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Do Philippine Households Lead a Carbon Intensive Lifestyle?

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Abstract

This paper estimates carbon emission from household consumption and investigates its determinants. We derive total household carbon emission by using the mechanism of input-output analysis combine with household expenditure for 2005 and 2006. Our estimation shows that fuel and light followed by transportation are the most carbon intensive goods while nondurable goods are the least carbon intensive. After controlling for household characteristics, the analyses reveal that income has a significant nonlinear relationship with carbon emission depicting an inverted U-shaped. However, when using asset index as proxy for households' economic status, no turning point is observed and emission increases as households accumulate more assets. Quintile estimates show that there is a huge disparity in emission between households from the poorest quintile and richest quintile. With this, an option for low-carbon consumption is deemed necessary; else it is imminent that households tend to lead a carbon intensive lifestyle as they get more affluent.

Key words: carbon emission, household consumption, income quintiles, input-output

JEL classifications: Q56, R15, R20, D12

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1. Introduction

The Philippines, being one of the countries who ratified the convention on climate change, is required to report its national greenhouse gas inventory as stipulated by the IPCC guidelines (UNFCC, 2013; IPCC, 2013a). Data from World Bank shows that the total emission in the Philippines jumped almost 10 times from its level in 1960 (WDI, 2014). In 2010, the average emission per capita in Philippines amounts to 0.82 tons much lower than OECD which stood at 10.41 tons per capita (IEA, 2013). However, the recent surging increase in carbon emission is largely driven by the rising volume from developing countries. Consequently from 2008 onwards, the aggregate emission coming from developing countries surpassed those of the industrialized countries (IEA, 2013). The new report on Intergovernmental Panel on Climate Change (IPCC) concludes that human influence on the climate system is very clear (IPCC, 2013b). However, less has been known on the household side. Households directly or indirectly contribute to the rise of CO_2 emission from the consumption of various goods and services. Girod and De Haan (2010) stated that households exert an important influence on total greenhouse gas emissions and that their consumption behavior is of interest in evaluations of climate policy options and projections of future emission paths.

Consumption behavior reflects household lifestyle which in turn influences total emission. According to Bin & Dowlatabadi (2005) in the US more than 80% of the energy used and the CO_2 emitted are a consequence of consumer demands while in UK, households contribute more than 70% to the total emission (Baiocchi et al., 2010). However, there is limited information that estimates and investigates household emission from developing countries. Much of the available studies in the literature were mostly evaluated from developed countries. Hence, we contribute to the existing literature by revealing information about household carbon emission from a developing country, particularly the Philippines. To the best of our knowledge, this is the first study focusing on the Philippines that attempts to estimate household emission and investigate its determinants. The Philippines is of particular interest because, being an archipelago, it is vulnerable to the adverse effects of climate change. Increases in sea level will affect low lying islands and will displace people. In addition being situated in the Pacific, it will have to endure the effects of stronger typhoons, flooding, drought and other climate disturbances. These would have tremendous effect in the Philippine economy where more than a quarter (26.5%) of its population live below poverty line (NSCB, 2009). With all these threats, the Philippines needs to be actively involved in mitigating climate change.

Our paper aims to shed some light on the contribution of households to the worsening concentration of green house gas emission. As households get more affluent, how does this influence carbon emission? There is quite an impressive literature on this issue and we hope to contribute to this strand of literature by bringing in perspective from developing countries. Results from other studies conclude that emissions rise with household income (e.g. Parikh et al., 1997; Weber and Matthews, 2008; Baiocchi et al., 2010; Büchs and Schnepf, 2013). Our study also confirms this result showing strong and robust evidence that income influences household carbon emission. As households move from lower income quintile to higher income quintile, this is associated with dramatic increase in carbon emission. This result is consistent in all specification. On the other hand, environmental Kuznets curve (EKC)[2] is only evident with income variable and no turning point observed when we used asset index in the analysis. Hence, we cannot confirm the robustness of the EKC hypothesis in this situation. This result is consistent with what was reported by Stern (2004), Lenzen et al. (2006), Yaguchi et al. (2007), and Galeotti et al. (2009) finding no or little evidence for the EKC hypothesis.

Result of our estimation shows that the Philippine households' carbon emission may still not be at an alarming level as compared to those households from developed countries. Then, why should we care? Perhaps the answer is straight forward that as more households are stepping up the economic ladder, household emission will increase at an enormous level and consequently the effect of that to the climate will be critical in the effort of mitigating climate change.

2. Literature Review

Living means consuming, and consuming requires producing consumer items which causes depletion of non-renewable energy resources and emissions of greenhouse gases (Lenzen, 1998). Hence, household consumption behavior exerts strong influence on total CO_2 emission[3] because by consuming goods and services, they contribute to the rising carbon emission. Hertwich & Peters (2009) quantify greenhouse gas emissions associated with the final consumption of goods and services for 73 nations and 14 aggregate world regions. They found that 72% of greenhouse gas emissions are related to household consumption, 10% to government consumption, and 18% to investments. On a household level, Girod & De Haan (2010) reported consumption categories which together amount to nearly 70% of total greenhouse gas emissions include living (shelter), car driving, and food. Also Kenny & Gray (2009) using a model Irish households found 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. A study by Parikh et al. (1997) in India showed that the rich are consuming carbon intensive products like electricity, transport and used relatively more resources in the form of minerals and metal products.

The key challenged in evaluating household carbon emission is the absence of data. To estimate the embodied emission from household consumption, the method of environmental input-output analysis combined with household expenditure has been widely used in the literature (e.g. Parikh et al., 1997; Lenzen, 1998; Weber and Perrels, 2000; Pachauri and Spreng, 2002; Bin and Dowlatabadi, 2005; Lenzen et al., 2006; Weber and Matthews, 2008; Kerkhof et al., 2009; Baiocchi et al., 2010). However this method is not immune to criticism (

[2] The environmental Kuznets curve (EKC) is a hypothesized relationship between various environmental pressured and income. For a given society, in the early stages of economic development environmental pollution increase reaches a maximum and then decline with further increase in income (Stern, 2004).
[3] CO_2 emission and carbon emission are used interchangeably in this paper.

see for example Baiocchi et al., 2010). But due to lack of other sound alternatives, this method is still commonly used in estimating household carbon emission. As Kenny & Gray (2009) stated, carbon emission models are increasingly being used to manage personal and household carbon dioxide emissions.

Lenzen (1998) used input-output derived carbon intensities in calculating the Australian household carbon emission. He found out that most of the greenhouse gas emissions attributable to Australians are ultimately caused by household purchases of goods and services and the present increase in emissions can be strongly correlated to income growth. In another study by Lenzen et al. (2006), they focus on the importance of income growth in a cross country analysis and tried to search for evidence on the EKC. The EKC hypothesis proposes an inverted U-shaped relationship between per capita income and environmental degradation. However, they found out that the data does not support the Kuznets curve. Household energy requirements increase monotonically with household expenditure and no turning point was observed (Lenzen et al., 2006). Yaguchi et al. (2007) also found out in a comparative study between China and Japan that EKC hypothesis only holds true with SO_2 emission but not with CO_2 emission. This finding on carbon emission is echoed by Golley and Meng (2012).

