Environment and Development Economics 22: 546–570 © Cambridge University Press 2017
doi:10.1017/S1355770X17000262

Affluence and emission tradeoffs: evidence from Indonesian households' carbon footprint

MOHAMMAD IQBAL IRFANY
Faculty of Economic Sciences, Georg-August-University of Goettingen, Oeconomicum, Platz der Göttinger Sieben 3, 37073 Göttingen, Germany; and International Centre for Applied Finance and Economics (InterCAFE), Bogor Agricultural University, Indonesia.
Email: mirfany@uni-goettingen.de

STEPHAN KLASEN
Faculty of Economic Sciences, Georg-August-University of Goettingen, Germany.
Email: sklasen@uni-goettingen.de

Submitted 21 October 2014; revised 15 December 2015, 2 November 2016, 2 March 2017; accepted 22 April 2017

ABSTRACT. This study estimates Indonesian households' carbon emissions that are attributed to their expenditures in 2005 and 2009 to analyze the pattern, distribution and drivers of their carbon footprint. Employing an input-output-emission-expenditure framework, the authors find a significant difference in household carbon emissions between different affluence levels, regions and educational levels. They also find that, while many household characteristics influence emissions, total expenditure is by far the most important determinant of household emissions, both across households and over time. Consequently, emissions inequality is very similar to expenditure inequality across households. The decomposition analysis confirms that changes in emissions are predominantly due to rising expenditures between the two periods, while expenditure elasticities analysis suggests that the rise in household emissions is mainly caused by the overall rise in total household expenditure, and not by shifting consumption shares among consumption categories. The paper discusses policy options for Indonesia to reduce this very strong expenditure–emissions link.

1. Introduction

Climate change is one of the most pressing challenges for the world, including Indonesia. In this emerging economy, rising affluence across the income distribution has sharply increased consumption levels, causing households to directly and indirectly contribute to rising emissions. Indonesia, in the 2015 Paris Climate Agreement, committed itself, however, to reducing emissions by 26 per cent in 2020 and 29 per cent in 2030 below the business as usual (BAU) scenario, and 41 per cent below BAU if it received international support (GOI, 2015). This will require substantial reductions of the carbon footprint of Indonesian households.

A quick glance at the literature on the household carbon footprint shows that most analyses were conducted in developed countries (e.g., Murthy *et al.*, 1997; Parikh *et al.*, 1997; Girod and de Haan, 2009; Kenny and Gray, 2009). With that in mind, this study will fill a research gap in the carbon footprint studies from developing countries by estimating the average household carbon footprint of Indonesia. As one of the emerging economies with a sizeable contribution to global CO_2 emissions from fossil fuel use and industrial processes, Indonesian emissions account for 1.39 per cent (in 2015) and 0.70 per cent (in 1990) of global CO_2 emissions (EDGAR, 2016).[1]

Several studies investigate the components of the greenhouse gas (GHG) emissions of households. Lenzen (1998a) analyzed energy and GHG in the case of Australian households. It was found that direct expenditure of fuels and electricity represented about 30 per cent (17 per cent) of the overall energy expenditure (the overall GHG expenditure), while the remainder was spent on non-energy commodities that used energy in their production process. Bin and Dowlatabadi (2005), using the US Consumer Lifestyle Approach to energy use and associated CO_2 emissions, estimated that more than 80 per cent of the energy used and the CO_2 emitted in the United States were a consequence of consumer demands and their supporting activities. Kenny and Gray (2009) showed that the total CO_2 emissions of Irish households were associated with home energy usage (42 per cent), transportation (35 per cent), air travel and other fuel-intensive leisure activities (21 per cent). Moreover, using the Swiss household expenditure database, Girod and de Haan (2009) found that the most important consumption categories were living, transportation and foods, which together accounted for almost 70 per cent of overall GHG emissions.

In addition, there are other studies that investigate the determinants of the household carbon footprint. Many studies have particularly focused on the role of incomes on emissions, in the context of the so-called environmental Kuznets curve (EKC) hypothesis, which proposes an inverted U-shaped relationship between per capita output and environmental degradation. Most studies investigate this by taking an aggregate cross-country perspective. For example, Lenzen *et al.* (2006) focused on the investigation of the EKC hypothesis. However, their findings do not support the EKC hypothesis. They argue that household energy use monotonically rises due to rising consumption and show that no turning point is observed. For a specific discussion on the EKC for CO_2, Chow and Li (2014) examine the hypothesis using panel data. They discuss several key economic problems of the EKC hypothesis from the literature. Applying t-tests, their study suggests that the EKC can be conclusively confirmed.

[1] Including high emissions in Indonesia associated with land use change, forest fires and agricultural waste (which are not considered in this study) roughly doubles Indonesia's share in global emissions (IPCC, 2014; Siagian *et al.*, 2015).

Other studies that investigate the EKC hypothesis and point to econometric difficulties in its estimation include Stern *et al.* (1996), Wagner (2008) and York (2012). The key difference of our study is that we examine the drivers of carbon emissions, including possible EKC effects, using household-level micro data. This way we can investigate whether the EKC hypothesis also holds within a country for different income groups (and over time). In addition, we can study other drivers of the household carbon footprint beyond incomes, such as education, urbanization, regional differences and household size, among others. Understanding these other drivers can also be helpful in designing policy interventions to reduce emissions.

There have been very few studies that have considered the EKC hypothesis at the household level. In these studies, income portfolios and levels as well as the related patterns of consumption and production are considered as important determinants. Often income is found to be the main driver of carbon footprints (Murthy *et al.*, 1997; Parikh *et al.*, 1997; Li and Wang, 2010). For the Indian case, Parikh *et al.* (1997), for instance, analyzed expenditure patterns by income groups as well as their resulting CO_2 emissions. Their approach is based on an input-output (IO) analysis, which uses an expenditure database examining the direct and indirect CO_2 emissions from household expenditure items. Considering only emissions from final demand categories, they found that of total CO_2 emissions of 167 mtC, 62 per cent was attributed to private household consumption, of which 12 per cent was due to direct consumption by households, and the remaining 50 per cent was attributed to indirect consumption of households via intermediates such as power, steel and cement. The remaining 38 per cent was contributed by investment, government consumption and exports. It also indicated that the rich have a more carbon-intensive lifestyle than the poor.

Grunewald (2013) and Serino and Klasen (2015) are most closely related to this study as they use similar methods to study the determinants of the household carbon footprint in India and the Philippines, respectively. They find that aggregate consumption is the most important driver of carbon footprints, but other characteristics are also significant. This is in line with other studies that found that household characteristics also matter as drivers of their emissions, such as household size, education, age of household head and other demographic factors (e.g., Wier *et al.*, 2001; Li and Wang, 2010). Additionally, a study from Pachauri and Spreng (2002) suggests that household energy requirements and increasing emission intensity in food and agricultural sectors are among important drivers. Lastly, Irfany and Klasen (2016) examined the determinants of inequality in the Indonesian household carbon footprint and found that expenditure inequality is the predominant driver of emission inequality and the energy-transportation sectors contribute primarily to the overall emission inequality.

Building on this literature, this study attempts to answer the following questions. First, what are the levels and determinants of CO_2 emissions of households in Indonesia? How do they differ by affluence and other household characteristics? Secondly, what are the main determinants of the growing carbon footprint over time in this fast growing emerging economy, and which consumption categories are the most carbon intensive? Thirdly, how will carbon emissions develop over time when household incomes increase?

Our findings can be summarized as follows. We find that fuel-light and transportation expenditures are the two most carbon-intensive items. The carbon footprint also differs by household characteristics, including household size, location, gender and education of the head. Household income (proxied by expenditure) is, however, by far the most important driver of the household carbon footprint across households and over time, which is confirmed by the decomposition of emission growth between 2005 and 2009, suggesting that rising emissions are mainly attributed to the income effect. The expenditure elasticity of emissions also suggests that the strong increase in household carbon footprint is mainly due to the overall rise in expenditures, and not to the shifting consumption shares of the consumption basket.

