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Abstract
Household carbon footprints account for a large proportion of total emissions. When considering indirect emissions through the consumption of goods and services, a high level of carbon footprint inequality exists both worldwide and within China. Utilizing both provincial level input-output tables and micro-level household survey data, this paper aims to measure Chinese households' indirect carbon footprints, estimate the level of indirect carbon footprint inequalities, and analyze the main drivers of carbon footprint disparities. The main findings are as follows. First, there is widespread inequality in terms of indirect carbon footprints at the individual household level, and the urban-rural disparity has a significant impact on carbon footprint inequalities. Second, inequalities in terms of carbon footprints are higher than those in relation to income and expenditure, with the main source being between-group inequalities. Third, disparities in income, education, living conditions, and asset ownership, as well as urban-rural disparities, are the main factors contributing to carbon footprint differentials. These results imply that the urban rich in China have contributed significantly to emissions growth by means of their daily consumption. With the largest population in the world, the reduction of China's household carbon footprint has significant implications for global carbon emissions mitigation. China's future policies should include consideration of low carbon emissions initiatives, such as a progressive carbon tax, that emphasizes the responsibility of the rich.

Keywords: carbon inequality; indirect carbon footprint; input–output analysis; China household survey data

JEL classification: Q54, Q56, C67, O15

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1. Introduction

Growing carbon emissions pose a potential threat to the ecological environment, human living standards, and sustainable development (Lin and Jia, 2019). Increasing household demands and their environmentally detrimental consuming habits have become a major part of this challenge (Munksgaard *et al.*, 2000). Household emissions, specifically household carbon footprints, account for a large proportion of total emissions (Li *et al.*, 2019; Schipper *et al.*, 1989), for instance, 80% in the United States (US) (Bin and Dowlatabadi, 2005), 75% in India (Pachauri and Spreng, 2002), and more than 40% in China (Liu *et al.*, 2011). A considerable proportion of household carbon footprints are in the form of indirect emissions from the consumption of goods and services rather than direct emissions from fossil fuel combustion. Indirect energy consumption and carbon dioxide (CO_2) emissions account for 77% and 84%, respectively, of household total energy consumption and carbon emissions in 2010 (Zhang *et al.*, 2017). The indirect proportion of household carbon footprints is a major source of total emissions and has great potential in relation to future emissions reduction strategies. In this study, we focus on the indirect portion of Chinese households' carbon footprints, that is, their indirect carbon footprints.

The role of households in contributing to and combating global climate change has received extensive attention in the literature. In order to adapt to global climate change, effort is required not only from the industrial production sectors but also from the household consumption perspective (Feng *et al.*, 2011; Hamamoto, 2013; Meng *et al.*, 2018; Peters, 2010). Having a carbon footprint, or producing carbon emissions, has been recognized as a basic human right, especially the right to subsistence and development (Lininger, 2013). An individual's carbon footprint also provides a new measure of personal welfare, replacing traditional measures such as income or asset ownership (Jorgenson, Dietz & Kelly, 2017). Carbon footprints not only reflect the level of basic human rights and welfare, but also indicate various levels of responsibility for the climate change issue. It is essential to measure household carbon footprints to understand how much each individual contributes to climate change and quantify their precise degree of responsibility.

The successful mitigation of China's carbon emissions largely depends on a reduction in indirect carbon footprints. Since 2005, China has been the world's largest emitter; its per capita emissions surpassed those of the European Union in 2013 (Le Quéré *et al.*, 2015). The Chinese government announced ambitious mitigation targets at the 21st United Nations Conference on Climate Change (COP 21), including a 60 to 65% reduction in carbon emissions intensity by 2030, as compared to their 2005 baseline emissions, which represented a peak in total emissions at that time. Given China's population of 1.4 billion people, the reduction of Chinese households' indirect carbon footprints has significant implications for global emissions mitigation. The timely achievement of China's mitigation targets requires not only emissions reductions at the national level, but also the control of each individual's carbon footprint.

During the mitigation process, carbon footprint equality is of great importance. The responsibility for addressing climate change varies significantly because the distribution of carbon footprints is highly unequal (Hubacek, 2017; OXFAM, 2015; Piketty, 2015; Wiedenhofer *et al.*, 2016). Studies have found solid evidence of carbon footprint inequalities both worldwide and within China. For instance, the richest 10% of the global population is responsible for nearly 50% of all global emissions (OXFAM, 2015). Meanwhile, there is extreme poverty in terms of both wealth and emissions, with the poorest 12% of the global population contributing only 4% of all global emissions (Hubacek *et al.*, 2017). Thus, the carbon footprint of an individual in the richest 1% of the population could be up to 175 times that of someone in the poorest 10% (OXFAM, 2015). Meanwhile, the unequal distribution of carbon footprints has also been found within China (Hubacek *et al.*, 2017; Wiedenhofer *et al.*, 2016). The carbon footprints of Chinese households vary considerably based on their level of income and on urban-rural disparities (Hubacek *et al.*, 2017; Wiedenhofer *et al.*, 2016). Studies have found that the richest 10% of the urban population is responsible for 19% of China's total carbon footprint (Wiedenhofer *et al.*, 2016). The unequal distribution of carbon footprints between the rich and the poor reflects the different levels of contribution of these groups to global climate change. Carbon footprint inequality has resulted in a mismatch between those who contribute most to climate change and those who suffer the greatest consequences (Hubacek *et al.*, 2017).

A fundamental principle in tackling the global climate challenge is "common but differentiated responsibilities." This idea is closely associated with carbon footprint inequality, in which variations in various people's contributions to global emissions are taken into consideration. Accordingly, an emerging body of research has tried to "give credit where credit is due" (Koopman *et al.*, 2014), and to address the following question: who is the most responsible for larger carbon footprints? Thus, in this study, we aim to measure Chinese households' indirect carbon footprints, estimate the level of indirect carbon footprint differentials, and analyze the main drivers of carbon footprint disparities. We first measure household carbon footprints at the micro level by combining household expenditures in each category with consumption-based indirect carbon emissions intensity estimated using provincial-level extended input-output tables. The use of the provincial extended method allows us to identify different emissions intensities for each type of expenditure in each province. Then, we assess the level of carbon footprint inequalities using the Gini index and the Theil index, which are frequently used in inequality studies. The results provided by these indicators are then compared with those obtained using income and expenditure inequality indicators and the same survey data. Finally, we analyze the driving forces behind carbon footprint disparities on a per capita basis using regression models. The factors in our model include demographic characteristics such as gender, age, family size, number of elderly people and children in the family, financial characteristics such as disposable income, housing ownership, and vehicle ownership, and control factors such as the year, province, and urban identity, as well as other variables of interest.

The rest of the paper is structured as follows. Section 2 presents a review of the existing literature on carbon footprints and related inequalities. Section 3 introduces the methodology used in this study and presents descriptive statistics in relation to the measured carbon footprints. In Section 4, we (1) describe the three household survey databases used in this study, (2) report on the inequality status of carbon footprints, and (3) describe the specification of the model, discuss the empirical results, and present the results of robustness checks. In Section 5, we present our conclusions and the implications of this study.

2. Literature Review

Over the past few decades, the issue of carbon footprints has received extensive attention in the academic literature. In addition to studies investigating production-based emissions, a vast body of literature has investigated the consumption side of the story (Atkinson *et al.*, 2011; Peters, 2008; Steininger *et al.*, 2014). The notion of consumption-based emissions involves emissions indirectly generated by residents and governments during the process of consuming goods and services that have already produced carbon emissions during the production process (Davis and Caldeira, 2010; Feng *et al.*, 2014; Takahashi *et al.*, 2014; Tian *et al.*, 2014; Wiedmann *et al.*, 2011). Specifically, a growing body of literature has focused on the emissions produced by household consumption (Lenzen, 1998; Reinders *et al.*, 2003; Su *et al.*, 2017; Tukker & Jansen, 2006), and the concept of carbon footprints has also been introduced to measure these emissions (Feng el al., 2016; Liu *et al.*, 2011; Ottelin *et al.*, 2015; Wiedenhofer *et al.*, 2013; Wiedenhofer *et al.*, 2016).

As the largest carbon emitter and a country with a high level of income inequality (Xie and Zhou, 2014), China has addressed the issue of carbon footprint inequalities from several perspectives. First, scholars have developed a series of indexes to assess carbon footprint inequalities (Cantore, 2011; Duro & Padilla, 2006, 2011;Heil & Wodon, 1997, 2000; Padilla & Serrano, 2006), and have estimated the carbon footprint inequalities in China using the Gini index and the Theil index (Clarke-Sather, 2011). Second, some important studies have attempted to identify the uneven distribution of household carbon footprints in China using a systems approach to measure household carbon footprints (Kok *et al.*, 2006). Some studies have estimated household carbon footprints in China by income group (Wiedenhofer *et al.*, 2016; Hubacek, 2017), and have found great disparities between the groups. A few studies have analyzed household carbon footprint inequalities using data from large survey samples (Golley and Meng, 2012; Xu *et al.*, 2016; Zhang *et al.*, 2017; Li *et al.*, 2019). Third, scholars are also interested in the main drivers of carbon footprint inequality. Usually, income difference is their main focus, with other variables being controlled for (Golley and Meng, 2012; Hubacek, 2017; Wiedenhofer *et al.*, 2016).

