International Studies Program

International Studies Program
Working Paper 09-01
February 2009

Food Consumption in Jamaica: A Household and Social Behavior

Shiyuan Chen
Sally Wallace

Georgia State University

Andrew Young School of Policy Studies

International Studies Program
Working Paper 09-01

Food Consumption in Jamaica: A Household and Social Behavior

Shiyuan Chen
Sally Wallace

February 2009

International Studies Program
Andrew Young School of Policy Studies
Georgia State University
Atlanta, Georgia 30303
United States of America

Phone: (404) 651-1144
Fax: (404) 651-4449
Email: ispaysps@gsu.edu
Internet: http://isp-aysps.gsu.edu

International Studies Program
Andrew Young School of Policy Studies

The Andrew Young School of Policy Studies was established at Georgia State University with the objective of promoting excellence in the design, implementation, and evaluation of public policy. In addition to two academic departments (economics and public administration), the Andrew Young School houses seven leading research centers and policy programs, including the International Studies Program.

The mission of the International Studies Program is to provide academic and professional training, applied research, and technical assistance in support of sound public policy and sustainable economic growth in developing and transitional economies.

The International Studies Program at the Andrew Young School of Policy Studies is recognized worldwide for its efforts in support of economic and public policy reforms through technical assistance and training around the world. This reputation has been built serving a diverse client base, including the World Bank, the U.S. Agency for International Development (USAID), the United Nations Development Programme (UNDP), finance ministries, government organizations, legislative bodies and private sector institutions.

The success of the International Studies Program reflects the breadth and depth of the in-house technical expertise that the International Studies Program can draw upon. The Andrew Young School's faculty are leading experts in economics and public policy and have authored books, published in major academic and technical journals, and have extensive experience in designing and implementing technical assistance and training programs. Andrew Young School faculty have been active in policy reform in over 40countries around the world. Our technical assistance strategy is not to merely provide technical prescriptions for policy reform, but to engage in a collaborative effort with the host government and donor agency to identify and analyze the issues at hand, arrive at policy solutions and implement reforms.

The International Studies Program specializes in four broad policy areas:

- Fiscal policy, including tax reforms, public expenditure reviews, tax administration reform
- Fiscal decentralization, including fiscal decentralization reforms, design of intergovernmental transfer systems, urban government finance
- Budgeting and fiscal management, including local government budgeting, performance-based budgeting, capital budgeting, multi-year budgeting
- Economic analysis and revenue forecasting, including micro-simulation, time series forecasting,

For more information about our technical assistance activities and training programs, please visit our website at http://isp-aysps.gsu.edu or contact us by email at ispaysps@gsu.edu.

Food Consumption in Jamaica: A Household and Social Behavior

Shiyuan Chen
Microfinance Risk Management, L.L.C., Kansas City, Missouri

Sally Wallace
Department of Economics, Georgia State University, Atlanta, Georgia

Abstract

This paper explores household food consumption in Jamaica and estimates the effects of related variables on the intensity of consumption. Use of data from the 2001 Jamaica Survey of Living Conditions permits estimation of an Engel curve that reflects the relationship between household food consumption and related variables. As a means to investigate a possible neighborhood effect on food consumption, spatial correlations pertaining to neighborhood food consumption were tested and estimated. The estimated results can be used to help formulate policies that may produce more effective food support distribution programs.

Keywords: food, consumption, Engel, spatial, poverty

JEL classification: Q18; I3; D1

Introduction

The Engel curve is a tool that has been used to show the relationship between consumption and income (ceteris paribus) (Rowntree, 1901, Fisher 1992, Ravallion and Bidani 1994, and Boltvinik 1998). Based on surveys of families' budgets and spending patterns, Engel (1857) found that the income elasticity of the demand for food was relatively low—giving rise to the well-known Engel's law: As incomes increase, the share of expenditure for food declines demonstrating that the income elasticity of food is less than unity.

The concept of the Engel curve is important because of its wide application. It has been used to estimate the income elasticity of household consumption of various items, including food, and therefore to predict food consumption in the case of income growth. It can be used to measure the economic development level of a region or a country by analyzing cross-comparisons of food consumption shares of total expenditures (as a proxy for income)—or Engel's coefficients. Poor countries usually have higher Engel's coefficients in cross-country studies, and rich countries have lower ones reflecting their relative level of income and development.

An expansive literature has grown up regarding the Engel curve. Most of it shares a common assumption about the independence of consumption behavior. This assumption says that people (families, households, etc.) will be unaffected by the behavior of others. However, more recent literature dealing with individual-level behavior takes into account interactive behavior which are very likely applicable in the case of food consumption.[1] Studies of interdependent preferences show that preferences and choices of behavior are influenced not only by an individual's own tastes but also by the tastes of others. Such interactions are referred to as social norms, bandwagons, neighborhood effects, peer influences, conformity, and herd behavior, among other terms (Hyman, 1942; Merton, 1957; Granovetter, 1979; Manski, 2000). In the context of our research, we are interested as to whether neighborhood or peer affects influence the level of food consumption in a developing country and therefore affect the estimation of the Engel curve.[2] Why might this be so?

Individuals in geographic proximity may simply have similar consumption opportunities related to their ability to get to markets or grow food. In empirical analysis of consumption, these effects should be controlled for by basic regional characteristics and do not necessarily require a spatial estimation technique to accurately measure the determinants of food consumption. Spatial interdependence in food consumption may be affected by a form of competition. Consumption of specific products can be a signal of well-being (if not wealth). In developing countries, families in close proximity may "compete" with one another to appear in better health by their food consumption choices. It is important to determine the interdependence of consumption to develop an Engel's coefficient that is free of the bias introduced by the potential spatial correlation. Failure

1 Lancaster (1966) is an example of one of the earlier studies of interactive behavior.
2 Neighborhood and peer effects are further discussed in the following sections.

to do so could result in a misleading Engel's coefficient as a measure of poverty. Additionally, if spatial interdependence holds, this may provide insight regarding a more effective food support distribution program. If, for example, household food consumption in Jamaica is positively correlated with neighbors' food consumption, government officials may capitalize on the spatial impacts to target their food aid, education of food consumption, and distribution. This could result in more effective consumption aid for the impoverished in Jamaica.

In this paper, we use the Jamaica Survey of Living Conditions (SLC) 2001 data to create spatial econometric models to estimate Engel curves for food consumption in Jamaica and we incorporate a spatial component to consumption. The data are a micro-level sample of Jamaican households and allow us to consider a variety of factors that affect consumption in addition to income. Effects to be considered are household factors (household income, household size, household structure, etc.) as well as the effects of social factors (income level in the society, neighborhood's food consumption, etc.). We find evidence of a spatial dependence regarding food consumption and we also find a number of significant covariates explaining differences in consumption among families. In the concluding section we discuss how these results might be used to increase the effectiveness of government food support policies.

The paper is organized as follows: Section 2, introduces the spatial models and the model specification that we use to estimate the Engel curve and coefficients. Section 3 introduces the data and defines the weight matrix. Section 4 reports the estimations of the spatial models and compares them. Section 5 discusses and summarizes the results of the estimations. And Section 6 assesses the policy implications of our estimation.

Spatial Models and Diagnostic Methods

Engel's coefficients are often derived by estimation of the share of expenditures on food relative to total expenditures in a family budget.[3] While understanding the role of the spatial impact (and controlling for its impact on the parameter estimates) of food consumption is important to our estimation, we are also interested in the role of various family variables on consumption. Our empirical model therefore takes account of both spatial as well as other family and socio-economic characteristics of the household to help us isolate the "income component" of the traditional Engel curve analysis. Various forms of Engel's curve have been estimated, and this paper uses the Working-Leser share expenditure system (Working, 1943; Leser, 1963), which has been developed into the widely used Almost Ideal Demand System (AIDS) by incorporating price variables (Deaton and Muellbauer, 1980). The application of the Working-Leser system enables us to compare our estimation to the recent literature. Meanwhile, a preliminary exploration shows that the interdependence of household food consumption might exist in terms of Engel's coefficient, and the interdependence is ambiguous and inconsistent in terms of food consumption amount (or its log form). Because we estimate an Engel's curve for

[3] There has been significant controversy on the appropriate functional form for household expenditure or consumption estimation. See for example Hausman et al 1995.

household food consumption and the other expenditures are not our interest, the Working-Leser system can be simplified as (without price variables and without spatial effects):

$$\text{Engel's coefficient} = \text{constant} + b * \log(\text{total income}) + c * \text{other variables} + \text{residual} \quad (1)$$

(where b and c are coefficients, the residual is i.i.d.)