The overriding importance of income for emissions is of course not a new or unique finding and mirrors findings from other countries as well as from cross-country analyses. However, there are hardly any studies at the micro level from developing countries which investigate whether this is also true at the household level, or whether other drivers (such as location, education) are more important. Our contribution is thus first to show the key drivers of the household carbon footprint in a developing country setting, including a consideration of changes in household emissions over time. Our study is also the first to investigate this in the context of Indonesia which is among the world's largest emitters of GHGs. A second contribution is to estimate the income elasticities at the household level (also with a view of testing a micro-based EKC). Lastly, we can show the drivers of emissions in terms of expenditure categories in a developing country setting. The results of the analysis can then be used to consider policies to reduce the carbon intensity of economic activities in a country such as Indonesia, which is critical if the international commitments to limit emissions are to be reached.

The rest of this paper is organized as follows. Section 2 provides data and methodology, followed by the empirical results and discussions in section 3. The final section provides conclusions and possible policy implications.

2. Data and methodology

For our analysis, we use several databases including sectoral emissions from the 2004 Global Trade Analysis Project – Environmental Account (GTAP-E), the 2005 Indonesian Input-Output (IO) table from Badan Pusat Statistik (BPS, Statistics Indonesia), and the Indonesian household expenditure survey (SUSENAS) from the years 2005 and 2009. SUSENAS 2005 and 2009, also published by BPS, consist of a large household data set on household expenditures of more than 257,000 and 291,753 Indonesian households, respectively. The GTAP-E includes CO_2 emissions from fossil fuels combustion (coal, oil, gas, petroleum products) and cement production, but does not include emissions from land use change, which

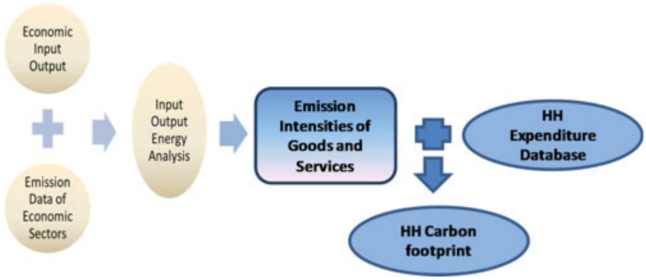

Figure 1. *IO emission analysis: expenditure approach*
Source: Modified from Kok et al. *(2006).*

is also important for the Indonesian case (PEACE, 2007). We combine the IO analysis with GTAP-E and SUSENAS to calculate the indirect and direct carbon emissions of households. This approach is appropriate for analyzing the environmental impact with respect to different household characteristics (Kok *et al.*, 2006). Expenditure amounts on consumption items in SUSENAS are multiplied by the corresponding value of the emission intensity. Each consumption item in the expenditure survey is categorized into a specific economic sector. In the next section, we provide more details on the methods used.

2.1. Measuring emission intensities and deriving the household carbon footprint

This study only focuses on CO_2 emissions since it represents the largest share of GHG emissions (UNFCCC, 2010).[2] To estimate an Indonesian household's carbon footprint, we follow Lenzen's (1998b) approach, which computed carbon embedded in an Australian household's final consumption. Thus we are focusing here on consumption-based (rather than territorially based) emissions.[3] We basically trace the CO_2 emitted by the final consumption element back to its intermediates and consider both the direct and indirect emissions that occur from household expenditure. Applying the expenditure approach, figure 1 shows how CO_2 intensities of goods and services in a given economy can be traced using IO analysis.[4]

[2] Also, the emissions associated with land use changes cannot be attributed to households as the GTAP emission intensities only capture CO_2 emissions associated with energy use and cement production. One should also note, however, that the carbon footprint of Indonesian households may not be strongly affected by land use change, particularly since much of the land use change is associated with cash crop production (such as palm oil, rubber or cocoa) for exports that are thus not consumed by Indonesian households.

[3] See, for example, IPCC (2014) for a detailed discussion of the difference between territorial and consumption-based emissions.

[4] There are three available methods in accounting for the environmental load of GHG emissions released by household consumption which are primarily from IO analysis, including the basic approach, the expenditure approach and the process approach (Kok *et al.*, 2006). First, 'the basic approach' is a pure top-down approach as it simply utilizes national accounts to calculate energy requirements

In the first step, CO_2 intensities of each Indonesian IO sector (in the local currency unit, Rp) are estimated. We assume the Single Region Model, which suggests that emissions of both imported and domestic products are assumed to have the same emission intensity, implying that they are produced by the same or similarly carbon-intensive technology. One may argue that products in the developed world are produced more efficiently and may have lower emission intensities. On the other hand, imports require transport that might increase emissions. However, such issues are beyond the scope of this study.[5] In this study, the CO_2 emission intensities were derived using the Leontief inverse of the IO table multiplied by the carbon intensities derived from GTAP.

In the second step, the CO_2 emission intensities of each economic sector were matched to their household expenditure category. We refer to the SUSENAS questionnaire and GTAP sector classification (Huff *et al.*, 2000) to match these sectors. Consumption expenditures from SUSENAS are then multiplied by the derived CO_2 emission intensity, and then by summing them up we get the household carbon footprint.[6]

As the Single Region Model assumes that the domestic energy and environmental technologies used in production are the same as abroad, we just calculate direct and indirect CO_2 emissions from the final demand of sectors. First, the direct CO_2 emission intensities from final demand, CO_2^{fd} are

(emissions). One particular drawback of this approach is that it does not consider the possibility that the price of energy may vary between sectors and it cannot calculate the carbon footprint at the household level. Secondly, 'the expenditure approach' combines the IO-energy/emission account with the expenditure database. Here, the consumption database is more disaggregated as it is taken from household expenditure surveys instead of the consumption database from the IO table. Thirdly, the 'process or hybrid approach' combines the IO-energy/emission account with process analysis, which proposes that the life cycle process of any product (consumption item) is denoted in physical terms (e.g., energy use per unit materials or energy use per transport distance, etc.). Although it could be more accurate as it avoids truncation errors, this process is more time consuming. In this study, the expenditure approach is utilized as we will use a national household expenditure database.

5 There is also another version of an input-output table known as World IO Data (http://www.wiod.org), which has a set of synchronized use and supply tables along with an international trade database. However, the data set is quite aggregated and consists of only 38 industrial sectors as well as a final household consumption sector. This study does not employ it, partly to allow more flexibility to construct emission intensities. In this regard, the fact that the Indonesian IO table has 175 sectors allows us to have the more disaggregated sectoral emission intensities matched with consumption items in SUSENAS.

6 The overview of the data-matching scheme of the IO sectors with the household expenditure categories via the GTAP energy intensity is outlined as follows. There are 175 economic sectors in Indonesia, which were mapped using the GTAP sectors and aggregated into 57 sectors (Huff *et al.*, 2000). The data on household expenditure are rather disaggregated, consisting of around 340 expenditure categories.

expressed by the following:

$$CO_2^{fd} = c' E^{fd} y, \tag{1}$$

where c', E^{fd}, and y represent the inverse of the emissions coefficient vector, the matrix of energy use and the vector of final demand. The final demand vector is not disaggregated into household expenditure, exports and investment.

Secondly, the indirect emissions, CO_2^{ind}, can be divided into three sources of emissions: (a) from domestic production for domestic final demand; (b) from imported intermediates; and (c) from imported products for domestic final demand (excluding exports). Then, the sectoral CO_2 emissions can be estimated by multiplying each sector's final demand, y, the transposed emissions coefficients, c', the matrix of industrial energy use, E^{ind}, and with the domestic Leontief inverse $(I\text{-}A)^{-1}$, as follows:

$$CO_2^{ind} = c' E^{ind} \Big[(I-A)^{-1} y_{\neq \exp} + \left((I-A_{tot})^{-1} - (I-A)^{-1} \right) y_{\neq \exp} + (I-A_{tot})^{-1} y_{imp_{\neq \exp}} \Big], \tag{2}$$

where $A_{tot} = A + A_{imp}$, and $y_{tot} = y + y_{imp}$. $y_{\neq \exp}$ and I represent domestic final demand and identity matrix, while A indicates the matrix of technical coefficients that reflects the intermediates' contribution to one unit of final output.