In summary, previous studies have made important contributions to the analysis of household carbon footprint inequality in China. However, this area remains under-researched in several areas. First, most of the studies measured household carbon footprints using average income groups, rather than on a more detailed basis. Further, studies measuring individual carbon footprints focused on urban residents, while neglecting rural residents. Second, the measurement approach is usually based on a national input-output analysis, which assumes a constant industrial emissions intensity for the entire country. Thus, provincial differences and urban-rural disparities might have been neglected, and the level of inequalities might have been either over- or under-estimated. Third, while important descriptive studies have been undertaken, empirical studies are scarce. Although it is of great importance to understand what drives carbon footprint inequalities, there have been few empirical studies due to low data availability and a lack of proper measures combining input-output analysis with micro data. Fourth, most of the existing studies are based on a single year of data or rely on a single database, thus robustness checks of their results as well as comparability of different studies are lacking.

This study contributes to the existing literature in three essential ways. First, we integrate an Environmentally Extended Input-Output Analysis with a Consumer Lifestyle Approach, taking provincial and urban-rural disparities into consideration. The method used in this study provides a more accurate measurement of household carbon footprints and further analyses of carbon footprint inequalities. In this study, we not only compile an extended input-output table for each province for each year, but we also take urban-rural disparities into consideration in each province.

Second, we estimate the level of carbon footprint inequalities using the Gini index and the Theil index based on micro data and compare this with income levels and expenditure inequalities. Third, we analyze the factors contributing to greater carbon footprints using empirical analysis based on the Chinese Urban Household Survey (CUHS), the Chinese Household Income Project (CHIP) survey, and the China Household Finance Survey (CHFS). This enables us to include rural households in our analysis, thereby complementing existing empirical studies that focus on urban populations. This also provides a much larger sample set and allows us to check for robustness and consistency across databases.

3. Methods

The indirect household carbon footprints are generated by household consumption of non-energy commodities and services rather than by direct fossil fuel combustion (Munksgaard *et al.*, 2000). Previous studies have developed different models to calculate household carbon footprints, including the top-down Environmental Extended Input-Output Model (Peters, 2008; Peters and Hertwich, 2008a, 2008b), the bottom-up Life Cycle Analysis (Jones and Kammen, 2011) and Consumer Lifestyle Approach (Bin and Dowlatabadi, 2005), and hybrid approaches integrating both top-down and bottom-up approaches, for instance, the Environmental Extended Input-Output Life Cycle Analysis (Bin and Dowlatabadi, 2005; Xia *et al.*, 2019) or the Input-Output plus Expenditure Model (Kok *et al.*, 2006). The main idea behind household carbon footprint estimation is to link household expenditure data to productive sectors in order to derive relevant carbon intensity through input-output analysis (Sager, 2019). This study applies the hybrid Input-Output plus Expenditure Model to estimate the indirect carbon footprints of households in Chinese provinces, which integrates an Environmentally Extended Input-Output Model with a Consumer Lifestyle Approach.

3.1 Environmentally Extended Input-Output Model

The Environmental Extended Input-Output (EIO) model is widely used to calculate consumption-based emissions (Leontief, 1970; Peters, 2008; Peters and Hertwich, 2008a, 2008b). It measures household carbon emissions using macro-level data and an input-output matrix from a top-down perspective (Xia *et al.*, 2019). There is a vast body of literature that measures consumption-based emissions using an EIO model at the global level (Hubacek *et al.*, 2017; Su *et al.*, 2010), country level (Das and Paul, 2014; Kerkhof *et al.*, 2009; Lenzen, 1998; Liu *et al.*, 2011; Munksgaard *et al.*, 2000; Perobelli *et al.*, 2015; Su and Ang, 2010; Vringer and Blok, 1995) and at the regional level (Feng *et al.*, 2013). Given that China is a vast country with considerable regional variations, using a national input-output model may neglect regional disparities. This study expands the input-output analysis to a two-region extended input-output model that includes “local” and “rest of China” categories for each province in each table. In this extended input-output model, the goods and services imported from the rest of China or foreign countries are presented in a more detailed form as an inter-regional matrix, while the goods and services exported to the rest of China or foreign countries are listed in a single column. The extended input-output model for each province is a quasi-multiregional or two-regional input-output table which was developed in previous studies on country level (Druckman and Jackson, 2009). By compiling this extended input-output table, it is possible to obtain consumption-based emissions by different industries across various provinces in different years, which increases the accuracy of carbon footprint measurement. Table 1 shows an example of a common extended input-output model.

Table 1. Structure of the Extended Input-Output Model

		Intermediate Use				Final Use						Total Output
						Consumption			Capital Formation	Export		
						Household		Government				
		Industry 1	…	Industry n	Total	Rural	Urban					
Province i	Industry 1											
	…											
	Industry n											
	Total											
Rest of China & Import	Industry 1											
	…											
	Industry n											
	Total											
Value Added												
Total Input												

We apply a separate Environmentally Extended Input-Output Analysis to each province to measure the amount of emissions generated by each type of final consumption in province i. The basic expressions of the environmentally extended input-output model are as follows:

$$X_i = (\mathrm{I} - \mathrm{A}_i)^{-1}\mathrm{Y}_i \tag{1}$$

$$HC_i = HC_i^{local} + HC_i^{roc} = F_i^{local}\left(I - A_i^{local}\right)^{-1}\mathrm{Y}_i^{local} + F_i^{roc}(I - A_i^{roc})^{-1}\mathrm{Y}_i^{roc}, \tag{2}$$

where X_i represents the column vector of the total output of province i , HC_i, HC_i^{local}, and HC_i^{roc} represent the column vectors of the total indirect carbon footprint, the indirect carbon footprint produced by consuming goods and services produced in province i, and the indirect carbon footprint produced by consuming goods and services produced in the rest of China, respectively, $F_i^{local}$and F_{roc} are diagonal matrixes of the emissions intensity for province i and the rest of China, respectively, $\left(I - A_i^{local}\right)^{-1}$ and $(I - A_i^{roc})^{-1}$ are the Leontief inverse matrixes for province i and the rest of China, respectively, and Y_i^{local} and Y_i^{roc} are the column vectors of final consumption by households in province i that consume goods and services produced in province i and the rest of China, respectively.

3.2 Consumer Lifestyle Approach

A growing literature has aimed to estimate the emissions related to the consumption basket of households (Weber and Matthews, 2008; Sager, 2019). Among these methods, the Consumer Lifestyle Approach measures the household carbon footprint associated with each good or service consumed by the household by linking each type of household expenditure with its emissions intensity (Bin and Dowlatabadi, 2005; Wei *et al.*, 2007). For instance, the carbon footprint generated by household j buying a vehicle, which belongs to the transportation category, can be obtained by multiplying the expenditure on the vehicle by the emissions intensity of the transportation category. Similarly, the carbon footprint generated by household j through consuming electricity, which belongs to the electricity category, can be obtained by multiplying the expenditure on electricity by the emissions intensity of the electricity category. Thus, the carbon footprint of household j in province i can be expressed as follows:

$$HC_{ij} = HC_{ij}^{local} + HC_{ij}^{roc} \tag{3}$$

$$HC_{ij} = \sum_t \rho_i^{local,t} Y_{ij}^{local,t} + \sum_t \rho_i^{roc,t} Y_{ij}^{roc,t}, \tag{4}$$

where HC_{ij} represents the total indirect carbon footprint of household j, which consists of two parts: HC_{ij}^{local}, which represents the indirect carbon footprint produced by consuming goods and services produced in province i and HC_{ij}^{roc}, which represents the indirect carbon footprint produced by consuming goods and services produced elsewhere in China. Here, $\rho_i^{local,t}$ and $\rho_i^{roc,t}$ represent the emissions intensity of expenditure type t in province i and the rest of China, respectively. $Y_{ij}^{local,t}$ and $Y_{ij}^{roc,t}$ represent household j's expenditure on type t of goods and services produced in province i and the rest of China, respectively. Household expenditure is, to some extent, a micro foundation of household final consumption at the macro level. Following previous studies (Wei *et al.*, 2007; Feng *et al.*, 2011; Xu *et al.*, 2016), household expenditure is divided into eight categories, including food, clothing, housing, housing equipment, medicare and health services, transport and communication services, education cultural and recreational services, and all other expenditures. The concordance of input-output table sectors and household expenditures is provided in Appendix B.

3.3 Input-Output plus Expenditure Model

Finally, we integrate the environmentally extended input-output model with the consumer lifestyle approach, as mentioned above. Similar methods have been taken to measure household carbon footprints for individual families based on survey data (Golley and Meng, 2012; Xu *et al.*, 2016; Zhang *et al.*, 2017; Li *et al.*, 2019). This study is unique by compiling an extended input-output table for each province rather than using the national input-output table as a whole. By introducing separate provincial input-output tables and detailed survey data into the model, we can take different emissions intensity for each province's sectors into consideration. Based on this extended method, this study is able to provide a more accurate measurement of household carbon footprints. By replacing the consumption emissions intensities in the Consumer Lifestyle Approach with those obtained from an Environmentally Extended Input-Output Analysis, the indirect part of the carbon footprint of household j in province i can be expressed as follows:

$$HC_{ij} = F_i^{local}\left(I - A_i^{local}\right)^{-1} Y_{ij}^{local} + F_i^{roc}(I - A_i^{roc})^{-1} Y_{ij}^{roc}, \tag{5}$$

where Y_{ij}^{local} and Y_{ij}^{roc} are the column vectors of household j's expenditure on goods and services produced in province i and the rest of China, respectively.

