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The household production function approach to valuing climate: the case of Japan

David Maddison · Katrin Rehdanz · Daiju Narita

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Abstract According to household production function theory households combine marketed goods and nonmarket environmental goods to produce service flows of direct value to the household. This readily explains why, as an input to household production activities, households might have preferences over the climate. Using techniques more frequently employed to account for differences in the demographic composition of households we use household production function theory to estimate climate equivalence scales using household expenditure data drawn from 51 Japanese cities over the period 2000–2009. Our results indicate that warmer temperatures result in a small but statistically highly significant reduction in the cost of living. Combining these estimates with climate change scenarios associated with the IPCC A2, A1B, and B1 emissions scenarios other things being equal points to a slight reduction in Japanese households' cost of living.

1 Introduction

According to the household production function theory of Becker (1965) households seldom consume marketed commodities directly. Rather, households combine marketed commodities with nonmarket environmental goods and household labour according to some household production technology in order to provide services flows.[1] And it is only these which are of direct value to the household.

Household production function theory explains why households inhabiting areas characterised by different levels of nonmarket environmental goods might experience differences in wellbeing.

[1] Henceforth we ignore the role of household labour in the production of service flows.

D. Maddison (✉)
Department of Economics, University of Birmingham, Birmingham B15 2TT, UK
e-mail: d.j.maddison@bham.ac.uk

K. Rehdanz · D. Narita
Kiel Institute for the World Economy, Hindenburgufer 66, 24105 Kiel, Germany

K. Rehdanz
Department of Economics, Christian-Albrechts-University of Kiel, Ohlshausenstrasse 40, 24118 Kiel, Germany

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The theory also explains why households inhabiting areas characterised by differing quantities of nonmarket environmental goods might purchase different patterns of marketed goods. Differences in the levels of nonmarket environmental goods cause households to substitute marketed goods for nonmarket environmental goods in household production activities. And differences in the 'price' of service flows in turn causes households to substitute between different service flows with additional consequences for the derived demand for marketed goods (Smith 1991).

The main purpose of this paper is to provide an empirical test of the hypothesis that climate is an important input to household production functions and to measure the impact of climate on households' cost of living.

Although logical to ask about the impact of climate change on the cost of living estimating the direct value of climate to households is on the face of it very difficult.[2] This is because climate is potentially an input to the production of numerous service flows, none of which are directly observable.[3] Some researchers therefore regard household production function theory as a purely heuristic device, explaining the importance of nonmarket environmental goods, but not actually providing a basis for estimating the value of changes in their availability. Such views may however be misguided since the techniques we employ below involve neither estimating household production functions nor the demand for unobservable service flows.

In fact ours is not the first attempt to use the household production function technique empirically to estimate the value of climate and the impact of climate change on households. But our analysis uses repeated cross sectional data from 51 cities within a single country (Japan) and because the key assumptions of common tastes and common household production functions are more plausible any differences in household patterns of demand can more credibly be attributed to environmental conditions. Furthermore, because the household expenditure data are drawn from specific cities the corresponding climate variables can be measured with great accuracy. And of course, with repeated cross sectional data it is possible to assess the temporal stability of any observed relationship between climate and household expenditure patterns.

To anticipate our findings it appears that climate provides a statistically significant explanation of the observed geographical variation in Japanese households' expenditure patterns. Furthermore estimated climate equivalence scales point to small, but statistically highly significant, differences in the cost of living arising from climatic conditions.[4] Changes in climate associated with popular IPCC emissions scenarios point to a small reduction in the cost of living in Japan, other things being equal.

The remainder of the paper is organised as follows. Section 2 contains a general review of the empirical literature estimating the value of climate to households. Section 3 focuses in particular on studies employing the household production function technique to value the climate. In section 4 the paper demonstrates how climate variables can be incorporated into a system of demand equations in a theoretically consistent manner. Section 5 describes the data underlying the empirical exercise and section 6 describes the results from two very different models of consumer demand. Section 7 investigates further the extent to which climate contributes to differences in the cost of living in various Japanese cities. The final section concludes.

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[2] Writing the utility function of a household in location i as $v(p(z_i), y(z_i), z_i)$ where v is utility, p is a vector of prices and z is climate the direct effect of climate on households is the direct effect of z_i on v_i and not the indirect effect via p and y. We do not measure the value of a change in climate in alternative location j even if the household does have preferences over z_j.

[3] It may be for this reason that researchers, intent on estimating the economic costs of climate change, have focused attention on measuring changes in agricultural productivity or the cost of building sea defenses.

[4] Climate equivalence scales are analogous to household equivalence scales but include climate variables rather than, as is more commonly the case in economics, the numbers of adults and children.

2 Literature review

It is possible to measure in monetary terms the impact on households of a change in climate. But assuming that households have property rights to the current climate the appropriate measure depends on the direction of change. For a move to an inferior climate the appropriate measure is the minimum compensation necessary to persuade the household to accept the change. For a move to a superior climate the appropriate measure is the maximum willingness to pay to secure the change. Together, these are referred to as compensating surplus (CS) measures of welfare change.[5]

Researchers have employed a wide variety of valuation techniques to estimate the CS for a marginal or a non-marginal change in climate. None appear to have involved asking individuals e.g. “What is the maximum amount your household is willing to pay in order to enjoy a climate similar to that of Nice?” For although conceptually meaningful this type of question is regarded as simply too difficult. Instead, studies have relied on revealed preference techniques exploiting the existence of spatial variation in climate such as the hedonic technique.[6]

The hedonic technique uses as its point of departure the observation that if households are able to select from different localities then climate becomes a ‘choice’ variable. And the diverse costs and benefits associated with particular climates should therefore be reflected in geographical differences in house prices and wage rates induced by hedonic (literally ‘pleasure-seeking’) migration. The value to the household of marginal changes in climate variables can thus be inferred from the derivatives of the hedonic house price and wage rate functions, evaluated at the chosen location of the household.

Using the hedonic technique Nordhaus (1996) analyses county level wage rate data, adjusted for regional differences in the cost of living, to estimate the value of climate to US households. He then utilises his results to predict the impact of various climate change scenarios. Maddison (2001a) presents hedonic house price and wage rate regressions for 127 counties, metropolitan areas and unitary authorities in Great Britain using data from 1994. His work involves running separate regressions for house prices, and for wage rates paid to blue collar and white collar workers. Households prefer higher annual average temperatures and lower annual precipitation. Mendelsohn (2001) presents another hedonic analysis for the US. Using county level data he estimates separate regressions for rents and for four different kinds of employment using 30-year averages for winter, spring, summer and fall temperature and precipitation as explanatory variables.

Maddison and Bigano (2003) use the hedonic technique to analyse the amenity value of the climate of Italy. Using data on Italian provinces they find that labour incomes net of housing costs are significantly higher in areas with high July mean temperatures and high January precipitation implying these are disamenities. Rehdanz and Maddison (2009) use the hedonic approach to measure the value of climate to households in Germany. Their work suggests that households are compensated for climate mainly through the operation of

[5] The compensating surplus (CS) is implicitly defined by the difference in income required to maintain welfare constant as environmental quality changes from z^0 to z^1.

$$v(p, y - CS, z^0) = v(p, y, z^1)$$

[6] Revealed preference techniques use spatial variation in climate as an analogue for future climate change. In so doing, they address the issue of adaptation by making comparisons between households that have already perfectly adapted to the climate.

hedonic housing markets rather than hedonic labour markets.[7] Houses are significantly more expensive in areas with higher January mean temperatures and lower precipitation in January, as well as in areas with lower July mean temperatures.