Hence the direct and indirect CO_2 emission intensities can be calculated as follows:

$$CO_2 = CO_2^{fd} + CO_2^{ind} \tag{3}$$

$$CO_2 = c' \left\{ E^{fd} y + E^{ind} \Big[(I-A)^{-1} y_{\neq exp} + \left((I-A_{tot})^{-1} - (I-A)^{-1} \right) y_{\neq exp} + (I-A_{tot})^{-1} y_{imp \neq exp} \Big] \right\} \tag{4}$$

Finally, the above carbon intensities (in kg CO_2/Rp) of each sector are multiplied by the household consumption recorded from SUSENAS (in Rp) for the respective category and then the products from all categories are summed up for each household. The carbon footprint CO_2^{hh} (in kg of CO_2) for each household is calculated by the following equation:

$$CO_{2i}^{hh} = \sum_{i}^{j} \left(CO_{2j} * Exp_{ij} \right), \tag{5}$$

where i and j denote household and expenditure item, respectively.

2.2. *Drivers of the household carbon footprint*

This section will investigate how we analyze the determinants of the household carbon footprint as calculated above. The linkage between the expenditure choices and the carbon footprints will be determined from

https://doi.org/10.1017/S1355770X17000262 Published online by Cambridge University Press

the carbon intensity of particular items consumed in Indonesia. From the list of consumption items in SUSENAS, we will analyze the determinants of particular carbon-intensive consumption preferences, including choices related to household operations such as fuel-light and transportation. The empirical analysis is postulated as follows.

$$\ln CO_{2i}^{hh} = \alpha + \beta_1 lnEXP_i + \beta_2 X_i + \varepsilon_i. \tag{6}$$

The ordinary least squares (OLS) method will first be employed to regress the log of household carbon footprint CO_2^{hh} per capita on log of household expenditure per capita, ln*EXP*, as a proxy for per capita income, and a range of other determinants, X, including *region, household members, education, gender* and *age of household head.* To capture the possible nonlinearity of expenditures on household emissions (i.e., to test for a household-level EKC), a squared term for the expenditure per capita and age will be incorporated as well.

As we derived CO_2 emissions from expenditures, one can argue that our expenditure variable could have high in-built correlation with computed CO_2 emissions by construction. Dealing with this issue, we can proxy expenditure with expenditure quintile dummies,[7] Q; then regression (6) could be split into two stages, as follows:

$$\ln CO_{2i}^{hh} = \alpha + \beta_q \sum_{q=1}^{5} Q_{qi} + \varepsilon_i \tag{7}$$

and

$$\varepsilon_i = \alpha + \beta_1 X_i + \gamma_i, \tag{8}$$

where ε_i is the residual from regression (7) to study drivers that are unrelated to the expenditure–emissions link.

In other words, we regress emissions on the expenditure quintiles in (7) and then regress its residuals on other control variables (i.e., household characteristics excluding expenditure) in (8). This approach can determine the effect of characteristics of households on their emissions, over and above the expenditure–emissions link. Of particular interest is to understand the drivers of the heterogeneity of the household emissions at a given level of expenditure, and thereby to identify possible policy implications to reduce emissions without compromising the wellbeing of households.

In addition, we will also apply quantile regressions in the analysis to account for the possibility that the household emissions distribution is highly skewed and heteroscedasticity might be an issue. In this case, compared with the OLS regression, the quantile regression could be more robust to outliers, partly since it does not assume that the residuals are iid. Another reason is that we will be allowed to analyze the effect of the right-hand side variables on the location and the scale parameters in the model. Technically, while OLS minimizes the residuals sum of squares,

[7] Household affluence quintiles are constructed based on per capita expenditure.

$\sum e_i^2$, the quantile regression minimizes the sum that gives penalties of about $(1-q)\,|ei|$ for overprediction and of about $q|ei|$ for underprediction (Cameron and Trivedi, 2010).

Substantively, our quantile analysis presumes that the impact of income and other determinants for lower carbon-emitting households might be different from their impact for households with a high carbon footprint. With this in mind, the quantile regression estimates the effect of a one-unit expenditure change on a particular quantile q of our dependent variable (household emissions). Technically, by linear programming, the qth quantile regression minimizes over βq:

$$Q\left(\beta_q\right) = \sum_{i:y \geq x'\beta}^{N} q \left| y_i - x'_\beta \right| + \sum_{i:y \leq x'\beta}^{N} (1-q) \left| y_i - x'_\beta \right|. \tag{9}$$

We can choose q ($0 < q < 1$) which uniquely estimates the value of β. Suppose choosing $q = 0.9$, instead of $q = 0.1$, indicates that more weight is to be assigned to the estimation for observations with $y_i \geq x'_i \beta_q$.

2.3. *Decomposing the changes in the carbon footprint*

Since we have two waves of the national household survey available, we can investigate not only the drivers of emissions across households, but also over time. One approach to doing so is given by Kaya (1990), who provides an intuitive approach to the interpretation of the historical trend of CO_2 emissions. This method, which is widely known as the Kaya Identity, suggests that changes in the total emissions level can be decomposed into the changes in four inputs, i.e., population size, per capita income, energy use per unit of GDP, and CO_2 emissions per unit of energy used. While this is usually applied to decompose trends in aggregate emissions, one can also apply this approach to study household-level emissions. Using this decomposition technique, we can then directly link CO_2 emission levels to the population effect, level of economic affluence (measured by per capita expenditure), carbon emission intensity (per energy use) and energy intensity (per unit of output).[8] In this way, we can find the main driving forces of changes in emission levels in the periods observed.

In macro analyses, the Kaya Identity suggests that CO_2 emission levels are the product of: (i) the carbon intensity of the energy supply; (ii) the energy intensity of the economic activity; (iii) the economic per capita output, and population. However, since we do not have the data for energy intensities, in our analysis the Kaya Identity is modified as follows:

$$CO_{2_i} = HHsize_i * \frac{EXP_i}{HHSize_i} * \frac{CO_{2_i}}{EXP_i}, \tag{10}$$

where the household CO_2 emissions level is a function of household size, *HHsize*, per capita expenditure, *EXP/HHsize*, and emission intensity, CO_2/EXP.

[8] In terms of policy, the CO_2 intensity of output generally focuses on the promotion of low (or zero) carbon sources of energy.

In other words, we set up an emissions equation to calculate and decompose the growth of CO_2 emissions into the population effect, a per capita expenditure effect (Rp/capita) and a carbon intensity effect (CO_2/Rp), and express the result as a percentage of the baseline CO_2 emissions level. Following Ang (2005), our decomposition will be employed using the Logarithmic Mean Divisia Index (LMDI), which has several advantages; apart from it being consistent in aggregation, it also gives a perfect decomposition as the results will not contain unexplained residuals. The LMDI approach is modified (10) to construct the following formula:

$$\Delta CO2_i = C^T - C^0 = \Delta CO2_{HHsize} + \Delta CO2_{\frac{EXP}{HHsize}} + \Delta CO2_{\frac{CO2}{EXP}} \tag{11}$$

Where

$$\Delta CO2_{HHsize} = \sum_i \frac{C_i^T - C_i^0}{lnC_i^T - lnC_i^0} \ln\left(\frac{HHsize_i^T}{HHsize_i^0}\right)$$

$$\Delta CO2_{EXP/HHSize} = \sum_i \frac{C_i^T - C_i^0}{lnC_i^T - lnC_i^0} \ln\left(\frac{\left(\frac{EXP}{HHsize}\right)_i^T}{\left(\frac{EXP}{HHsize}\right)_i^0}\right)$$

$$\Delta CO2_{CO2/EXP} = \sum_i \frac{C_i^T - C_i^0}{lnC_i^T - lnC_i^0} \ln\left(\frac{\left(\frac{CO2}{EXP}\right)_i^T}{\left(\frac{CO2}{EXP}\right)_i^0}\right)$$

where $\Delta CO2_{HHsize}$, $\Delta CO2_{EXP/HHSize}$, and $\Delta CO2_{CO2/EXP}$ represent changes in CO_2 emissions because of population, expenditure, and the carbon intensity effect, respectively.