In addition, we assume that all households in the same province have similar preferences between within-province and outside-province goods. That is, the within-province and outside-province shares of any type of good are the same for both a single family's consumption and the aggregate household consumption of the province. Using λ_i to denote the share vector between within-province and outside-province goods, and diag (λ_i) to denote the diagonal matrix of λ_i, the expenditure of household j in province i can be determined as follows:

$$Y_{ij} = Y_{ij}^{s} + Y_{ij}^{roc} = diag\ (\lambda_i)\ Y_{ij} + [I - diag\ (\lambda_i)\ ]Y_{ij} \tag{6}$$

$$HC_{ij} = F_i^{local}\left(I - A_i^{local}\right)^{-1} diag\ (\lambda_i)\ Y_{ij} + F_i^{roc}(I - A_i^{roc})^{-1}[I - diag\ (\lambda_i)\ ]Y_{ij} \tag{7}$$

$$HC_{ij} = \left\{F_i^{local}\left(I - A_i^{local}\right)^{-1} diag\ (\lambda_i)\ + F_i^{roc}(I - A_i^{roc})^{-1}[I - diag\ (\lambda_i)\ ]\right\}Y_{ij} \tag{8}$$

$$HC_{ij} = B_i Y_{ij}. \tag{9}$$

Note that we already have information regarding B_i from the environmentally extended input-output model:

$$HC_i = B_i Y_i \tag{10}$$

$$B_i = HC_i diag\ (Y_i)^{-1}. \tag{11}$$

The expression of the household carbon footprint can be further simplified as follows:

$$HC_{ij} = HC_i diag\ (Y_i)^{-1} Y_{ij} \tag{12}$$

$$HC_{ij}^{u} = HC_i^{u} diag\ (Y_i^{u})^{-1} Y_{ij} \tag{13}$$

$$HC_{ij}^{r} = HC_i^{r} diag\ (Y_i^{r})^{-1} Y_{ij}, \tag{14}$$

where HC_{ij} denotes a general expression of the household carbon footprint, while HC_{ij}^{u} and HC_{ij}^{r} denote specific expressions for urban and rural households' carbon footprints, respectively.

3.4 Descriptive statistics for the household carbon footprint

To provide a general picture of the distribution of carbon footprints, we present descriptive statistics, as well as decile estimates of per capita carbon footprints using our measurement method.

Table 2 shows the distribution of per capita carbon footprints for three household survey databases, the CUHS, the CHIP survey, and the CHFS. The per capita carbon footprint is already winsorized at the 99th percentile to exclude extreme values. This reveals that individuals in the bottom decile (10th percentile) are likely to produce 0.83 t of CO_2 in the CUHS, 0.25, 0.25, and 0.64 t of CO_2 in the CHIP survey in 2002, 2007, and 2013, respectively, and 0.21 and 0.35 t of CO_2 in the CHFS in 2011 and 2013, respectively. As for the other side of the distribution, individuals in the top decile

(90th percentile) are likely to produce 8.29 t of CO_2 in the CUHS, 4.40, 5.52, and 9.12 t of CO_2 in the CHIP survey in 2002, 2007, and 2013, respectively, and 5.18 and 6.43 t of CO_2 in the CHFS in 2011 and 2013, respectively. Thus, an individual in the 9th decile produces a carbon footprint more than 10 times greater than that of an individual in the 1st decile. There is also an increasing trend in terms of the size of the average carbon footprint. Based on the CHIP survey database, the average carbon footprint has increased from 2.10 t of CO_2 in 2002 to 2.32 t in 2007 and 3.88 t in 2013, while the CHFS database indicates that the average carbon footprint has increased from 5.18 t of CO_2 in 2011 to 6.43 t in 2013. Since the CUHS only includes urban residents, the average carbon footprint of pooled CHUS data from 2002 to 2009 is 4.15 t of CO_2, higher than that of the other databases, which includes both rural and urban residents.

Table 2. Distribution of Household Carbon Footprints

	CUHS	CHIP02	CHIP07	CHIP13	CHFS11	CHFS13
Deciles						
10	0.83	0.25	0.25	0.64	0.21	0.35
20	1.20	0.41	0.38	0.95	0.38	0.58
30	1.55	0.58	0.55	1.27	0.57	0.84
40	1.94	0.80	0.77	1.65	0.83	1.15
50	2.40	1.05	1.07	2.18	1.21	1.51
60	3.00	1.37	1.52	2.93	1.64	1.97
70	3.83	1.83	2.17	4.02	2.20	2.61
80	5.18	2.57	3.19	5.67	3.13	3.67
90	8.29	4.40	5.52	9.12	5.18	6.43
Minimum, Maximum, Mean and Observations						
Min	0.29	0.08	0.10	0.28	0.05	0.10
Max	41.85	23.57	22.40	26.18	37.60	54.37
Mean	4.15	2.10	2.32	3.88	2.65	3.52
N	127,233	17,830	17,973	16,907	6,833	22,790

To address the urban-rural disparities, we plot the average carbon footprint per capita of rural and urban residents, as shown in Figure 1. Although there are slight differences between the results based on various data sources, they all show a similar urban-rural gap. For instance, the urban indirect carbon footprint from the CHIP 2013 survey is higher than that from the CHFS 2013 because of differing province coverage, although they both indicate a large urban-rural disparity. The average carbon footprint of an urban resident is nearly twice that of a rural resident without controlling for other factors. The average carbon footprint per capita based on CHIP 2002, 2007, and 2013 survey figures is 1.31, 1.36, and 2.21 t of CO_2, respectively, for rural residents, and 2.38, 2.61, and 6.50 t of CO_2, respectively, for urban residents, while the average carbon footprint per capita based on CHIFS 2011 and 2013 survey figures is 1.55 and 2.49 t of CO_2, respectively, for rural residents, and 3.39 and 3.99 t of CO_2, respectively, for urban residents. Thus, there is a clear urban-rural disparity in terms of indirect carbon footprints.

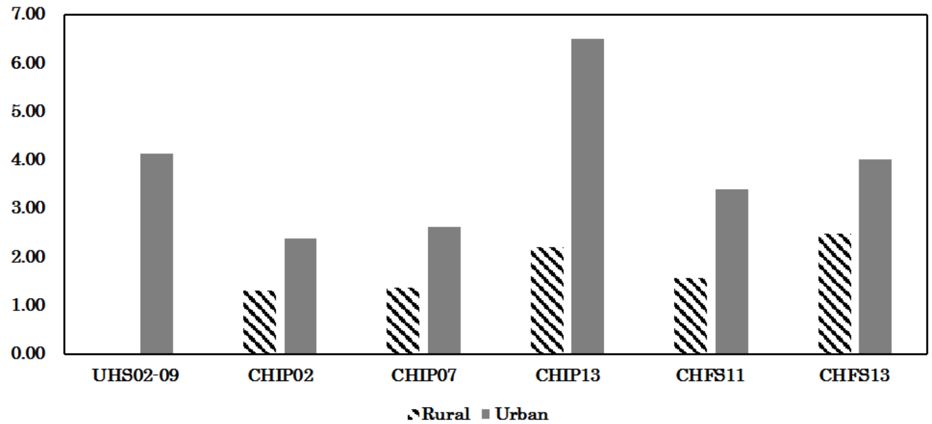

Figure 1. Average Carbon Footprint Per Capita for Rural and Urban Residents

4. Results and Discussion

In this section, we describe the data sources used in this study, namely, the three databases created by the CUHS, the CHIP survey, and the CHFS. Then, we estimate the level of indirect carbon footprint inequality and decompose the overall inequality into its within-group and between-group parts based on whether the household registration status is rural, urban, or migrant. Finally, we undertake empirical analysis of the factors driving the carbon footprint disparities. In addition, we check the robustness of our results by using sub-samples and adding more variables to the specification.

4.1 Data Sources

Four categories of data are used in this study. First, production-based carbon emissions for each province and each sector are necessary for Environmentally Extended Input-Output Analysis. These data are taken directly from the China Emission Accounts and Datasets (CEADS). Second, official input-output tables at the national and provincial levels for 2007 and 2012 are needed to compile extended input-output tables for each province in other years via the widely used Biproportional Scaling Method (or Richard Stone method, in short RAS method). The RAS method enables us to compile new input-output tables for a given year based on the intermediate usage structure in the base year and total intermediate inputs and total intermediate usage in the given year. Third, final consumption at the provincial level is required for Environmentally Extended Input-Output Analysis. The aggregate final consumption for each province is obtained from the National Bureau of Statistics and sectoral data are obtained by splitting the aggregate data based on the structure used in the official input-output tables (assuming the same final consumption structure in different sectors in the official input-output years and other years). Finally, and most importantly, this research draws on household survey data to measure carbon footprints at the micro level.