Alessie and Kapteyn (1991) modeled the interdependence of preferences by making current budget shares of a household dependent upon mean budget shares in the reference group of the household. Kapteyn, Geer, Stadt and Wansbeek (1997) modeled the interdependence by making parameters in the Linear Expenditure System (LES) dependent upon current quantities in the reference group of a household. We use spatial econometric techniques to estimate interdependence of consumption choices in this paper.

Spatial models can be used to estimate the interdependence or correlation among neighborhoods. The widely used general form of spatial models can be expressed as (SAC):

$$(2) \quad \begin{aligned} & y = x\beta + \rho wy + u, \\ & u = \lambda wu + \varepsilon, \\ & \varepsilon \sim i.i.d. \end{aligned}$$

where y is a dependent variable, x is a covariate, and u and ε are error terms. “w” is a predefined weight matrix, *wy* and *wu* are the spatial lag and spatial error terms. ρ and λ will measure the spatial correlation (or interdependence) among neighborhoods. A positive (negative) sign of ρ or λ reflects the positive (negative) spatial correlation among the neighborhood’s *y*s or errors. In spatial models, the development of a weight matrix is crucial, and neighbors affect each other through the spatial lag and/or spatial error terms.

The interaction among neighborhood behaviors has three possibilities (Manski, 2000). These are (1) endogenous interactions: neighbors affect each other's behavior directly; (2) contextual interactions: the behavior of people is affected by the exogenous variables of their neighbors; and (3) correlated effects: neighborhoods tend to behave similarly because of common characteristics or similar environments.

In empirical work, contextual interactions are typically assumed not to exist. In other words, researchers assume that people will not be affected by the exogenous variables of their neighbors. Thus, the interactions of the behaviors among neighbors will be either endogenous interactions or correlated effects. In the general spatial models described above, the endogenous interactions can be estimated by the coefficient of the spatial lag term (ρ), and the correlated effects can be estimated by the coefficient of the spatial error term (λ).

If λ=0, the spatial model can be reduced to a spatial autoregressive model or to spatial lag model (SAR):

$$(3)\quad \begin{aligned} & y = x\beta + \rho wy + u, \\ & \varepsilon \sim i.i.d. \end{aligned}$$

If ρ =0, the spatial model can be reduced to a spatial autoregressive error model or spatial error model (SEM):

$$(4)\quad \begin{aligned} & y = x\beta + u, \\ & u = \lambda wu + \varepsilon, \\ & \varepsilon \sim i.i.d. \end{aligned}$$

If ρ =0 and λ =0, it's a normal linear model and the ordinary least square model (OLS) model is appropriate. However, for spatial models, OLS will be either biased or inefficient. If the spatial lag term is ignored but ρ isn't equal to zero, then the OLS estimate will be biased and inconsistent. Conversely, if the spatial error term is ignored but λ is not equal to zero, then OLS will be inefficient because of the heterogeneity in errors. The spatial models can be estimated by the maximum likelihood estimation (MLE), the generalized method of moments (GMM) or other econometric methods. However, before estimating the spatial models, we need to identify the real forms of the spatial models. Several statistical tests for this are available.

Diagnostics for Spatial Dependence:

Lagrange Multiplier (LM) tests

There are two basic LM tests: The first one is a test for spatial lag dependence, and the other is for spatial error dependence. According to Anselin and Rey (1991), the two LM tests take the following forms:

LM test for spatial lag dependence:

(5) $$LM_{lag} = [Ne'W_1y/e'e]^2[N(W_1X\hat{\beta})'M(W_1X\hat{\beta})/e'e + tr(W_1^{'}W_1 + W_1^2)]^{-1}$$

LM test for spatial error dependence:

(6) $$LM_{Error} = [Ne'W_2e/e'e]^2[tr(W_2^{'}W_2 + W_2^2)]^{-1}$$

where N is the number of observations, e is the OLS residuals,

$M = I - X(X'X)^{-1}X'$, $\hat{\beta}$ is the OLS estimate of β, and W_1 and W_2, respectively, are the weight matrixes for the spatial lag and spatial error terms.

Both tests share the hypothesis (H0) of no correlation (ρ =0 and λ =0 respectively). When we reject H0 by either the LM lag test or the LM error test, we can expect either spatial lag dependence or spatial error dependence. We can use a maximum likelihood estimator (MLE) or generalized method of moments (GMM) or other methods to estimate the specified spatial models.

Robust Lagrange Multiplier tests

One main limitation of the LM tests is that they are non-nested. That is, they will reject H0 even if ρ =0 (or λ =0), if spatial error (or spatial lag) dependence exists λ^=0 (or ρ^=0). The robust Lagrange Multiplier tests overcome this limitation by accounting for any spatial error (or spatial lag) when testing for spatial lag (or spatial error) dependence. This more robust LM application also accounts for the noncentrality problem of LM tests. (Anselin, Bera, Florax, and Yoon, 1996) However, robust LM tests have less power than the LM lag (or error) test when no spatial error (or spatial lag) dependence exists. Robust LM tests take these forms:

Robust LM test for spatial lag dependence:

(7) $$LM^*_{lag} = \frac{(e'W_1y/s^2 - e'W_1e/s^2)^2}{(N\tilde{J}_{1\rho\cdot\beta})^{-1} - t_1}$$

Robust LM test for spatial error dependence:

(8) $$LM^*_{Error} = [(e'W_2e/s^2 - t_2) - (N\tilde{J}_{1\rho\cdot\beta})^{-1}(e'W_2y/s^2)]^2 / [t_2 - t_2^2(N\tilde{J}_{1\rho\cdot\beta})^{-1}]$$

where $s^2 = e'e/N$, $(N\tilde{J}_{1\rho\cdot\beta})^{-1} = [t_1 + (W_1X\beta)'M(W_1X\beta)/s^2]^{-1}$,

$M = I - X(X'X)^{-1}X'$, $t_1 = tr(W_1^{'}W_1 + W_1^2)$, $(N\tilde{J}_{2\rho\cdot\beta})^{-1} = [t_2 + (W_2X\beta)'M(W_2X\beta)/s^2]^{-1}$,

$t_2 = tr(W_2^{'}W_2 + W_2^2)$.

Moran's I test

(9) $I = \frac{N}{S}\frac{e'We}{e'e}$

Moran's I test also is used to test for spatial error dependence. However, it is powerful against both error and lag dependence and consequently should be used conservatively.

Data: Jamaica Survey of Living Conditions

Our data comes from the Jamaica Survey of Living Conditions 2001. It is a survey of randomly selected households and contains 1,668 observations. The survey covered 14 parishes, 58 constituencies, and 159 districts. The following is a list of variables we used in our model:

Engel: Dependent variable--Engel's coefficient of household and equal to total household food consumption divided by total household expenditure

totfood: Total household food consumption

totexp: Total household expenditure.In this paper, total household expenditure is assumed to be equivalent to total household income

logexp: Equal to the log of total household expenditure

popdec: Deciles of household's total per capita consumption in the society, used to reflect the household's social status

popexp: Interaction of popdec and logexp

sex: Gender of the head of household

logsize: Log of household size (label as **size**)

marr1-5: Dummy variables for the five indicators of marriage status: "Married," "Never married," "Divorced," " Separated," and "Widowed"

union1-5: They are dummy variables for five marriage statuses: "Married," "Common Law," "Visiting" "Single," and "None"

adsex1-4: Number, respectively, of male adults, female adults, male children, and female children

A summary of the data is included in Table 1 and Table 2. Figure 1 shows the household expenditure structure in Jamaica. Figure 2 displays a pattern of negative correlation between Engel's coefficient and household total expenditure, which is exactly what we expect according to Engel's law. After the log transformation of household total expenditure, a linear correlation between Engel's coefficient and household total expenditure comes up. Meanwhile, we also see that the Engel's coefficient of a group decreases as population deciles measured by household total expenditure (or income) increases.

