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The greenness of China: household carbon dioxide emissions and urban development

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Abstract

China urbanization is associated with both increases in per capita income and greenhouse gas emissions. This article uses micro data to rank 74 major Chinese cities with respect to their household carbon footprint. We find that the 'greenest' cities based on this criterion are Huaian and Suqian while the 'dirtiest' cities are Daqing and Mudanjiang. Even in the dirtiest city (Daqing), a standardized household produces only one-fifth of the emissions produced in America's greenest city (San Diego). We find that the average January temperature is strongly negatively correlated with a city's household carbon footprint, which suggests that current regional economic development policies that bolster the growth of China's northeastern cities are likely to increase residential carbon emissions. We use our city-specific income elasticity estimates to predict the growth of carbon emissions in China's cities.

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1. Introduction

Today, per capita carbon emissions in the United States are about five times per capita emissions in China, which implies that if China's per capita greenhouse gas emissions rose to US levels, then global carbon emissions would increase by more than 50 percent. China's urban population has grown by 300 million since 1990, and China is investing in the infrastructure needed for hundreds of millions of future urbanites. China's urban development policies could have large potential impacts on global carbon emissions.

Knowing a nation's per capita income and total population size is not sufficient for estimating a nation's greenhouse gas production. The spatial distribution of this population across diverse cities is a key determinant of the size of the household sector's emissions (Kahn, 2006). In this article, we estimate the carbon emissions associated with the development of different Chinese cities. The more dramatic these differences are, the larger the impact that urban policy can have on Chinese and global carbon emissions.

Using US data, Glaeser and Kahn (2010) found that places with moderate temperatures, like coastal California, have significantly lower emissions than places with extreme temperatures, like Texas: a standardized household's carbon emissions are 78% higher in Memphis than in San Diego. Denser places have lower carbon emissions than sprawling car-oriented locales. If these relationships hold in China as well, denser development in the more temperate locales of that country will lead to lower carbon emissions.

In this article, we calculate household carbon emissions using several data sources including the Chinese Urban Household Survey. This survey provides information on energy usage for 25,000 households across 74 cities in 2006. Relative to US households, transportation represents a smaller share of Chinese urban household emissions and household heating represents a much larger share. A poorer country can do without air conditioning and cars, but not without heat in the winter.

As in Glaeser and Kahn (2010), we do not attempt to estimate an average carbon 'footprint', but rather the marginal emissions associated with the movement of a typical new family to a particular locale. For this reason, we calculate a predicted level of carbon emissions in different cities for a standardized household with a fixed size, level of income and household head's age. Glaeser and Kahn (2010) measure the emissions for households who live in newer housing in each city. They adopt this strategy to attempt to measure the impact of the marginal migrant. In the Chinese case, the nation's cities are so new and are undergoing such rapid transformation that most of the housing stock is new. This means that a standardized household's average emissions in a specific city is likely to be a good indicator of what emissions for a similar household would be if it moved to this city.

Controlling for survey measures of individual income, we find that richer cities have significantly higher household carbon emissions. One possible explanation for this fact is that richer cities may have invested more in infrastructure that complements energy use. In China, carbon emissions are particularly high in places with cold Januarys, because of government-provided centralized home heating. For example, Shanghai (without centralized home heating) is much greener than Beijing (with centralized home heating). The prominent role played by the centralized fixed provision of heating indicates that carbon emissions could fall significantly if greener sources of energy were used by the government for that purpose, as argued by Almond et al. (2009).

China currently has three significant regional policies, which support growth in the Northeast, the Western hinterland and the Beijing–Tianjin–Bohai Sea region. Relative to the average city household carbon emissions are 69% higher in the Northeast, 40% higher in the Beijing–Tianjin–Bohai Sea region and 17% lower in the West. These findings suggest that regional development policies that favor growth in the Northeast and in the greater Beijing areas are likely to increase China's overall carbon emissions in the residential sector.

The range of emissions across China's cities today does not capture the diversity of possible long run outcomes. We use our cross-sectional estimates to predict the increase in Chinese household emissions by 2026 if Chinese incomes increase by 200%. We find that the increases predicted by current cross-sectional relationships are quite modest, relative to the current gap between the US and China. This illustrates the range of possibilities for Chinese future emissions.

The average Chinese household in the year 2026 will be richer than the average household today. Assuming that energy Engel curves are stable over time, we can use our cross-sectional estimates to predict how Chinese urban income growth will affect future carbon emissions. We predict that emissions will grow only modestly. New energy efficiency policy initiatives, such as China's recent announcement of its intent to reduce its carbon intensity (CO_2/GNP) by 40% by the year 2020, can offset some of the pollution consequences of growth.[1] But if China invests in infrastructure and changes its urban forms so that China looks more like the United States, then emissions of both China and the world will increase dramatically.

2. Household carbon production and urban development in a developing country

Urban infrastructure is long lived, and decisions made decades ago still shape older cities like London and New York. In declining areas, like Detroit, where there is little new construction, history is even more important. Today, China is making choices over investments in roads, public transit, electricity generation and housing that will have implications for resource consumption and greenhouse gas production for decades. The combination of irreversibility of investment and China's vast size makes its current development decisions relevant for long-term global carbon emissions.

No nation, including China, has a unilateral incentive to tax carbon emissions so that actions internalize global consequences of greenhouse gases. As Glaeser and Kahn (2010) note, in the absence of an appropriate carbon tax, there will be lower social costs created when urban activity locates in a low emissions place rather than a high emissions place. There may also be distortions that come from other public policies, like subsidizing highways or homeownership, which encourage energy intensive lifestyles.