The micro-level household survey data used in this paper include the CUHS, which includes data from 127,234 urban households in nine provinces from 2002 to 2009, the CHIP survey, covering rural, urban, and migrant populations in 15 provinces in 2002, 2007, and 2013, and the CHFS, covering both rural and urban households in 29 provinces in 2011 and 2013. Detailed information on the CUHS, the CHIP survey, and the CHFS databases is shown in Table 3.

The main reasons for using these three household survey databases are as follows. Firstly, the sample size is larger, the timespan is longer, and the representativeness is higher. The data are more representative and reliable through the inclusion of urban, rural, and migrant populations in the sample. Secondly, apart from some common information, the three databases embody different characteristics and advantages. Specifically, the CUHS provides detailed expenditure data, the CHIP survey includes rural, urban, and migrant populations, and the CHFS provides detailed data in relation to family assets. Using different databases enables us to examine the effects of various independent variables. Thirdly, using samples from different databases allows us to cross-check the data, confirming the robustness of our results.

Table 3. Household Survey Data

		CUHS	CHIP			CHFS	
Survey		Chinese Urban Household Survey	Chinese Household Income Project Survey			China Household Finance Survey	
Year		2002-2009	2002	2007	2013	2011	2013
Sample	Urban	127,234	6,835	5,000	7,175	5,194	16,356
	Rural	0	9,200	8,000	11,013	3,244	11,786
	Migration	0	2,000	5,000	760	0	0
	Total	127,234	54,983			36,580	

To ensure comparability between databases and the robustness of the data, we provide summary descriptive statistics of the main variables used across the databases (see Table 4). As the CUHS only includes urban residents, the carbon footprint and disposable income per capita are higher than those in the CHIP survey and the CHFS. The disposable income per capita increases over time in each database, which accords with the actual situation in China. Variables such as age, gender, average family age, family size, and family structure are basically comparable across databases and years. In terms of educational attainment, 30% of householders in the CUHS have at least an undergraduate degree, while the figures for the CHIP survey and the CHFS are slightly more than 10% and close to 20%, respectively. These differences are the result of the different coverage of the three surveys. For instance, the CHIP survey included more rural residents and migrants than urban residents. Thus, the proportion of householders with an undergraduate degree or higher was lowest in the CHIP survey, while it was highest in the CUHS. Overall, the main variables in the three databases were able to be cross-validated, and the differences were found to be reasonable.

Table 4. Summary Statistics across Databases

iables	CUHS	CHIP			CHFS	
	2002-2009	2002	2007	2013	2011	2013
Carbonkg	12.89	7.15	6.59	12.33	9.01	10.95
household carbon footprint (kg)	(36.57)	(32.84)	(17.6)	(19.07)	(15.54)	(23.35)
Carbonkgcap	4.66	2.32	2.56	4.01	2.93	4.01
household carbon footprint per capita (kg)	(13.3)	(13.1)	(5.84)	(8.11)	(5.57)	(8.09)

de_ income	12104	5245	7405	13603	8599	11035
constant price disposable income per capita	(29,870)	(10,474)	(4,993)	(11,380)	(14,189)	(30,247)
Headage	48.84	45.81	43.93	50.8	48.29	49.78
age of householder	(14.78)	(11.64)	(11.13)	(13.77)	(12.41)	(14.25)
Gender	0.7	0.83	0.8	0.84	0.54	0.53
gender of householder (male=1)	(0.5)	(0.46)	(0.37)	(0.4)	(0.37)	(0.5)
Education	0.3	0.11	0.1	0.12	0.17	0.18
education of householder (>=undergraduate)	(0.38)	(0.46)	(0.31)	(0.3)	(0.32)	(0.37)
family_size	2.92	3.55	3.05	3.42	3.52	3.1
number of family members	(1.46)	(0.81)	(1.24)	(1.5)	(1.37)	(1.55)
mean_age	40.79	35.68	35.69	41.05	40.48	41.74
mean age of the family	(14.89)	(12.67)	(11.42)	(12.44)	(14.2)	(14.73)
OLD	0.19	0.06	0.06	0.12	0.14	0.15
share of elders in the family (>=65, %)	(0.29)	(0.33)	(0.17)	(0.18)	(0.27)	(0.28)
CHILD	0.11	0.15	0.1	0.12	0.12	0.12
share of childs in the family (<=14, %)	(0.16)	(0.15)	(0.18)	(0.16)	(0.16)	(0.16)
male_ratio	0.49	0.51	0.54	0.51	0.51	0.51
share of male in the family	(0.2)	(0.17)	(0.17)	(0.25)	(0.18)	(0.2)

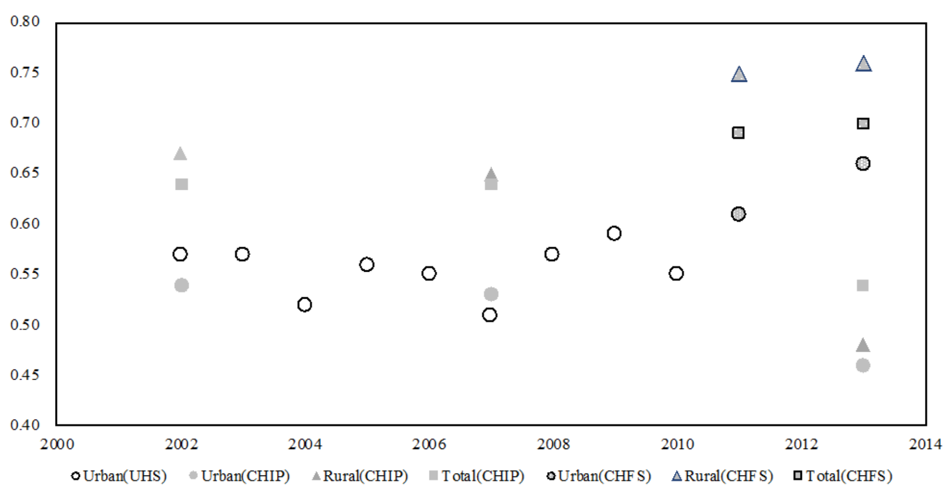

Figure 2. Carbon Footprint Inequality based on CUHS, CHIP and CHFS

4.2 The level of indirect carbon footprint inequality and its decomposition

In this study, we use inequality indexes to measure the level of indirect carbon footprint inequality. A vast body of literature has documented the application of the Gini index and the Theil index to the measurement of unequal distributions, for instance, in relation to income, wealth, and expenses, as well as carbon footprints. In this section, we present estimates of carbon footprint inequality based on the Gini index and the Theil index, and also provide income and expenditure inequality figures for comparison. The inequality indexes are measured using data from the CUHS, the CHIP survey, and the CHFS. Figure 2 shows the carbon footprint inequalities estimated using these survey databases from 2002 to 2013.

The indirect carbon footprint inequality results are presented in Appendix A. First, we present the inequality levels among urban households from 2002 to 2009 based on the CUHS, which compares the inequality levels in relation to per capita income, expenditure, and indirect carbon footprints. Income and expenditure are measured using constant 2000 prices, the carbon footprint is measured in kilograms, and family size is used as a weighting measure. Both the Theil index and the Gini index are used. The average Gini index values for income, expenditure, and carbon footprints from 2002 to 2009 are 0.35, 0.35, and 0.55, respectively, indicating that the inequalities in relation to indirect carbon footprints are greater than those relating to income and expenditure among urban households.

Next, we estimate the overall inequality level based on the CHFS in 2011 and 2013, which includes both urban and rural families. The inequality level measured using the CHFS data was higher than that obtained using the CUHS data. This is possibly because by including more provinces and the rural population, the CHFS captures greater disparities among households. It revealed that the level of carbon footprint inequality was about the same as that of income inequality, and higher than that of expenditure inequality. The Gini index values for the indirect carbon footprints of the urban, rural, and total samples were 0.61, 0.75, and 0.69, respectively, in 2011 and 0.66, 0.76, and 0.70, respectively, in 2013. This is consistent with previous results indicating a high level of inequality in terms of carbon footprints.

Further, we calculate the inequality levels based on the CHIP survey data, which includes urban, rural, and migrant families. The Gini index and Theil index values were calculated for 2002, 2007, and 2013. The level of carbon footprint inequality was higher than that of income and expenditure inequalities, which is consistent with the results obtained using the CUHS and CHFS data. The overall levels of indirect carbon footprint inequalities in 2002, 2007, and 2013 were 0.64, 0.64, and 0.54, respectively, higher than the levels of income inequalities, which were 0.45, 0.56, and 0.47, respectively, and expenditure inequalities, which were 0.48, 0.47, and 0.45, respectively. Further, the carbon footprint inequalities among rural households were higher than those among urban residents and migrant families. The indirect carbon footprint inequalities among rural households in 2002, 2007, and 2013 were 0.67, 0.65, and 0.48, respectively, higher than those among urban residents, which were 0.54, 0.53, and 0.46, respectively, and migrants, which were 0.48, 0.56, and 0.47, respectively. The carbon footprint inequalities among rural families were highest in both the CHIP survey and CHFS data.

