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RESEARCH ARTICLE

Effects of Affluence on Rising Household Carbon Emission in the Philippines: An Application Using Quantile Regression Approach

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Abstract: This study investigates whether rising affluence affects carbon emission differently by considering the distribution of households based on the level of emission. Whereas there are several empirical studies that examine this issue with mean based regression approach, limited studies have investigated the effect of affluence on the quantiles of household emission controlling for several household characteristics. Employing the methods of quantile regression, results show that rising affluence affects household emission differently. The effect is more pronounced among households in the upper emission quantile as compared to households in the lower emission quantile. This suggests that an increase in income translates to higher increase in emission among households with relatively higher level of emission compared to households with lower level of emission. With this, policy makers should take caution in devising policies mitigating climate change by capping emission because the distributional implications of such policies will vary depending on how carbon intensive the household consumption is.

Keywords: household emission, quantile regression, socio-economic factors, elasticities

JEL classification: D57, Q40, Q56, R20

Households directly or indirectly contribute to the surging increase in carbon emission by consuming various goods and services. Girod and De Haan (2010) stated that households exert an important influence on total greenhouse gas (GHG) emission and that their consumption behavior is of interest in evaluations of climate policy options and projections of future emission paths. According to Bin and Dowlatabadi (2005), lifestyle is a way of living that influences and is reflected by one's consumption behavior. In their study using the consumer lifestyle approach, they revealed that, in the United States, more than 80% of the energy used and the carbon dioxide emitted are a consequence of consumer demands. In the United Kingdom, households contribute roughly more than 70% to total emission (Baiocchi, Minx, & Hubacek, 2010). For the Philippines, limited information is available on household emission. Seriño (2015) reported that household emission in the Philippines appears to be increasing in level and there is worsening emission inequality. However, households' emission level in the Philippines may not be as alarming as compared to the households in the developed countries (Seriño & Klasen, 2015). This study will provide further information at the household level which will be relevant and necessary in mitigating climate change.

Consumption patterns and household emission differ due to differences in characteristics. However, information on household emission from developing countries is relatively limited. Hence, this study attempts to fill that gap in the literature by investigating household carbon emission, particularly from a developing country's perspective. In particular, my interests lay in evaluating the distributional effect of income on emission which is mostly overlooked in the literature. Most of the available studies in the literature used mean based regression in investigating the determinants of carbon emission (Baiocchi et al., 2010; Golley& Meng, 2012; Büchs & Schnepf, 2013). While such approach provides information on the effect of income on emission, it cannot capture the effect of income on the quantiles of household emission. Does rising income affect differently carbon emission for households with lower emission than those with higher emission? Hence for this study, I used quantile regression to capture such effect. This approach will have an important implication in formulating policies related to mitigating climate change. In addition, quantile regression can better handle outliers because it is not regressing through the mean of the distribution but rather through the quantiles of the distribution, thereby reducing potential bias in the estimates.

In the Philippines, there is currently no representative data set that captures household emission. Hence, I first attempted to estimate the embodied carbon emission from household consumption. To do this, I combined input–output table and household expenditure survey. Seriño and Klasen (2015) did a detailed estimation of household carbon footprint in the Philippines and I used their results for this study. The quantile regression results show that rising income affects households differently. An increase in income translates to higher increase in emission for households who have higher levels of emission as compared to households who have lower levels of emission. This shows that households in the upper emission quantile tend to emit more as income increases as compared to households in the lower emission quantile. Other household characteristics also matter in explaining the variation in household carbon emission. In addition, the elasticity analysis shows which household consumption will increase (or decrease) in emission as income increases. Given the current economic situation in the Philippines, this might be an opportunity for policy makers to devise policies that will promote a low carbon consumption path for Philippine households and my paper provides a step towards that direction by investigating the effect of income on the quantiles of household emission.