2.4. Expenditure elasticities of emissions

Lastly, one can also study the link between expenditure and emissions using demand analysis and the expenditure elasticity of spending on particular goods. Demand analysis is generally utilized to measure the change in demand for any particular good due to the change in income or price. This demand function originates from the consumers' utility maximization equation, which depends on the prices of goods and individuals' income (Deaton and Muellbauer, 1980). We modify this demand theory by replacing the demand for goods with CO_2 emissions associated with the consumption of the respective goods. By applying this, we can analyze the responsiveness of CO_2 emissions of any household consumption category to a change in household income, which is proxied by household expenditure.

As suggested by the conventional Engel curves, we should include prices as one of the independent variables. However, since there are no price data available in SUSENAS, we will estimate the impact of expenditure on the sectoral emission shares without using prices, meaning that the response of share of CO_2 emissions of a particular consumption item will only be dependent on the expenditure amount of the particular consumption item and the socio-economic level of the households. We estimate the following model:

$$sCO2_{ij} = \beta_0 + \beta_{1_{ij}} \ln EXP_i + \beta_{2_{ij}} X_i + \varepsilon_{ij}, \tag{12}$$

where $sCO2_{ij}$ represents the share of CO_2 emissions of the jth consumption category to total CO_2 emissions by the ith household, and $\ln EXP_i$ is the natural logarithm of total household i expenditure. X_i represents a vector of household characteristics and ε_{ij} is an error term.[9]

3. Results and discussions

3.1. Descriptive analysis

Figure A1, in the online appendix available at https://doi.org/10.1017/S1355770X17000262, provides an overview of the allocation of household expenditure in 2005 and 2009.[10] In general, mean household expenditure increased by 72.27 per cent (nominal) and 24.83 per cent (real). The figure also shows large differences in expenditure shares in urban and rural areas. Compared to urban households, households in rural areas have, unsurprisingly, a larger expenditure share on foods and a much smaller share on services, recreation, rents and taxes. In general, by comparing the two surveys we find that the share allocated to food expenditure declined as is to be expected in a growing economy. Moreover, the shares of telecommunication, transportation, health, education and taxes have been increasing in both the rural and urban areas. The share of spending on beverages has been increasing in urban areas as opposed to rural areas where it has been decreasing. In contrast, the share of income that is spent on housing and durable expenditures has been increasing for households in rural areas as opposed to households in urban areas where it has indeed been decreasing.

Before we begin the computation of the carbon footprint, it is very important to point out the relationship between mean consumption in SUSENAS and mean consumption in the national accounts. If we compare the two databases, we note that the expenditure computation from SUSENAS is

[9] One might argue that there is a potential endogeneity problem due to the fact that our CO_2 emissions are derived from expenditure. We could apply the instrumental variables estimation using (for instance) the household's asset index as an instrument for household expenditure. However, due to data limitations this is beyond our scope of study. Note that other studies that did use assets to instrument for expenditures did not significantly affect the size of the expenditure–emission relationship. See, for example, Grunewald (2013).

[10] For both surveys, the consumption is disaggregated to around 300 consumption items. In 2005 (and 2009), about 62.57 per cent (64.64 per cent) of households were located in rural areas. About 12.12 per cent (13.61 per cent) of households were headed by a woman. The households consisted of about 4.08 (3.96) members and 81.36 per cent (83.30 per cent) of them had a maximum five household members. On average, household head's years of schooling was 6.1 (6.49) years. The annual household expenditure equaled Rp 11.90m (Rp 20.50m). Urban households spent about Rp 16.50m/year (Rp 27.70m/year) compared to Rp 9.13m/year (Rp 16.60m/year) in urban areas.

significantly lower than consumption expenditures reported in the national accounts (this underestimation measure can also be found in other studies, e.g., Yusuf, 2006, and Mishra, 2009). The deviation between the two measures is partly because of the computations in the national accounts which were constructed from the supply side of the economy whereas SUSENAS expenditures were taken from representative sample surveys. In addition, national accounts also include the consumption by non-households. There might also be measurement error in the survey with households understating their total consumption, an issue that has been discussed extensively in the development economics literature (e.g., Deaton and Kozel, 2005).

Table A1 in the online appendix portrays the calculations of household expenditure using the national accounts and SUSENAS. Given the difference in the measurements from SUSENAS, which accounted for around 42–49 per cent of the national account measurements, we scaled up the computation of household emissions by dividing household consumption by the percentage of SUSENAS to total expenditure based on national accounts when we computed the carbon emissions (Mishra, 2009). However, the fact that the aggregate from SUSENAS expenditures falls short of the national accounts (including in our calculation with the scaled-up household emissions) would not imply anything about the distribution of the expenditures across households. Hence we assume that the discrepancies between expenditure items are more or less at the same amount across households.

In the next step, by incorporating the Indonesia IO table and GTAP's energy use matrix, we extract the CO_2 emission intensity level of the 175 economic sectors.[11] The CO_2 emission intensity is measured in terms of kilotons per million rupiah (or gram CO_2/Rp), which captures the amount of CO_2 released from the production of goods and services in the Indonesian economy. Table A2 in the online appendix presents the 10 most and least CO_2 intensive sectors, measured by emissions per unit of expenditures. It can be seen that sectors that emit CO_2 intensively include: electricity, gas, cement, non-metallic minerals, glasses and their products, ceramics and clay products. In addition to those electric and manufacturing sectors, all transportation services are also very carbon intensive.

In contrast, the least CO_2 intensive sectors in Indonesia are associated with agricultural crops sectors, including fiber crops, grains, sweet potatoes, fruits and beans. These figures reflect the fact that these products do not use much energy in production compared to manufacturing and transportation sectors.[12] In addition to the agricultural sectors, service sectors also have a lower CO_2 intensity, including such industries as film and distribution services, building and land rent. In general, agricultural and service-related activities emit less CO_2 compared to manufacturing sectors.

The derived CO_2 emission intensities were then matched with the consumption categories in the SUSENAS 2005 and 2009. There are around 340

[11] We follow Huff *et al.* (2000), using a concordance matrix between GTAP's emission data and all IO sectors.

[12] But note again that emissions from land use change are not considered here.

consumption items in the expenditure survey and this was aggregated to represent the major household expenditures. Figure A2 in the online appendix shows the average CO_2 emissions (in kg) from major expenditure categories. It is observed that CO_2 emissions vary greatly by consumption item. The lowest CO_2 emissions were observed from the consumption of cereals, medical services, telecommunication services and recreation. On the other hand, the highest CO_2 emissions were observed from the consumption of transportation as well as fuel and light.

From 2005 to 2009, household emissions from all expenditure categories increased (by 29 per cent on average), but at a different pace. Emissions from fuel-light expenditures grew proportionately less, from 1,688 kg to 2,768 kg (19 per cent). Meanwhile, emissions from transportation, the second highest emission source, rose more proportionately, from 183 kg to 290 kg (58 per cent), pointing to the importance of transportation in emissions growth. Emissions from food-related expenditures grew around 20–36 per cent. We also note that health, transportation and tax have the fastest growth rates of emissions (albeit from a low base).

The disaggregation of the CO_2 emissions into regions and income levels is presented in figure 2. We also find a very large difference in CO_2 emissions with respect to household affluence. In more detail, the per capita emissions from the richest quintile are about seven times higher than the per capita emissions from the lowest quintile, and still about three times as high as the level from the third quintile (middle income group).