Table 1: A Summary of Data (1)

	N	MIN	MAX	MEAN
Engel	1665	3.09%	93.88%	48.77%
totfood	1665	888	706,866	118,980
totexp	1668	7,872	4,137,979	284,186
size	1668	1	28	3.42
adsex1	1668	0	8	1.10
adsex2	1668	0	6	1.18
adsex3	1668	0	7	0.61
adsex4	1668	0	7	0.53

Table 2: A Summary of Data (2)

sex	N	totfood	totexp	Engel
Male	944	117,090	285,428	49%
Female	719	121,223	282,838	49%
union	N	totfood	totexp	Engel
others	19	159,076	365,500	48%
1	465	139,473	369,193	45%
2	239	140,946	310,404	51%
3	288	113,823	259,585	48%
4	362	95,908	226,259	51%
5	290	98,568	218,388	51%
marr	N	totfood	totexp	Engel
Others	6	119,088	230,969	53%
1	507	138,575	366,855	45%
2	940	110,354	244,539	51%
3	18	121,147	366,324	40%
4	29	114,373	312,076	42%
5	163	107,115	244,862	49%

Figure 1: Household Expenditure Structure in Jamaica, 2001

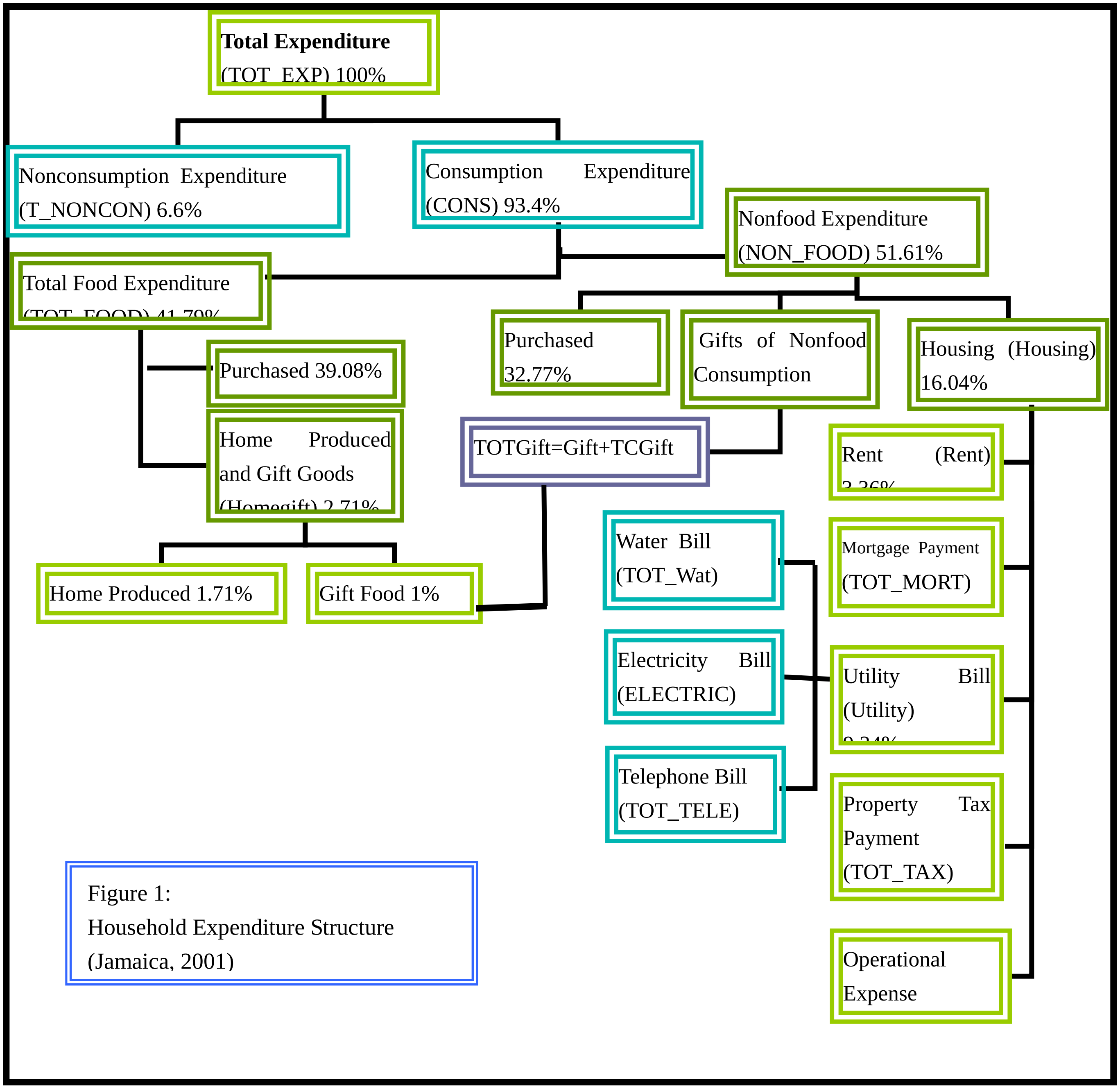


Figure 2-1: Plots for Totexp, Totfood, and Engel's Coefficient:

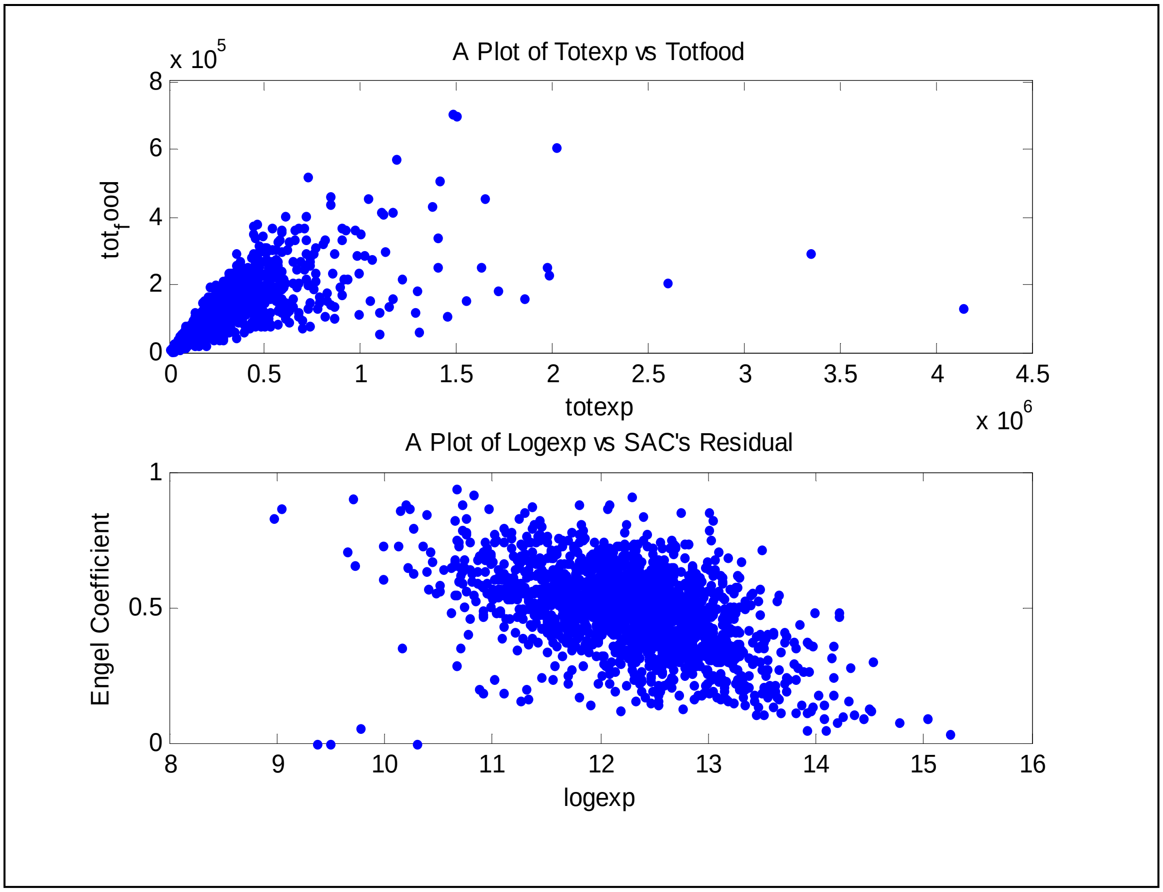
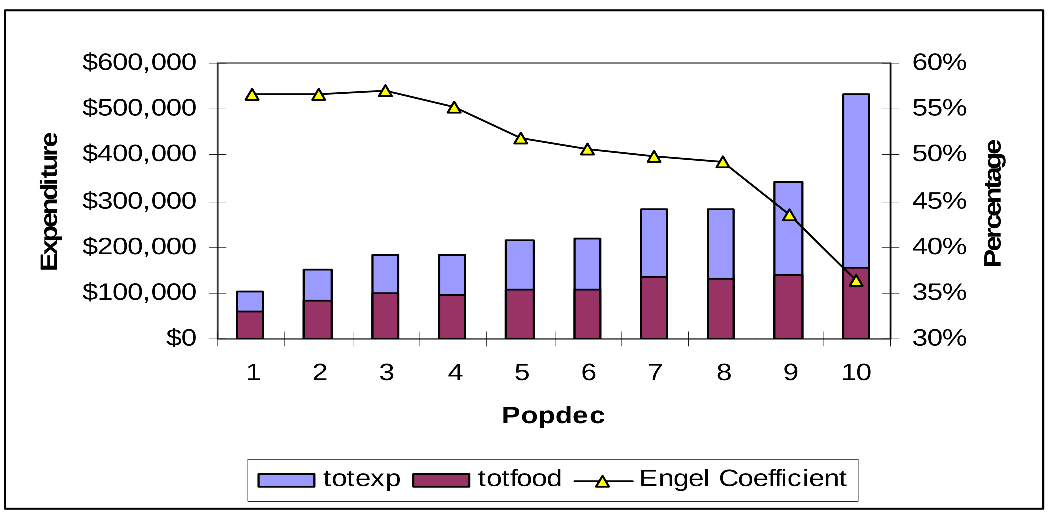


