models is selected based on the AIC criterion. *, **, and *** denote 10%, 5%, and 1% levels of significance, respectively. All models include lnR, and the logs of temperature, humidity, rainy day, precipitation, and sunlight as exogenous variables that affect only short-run dynamics.

Table 3 Univariate ARDL estimates of the speed of adjustment and long-run coefficient

Model	Speed of adjustment	Long-run coefficient	ARDL (p, q)
lnW=f(lnP)	-0.206***(0.057)	2.053**(0.900)	(4,1)
lnW=f(lnM)	-0.340***(0.058)	-5.275***(1.337)	(2,1)
lnW=f(lnO)	-0.271***(0.071)	1.578***(0.577)	(4,0)
lnW=f(lnS)	-0.420***(0.066)	10.144***(1.660)	(3,0)

Notes: Dep. Var.=ΔlnW_t. *, **, and *** denote 10%, 5%, and 1% levels of significance, respectively. The speed of adjustment is the coefficient on ECT_{t-1}. All models include a time trend, log real wage income, and the logs of temperature, humidity, rainy day, precipitation, and sunlight as exogenous variables that affect only short-run dynamics.

Table 4 Estimation results for the multivariate ARDL (3,2,0,0) model lnW=f(lnP, lnM, lnS)

	Coef.	S.E.	t-value
Speed of adjustment			
ECT_{t-1}	-0.498***	0.075	-6.68
Long-run coefficient			
lnPt-1	1.227***	0.399	3.07
lnMt-1	-2.385**	1.219	-1.96
lnSt-1	5.684***	1.969	2.89
Time trend	-0.006***	0.002	-3.14
Short-run coefficient			
ΔlnWt-1	0.252***	0.088	2.88
ΔlnWt-2	0.181**	0.080	2.25
ΔlnPt	1.195***	0.336	3.56
ΔlnPt-1	-0.553	0.338	-1.63
ΔlnMt	-1.188*	0.638	-1.86
ΔlnSt	2.830***	1.083	2.61
ΔlnRt	-0.002	0.023	-0.09
ΔlnRt-1	0.066***	0.024	2.72
ΔlnRt-2	0.026	0.022	1.22
ΔlnTempt	-0.019	0.051	-0.37
ΔlnTempt-1	-0.164***	0.053	-3.1
ΔlnHumidt	-0.178*	0.097	-1.83
ΔlnHumidt-1	0.185*	0.101	1.84
ΔlnRainydayt	0.009	0.014	0.64
ΔlnRainydayt-1	-0.006	0.015	-0.38
ΔlnRainfallt	-0.005	0.006	-0.82
ΔlnRainfallt-1	-0.001	0.006	-0.21
ΔlnSunlightt	0.004	0.013	0.32
ΔlnSunlightt-1	0.045***	0.013	3.52
Constant	0.285	3.799	0.08

Notes: Dep. Var. =ΔlnW_t. *, **, and *** denote 10%, 5%, and 1% levels of significance, respectively.

Table 5 Estimation results for the multivariate ARDL (3,2,0,0) model lnW=f(lnP, lnO, lnS)

	Coef.	S.E.	t-value
Speed of adjustment			
ECT_{t-1}	-0.512***	0.076	-6.74
Long-run coefficient			
lnPt-1	1.143***	0.391	2.92
lnOt-1	0.723**	0.329	2.2
lnSt-1	6.687***	1.573	4.25
Time trend	-0.006***	0.002	-3.34
Short-run coefficient			
ΔlnWt-1	0.266***	0.088	3.01
ΔlnWt-2	0.189**	0.081	2.34
ΔlnPt	1.154***	0.335	3.45
ΔlnPt-1	-0.556*	0.337	-1.65
ΔlnOt	0.370*	0.181	2.05
ΔlnSt	3.424***	0.969	3.53
ΔlnRt	-0.004	0.023	-0.17
ΔlnRt-1	0.063***	0.024	2.63
ΔlnRt-2	0.025	0.022	1.13
ΔlnTempt	-0.025	0.051	-0.5
ΔlnTempt-1	-0.163***	0.053	-3.08
ΔlnHumidt	-0.173*	0.097	-1.78
ΔlnHumidt-1	0.186*	0.100	1.85
ΔlnRainydayt	0.008	0.014	0.55
ΔlnRainydayt-1	-0.006	0.015	-0.39
ΔlnRainfallt	-0.005	0.006	-0.84
ΔlnRainfallt-1	-0.001	0.006	-0.21
ΔlnSunlightt	0.005	0.013	0.35
ΔlnSunlightt-1	0.045***	0.013	3.53
Constant	-6.062***	1.394	-4.35