Moreover, per capita carbon emission levels rise with educational attainment of the household head. The pattern of emissions with respect to educational attainment is surely related to income levels, although the differences between are not as steep as with the affluence level. Lastly, based on location, both surveys indicated that urban household emissions are about twice the amount of rural households. Looking at change from 2005 to 2009, we observe that overall household per capita emissions grew on average from 0.70 tons (2005) to 0.90 tons (2009), an increase of about 29 per cent.[13]

Comparing emission shares to expenditure shares (online appendix figure A3), we note first that they are very similar, suggesting a very close linkage between incomes and emissions. One can also see, however, that expenditures appear to be slightly less unequally distributed than emissions, particularly in 2005 (see also Irfany and Klasen, 2016).

3.2. Drivers of household carbon footprint

The regression analysis of the determinants of household emissions is presented in table 1. Various model specifications were employed to analyze the drivers of the variation in CO_2 emissions. In Regressions I and II, we regress the log of per capita emissions with log per capita expenditure and

[13] Estimated per capita CO_2 emissions in Indonesia from IEA (2013) were about 1.48 tons (2005) and 1.61 tons (2009). Our calculation is relatively lower than the estimation provided by IEA (2013), partly because our focus is only on household consumption (around 340 items in SUSENAS) and not on all economic activities (e.g., government consumption, final consumption of non-household entities).

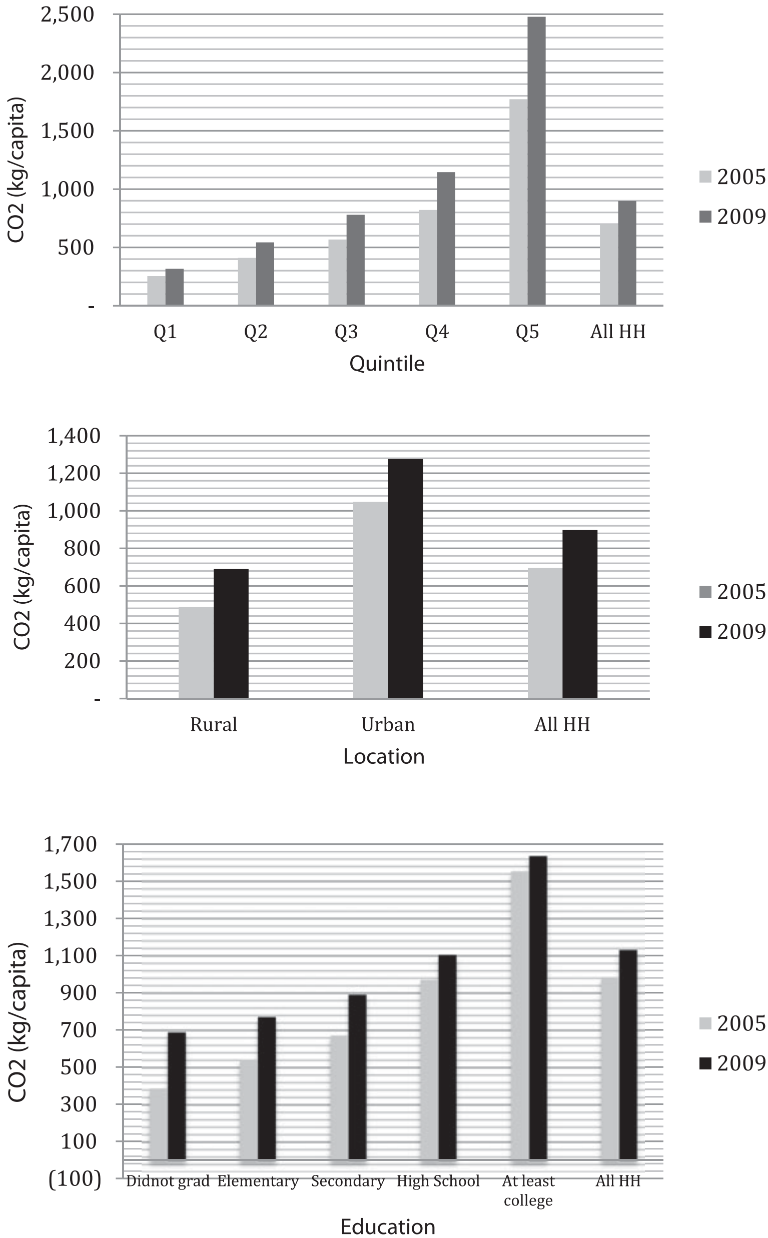

Figure 2. *Carbon footprint by household expenditure quintile, location, and education of the head (2005 and 2009)*
Source: Author's computation based on SUSENAS 2005–2009; IO 2005; GTAP-E 2005.

https://doi.org/10.1017/S1355770X17000262 Published online by Cambridge University Press

Table 1. *The determinants of household carbon footprint, 2005–2009*

	I	*II*	*III*	*IV*	*V*
	Dep. variable: lnCO2_cap	*Dep. variable: lnCO2_cap*	*Dep. variable: lnCO2_cap*	*Dep. variable: Residuals III*	*Dep. variable: Residuals III*
lnexp_cap	1.083***	1.947***			
lnexp_capsq		−0.028***			
Per capita exp. quintile					
2			0.616***		
3			1.037***		
4			1.494***		
5			2.315***		
HH-head age dummy					
25–44	0.085***	0.079***			
45–64	0.114***	0.107***			
65+	0.118***	0.111***			
HH-head age				5.52*E*-03***	1.01*E*-02***
HH-head agesq				−3.99*E*-05***	−1.34*E*-04***
HH-head agecub					6.02*E*-07***
HH size	0.010***	0.011***		−0.009***	−0.009***
Urbanity	0.103***	0.101***		0.130***	0.131***

(*continued*)

Table 1. *Continued*

	I	*II*	*III*	*IV*	*V*
	Dep. variable: lnCO2_cap	*Dep. variable: lnCO2_cap*	*Dep. variable: lnCO2_cap*	*Dep. variable: Residuals III*	*Dep. variable: Residuals III*
Education					
Elementary	0.037***	0.033***		0.041***	0.041***
Secondary	0.056***	0.051***		0.062***	0.062***
High school	0.086***	0.080***		0.095***	0.095***
At least college	0.093***	0.092***		0.156***	0.156***
Married HH-head	0.057***	0.048***		−0.023***	−0.024***
Female HH-head	0.052***	0.049***		0.024***	0.024***
Survey year 2009	−0.020***	−0.023***		−0.005***	−0.005***
_cons	−11.058***	−17.647***	4.651***	−0.409***	−0.475***
#Observations	549,659	549,659	549,659	549,659	549,659
R^2	0.837	0.838	0.718	0.121	0.121
Incl. dummy provinces	Yes	Yes	Yes	Yes	Yes

Notes: In Regressions I–III, the dependent variable is log of per capita carbon footprint, while in Regressions IV and V, the dependent variable is the residual from regression III. ***indicates significance at the 1% level. Province dummies are included but not reported here.
Source: Author's estimation.

other control variables, including dummies for different household characteristics. In the third regression, we regress the per capita carbon footprint only on income quintiles. Regressions IV and V use the residuals from Regression III as the dependent variable and household characteristics as control variables, with the cube of HH-head as an additional independent variable in Regression V.