Figure 2-2: A Plot for Totexp, Totfood, and Engel's Coefficient by Popdec:



Weight Matrix

To apply spatial econometric techniques, however, we must first define a suitable weight matrix, which will be used to identify the neighbors or measure the magnitude of influence among subjects. In this research, the weight matrix should reflect the social connections among households that form a neighborhood/jurisdiction. Our hypothesis is that households in the same neighborhood might affect each other's behaviors for various reasons that we have referred to previously. Thus, in our paper, we define a neighborhood as consisting of people within a certain jurisdiction.

Jamaica is divided into 14 administrative regions called parishes. Each of these parishes is then subdivided into several constituencies (typically four constituencies in a parish: northwest, north east, south west, and southeast). An enumeration district (ED) is a group of dwellings established for the national census. Figure 3 describes the Jamaican jurisdictional structure. In this paper, people living in the same neighborhood are expected to tend to interact with each other, and EDs are considered a suitable neighborhood for such interaction. Thus, our paper defines a neighborhood as households within the same enumeration district (ED).

A unit weight is assigned to all households within the same district; otherwise, the assigned weight is 0. Then the weight matrix is standardized so that for each household the sum of the weights is equal to one. Table 3 provides an example of the weight matrix.

Figure 3: Jurisdiction Structure & Weight Matrix

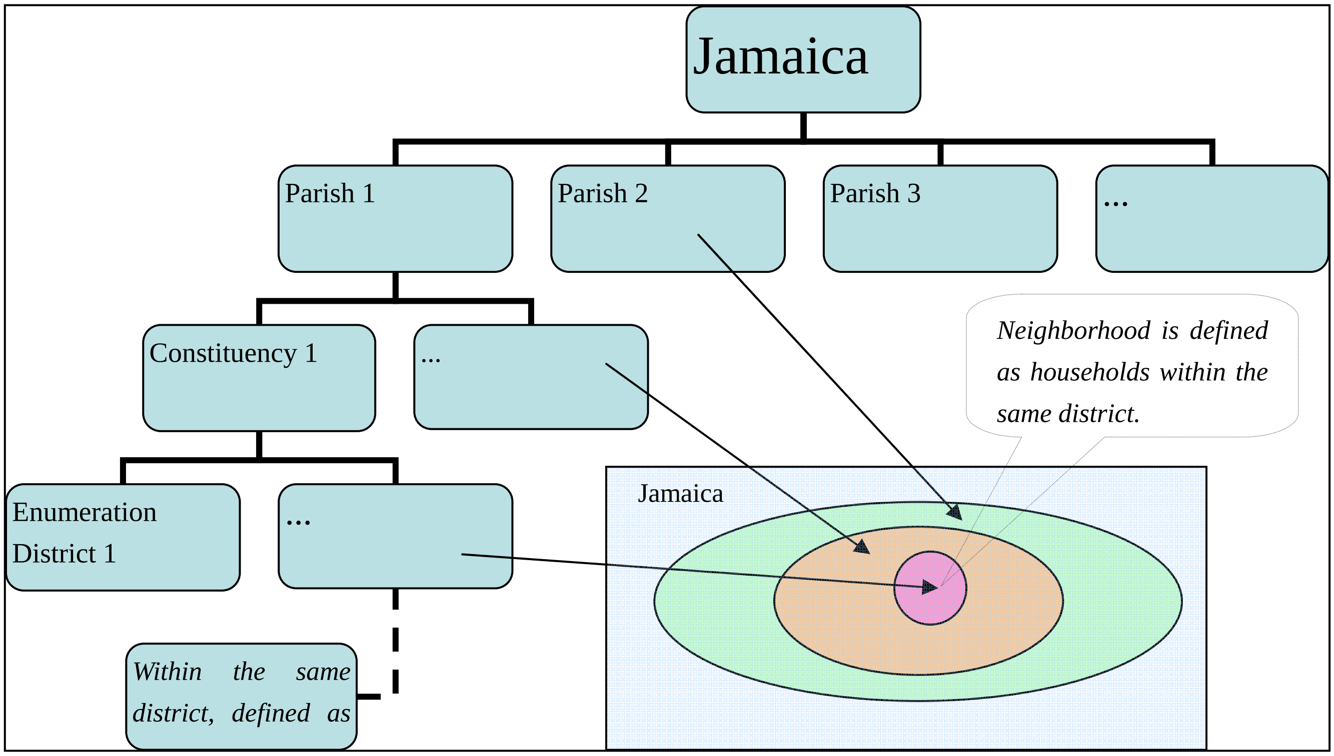


Table 3: An Illustration of Weight Matrix defined by EDs

Weight Matrix	ED1:Dwelling 1	ED1:Dwelling 2	ED1:Dwelling 3	ED2:Dwelling 1	ED2:Dwelling 2	ED2:Dwelling 3	…
ED1: Dwelling 1	0	1/2	1/2	0	0	0	0
ED1: Dwelling 2	1/2	0	1/2	0	0	0	0
ED1: Dwelling 3	1/2	1/2	0	0	0	0	0
ED2: Dwelling 1	0	0	0	0	1/2	1/2	0
ED2: Dwelling 2	0	0	0	1/2	0	1/2	0
ED2: Dwelling 3	0	0	0	1/2	1/2	0	0
…	0	0	0	0	0	0	…

Model Specification and Estimation

We undertook to estimate whether a household's food consumption as a ratio to total household expenditure will be affected by the household's characteristics such as household income, head of household structure, and other factors and also whether this ratio will be affected by spatial interactions. Thus, our dependent variable is the ratio of household food consumption to household total expenditure-- the household Engel coefficient. Our explanatory variables include variables such as household total expenditure (household income), household income deciles in the society, household size, marriage status, union status, and household structure (numbers of adults and children by gender). The models are also integrated with the spatial (spatial lag/error) terms to estimate the neighborhood effect. A summary of the factors affecting the household Engel's coefficient is as follows:

a. Household factors: log of household income, marriage status, union status, and household structure.

b. Social factors: household income deciles in the society; spatial effects from neighbors. Fan and Abdel-Ghany (2004) tested the importance of integrated permanent and relative income model in explaining consumer expenditure behavior and argued that both are important determinants of household expenditure behavior even in the presence of the other. Thus in our model we will integrate the variable of household income deciles and estimate its effect on household consumption behavior. The spatial effects have been discussed previously in this paper.

Diagnostics for Spatial Lag and Spatial Error Dependence

Before we can choose a spatial model for our analysis, we need to test statistically for spatial dependence. These tests for spatial dependence use Moran's I test for spatial dependence, the LM tests and Robust LM tests for spatial lag and spatial error dependence introduced above.

Diagnostics for Spatial Lag and Spatial Error Dependence

Diagnostic tests using Moran's I, LMs and Robust LM tests for spatial error and spatial lag dependence were run on the model.[4] Moran's I test yielded a p value lower than 0.001, which reflects the existence of spatial dependence. Moreover, not only the LM tests for spatial lag/error dependence, but also their robust counterparts showed a high degree of spatial lag and error dependence in the model. Accordingly, we conclude that both spatial lag and spatial error dependence are present to a significant degree. Thus, a general spatial model (or SAC) is suggested.