Turning to other less commonly employed revealed preference valuation techniques, according to the Random Utility Model (RUM) of choice, migration decisions are made on the basis of differences in wage rates, housing costs and employment possibilities. But do regions with more desirable climates ceteris paribus experience net inward migration? Using the RUM modelling framework Cragg and Kahn (1997) examine the propensity of individuals to move to different US states as a function of their climate holding constant a range of other site-specific factors. Results indicate that individuals are attracted by higher wintertime temperatures and lower summertime temperatures.

In the hypothetical equivalence scales technique a respondent is asked whether they would describe a particular household income as 'good' or 'bad' for a household sharing the same set of circumstances. Alternatively, respondents are asked about the minimum income necessary to achieve a standard of living that they would for example, describe as 'satisfactory'. Statistical analysis aims to identify which factors explain why certain households require higher or lower incomes to reach a verbally-described standard of living.

Van Praag (1988) uses hypothetical equivalence scales to analyse the effect of climate on European households' standard of living. He asks survey respondents about the minimum income required for their household to reach a variety of welfare levels ranging from 'very bad' to 'very good'. Dividing his data into 90 different climatic zones results suggest that households living in areas characterised by higher annual mean temperatures, higher annual precipitation and higher annual average relative humidity require less income to achieve the same standard of living.

Recently economists have started inviting individuals to state how happy or how satisfied they feel on a numerical scale in order to explore important economic questions e.g. what are the welfare costs of inflation and whether individuals are voluntarily unemployed. Adopting this approach, Frijters and Van Praag (1998) use the responses of individuals asked to rate their happiness on a 1–10 scale to construct climatic equivalence scales for six Russian cities. The cost of living in Dudinka, located on the edge of the Arctic Circle, is almost two and a half times greater than the cost of living in Moscow.

Rehdanz and Maddison (2005) analyse cross-country data on subjective wellbeing. Despite including a large number of covariates only GDP per capita and climate provide a statistically significant explanation of the cross-country variation in subjective wellbeing. Lower temperatures in the coolest month and higher temperatures in the warmest month reduce subjective wellbeing. Rehdanz and Maddison use their results to estimate the CS for various climate change scenarios.

Summarising the literature, some studies employ international data but most use data from a single country.[8] Particularly in cross-country studies, data are frequently aggregated over large, climatically diverse regions. Most studies include temperature and precipitation but far fewer include other potentially important climate variables such as sunshine and relative humidity. Researchers characterise climate variables in a different way e.g. annual mean temperature versus heating and cooling degree-days. Households' preferences for changes in the climate are likely to depend on the baseline climate. Geographical context

[7] For a discussion of the circumstances in which compensation for nonmarket goods should occur in the housing market rather than the labour market or vice-versa see Roback (1982).

[8] The more diverse the climate the easier it is to identify households' preferences for particular types of climate.

therefore frustrates any attempt to compare the results obtained by different studies. Some studies have used their results to estimate the CS for particular climate change scenarios. Despite the uneven quality of the data most studies indicate that households are willing to pay substantial sums to enjoy more preferred types of climate.

3 The household production function approach

Economists often analyse household expenditure patterns in order to calculate equivalence scales for households with differing demographic composition. Such analyses are motivated by questions like "How much more money would a family with two adults and two children need before it attains the same level of wellbeing as a household of two adults but without any children?" This same approach can be extended to answer questions, not about the relative costs of households with different numbers of children and adults, but about the relative costs of households enjoying different quantities of nonmarket environmental goods (in our case, a different climate).

Determining the value of the climate using the household production function approach requires data on expenditures by households inhabiting different climates, in addition to some variation in commodity prices and household incomes. Many countries conduct annual surveys of household expenditures potentially suitable for empirical analysis.

Compared to other techniques used to estimate the value of climate to households this approach possesses certain appeal. It is neither necessary to assume the existence of a unified market for land and labour, nor to assume that households are, without incurring any costs, willing to move significant distances to eliminate the net benefits of particular locations. And many economists are unwilling to believe that different individuals use the identical same function for mapping utility onto an integer scale which is a necessary assumption for analyses based on subjective wellbeing.

But the household production function approach itself involves a number of assumptions. As such it is best viewed as a complementary rather than a superior valuation technique. It is assumed for example, that households possess the same underlying tastes and production technologies, and that expenditures therefore differ only to the extent that households face different prices, enjoy different incomes, are of a different demographic composition or enjoy a greater abundance on nonmarket environmental goods.[9] More importantly, the technique also assumes that non-market environmental and marketed goods exhibit demand dependency (Bradford and Hildebrand 1977). Demand dependency requires that there exists a price vector where marginal changes in the quantity of nonmarket environmental goods do not affect utility. The root purpose of this assumption is to ensure that all relevant parameters of the indirect utility function can be obtained through econometric estimation of the Marshallian demand functions.

As mentioned the household production function approach has already been used to estimate the value of climate. Maddison (2001b) invokes procedures identical to those used to incorporate demographic variables into systems of demand equations.[10] Using per capita expenditure data provided by the 1980 International Comparisons Project, Maddison finds that including climate variables greatly enhances the ability of the Quadratic Expenditure System to explain international variations in the pattern of household expenditures. Maddison then uses his results to estimate the CS for a 1 °C increase in annual mean temperature and a

[9] On the assumption of common tastes see Stigler and Becker (1977).

[10] These techniques are described in more detail in the next section.

1 mm increase in annual precipitation for each of 60 countries. Building on his earlier work, Maddison (2003) analyses household expenditures for 88 countries once more using data from the International Comparisons Project. This time however he uses the Quadratic Almost Ideal Demand System and calculates the CS for a climate change scenario associated with a doubling of carbon dioxide equivalent concentrations.

But although climate variables demonstrably help explain cross-country variation in per capita expenditure patterns there are serious concerns with the existing literature. Whilst the International Comparisons Project uses consistently defined expenditure categories it cannot realistically be assumed that people in different countries share identical tastes and technologies. Maddison's analyses also fail to account for differences in the demographic composition of households, which are probably a much more important determinant of household expenditure than climate.[11] And cross-country differences in demographic composition are likely to be profound. Maddison also uses nationally averaged data from large, climatically diverse countries. Amongst other things this involves creating for each country a population-weighted 'average' climate. Finally, surveys undertaken as part of the International Comparisons Project might not reflect year-round consumer expenditures and might be affected by one-off macroeconomic factors or atypical weather conditions.

The empirical analysis described in this paper uses repeated cross-sectional data from Japan. It does not suffer from any of the aforementioned shortcomings (i.e. including people with potentially different tastes and technologies, absent controls for demographic composition of the household, errors in the measurement of climate and using data from a single, potentially atypical year). It therefore provides a decidedly superior test of whether household production function theory has any empirical content. And it yields for the first time an estimate of the value of climate to Japanese households.