From Regression I, we find that expenditure has a very high and significant relationship to emissions, with an elasticity of slightly above 1, suggesting that as per capita expenditures rise, emissions rise in equal (actually slightly higher) proportion. In Regression II, we include the square of per capita expenditures and find the square to have a negative effect. This implies an inverted U-shaped pattern of the carbon footprint with respect to expenditure. In other words, rising affluence leads to increasing CO_2 emissions, *ceteris paribus*, but eventually declines as per capita expenditure rises even further; this, in principle, supports a micro-level EKC, but one should also note that the turning point is far beyond the sample included here so that it is, for all practical purposes, empirically not relevant and just suggests that household emissions are increasing with expenditures at falling marginal rates. Furthermore, we also indicate that the greater the age (of the household head), if the gender (of household head) was female, if the household head was married, and if the region was an urban area, the more carbon was emitted; thus the unconditional effects we showed descriptively above still hold in a multivariate setting, although the effects of these covariates are rather small, certainly when compared to the income effect. This suggests that higher education and urban location are not just associated with higher per capita expenditures, but also with more carbon-intensive lifestyles even conditioning on expenditure; this is likely to be related to higher transportation as well as energy use in urban and more educated households. Moreover, household size has, somewhat surprisingly, a small positive impact on per capita carbon emissions, suggesting that larger households are apparently unable to economize on per capita carbon emissions and, in fact, have slightly more carbon-intensive lifestyles.

In Regression III we regress per capita emissions on affluence quintiles, which divide households into five equal parts by sorting the per capita expenditure out from lowest to highest. It is observed that households in the higher quintiles have a larger carbon footprint and the coefficients are statistically significant. Moving from the first to the second quintile increases the per capita emissions by 62 per cent, whereas moving from the first to the richest quintile increases household emissions by 231 per cent.

We then utilize the residuals from Regression III as the dependent variable of Regressions IV and V, and household characteristics as control variables. The idea is to purge the impact of incomes that would then reveal the effect of certain household characteristics on their emissions, beyond the effect of incomes. As indicated, it is not surprising that the coefficients of household characteristics (the control variables) are statistically significant and consistent with the previous specifications. The two exceptions are the effect of household size and marital status which switches from slightly positive to slightly negative. In emissions unrelated to expenditures, larger and married households now seem to have slightly lower emissions. This suggests that the previous positive effect was influenced by a correlation between household size, marital status and household expenditures; once considering the residuals of emissions unrelated to household expenditures, larger (and married) households appear to be able to (slightly) economize on per capita emissions. It is also interesting to note that, in all regressions, the dummy variable for the second year (2009) is slightly negative, suggesting that, controlling for rising expenditure, urbanization and education, per capita emissions have been falling by about 2 per cent; this could suggest slight improvements in expenditure patterns (controlling for incomes) towards less carbon-intensive products.

Lastly, in all regressions we include dummies for all of the provinces (available on request). The estimated coefficients for all control variables with and without dummies do not change significantly. However, from the province fixed-effects regression we find that the emissions of provinces in Java and Bali, Kalimantan Timur, Kalimantan Selatan, Sulawesi Selatan and Sulawesi Tenggara were higher than the amount in other provinces.

Table 2 presents quantile regression estimates using $q = 0.10; q = 0.25; 0.50; 0.75;$ and 0.90. Apart from its statistical advantages (particularly in the case of heteroscedasticity), it helps us understand whether household affluence and other covariates might have a different effect at different quantiles of the emission distribution.

We find that households with low emissions seem to have slightly higher expenditure elasticities to emit: from about 1.070 (at 25 per cent quantile), the magnitudes then fall slightly to 1.044 (at median quantile), and to 1.027 (at 75 per cent quantile) and to 1.021 (at 90 per cent quantile). In other words, low-emitter household groups seem to be slightly more responsive to emit and then the effect decreases for those with higher emissions. But for all households, the emission elasticity remains above one.[14] Finally, similarly to the OLS estimation, we again observe that other household characteristics also matter as determinants of the household carbon footprint, but do not differ greatly between quantiles. Interestingly, the effect of household size is slightly negative in most quantiles.

3.3. The decomposition analysis of emission growth

Figure 3 presents the decomposition of the growth of household CO_2 emissions from 2005 to 2009. From the perspective of contributors to CO_2 emissions growth, we can clearly show that rising per capita expenditures is the largest contributor to the rise in CO_2 emissions in all quintiles. This rise in expenditures has the largest effect in the lowest quintile, which means that rising per capita expenditure of households in this quintile has increased CO_2 emissions more than the same rise in per capita expenditures of households in the upper quintiles. Moving to affluent households, the expenditure effect then decreases gradually, but the effects in all quintiles remain positive.

[14] In further work, not shown here, we also include the square of emissions and find the relationship to be concave throughout, but less so at higher quantiles. Results are shown in online appendix table A4.

Table 2. *Quantile regression estimates*

	OLS		*Q(0.1)*		*Q(0.25)*		*Q(0.50)*		*Q(0.75)*		*Q(0.90)*	
	Coef.	*SE*	*Coef.*	*SE*	*Coef.*	*SE*	*Coef.*	*SE*	*Coef.*	*SE*	*Coef.*	*SE*
lnexp_cap	1.054	0.001	1.089	0.002	1.070	0.001	1.044	0.001	1.027	0.001	1.021	0.002
HH-head age	0.023	0.001	0.029	0.002	0.027	0.001	0.024	0.001	0.020	0.001	0.015	0.001
HH-head agesq	−3.40E-04	1.82E-05	−4.49E-04	3.48E-05	−4.06E-04	2.58E-05	−3.64E-04	2.18E-05	−2.93E-04	2.26E-05	−2.05E-04	2.87E-05
HH-head agecub	1.67E-06	1.16E-07	2.30E-06	2.22E-07	2.07E-06	1.65E-07	1.83E-06	1.39E-07	1.40E-06	1.44E-07	9.35E-07	1.83E-07
HH size	−0.008	0.000	0.004	0.001	−0.003	0.001	−0.010	0.000	−0.014	0.000	−0.0135	0.0006
Urbanity	0.169	0.001	0.229	0.002	0.213	0.002	0.176	0.001	0.135	0.002	0.1027	0.0019
Married HH-head	0.072	0.002	0.099	0.005	0.084	0.003	0.070	0.003	0.054	0.003	0.0396	0.0037
Female HH-head	0.052	0.003	0.063	0.005	0.055	0.004	0.051	0.003	0.045	0.003	0.0397	0.0040
Elementary school	0.047	0.002	0.062	0.003	0.058	0.002	0.050	0.002	0.036	0.002	0.0312	0.0026
Secondary school	0.053	0.002	0.073	0.004	0.065	0.003	0.053	0.002	0.042	0.003	0.0299	0.0032
High school	0.082	0.002	0.106	0.004	0.097	0.003	0.084	0.002	0.069	0.002	0.0556	0.0032
At least college	0.097	0.003	0.120	0.005	0.112	0.004	0.101	0.003	0.086	0.003	0.0733	0.0041
Survey year 2009	−0.022	0.001	−0.015	0.002	−0.024	0.002	−0.028	0.001	−0.028	0.002	−0.0283	0.0020
_cons	−10.772	0.020	−12.027	0.039	−11.369	0.029	−10.617	0.024	−9.983	0.025	−9.5409	0.0323
#Observations	549,659		549,659		549,659		549,659		549,659		549,659	
(pseudo) R^2	0.819		0.532		0.554		0.578		0.5992		0.6165	

Source: Author's estimation.

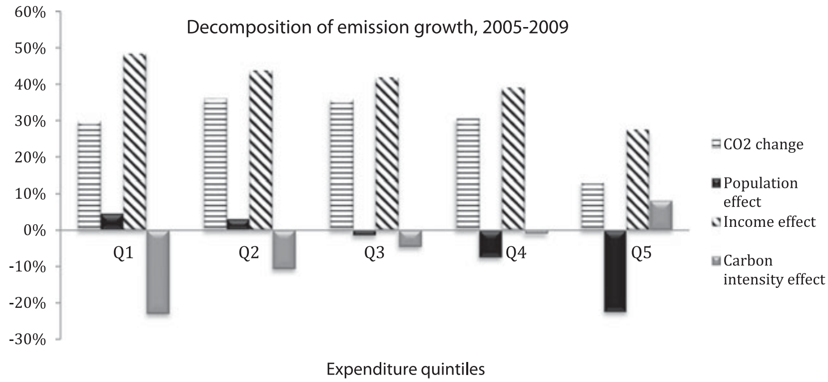

Figure 3. *Decomposition of CO_2 emission growth*
Note: Total expenditures used here are deflated to reflect real values.
Source: Author's computation based on SUSENAS 2005–2009; IO 2005; GTAP-E 2005.