Table 4: Diagnostic Tests

Diagnostics Tests	Statistic	df	p-value
Moran's I	15.145	1	<0.001
Spatial error:			
Lagrange multiplier	224.298	1	<0.001
Robust Lagrange multiplier	54.997	1	<0.001
Spatial lag:			
Lagrange multiplier	178.938	1	<0.001
Robust Lagrange multiplier	9.636	1	0.002

[4] The statistical software we used for OLS estimation and diagnosis for spatial dependence is STATA. The STATA package is sg162: Tools For Spatial Data Analysis, downloaded from http://www.stata.com/stb/stb60.

Model Estimation

We used both MLE and GMM to estimate the SAC spatial models.[5] At the same time, for comparison, we also estimate SAR and SEM models. As we can see, the estimated coefficients of different spatial models are quite similar for both MLE and GMM. However, when using MLE, we can see that the SAC model has a larger log likelihood than either the SAR or SEM model. At the same time, when we compare the results with the OLS estimate, we also find similar estimated coefficients, but the spatial model gives us a much lower standard error. Thus, we are able to conclude that the SAC model is suitable.

Table 5: MLE Estimate for SAC, SAR, SEM models

Variable	SAC	SAR	SEM
Const	1.454668***	1.321773***	1.555184***
Logexp	-0.102501***	-0.097878***	-0.103335***
Popdec	0.119934***	0.116896***	0.120293***
Popexp	-0.008733***	-0.008436***	-0.008811***
marr2	0.035220***	0.036578***	0.034160***
Logsize	0.091366***	0.088860***	0.091153***
adsex1	0.015170***	0.014369***	0.015376***
adsex3	0.006377*	0.006645*	0.006173*
Rho	0.176000***	0.328985***	
Lambda	0.263999***		0.405982***
R-squared	0.404	0.348	0.408
Rbar-squared	0.401	0.346	0.406
sigma^2	0.014	0.014	0.014
log-likelihood	2696.424	1736.226	1739.173

(*: 15% significant level; **: 10% significant level; ***: 1% significant level.)

5 We use MATLAB for our estimation. The MATLAB toolbox is available from "Econometrics Toolbox" created by James P. LeSage. (http://www.spatial-econometrics.com)

Table 6: GMM estimate for SAC, SAR, SEM models

Variable	SAC	SAR	SEM
Const	1.104769***	1.378375***	1.554316***
Logexp	-0.10208***	-0.09758***	-0.10326***
Popdec	0.119744***	0.124798***	0.120548***
Popexp	-0.008709***	-0.00913***	-0.00883***
marr2	0.035427***	0.037047***	0.034205***
Logsize	0.091216***	0.089462***	0.091153***
adsex1	0.015093***	0.014645***	0.015374***
adsex3	0.006413*	0.006438*	0.00617*
Rho	0.201735***	0.21183***	
Lambda	0.230879***		0.399549***
R-squared	0.403	0.389	0.407
Rbar-squared	0.400	0.387	0.404
sigma^2	0.014	0.015	0.014

(*: 15% significant level; **: 10% significant level; ***: 1% significant level.)

Then, we can write our estimated model as follows (using the GMM estimate for the SAC model):

$$\begin{aligned}&Engel = 1.104769 - 0.10208 \cdot \log\exp + 0.119744 \cdot \text{popdec} - 0.008709 \cdot \text{popexp} + 0.035427 \cdot \text{marr2}\\&+ 0.091216 \cdot \text{logsize} + 0.015093 \cdot \text{adsex1} + 0.006413 \cdot \text{adsex3} + 0.201735 \cdot \text{w} \cdot \text{Engel} + \text{u}\\&\text{u} = 0.230879 \cdot \text{u} + \varepsilon\end{aligned}$$

When the predicted Engel’s coefficient is plotted against the logexp in Figure 4-1and2, it captures the trend quite well. The normality plot of the residual also suggests a normal distribution of the residual.

Figure 4-1: Plots of SAC Estimation-1

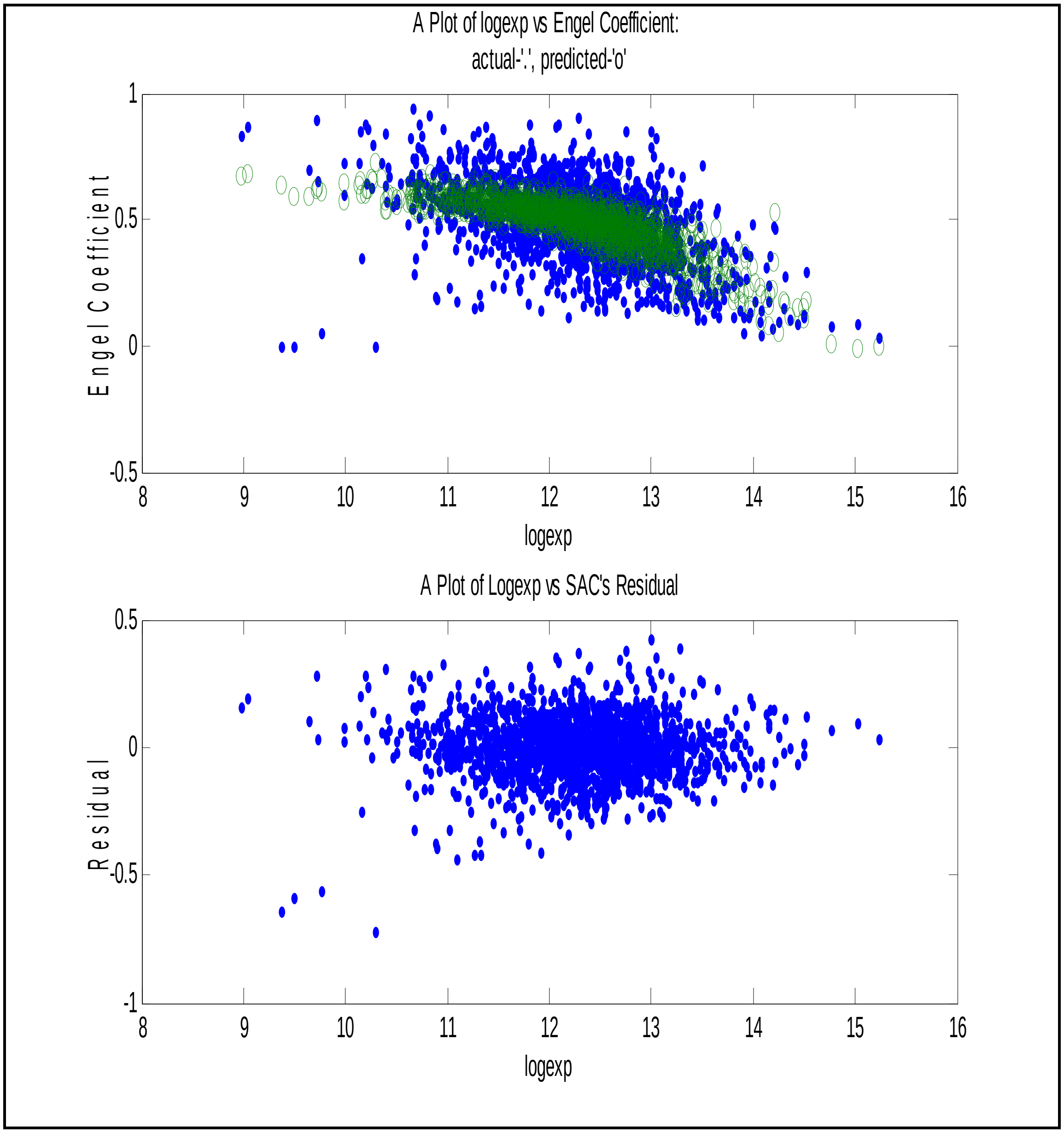
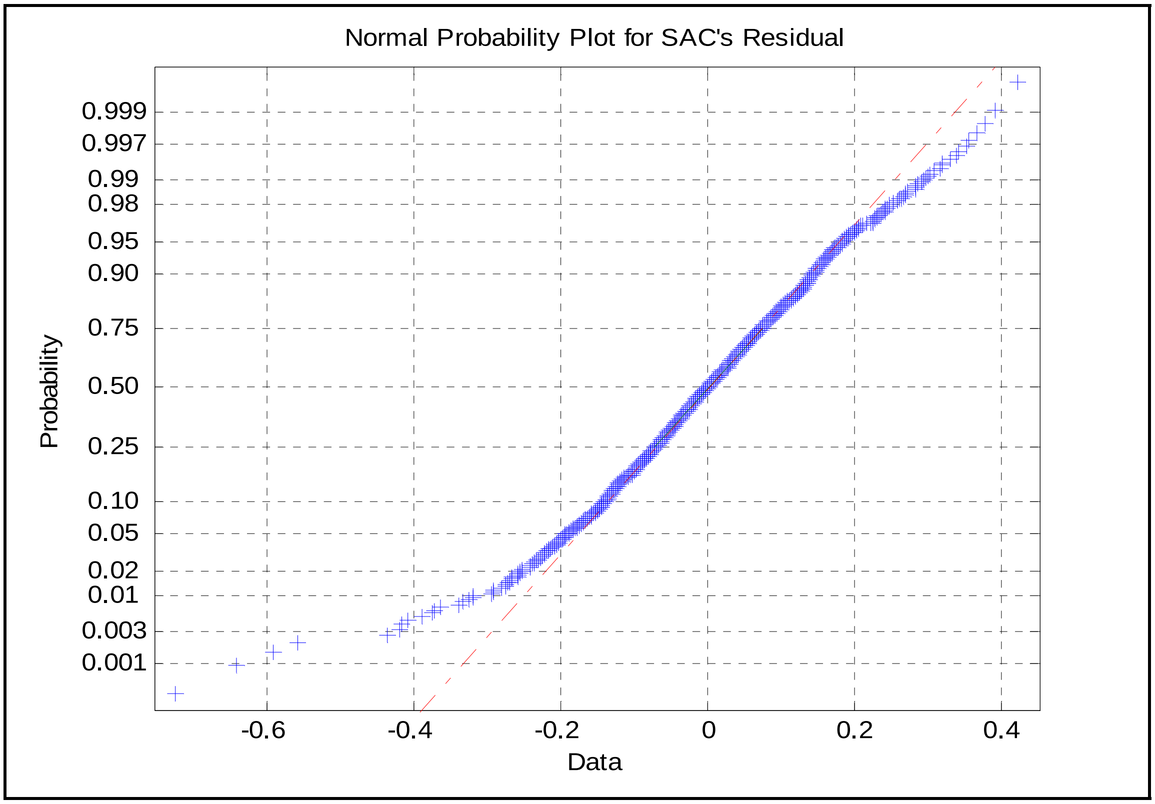