The size of the externality associated with a household locating in place A rather than place B equals the increase in carbon emissions in place A minus the decrease in emissions in places B times the social cost of carbon emissions minus the current carbon tax. We will provide new estimates of these externality costs for 74 major Chinese cities. These estimates will allow us to evaluate the unintended environmental consequences of China's current regional development policies.[2]

Throughout this article, we will focus solely on household carbon dioxide emissions as our measure of city 'greenness'. In a recent work (see Zheng et al., 2010), we have examined how ambient particulate levels and sulfur dioxide levels vary across 35 major Chinese cities as a function of city per capita income and FDI. Unlike carbon emissions, these other forms of pollution typically decline with income after a certain point, known as the peak of the Environmental Kuznets Curve turning point. For that reason, we expect that further increases in Chinese per capita income will be associated with local pollution reductions (Zheng and Kahn, 2008; Zheng et al., 2009). For example, China is now phasing in Euro IV new vehicle emissions standards in Beijing, which will reduce smog by reducing vehicle emissions per mile of driving.

1 http://www.nytimes.com/reuters/2009/11/26/world/international-uk-climate-china-copenhagen.html.

2 Assessing the size of the environmental externality from migration requires us to know the marginal impact of an extra household on carbon emission, but we will only be able to measure average emissions. Marginal and average emissions may differ because of increasing or decreasing returns in the production of energy. We have no way of addressing this problem and cannot even be sure of the direction of the bias. Average and marginal emissions may also diverge because new households are more likely to live in larger or more energy-efficient homes or homes on the urban edge.

Several studies have examined the industrial sector using decomposition techniques to study the role of industrial scale, composition and technique effects in explaining trends over time (see Huang 1993, Sinton and Levine 1994, Sinton and Fridley 2000, Shi and Polenske 2006). In this article, we focus on household energy consumption. In the US, the household carbon emissions account for 40% of total carbon emissions, while in China this share is smaller than 20%. However, the household's share of total per capita carbon emissions will surely grow as China transitions from a manufacturing economy to a service economy. As domestic households become richer they will consume more electricity and the demand for private transportation services will increase.[3]

3. Data

3.1. Estimation framework

We estimate how much carbon dioxide emissions a standardized Chinese household produces in year 2006 if it resides within one of China's 74 cities, including all the 35 major cities (all municipalities directly under the federal government, provincial capital cities and quasi-provincial capital cities) plus some cities that have enough sample observations. We focus on four major household sources of carbon dioxide emissions: transportation, residential electricity consumption, residential heating and domestic fuel. The following equation provides an accounting framework for organizing our empirical work.

$$\text{Emissions} = \gamma_1 * \text{Transportation} + \gamma_2 * \text{Electricity} + \gamma_3 * \text{Heating} + \gamma_4 * \text{Domestic Fuel} \tag{1}$$

Our main goal is to estimate Equation (1) for each Chinese major city for a standardized household. In this equation, transportation represents energy use from a vector of activities including liters of annual gasoline consumed for households who own a car. Transportation also includes miles traveled on cabs and the energy use of buses and subways. All forms of energy use are multiplied by an emissions factor vector defined as γ_1. For example, each liter of # 93 gasoline (the most commonly used gasoline type for private cars in Chinese cities) consumed produces 2.226 kg of carbon dioxide.

The second term in this equation represents carbon dioxide emissions from residential electricity consumption. In the US, Glaeser and Kahn (2010) found a tight link between electricity consumption and hot summers, presumably because of extensive use of air conditioning. To convert electricity usage into carbon emissions, we must use the regional area power plants' average emissions factor, denoted by γ_2, defined as carbon dioxide emissions per megawatt hour of power generated. Coal-fired power plants have a higher emissions factor than natural gas-fired power plants or power plants that run on renewable power such as wind, hydro or solar power.

Major Chinese cities differ with respect to their geography and available natural resources that can be used for producing electricity. For instance, some cities are located in regions that receive more of their power from power plants with a lower emissions

3 Our study focuses on transportation and household consumption of energy to provide heating and cooling services. We recognize that households consume other products (such as what they eat) that have carbon consequences.