Literature Review

Most of the studies available in the literature on household carbon emission are usually concentrated in developed countries. For example, Kenny and Gray (2009), using a model for Irish households, found out that the average annual household emission comprises 42.2% related to home energy use, 35.1% to transport, 20.6% to air travel and other fuel intensive leisure activities, and just 2.1% associated with household waste disposal. Druckman and Jackson (2009) took into account all CO_2 emissions that arise from energy used in production of goods and services to satisfy UK household demand. Results show that in 2004, CO_2 emission attributable to households were 15% above the 1990 levels and that recreation and leisure are responsible for over one quarter of CO_2 emission in a typical UK household in 2004. Girod and De Haan (2010) found out in their study that the most important consumption categories, which together amount to nearly 70% of total greenhouse gas emission were living (shelter), car driving, and food. A study by Parikh, Panda, & Murthy (1997) in India showed that 62% of the total emission was due to private consumption, 12% from direct consumption by households and the remaining 50% due to indirect consumption of intermediates. The rich are consuming carbon intensive products like electricity, transport, and used relatively more resources in the form of minerals and metal products. In China, rapid urbanization has driven up the share of indirect energy consumption, suggesting that the economy is transitioning from a production dominated economy to a consumption dominated economy (Zhang, Hu, & Zhang, 2014). Urbanization has been documented as one of the major determinant of increases in China's carbon emission (Wang and Yang, 2014; Yuan, Ren, & Chen, 2015).

One of the challenges in investigating household emission is the availability of data. Several authors (Kok, Benders, & Moll, 2006; Minx et al., 2009; Büchs & Schnepf, 2013) provided a comprehensive review on the use of input–output in estimating carbon emission.

Lenzen (1998) used input–output derived carbon intensities and household expenditure in calculating the Australian household carbon footprints. He found out that most of the greenhouse gas emissions attributable to Australians are ultimately caused by households' purchase of goods and services from industries and the present increase in emission can be strongly correlated to income growth.

The method of input–output analysis have been used quite often in accounting for the embodied emission in household consumption (Parikh et al., 1997; Lenzen, 1998; Bin & Dowlatabadi, 2005; Kok et al., 2006; Baiocchi et al., 2010) but this approach can be challenged on several grounds. Baiocchi et al. (2010) outlined some salient grounds where the estimation of carbon emission using input–output can be criticized. However, due to lack of other good alternatives, still researchers rely on input–output analysis combined with household expenditure in estimating household carbon emission.

Aside from estimating household emission, several studies have investigated the determinants of household emission. Income plays a significant role in explaining the variation in household emission and all studies conclude that emission increases with income (Büchs & Schnepf, 2013). For example in India, Parikh et al. (1997) revealed that the consumption of the rich households is oriented towards energy intensive sectors. In another study by Lenzen et al. (2006), they focused on the importance of income growth in a cross country analysis and tried to search for evidence on the Environmental Kuznets Curve (EKC). The EKC hypothesis proposes an inverted U-shaped relationship between per capita income and environmental degradation. Environmental degradation is expected to worsen in the early stages of growth, but eventually it will reach a peak and decrease as income exceeds a certain level. However, they found out that the data does not support the environmental Kuznets curve. Household energy requirements increase monotonically with household expenditure and no turning point was observed by Lenzen et al. (2006). Kerkhof, Benders, & Moll (2009) evaluated the determinants of variation in household carbon emission across four countries and they found out that high-income households have less carbon intensive consumption patterns than low-income households in the Netherlands and UK. On the contrary, in Sweden and Norway the consumption patterns of rich households are more carbon intensive than low-income households. In the UK, papers by Baiocchi et al. (2010) and Büchs and Schnepf (2013) showed that household emission increases with income. In China, Golley and Meng (2012) confirmed positive relationship between emission and income and found an increasing marginal propensity to emit over relevant income range. Seriño (2014) also documented a positive relationship between household carbon emission and income when disaggregating emission across income distribution. My current study will add to this strand of literature by documenting that while it is true that household emission increases as income increases, the increase differs relatively between households with low level of emission and high level of emission. This study hypothesizes that there is an inherent difference across household groups and that the distributional implications of increasing income is disregarded when we regress through the mean. Quantile regression will document this by exploring the differences in emission across household groups.