As the CHIP survey covers a relatively long period, from 2002 to 2013, and includes all types of residents, we further decompose the carbon footprint inequalities measured using the CHIP survey data. Based on the household registration status of residents, that is, urban, rural, or migrant, we decompose the overall Theil index values into two parts: within-group and between-group measures. Table 5 presents the decomposition results for the CHIP survey and CHFS data. It can be seen that within-group inequality accounts for a large proportion of overall carbon footprint inequality. In 2002, 2007, and 2012, the within-group Theil index value was 0.86, 0.85, and 0.41, respectively, accounting for 89.92%, 90.81%, and 73.67%, respectively, of total carbon footprint inequalities. Meanwhile, the between-group Theil index value in 2002, 2007, and 2012 was 0.10, 0.09, and 0.15, respectively, accounting for 10.08%, 9.19%, and 26.33%, respectively, of total carbon footprint inequalities. It can also be seen that the contribution of between-group inequalities has increased significantly, from 10.08% in 2002 to 26.33% in 2013. While the within-group Theil index value fell from 0.86 in 2002 to 0.41 in 2013, the between-group Theil index value increased from 0.10 in 2002 to 0.15 in 2013. This reflects the widening urban-rural disparity. Although the social security system, minimum wage policy, and pension system have reduced within-group inequalities, imbalanced economic development has led to a widening gap between rural and urban households. This widening urban-rural gap is a potential source of increasing carbon footprint inequalities. Table 5 also presents the results obtained using the CHFS data for comparison. Although the timespan is insufficient to capture any trend in inequalities, these results confirm that within-group inequalities account for a large share of total inequalities.

Table 5. Decomposition of Carbon Footprint Inequality based on CHIP and CHFS

CHIP	2002		2007		2013	
	Theil	%	Theil	%	Theil	%
Within-group	0.86	89.92	0.85	90.81	0.41	73.67
Between-group	0.10	10.08	0.09	9.19	0.15	26.33
Total	0.95	100.00	0.94	100.00	0.56	100.00
CHFS	2011		2013			
	Theil	%	Theil	%		
Within-group	1.03	94.50	1.22	98.39		
Between-group	0.07	6.42	0.02	1.61		
Total	1.09	100.00	1.24	100.00		

These results show that indirect carbon footprint inequalities among Chinese households are significant, with the findings proving robust and consistent using data from different surveys. In terms of generating indirect carbon emissions through the consumption of goods and services, high-income residents are more likely to generate carbon emissions because they are able to purchase more refined, multi-processed, high-carbon goods and services, as well as consuming more one-off goods and services. This results in the inequalities in terms of carbon footprints being greater than those relating to consumption. Households generate indirect carbon footprints by consuming goods and services, and higher-income households are more likely to consume more refined, multi-processed goods and one-off goods and services. Thus the consumption of higher-income households is likely to be more carbon intensive than that of lower-income households, leading to an increasing marginal propensity for emissions, which is consistent with the findings of previous studies (Golley and Meng, 2012).

4.3 Empirical analysis: the main drivers of a larger carbon footprint

In this section, we further investigate the factors contributing to differences between households in terms of carbon footprints. We use the following formula to estimate the main driving factors behind a larger carbon footprint:

$$lncarbon = \alpha + \beta_1 lndeincome + \beta_2 lnhead\_age + \beta_3 lnhead\_age2 + \beta_4 male + \beta_5 education + \beta_6 family\_size + \beta_7 OLD + \beta_8 CHILD + \beta_9 urban + \mu_i + \nu_t + \varepsilon_{it} \quad (15)$$

where $lncarbon$, the dependent variable, indicates the logarithm of the indirect carbon footprint per capita of the household. The independent variables include income level, demographic characteristics, and household registration status, as well as fixed effects. $lndeincome$ is the logarithm of household disposable income per capita, which is adjusted to constant 2000 prices using the urban and rural CPI indices for each province. $lnhead\_age$ is the logarithm of the householder's age, and $lnhead\_age2$ is the square of $lnhead\_age$. $gender$ is a dummy variable representing the householder's gender, taking a value of 1 for males and a value of 0 for females. $education$ is a dummy variable representing the householder's level of education, taking a value of 1 for at least a college-level education and 0 otherwise. As for family structure, $family\_size$ represents the size of the family, OLD represents the proportion of elderly family members, where 'elderly' is defined as being aged 65 or above, and $CHILD$ represents the proportion of children aged 14 or younger in the family. To address the urban-rural disparity, $urban$ is a dummy variable representing household registration status, taking a value of 1 for an urban household and a value of 0 for a rural household. Finally, μ_i represents the province fixed effect, ν_t represents the survey fixed effect, and ε_{it} is an error term. It is worth noting that both carbon footprint per capita and real disposable income per capita are winsorized at the 99th percentile of their distribution in each year and each database to mitigate the impact of outliers.

Table 6. Main Drivers of Carbon Footprints

	CUHS	CHIP	CHFS
	(1)	(2)	(3)
ln_income	0.641***	0.528***	0.0706***
	(139.27)	(73.27)	(15.84)
ln_headage	0.344	1.927***	1.442**
	(1.23)	(4.65)	(2.29)
ln_headage2	-0.0386	-0.264***	-0.214**
	(-1.05)	(-4.86)	(-2.51)
Gender	-0.0185***	-0.0770***	-0.00520
	(-3.89)	(-7.37)	(-0.40)
Education	0.0337***	0.142***	0.277***
	(6.52)	(11.32)	(16.09)
family size	-0.0735***	-0.0735***	-0.140***
	(-24.49)	(-20.30)	(-26.03)
OLD	-0.00414	0.0370*	-0.104***
	(-0.39)	(1.76)	(-2.99)
CHILD	-0.0571***	-0.201***	-0.366***
	(-3.42)	(-7.14)	(-7.80)
Vehicle	0.166***		0.495***
	(15.97)		(27.79)
Urban		0.218***	0.665***
		(18.73)	(41.29)
Cons	-5.572***	-7.524***	-2.756**
	(-10.37)	(-9.49)	(-2.39)
Year	Y	Y	Y
Province	Y	Y	Y
N	127198	44786	24051
adj. R^2	0.347	0.500	0.354

t statistics are shown in parentheses
* $p < 0.01$, ** $p < 0.005$, *** $p < 0.001$

We start our empirical analysis by providing OLS estimates based on the CUHS, CHIP survey, and CHFS. Table 6 presents the baseline results using the specifications outlined above. All regressions include the province and survey wave fixed effects when multiple surveys are included in a single column.

Table 6 shows that the main findings are consistent across the three databases. First, an increase in disposable income per capita significantly increases the indirect carbon footprint per capita of the household. Columns 1 and 2, which are based on the CUHS and CHFP survey data, respectively, show that the indirect carbon footprint per capita increases by 0.5%–0.6% for every 1% increase in real household disposable income, while Column 3, which is based on the CHFS data, shows that the household's indirect carbon footprint increases by about 0.1% for every 1% increase in real household income. The estimated carbon footprint–income elasticity is slightly different across databases, mainly because of the variations in population coverage, sampling methods, and survey methods. For instance, the CUHS only includes urban residents, while the CHIP survey and the CHFS include both urban and rural residents. Therefore, the income distributions among households in the three databases also differs. In fact, we find that if the real income per capita were limited to a narrower range, the estimated elasticities calculated using the three databases would converge.

Second, we find that a higher level of education results in a higher per capita household carbon footprint. It can be seen from Column 3 that if the householder has a college degree or above, the carbon footprint per capita increases by up to nearly 30%. The impact of education on the carbon footprint is lowest in the CUHS data, which only includes the urban population, and thus there is less educational attainment disparity. Some previous studies expected that higher education levels would raise householders' levels of environmental awareness (Zografakis *et al.*, 2010), thereby reducing their carbon emissions, but our results paint a different picture.

Third, family size is a critical factor in determining the carbon footprint per capita. It is clear that larger families produce larger carbon footprints. However, the carbon footprint per capita decreases as the size of the family increases because family members can share various goods and services, thus a scaling effect within the household reduces the carbon footprint per capita. Since the introduction of the one-child policy in China, the average family size has decreased significantly, and today, with an increasing number of nuclear families rather than extended families, the carbon footprint per capita is increasing.

Fourth, the results in Columns 1 and 3 show that vehicle ownership significantly increases a household's indirect carbon footprint. Vehicle ownership not only represents a higher living standard, but also changes the lifestyle and consumption habits of the family, resulting in a larger carbon footprint. The effect of vehicle ownership on the household carbon footprint is highest when calculated using the CHFS database because household expenditure as measured in the CHFS includes expenditure on fuel for transportation, resulting in an overestimation of the indirect portion of the household carbon footprint. Further, the CHFS data cover both urban and rural residents, whose consumption patterns are influenced heterogeneously by vehicle ownership.

Finally, the results presented in Columns 2 and 3 show that urban residents have significantly higher carbon footprints than rural residents. This is consistent with the carbon footprint disparities between rural and urban residents that were identified in the previous section. It is estimated that the carbon footprint of an urban resident is generally 30% to 70% higher than that of a rural resident.