Moreover, moving from the lowest to the highest households, we can clearly identify that the population effect has a decreasing pattern, which has a positive effect on the first two quintiles and has a negative effect on the third to the highest quintile; here we see the effect of fertility decline which affects household size in the richer quintiles. Finally, the CO_2 intensity effect (measured as kg CO_2/Rp) has the largest negative contribution to CO_2 emissions rising in the lowest quintile. This effect has a negative sign from the first until the third quintile and has a positive sign in the highest quintile, suggesting that consumption changes in that quintile have served to significantly increase emissions. Increases in the energy expenditure share (mainly transportation) in 2009 are the most important driving factor of this positive carbon intensity effect among the richest household group (compared to a falling expenditure share in the lower income groups).[15] To sum up, richer households have lower emissions growth because of their population (household size) effect as well as a smaller increase in per capita expenditures, but this is partly offset by choosing more carbon-intensive goods due to rising affluence.

3.4. *Expenditure elasticities of emissions*

Due to the fact that expenditure is the most important driver of the household carbon footprint, we conduct an analysis of expenditure elasticities of CO_2 emissions that measure the responsiveness of CO_2 emissions (as a share of total household emissions) to a change of total household expenditure. There are some important issues to be taken into consideration for our analysis. First, dealing with the potential endogeneity problem, one could have a valid instrument for total expenditures, say for instance, for the asset index, and employ the instrument in a two-stage least squares procedure. However, our database unfortunately does not provide sufficient

[15] See, for instance, online appendix table A5.

candidates as valid instruments for total expenditure, as we do not have sufficient data on assets in SUSENAS. Secondly, in addition to the national estimation, we will also analyze expenditure elasticities for both rural and urban areas, as well as computing expenditure elasticities by household quintiles.

As the demand theory suggests, a negative coefficient of expenditure elasticities reflects a decreasing share of any particular expenditure group due to rising affluence, and vice versa. Our results on expenditure elasticities on CO_2 emissions generally have the same direction as found in conventional Engle curve studies in the literature. Table A3 in the online appendix reveals some important findings. We find that inferior goods, such as vegetables and cereals, have negative signs, meaning that rising expenditure will reduce their share of CO_2 emissions of these consumption categories, due to a falling expenditure share on these goods as incomes rise. In the opposite direction, luxury goods such as health expenditures, housing, durable goods, transportation, services and rent have positive value, meaning that the rising of household affluence tends to contribute a higher share of CO_2 emissions to the total household emissions. Specifically, the rising affluence will promote carbon-intensive transportation expenditures in that a 1 per cent increase in household expenditure will increase the share of CO_2 emissions from transportation by about 0.03 per cent (both in 2005 and 2009); an even larger effect is observed for the impact of rising expenditures on housing and durable goods. Fuel and light consumption, another carbon-intensive category, has a negative elasticity, which means that a 1 per cent increase in household income will reduce the share of CO_2 emissions from these consumption items by about 0.07 per cent in 2005 (0.08 per cent in 2009).

Last but not least, most of the estimated expenditure elasticities coefficients are generally very small, but generally the directions of these expenditure elasticities to CO_2 emissions have the same signs as the conventional Engle curve. However, they have different sensitivities due to the different CO_2 intensities of the consumption categories. The small size of the expenditure elasticities indicates that the household emission change can mainly be attributed to a general volume increase in overall expenditure, and not so much to shifting the expenditure shares within the consumption basket. These findings support the previous results on the decomposition of emission growth that suggest that emission growth is mainly due to rising overall income (expenditure) level.

4. Conclusion

The objectives of this study are to analyze the household carbon footprint pattern in Indonesia and to analyze the determinants of the growing carbon footprint in this emerging economy. Of particular relevance is identifying possible tradeoffs between increasing incomes (which will promote income poverty reduction) and the carbon-intensive behavioral choices of households from the consumption side. Of particular interest is the study of the determinants of the carbon footprint as household consumption rises. This study combines national IO and the GTAP emission database to compute CO_2 emission intensities for all IO sectors in Indonesia. These intensities were then matched with two waves of national expenditure surveys from 2005 and 2009 to calculate the carbon footprint for every household in the surveys. We further use this household CO_2 emissions information in investigating the drivers of the rise in emissions from a micro cross-sectional perspective.

Comparing CO_2 intensities, the results show that the fuel-light and transportation consumption categories are the two most CO_2 intensive emitting sectors in Indonesia. These expenditures are also the main sources of overall household emission. In contrast, food- or agriculture-related expenditures post the lowest CO_2 intensities as well as carbon emission levels. In terms of numbers, we found that there was an increase in households' carbon footprint from 2005 to 2009 by about 29 per cent. Dividing households into per capita expenditure quintiles, we showed emission disparities between household quintiles as the richest households emit almost five and three times as much compared to the first and third quintiles (seven and three times based on per capita emission terms). In addition, we found that there is a significant difference in household carbon emissions between different income levels, regions and education levels.

To understand the drivers of the variations in the household carbon footprint, we apply various regressions of household CO_2 emissions on household characteristics such as income, education, region, household population, and gender and age of the household head. We found that rising household expenditure is the main determinant of rising household emissions. It is clearly shown that varying income levels differ significantly in terms of their carbon footprint. Other household characteristics also contribute to the variation in emission levels. Urban areas, more educated, older and female household heads, as well as households in Java provinces, all have a higher profile of CO_2 emissions. Quantile regression indicates that those low-emitter households have a larger expenditure elasticity of emissions, while households with a high carbon footprint have an income elasticity that is slightly lower (but still above 1). Last but not least, the results of the decomposition analyses also show that changes in household emission levels are due primarily to the income (expenditure) effect, between household levels and over the two periods. The expenditure elasticities analysis suggested that the rise in household emissions is mainly caused by general increases in overall household expenditure, and not by shifts in the consumption basket.

Regarding the EKC hypothesis that proposes the nonlinear income–emissions link (see Grossman and Krueger, 1995; Torras and Boyce, 1998), we find weak evidence of an EKC with turning points far outside our sample, suggesting that one cannot expect that further income growth will automatically lead to declining emissions any time soon in an emerging economy such as Indonesia.

Finally, our study suggests possible policy implications. As Indonesian per capita income is likely to continue to grow, without strong policy action one can assume that emissions will rise more or less proportionately with income, a finding that appears to be true in other emerging economies as well (e.g., Jakob *et al.*, 2014). To prevent that, a transformation towards less carbon-intensive consumption would need to play a role. In the Indonesian case, the phase-out of existing costly fuel subsidies would be one of the most promising avenues to reduce emissions, which at the same time would save scarce fiscal resources and would generally be pro-poor, especially if some of the saved funds are used for targeted transfer programs (Renner *et al.*, 2015). Fortunately, the government of Indonesia began reducing fuel subsidies in 2015, but some subsidies have remained. Moreover, supporting policies to reduce the emissions–income link could be measures to promote energy efficiency (e.g., in the power and transport sectors), a low-carbon energy system making greater use of renewable energy technologies including wind, solar and geothermal energy, and investments in sustainable public transport systems. Taking those strategies together would allow rising affluence which could be translated into sustainable consumption patterns that might minimize the scale of the emission trade-offs of development and thus promote low-carbon development paths. Some of these issues are tackled in the strategy Indonesia has proposed in order to fulfill the pledges of its Nationally Determined Contribution under the UNFCCC Paris Agreement. In particular, the government aims to increase the share of renewable energy in the primary energy mix to 23 per cent by 2025, and to reduce the share of oil, coal and gas to 25 per cent, 30 per cent and 22 per cent by 2025, respectively, with further shifts towards renewable energy thereafter. Increasing use of biofuels, the phase-out of fuel subsidies, the move to clean coal technology, the shift from coal and oil to gas, and support for renewable energies are all part of this approach (GOI, 2016).[16] It is too early to assess the success of these plans which will have to be closely monitored in the future.