Methodology

Data and Estimation of Household Carbon Emission

To estimate the carbon emission embodied in household consumption, I used the concept of input–output analysis combined with household expenditure. This method is widely used in the literature (Parikh et al., 1997; Pachauri & Spreng, 2002; Lenzen et al., 2006; Kerkhof et al., 2009; Baiocchi et al., 2010). To carry out the estimation, I used the following data sets: (1) Philippine Input–Output (IO) table for year 2000, (2) the carbon emission coefficient from Global Trade Analysis Project (GTAP), and (3) the list of household consumption taken from Family Income and Expenditure Survey (FIES) for year 2000 and 2006.

I estimated the total carbon emission embodied in household consumption on various goods and services for year 2000 and 2006. First, I combined (i) the Philippine input–output (IO) table for 2000, (ii) the carbon emission intensity for different goods from the Global Trade Analysis Project (GTAP). The input–output table has 240 disaggregated sectors while GTAP has only 57 sectors. Thus, I need to map out the sectors in GTAP to accommodate all the sectors from our IO table. By applying the mechanism of input–output table, we can derive the carbon intensity of a given output in a sector by tracing the associated carbon emission of all the inputs used in the production (Parikh et al., 1997; Lenzen, 1998; Bin and Dowlatabadi, 2005; Kok & et al., 2006; Baiocchi et al., 2010; Golley & Meng, 2012). Correspondingly, the carbon intensities can be estimated as follows:

$$CIj = c' (I - A)^{-1}y \quad (1)$$

where CIj is the carbon intensity of each economic sector in the input–output table and c is a vector of carbon coefficients taken from the Global Trade Analysis Project (GTAP) (Lee, 2008). A is the technical coefficients, (I-A)-1 is known as the Leontief inverse, and y is the vector of final demand for commodities.

Then in the second step, I matched these derived carbon intensities with the consumption categories (Expi) listed in the household survey expenditure. Summing up all the individual emission from several expenditures, I derived the estimated household carbon emission (CO_{2hh}).

$$CO_{2hh} = \sum CI_j * Exp_i \quad (2)$$

Based on my estimation, the carbon emissions of Philippine households in 2000 were on average 1.5 tons of CO_2 per household and this amount increased to 1.9 tons in 2006. Seriño and Klasen (2015) provided a detailed discussion on the estimation of Philippine household carbon emission. However, this method of estimating household emission by combining IO table with household expenditure can be challenged on several grounds (Baiocchi et al., 2010; Büchs & Schnepf, 2013). But because of limited availability of good alternatives, this method is still widely used in the literature (Parikh et al., 1997; Pachauri & Spreng, 2002; Lenzen et al., 2006; Kerkhof et al., 2009; Baiocchi et al., 2010; Golley & Meng, 2012).

Estimation Using Quantile Regression

After estimating the embodied carbon emission in household consumption, I employed the methods of quantile regression to analyze the effect of rising income and other socio-economic characteristics on household carbon emission. The quantile regression model was first introduced by Koenker and Bassett (1978) as an alternative to the conventional least square estimator. The major advantage of using quantile regression over ordinary least square (OLS) is that quantile regression does not rely on the mean of the distribution. OLS regression provides an estimate of the effect of explanatory variables on the mean of the dependent variable assuming that it follows normality assumption. OLS estimation is prone to distortions in the presence of an outlier. However, in the context of quantile regression, extreme values will not distort the estimation since the analysis is based on the median. This implies that quantile regression helps preserve efficiency (Buchinsky, 1994). In addition, quantile regression provides different estimates at different quantiles, which means that we can evaluate the effect of independent variables across the quantiles of the dependent variables. This is a big advantage of quantile regression over other regressions since the distribution can be dissected into desired number of parts. If we suspect that the effect of independent variables varies across the distribution, quantile regression will capture these varying effects. In this study, I assumed that the effect of an increase in income varies across the distribution of household emission. An increase in income among households with low level of emission may translate to a different change in emission as compared to households with higher level of emission.