Other factors also contribute to carbon footprint disparities, such as the age and gender of the householder, and the family structure. The baseline regressions reveal that the main factors driving differences in terms of carbon footprints are income disparity, educational inequality, asset possession, and differences in living conditions, as well as urban-rural differences.

4.4 Robustness checks and further analysis

Table 7. Main Drivers of Carbon Footprint Differences based on CUHS Data

	(1)	(2)	(3)	(4)	(5)
ln_income	0.657***	0.657***	0.657***	0.630***	0.569***
	(146.95)	(146.23)	(146.23)	(133.37)	(116.30)
ln_headage	0.0456***	0.0443***	0.0443***	0.0496***	0.108***
	(4.86)	(3.33)	(3.33)	(3.71)	(8.21)
Gender	-0.0186***	-0.0160***	-0.0160***	-0.0157**	-0.00963*
	(-3.91)	(-3.32)	(-3.32)	(-3.25)	(-2.03)
Education	0.0333***	0.0348***	0.0348***	0.0266***	0.00468
	(6.46)	(6.74)	(6.74)	(5.11)	(0.91)
family size	-0.0700***	-0.0680***	-0.0680***	-0.0783***	-0.0996***
	(-24.58)	(-22.78)	(-22.78)	(-25.63)	(-32.86)
family structure					
OLD		-0.0164	-0.0164	-0.0117	0.0628***
		(-1.87)	(-1.87)	(-1.34)	(7.19)
CHILD		-0.0537**	-0.0537**	-0.0610***	-0.0233
		(-3.25)	(-3.25)	(-3.70)	(-1.44)
male ratio		-0.0431***	-0.0431***	-0.0455***	-0.0321*
		(-3.35)	(-3.35)	(-3.54)	(-2.56)
living standards					
Vehicle				0.159***	0.160***
				(15.29)	(15.19)
house luxury				0.00736	0.00922
				(0.40)	(0.51)
house ordinary				0.0642***	0.0569***
				(5.85)	(5.33)
floor square				0.000538***	0.000665***
				(8.00)	(10.02)
house age				-0.000176	-0.000145
				(-0.83)	(-0.70)
consumptive habits					
Service					1.276***
					(58.63)
eat out					-0.0181
					(-1.03)
Cons	-5.142***	-5.115***	-5.115***	-4.954***	-4.914***
	(-90.90)	(-75.45)	(-75.45)	(-71.97)	(-72.80)
Province	Y	Y	Y	Y	Y
Wave	Y	Y	Y	Y	Y
N	127,198	127,198	127,198	127,198	127,198
adj. R^2	0.346	0.346	0.346	0.348	0.371

t statistics are shown in parentheses
* $p < 0.01$, ** $p < 0.005$, *** $p < 0.001$

Are the above results robust? Are there other factors that contribute to carbon footprint disparities? Do these factors change when a heterogeneous population is considered? To address these questions, in this section we conduct robustness checks using the different databases separately, as well as using sub-samples and different control variables.

Table 8. Main Drivers of Carbon Footprint Differences based on CHFS and CHIP Survey Data

	CHFS 2011		CHFS 2013		CHIP 2013		
	urban	rural	Urban	rural	Urban	rural	migrant
ln_income	0.0606***	0.144***	0.0464***	0.109***	0.652***	0.434***	0.700***
	(6.61)	(8.54)	(8.21)	(9.97)	(39.55)	(38.20)	(11.45)
ln_headage	-0.192***	-0.468***	-0.0944**	-0.499***	0.241***	-0.228***	0.185
	(-3.32)	(-5.20)	(-2.82)	(-6.97)	(5.67)	(-6.59)	(1.24)
gender	0.0217	0.0211	-0.00591	0.00229	-0.0378*	-0.0989***	0.149
	(0.77)	(0.49)	(-0.34)	(0.07)	(-2.09)	(-3.85)	(1.67)
Education	0.319***	0.497***	0.292***	0.235	0.183***	0.163**	0.0115
	(9.67)	(4.51)	(14.43)	(1.81)	(9.66)	(2.70)	(0.09)
family size	-0.157***	-0.0974***	-0.184***	-0.133***	-0.111***	-0.0977***	-0.0202
	(-12.45)	(-6.70)	(-23.17)	(-11.47)	(-12.52)	(-16.84)	(-0.62)
OLD	0.131*	-0.412***	0.0239	-0.578***	-0.00459	-0.104***	-0.213
	(2.18)	(-5.09)	(0.67)	(-9.53)	(-0.14)	(-3.32)	(-0.79)
CHILD	-0.139	-0.451**	-0.261***	-0.689***	0.152*	-0.263***	0.113
	(-1.41)	(-3.10)	(-4.38)	(-5.82)	(2.57)	(-5.39)	(0.59)
male ratio	0.0788	-0.0816	-0.0378	-0.109	-0.0861	-0.0990*	-0.107
	(1.11)	(-0.69)	(-0.89)	(-1.24)	(-1.87)	(-2.31)	(-0.60)
Vehicle	0.502***	0.911***	0.415***	0.617***			
	(13.20)	(11.16)	(19.37)	(11.26)			
House	0.302***	0.120	0.178***	0.128*			
	(8.39)	(1.42)	(9.06)	(2.05)			
Cons	0.804**	0.947*	0.951***	2.164***	-5.443***	-1.290***	-6.591***
	(3.17)	(2.32)	(6.52)	(6.17)	(-22.91)	(-6.81)	(-7.41)
Province	Y	Y	Y	Y	Y	Y	Y
N	3,992	2,707	12,061	5,291	6,241	9,908	665
adj. R^2	0.313	0.314	0.278	0.226	0.519	0.382	0.293

t statistics are shown in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7 shows the results obtained using CUHS data. In line with previous findings, real income and educational attainment both have significant impacts on the household carbon footprint per capita. We investigate the impact of other factors by adding family structure, the square of the baseline regression, and variables representing living standards and consumption habits to the model. The results show that higher living standards increase the size of the carbon footprint. Specifically, we divide housing type into three groups: luxury, ordinary, and modest, and find that living in a luxury or ordinary house produces a larger household carbon footprint than living in a modest house, while living in a larger house also increases the carbon footprint. Living in an old house reflects a limited ability to move into a newly built house that offers better living conditions. Therefore, the age of the house has a negative, albeit insignificant, effect on the size of the household carbon footprint. As for consumption habits, we find that greater expenditures on services as a share of total expenditures increases the size of the household carbon footprint. On one hand, a higher share of expenditures on services indicates greater outsourcing of tasks such as housekeeping, baby-sitting, and cooking, and additional spending on leisure activities. On the other hand, service consumption is more likely to involve instant consumption in contrast to the consumption of goods. Thus, consumption that includes a higher share of expenditures on services results in a higher carbon footprint.

We conduct similar analyses using CHIP survey and CHFS data, dividing the urban, rural, and migrant populations into sub-samples. The results are shown in Table 8 and indicate that the previous findings are robust when we take the heterogeneous sub-samples into consideration. Once again, the main factors driving carbon footprint differences are income disparity, educational inequality, asset possession, and differences in living conditions, as well as urban-rural differences.

4.5 Factors contributing to carbon footprint inequality

After investigating the driving forces that contribute to a larger carbon footprint, in this section, we try to quantify how each of the factors contribute to total carbon footprint inequality. We adopt a regression-based inequality decomposition method (Fiorio and Jenkins, 2010; Shorrocks, 1982; Wan, 2004; Wan and Zhou, 2005) to separate each variable's contribution. To identify the changing trends and relevant factors of overall inequality, we apply this decomposition method on the CHIP database for the years 2002, 2007, and 2013 which cover the longest time span of all three datasets. We use the following formula to conduct regression-based inequality decomposition.

$$lncarbon = \alpha + \beta_1 lndeincome + \beta_2 lnhead\_age + \beta_3 education + \beta_4 family\_size + \beta_5 OLD + \beta_6 CHILD + \beta_7 urban + \mu_i + \varepsilon \quad (16)$$

where the dependent and independent variables are defined in Section 4.3 and μ_i represents the province fixed effects. The predicted value of the dependent variable is $\widehat{lncarbon}$. The only difference is that the year dummy variable has been removed since the analysis is conducted for each year separately. To have a clear picture of how variables contribute to total inequality, we group the independent variables into five categories, which are: income, including $lndeincome$; characteristics of the family head, including $lnhead\_age$ and $education$; family characteristics including $family\_size$, OLD and $CHILD$; household registration status, including $urban$; as well as region, including all province fixed effects μ_i. The overall level of left-hand side carbon footprint inequality can be decomposed into a set of additive terms according to the contributions of the right-hand side variables and the residuals (Shorrocks, 1982)

$$I(lncarbon) = I(income) + I(head) + I(family) + I(urban) + I(province) + I(residual) \quad (17)$$

$$I(residual) = I(lncarbon) - \mathrm{I}(\widehat{lncarbon}) \quad (18)$$

Then the share of contribution to total carbon footprint inequality of each factor can be obtained as follows.

$$C(residual) = I(residual)/I(lncarbon) \quad (19)$$

$$C(X_i) = I(X_i)/I(lncarbon) \quad (20)$$

The share of contribution to total carbon footprint inequality, the shapley value, and the relative rank according to these two methods are presented in Table 9.