Kerkhof et al. (2009) evaluated the relationships between expenditures and the environmental impact of climate change by combining household expenditures with environmentally extended input– output analysis using data from the Netherlands. They found that environmental impact arising from consumption of goods and services increases with household expenditures. Several other studies have analyzed the effect of income on household emission (e.g. Lenzen et al., 2006; Druckman and Jackson, 2008; Baiocchi et al., 2010; Golley and Meng, 2012; Büchs and Schnepf, 2013). All of these studies confirmed a positive relationship between income and household emission.

Baiocchi et al., (2010) criticized that most input-output based lifestyle studies on household carbon emission are purely descriptive in nature and emphasized the importance of establishing the link between emission and households' socioeconomic factors. Recently, Büchs and Schnepf (2013)evaluated the association between socio-economic factors and UK households' carbon emission and found out that aside from income, other household characteristics also significantly influenced household emission. Considering household characteristics in understanding emission has distributional implication in mitigating policies towards climate change. In our paper, we offer a step towards this issue raised by Baiocchi et al. (2010) by investigating not just the influence of income on carbon emission but also including household characteristics particularly from a developing country's perspective which is mostly overlook in the literature.

3. Methodology

Households contribute to the surging increase in carbon emissions either directly or indirectly from consuming various goods and services. Direct emissions come from households' direct use of energy such as lighting, heating and fuel for transportation while indirect emissions take into account the embedded carbon emitted from the production of household goods like clothing, durables, toiletries and other household items (Weber and Perrels, 2000; Bin and Dowlatabadi, 2005; Kok et al., 2006).

A paper by Kok et al. (2006) highlighted three different methods of using input-output analysis in estimating embodied energy or emission namely: basic, expenditure and process approach. Basic approach uses national accounts, expenditure approach uses data from household consumption and process approach determines the emissions generated through the lifecycle of a product starting from production through to disposal. For practical purposes, we used expenditure approach in accounting the embeded carbon emission from households' consumption. This method has been widely used in the literature (e.g. Parikh et al., 1997; Pachauri and Spreng, 2002; Lenzen et al., 2006; Kerkhof et al., 2009; Baiocchi et al., 2010).

3.1. Estimation of household carbon footprint

Many authors have explored the mechanism of input-output analysis and extended it to investigate environmental issues. Minx et al. (2009) provides a comprehensive literature review on studies using input-output analysis in estimating carbon emissions[4]. The method of input-output was developed by Leontief in 1941 when he studied the relations between economic sectors. The main equation of the input-output analysis is as follows:

$$X = (I - A)^{-1} y \tag{1}$$

where X is the vector of total outputs, A is the technology matrix, I is the unit matrix, and y is the vector of final demand. Equation 1 is the fundamental representation of input-output analysis and the $(I - A)^{-1}$ matrix is generally known as the Leontief inverse matrix. Correspondingly, the carbon intensity (CI) of each economic sector can be computed as follows:

$$CI = c' (I - A)^{-1} y \tag{2}$$

where c is a vector of carbon coefficients taken from Global Trade Analysis Project (GTAP) (Lee, 2008). Mapping of the sectors has to be done for consistency of matrix operations. The carbon coefficients were coming from 57 sectors while the input-output table is 240x240 matrices. We follow the disaggregation method available in GTAP to map the carbon

[4] If readers are interested in an in depth understanding of using input-output analysis in computing carbon emission please refer to Minx et al. (2009) paper. Their paper includes comprehensive survey on papers using input-output analysis and carbon emission.

coefficients with the input-output table. The computation yields 240 CO_2 emission intensities measured in tons of CO_2 per thousand Philippine pesos.

The carbon emission of each consumption category was calculated by multiplying (i) the CO_2 emission intensity of each individual sector in the economy (*CI*) and (ii) the corresponding household expenditure category (*cons*). Then summing up all the carbon emission of each consumption categories yield the total carbon emission for every household, that is,

$$hhCO_{2i} = \Sigma_i^{\,j} (CI * cons^{hh}_{ij}) \tag{3}$$

where $cons^{hh}$ are the household consumption items, i represents the individual household and j the expenditure category. Then summing up all the carbon emission from each consumption categories yields the total carbon emission for every household ($hhCO_{2i}$). The household carbon emission is measured in tons of CO_2 per household.

3.2. Determinants of household carbon emission

Our main concern is to evaluate how households' carbon emission is affected as households get more affluent. Will an increase in income translates to a carbon intensive lifestyle? To evaluate the relationship between CO_2 emission and income while controlling for several relevant household characteristics, the following regression model is postulated as follows:

$$ln(hhCO_{2i}) = \alpha + \beta_1 ln(inc_i) + \gamma_i X_i + \varepsilon_i \tag{4}$$

where $ln(hhCO_{2i})$ is the log of household carbon emission, $ln(inc)$ is the log of household income or can also be represented with total household expenditures, X is a vector of control variables including age, sex, marital status, level of education, household size, household location whether in rural or urban areas, access to electricity, size of the dwelling place of different regions where households are located, and others household characteristics and ε_i is the usual disturbance term. Since we have two time periods of household survey used in this study, we run pooled regression analysis with a year dummy included in the control variables.

The main coefficient of interest is β_1. It captures how carbon emission changes as household income changes. We hypothesize based on previous studies that as household income increases, carbon emission will increase accordingly. To further analyze the effect of rising income on household carbon emission, we replaced the income variable with income quintiles. It looks into detail how carbon emissions behave across quintile, that is,

$$ln(hhCO_{2i}) = \alpha + \beta_1 Quint1_i + \ldots + \beta_5\, Quint5_i + \gamma_i X_i + \varepsilon_i \tag{5}$$

Since the income quintile is potentially correlated with some of the household characteristics, we proceed as follows. First we regress household carbon emission with only income quintiles then in the second stage, we collect the predicted residuals from the previous analysis and run the regression with household characteristics on the independent side and the residuals as the dependent variable.

Income or expenditure data are interchangeably used as measurement of households' economic profile. However, many studies are inclined to use expenditure rather than income because expenditure data is more reliably reported and more stable than income, especially among poor people (Klasen, 1997). Hentschel & Lanjouw (1996) stated that income data is unreliable and difficult to collect in developing countries especially in rural settings, thus, household expenditure may provide a better proxy for long term economic status (Deaton, 1992). However, in this analysis the expenditure variable is endogenous since household carbon emission is derived as the product of carbon intensity and household expenditure. So, we rely on income data. But then again considering the arguments above on the reliability of income data in developing country, we therefore build an asset index as a proxy for households' economic status.