4 Extending systems of demand equations to reflect the role of environmental goods

The household production function approach employs techniques identical to those used to account for differences in the demographic composition of households in systems of demand equations (see Pollak and Wales 1981).

The advantage of using these techniques is that first, they make very clear the implied household production function technology and second, they can be used in conjunction with well established systems of demand whose limitations are already well understood. We discuss one such technique called 'demographic scaling'.[12, 13]

In demographic scaling the prices of marketed goods are scaled according to the level of environmental nonmarket goods. Scaling replaces the original system of demand equations

$$q_i = q_i(p_1, p_2, \ldots, y) \tag{1}$$

Where q is the quantity of commodity i, the p's are prices, y is income and $q_i(\bullet)$ is the Marshallian demand function, by

$$q_i = m_i q_i(p_1 m_1, p_2 m_2, \ldots, y) \tag{2}$$

[11] In fact he analyses per capita expenditures rather than household expenditures.

[12] For an example of an environmental valuation study which does not use demographic scaling see Shapiro and Smith (1981).

[13] We note that scaling is not the only way of pooling data from households with a different demographic composition.

Where the m's are scaling functions whose value is given by

$$m_i = 1 + \sum \delta_{ij} z_j \tag{3}$$

Where z_j represents one of j measures of environmental quality and δ_{ij} are parameters. This corresponds to the direct utility function

$$u = u(q_1/m_1, q_2/m_2, \ldots) \tag{4}$$

Where u is household utility. Demographic scaling therefore, describes a situation in which a change in the quantity of nonmarket environmental goods results in a proportionate change in the level of the service flow associated with that commodity. When the z_j refer not to the levels of nonmarket environmental goods but instead to the numbers of additional adults and children in the household, the scaling function is often interpreted in terms of 'adult equivalents' and the m's are referred to as commodity specific scales (Barten 1964).

A simple case is one in which the all of the commodity specific scales m are identical

$$m_1 = m_2 = \ldots = m \tag{5}$$

Where m contains details regarding the demographic composition of the household it is often referred to as the Engel scale.[14] Whereas commodity specific scales require some relative price variation, Engel scales can be identified even in the absence of price variation. The equivalence scale for a household with environmental quality z^1 relative to a household with environmental quality z^0 is given by

$$\frac{m(z^1)}{m(z^0)} \tag{6}$$

In what follows we calculate Engel equivalence scales for Japanese households with different numbers of individuals inhabiting different climatic zones.

5 Data

Household expenditure data are taken from the Household Expenditure Survey (HES) conducted by the Japanese Ministry of Internal Affairs and Communications (MIAC).[15] The HES is a nationwide survey of approximately 9,000 households, conducted on a monthly basis and collecting expenditure data for 10 categories of expenditures (see Tables 1 and 2). We use annual data from 2000 to 2009 for 47 prefectural capital cities, and annual data from 2008 to 2009 for another 4 large cities (Kawasaki, Hamamatsu, Sakai, and Kitakyushu). Observations represent average expenditure shares (s) for each commodity category i for each city. The HES also contains information on the average number of persons (PERSON) in each household.

Price data are obtained from the Consumer Price Index (CPI) database. This database provides an annual price index (p) for each prefecture for each category of expenditure. But to account for regional differences in base prices we further adjust these indices using data from the 2005 National Survey of Prices (NSP) conducted every 5 years by the MIAC. Because price data are available only at the level of the prefecture prices for four cities

[14] This relates to Engel's claim that a comparison of the money income of households of different size but with the same food share would yield a household equivalence scale (Engel 1895).

[15] Expenditure and price data used for analysis are all downloaded at http://www.e-stat.go.jp.

Table 1 Marketed commodity definitions

Commodity	Definition
Food	Food and drink
Housing	Rents, repairs and maintenance
Utility	Fuel, lighting and water
Furniture	Furniture and household utensils
Clothing	Clothing and footwear
Medical	Medical goods
Transport	Transport and communications
Education	Education
Recreation	Reading material and recreation
Miscellaneous	Miscellaneous

See text

(Kawasaki, Hamamatsu, Sakai, and Kitakyushu) are identical to those of the capital cities of the same prefecture. The price for each commodity (averaged over the entire country) in 2005 is set at 100.

Table 2 The data

Variable	Mean	Std. Dev.	Min.	Max.
S_{Food}	0.2274822	0.0169606	0.1672028	0.280174
$S_{Housing}$	0.082	0.0213399	0.034587	0.1672298
$S_{Utility}$	0.0691227	0.0091723	0.0477486	0.1102496
$S_{Furniture}$	0.03156	0.0053582	0.0209012	0.0880581
$S_{Clothing}$	0.0462165	0.0067474	0.027613	0.07161
$S_{Medical}$	0.0387165	0.0056967	0.0233006	0.06014
$S_{Transport}$	0.1236708	0.0193109	0.0799011	0.2828076
$S_{Education}$	0.032498	0.0079035	0.0127734	0.0588525
$S_{Recreation}$	0.1069505	0.0130747	0.0765576	0.1800075
$S_{Miscellaneous}$	0.241783	0.0307833	0.1584583	0.4388694
P_{Food}	99.58866	2.856619	93.99015	108.6211
$P_{Housing}$	91.47299	14.2919	66.16905	151.2386
$P_{Utility}$	100.3825	6.090368	86.28955	125.7363
$P_{Furniture}$	106.6447	11.03946	83.24025	147.2177
$P_{Clothing}$	97.85642	10.74903	57.05212	130.318
$P_{Medical}$	99.67389	1.69173	95.32054	105.7439
$P_{Transport}$	98.54667	2.961194	92.19762	110.2093
$P_{Education}$	94.26401	7.78037	76.98318	115.4926
$P_{Recreation}$	102.406	5.32742	91.95471	118.0698
$P_{Miscellaneous}$	96.83266	4.333254	84.84776	105.9442
PERSON	2.402814	0.2474093	1.8	3.4
TEMP (°C)	14.58224	2.216319	8.226666	22.42
PREC (mm)	1627.989	422.3395	938.3	2592.603

See text

Climate data are from the Japan Meteorological Agency.[16] These data represent the 1961–1990 annual average temperature (TEMP) and precipitation (PREC) from meteorological stations located within each city. Four cities (Saitama, Otsu, Kawasaki, and Kitakyushu) do not have meteorological stations and records from the nearest available stations are used instead for these cities.[17]

6 Empirical analysis

Before analysing the data, it is first necessary to select a particular system of demand. In order to observe the extent to which different models of consumer demand might result in different estimates of the scaling function we choose two very different systems of demand. For the purposes of comparison each of these models is estimated with and without a common scaling function for location k given by

$$m_k = 1 + \delta_1 PERSON_k + \delta_2 TEMP_k + \delta_3 PREC_k \tag{7}$$

Note that we do not include city-specific dummy variables. This is because the purpose of the paper is to examine whether it is possible to explain regional heterogeneity by reference to the climate and not to absorb all city-specific heterogeneity. It is also not possible to estimate commodity specific scaling functions because this would involve too many parameters. Fitting commodity specific scaling functions furthermore requires relative price variation for the purposes of identification.[18]

The Linear Expenditure System (LES) of Stone (1954) is in share form

$$s_i = \frac{p_i \gamma_i}{y} + \beta_i \left(1 - \frac{\sum p_i \gamma_i}{y} \right) \tag{8}$$

Where s_i refers to the share of commodity bundle i and γ_i and β_i (interpreted as subsistence requirements for commodity i and the proportion of supernumerary expenditure spent on commodity i respectively) are parameters to be estimated. In addition

$$\sum_i \beta_i = 1 \tag{9}$$

Fitting the LES involves estimating only 2n-1 parameters where n is the number of commodities.[19] The theoretical requirements of symmetry, homogeneity and adding up are all automatically satisfied.