Table 9. Decomposition of total carbon footprint inequality

	CHIP2002			CHIP2007			CHIP2013		
	inequality	shapley	rank	inequality	shapley	rank	inequality	shapley	rank
income	55.37	37.43	1,1	74.21	49.38	1,1	51.31	40.24	1,1
head	2.32	5.60	5,5	5.00	7.93	4,5	4.03	7.42	5,5
family	8.41	10.99	4,4	7.43	9.64	3,4	10.29	12.42	4,4
urban	18.00	19.21	2,3	-0.85	16.02	5,3	17.09	21.44	3,2
province	15.91	26.78	3,2	14.21	17.03	2,2	17.29	18.47	2,3
total	100	100		100	100		100	100	

Note: The share of contribution is calculated net of the residual.

The decomposition results reveal that income inequality has been the major determining factor of overall carbon footprint inequality. Income inequality has contributed to about half of overall carbon footprint inequality. This is in line with previous findings that determined the very rich have contributed to a considerably large part of total household carbon footprints both in China (Hubacek *et al.*, 2017; Wiedenhofer *et al.*, 2016) and globally (OXFAM, 2015). Rural-urban disparity and provincial disparity are the other two important factors that contribute to carbon footprint inequality. Individual- and family-level characteristics also contribute to carbon footprint inequality. The decomposition results indicate that carbon footprints, as another kind of welfare, is largely inequal due to income disparities. The rich and the poor have essentially different responsibilities to the climate change problem. If the government intends to reduce both carbon emissions and inequality simultaneously, the rich must take most of the responsibility.

5. Conclusions

This study focuses on household indirect carbon footprint inequalities. We firstly develop a more accurate method for measuring per capita carbon footprints based on household survey data, combining a macro provincial Environmentally Extended Input-Output Analysis with a micro Consumer Lifestyle Approach. Then, we present descriptive statistics on the per capita distribution of carbon footprints and estimate the level of carbon footprint inequality using the Gini index and the Theil index. Finally, we analyze the factors driving carbon footprint disparities using regression analysis at the individual level. We control for demographic characteristics, region, and survey waves, and analyze the influence of income, educational attainment, asset ownership, and consumption habits, as well as household registration status.

The mains findings of our study can be summarized as follows. First, there is widespread inequality in terms of indirect carbon footprints at the individual level. The results show that an individual in the 9th decile produces a carbon footprint more than ten times greater than that of an individual in the 1st decile. Urban-rural disparities have a significant impact on carbon footprint inequality. On average, an urban resident generates a carbon footprint nearly twice the size of that generated by a rural resident. Further, it is estimated that the carbon footprint of a rural resident is generally 30% to 70% lower than that of an urban resident after controlling for other variables. Second, the inequality indexes show that inequalities in relation to carbon footprints are greater than those relating to income and expenditure, and carbon footprint inequalities among rural residents are greater than those among urban residents and migrants. We also decompose the Theil index estimates into within-group and between-group estimates. The results indicate that although carbon footprint inequalities have declined slightly at the within-group level, between-group inequalities have been increasing, and may prove to be an important source of carbon footprint inequalities in the future. Finally, our econometric analysis confirms that the main factors contributing to carbon footprint inequalities are income disparity, educational inequality, and differences in living conditions and asset ownership, as well as urban-rural differences. A higher real income and a higher education level significantly increase the indirect carbon footprint of the household, while living conditions can also significantly affect a household's carbon footprint. Residents living in luxurious or larger houses generate more indirect CO_2 than those living in ordinary or modest houses. Further, vehicle ownership contributes to a larger carbon footprint. Households tend to emit more carbon if there is a higher share of services consumption in their total consumption, which is more likely to be instant consumption.

The higher level of inequalities in terms of household carbon footprints compared with income and expenditure inequalities indicates that high-income households in China generate more carbon as a result of their better living conditions and prefer goods that produce more carbon emissions. Interestingly, this has mainly occurred in households whose members are younger and better educated. Therefore, when discussing carbon emissions mitigation policies, this form of heterogeneity is a key issue. China has increasingly emphasized the responsibilities of large firms in relation to carbon emissions over recent decades. However, over the next few decades, the increasing carbon footprints of high-income households will no doubt lead to increased consideration of low carbon emissions initiatives at the household level. Meanwhile, urban-rural disparities may further exacerbate carbon footprint inequalities in the future. Rural households should continue to enjoy their "differentiated responsibility" in comparison. Understanding China's carbon footprint inequalities and the forces driving them will have implications for carbon emissions mitigation not only in China but also in other emerging economies that are likely to face similar challenges sooner or later.

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Appendix A. Carbon Footprint Inequalities based on CUHS, CHIP survey, and CHFS data

Table A1. Carbon Footprint Inequalities based on CUHS data

	Income		Expenditure		Carbon Footprint	
Year	Theil	Gini	Theil	Gini	Theil	Gini
2002	0.19	0.33	0.20	0.34	0.82	0.57
2003	0.20	0.34	0.22	0.34	0.88	0.57
2004	0.21	0.35	0.23	0.35	0.65	0.52
2005	0.21	0.35	0.24	0.36	0.73	0.56
2006	0.21	0.35	0.24	0.36	0.74	0.55
2007	0.20	0.34	0.22	0.34	0.63	0.51
2008	0.22	0.35	0.24	0.36	0.75	0.57
2009	0.22	0.35	0.24	0.36	0.88	0.59
Mean	0.21	0.35	0.23	0.35	0.76	0.55

Table A2. Carbon Footprint Inequalities based on CHFS data

2011	Income		Expenditure		Carbon Footprint	
	Theil	Gini	Theil	Gini	Theil	Gini
Urban	1.02	0.68	0.47	0.48	0.85	0.61
Rural	1.15	0.68	0.49	0.49	1.50	0.75
Total	1.15	0.71	0.53	0.51	1.09	0.69
2013	Income		Expenditure		Carbon Footprint	
	Theil	Gini	Theil	Gini	Theil	Gini
Urban	0.84	0.62	0.44	0.46	1.13	0.66
Rural	0.60	0.57	0.44	0.48	1.50	0.76
Total	0.87	0.63	0.48	0.48	1.24	0.70

Table A3. Carbon Footprint Inequalities based on CHIP survey data

2002	Income		Expenditure		Carbon Footprint	
	Theil	Gini	Theil	Gini	Theil	Gini
Urban	0.18	0.33	0.20	0.34	0.76	0.54
Rural	0.24	0.37	0.28	0.37	1.17	0.67
Migrant	0.26	0.37	0.17	0.31	0.42	0.48
Total	0.35	0.45	0.40	0.48	0.95	0.64
2007	Income		Expenditure		Carbon Footprint	
	Theil	Gini	Theil	Gini	Theil	Gini
Urban	0.24	0.36	0.21	0.34	0.81	0.53
Rural	0.23	0.36	0.29	0.38	1.09	0.65
Migrant	0.19	0.31	0.21	0.33	0.58	0.56
Total	0.57	0.56	0.39	0.47	0.94	0.64
2013	Income		Expenditure		Carbon Footprint	
	Theil	Gini	Theil	Gini	Theil	Gini
Urban	0.21	0.35	0.24	0.37	0.38	0.46
Rural	0.28	0.40	0.24	0.36	0.46	0.48
Migrant	0.22	0.35	0.23	0.36	0.39	0.47
Total	0.38	0.47	0.36	0.45	0.56	0.54

Appendix B. Concordance of Household Expenditure Types and Sectors in Input-Output Tables

Table B1. Household Expenditure Types and Sectors in Input-Output Tables

28 Input-Output Table Sectors		8 Household Expenditures	
1	Farming, Forestry, Animal Husbandry, Fishery	1	Food
2	Coal Mining and Dressing		NA
3	Petroleum and Natural Gas Extraction		NA
4	Ferrous Metals Mining and Dressing		NA
5	Nonmetal Minerals Mining and Dressing		NA
6	Food Processing	1	Food
7	Textile Industry	2	Clothing
8	Garments and Other Fiber Products	2	Clothing
9	Logging and Transport of Wood and Bamboo	4	Housing Equipment
10	Papermaking and Paper Products	7	Education & Entertainment
11	Petroleum Processing and Coking		NA
12	Raw Chemical Materials and Chemical Products	5	Medicare and Health
13	Nonmetal Mineral Products	3	Housing
14	Smelting and Pressing of Ferrous Metals	3	Housing
15	Metal Products	3	Housing
16	Ordinary Machinery	4	Housing Equipment
17	Transportation Equipment	6	Transportation, Communication
18	Electric Equipment and Machinery	4	Housing Equipment
19	Electronic and Telecommunications Equipment	6	Transportation & Communication
20	Instruments, Meters and Office Machinery	6	Transportation & Communication
21	Other Manufacturing Industry, Scrap and Waste	6	Transportation & Communication
22	Production and Supply of Electricity, Heat, Hot Water	3	Housing
23	Production and Supply of Gas	3	Housing
24	Production and Supply of Tap Water	3	Housing
25	Construction	3	Housing
26	Transportation, Storage, Post and Telecommunication	6	Transportation & Communication
27	Wholesale, Retail Trade and Catering Services	8	Other
28	Others	8	Other

Appendix C. Carbon Footprint per capita and Disposable Income per capita

Our analysis indicates that richer families should be more responsible for larger carbon footprints. Take the CHIP 13 data as an example, we first winsorize both carbon footprint per capita and disposable income per capita. Then we plot the log of the carbon footprint against the log of the disposable income Figure C1 shows that carbon footprint per capita monotonically increases with disposable income per capita of the family and it increases even faster when per capita income increases.