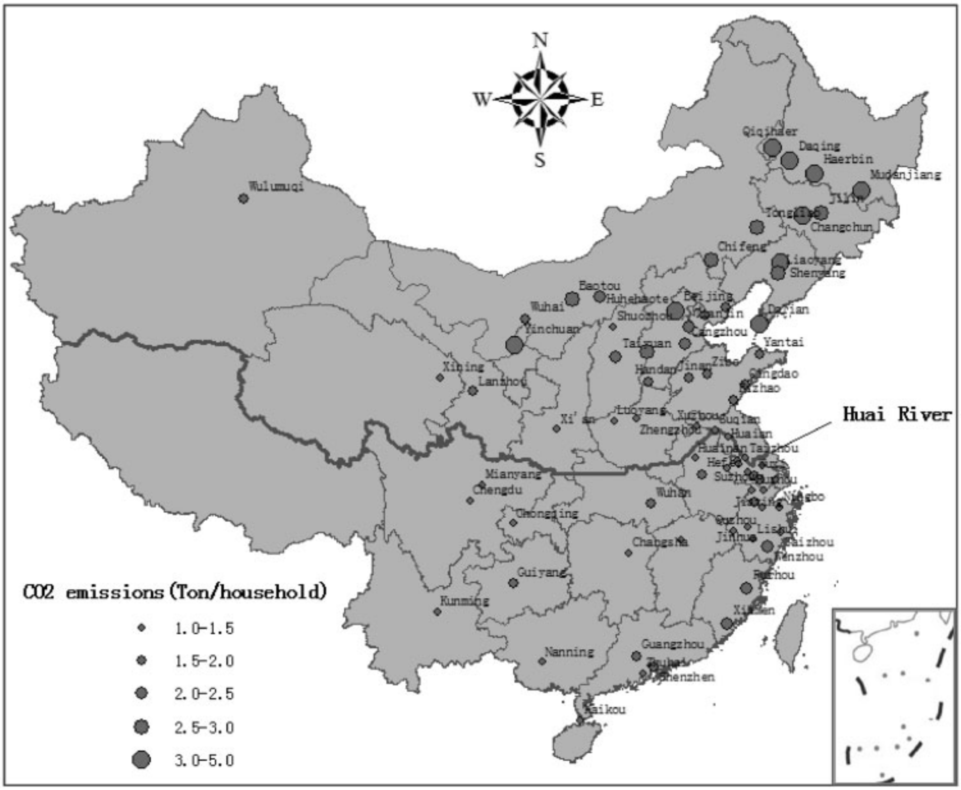

Figure 1. Carbon dioxide emissions per household in 74 Chinese cities.

factor. In our calculations we report below, we will use recent regional emissions factors for power plants as an input in estimating household carbon emissions from electricity consumption based on Equation (1). It is important to note that today's average emissions factor may not be an accurate estimate of future regional emissions factors if China were to sign a global carbon reduction treaty or if its recent investments in renewable power allow it to significantly reduce its share of power generation using fossil fuels.

The third term in Equation (1) is emissions from winter heating. China's cities differ greatly with respect to their winter temperatures. Northern cities are much colder than southern cities. In northern Chinese cities (north to the Qinling Mountains–Huai River line. See Figure 1 for the location of this line), heating is provided in a government-determined amount between November 15 and March 15 (centralized heating system), because heating is considered a basic right. The amount of heating provided per square meter in floor area is fixed. Individual households are unable to control their indoor temperature when centralized heating is provided. This system is highly subsidized by the government. Though some households (who live in new commodity-housing projects) pay market rates for the centralized heating, many households pay very low subsidized prices, and some even consume it for free. Such a government-provided heating system does not exist in southern China (south to the Qinling Mountains–Huai River line), where people pay market rates for energy (usually electricity) used to heat their homes/offices. We assume that energy usage for heating in the northern cities is proportional to the floor area of the home. In the north, heating using coal creates high level of carbon emissions (Almond et al., 2009). For southern cities without centralized heating data, we cannot separate electricity used for heating from other purposes.

The fourth term in Equation (1) is emissions from domestic fuels, which are also used, in some cases, to heat homes. This term includes three components: coal, liquefied petroleum gas (LPG) and coal gas. Coal is inexpensive, but it is carbon intensive. A byproduct of using it is elevated ambient air pollution level such as sulfur dioxide and particulates. LPG and coal gas are extracted from petroleum oil and coal, and are much cleaner and less carbon intensive.

3.2. Energy consumption data

Our first source of data is the Chinese Urban Household Survey (UHS) in the year 2006. This survey is conducted annually by the Urban Survey Department of the State Statistic Bureau of China. The survey targets households living in cities and towns for more than half a year. The data collected from the survey is primarily used for estimating the urban consumer expenditure component in GDP and CPI. The UHS data set that we use in this article includes approximately 25,300 observations across the 74 cities[4]. We compute the energy consumptions from electricity use, private car, taxi and three domestic fuels based on this micro data set. The survey also provides information on city economic and demographic variables such as per household income, household size and age of household head. Households' energy consumption from the uses of buses and subways as well as heating is not available in the UHS.

Since many households in northern cities still receive centralized heating services, there is no record of heating expenditure in the UHS. In the markets where centralized heating is adopted, there is no heating meter since heating is provided by the state in fixed quantities per square meter in floor area. Therefore, the best predictor of energy usage in such households, that we know of, is floor area. Conversion factors are used to transform the standardized household's consumption of floor area to its carbon emission from winter heating.

Given the current relatively low private vehicle ownership level in China, it is important to measure public transportation's contribution to the average household's carbon emissions. Since the UHS does not provide us such information, we turn to aggregate data in China Urban Statistic Yearbooks and additional sources.[5] The Yearbooks provide data on the total numbers of standard buses, LPG buses and CNG buses. We assume that the bus operating rate is 90%, and every bus travels ~150 km/day. The fuel consumption of a standard bus is 25 l/100 km. A LPG (or CNG) bus consumes three-fourths of the fuel that a conventional bus consumes for an equal distance. We then calculate each city's total bus fuel consumption and divide by the total number of households in the city to obtain per-household bus fuel consumption.

4 Here a 'city' is defined as the built-up area in an administrative city. The built-up area is where most urban economic activities take place and can be regarded as an integrated labor market. This definition is comparable to the MSA definition in the US.

5 Glaeser and Kahn (2010) follow the same strategy in their United States study ranking cities with respect to their household carbon footprint.