Model 1 sets the parameters of the scaling function equal to zero. The parameters of the LES are well determined but the model fails to explain much variation in expenditure shares. Here and elsewhere the parameters of the demand system are presented in an Appendix

[16] Data are downloaded at http://www.data.jma.go.jp/obd/stats/data/en/smp/index.html.

[17] We use meteorological data from Kumagaya which is 40 km from Saitama; Hikone which is 55 km from Otsu; Yokohama which is neighbouring Kawasaki; and Iizuka which is 40 km from Kitakyushu.

[18] Although Japanese HES data does exhibit relative price variation this is insufficient to identify separate commodity scales. Maddison (2001a, b) solves the problem of too many parameters by aggregating the data into four expenditure categories thereby enabling him to estimate separate equivalence scales for each commodity. But the process of aggregation obscures the precise role of climate just as much as estimating a single commodity scale does.

[19] For this reason in what follows β_{10} is not separately estimated. It is customary to estimate demand equations in share form in order to combat heteroscedasticity.

because they are voluminous and not the main focus of the paper. Note that standard errors assume clustering at the level of the city.

Model 2 allows the parameters of the scaling function to vary. The estimated parameters of the scaling function are displayed in Table 3. The coefficients on PERSON and TEMP are both statistically significant at the 1 % level of confidence. The more people there are in the household the higher the household's cost of living whereas higher average annual temperature has the opposite effect. Higher annual precipitation has no statistically significant effect, not even at the 10 % level of confidence.

Next we present results from a more flexible demand system containing many more parameters. In the Almost Ideal Demand System (AIDS) of Deaton and Muellbauer (1980) the commodity share equations are given by

$$s_i = \alpha_i + \sum \gamma_{ij} \log p_j + \beta_i \log(y/P) \tag{10}$$

Where

$$\sum \alpha = 1 \tag{11}$$

$$\sum \beta = 0 \tag{12}$$

$$\sum_i \gamma_{ij} = \sum_j \gamma_{ij} = 0 \tag{13}$$

$$\gamma_{ij} = \gamma_{ji} \tag{14}$$

As before α, β and now γ are parameters to be estimated. The aggregate price index P is given by[20]

$$\log P = \alpha_0 + \sum_i \alpha_i \log p_i + \frac{1}{2} \sum_i \sum_j \gamma_{ij} \log p_i \log p_j \tag{15}$$

Unlike in the LES symmetry and homogeneity may be explicitly tested in the AIDS model.[21]

Model 3 estimates the AIDS model setting the parameters of the scaling function equal to zero and ignoring the theoretical restrictions imposed by symmetry and homogeneity.[22] The parameters of the demand system are presented in the Appendix. Model 4 imposes the theoretical restrictions imposed by symmetry and homogeneity. Once more the parameters of the demand system are presented in the Appendix. A Likelihood Ratio test suggests that the theoretical restrictions of symmetry and homogeneity are not valid. This finding is very common in the literature.[23]

[20] Here as in many other studies the price index is approximated.

[21] The Japanese HES data has been analysed before by Asano (1997) and Asano and Fukushima (2006) both of whom used the AIDS model.

[22] As expected the AIDS offers a much improved fit to the data. This is the finding of many other papers that have compared the LES and the AIDS models of consumer demand.

[23] It is not possible to test whether the Hicksian matrix of compensated price elasticities is negative semi definite but this can be assessed by examining the eigenvalues of the matrix.

Table 3 Scaling parameters

	Model 2	Model 5	Difference
PERSON	0.5301221*** (5.74)	0.5745269*** (5.52)	−0.0444048
TEMP	−0.0251642*** (−5.72)	−0.0204463*** (−4.32)	0.0047179
PRECIP	0.0000258 (0.91)	0.0000295 (0.92)	−0.0000037

See text. Note that *** means statistically significant at the 1 % level of confidence; ** means statistically significant at the 5 % level of confidence; and \ast means statistically significant at the 10 % level of confidence

Model 5 imposes symmetry and homogeneity and allows the parameters of the common scaling function to vary. The parameters of the scaling function indicate that the main determinant of the household's cost of living is once more the number of persons in the household. And yet again higher annual average temperature has a beneficial impact on the cost of living that is statistically significant at the 1 % level of confidence. But although the statistical significance of temperature is high the impact of the higher annual mean temperature on the cost of living is nevertheless relatively small.

It is interesting that the two different systems of demand (the LES and AIDS) do not provide dramatically different estimates of the parameters of the common scaling function (see Table 3).

Finally in this section we ask to what extent the addition of a common scale improves the ability of the system of demand equation to explain the variation in the demand for marketed commodities.

Table 4 displays the R^2 statistics for the AIDS model (imposing symmetry and homogeneity) first without (Model 4) and then with the common scale (Model 5). There is a substantial improvement in the fit of some of the commodity share equations particularly for spending on fuel, water and lighting. But overall the overall fit of many of the share equations remains quite poor. This indicates that the AIDS model is not wholly adequate or that the assumption of common tastes and technologies is not valid or that important environmental goods have been omitted from the model, or something else.

Table 4 Goodness of fit

	Model 4	Model 5
S_{Food}	0.5112	0.6253
$S_{Housing}$	0.1567	0.0780
$S_{Utility}$	0.3424	0.6513
$S_{Furniture}$	0.0803	0.0825
$S_{Clothing}$	0.2465	0.2305
$S_{Medical}$	0.1810	0.2235
$S_{Transport}$	0.1523	0.2134
$S_{Education}$	0.2347	0.1481
$S_{Recreation}$	0.2718	0.3291
$S_{Miscellaneous}$		

See text

7 Discussion

This section further explores the relationship between climate and the cost of living in Japan. In this section we present econometric estimates of the scaling function for a range of alternative specifications using the AIDS model with symmetry and homogeneity imposed.[24]

First we investigate whether at some point households find higher annual average temperatures increase rather than decrease the cost of living. Model 6 therefore includes temperature squared as an additional scaling variable. Temperature is demeaned by subtracting long run nationally averaged temperature $\overline{TEMP}$ before it is squared in order to reduce multicollinearity. The scaling function is thus

$$m_k = 1 + \delta_1 PERSON_k + \delta_2 TEMP_k + \delta_3 \left(TEMP_k - \overline{TEMP}\right)^2 + \delta_4 PREC_k \tag{16}$$

The results shown in Table 5 indicate that temperature squared is not statistically significant at the 10 % level of confidence. This is not to deny the existence of a point at which higher annual average temperatures start to increase rather than reduce the costs of living. It may be that any turning point lies outside the range of annual average temperatures encountered within Japan and as such cannot be identified.