Figure 4-2: Plots of SAC Estimation-2



Discussion and Summary

Effect of Income

As demonstrated by the estimation results (for the SAC model by the GMM estimate), the coefficient of logexp is -0.10208. At the same time, the interaction term of logexp and popdec is -0.008709. So the effect of total expenditure (or income) on Engel's coefficient will depend on popdec: As popdec increases, the effect of total expenditure becomes larger. The following table shows how much Engel's coefficient decreases in each popdec in response to each 1 percent increase in total expenditure.

Table 7: Change in Engel's Coefficient With 1% Increase in Totexp by Popdec

Popdec	1	2	3	4	5	6	7	8	9	10
Change	-0.0011	-0.0012	-0.0013	-0.0014	-0.0015	-0.0015	-0.0016	-0.0017	-0.0018	-0.0019

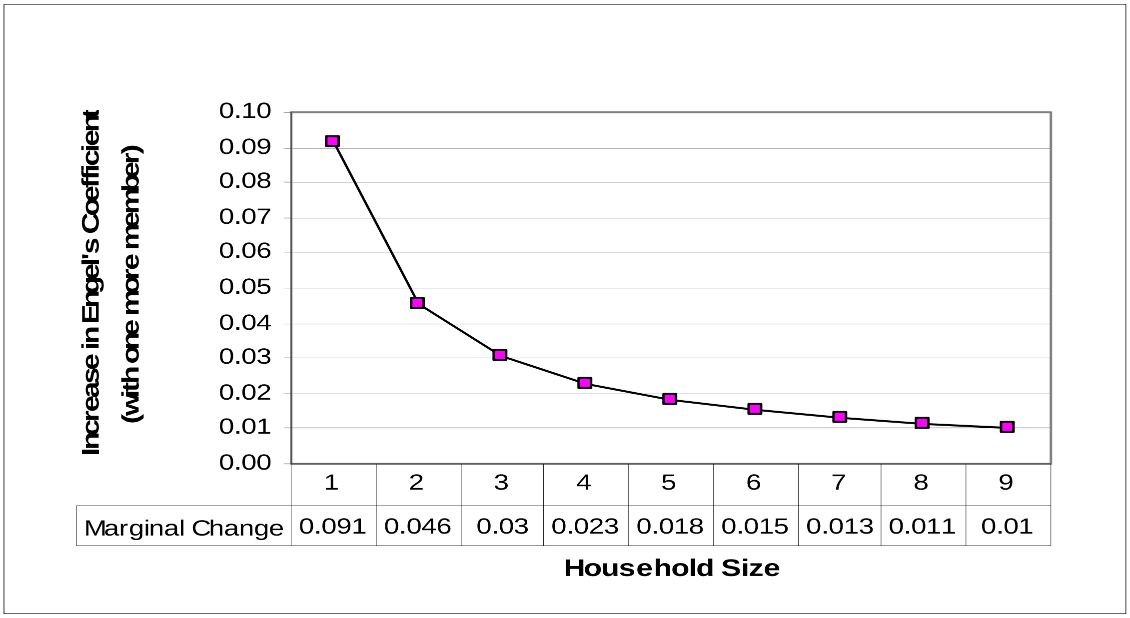
Effect of Household Structure

The gender of the head of household and the union status have no significant effects.

"Never Married" status for a head of household differs significantly from the other marital statuses ("Married," "Divorced," "Separated," and "Widowed"). These households will have an Engel Coefficient that is 0.035427 higher than the others, ceteris paribus. This is a large difference and means that these households spend 3.5 percent more of their total income on food.

Household size and structure effect food consumption significantly. The coefficient of logsize is 0.091216. The effect of an additional household member on Engel's coefficient is illustrated in the following graph. The effect of additional members decreases as household size increases. The graph in Figure 5 also shows the economy of household food consumption: Food consumption doesn't increase proportionately to an increase in household size, and thus per capita food consumption will decrease when household size increases.

Figure 5: Plot for Marginal Increase in Engel's Coefficient



We can also see that male members of a household have a positive effect on the Engel's coefficient. A male adult will increase the Engel's coefficient by 0.015093 (or increase food share as a proportion to total household expenditure by 1.51 percent); a male child will increase the Engel's coefficient by 0.006413 (or increase food share as a proportion to total household expenditure by 0.64 percent). Neither female adults nor female children have a significant effect.

Effect of Social factors: Income Level in the Society and Neighborhood

The household deciles variable has a very significant effect. It shows that when a household moves upward from one decile to the next, the Engel's coefficient will increase by 0.119744, which translates into an 11.97 percent increase in food share.

(Interestingly, the same decile upward mobility will increase the negative effect of logexp.) And although the popdec variable increases the Engel's coefficient, it also accelerates the decrease of Engel's coefficient with the increase in log income. This can be described as a typical tendency by people to decrease the percentage of income they spend on food as income increases, but an atypical jump in income that moves the same people into an upper decile may be accompanied by an increase in consumption of food as they indulge because of their higher status. In the higher deciles, the percentage of income spent on food declines at a faster rate than in the lower deciles when the same increase of income in log form is involved, however it declines at a slower rate when the same increase of income is involved.

We have talked about the improvement in performance gained by adopting the SAC model for our analysis. The SAC model estimates the effects of the neighborhood on a household. The significant positive coefficients of spatial lag term and spatial error term suggest a strong positive correlation among neighbors. The estimated coefficients for spatial lag and error terms differ slightly. The GMM estimates are $\rho = 0.201735$ and $\lambda = 0.230879$. The positive spatial lag dependence demonstrates that when the neighborhood's Engel's coefficients increases by 1 percent on average, this increase will be followed by a 0.20 percent increase in the Engel coefficients for households. The positive spatial error dependence reflects the highly correlated unspecified factors of neighbors.

Spatial lag dependence can lead us to a very interesting deduction: A household will have a higher (or lower) food share as a proportion to total household expenditure if it is located in a poor (or rich) neighborhood. Stated another way, a poor (or rich) household located in a rich (or poor) neighborhood will consume less (or more) food compared to their counterparts in the poor (or rich) neighborhood. It is interesting to see that the interaction is through food share (or expenditure) but not through the amount of food consumed.[6].