Table 1. Summary statistics and definitions

Variable name	Definition	Unit	Mean (SD)
Household level variables			
ELECQ	Household's electricity consumption in 2006	kWh	1699 (1089)
CAR_USE	Binary: 1 = own a car, 0 = otherwise. In 2006.		0.164 (0.370)
CARQ	Household's fuel consumption by driving car in 2006	l	178.8 (202.9)
TAXIQ	Household's fuel consumption by taking taxi in 2006	l	13.2 (21.2)
COAL_USE	Binary: 1 = use coal as domestic fuel, 0 = otherwise. In 2006.		0.092 (0.289)
COALQ	Household's coal consumption in 2006	kg	760.4 (654.7)
LPG_USE	Binary: 1 = use LPG (liquefied petroleum gas) as domestic fuel, 0 = otherwise. In 2006.		0.419 (0.493)
LPGQ	Household's LPG consumption in 2006	kg	82.9 (55.4)
COALGAS_USE	Binary: 1 = use coal gas as domestic fuel, 0 = otherwise. In 2006.		0.582 (0.493)
COALGASQ	Household's coal gas consumption in 2006	m^3	252.9 (189.5)
HHSIZE	Household size	Person	2.9 (0.8)
AGE	Household head's age	Year	50.5 (11.9)
INCOME	Annual household income	yuan/household	39,639 (23,056)
HSIZE	Housing unit size	Sq. m	74.271 (33.789)
City-level variables			
CINCOME	City average household income	yuan	37,977 (10,273)
POP	City population	1000 persons	2556 (2652)
DENSITY	City population density	1000 persons/km^2	13.4 (5.3)
JAN_TEMP	Average temperature on January	°C	0.46 (8.66)
JULY_TEMP	Average temperature on July	°C	27.21 (2.65)

There are only 10 Chinese cities that have subway lines: Beijing, Shanghai, Guangzhou, Shenzhen, Tianjin, Dalian, Changchun, Nanjing, Wuhan and Chongqing. There is no public data available on the electricity usage of subways, so we must rely on the internal data we obtained from government agencies. We follow the same procedure as we estimate bus fuel consumption. For each city with subway lines, we calculate total electricity consumption by the subway system and then divide this by the city's household count. This yields an estimate of a city's per-household average electricity consumption from subway use.

Table 1 lists the names, definitions, means and standard deviations of our key variables. Table 2 reports the summary statistics. The average household in our sample has an annual income of 40,000 Yuan, or 5700 dollars. It consumes 1700 kWh of electricity and spends 130 Yuan on taxis in 2006. Across our 74 city sample, 16.4% of the 25,300 households own cars. Auto ownership in Chinese cities is growing rapidly as incomes escalate. For instance, between 2002 and 2007, the number of private cars in Beijing increased from 1.5 to 3 million.

3.3. Carbon emission conversion factors

To construct common units measured in tons of carbon dioxide, we need access to carbon emission conversion factors associated with the four types of energy