All of the above issues of the strong income–emission link and ways to reduce this link could have significant relevance to other developing countries as well as to global debates on how to reduce the carbon intensity of development paths (see also Jakob *et al.*, 2014).

Supplementary material and methods

To view supplementary material for this article, please visit https://doi.org/10.1017/S1355770X17000262.

References

Ang, B.W. (2005), 'The LMDI approach to decomposition analysis: a practical guide', *Energy Policy* **32**: 1131–1139.

Bin, S. and H. Dowlatabadi (2005), 'Consumer lifestyle approach to US energy use and the related CO_2 emissions', *Energy Policy* **33**(2): 197–208.

[16] Given the importance of land use change, and emissions from forestry and agriculture, the government places great emphasis on reducing emissions from those sectors, which are unrelated to the analysis in this paper.

Cameron, A.C. and P.K. Trivedi (2010), *Microeconometrics Using Stata* (revised edn) College Station, TX: Stata Press.
Chow, G.C. and J. Li (2014), 'Environmental Kuznets curve: conclusive econometric evidence for', *Pacific Economic Review* **19**(1): 1–7.
Deaton, A. and V. Kozel (2005), 'Data and dogma: the great Indian poverty debate', *World Bank Research Observer* **20**(2): 177–199.
Deaton, A. and J. Muellbauer (1980), *Economics and Consumer Behavior*, Cambridge: Cambridge University Press.
EDGAR (2016), *Emission Database for Global Atmospheric Research (EDGAR)*, Release Version 4.3.2, [Available at] http://edgar.jrc.ec.europa.eu/
Girod, B. and P. de Haan (2009), 'GHG reduction potential of changes in consumption patterns and higher quality levels: evidence from Swiss household consumption survey', *Energy Policy* **37**(12): 5650–5661.
GOI (Government of Indonesia) (2015), *Intended Nationally Determined Contribution, Republic of Indonesia*, Geneva: UNFCCC.
GOI (Government of Indonesia) (2016), *First Nationally Determined Contribution, Government of Indonesia*, Geneva: UNFCCC.
Grossman, G.M. and A.B. Krueger (1995), 'Economic growth and the environment', *Quarterly Journal of Economics* **110**(2): 353–377.
Grunewald, N. (2013), 'Growth, carbon dioxide emissions, climate and wellbeing', PhD thesis, Wirtschaftswissenschaftlichen Fakultät, University of Göttingen.
Huff, K., R. McDougall, and T. Walmsley (2000), 'Contributing input-output tables to the GTAP data base', GTAP Technical Paper 1(4.2), Global Trade Analysis Project, West Lafayette, IN.
IEA (International Energy Agency) (2013), *CO_2 Emissions from Fuel Combustion*, [Available at] http://www.iea.org/publications/freepublications/publication/co2emissionsfromfuelcombustionhighlights2013.pdf.
IPCC (Intergovernmental Panel on Climate Change) (2014), *Climate Change 2014: Mitigation of Climate Change, Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [O. Edenhofer, R. Pichs-Madruga, Y. Sokona, *et al*. (eds)], Cambridge and New York, NY: Cambridge University Press.
Irfany, M.I. and S. Klasen (2016), 'Inequality in emissions: evidence from Indonesian household carbon footprint', *Environmental Economics and Policy Studies* **8**(4): 459–483.
Jakob, M., J.C. Steckel, S. Klasen, *et al*. (2014), 'Feasible mitigation actions in developing countries', *Nature Climate Change* **4**(11): 961–968.
Kaya, Y. (1990), 'Impact of carbon dioxide emission control on GNP growth: interpretation of proposed scenarios', Energy and Industry Subgroup Memorandum, IPCC Response Strategies Working Group, Geneva.
Kenny, T. and N.F. Gray (2009), 'A preliminary survey of household and personal carbon dioxide emissions in Ireland', *Environment InterTotal Expenditure* **35**: 259–272.
Kok, R., R.M.J. Benders, and H.C. Moll (2006), 'Measuring the environmental load of household consumption using some methods based on input–output energy analysis: a comparison of methods and a discussion of results', *Energy Policy* **34**(17): 2744–2761.
Lenzen, M. (1998a), 'Energy and greenhouse gas cost of living for Australia during 1993/94', *Energy* **23**(6): 497–516.
Lenzen, M. (1998b), 'Primary energy and greenhouse gases embodied in Australian final consumption: an input-output analysis', *Energy Policy* **26**(6): 495–506.
Lenzen, M., M. Wier, C. Cohen, H. Hayami, S. Pachauri, and R. Schaeffer (2006), 'A comparative multivariate analysis of household energy requirements in Australia, Brazil, Denmark, India and Japan', *Energy* **31**(2–3): 181–207.

Li, J. and Y. Wang (2010), 'Income, lifestyle and household carbon footprints (carbon–income relationship), a micro-level analysis on China's urban and rural household surveys', *Environmental Economics* **1**(2).
Mishra, S.C. (2009), 'Economic inequality in Indonesia: trend causes and policy responses', UNDP Regional Office Paper, Strategic Asia.
Murthy, N., M. Panda, and J. Parikh (1997), 'Economic development, poverty reduction and carbon emissions in India', *Energy Economics* **19**(3): 327–354.
Pachauri, S. and D. Spreng (2002), 'Direct and indirect energy requirements of households in India', *Energy Policy* **30**(6): 511–523.
Parikh, J., M. Panda, and N.S. Murthy (1997), 'Consumption patterns by income groups and carbon dioxide implications for India: 1990–2010', *International Journal of Global Energy* **9**(4–6): 237–255.
PEACE (2007), *Indonesia and Climate Change: Current Status and Policies*, [Available at] http://siteresources.worldbank.org/INTINDONESIA/Resources/Environment/ClimateChange_Full_EN.pdf.
Renner, S., J. Lay, M. Schleicher, and N. Nuryartono (2015), 'Poverty and distributional impact of energy subsidy reform in Indonesia', Mimeo, GIGA Institute, Hamburg.
Serino, M.N. and S. Klasen (2015), 'Estimation and determinants of the Philippines' household carbon footprint', *Developing Economies* **53**(1): 44–62.
Siagian, U.W.R., R.G. Dewi, R. Boer, I. Hendrawana, B.B. Yuwono, and G.E. Ginting (2015), *Pathways to Deep Decarbonization in Indonesia*, Paris: Sustainable Development Solutions Network (SDSN) and Institute for Sustainable Development and International Relations (IDDRI).
Stern, D., M.S. Common, and E. Barbier (1996), 'Economic growth and environmental degradation: the environmental Kuznets curve and sustainable development', *World Development* **24**(7): 1151–1160.
Torras, M. and J.K. Boyce (1998), 'Income, inequality, and pollution: a reassessment of the environmental Kuznets curve', *Ecological Economics* **25**: 147–160.
UNFCCC (2010), 'United Nations Framework Convention on Climate Change', [Available at] http://unfccc.int/2860.php.
Wagner, M. (2008), 'The carbon Kuznets curve: a cloudy picture emitted by bad econometrics?', *Resource and Energy Economics* **30**(3): 388–408.
Wier, M., M. Lenzen, J. Munksgaard, and S. Smed (2001), 'Effects of household consumption patterns on CO_2 requirements', *Economic Systems Research* **13**: 259–274.
York, R. (2012), 'Asymmetric effects of economic growth and decline on CO_2 emissions', *Nature Climate Change* **2**: 762–764.
Yusuf, A.A. (2006), 'On the re-assessment of inequality in Indonesia: household survey or national account?', MPRA Paper No. 1728, [Available at] https://mpra.ub.uni-muenchen.de/1728/.