Model 7 considers the possibility that the variability of temperatures is also an important determinant of the household's cost of living. Model 7 therefore replaces annual average temperature with the expected number of degree-days for each location.[25] More specifically the variable DD_k represents average annual degree days measured over a period of 5 years (1826 days).[26]

$$DD_k = \frac{\left(\sum_{t=1}^{t=1826} ABS(TEMP_{tk} - 65)\right)}{5} \tag{17}$$

The scaling function for model 7 is

$$m_k = 1 + \delta_1 PERSON_k + \delta_2 DD_k + \delta_3 PREC_k \tag{18}$$

The econometric estimates for model 7 suggest that degree days are not statistically significant even at the 10 % level of confidence. This may be because the base temperature of 65°F is not appropriate, because the data refer only to 5 year averages instead of the more customary 30 year averages, because the concept of degree days is not appropriate or some other reason.

Model 8 includes in the scaling function nine dummy variables (DUM01-DUM09) each denoting a different year. These variables account for technological progress in households' production functions but they also absorb any inter-annual variation in the cost of living caused by atypical weather conditions or macroeconomic disturbances. The scaling function is

$$\begin{aligned} m_k = 1 &+ \delta_1 PERSON_k + \delta_2 TEMP_k + \delta_3 PREC_k + \delta_4 DUM01 + \delta_5 DUM02 + \delta_6 DUM03 \\ &+ \delta_7 DUM04 + \delta_8 DUM05 + \delta_9 DUM06 + \delta_{10} DUM07 + \delta_{11} DUM08 + \delta_{12} DUM09 \end{aligned} \tag{19}$$

[24] The results for the AIDS model without symmetry and homogeneity imposed are very similar.

[25] Information on degree days is taken from http://www.degreedays.com.

[26] Most analyses employ as we do, 30-year averages for climate but data from http://www.degreedays.com goes back only 5 years.

Table 5 Scaling parameters

	Model 6	Model 7	Model 8
PERSON	0.8990408*** (4.50)	1.166491*** (3.18)	0.6662847*** (4.51)
TEMP	−0.0324456*** (−6.27)		−0.022744*** (−4.56)
PRECIP	0.0000273 (0.65)	0.0000328 (0.45)	0.0000391 (1.06)
$(\text{TEMP-TEMP})^2$	−0.0041023 (−1.92)		
DEGREEDAYS		0.0001142 (1.16)	
DUM01			−0.0125534 (−0.76)
DUM02			0.0318989 (1.14)
DUM03			0.0536639 (1.58)
DUM04			0.0736079 (1.69)
DUM05			0.0679291 (1.49)
DUM06			0.1062695* (1.82)
DUM07			0.0753258 (1.27)
DUM08			0.1255019 (1.79)
DUM09			0.1715247** (2.10)

See text. Note that *** means statistically significant at the 1 % level of confidence; ** means statistically significant at the 5 % level of confidence; and * means statistically significant at the 10 % level of confidence

One of the year dummies is statistically significant at the 5 % level of confidence. Another dummy is statistically significant at the 10 % level of confidence. But both the number of persons present in the household and annual mean temperature remains statistically significant at the 1 % level of confidence. And neither does the magnitude of any of the coefficients change.

We now use the results of Model 5 to estimate the extent to which households' cost of living differs between different cities in Japan. The climate equivalence scales displayed in Fig. 1 use the climate of Tokyo as a base (see Appendix 4 for a complete listing). Darker colours indicate higher costs of living due to the climate. Note carefully that the geographical differences in the cost of living shown in Fig. 1 reflect only differences in the climate. Even greater differences occur because of geographical differences in prices but these are suppressed in both Fig. 1 and Appendix 4. For example, the price index for Tokyo for 2009 is 108.2 whilst the price index for Naha is 93.0. These are respectively the most expensive and the cheapest cities in Japan. The price index for Sapporo, the coldest city, is 99.3. Combining the price index and the climate equivalence scale together indicates that the overall cost of living in Naha is 0.809 whilst in Sapporo it is 0.979. The place with the highest overall cost of living is Tokyo with an overall cost of living index of 1.000. Even if its climate is not as cold as other cities further north this is not enough to overturn the fact that in Tokyo prices are very high. Finally, the cost of living index for a three person household in Tokyo compared to a two person household is 1.306 which points to significant economies of scale in living arrangements.

Last of all we turn our attention to the potential impact of climate change on Japanese households suggested by this exercise. According to the Japanese Ministry of the Environment by 2100 annual mean temperatures will increase by 2.1–4.0 °C whereas precipitation will increase by around 5 %. These estimates are based on the IPCC's A2, A1B, and B1 emissions scenarios (A2 is the highest and B1 the lowest). Combining these climate change scenarios with

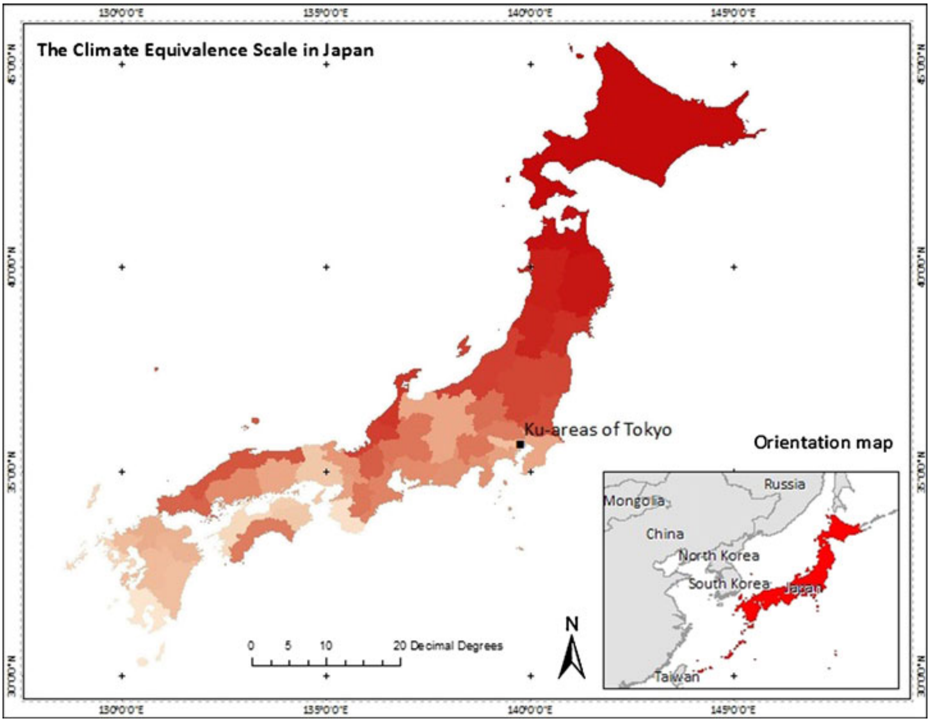

Fig. 1 Climate equivalence scales for Japan

results from Model 5 suggests that climate change may result in a slight reduction in the cost of living. The climate equivalence scale for Tokyo for example falls from 1.000 to between 0.980 and 0.962 depending on the precise climate change scenario. Note however that, particularly for the southern most cities such estimates involve prediction outside the range of average mean temperatures currently experienced by Japan.[27] And once again these estimates refer only to the 'direct' impact of climate change on Japanese households.