Table 2. City level summary statistics for year 2006

City	Obs	Average income (Yuan)	Average household head's age (year)	Average household size (people)	Population (thousand people)	Population density (thousand people per sq. km)	January temperature	July temperature	Average electricity use (kWh)	Car ownership (%)	Average gas use (l)
All	*25330*	*40,058*	*45*	*2.88*	*2556*	*13.41*	–	–	*1699.0*	*16.4*	*178.8*
Beijing	2081	55,718	46	2.89	11,269	8.98	−1.9	25.9	2286.2	23.0	309.3
Tianjin	1554	40,441	49	2.88	7779	14.41	−2.7	25.9	2151.4	11.0	204.1
Shijiazhuang	301	32,201	47	2.82	2314	13.22	−0.9	27.0	1470.7	7.3	126.5
Tangshan	200	37,647	48	3.04	3012	14.40	−0.9	27.0	1137.7	16.0	199.4
Qinhuangdao	200	29,472	46	2.74	789	9.55	−0.9	27.0	1132.1	23.5	141.5
Handan	200	28,633	47	2.80	1442	14.16	−0.9	27.0	1121.4	12.0	88.3
Cangzhou	150	30,080	44	3.04	501	11.92	−0.9	27.0	1152.5	18.0	69.8
Taiyuan	310	32,039	47	2.75	2710	13.75	−3.6	25.7	1293.2	8.1	159.7
Shuozhou	150	31,747	40	3.22	612	20.77	−3.6	25.7	853.6	26.0	74.4
Huhehaote	400	37,383	45	2.77	1115	7.43	−9.2	24.5	1293.2	11.8	188.8
Baotou	400	40,109	44	2.72	1374	7.71	−9.2	24.5	1361.4	19.0	111.9
Wuhai	150	34,596	41	3.30	434	11.56	−9.2	24.5	1162.8	65.3	64.4
Chifeng	200	26,572	40	3.03	1150	15.97	−9.2	24.5	1141.7	16.5	59.2
Tongliao	150	28,275	45	3.34	813	25.15	−9.2	24.5	1680.5	26.7	75.7
Shenyang	502	31,190	49	2.74	4999	15.38	−12.7	24.2	1343.2	4.0	241.7
Dalian	508	37,514	47	2.89	2877	11.15	−12.7	24.2	1242.8	3.0	147.2
Liaoyang	200	27,259	47	2.83	719	8.60	−12.7	24.2	1182.8	5.5	60.7
Changchun	322	33,444	45	3.02	3488	13.04	−14.5	23.5	1224.8	6.8	206.8
Jilin	300	29,074	47	2.87	1805	1.78	−14.5	23.5	1366.9	3.0	196.4
Haerbin	541	31,125	47	2.83	4728	14.27	−17.7	23.4	1571.0	3.9	132.7
Qiqihaer	300	22,989	44	2.87	1442	10.70	−17.7	23.4	1012.3	7.7	62.1
Daqing	200	37,427	42	2.77	1254	7.87	−17.7	23.4	1708.0	4.0	72.1
Mudanjiang	200	22,349	45	2.81	792	12.75	−17.7	23.4	1254.9	6.5	100.3
Shanghai	1018	56,717	46	3.02	12,981	15.09	5.7	29.4	1778.3	16.4	183.6
Nanjing	821	47,448	49	2.78	5246	9.13	3.9	28.7	1960.7	15.1	197.9
Wuxi	301	48,705	49	2.81	2323	11.76	3.9	28.7	2057.3	18.9	194.8
Xuzhou	301	35,331	46	2.79	1816	12.60	3.9	28.7	1278.4	9.6	93.1
Changzhou	301	42,536	46	2.83	2225	20.68	3.9	28.7	1746.6	42.5	142.8
Suzhou	300	49,096	49	2.79	2302	10.73	3.9	28.7	1960.2	22.3	173.6
Nantong	205	38,890	45	2.80	866	14.61	3.9	28.7	1524.7	5.4	179.0
Huaian	200	29,379	45	2.81	2765	31.07	3.9	28.7	1289.0	16.0	51.2
Yangzhou	200	36,080	48	2.84	1168	16.69	3.9	28.7	1655.5	27.5	70.1
Zhenjiang	200	40,896	49	2.90	1027	11.40	3.9	28.7	1593.5	10.0	52.1
Taizhou	200	33,580	47	2.75	643	12.84	3.9	28.7	1468.5	40.5	88.8
Suqian	207	26,626	44	3.23	1554	32.64	3.9	28.7	1038.6	21.3	54.0
Hangzhou	614	51,432	46	2.81	4142	12.65	5.8	30.1	2286.5	18.1	243.7
Ningbo	406	48,805	44	2.76	2158	10.03	5.8	30.1	1768.0	15.0	262.4
Wenzhou	204	54,042	46	2.75	1406	9.97	5.8	30.1	2836.0	43.1	335.7
Jiaxing	150	44,866	45	2.79	814	11.13	5.8	30.1	1716.0	38.0	186.4
Huzhou	200	42,087	47	2.56	1082	15.20	5.8	30.1	1727.5	21.0	97.4
Shaoxing	200	49,815	45	2.70	649	7.80	5.8	30.1	1568.6	9.0	150.6
Jinhua	153	43,932	44	2.61	922	13.62	5.8	30.1	1514.1	37.3	137.5
Quzhou	150	37,848	45	2.65	810	19.02	5.8	30.1	1415.4	16.7	128.1
Taizhou	150	52,123	46	2.76	1502	13.19	5.8	30.1	1914.5	39.3	263.3
Lishui	150	44,803	44	2.78	378	15.41	5.8	30.1	1881.5	48.7	152.8
Hefei	410	31,293	43	2.87	1931	8.59	3.4	28.8	1624.5	5.6	106.4
Huainan	411	31,410	42	2.96	1650	17.63	3.4	28.8	1255.3	6.3	84.9
Fuzhou	303	44,596	44	3.14	1817	10.26	12.5	29.4	2804.7	24.8	144.8
Xiamen	201	52,711	45	2.93	1604	10.15	12.5	29.4	2776.8	25.9	172.1
Nanchang	300	28,905	48	2.61	2213	13.17	6.6	30.0	1537.2	1.7	50.0
Jinan	416	43,605	41	2.88	3523	11.55	0.0	27.4	1573.0	31.3	133.2

(continued)

Table 2. Continued

City	Obs	Average income (Yuan)	Average household head's age (year)	Average household size (people)	Population (thousand people)	Population density (thousand people per sq. km)	January temperature	July temperature	Average electricity use (kWh)	Car ownership (%)	Average gas use (l)
Qingdao	407	43,263	44	2.84	2710	11.91	0.0	27.4	1668.9	10.3	236.3
Zibo	150	38,050	42	2.77	2765	14.13	0.0	27.4	1299.7	42.7	79.6
Yantai	200	40,448	40	2.84	1789	10.02	0.0	27.4	1248.6	26.0	72.6
Rizhao	102	31,736	38	2.87	1213	19.79	0.0	27.4	1412.1	60.8	136.6
Zhengzhou	462	35,124	47	2.95	2612	9.26	0.3	27.1	1508.3	7.4	97.6
Luoyang	307	32,683	43	2.84	1537	10.64	0.3	27.1	1402.5	22.5	87.7
Wuhan	531	34,558	48	2.82	5012	22.55	4.2	30.2	2092.8	5.5	222.0
Changsha	409	38,758	45	2.80	2146	13.85	5.3	30.1	1918.3	16.4	207.9
Guangzhou	304	59,751	41	3.10	6253	8.02	15.8	29.8	2361.1	27.0	242.3
Shenzhen	101	82,429	39	3.23	1968	2.73	15.8	29.8	2893.5	42.6	466.6
Zhuhai	101	55,577	39	3.07	926	8.57	15.8	29.8	2039.5	36.6	295.0
Nanning	202	32,663	45	3.01	2549	14.99	14.3	28.0	1591.5	39.1	136.2
Haikou	306	35,693	43	3.34	1767	19.33	18.5	30.0	1580.0	33.7	193.4
Chongqing	308	35,571	45	3.10	15,110	23.93	7.8	31.0	2051.0	3.2	155.7
Chengdu	430	36,138	44	2.99	4972	12.52	5.8	26.9	1821.8	20.9	262.3
Mianyang	200	27,587	43	2.77	1163	14.45	5.8	26.9	1394.5	9.5	188.8
Guiyang	316	33,034	44	2.97	2098	15.89	4.3	23.8	2155.4	15.5	128.0
Kunming	600	30,445	47	2.84	2320	9.97	10.8	21.3	1522.3	14.3	181.1
Xi'an	366	31,172	48	2.91	5410	20.70	−0.2	28.2	1396.1	6.6	50.2
Lanzhou	321	25,819	48	2.79	2038	13.23	−6.9	22.2	911.7	3.1	47.4
Xining	300	27,781	45	2.98	1051	16.44	−6.5	18.7	1507.6	4.7	111.8
Yinchuan	314	27,870	43	2.79	880	8.33	−7.4	24.8	1334.8	15.3	71.7
Wulumuqi	402	29,294	41	2.80	1931	8.19	−14.2	24.5	1053.5	4.0	37.4