Given these aforementioned advantages, quantile regression is gaining popularity in empirical analysis. However despite these advantages, few studies applied quantile regression in analyzing emission. To the best of my knowledge, this is the first study that attempts to employ quantile regression on household carbon emission. Most of the studies that evaluated the effect of household income and other socio-demographic characteristics of households employed mean-based regression (e.g. Lenzen et al., 2006; Baiocchi et al., 2010; Golley & Meng, 2012; Büchs & Schnepf, 2013).

The main specification of quantile regression in investigating the effect of income on household emission controlling for other household characteristics is as follows:

$$hhCO_2 = f(\textit{income, age, gender, marital status, members, education, location, electricity, dwelling, year, regions}) \quad (3)$$

where $hhCO_2$ denotes the log values of household carbon emission measured in tons of CO_2, income captures the log of total income of households as a measure of affluence, age refers to the age of household head, gender is a dummy variable whether the household head is a male or female, marital status is a dummy variable whether a particular person is married, single, separated or widowed, members captures the household size, education represents the educational attainment of household head, location represents urban or rural location, electricity is a dummy variable for access to electricity, and dwelling captures how big is the house measured in floor size. I also included as controls the dummy variables for different regions in the Philippines[1] and time variations represented by year.

Based on equation 3, I can specify the quantile regression as follows:

$$emit_i = \mathbf{X}_i\beta_\theta + \varepsilon_{\theta i}\ ,\ \ Quant_\theta(emit_i|\mathbf{X}_i) = \mathbf{X}_i\beta_\theta \qquad (4)$$

where $Quant_\theta(Emit_i|\mathbf{X}_i) = X_i\beta_\theta$ denotes the θth conditional quantile of household carbon emission (emit), X is the set of independent variables which include income and other household characteristics, and ε_i is the usual disturbance term.[2] This specification aimed to analyze the effect of an increase in income in the specified quantile of carbon emission. To capture this effect, I deliberately chose five quantiles (θ = 0.10, 0.25, 0.50, 0.75, 0.90) to cover all parts of the distribution. The lowest quantile is θ = 0.10 representing the 10th part of the distribution, θ = 0.50 is the median while θ = 0.90 representing the highest quantile of household carbon emission or the 90th part of the emission distribution. I estimated a vector of coefficients, β_θ, for each of the specified quantiles of the model specified above.

Emission Elasticity

As household income increases, it is interesting to identify which household consumption will increase. This will have implications as to which emission sources will increase. I used the concept of elasticity to analyze the percentage change in emission from a particular household consumption item as income increases. That is,

$$se_{ij} = \alpha + \eta_{ij} ln(inc)_i + \gamma_{ij} X_i + \varepsilon_{ij} \qquad (5)$$

where se_{ij} represents the share of emission from a particular j_{th} consumption item to total household emission by the i_{th} household, *ln(inc)* is the log of household income, *X* is the control variables, a vector of household characteristics, and ε is the error term. I am interested in the coefficient η_{ij}. This captures the percentage change in emission from a particular consumption item as income change by a percentage point.

Results and Discussions

Figure 1 shows the scatter plot between income and household carbon emission. I provided a scatter plot smoothing by using nonparametric estimation of the relationship between income and emission. Results