8 Conclusion

Compared to alternative valuation techniques the household production function methodology offers both advantages and disadvantages. Unlike the hedonic technique it does not assume a nationally unified market in land and labour. And unlike analyses based on the spatial variation in subjective wellbeing it does not assume that different individuals use the identical same function for mapping utility onto an integer scale. The household production function technique's chief limitation is the non-testable assumption of demand dependency.

We use repeated cross-sectional data on household commodity expenditures from 51 Japanese cities to estimate climate equivalence scales using the household production function methodology. Our results indicate that higher annual average temperatures are

[27] Source: http://www.env.go.jp/earth/ondanka/rep091009/pamph_full.pdf

associated with a small but statistically highly significant reduction in households' cost of living. By contrast, precipitation does not appear significantly to affect the cost of living. Our results are unaffected by the choice of two popular but very different systems of demand. Neither are they affected by the inclusion of time dummies.

Combining our estimates of the impact of temperature and precipitation on the cost of living with IPCC climate change scenarios suggests a small reduction in the cost of living. But because they do not account for the indirect impacts of climate change such estimates do not provide a comprehensive account of the impact of climate change on Japanese society. In particular, there may be additional impacts arising from changes in prices or changes in household incomes. These are impacts not included in the foregoing analysis.

Future analyses should endeavour to obtain data on household expenditures from households in more extreme climates in order to identify better the impact of climate on the cost of living. At the same time it is important to include, where possible, a wider range of climate variables as well as non-climate geographical variables. Should data with sufficient price variation be available another obvious step would be to estimate commodity specific equivalence scales.

Appendix

Table 6 LES models

	Model 1 Coefficient (Z-statistic)	Model 2 Coefficient (Z-statistic)
γ1	290.2903 (11.47)	149.7763 (5.76)
γ2	142.7235 (3.53)	26.83411 (1.02)
γ3	107.5634 (7.45)	81.23322 (6.60)
γ4	14.01085 (2.67)	8.897586 (2.86)
γ5	13.24078 (1.55)	8.549464 (1.38)
γ6	43.34672 (5.33)	22.69661 (4.91)
γ7	−59.07475 (−1.90)	−67.98703 (−2.57)
γ8	−4.098496 (−0.31)	17.09272 (2.42)
γ9	−24.11557 (−1.08)	−46.5604 (−3.50)
γ10	−229.6767 (−2.15)	−111.6541 (−1.65)
β1	0.1291895 (13.21)	0.1227787 (8.98)
β2	0.035174 (2.38)	0.0680832 (4.02)
β3	0.0303375 (5.73)	0.0077566 (1.78)
β4	0.029022 (9.78)	0.026146 (11.63)
β5	0.0464297 (13.56)	0.0428116 (8.25)
β6	0.0246357 (6.14)	0.0231308 (6.58)
β7	0.1650218 (13.99)	0.1870283 (13.26)
β8	0.0383526 (7.46)	0.0217954 (3.78)
β9	0.1313919 (11.04)	0.1534316 (11.66)

See text

Table 7 AIDS models

	Model 3 Coefficient (Z-statistic)	Model 4 Coefficient (Z-statistic)	Model 5 Coefficient (Z-statistic)
α1	0.8318402 (2.18)	1.044739 (10.48)	1.229908 (13.23)
α2	0.0337627 (0.06)	0.5686559 (3.04)	0.0187876 (0.09)
α3	0.602629 (1.73)	0.1962303 (3.21)	0.5379053 (8.99)
α4	0.0187468 (0.14)	0.0469519 (1.35)	0.0856397 (2.92)
α5	−0.1401684 (−0.72)	0.0333797 (0.74)	0.0167893 (0.46)
α6	0.4413313 (2.53)	0.1045721 (2.59)	0.1740774 (6.01)
α7	0.55387 (1.08)	−0.1248597 (−0.99)	−0.3601871 (−2.66)
α8	−0.3272966 (−1.35)	−0.147098 (−2.81)	0.0542872 (1.07)
α9	0.1157041 (0.29)	0.081727 (0.82)	−0.1407331 (−1.61)
β1	−0.0994576 (−7.74)	−0.1035015 (−8.19)	−0.1402724 (−11.95)
β2	−0.0532592 (−2.59)	−0.061878 (−2.62)	0.0088665 (0.29)
β3	−0.0181556 (−2.14)	−0.0162753 (−2.11)	−0.0659449 (−8.41)
β4	−0.0035411 (−0.84)	−0.0021001 (−0.47)	−0.00775 (−1.89)
β5	0.0034007 (0.64)	0.0016221 (0.28)	0.0041092 (0.79)
β6	−0.0094008 (−1.97)	−0.0080887 (−1.57)	−0.01868 (−4.65)
β7	0.0310741 (2.05)	0.0321313 (2.01)	0.0685058 (3.63)
β8	0.0258515 (4.05)	0.0230171 (3.45)	−0.0029032 (−0.41)
β9	0.0064174 (0.55)	0.0039207 (0.31)	0.0355986 (2.91)
γ10	0.0649024 (1.74)		
γ11	0.0694668 (1.62)	−0.0162959 (−0.59)	−0.0110152 (−0.30)
γ12	0.0188938 (1.35)	0.0316741 (2.79)	0.0327838 (3.22)
γ13	−0.0473854 (−2.10)	−0.0339433 (−3.09)	−0.0380756 (−3.90)
γ14	0.0157162 (0.93)	0.020098 (2.37)	0.0217394 (2.37)
γ15	−0.0225707 (−1.52)	−0.0256329 (−2.38)	−0.0147688 (−1.59)
γ16	−0.117343 (−2.26)	−0.0588132 (−5.09)	−0.0648828 (−5.18)
γ17	0.0304154 (0.60)	0.0139007 (0.48)	−0.0049687 (−0.16)
γ18	0.0061252 (0.26)	0.0026153 (0.22)	0.0193433 (1.29)
γ19	0.0210318 (0.56)	0.0078984 (0.56)	−0.0062854 (−0.44)
γ20	−0.0782061 (−1.32)		
γ21	−0.016229 (−0.23)		
γ22	0.015668 (0.64)	0.0322817 (1.32)	0.0282643 (1.06)
γ23	−0.0047751 (−0.12)	0.0023599 (0.33)	0.0039287 (0.72)
γ24	0.0351199 (1.30)	−0.0115596 (−3.63)	−0.0117424 (−3.83)
γ25	−0.0251842 (−0.84)	0.0069863 (1.78)	0.0073083 (1.81)
γ26	0.001627 (0.02)	−0.0004178 (−0.10)	−0.0001662 (−0.04)
γ27	0.2012398 (2.80)	0.0129969 (0.81)	0.0134218 (0.92)
γ28	0.0125732 (0.44)	0.0040101 (0.82)	0.0066426 (1.21)
γ29	−0.0402127 (−0.67)	0.0381376 (5.16)	0.0352866 (5.18)
γ30	−0.0574649 (−2.79)		
γ31	0.0273417 (0.82)		
γ32	0.0039487 (0.41)		
γ33	0.0418494 (2.64)	0.0628735 (6.12)	0.0496201 (4.98)
γ34	−0.0066428 (−0.69)	−0.0038892 (−0.98)	−0.0059797 (−1.60)