3.3. Asset index construction

We use the method suggested by Filmer & Pritchett (2001) in constructing an asset index[5]. They used data on household ownership of durable goods, characteristics of household dwellings and land ownership to construct a proxy for wealth. This method is being used by the World Bank (Gwatkin et al., 2007) as way to assess the socio-economic status of households based on asset ownership. An improvement of the method by taking into account discrete data without breaking them into dummies was proposed by Kolenikov & Angeles (2009). We construct a linear index from households' asset ownership using the concept of principal component analysis. The Philippine household survey includes several asset indicators; we classify them into three major categories: (i) household ownership of durable goods with 14 indicators including ownership of radio, tv, stereo, vtr/dvd player refrigerator , washing machine, aircon, phone, oven, computer, sala & dining set, car, motorbike; (ii) characteristics of household dwelling with 8 indicators such as whether house is made of strong or light materials, kind of toilet either flush toilet or pit/latrine or no toilet at all, and sources of water either from the water system, pump/well or from river; and (iii) ownership of house and lot with 3 indicators like owning house & lot, renting house & lot or not owning or renting house & lot.

3.4. Income elasticity

It is then noteworthy to analyze which consumption items households will prioritize as they become richer. Will it be the carbon intensive goods or the other? We use the concept of elasticity to analyse the percentage change in consumption resulting from a percentage change in household income,

$$w_{ij} = \alpha + \eta_{ij} ln(inc)_i + \gamma_{ij} X_i + \varepsilon_{ij} \qquad (6)$$

[5] For more discussion of the methods, readers may refer to the paper of Filmer & Pritchett (2001).

where w_{ij} represents the share of total income allocated to the *jth* consumption category by the *ith* household, $ln(inc_i)$ is the income of household *i* in logs, X_i is a vector with household characteristics and ε_{ij} is the usual error term. In addition, we split the analysis by location to capture the difference in lifestyle between urban and rural households.

3.5. Data

To carry out the estimation of household carbon emission, we need three data sets. First, the Philippine Input-Output (IO) table for year 2000 acquired from the National Statistical Coordination Board (NSCB). The 2000 IO table is a matrix of 240x240 industrial sectors. Second, we need Global Trade Analysis Project (GTAP)'s carbon emission coefficient (Lee, 2008). Then we need to map the 240 IO sectors with the 57 sectors in GTAP. Third, we need data on household consumption of various goods and services. For this, we use the Family Income and Expenditure Survey (FIES) of the National Statistics Office (NSO). The survey data has more than 100 disaggregated household consumption categories. The household survey in 2000 included 37,766 households while in 2006 the sample households were 38,483. We will use two rounds of household survey, year 2000 and 2006, to capture how carbon emission changes with time. Due to data limitation, we use the carbon intensity for year 2000 to compute household carbon emission in 2006[6].

4. Results and Discussion

4.1. Characteristics of household carbon footprint

Results of our estimation show that on average households emit 1.46 tons of CO_2 in 2000 and in 2006 it increases to 1.86 tons per household. On per capita basis, the average per capita emission in 2000 amounts to 0.32 tons and in 2006 it amounts to 0.44 tons of CO_2. We then disaggregate total carbon emission into twenty major consumption items (Figure 1). Emissions from fuel and light followed by transportation are relatively higher compared to the rest of consumption categories. This is plausible because these household items are energy intensive. Among the food related expenditure, fruits and vegetables have low carbon emission while consumption of meat, dairy and egg show relatively higher carbon emission. On the other hand, nondurable goods, recreation and communication have the lowest emission. This observation is consistent in both years.

In Figure 2, we look at the average emission by income quintile and further disaggregate it into major consumption categories. Results show that there is a huge gap in carbon emission between the lowest and highest quintile. In 2000, households in the poorest quintile (quintile 1) emit on average 0.10 tons of CO_2 while the richest quintile (quintile 5) emit on average 0.77 tons of CO_2. In 2006, generally we observed an increase in emission across income quintiles as compared to its level in 2000 but the increase in emission in the richest quintile is

[6] We assume that there is no strategic shift in production structure towards a cleaner and efficient production and further assume that carbon intensity is similar for this time period.

more evident. Households in poorest income quintile emit 0.12 tons of CO_2 while households in the richest quintile emit 1.02 tons of CO_2. Notably, from lowest income quintile to the 4th income quintile, we observed a gradual increase in per capita emission but from the 4th quintile to the 5th quintile we observed a rather huge jump in the level of emission. This is an indication that the rich households are leading a carbon intensive lifestyle.

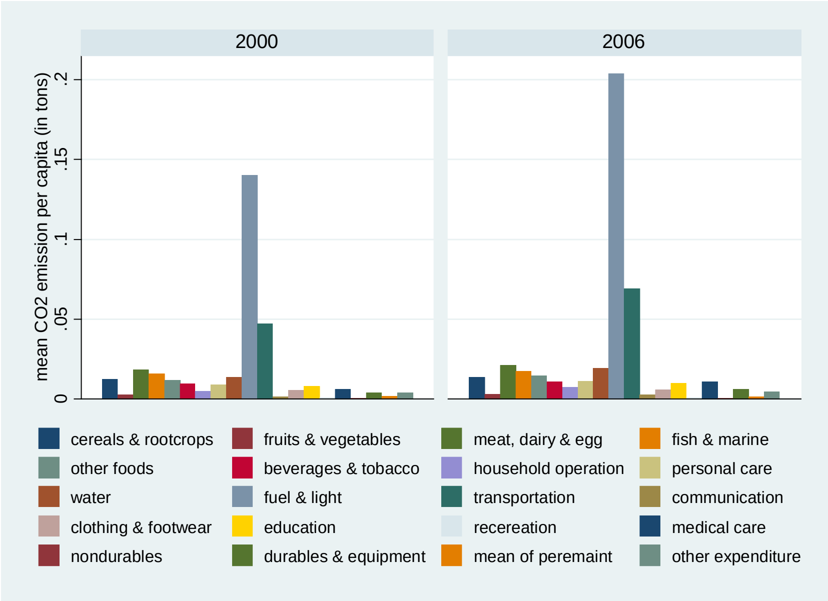

Fig.1. Mean household CO_2 emission by expenditure categories.

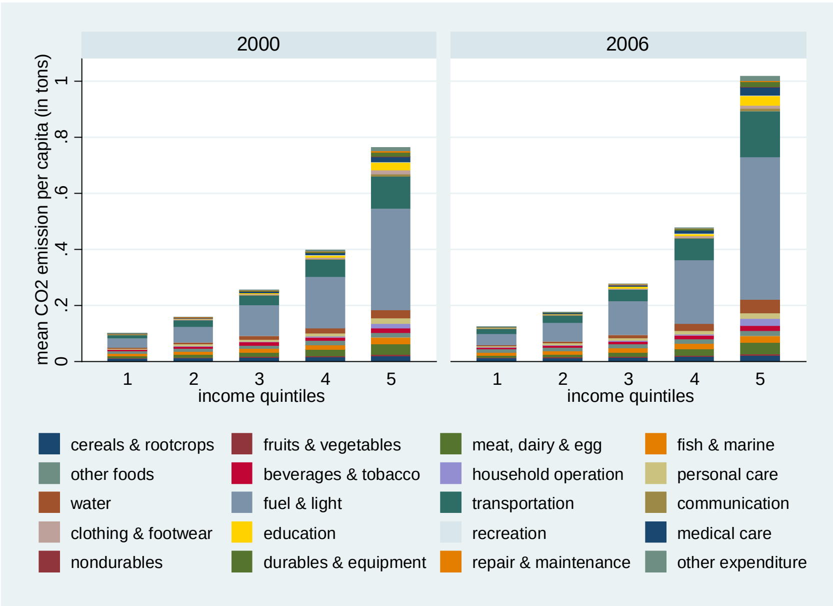

Fig.2. Mean household CO_2 emission by income group.