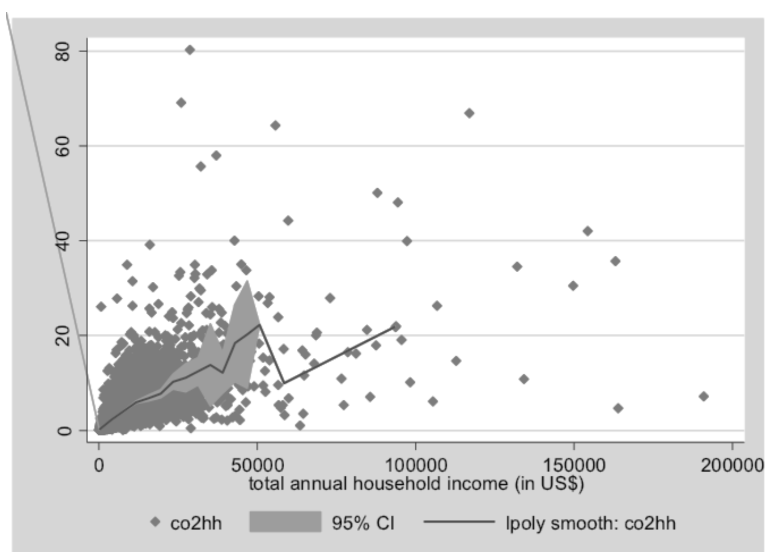

Figure 1. Scatter plot of household carbon emission and income.

show that household emission increases as income increases. This positive association is more pronounced in the lower income bracket while a fluctuating trend is observed in the upper income bracket. This kink in the observation could be driven by few observations. Most households are located below US$50,000 annual income where I documented a solid increasing trend of carbon emission as income increases. This kind of skewed distribution and presence of outliers gives a good rationale that applying quantile regression is valid in this case. While mean based regression is still helpful, nevertheless quantile regression can give more useful information on the effect of rising income on the different quantiles of household emission.

Determinants of Household Carbon Emission

The estimation results of quantile regression are presented in Table 1. I also included the result from mean based regression or the ordinary least square (OLS) regression for comparison. The dependent variable is the log of household carbon emission. I investigated the effect of rising income on carbon emission across quantiles controlling for other household characteristics. Emission and income variables are in logarithmic form, hence, the coefficients can be interpreted as elasticities. Results show that income has a positive significant relationship with household emission both using OLS and quantile regression. This implies that as households get richer, the carbon emission embodied in households' consumption will also increase, holding other factors constant. The OLS estimate and the coefficients of the 25th quantile are relatively similar but OLS result is quite different from the other quantile estimates. The OLS model underestimates the effect of income on the other quantiles of household emission more specifically among households with high level of emission.

Looking at the quantile regression, the magnitude of coefficients differs significantly across quantiles. For example, a 1% percent increase in income in the lowest quantile translates to a 0.765% increase in emission while a percentage increase in income in the upper quantile increases household carbon emission by 0.824%. There is a gradual increase in coefficient estimate as we move along the quantiles of carbon emission. The effect of an increase in household income is more pronounce among households who are emitting more. This means that an increase in income among households who have a carbon intensive consumption is associated with higher increase in total emission as compared to households who have relatively lower carbon emission. The result is plausible because households in the lowest quantile spend much of their income satisfying their daily food needs while those in the upper quantile tend to consume more on energy intensive goods translating into a higher carbon emission.

Figure 2 presents the comparison of quantile coefficients with OLS result and confidence interval included. The regression coefficient at a given

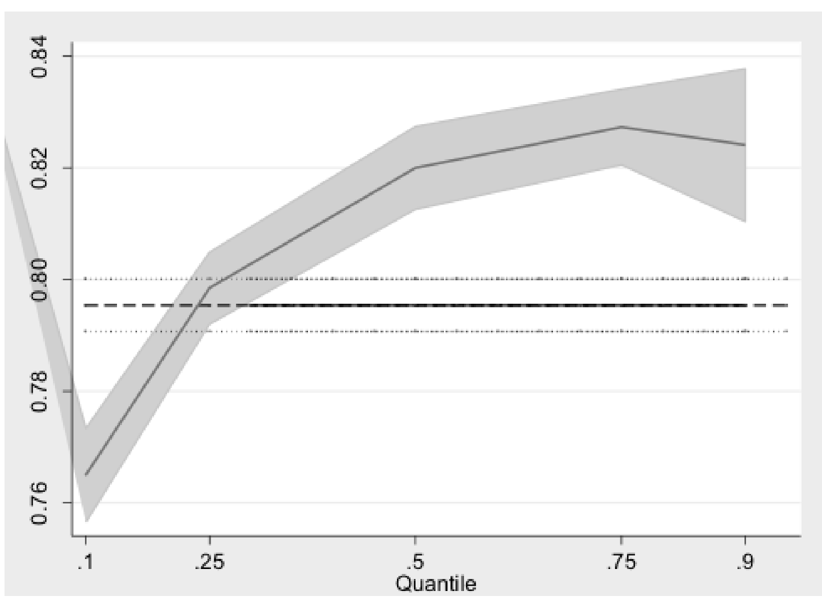

Figure 2. OLS, quantile coefficients and confidence interval of household carbon emission.