Notes: Dep. Var. = ΔlnW_t. *, **, and *** denote 10%, 5%, and 1% levels of significance, respectively.

Table 8 Varying-coefficient cointegration test

Model	t-statistic	Conclusion
$\mathbf{lnW_t = \beta_0(lnR_t) + \beta_1(lnR_t)lnP_t + \beta_2(lnR_t)lnS_t + \beta_3(lnR_t)lnM_t}$	-1.516	Fail to reject H_0
$\mathbf{lnW_t = \beta_0(lnR_t) + \beta_1(lnR_t)lnP_t + \beta_2(lnR_t)lnS_t + \beta_3(lnR_t)lnO_t}$	-1.494	Fail to reject H_0
$\mathbf{lnW_t = \beta_0(lnR_t) + \beta_1(lnR_t)lnP_t + \beta_2(lnR_t)lnS_t + \beta_3(lnR_t)lnU_t}$	-1.464	Fail to reject H_0

Note: H_0: The cointegration relationship holds.

Figure 1 Edible and inedible food scraps and their ratio

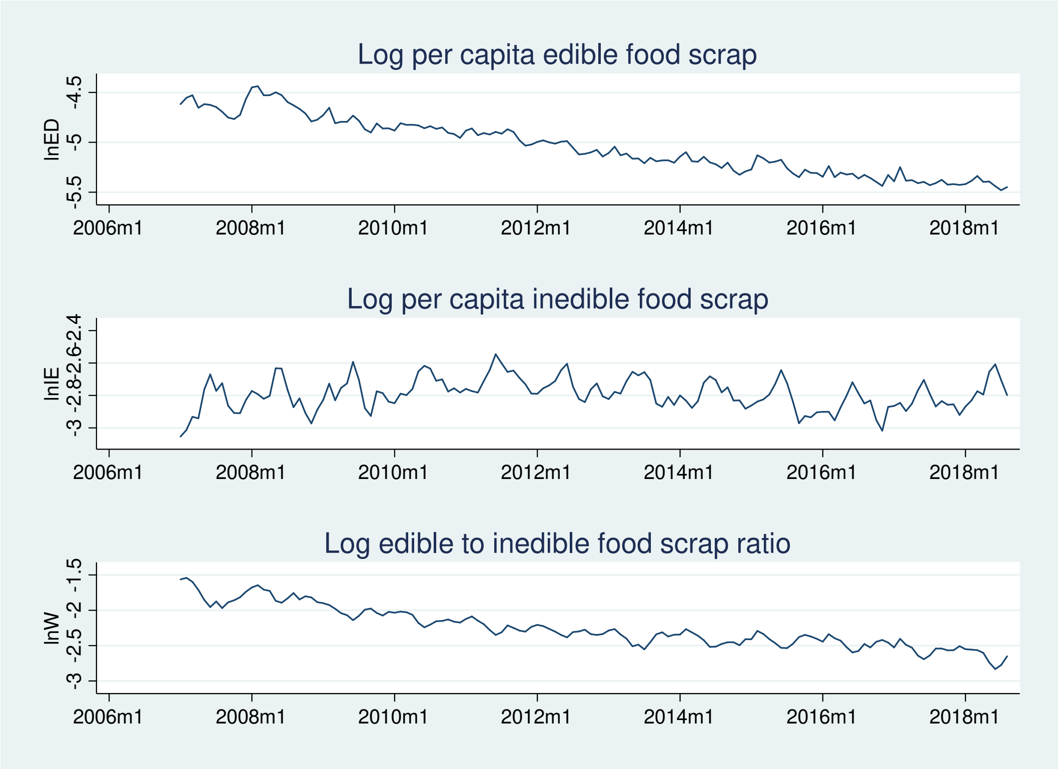


Figure 2 Population age structure

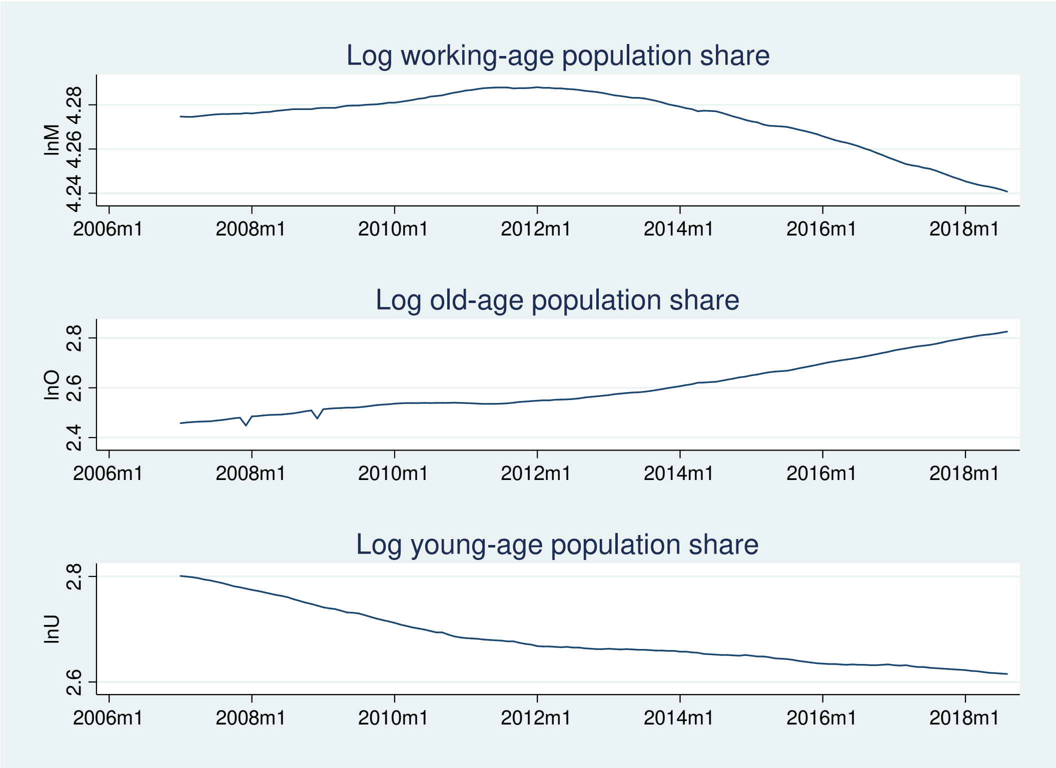


Figure 3 Household size, real wage income and food price

Figure 4 Varying-coefficient model estimates