Looking at the major consumption category, we observed that the emission from fuel & light and transportation increases dramatically as households' income increases while the emissions from food items does not change that much as households become more affluent. Particularly the emissions attributed to cereals, root crops, fruits and vegetables do not vary that much across income quintiles as compared to the emission from meat and dairy products.

Overall, the increase in emission from 2000 to 2006 is driven by the increase in emission of the richest quintile and across income quintile we observed that fuel & light and transportation occupy a larger share of household emission.

4.2. Household carbon emission and income

Table 1 shows the summary statistics of the variables used in the analysis. Aside from asset index which we will construct later, we use expenditure data as well as income data to capture households' economic profile. We observe that there is a slight decline in households' average income and expenditure but we also observe an improvement in households who are above poverty line. In 2000, 67% of the households are above poverty line and in 2006 it increases to 71%. Generally, the household heads are married male with an average age close to 50 years. Household size decreases from 5.24 average members in 2000 to 4.94 members in 2006. We also observe an improvement in the access to electricity. In 2000, only 77% of the households have access to electricity and in 2006 it increased to 80%. However, contrary to classical observation we observe a decline of households residing in urban areas. In 2000, almost 60% of the households reside in urban areas but in 2006 it reduces to only 45%. Perhaps this capture the effort of the government to decentralized congested and densely populated mega cities in the Philippines but this should merit further investigation which we will not cover in this current analysis.

Table 1. Summary statistics of household characteristics

Variable	2000				2006			
	Mean	Stdev	Min	Max	Mean	Stdev	Min	Max
HH income (US$)	3222.48	4516.06	96.70	191021.5	3187.05	3931.92	103.20	154338.3
HH expenditure (US$)	2605.28	2935.36	85.15	140065.6	2579.70	2658.31	76.36	78791.0
Above poverty line	0.67	0.472	0	1	0.71	0.454	0	1
Age	48.89	13.870	15	99	48.44	14.029	13	99
Male	0.79	0.409	0	1	0.82	0.384	0	1
Single	0.08	0.270	0	1	0.04	0.191	0	1
Married	0.77	0.422	0	1	0.80	0.397	0	1
Widow	0.15	0.359	0	1	0.16	0.365	0	1
Household size	5.24	2.249	1	19	4.94	2.200	1	19
No formal educ	0.04	0.205	0	1	0.03	0.179	0	1
Elementary	0.39	0.487	0	1	0.42	0.494	0	1
High school	0.30	0.460	0	1	0.33	0.471	0	1
At least college	0.22	0.412	0	1	0.21	0.411	0	1
Urban	0.59	0.491	0	1	0.45	0.497	0	1
Access to electricity	0.77	0.423	0	1	0.80	0.400	0	1

Note: The sample size for year 2000 is 37,766 households while for year 2006 is 38,483 households.

Our main objective is to investigate how carbon emission is influenced as households get more affluent. We use several OLS regression analysis to address our aim while controlling for other household characteristics. We use expenditure and income data to capture affluence. Results are presented in Table 2. The elasticity between expenditure and carbon emission is captured in the first regression. Results show that there is a significant positive relationship between carbon emission and expenditure. In the second regression, the squared term of expenditure is included. We observe a significant nonlinear effect of expenditure on carbon emission. However, the expenditure variable is endogenous because carbon emission was estimated based on expenditure. To deal with this problem, we replace expenditure variable with income. Results show that income has a significant positive effect on emission. The coefficient of income is lower than that of expenditure. This is a manifestation of removing the bias that comes with using expenditure variable. A percentage increase in the household income is associated with an increase in household CO_2 emission by 0.842%, holding other factors constant.

In regression 4, we included the squared term of income to capture the nonlinear effect of income on emission. The result shows that the squared term is negative and significant implying an inverted U-shaped behavior of carbon emission with respect to income. Holding other factors constant as income increases, CO_2 emission rises reaching a turning point and then emission starts to decline as income increases even more. However, the turning point is way outside the income distribution of households. The presence of EKC hypothesis is contested in the literature. Several studies have concluded that EKC does not exist (Stern, 2004; Lenzen et al., 2006; Yaguchi et al., 2007; Galeotti et al., 2009). However in a bivariate regression analysis between income and emission, EKC exists but a cubic relationship is also evident implying a non-monotonic increase in emission with income (Golley and Meng, 2012). In addition, we replace income variable with dummy variable on whether households fall below the poverty line. Result shows that households above the poverty line are 65.7% higher in emission compared to households below the poverty line. This specification of using a dummy for household above the local poverty line explains around 75% of the variation in household carbon emission.

In the sixth regression, we replace income variable with income quintiles. We sorted households based on their income and partition them into five groups. The lowest quintile (control group) represents the poorest 20% of the households while the 5^{th} quintile represents the richest 20% of the households. Results show that moving from lowest quintile to second lowest quintile increases household carbon emission by 44% while moving from lowest quintile to highest income quintile increases household carbon emission by 165.7%. This specification explains 84% of the total variation in household carbon footprint. To further analyze the heterogeneity of household carbon emission by overcoming the potential correlation of control variables to household income, we divide the analysis into two steps. First, we regress household emission with only income quintiles as covariates (Reg7) then in the second step our control variables were regressed on the predicted residuals from the previous regression. Results show that the highest quintile is 251.3% higher in emission compared to the lowest quintile and moving from lowest quintile to the next higher quintile increases carbon emission by 72.9%. The quintile estimates in regression 7 is relatively higher to that of the results in regression 6 since there were no other control variables included in regression 7. This point out that income greatly matters in explaining household carbon emission.