Table 1. *Determinants of Household Carbon Emission Using Quantile Regression*

VARIABLES	OLS	q10	q25	q50	q75	q90
log income	0.795***	0.765***	0.798***	0.820***	0.827***	0.824***
	(0.0024)	(0.0043)	(0.0033)	(0.0038)	(0.0034)	(0.0070)
age	0.005***	0.004***	0.004***	0.005***	0.005***	0.005***
	(0.0006)	(0.0014)	(0.0009)	(0.0008)	(0.0007)	(0.0009)
age_squar	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
male	-0.044***	-0.032***	-0.035***	-0.038***	-0.041***	-0.046***
	(0.0048)	(0.0089)	(0.0048)	(0.0052)	(0.0068)	(0.0107)
married	0.047***	0.063***	0.059***	0.040***	0.034**	0.023
	(0.0078)	(0.0098)	(0.0088)	(0.0096)	(0.0143)	(0.0195)
widow/separated	0.013	0.037***	0.024***	0.004	0.006	-0.004
	(0.0081)	(0.0142)	(0.0088)	(0.0081)	(0.0119)	(0.0179)
household size	0.137***	0.184***	0.152***	0.127***	0.104***	0.087***
	(0.0050)	(0.0088)	(0.0063)	(0.0055)	(0.0071)	(0.0109)
household size_sq	-0.017***	-0.022***	-0.018***	-0.016***	-0.014***	-0.011***
	(0.0008)	(0.0013)	(0.0010)	(0.0008)	(0.0011)	(0.0016)
household size_cubic	0.001***	0.001***	0.001***	0.001***	0.001***	0.000***
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
elementary	0.025***	0.032***	0.027***	0.029***	0.016	0.011
	(0.0071)	(0.0099)	(0.0089)	(0.0084)	(0.0122)	(0.0177)
highschool	0.101***	0.102***	0.093***	0.102***	0.090***	0.087***
	(0.0075)	(0.0128)	(0.0106)	(0.0099)	(0.0143)	(0.0197)
college	0.155***	0.174***	0.154***	0.149***	0.132***	0.126***
	(0.0080)	(0.0139)	(0.0100)	(0.0098)	(0.0137)	(0.0209)
urban	0.127***	0.119***	0.126***	0.127***	0.125***	0.117***
	(0.0031)	(0.0054)	(0.0047)	(0.0041)	(0.0044)	(0.0063)
electricity	0.533***	0.507***	0.503***	0.516***	0.540***	0.567***
	(0.0037)	(0.0052)	(0.0044)	(0.0040)	(0.0052)	(0.0064)
floor size	0.047***	0.046***	0.042***	0.039***	0.042***	0.047***
	(0.0020)	(0.0040)	(0.0024)	(0.0023)	(0.0027)	(0.0041)
year 2006	0.212***	0.202***	0.192***	0.184***	0.196***	0.211***
	(0.0056)	(0.0085)	(0.0054)	(0.0062)	(0.0072)	(0.0116)
regional dummies	YES	YES	YES	YES	YES	YES
R-squared	0.873					
Pseudo R-squared		0.6385	0.6536	0.6617	0.6502	0.6331

Note: Number of observations across quantiles is 76,242.
Standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

quantile indicates the effect on household emission of a unit change in household income with 95% confidence interval, controlling for other household characteristics. According to the OLS model, a percentage change in household income is associated with a .795% change in household emission. The straight line in Figure 2 represents the OLS estimate. The quantile regression results indicate that the effect of rising income on the lower quantiles of household emission has a smaller effect as compared to the upper quantiles of household emission. This reiterates my argument that OLS model underestimated the effect of rising income starting at the 50th quantile. Using only mean based regression will fail to capture the distributional effect of income on household carbon emission.