City	Average taxi expenditure (Yuan)	Standard bus Mileage (1e3 km)	LPG/CNG bus mileage (1e3 km)	Rail electricity use (1e3 kWh)	Heated floor space (m^2)	coal use rate (%)	Average coal use (kg)	LPG use rate (%)	Average LPG Use (kg)	Coal gas use rate (%)	Coal gas use (m^3)	House unit Size (m^2)
All	*130*	*99,926*				*9.2*	*760.4*	*41.9*	*82.9*	*58.3*	*252.9*	*64.9*
Beijing	255	758,835	174,926	244,907	222,180	7.4	1159.9	22.1	97.2	74.8	233.6	65.8
Tianjin	176	356,505	2119	54,741	109,680	8.8	808.2	7.9	73.9	90.9	148.5	76.1
Shijiazhuang	120	75,785	29,466		38,280	5.3	1150.6	53.2	85.4	53.2	340.0	68.4
Tangshan	165	117,915			21,640	0.0	0.0	0.0		100.0	406.6	68.9
Qinhuangdao	103	39,075			9120	4.5	1411.1	65.0	76.2	39.0	368.3	73.4
Handan	75	63,023			10,030	9.5	396.4	10.0	28.8	95.0	361.8	93.0
Cangzhou	134	19,217			5830	4.0	1200.0	92.0	83.1	38.0	112.0	70.4
Taiyuan	102	99,683			37,850	3.2	528.0	7.1	83.8	92.9	447.6	85.3
Shuozhou	95	4977			2470	22.0	1597.0	48.7	60.2	57.3	131.1	72.9
Huhehaote	189	10,200	44,200		12,030	9.0	1377.0	45.8	72.4	53.0	247.3	75.5
Baotou	209	39,962	13,945		23,680	10.8	1215.0	37.5	67.2	42.5	242.3	85.9
Wuhai	135	20,548			2600	31.3	1567.9	27.3	54.4	13.3	214.8	75.9
Chifeng	103	16,803	1183		12,210	8.5	1386.5	89.0	46.5	1.5	42.7	72.9
Tongliao	193	7983			4660	8.7	1923.8	78.0	85.1	5.3	60.8	65.8
Shenyang	180	196,410	54,695		117,776	0.4	175.0	5.8	69.3	95.6	175.7	68.8
Dalian	239	207,842		17,987	60,350	0.2	1275.0	11.4	56.9	94.1	344.0	71.2
Liaoyang	124	18,774			12,630	3.5	62.7	56.0	102.7	63.0	87.6	77.5
Changchun	210	86,823	100,028	14,680	49,480	5.3	1517.6	5.6	58.4	92.5	236.8	78.7
Jilin	226	289,195	138,364		21,610	0.7	177.0	88.0	92.6	17.7	159.8	65.7
Haerbin	162	124,666	102,837		55,750	1.3	426.9	16.5	108.2	88.5	403.5	64.8
Qiqihaer	108	46,466			20,300	1.0	1666.7	18.3	106.1	90.3	198.8	86.1

(continued)