Table 2. Factors affecting household CO_2 emission with log of CO_2 as dependent variable.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)§
log expenditure	1.049***	1.939***						
	(0.0025)	(0.0375)						
log expend_sq		-0.040***						
		(0.0016)						
log income			0.842***	1.580***				
			(0.0028)	(0.0427)				
log income_sq				-0.033***				
				(0.0018)				
above poverty					0.657***			
					(0.0045)			
2nd inc quint						0.440***	0.729***	
						(0.0047)	(0.0058)	
3rd inc quint						0.758***	1.258***	
						(0.0052)	(0.0058)	
4th inc quint						1.121***	1.803***	
						(0.0059)	(0.0058)	
5th inc quint						1.657***	2.513***	
						(0.0069)	(0.0058)	
age	0.002***	0.003***	0.003***	0.005***	0.016***	0.008***		0.026***
	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0009)	(0.0007)		(0.0010)
age_sq	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***		-0.000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)
male	-0.047***	-0.046***	-0.053***	-0.047***	-0.123***	-0.052***		-0.092***
	(0.0042)	(0.0042)	(0.0052)	(0.0051)	(0.0075)	(0.0060)		(0.0078)
married	0.044***	0.048***	0.042***	0.050***	0.052***	0.055***		-0.028**
	(0.0072)	(0.0072)	(0.0086)	(0.0085)	(0.0122)	(0.0099)		(0.0130)
widow/separated	0.025***	0.028***	0.009	0.015*	-0.075***	-0.002		-0.113***
	(0.0075)	(0.0075)	(0.0090)	(0.0089)	(0.0128)	(0.0105)		(0.0136)
hhsize	0.034***	0.024***	0.122***	0.121***	0.451***	0.231***		0.285***
	(0.0048)	(0.0048)	(0.0059)	(0.0059)	(0.0093)	(0.0078)		(0.0089)
hhsize_sq	-0.007***	-0.005***	-0.016***	-0.015***	-0.044***	-0.029***		-0.028***
	(0.0007)	(0.0007)	(0.0009)	(0.0009)	(0.0016)	(0.0013)		(0.0014)
hhsize_cube	0.000***	0.000***	0.001***	0.001***	0.002***	0.001***		0.001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)		(0.0001)
elementary	0.017***	0.017***	0.030***	0.017**	0.063***	0.060***		0.057***
	(0.0058)	(0.0058)	(0.0070)	(0.0071)	(0.0099)	(0.0089)		(0.0107)
high school	0.069***	0.065***	0.108***	0.089***	0.230***	0.144***		0.286***
	(0.0061)	(0.0061)	(0.0074)	(0.0075)	(0.0104)	(0.0093)		(0.0115)
at least college	0.050***	0.080***	0.130***	0.156***	0.618***	0.287***		0.729***
	(0.0066)	(0.0066)	(0.0081)	(0.0081)	(0.0112)	(0.0098)		(0.0122)
urban	0.132***	0.101***	0.176***	0.124***	0.275***	0.148***		0.251***
	(0.0025)	(0.0025)	(0.0032)	(0.0031)	(0.0043)	(0.0035)		(0.0052)
electricity access	0.490***	0.465***	0.541***	0.511***	0.670***	0.561***		0.462***
	(0.0030)	(0.0031)	(0.0037)	(0.0038)	(0.0049)	(0.0042)		(0.0057)
floor area	0.006***	0.014***	0.037***	0.050***	0.208***	0.104***		0.232***
	(0.0017)	(0.0017)	(0.0021)	(0.0021)	(0.0030)	(0.0025)		(0.0033)
year 2006	0.074***	0.092***	0.183***	0.214***	0.781***	0.384***		0.751***
	(0.0047)	(0.0047)	(0.0059)	(0.0058)	(0.0080)	(0.0068)		(0.0088)
region dummies	NO	YES	NO	YES	YES	YES	NO	YES
constant	-12.603***	-17.589***	-10.897***	-15.059***	-4.479***	-2.890***	-1.240***	-3.779***
	(0.0260)	(0.2143)	(0.0309)	(0.2471)	(0.0327)	(0.0285)	(0.0041)	(0.0345)
Observations	76,239	76,239	76,239	76,239	76,239	76,239	76,249	76,239
R-squared	0.913	0.917	0.865	0.874	0.751	0.836	0.746	0.555

Note: Robust standard errors are presented in parentheses,
*** $p<0.01$, ** $p<0.05$, * $p<0.1$,
§ dependent variable is the residual from regression 7

4.3. Household carbon emission and asset index

As argued before, the income variable might not be that reliable in capturing households' economic profile. Hence, we run the same regression specification replacing income variable with our constructed asset index. Since we took the log values of asset index, its coefficient can be interpreted as elasticities. Results show that the asset index has a positive significant relationship with household carbon emission. Holding other factors constant, a percentage unit added in the asset index increases household carbon emission by 0.245% (Reg9, Table3). In regression 10, we added the squared term of the asset index. Result shows that the squared term of the asset index has positive sign implying that an inverse U-shaped relationship is not evident. This finding shows that as households get affluent as represented by its accumulation of assets, emission tends to increase and no turning point is observed. This result reflects what was found out by Stern (2004), Lenzen et al. (2006), Yaguchi et al. (2007), and Galeotti et al. (2009) showing that carbon emission did not satisfy the EKC hypothesis but were continually increasing with income. With more households climbing up the economic ladder, this would translate to a tremendous increase in carbon emission.

Though we observe that EKC hypothesis does not exist when we use asset index but it is evident when we use income variable, it is noteworthy to take caution in this regard. The difference in the squared term between income variable and asset index could be attributed to the spread of the distribution. Income variable is unbounded which means households can have different sources of income while asset index is bounded with the number of assets household could have. With this, asset index may not be able to capture the inverted U-shaped association with emission as suggested by the income variable. However when we also compute the turning point with income variable, the turning point is out of range in the stated income of households. With this, we cannot strongly assert the presence of EKC on household emission. Nevertheless, what is quite certain is that emission greatly increases as households become more affluent.

Similar with income quintile, we find huge differences in the carbon emissions across quintiles of asset index. For example in regression 11, moving from the lowest quintile to highest quintile increases carbon emission by 84.9%. This estimate is relatively low compared to using the income quintile. This may be due to the underlying potential correlation between the asset index and other explanatory variables such as access to electricity or house floor area. To deal with this problem, we proceed in two steps following the same procedure with the methods applied in using the income quintile. In the first step, we regress household emission only with the quintiles of asset index and then in the second step, the control variables were regressed on the residual from the previous regressions. Results show that coefficients of asset index are behaving similarly with income. We observed that moving from lowest quintile to the next higher quintile increases carbon emission by 45.4% and moving from the lowest quintile to the richest quintile increases carbon emission by more than 200%.

Table 3. Regressing asset index on household carbon emission.