Table 7 (continued)

	Model 3 Coefficient (Z-statistic)	Model 4 Coefficient (Z-statistic)	Model 5 Coefficient (Z-statistic)
γ35	0.005818 (0.73)	−0.013135 (−3.19)	−0.0085104 (−2.10)
γ36	−0.0122185 (−0.27)	0.0118594 (2.27)	0.0097154 (1.84)
γ37	−0.0278481 (−0.78)	0.0379159 (2.60)	0.0390203 (2.75)
γ38	−0.0203188 (−1.23)	−0.0178034 (−2.95)	−0.0183574 (−3.27)
γ39	−0.0396866 (−1.78)	−0.0236273 (−3.42)	−0.0202934 (−3.02)
γ40	−0.0031134 (−0.30)		
γ41	0.0135252 (1.10)		
γ42	−0.0086471 (−2.54)		
γ43	−0.001886 (−0.25)		
γ44	−0.00665 (−1.30)	0.0023488 (0.57)	0.0026527 (06.8)
γ45	0.0093635 (2.12)	0.0083054 (3.22)	0.009451 (3.52)
γ46	0.021843 (1.14)	−0.0066752 (−1.62)	−0.0071774 (−1.73)
γ47	−0.0272954 (−2.12)	−0.0161779 (−1.75)	−0.0191066 (−1.94)
γ48	−0.0061606 (−0.95)	−0.0017816 (−0.46)	−0.0011415 (−0.28)
γ49	0.0175561 (1.81)	0.0017814 (0.26)	0.0013682 (0.22)
γ50	0.0135618 (1.10)		
γ51	−0.0357189 (−1.88)		
γ52	0.0027939 (0.55)		
γ53	−0.0037138 (−0.45)		
γ54	−0.0018344 (−0.27)		
γ55	0.0072921 (1.25)	0.0137508 (3.99)	0.0148486 (4.05)
γ56	−0.015881 (−0.57)	−0.0030218 (−0.76)	−0.0024088 (−0.59)
γ57	0.0113637 (0.42)	−0.0026963 (−0.30)	−0.0124383 (−1.28)
γ58	0.0025592 (0.28)	−0.0097364 (−1.87)	−0.0074568 (−1.47)
γ59	0.054231 (3.22)	0.0136508 (2.24)	0.0098027 (1.66)
γ60	0.0084644 (0.56)		
γ61	−0.0394364 (−2.48)		
γ62	0.0010929 (0.25)		
γ63	0.0021961 (0.30)		
γ64	−0.0139025 (−2.17)		
γ65	0.0057975 (1.29)		
γ66	−0.003438 (−0.20)	0.0242918 (1.71)	0.0227606 (1.64)
γ67	−0.018483 (−0.86)	0.0219022 (1.19)	0.0249508 (1.31)
γ68	0.0077391 (0.82)	0.0055215 (0.67)	0.0063271 (0.71)
γ69	−0.0209975 (−1.85)	−0.0237568 (−3.27)	−0.022938 (−3.24)
γ70	0.0755765 (2.25)		
γ71	−0.0914399 (−1.85)		
γ72	0.0157743 (1.02)		
γ73	0.0487516 (1.93)		
γ74	−0.0428197 (−2.44)		
γ75	−0.0095155 (−0.79)		
γ76	−0.0382413 (−0.54)		
γ77	−0.1400733 (−2.66)	−0.1143007 (−2.25)	−0.0901137 (−1.69)

Table 7 (continued)

	Model 3 Coefficient (Z-statistic)	Model 4 Coefficient (Z-statistic)	Model 5 Coefficient (Z-statistic)
γ78	0.0329957 (1.41)	0.0048133 (0.26)	−0.0096573 (−0.45)
γ79	0.0037113 (0.09)	−0.0358631 (−2.18)	−0.0223213 (−1.30)
γ80	0.0124987 (0.93)		
γ81	0.0268576 (0.96)		
γ82	−0.002436 (−0.43)		
γ83	−0.0155253 (−1.65)		
γ84	0.0138002 (1.51)		
γ85	−0.0206476 (−3.49)		
γ86	−0.0359357 (−1.20)		
γ87	0.0301919 (1.33)		
γ88	0.0324404 (2.73)	0.0293627 (3.20)	0.0257923 (2.26)
γ89	−0.0069565 (−0.34)	0.0035083 (0.43)	0.004917 (0.56)
γ90	0.0685391 (2.62)		
γ91	−0.0326104 (−0.97)		
γ92	0.0368416 (3.47)		
γ93	−0.0043717 (−0.26)		
γ94	−0.0147928 (−0.98)		
γ95	−0.0081262 (−0.74)		
γ96	−0.0844835 (−1.46)		
γ97	−0.0219366 (−0.50)		
γ98	0.0209796 (1.09)		
γ99	0.0285128 (0.87)	−0.0223313 (−1.42)	−0.0213009 (−1.51)

See text

Table 8 More AIDS models

	Model 6 Coefficient (Z-statistic)	Model 7 Coefficient (Z-statistic)	Model 8 Coefficient (Z-statistic)
α1	1.101702 (13.37)	1.121826 (12.33)	0.9706328 (12.06)
α2	0.0916689 (0.45)	−0.2383186 (−1.60)	−0.183355 (−1.48)
α3	0.4630853 (8.95)	0.5396137 (9.82)	0.4415478 (9.35)
α4	0.0720713 (2.74)	0.0977546 (3.96)	0.0893086 (4.59)
α5	0.0198962 (0.61)	0.0356379 (1.03)	0.0417485 (1.47)
α6	0.1519412(5.70)	0.1704851 (7.05)	0.1418664 (7.53)
α7	−0.2917845 (−2.64)	−0.3614749 (−2.88)	−0.2838003 (−2.99)
α8	0.0482979 (1.11)	0.1081263 (2.18)	0.0842077 (2.11)
α9	−0.1025272 (−1.37)	−0.1442084 (−1.82)	−0.1171005 (−1.80)
β1	−0.1362677 (−11.98)	−0.1295208 (−10.58)	−0.1242541 (−10.95)
β2	−0.0015403 (−0.05)	0.0465773 (2.15)	0.044542 (2.14)
β3	−0.061785 (−8.00)	−0.0685405 (−9.63)	−0.0627475 (−9.59)
β4	−0.0065106 (−1.57)	−0.0097836 (−2.73)	−0.0098873 (−2.97)

Table 8 (continued)