While there is no doubt income is the main determinant of household carbon emission, other household characteristics such as age, location, education, household size also matter in explaining the variation in household emission. Table 1 shows that control variables in both OLS and quantile regression behave similarly. Looking at the controls, we observe that age has a nonlinear effect on carbon emission. This captures the changing consumption pattern of households, as they get older. As households get older, demand for goods and services increases, thereby driving carbon emission to rise and later on decline as households reach old age. With regards to gender, results show that male-headed households have lower carbon emission compared to female headed households. While this may seem odd, this is somehow reasonable in Philippines setting because, in general, husbands tend to focus more on working while wives handle the household expenditure. But somehow this merits further investigation and is beyond the scope of the current study.

Being married is associated with higher carbon emission as compared to being single. Household size is an important factor in explaining household emission. Several studies have included household size in their analysis and reported that it has a nonlinear effect because there are economies of scale (Lenzen et al., 2006; Druckman & Jackson, 2008; Golley & Meng, 2012b; Büchs & Schnepf, 2013). Similarly, the results showed nonlinear effect. I document a cubic relationship that is consistent in both OLS and quantile regression. This nonlinear effect captures the economy of scale within the household implying that members do share resources. With regards to the effect of education on carbon emission, results show that household with better education is associated with higher carbon emission. Lenzen et al. (2006) also reported positive effect of education to emission in Brazil and India. They argued that for these countries, education is a privilege for the rich group. This could also explain the situation in the Philippines wherein those who were able to attain higher education are relatively well off.

The location of households also has a significant effect on carbon emission. Households situated in urban areas emit more than households in the rural areas. This is particularly driven by the consumption of energy intensive goods such as fuel, light, and transportation which is more readily available and accessible in urban areas than in rural areas. This result is in contrast with Büchs and Schnepf (2013) where, in the UK, households from rural areas posted higher emission than from those in the urban areas. This is plausible because rural households from developed countries have greater car dependency for transport. But this situation is different in rural Philippines where households have less access to car transport and electricity as compared to those in the cities. In addition, I also include as additional control access to electricity and floor size. Holding other factors constant, results show that households who have access to electricity have higher carbon emission than those who do not have and similarly bigger floor area is associated with higher carbon emission. I also control for geographic differences among households and included in the regression regional dummies.[3] The results for regional dummies highlight that there are differences in emissions across regions. Regions with relatively higher income as reflected by its gross regional domestic product posted higher emission on average.

Emission Elasticity

To capture the effect of a percentage change in income to emission sources, I used the concept of elasticity. I conducted the analysis for the whole sample and, in addition, split the sample in different parts and analyze the change in emission by consumption category as income increases. I disaggregated the households by group. Group 1 represents the poorest 20% of the households, group 2 represents the middle 20% of the households, and group 3 represents the richest 20% of the households. By dividing the households into groups, we can investigate the differences in emissions across income groups when affluence will increase. The dependent variable is the share of emission from a particular household consumption item to the total emission and the main determinant is household income controlling for other household characteristics. Table 2 provides information as to which emission sources will increase or decrease as households' income increases.

Considering the whole sample, results show that as income increases, emission from food related consumption declines. On one hand, I observed a decline in emission from household operation, personal care, nondurable goods, and fuel and light as income increases. On the other hand, emission mostly from