Summary

We have examined the effect of household factors and social factors on Engel's coefficient (or food share). Joint consideration of household factors and social factors not only improves our estimation, but also shows us that household food consumption is both a household behavior and a social behavior. In summary, we find that:

1. Household income has a significant negative effect, which increases as the income deciles in the society increase;
2. The gender and the union status of the head of household have no significant effects on food consumption. The head of household's marital status has a significant effect in the sense that heads of household who report "never married" tend to have a higher Engel's coefficient than others. This may be a topic for further research.

[6] If interaction were through the amount of consumption, then on the effect on Engel's coefficient is the opposite: A household will consume more (or less) food and have a higher (or lower) food share if it is in a rich (or poor) neighborhood with higher (or lower) food consumption amount.

3. Household size has significant effects. The increase in household size will lead to an increase in total food consumption and there is evidence of economies in household food consumption. The presence of male members (adults and children) has a significant effect not found with female adults or children in a household. This might reflect discrimination against females in household food consumption.
4. The income deciles have significant effects. These deciles increase Engel's coefficient on one hand, and enlarge the negative effect of log income on Engel's coefficient on the other.
5. Neighborhood effects are significantly positive. An increase in a neighborhood's average Engel's coefficient will lead to an increase in its household members' Engel's coefficient. The unknown variables of neighbors that affect Engel's coefficient are positively correlated with each other.

Application to the Poverty Problem

Poverty Line

Ravallion and Bidani (1994) proposed the use of household level data to estimate an Engel curve for food consumption and then used the estimated curve to calculate the poverty line. Suppose that we estimate an Engel curve as $\text{Engel} = f(\text{Income}|\,X)$, where income is the total household income (or expenditure) and X represents the conditional variables, such as the previously discussed household factors and social factors. If we think the household food poverty line is F, then we can find the household income poverty line I by solving $\text{Engel} = F / Income = \text{f}(\text{Income}|\,\text{X})$; or if we think household poverty is measured by a certain Engel coefficient E, we can find household income poverty line I by solving $E = \text{f}(\text{Income}|\,\text{X})$. The reason to determine a poverty line measured by household income is that such a line is easy to define by comparing a household's Engel's coefficient and household food consumption.

The poverty incidence in Jamaica was 16.9 percent in 2004. The poverty line in Jamaica is defined as the minimum food basket divided by the average food share for the lowest income quintile. The minimum food basket is based on the nutritional requirements established by the World Health Organization, Pan American Health Organization, and the Jamaica Ministry of Health. The poverty line is computed for a reference family of five, which includes one adult male, one adult female, an infant, a teenager and a pre-teen child. The poverty line was J$221,130.78 for a "Reference Family of 5" in 2004 (or J$167,083.1 in 2001). The poverty line for individuals was J$58,508.5 in 2004 (or J$44,208.2 in 2001).[7]

The average food share for the lowest income quintile might be inappropriate for all households and might cause a biased estimate. The Engel curve estimated in this paper should be able to be used to set up a household income poverty line for different prespecified groups of households (grouped by the independent variables in our model, such as household size, household structure, neighborhood, etc.).

[7] From Jamaica National Poverty Eradication Programme: www.npep.org.jm .

An Estimation of Income Elasticity of Food Consumption

As mentioned before, the Engel curve by itself is a demand curve and useful for estimating income elasticity, a determination that is not only important for assessing food consumption by poor people but also serves to estimate food demand in a society. From the estimated curve, we are able to estimate the income elasticity of food consumption in Jamaica. It can be described as (10). [8]

$$(10) \quad \tau = 1 - 1.01 \cdot \frac{0.10208 + 0.008709 * \text{popdec}}{\text{Engel}}$$

For example, for three households with (popdec=2, Engel=.7), (popdec=5, Engel=.5) and (popdec=9, Engel=.4), respectively, we can calculate their income elasticity as 0.827581, 0.705838, and 0.544336. We can easily find there is a negative relationship between income elasticity and income, and there is also a negative relation between it and income deciles, i.e. the income elasticity is not only less than 1, but also decreases as income increases. Equation (10) should be useful when policy makers want to measure the effect on poor people of subsidies such as food stamps.

Neighborhood Matters

From the previous section, we know that when the neighborhood's Engel's coefficients increase 1 percent on average, this increase will cause a 0.20 percent increase in Engel's coefficient for households. The effect is significant. We know the household's

[8] A change in one household's Engel's coefficient has a very small effect on the neighborhood, and the feedback effect is minimal. Thus we can ignore the neighborhood effect here.

Engel's coefficient varies from 3 percent to 98 percent. If there are two identical households and they live in different neighborhoods with an average Engel's coefficient, respectively, equal to 40 percent (a rich neighborhood) and 70 percent (a poor neighborhood), then the first household will have a 6 percent lower Engel's coefficient compared with the second one. This might cause distortion in the household's expenditure. The unknown factors that cause neighbors to "copy" each other's expenditure structure have important implications for the issue of poverty. Will the neighborhood improve or worsen the poverty problem? And will it cause the migration of people? With a poverty policy that helps poor people through subsidies, the first problem can be solved by establishing appropriate income poverty lines in different neighborhoods as described in 10. The second question raises an issue for further research on the relationship between migration and preference interdependence among neighborhoods.

The positive correlation in the error term can be caused by correlated factors not captured in our model, such as geographic factors, the local economic environment, common risks, or common expectations. This correlation may also suggest that poverty policy, which now mostly targets households, should be able to target the common background of neighborhoods.

Possible Discrimination against Females

Our estimation shows that male members of a household have a significant positive effect. The increase in Engel's coefficient caused by an additional male adult (or child) is 0.015093 (or 0.006413), more than that caused by an additional female member (either adult or child). We can see that even male children could affect food consumption more than female adults do. It is very possible that in Jamaica, as in many other developing countries, discrimination exists against females in food consumption.

References

Aasness, J., Biorn, E., and Skjerpen, T. (1993). Engel Functions, Panel Data, and Latent Variables. Econometrica, 61(6), 1395-1422.

Aasness, J., and Rodseth, A. (1983). Engel Curves and Systems of Demand Functions. European Economic Review, 20(1-3), 95.

Aitchison, J., and Brown, J. A. C. (1954). A Synthesis of Engel Curve Theory. The Review of Economic Studies, 22(1), 35-46.

Alessie, R., and Kapteyn, A. (1991). Habit Formation, Interdependent Preferences and Demographic Effects in the Almost Ideal Demand System. The Economic Journal, 101(406), 404-419.

Anselin, L. (1999). Spatial Econometrics: University of Texas at Dallas.

Anselin, L., Bera, A. K., Florax, R., and Yoon, M. J. (1996). Simple diagnostic tests for spatial dependence. Regional Science and Urban Economics, 26(1), 77-104.

Baichen, J., and John, D. (2007). Household food demand in rural China. Applied Economics, 39(3), 373.

Bank, T. W. (2002). Jamaica Survey of Living Conditions 1988-2000: Basic Information. In P. a. H. R. Development Research Group, The World Bank (Ed.).

Banks, J., Blundell, R., and Lewbel, A. (1997). Quadratic Engel Curves and Consumer Demand. The Review of Economics and Statistics, 79(4), 527-539.

Bexk, N., Gleditsch, K. S.,and Beardsley, K. (2006). Space Is More than Geography: Using Spatial Econometrics in the Study of Political Economy. International Studies Quarterly, 50(1), 27-44(18).

Behrman, J. R., and Deolalikar, A. B. (1987). Will Developing Country Nutrition Improve with Income? A Case Study for Rural South India. The Journal of Political Economy, 95(3), 492-507.

Bell, A. M. (2002). Locally interdependent preferences in a general equilibrium environment. Journal of Economic Behavior and Organization, 47, 309-333.

Beneito, P. (2003). A complete system of Engel curves in the Spanish economy. Applied Economics, 35(7), 803 - 816.

Blaylock, J. R., and Smallwood, D. M. (1982). Analysis of Income and Food Expenditure Distributions: A Flexible Approach. The Review of Economics and Statistics, 64(1), 104-109.

Blow, L., Kalwij, A., and Ruiz-Castillo, J. (2004). Methodological issues on the analysis of consumer demand patterns over time and across countries.

Boltvinik. Poverty Measurement Methods-An Overview.

Buttel, F. H. (2000). Ending Hunger in Developing Countries. Contemporary Sociology, 29(1), 13-27.

Case, A. C. (1991). Spatial Patterns in Household Demand. Econometrica, 59(4), 953-965.