	Model 6 Coefficient (Z-statistic)	Model 7 Coefficient (Z-statistic)	Model 8 Coefficient (Z-statistic)
β5	0.0040922 (0.80)	0.0015251 (0.30)	0.0007464 (0.16)
β6	−0.0173556 (−4.34)	−0.0188194 (−5.38)	−0.0169507 (−5.70)
β7	0.0656603 (3.70)	0.0710896 (3.92)	0.0691028 (4.32)
β8	−0.0022895 (−0.33)	−0.0108409 (−1.50)	−0.0084973 (−1.28)
β9	0.0336905 (2.86)	0.0373635 (3.31)	0.0386185 (3.75)
γ10			
γ11	−0.0102799 (−0.28)	−0.0139846 (−0.35)	−0.0265037 (−0.71)
γ12	0.036775 (3.54)	0.0304042 (3.04)	0.0419244 (3.63)
γ13	−0.038221 (−3.93)	−0.0282923 (−2.90)	−0.0223933 (−2.21)
γ14	0.020423 (2.22)	0.0221282 (2.41)	0.021426 (2.60)
γ15	−0.0138017 (−1.57)	−0.0219792 (−196)	−0.0263852 (−2.35)
γ16	−0.0637423 (−5.14)	−0.0647997 (−4.91)	−0.0600719 (−4.75)
γ17	−0.0135086 (−0.44)	0.0096945 (0.30)	0.0156757 (0.54)
γ18	0.0157986 (1.09)	0.0222882 (1.43)	0.0179362 (1.19)
γ19	−0.0043985 (−0.30)	−0.0066469 (−0.46)	−0.0051747 (−0.39)
γ20			
γ21			
γ22	0.0296249 (0.45)	0.0270323 (1.04)	0.0252326 (0.97)
γ23	0.005515 (0.96)	0.0036702 (0.80)	0.009824 (1.81)
γ24	−0.0117045 (−3.82)	−0.0118611 (−4.05)	−0.010782 (−3.79)
γ25	0.0074735 (1.87)	0.0064693 (1.54)	0.0066357 (1.56)
γ26	0.0002376 (0.06)	−0.0000879 (−0.02)	0.0016232 (0.44)
γ27	0.0098729 (0.68)	0.0164548 (1.12)	0.0071104 (0.47)
γ28	0.0062809 (1.16)	0.0065066 (1.14)	0.0071259 (1.31)
γ29	0.0344982 (5.04)	0.0357715 (5.16)	0.0324086 (4.51)
γ30			
γ31			
γ32			
γ33	0.0501544 (4.86)	0.0536697 (5.45)	0.0594901 (6.31)
γ34	−0.006242 (−1.66)	−0.0054955 (−1.58)	−0.0046846 (−1.30)
γ35	−0.0084306 (−2.07)	−0.0100253 (−2.29)	−0.0109168 (−2.38)
γ36	0.0097696 (1.86)	0.0115112 (2.12)	0.0134365 (2.48)
γ37	0.0364404 (2.59)	0.03624 (2.69)	0.0279416 (1.78)
γ38	−0.0196663 (−3.24)	−0.0173941 (−3.34)	−0.0184939 (−3.27)
γ39	−0.0200324 (−2.97)	−0.0225809 (−3.40)	−0.0238083 (−3.39)
γ40			
γ41			
γ42			
γ43			
γ44	0.0023686 (0.60)	0.0025844 (0.67)	0.0027596 (0.65)
γ45	0.0093477 (3.48)	0.0093093 (3.52)	0.0090564 (3.54)
γ46	−0.0072212 (−1.76)	−0.0070035 (−1.68)	−0.0064974 (−1.54)
γ47	−0.0181442 (−1.85)	−0.0194914 (−1.98)	−0.0201363 (−2.01)

Table 8 (continued)

	Model 6 Coefficient (Z-statistic)	Model 7 Coefficient (Z-statistic)	Model 8 Coefficient (Z-statistic)
γ48	−0.0014482 (−0.36)	−0.0002144(−0.05)	−0.0005409 (−0.13)
γ49	0.0018664 (0.29)	0.0014224 (0.22)	0.0014208 (0.22)
γ50			
γ51			
γ52			
γ53			
γ54			
γ55	0.0149611 (4.01)	0.0144987 (4.12)	0.0140043 (4.11)
γ56	−0.0021984 (−0.55)	−0.003464 (−0.84)	−0.0032877 (−0.81)
γ57	−0.0136443 (−1.44)	−0.0073114 (−0.69)	−0.0043543 (−0.41)
γ58	−0.0077822 (−1.54)	−0.0065779 (−1.27)	−0.0073634 (−1.42)
γ59	0.0100356 (1.68)	0.0111956 (1.94)	0.0120598 (2.14)
γ60			
γ61			
γ62			
γ63			
γ64			
γ65			
γ66	0.0227431 (1.64)	0.0226429 (1.63)	0.0233831 (1.68)
γ67	0.0234335 (1.24)	0.0263163 (1.39)	0.0211146 (1.12)
γ68	0.0060397 (0.68)	0.0061987 (0.69)	0.0061922 (0.69)
γ69	−0.0230194 (−3.27)	−0.0233384 (−3.24)	−0.0242623 (−3.38)
γ70			
γ71			
γ72			
γ73			
γ74			
γ75			
γ76			
γ77	−0.0768968 (−1.46)	−0.1059527 (−2.10)	−0.1000888 (−1.96)
γ78	−0.0064268 (−0.31)	−0.0146736 (−0.67)	−0.0099457 (−0.46)
γ79	−0.0234514 (−1.35)	−0.0234363 (−1.38)	−0.0239902 (−1.44)
γ80			
γ81			
γ82			
γ83			
γ84			
γ85			
γ86			
γ87			
γ88	0.0257991 (2.26)	0.0272998 (2.29)	0.0259728 (2.24)
γ89	0.0057824 (0.66)	0.0037514 (0.42)	0.0042138 (0.50)
γ90			

Table 8 (continued)

	Model 6 Coefficient (Z-statistic)	Model 7 Coefficient (Z-statistic)	Model 8 Coefficient (Z-statistic)
γ91			
γ92			
γ93			
γ94			
γ95			
γ96			
γ97			
γ98			
γ99	−0.0217599 (−1.53)	−0.0215343 (−1.50)	−0.0214631 (−1.54)

See text

Table 9 Climate equivalence scales for Japan

City	Climate equivalence scale
Akita	1.048
Aomori	1.056
Chiba	1.003
Fukui	1.028
Fukuoka	0.996
Fukushima	1.024
Gifu	1.011
Hamamatsu	1.005
Hiroshima	1.007
Kagoshima	0.992
Kanazawa	1.031
Kawasaki	1.003
Kitakyushu	1.009
Kobe	0.999
Kochi	1.009
Kofu	1.011
Ku-areas of Tokyo	1.000
Kumamoto	1.001
Kyoto	1.005
Maebashi	1.012
Matsue	1.019
Matsuyama	0.996
Mito	1.021
Miyazaki	1.000
Morioka	1.054
Nagano	1.033
Nagasaki	0.997

Table 9 (continued)

City	Climate equivalence scale
Nagoya	1.007
Naha	0.942
Nara	1.011
Niigata	1.028
Oita	1.002
Okayama	1.003
Osaka	0.992
Otsu	1.017
Saga	1.001
Saitama	1.009
Sakai	1.017
Sapporo	1.067
Sendai	1.032
Shizuoka	1.008
Takamatsu	0.998
Tokushima	0.999
Tottori	1.019
Toyama	1.033
Tsu	1.008
Utsunomiya	1.024
Wakayama	0.994
Yamagata	1.038
Yamaguchi	1.014
Yokohama	1.006

See text. Note that these equivalence scales employ the climate of Tokyo as a base

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