Table 2. Continued

City	Average taxi expend-iture (Yuan)	Standard bus Mileage (1e3 km)	LPG/CNG bus mileage (1e3 km)	Rail electricity use (1e3 kWh)	Heated floor space (m^2)	coal use rate (%)	Average coal use (kg)	LPG use rate (%)	Average LPG Use (kg)	Coal gas use rate (%)	Coal gas use (m^3)	House unit Size (m^2)
Daqing	228	91,011			29,610	0.0	0.0	74.0	133.9	7.5	80.2	64.6
Mudanjiang	165	6701	15,226		13,590	6.0	1612.5	74.0	48.9	3.5	104.1	61.1
Shanghai	242	818,852	13,846	427,302		0.0	0.0	3.4	64.1	97.0	403.6	69.9
Nanjing	116	207,349	45,234	67,180		1.3	462.7	54.8	77.6	50.5	204.0	75.2
Wuxi	127	130,283	8968			2.7	259.4	35.2	76.0	65.4	350.0	66.0
Xuzhou	82	84,162				28.6	583.8	33.2	66.9	61.1	288.4	81.0
Changzhou	104	65,240	13,994			7.0	458.8	52.8	81.4	59.8	161.6	83.1
Suzhou	117	101,309				4.0	581.3	32.7	86.1	69.3	231.9	82.3
Nantong	61	37,498				3.4	284.0	29.3	81.4	82.4	311.7	79.6
Huaian	60	28,974				42.0	403.5	70.5	56.6	27.0	87.4	91.9
Yangzhou	71	36,562				10.5	250.5	49.0	64.5	58.0	278.7	81.4
Zhenjiang	98	36,119				24.0	532.0	40.5	54.2	69.0	149.6	87.9
Taizhou	49	11,727				22.5	539.0	60.5	62.1	28.0	71.7	117.9
Suqian	42	16,162				43.5	503.0	87.4	48.3	1.4	26.0	78.4
Hangzhou	96	234,795				4.6	262.1	66.9	81.1	42.3	128.3	69.2
Ningbo	90	130,776				2.2	351.7	78.1	112.3	27.6	60.9	87.3
Wenzhou	195	83,620				0.5	50.0	84.8	115.4	16.2	34.4	76.0
Jiaxing	87	32,374				5.3	197.3	80.0	98.0	25.3	55.0	80.7
Huzhou	90	29,910				5.5	456.4	87.0	89.9	18.5	163.5	74.2
Shaoxing	68	36,119				27.5	224.7	42.5	77.5	71.0	119.5	86.5
Jinhua	119	33,162				24.2	238.2	85.0	71.7	16.3	37.3	96.4
Quzhou	88	26,461				10.7	753.4	76.0	101.8	28.7	389.7	104.5
Taizhou	86	17,591				12.7	88.9	84.0	118.3	18.0	50.8	88.1
Lishui	50	4583				14.0	187.5	92.7	90.8	4.0	30.1	71.1
Hefei	222	96,776	21,927			27.8	417.3	58.8	83.7	48.5	177.6	68.3
Huainan	232	42,623				28.0	575.4	46.7	51.5	64.7	325.6	82.0
Fuzhou	76	91,750				0.3	30.0	68.6	117.8	36.3	120.3	87.0
Xiamen	121	126,883				6.5	584.3	67.7	93.1	34.8	106.3	70.8
Nanchang	38	108,159				0.3	150.0	75.0	85.4	38.3	250.8	75.6
Jinan	185	138,561	46,269		23,680	25.7	1140.4	52.9	50.3	39.4	143.8	67.6
Qingdao	172	177,291	20,646		18,370	20.4	1050.2	48.6	55.9	63.9	222.6	93.9
Zibo	149	82,339	4977		18,300	11.3	1205.3	66.7	81.2	29.3	148.9	72.8
Yantai	184	73,962	296		15,970	8.5	1273.5	55.0	61.4	52.0	205.5	81.0
Rizhao	139	35,527			5670	22.5	1163.2	59.8	47.9	8.8	67.3	80.4
Zhengzhou	52	87,857	70,365		10,610	14.7	991.9	30.3	87.2	79.9	241.4	82.6
Luoyang	72	40,948			3200	25.1	612.3	75.9	82.4	22.5	325.2	78.2
Wuhan	135	201,091	83,225	11,284		7.7	503.4	50.5	109.9	63.8	253.7	79.5
Changsha	227	131,564	2562			8.6	604.3	81.4	97.1	31.5	258.3	77.2
Guangzhou	166	209,271	316,444	185,417		0.7	66.0	69.1	112.6	50.3	260.7	95.5
Shenzhen	219			100,485		0.0	0.0	53.5	140.4	59.4	79.2	87.8
Zhuhai	162	57,504				5.0	118.8	97.0	137.3	12.9	48.4	74.2
Nanning	65	107,567				12.4	319.3	92.6	107.4	6.4	70.0	94.8
Haikou	64	42,377				4.2	577.3	85.6	97.3	15.0	139.4	75.5
Chongqing	119	40,504	349,113	26,120		1.0	783.3	2.6	67.9	98.4	341.2	76.4
Chengdu	116	3597	32,669			2.1	1596.7	5.1	103.9	94.4	348.4	80.6
Mianyang	100	2661	33,556			0.5	150.0	4.5	71.3	97.5	279.6	63.5
Guiyang	99	77,559				29.1	848.1	19.0	58.7	69.0	292.2	92.4
Kunming	45	123,582	77,756			10.3	372.8	41.7	74.9	51.3	399.0	62.5
Xi'an	108	135,309	131,466		18,390	20.8	678.6	38.5	58.2	53.3	247.2	61.9
Lanzhou	74	4139	91,159		22,140	6.5	667.2	44.9	61.6	59.5	166.5	73.8
Xining	113		86,379		130	17.0	1273.6	14.3	63.7	5.0	392.7	72.0
Yinchuan	191	40,455	12,713		21,230	10.5	467.9	66.2	42.7	20.7	233.5	69.4
Wulumuqi	136	12,812	196,755		29,000	0.7	500.0	26.9	54.1	61.7	233.5	64.9

consumptions in Equation (1) (γ_1–γ_4). The conversion factors come from various sources.

In the transportation category, private car, taxi and bus uses share the same conversion factor transforming gas consumptions to carbon emissions. For subway use, the electricity conversion factor is employed to obtain its carbon emission.

The electricity conversion factor (power plant emission factor, γ_2) is a key parameter that varies by region across China. Seven electricity grids (six regional grids on the Mainland plus one on the Hainan Island) support most of China's power consumption. The baseline emission factors (at both operating margin and build margin) for regional power grids are estimated for recent years by the Office of National Coordination Committee on Climate Change, a department within the National Development and Reform Commission.

Tsinghua University's Department of Building Science and Department of Environmental Engineering provided us with conversion factors (γ_3) that indicate how much carbon dioxide is emitted when heating a square meter of living space in each province for a given outside temperature. We then multiply this conversion factor with the predicted amount of floor space for a standardized household, which yields the standardized household's carbon emission from winter heating. The conversion factors of domestic fuels (γ_4) are quite standard and we obtain them from the Energy Statistic Yearbooks of China.