A. Model: $\ln W_t = \beta_0(\ln R_t) + \beta_1(\ln R_t)\ln P_t + \beta_2(\ln R_t)\ln S_t + \beta_3(\ln R_t)\ln M_t$

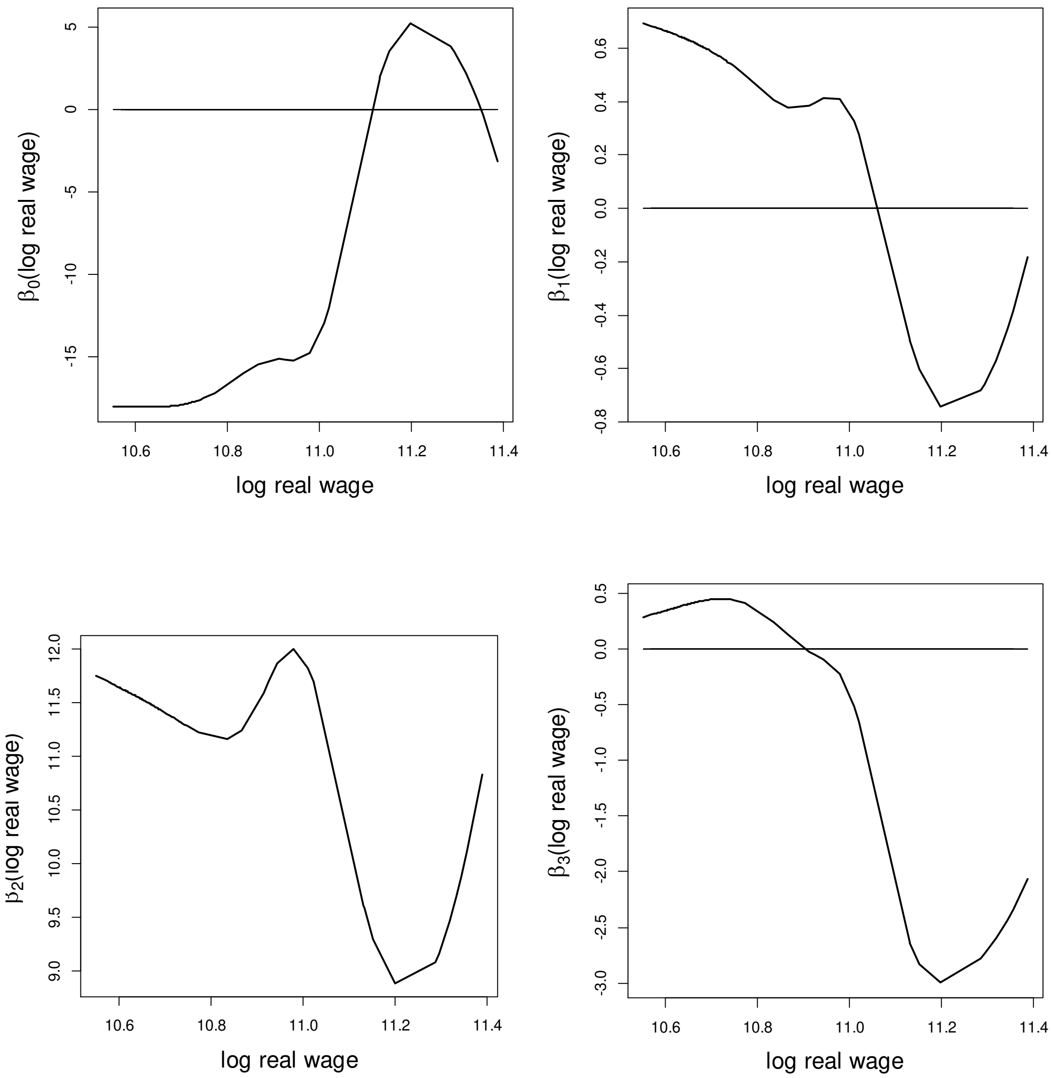
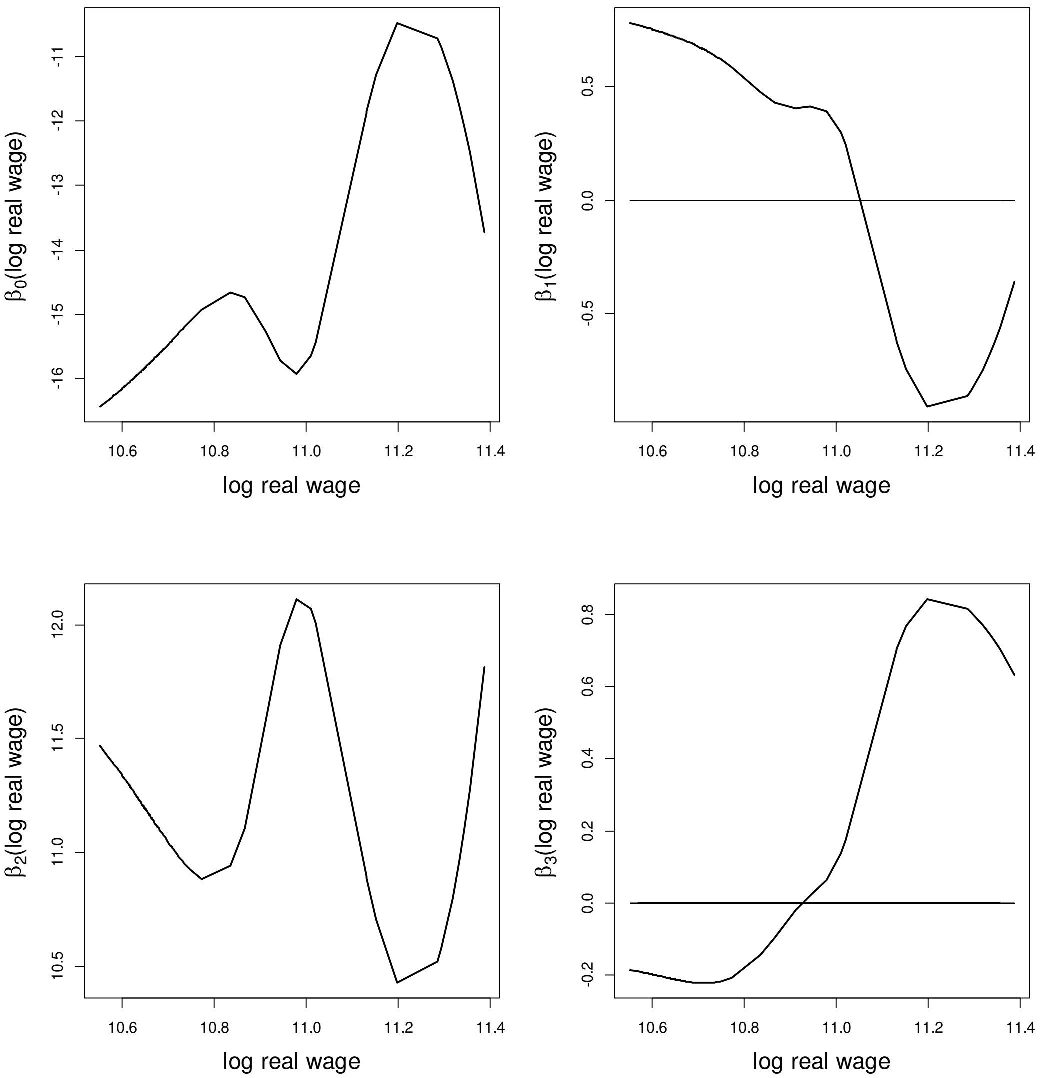


Figure 4 Varying-coefficient model estimates (continued)

B. Model: $\ln W_t = \beta_0(\ln R_t) + \beta_1(\ln R_t)\ln P_t + \beta_2(\ln R_t)\ln S_t + \beta_3(\ln R_t)\ln O_t$



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Declaration of Conflicting Interests

The authors whose names are listed immediately below certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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Author Contributions Statement

Yi-Chen Lin conceived and designed the analysis, collect the data, wrote the main manuscript text except the Methodology. Wen-Shuenn Deng developed the R code for econometric estimation and performed the analysis. All authors reviewed the manuscript.

Data Availability Statement

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.