Conley, T. G. (1999). GMM estimation with cross sectional dependence. Journal of Econometrics, 92(1), 1.

Crawford, I., Laisney, F., and Preston, I. (2002). Estimation of household demand systems with theoretically compatible Engel curves and unit value specifications: Institute for Fiscal Studies and University of Surrey.

Crombrugghe, D. d., Palm, F. C., and Urbain, J.-P. (1997). Statistical Demand Functions for Food in the USA and the Netherlands. Journal of Applied Econometrics, 15(5), 615-637.

Darmofal, D. (2006). Spatial Econometrics and Political Science. Paper presented at the Annual Meeting of the Southern Political Science Association, Atlanta, GA.

Darrough, M. N., Pollak, R. A., and Wales, T. J. (1983). Dynamic and Stochastic Structure: An Analysis of Three Time Series of Household Budget Studies. The Review of Economics and Statistics, 65(2), 274-281.

Deaton, A. (1980). An Almost Ideal Demand System. The American economic review, 70(3), 312.

Deaton, A., and Paxson, C. (1998). Economies of Scale, Household Size, and the Demand for Food. The Journal of Political Economy, 106(5), 897-930.

Dickens, W. T. (1990). Error Components in Grouped Data: Is It Ever Worth Weighting? The Review of Economics and Statistics, 72(2), 328-333.

Fagiolo, G. (2001). Engel Curves Specification in an Artificial Model of Consumption Dynamics with Socially Evolving Preferences: Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced Studies, Pisa, Italy.

Gibson, J. Why Does the Engel Method Work? Food Demand, Economies of Size and Household Survey Methods: SSRN.

Goh, A.-T., and Wan, H. Fragmentation, Engel's Law, and Learning: SSRN.

Gong, X., Soest, A. v., and Zhang, P. (2000). Sexual Bias and Household Consumption: A Semiparametric Analysis of Engel Curves in Rural China: Institute for the Study of Labor (IZA).

Hamilton, B. W. (2001). Using Engel's Law to Estimate CPI Bias. The American Economic Review, 91(3), 619-630.

Hausman, J. A., Newey, W. K., and Powell, J. L. (1995). Nonlinear errors in variables: Estimation of some Engel curves. Journal of Econometrics, 65(1), 205.

Heiberg, P. (1931). Has Engel's Law Its Limitations? Journal of the American Statistical Association, 26(174), 175-177.

Houthakker, H. S. (1957). An International Comparison of Household Expenditure Patterns, Commemorating the Centenary of Engel's Law. Econometrica, 25(4), 532-551.

Iyengar, N. S. (1967). Some Estimates of Engel Elasticities Based on National Sample Survey Data. Journal of the Royal Statistical Society. Series A (General), 130(1), 84-101.

Janeiro, R. d. (2004). Regional Workshop on Poverty Statistics in Latin America and the Caribbean: Draft Report.

Kalwij, A., and Machin, S. (2004). Changes in Household Demand Patterns: A Cross-Country Comparison.

Kapteyn, A., de Geer, S. V., de Stadt, H. V., and Wansbeek, T. (1997). Interdependent Preferences: An Econometric Analysis. Journal of Applied Econometrics, 12(6), 665-686.

Keen, M. (1986). Zero Expenditures and the Estimation of Engel Curves. Journal of Applied Econometrics, 1(3), 277-286.

Kohn, K. (2001). Estimation of Quadratic Expenditure Systems Using German Houshold Budget Data.

Lacombe, D. J. (2004). Does Econometric Methodology Matter? an Analysis of Public Policy Using Spatial Econometric Techniques. Geographical analysis, 36(2), 105.

Lanjouw, P., and Ravallion, M. (1995). Poverty and Household Size. The Economic Journal, 105(433), 1415-1434.

Leamer, E. E. (1997). Revisiting Tobin's 1950 Study of Food Expenditure. Journal of Applied Econometrics, 12(5), 533-553.

Leser, C. E. V. (1963). Forms of Engel Functions. Econometrica, 31(4), 694-703.

Lewbel, A. (1987). Characterizing Some Gorman Engel Curves. Econometrica, 55(6), 1451-1459.

Liviatan, N. (1961). Errors in Variables and Engel Curve Analysis. Econometrica, 29(3), 336-362.

Luengo-Prado, M. J., and Ruiz-Castillo, J. (2004). Demand Patterns in Spain.

Main, B. G. M. (1981). An Engel Curve for the Direct and Indirect Consumption of Oil. The Review of Economics and Statistics, 63(1), 132-136.

Massell, B. F. (1969). Consistent Estimation of Expenditure Elasticities from Cross-Section Data on Households Producing Partly for Subsistence. The Review of Economics and Statistics, 51(2), 136-142.

Mejia, J. A., and Vos, R. (1997). Poverty in Latin America and the Caribbean. An Inventory: 1980-95: The Inter-American Development Bank.

Naik, N. Y., and Moore, M. J. (1996). Habit Formation and Intertemporal Substitution in Individual Food Consumption. The Review of Economics and Statistics, 78(2), 321-328.

Ogaki, M. (1992). Engel's Law and Cointegration. The Journal of Political Economy, 100(5), 1027-1046.

Paelinck, J. H. P. (2005). Spatial Econometrics: History, State-of-the-art and Challenges Ahead. Paper presented at the Workshop on Spatial Econometrics, Kiel Institute for World Economics.

Phipps, S. A., and Burton, P. S. (1998). What's Mine is Yours? The Influence of Male and Female Incomes on Patterns of Household Expenditure. Economica, 65(260), 599-613.

Pollak, R. A., and Wales, T. J. (1978). Estimation of Complete Demand Systems from Household Budget Data: The Linear and Quadratic Expenditure Systems. The American Economic Review, 68(3), 348-359.

Prais, S. J. (1952). Non-Linear Estimates of the Engel Curves. The Review of Economic Studies, 20(2), 87-104.

Ravallion, M. (1992). Poverty Comparisons: A Guide to Concepts and Methods: The World Bank.

Ray, R. (1980). Analysis of a Time Series of Household Expenditure Surveys for India. The Review of Economics and Statistics, 62(4), 595-602.

Ryan, D. L., and Wales, T. J. (1999). Flexible and Semiflexible Consumer Demands with Quadratic Engel Curves. The Review of Economics and Statistics, 81(2), 277-287.

Seale, J., James , Regmi, A., and Bernstein, J. A. (2003). International Evidence on Food Consumption Patterns: Technical Bulletin No. (TB1904) 70 pp.

Singh, V. (2005). Estimating a third-order translog demand system using Canadian micro-data, EconWPA (Vol. Econometrics 0512011): EconWPA.

Song, H., Liu, X., and Romilly, P. (1997). A Comparative Study of Modelling the Demand for Food in the United States and the Netherlands. Journal of Applied Econometrics, 12(5), 593-608.

Stacey, M. (2007). Encyclopedia of World Poverty. Reference and User Services Quarterly, 46(4), 88.

Starzec, F. G. g. u.-p. f. a. C. (2004). Income Effects on Services Expenditures.

Subramanian, S., and Deaton, A. (1996). The Demand for Food and Calories. The Journal of Political Economy, 104(1), 133-162.

Summers, R. (1959). A Note on Least Squares Bias in Household Expenditure Analysis. Econometrica, 27(1), 121-126.

The Statistical Institute of Jamaica. (2001). Jamaica Survey of Living Conditions. In T. S. I. o. Jamaica (Ed.): Government of Jamaica

The United Nations. (2005). Handbook on Poverty Statistics: Concepts, Methods and Policy Use. In T. U. N. S. Division (Ed.): The United Nations.

Tobin, J. (1950). A Statistical Demand Function for Food in the U.S.A. Journal of the Royal Statistical Society. Series A (General), 113(2), 113-149.

Trigg, A. (2004). Deriving the Engel Curve: Pierre Bourdieu and the Social Critique of Maslow's Hierarchy of Needs. Review of Social Economy, 62(3), 393-406.

van Praag, B. M. S., Spit, J. S., and van de Stadt, H. (1982). A Comparison between the Food Ratio Poverty Line and the Leyden Poverty Line. The Review of Economics and Statistics, 64(4), 691-694.

Working, H. (1943). Statistical Laws of Family Expenditure. Journal of the American Statistical Association, 38(221), 43-56.

Fan, J. X. and M. Abdel-Ghany (2004). Patterns of Spending Behavior and the Relative Position in the Income Distribution: Some Empirical Evidence. Journal of Family and Economic Issues 25: 163-178.