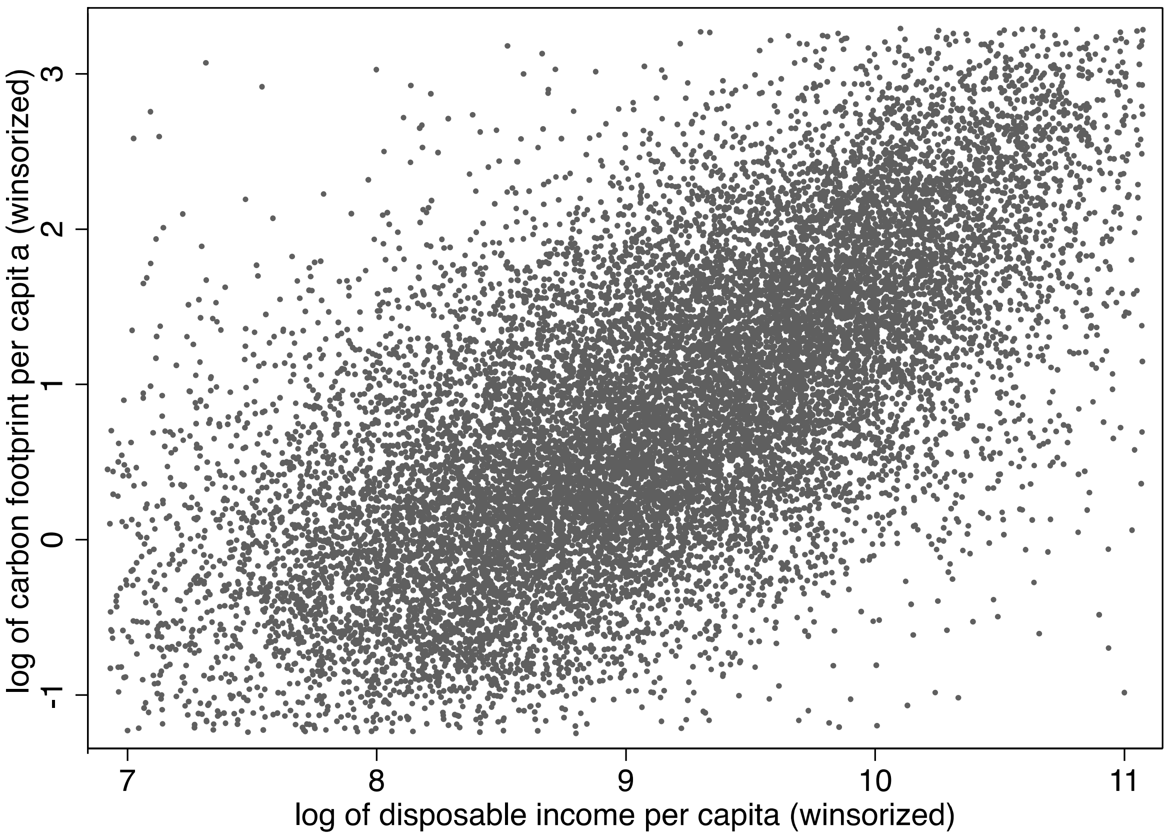

Figure C1. Carbon Footprint per capita and Disposable Income per capita

We further conduct empirical analysis to prove this increasing trend by including the log of disposable income per capita and its square in the regression. The results are presented in Table C1. As in Table C2, the symmetry axis of the quadratic function is -18.29, 3.26 and 5.76 respectively, which are all less than the average of log of disposable income per capita of the CUHS, CHIP and CHFS. This indicates the that carbon footprint per capita monotonically increases with disposable income per capita of the family and it increases even faster when per capita income increases.

Table C1. Increasing Trend of Carbon Footprint against Disposable Income

	CUHS	CHIP	CHFS
	(1)	(2)	(3)
ln_income	0.428***	-0.325***	-0.249***
	(5.66)	(-5.25)	(-8.41)
sq ln_income	0.0117***	0.0499***	0.0216***
	(2.81)	(14.02)	(11.00)
ln_headage	0.0521***	-0.0719***	-0.108***
	(3.91)	(-3.55)	(-4.21)
Gender	-0.0186***	-0.0758***	-0.00971
	(-3.91)	(-7.28)	(-0.75)
Education	0.0330***	0.103***	0.230***
	(6.39)	(8.15)	(13.08)
family size	-0.0733***	-0.0719***	-0.133***
	(-24.45)	(-19.98)	(-24.71)
family structure			
OLD	-0.0106	-0.0237	-0.138***
	(-1.22)	(-1.29)	(-4.99)
CHILD	-0.0588***	-0.218***	-0.341***
	(-3.57)	(-7.86)	(-7.39)
Vehicle	0.160***		0.471***
	(15.05)		(26.29)
Urban		0.199***	0.652***
		(17.12)	(40.44)
Cons	-4.052***	-0.161	1.106***
	(-11.66)	(-0.57)	(7.50)
Year	Y	Y	Y
Province	Y	Y	Y
N	127198	44786	24051
adj. R^2	0.347	0.502	0.357

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C2. Symmetry Axis and Average log of disposable income per capita

	CUHS	CHIP	CHFS
ln_income	0.428***	-0.325***	-0.249***
square ln_income	0.0117***	0.0499***	0.0216***
Symmetry Axis	-18.29	3.26	5.76
Average ln_income	9.18	8.52	8.15

Appendix D. Structure of Household Expenditure

To check whether the structure of household expenditure is consistent within different sources, we compare the structure computed from the micro survey data, statistics released by National Bureau of Statistics and those computed from input-output table. The results of 2007 are presented in Table D1 as an example. In panel A, we present the structure computed from CHIP data and National

Bureau of Statistics in 2007 and they are close to each other. In panel B we present the total expenditure of urban and rural residents (million yuan), the per capita expenditure, the expenditure structure and the adjusted structure after excluding the type of Other expenditure which is hard to relate into strict household expenditure categories. In panel C, we compare the four types of expenditure structures, and the structure are relative consistent.

Table D1. Structure of Household Expenditure

Panel A.	CHIP2007				National Bureau of Statistics			
	urban		rural		urban		rural	
	¥	%	¥	%	¥	%	¥	%
Food	5071	41.5	1748	44.3	3628	36.3	1389	43.1
Clothing	1188	9.7	218	5.5	1042	10.4	194	6.0
Housing	784	6.4	205	5.2	982	9.8	574	17.8
Housing Equipment	1253	10.3	658	16.7	602	6.0	149	4.6
Medicare and Health	925	7.6	257	6.5	699	7.0	210	6.5
Transportation	1123	9.2	401	10.1	1357	13.6	328	10.2
Education	1332	10.9	364	9.2	1329	13.3	306	9.5
Other	516	4.2	97	2.5	358	3.6	74	2.3
Sum	12215	100.0	3948	100.0	9998	100.0	3224	100.0

Panel B.	National Input-Output Table 2007							
	urban				rural			
	Total	Per Capita	%	adjusted %	Total	Per Capita	%	adjusted %
Food	1365546	2252	25.4	40.8	683277	956	38.3	55.2
Clothing	419221	691	7.8	12.5	102019	143	5.7	8.2
Housing	297187	490	5.5	8.9	56671	79	3.2	4.6
Housing Equipment	154077	254	2.9	4.6	41485	58	2.3	3.3
Medicare and Health	133355	220	2.5	4.0	47089	66	2.6	3.8
Transportation	756283	1247	14.0	22.6	200479	280	11.2	16.2
Education	224316	370	4.2	6.7	107356	150	6.0	8.7
Other	2035854	3358	37.8		547250	765	30.6	
Sum	5385839	8883	100.0	100.0	1785626	2498	100.0	100.0
Population	606				715			

Panel C.	Comparison of Household Expenditure Structure (%)							
	Urban				Rural			
	CHIP	NBS	IO	IO_adj	CHIP	NBS	IO	IO_adj
Food	41.5	36.3	25.4	40.8	44.3	43.1	25.4	55.2
Clothing	9.7	10.4	7.8	12.5	5.5	6.0	7.8	8.2
Housing	6.4	9.8	5.5	8.9	5.2	17.8	5.5	4.6
Housing Equipment	10.3	6.0	2.9	4.6	16.7	4.6	2.9	3.3
Medicare and Health	7.6	7.0	2.5	4.0	6.5	6.5	2.5	3.8
Transportation	9.2	13.6	14.0	22.6	10.1	10.2	14.0	16.2
Education	10.9	13.3	4.2	6.7	9.2	9.5	4.2	8.7
Other	4.2	3.6	37.8		2.5	2.3	37.8	
Sum	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0