Variables	(9)	(10)	(11)	(12)	(13) §
log asset	0.245***	0.222***			
	(0.0034)	(0.0031)			
log asset_sq		0.104***			
		(0.0015)			
2nd asset quint			0.087***	0.454***	
			(0.0063)	(0.0081)	
3rd asset quint			0.270***	0.964***	
			(0.0071)	(0.0081)	
4th asset quint			0.531***	1.437***	
			(0.0077)	(0.0081)	
5th asset quint			0.849***	2.010***	
			(0.0087)	(0.0081)	
age	0.021***	0.019***	0.019***		0.013***
	(0.0009)	(0.0009)	(0.0009)		(0.0009)
age_sq	-0.000***	-0.000***	-0.000***		-0.000***
	(0.0000)	(0.0000)	(0.0000)		(0.0000)
male	-0.094***	-0.074***	-0.069***		-0.097***
	(0.0077)	(0.0074)	(0.0074)		(0.0070)
married	0.036***	0.025**	0.021*		0.028**
	(0.0126)	(0.0121)	(0.0122)		(0.0112)
widow/separated	-0.058***	-0.053***	-0.054***		-0.057***
	(0.0133)	(0.0127)	(0.0127)		(0.0116)
hhsize	0.380***	0.365***	0.364***		0.109***
	(0.0101)	(0.0096)	(0.0096)		(0.0080)
hhsize_sq	-0.042***	-0.039***	-0.039***		-0.016***
	(0.0017)	(0.0016)	(0.0016)		(0.0013)
hhsize_cube	0.002***	0.002***	0.001***		0.001***
	(0.0001)	(0.0001)	(0.0001)		(0.0001)
elementary	0.054***	0.065***	0.082***		0.057***
	(0.0110)	(0.0108)	(0.0105)		(0.0089)
high school	0.237***	0.224***	0.245***		0.219***
	(0.0116)	(0.0113)	(0.0110)		(0.0096)
at least college	0.630***	0.546***	0.551***		0.501***
	(0.0123)	(0.0120)	(0.0118)		(0.0102)
urban	0.258***	0.220***	0.224***		0.195***
	(0.0046)	(0.0044)	(0.0044)		(0.0045)
electricity access	0.645***	0.617***	0.690***		0.469***
	(0.0060)	(0.0059)	(0.0059)		(0.0050)
floor area	0.209***	0.178***	0.180***		0.175***
	(0.0032)	(0.0031)	(0.0031)		(0.0029)
year 2006	0.735***	0.636***	0.641***		0.528***
	(0.0086)	(0.0084)	(0.0084)		(0.0078)
region dummines	YES	YES	YES	NO	YES
constant	-4.134***	-3.971***	-3.928***	-0.950***	-2.298***
	(0.0352)	(0.0341)	(0.0341)	(0.0057)	(0.0308)
Observations	76,017	76,017	76,239	76,249	76,239
R-squared	0.721	0.744	0.746	0.502	0.474

Note: Robust standard errors are presented in parentheses
*** p<0.01, ** p<0.05, * p<0.1
§ dependent variable is the residual from regression 12

4.4. Comparison of quintile estimates between income and asset index

Figure 3 shows the comparison of quintile estimates between income and asset index. We observed across quintile, that the estimates of asset index regression are lower than that of income variable. This reflects the potential bias associated with using income variable but we also cannot rule out that our estimate with asset index is biased downward because we were not able to capture all household assets[7]. Though the magnitudes of the estimates differ, it depicts a similar and consistent story across quintiles. Results show that the difference between the poorest and the richest quintile is enormous. Moving from the poorest quintile to richest quintile translates to an increase in carbon emission by more than 200%. This shows that the consequence of rising income is associated with huge increase in carbon emission. Hence, an interesting path to look is whether households can increase their income level without increasing their emission.

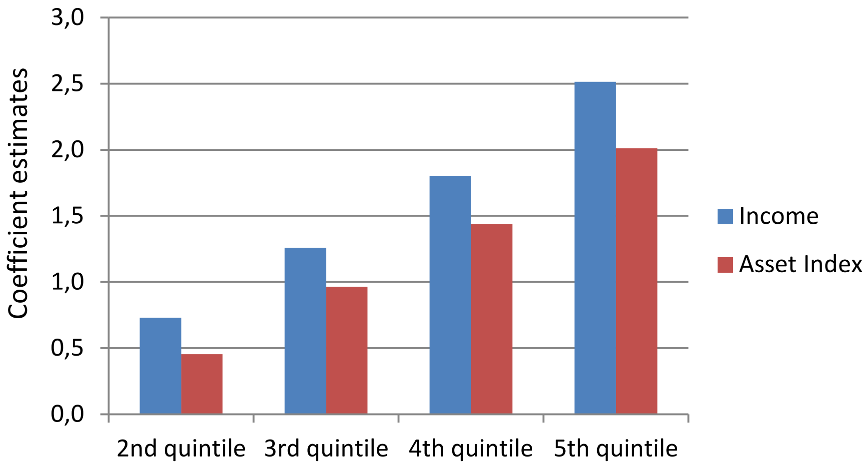

Fig.3. Comparison of estimates between income and asset index.

Compared to the US and UK households, where the average household emission accounts to as much as 50 and 21 tons of CO_2 respectively (Weber and Matthews, 2008; Druckman and Jackson, 2009), the emission from Philippine households is way lower than that. While its level is not that alarming and there may be no urgency in reducing Philippine households' carbon emission as compared to households from the developed countries, nevertheless it is relevant to scrutinize factors affecting household emission for projection of future consumption path. Several options are available in curbing household carbon emission. These include improving production efficiency, changing consumption pattern to a less carbon intensive and decreasing consumption in particular energy intensive goods (Lenzen, 1998b; Wier et al., 2001; Weber and Matthews, 2008). While reducing aggregate consumption may not be an attractive option (Weber and Matthews, 2008), households may exert effort in reducing aggregate emission by conserving and using household energy efficiently. Based

[7] Estimates from the asset index are lower compared to income. This could be due to the fact that the asset indicators used in this study did not capture all the assets that the households have. For example, agricultural asset is not included wherein many of the households from the rural areas do own these items. We recognize the potential that our asset index maybe poorly specified in the absence of agricultural assets. Nevertheless, we assume that asset index reliably captures households' economic status.

from our estimation, expenditure related to fuel, light and transportation have the highest emission among household items. These are largely emitted by the rich households. If households care, they can take initiative by efficiently utilizing energy intensive household consumption. Little things done collectively will have a huge effect. This can be a starting point in devising policies for mitigating climate change at the household level. In addition, policy makers should device policies to make alternative goods which are produced cleanly and efficiently be attractive in the market.

4.5. Income elasticities

To evaluate the relationship between different household consumption and income, we use the concept of elasticity. We run separate regressions for every consumption category using the share of consumption category to the total expenditure as the dependent variable and income as the main determinant with the rest of household characteristics as controls. This gives us information on which consumption items will increase or decrease as income changes. Goods that increase in consumption as income increases are referred to as normal goods while goods that decrease in consumption as income increases are referred to as inferior goods.

Results show that as income increases, mostly expenditure on food related items decline except for meat & dairy and food eaten out. This is because meat and dairy are relatively expensive food and highly valued. Also, households tend to dine out more as their income increases. Aside from food, consumption of alcoholic beverages and tobacco declines as income increases. This may indicate that households are more responsible towards their health because they tend to reduce their consumption on these items. This is also reflected with the increase in medical care as income increases. Expenditure on fuel, light and water also decline as income increases. This could be due to households opting for a cleaner source of energy as they become richer. This is a good indication of the possibility to reduce emission related to energy intensive consumption of households. Remember that expenditure on fuel & light is the most carbon intensive household consumption.