Table 2. *Emission Elasticity of Household Consumption Category*

	All		Poorest 20%		Middle		Richest 20%	
Consumption Category	**coef**	**se**	**coef**	**se**	**coef**	**se**	**coef**	**se**
Cereals & rootcrops	-0.468***	(0.0031)	-0.312***	(0.0125)	-0.550***	(0.0305)	-0.423***	(0.0108)
Vegetables & fruits	-0.292***	(0.0038)	-0.213***	(0.0190)	-0.302***	(0.0392)	-0.248***	(0.0117)
Meat and Dairy	-0.019***	(0.0043)	0.252***	(0.0242)	0.105***	(0.0406)	-0.222***	(0.0114)
Fish & marine goods	-0.378***	(0.0040)	-0.094***	(0.0171)	-0.485***	(0.0401)	-0.380***	(0.0128)
Beverages & tobacco	-0.198***	(0.0053)	0.242***	(0.0271)	-0.269***	(0.0506)	-0.251***	(0.0161)
Other food	-0.426***	(0.0035)	-0.141***	(0.0152)	-0.518***	(0.0324)	-0.378***	(0.0117)
Water	-0.209***	(0.0074)	-0.206***	(0.0509)	-0.100	(0.0848)	-0.203***	(0.0172)
Fuel & light	-0.005*	(0.0030)	-0.240***	(0.0152)	0.106***	(0.0332)	-0.005	(0.0079)
Transportation	0.122***	(0.0055)	0.106***	(0.0255)	0.160***	(0.0595)	-0.013	(0.0159)
Communication	0.501***	(0.0099)	0.098	(0.1190)	0.746***	(0.1165)	0.324***	(0.0179)
Household operation	-0.187***	(0.0055)	-0.377***	(0.0164)	-0.373***	(0.0428)	0.082***	(0.0235)
Personal care	-0.066***	(0.0038)	0.154***	(0.0214)	-0.142***	(0.0336)	-0.143***	(0.0115)
Clothing	0.182***	(0.0066)	0.268***	(0.0346)	0.101	(0.0682)	0.125***	(0.0179)
Education	0.201***	(0.0092)	-0.181***	(0.0387)	-0.059	(0.0796)	0.294***	(0.0306)
Medical care	0.297***	(0.0110)	-0.046	(0.0494)	0.265**	(0.1109)	0.368***	(0.0344)
Recreation	0.061***	(0.0156)	-0.211	(0.1391)	0.106	(0.1873)	0.176***	(0.0310)
Nondurable goods	-0.134***	(0.0125)	-0.178***	(0.0688)	-0.334***	(0.1136)	0.139***	(0.0366)
Durable goods	0.156***	(0.0215)	0.002	(0.2625)	0.443**	(0.2041)	0.175***	(0.0495)
Repair & maintenance	0.108***	(0.0252)	-0.139	(0.1263)	0.060	(0.2675)	0.015	(0.0699)
Other expenditure	0.090***	(0.0127)	-0.804***	(0.2240)	-0.159	(0.1266)	-0.035	(0.0256)

Note: The number of households included in the analysis is 76,242.
Standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

services including emission from transportation, clothing, and durable goods increases as income increases. While some of these observations hold true, there are specific differences observed between the poorest 20% and richest 20% of the households. Take for example, the decline in emission from cereals and root crops consumption is more pronounced in the richest group than in the poorest group. Increase in emission mostly coming from services including education, recreation, and medical care are higher for households in the richest group as compared to the poorest group.

Conclusion

This paper gives particular attention to the effect of rising household affluence across different quantiles of household emission. I employed the methods of input–output analysis in extracting carbon emission from household consumption and use the methods of quantile regression to untangle the effect of rising income between households with lower emission and higher emission. Results show that income as key determinants of household carbon emission affects households differently. An increase in income will translate to higher increase in emission from households who have relatively higher emission as compared to households with lower emission. This means that households who have already high levels of emission are more likely to emit more as income increases compared to households who have lower levels of emission. While it is convenient for policy makers to device policies across the board, they should consider distributional issue in devising policies aimed at lowering carbon emission. In addition, while income is the main determinant of emissions, households' socio-demographic characteristics such as age, gender, marital status, household size, educational attainment, location, and access to energy matter in explaining household emission. This suggests that in designing mitigating measures in curbing emission, household characteristics should also be considered.

Notes

1 Philippines is divided into 16 different regions.

2 The distribution of the error term is left unspecified since the quantile regression is a non-parametric approach (Koenker & Bassett, 1978).

3 Results are not presented here to save space but are available upon request.

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