To capture how households' lifestyle differences across location, we run separate analysis for households located in urban and rural areas. The elasticity coefficient differs across location but majority of both analyses, show similar results. As income increases, expenditure on cereals and root crops declines the most as compared to the other goods. Rural and urban households have contradicting elasticities with respect to consumption in meat & dairy. Urban households show declining consumption while rural households are on the opposite. Rural households are likely to eat more meat and dairy products with rising income compared to urban households. Another contrasting result is with household operation. Urban households have positive elasticity while the rural households report the opposite. Household operation include expenditure on cleaning, laundry others.

The priority of the households as their income increases is on communication, education, transportation, and expenditures related to gift & contributions. An increase in the share of transportation expenditure will have a strong effect in the increase of household carbon emission. Expenditures on recreation, medical care, special occasion, clothing and others also increase as households get more affluent. The elasticities of the rest of the consumption categories are shown in Table3 with robust standard errors included.

Table 4. Income elasticity of household consumption category.

Consumption category	All		Urban		Rural	
	coef	se	coef	se	coef	se
Cereals & rootcrops	-0.527***	0.003	-0.555***	0.003	-0.517***	0.003
Fruits & vegetables	-0.224***	0.004	-0.245***	0.005	-0.228***	0.005
Meat & dairy	0.075***	0.004	-0.020***	0.006	0.184***	0.007
Fish & marine goods	-0.292***	0.004	-0.365***	0.005	-0.234***	0.006
Non-alcoholic beverages	0.136***	0.006	0.033***	0.007	0.228***	0.010
Other food	-0.326***	0.004	-0.403***	0.005	-0.280***	0.005
Food eaten out	0.133***	0.008	0.057***	0.010	0.151***	0.013
Alcoholic beverages	-0.161***	0.013	-0.231***	0.017	-0.156***	0.018
Tobacco	-0.278***	0.013	-0.357***	0.017	-0.301***	0.019
Fuel, light & water	-0.178***	0.003	-0.160***	0.004	-0.175***	0.005
Transportation	0.314***	0.006	0.307***	0.008	0.300***	0.009
Communication	0.476***	0.011	0.520***	0.013	0.417***	0.017
Household operation	0.033***	0.005	0.136***	0.007	-0.077***	0.007
Personal care	-0.016***	0.004	-0.072***	0.005	0.045***	0.006
Clothing	0.199***	0.006	0.158***	0.008	0.252***	0.009
Education	0.356***	0.011	0.403***	0.014	0.348***	0.016
Recreation	0.226***	0.012	0.287***	0.015	0.194***	0.019
Medical care	0.264***	0.011	0.228***	0.014	0.315***	0.015
Nondurable goods	-0.022*	0.012	0.001	0.016	-0.040**	0.017
Durable goods	0.130***	0.020	0.080***	0.023	0.221***	0.030
House rent	-0.006	0.005	0.067***	0.006	0.055***	0.007
House repair & maintenance	0.119***	0.024	0.058*	0.032	0.191***	0.034
Special occasion	0.229***	0.008	0.201***	0.011	0.330***	0.012
Gifts & contribution	0.366***	0.010	0.384***	0.013	0.370***	0.015
Other expenditure	0.050***	0.008	0.140***	0.012	-0.101***	0.011

Note: Robust standard errors are used
*** p<0.01, ** p<0.05, * p<0.1

4.6. Carbon emission and other household characteristics

Studies on household emission based on combining input-output and expenditure are often descriptive in nature and only fewer studies dealt with regressing total carbon emission on socio-demographic characteristics of the households. Hence, our results provide further evidence on the association of household characteristics on carbon emission. Although income is the main determinants of household emission, other household characteristics play an important role in explaining emission. Information on household age, where they lived, their education, household size and access to electricity matter in explaining the variation in household emission.

Throughout the different specifications, the control variables behave similarly indicating the robustness of our estimation. Age has a nonlinear effect on carbon emission depicting an inverse U-shape kind of relationship. This implies that carbon emission increases with age then reaches a maximum after which it starts to decline at a certain age level. This is due to changes in needs and preferences of the household. Younger household heads are just starting to build their family and so there is an increasing carbon emission. As household heads get older, kids grow up and the demand for goods and services also increases, thereby driving the increase of the carbon footprint. Then later on carbon emission declines as households reach old age due to changes in preferences and consumption patterns. Older households are more inclined to consume service related goods which are rather less carbon intensive. This nonlinearity effect of age with emission is consistent with what was reported by Büchs and Schnepf (2013). Also Lenzen et al. (2006), and Golley and Meng (2012) reported strong influence of age emission but they did not include a squared term in their analysis.

In the household survey, we can extract the gender of household head and we include them in the regression. Results consistently show that male headed household posted lower carbon emission compared to female headed households. This is reasonable since in most household set up in the Philippines, the husband tends to focus more on working while housewives tend to handle more household expenditure. Even if both are working, still women are more likely to oversee household expenditure. Although more in-depth research has to be done on this issue, we can speculate that men are more likely to be dominant in bigger household expenditure but expenditures related to food, clothing, household maintenance, etc. women are more assertive. In the literature, limited studies have included gender in their analysis. Büchs and Schnepf (2013) showed that in UK female headed households have higher total emission than male headed households which is consistent with our result in the Philippine setting.

Most of the available studies did not include marital status but in this study, we found out that marital status has an influence on household emission. Being married is associated with higher emission compared to single households. On the other hand, most studies have shown that household size is an important factor in explaining household emission. We found out that household size has a nonlinear effect because there are economies of scale or simply household members share resources. This sharing of resources among household is also reported in other studies (Lenzen et al., 2006; Druckman and Jackson, 2008; Golley and Meng, 2012; Büchs and Schnepf, 2013). We documented a cubic relationship between household size and carbon emission and this result is quite robust since it is consistent in all specifications. With smaller household size, emission is increasing and tends to stabilize at around 4 to 7 household members and then eventually will increase further with additional members. The declining marginal emission in the middle household size captures the sharing of resources among household members but consequently with more added members aggregate household emission will increase.

We also classify households based on the educational attainment of the household head such as (1) no formal education, (2) elementary level, (3) high school level and (4) at least college level. Result shows that better educated household heads have higher carbon emission than households headed by someone who has no formal education. Consistent across all regressions, households headed by someone with at least college or university level of education posted higher carbon emission. This result is in contrast to Baiocchi et al., (2010) but is consistent with Golley and Meng (2012) and Büchs and Schnepf (2013). Lenzen et al. (2006) also reported contrasting effect of education to emission. They found negative effect in Australia but positive for Brazil and India. They argue that education is a privilege for the rich, hence, related to higher emission. This also explains the situation in the Philippines that mostly those household heads who have higher educational attainment generally belong to a higher income quintile.

We also found out that households situated in urban areas emit more CO_2 than those in rural areas. This is driven by consumption in energy intensive goods such as fuel, light and transportation. Rural households on the average consume relatively lower in these items compared to urban households. However, this result is in contrast to Büchs and Schnepf (2013) where they found that rural location is associated with higher emission due to greater car dependency and more isolated dwellings. Also Lenzen et al. (2006) found that urbanity is associated with lower fuel consumption in transportation because of proximity. For Philippines the set up is different, greater car dependency is observed mostly in the cities and less in the rural areas.

In addition, we also included other household characteristics not considered in previous studies. Households who have access to electricity have carbon emission roughly around 50% higher than households having no access to electricity. House size as measured by floor area has a positive significant relationship with total emission. Golley and Meng (2012) also reported positive relationship between large dwelling sizes and total emission. In order to control for geographic variations among households, regional dummies were included in the regressions. The Philippines is subdivided into seventeen regions. We use region 1 as control group for convenience[8]. And lastly, we also use time dummies to compare the emission in year 2000 and 2006. With time, we observe an increase in household carbon emission and this is more likely to happen in the coming years.

While this study is the first to look at household carbon emission in the Philippines, our analysis is limited in several ways. First is the treatment of imported goods. Here, we assume that imported goods have the same carbon intensity as locally produced goods. A proposed method to deal with this problem is using a multiregional input-output model (Weber and Matthews, 2008; Minx et al., 2009). However, due to data limitations we assume that products produced at home and abroad have the same carbon intensity. In addition, if we can apply the multiregion input-output model another hindrance is the matching of household items because we do not have information in the household survey which goods are imported. Second, is on converting expenditure to emission. According to Büchs and Schnepf (2013) expenditure does not necessarily equate to consumption on which emission is based. They said, for instance, that an expensive bread may have lower emission compared to a cheap one but expenditure translates the expensive bread as having the higher emission. This in turn would bias the

[8] Regional dummies are included in the regression. Households in the national capital region (region 13) emitted almost 30% higher than households in region 1. We do not report here the coefficient of regional dummies but is available upon request.

emission of the rich who can afford to buy quality goods which may have been cleanly and efficiently produced but are expensive. With input-output analysis it does not stratify the quality of goods produced. We only have information how carbon intensive the sectors are and not the individual products from that sector. A way to resolve this problem is to analyze carbon emission by using life cycle analysis of a given product but that is beyond the scope of our current paper. But due to practicality and lack of other good alternatives, estimation of emission combining input-output and expenditure approach is common in the literature (e.g. Parikh et al., 1997; Lenzen, 1998; Weber and Perrels, 2000; Pachauri and Spreng, 2002; Bin and Dowlatabadi, 2005; Lenzen et al., 2006; Weber and Matthews, 2008; Kerkhof et al., 2009; Baiocchi et al., 2010). Nevertheless with our current paper, we provide the baseline information on the estimation and determinants of household carbon emission in the Philippines.

5. Summary and Conclusion

We use the methods of input-output analysis to extract CO_2 emission intensity for every sector in the Philippine economy and match these sectors to households' consumption to derive household carbon emission. Estimation of carbon emission shows that households on average emitted 1.46 tons of CO_2 (0.32 tons of CO_2 per capita) in 2000 and in 2006 it increased to 1.86 tons (0.44 tons of CO_2 per capita). When disaggregating by major consumption categories, results show that emission from fuel & light and transportation are relatively higher compared to the rest of the household consumption. When disaggregating by income quintile, results show that there is a huge difference in the carbon emission between households in the poorest quintile and richest quintile. Overall, the increase in emission is largely due to the increase in emission from the richest quintile and mostly driven by the increase in emission from fuel, light and transportation.

The different regression analysis showed consistent results whether using expenditure or income as the main regressors. Because expenditure is endogenous, the estimation using income as the main determinant of household carbon emission is far more applicable. Our estimations show that there is a significant nonlinear relationship between income and household carbon emission, depicting an inverse U-shaped behavior. This means that as income increases the household carbon emission increase as well and reaches a turning point and then starts to decline later on with additional income. This observation depicts the environmental Kuznets' curve but the turning point is way beyond the households' income distribution. To analyze further the effect of income on household carbon emission at different income levels, the income variable was replaced with income quintiles. Result shows that there is a dramatic increase in emission when moving from the lowest quintile to the highest income quintile. This disparity in emission between the lowest and highest quintile captures how carbon intensive the lifestyle of households become as income increases.

Though income variable reflects the economic status of households, there are doubts about its reliability because collecting income data from household survey especially in developing countries is problematic. To deal with this issue we proxy household income with asset index. The asset index was constructed from ownership of household durables, house dwelling conditions and ownership of house and lot. The constructed asset index is coherent and reliable since the average asset ownership differs across groups and there is a clear difference separation between rich and poor households. Results of the regression analyses using asset index show that the inverse U-shaped behavior between economic status and emission is not evident. The log squared term of the asset index shows positive and significant relationship with emission. This means that as households accumulate more assets, their level of emission will eventually increase without a hint that sooner it will decline. Although the estimates using the asset index is relatively lower than the result using income, nevertheless, they tell a similar story.

Results from our regression analyses largely confirm previous findings that emission will rise with income (e.g. Weber and Matthews, 2008; Baiocchi et al., 2010; Büchs and Schnepf, 2013). We even find an inverse U-shaped relationship between income and emission but the turning point is way beyond the household income. While this concept is contested in the literature (Stern, 2004; Lenzen et al., 2006), this effect also vanishes when we use asset index as proxy for household economic status. Hence, we cannot strongly claim for an inverse U-shaped relationship between emission and households' economic status but certainly, we can argue here that there is strong evidence indicating that emission will rise as households get affluent.

The controls used in the regression are quite robust. The associated sign of the household characteristics and carbon emission remains as expected from almost all specifications. Age and household size consistently showed a nonlinear effect on household carbon emission. Emission increases as households get older reaches its peak and then emission declines. This reflects the change of preference in consumption as households get aged. The effect of household size on carbon emission is driven by economies of scale. With increasing household size, carbon emission increases but later on declines with an added household member. This captures the sharing of resources among household members. With regards to education, higher educational attainment is associated with higher carbon emission. In Philippines, education is relative privilege to the rich hence their correspondingly highly educated households are associated with higher carbon emission. Married people have higher carbon emission than single households and male headed households have lower emission than female. Urban households on the average emit more than the rural households. Having access to electricity and larger house is associated with higher household carbon emission.

If we compare the level of Philippine households' carbon emission to those in the developed countries, its level is still relatively way lower. Its level is not worrisome and does not pose a serious threat to the climate as compared to the level of emission in the developed countries. But it is quite relevant to investigate this issue because as income increases, households' carbon emissions are more likely to lead a carbon intensive lifestyle. As more households are stepping up the economic ladder and also moving out of poverty, it is imminent that households will be consuming more carbon intensive goods. With the current consumption bundles households have limited alternatives and will still opt to consume carbon intensive goods. Sooner, the increase in the emission will be enormous and the effect of that to the climate will be tremendous. This, however, does not imply that income should not increase but rather as income increases households should have an option for a less carbon intensive consumption. An alternative way of living should be made available without compromising the efforts in lifting them out of poverty. Households should also be made aware of greening their lifestyle.

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