4. Estimation strategies

4.1. The definition of a standardized household

To measure the carbon emissions of our 74 Chinese cities based on carbon dioxide emissions, we use the estimated city-specific energy consumptions for the four energy types (nine sub-types) for a standardized household and then convert those energy uses into carbon dioxide emissions. The standardized household is defined as a household with an annual income of 40,000 Yuan or 5714 dollars, 3 members and a household head aged 45 years, which are the means of these three variables for the whole sample. By predicting the carbon dioxide emission of a standardized household, we are able to answer; 'if a household moved from city i to city j, would aggregate carbon emissions rise or fall?'

4.2. Energy consumption equations

To estimate the components of Equation (1), we will estimate separate city-specific regressions for relevant carbon producing activities such as electricity and gasoline consumption. These city specific regressions allow us to predict energy consumptions for a standardized household in each of the 74 cities. This procedure generates an unwieldy number of regression coefficients, but generally these regression coefficients are similar in magnitude across places.

We regress travel behavior, household electricity use, heating consumption and domestic fuel consumption on basic demographics. For city j and energy type k, we estimate the city-specific regression:

$$\begin{aligned}\text{Log(energy consumption}_{ijk}) = {} & b_{1,jk} * \text{Log(Income}_{ij}) + b_{2,jk} * \text{Household Size}_{ij} \\ & + b_{3,jk} * \text{Age of Household Head}_{ij} + U_{ijk}\end{aligned} \tag{2}$$

The unit of analysis is household *i* in city *j*. Note that the regression coefficients have city and energy type specific subscripts. Thus, household demographics have different marginal effects on energy consumption across cities.

In Equation (2), we control for demographics but not for housing characteristics. After all, we are not attempting to estimate emissions assuming that people in Beijing live in Huaian's 'Southern-Huai River' small town style homes. If households live in smaller homes in more expensive areas, then the resulting reduction in carbon emissions should be attributed to that location. In Equation (2), we control for household income. We acknowledge that the same worker could earn a different income in different cities. This could happen because the factor prices for the worker's skills vary across cities or because the worker works more hours in a city featuring higher hourly wages (the substitution effect dominating the income effect) (see Kahn 1995). Concerned about this possible endogeneity issue, we discuss an alternative estimation strategy that yields quite similar results in the Appendix A.

With the exception of electricity consumption and taxi gas consumption, we estimate the other energy consumption regressions using a Heckman two-step procedure. Many households in our sample have literally zero consumption of a specific energy type. For example, in Beijing, we estimate the car ownership rate to be 23%. Thus, in this relatively wealthy city 77% of households are consuming zero gasoline and the remaining 23% are consuming a positive quantity of gasoline. In Shanghai, the vehicle ownership rate is even lower (16.4%) due to higher population density and a license plate quota policy. The same issue arises for household consumption of three domestic fuels (coal, coal gas and LPG), where many households consume none of these particular fuel.

In implementing the Heckman two-step estimator for each of these categories of energy consumption, we estimate a first stage probit of the form:

$$\begin{aligned}\text{Prob(consume fuel } k) = f(&b_1 * \text{Log(Income)} + b_2 * \text{Household Size} \\ &+ b_3 * \text{Age of Household Head})\end{aligned} \tag{3}$$

In the second stage, we estimate

$$\text{Log(consumption} \mid \text{consumption} > 0) = c_1 * \text{Log(Income)} + \text{e} \tag{4}$$

We have no theoretical reasons for including variables in the participation equation but not in the consumption equation; however, small sample sizes led us to exclude age and household size from the second stage regression. This procedure therefore corrects for the tendency of places with differently aged or larger households to have more cars or more strictly positive amounts of LPG consumption, but it does not correct for any connection between age or household size and consumption, conditional upon consumption being positive.

We will first run pooled regressions for each energy type using all the observations in 74 cities. In this case, we include city specific fixed effects in Equation (2), thus the constraint that household demographics have the same marginal effects on energy consumption across cities is imposed. Later, we relax this assumption and run city-specific regressions, but since this produces an enormous number of coefficients, we report the more consolidated estimates. From those city-specific regressions we predict for each energy type, the standardized household's energy consumption in each of the 74 cities, which are then converted to carbon dioxide emissions using various conversion factors.

After we generate our city specific rankings, we will examine the role of urban form and other city specific attributes for explaining cross city differences. Given that we generate estimates for 74 different cities that span different population sizes, per capita income levels, climate conditions and population densities, we are able to test several hypotheses.

5. Measuring household carbon emissions across Chinese cities

5.1. Pooled cross-city regressions results

We first estimate the pooled cross-city regressions to examine the determinants of Chinese household energy use. In the case of household electricity consumption, we estimate:

$$\begin{aligned}\text{Log}(\text{Electricity}_{ij}) = {} & \text{City Fixed Effects} + b_1 * \text{Log}(\text{Income}_{ij}) + b_2 * \text{Household Size}_{ij} \\ & + b_3 * \text{Age of Household Head}_{ij} + U_{ij}\end{aligned} \tag{5}$$

The unit of analysis is household i in city j. Note that the regression coefficients do not have city-specific subscripts.

The results in Table 3 indicate that taxi use is a luxury good with an income elasticity > 1. Car ownership and gasoline consumed have high income elasticities. The income elasticity of electricity consumption is 0.29. Richer urban Chinese households are moving up the energy ladder by substituting away from dirty home heating fuels such as coal and increasing consumption of cleaner fuels such as electricity and coal gas. These urban China results are in accord with past household Environmental Kuznets Curve (EKC) work by Pfaff et al. (2004). Richer people consume cleaner energy sources and this can reduce local air pollution despite a rising quantity of consumption. Household consumption of coal and LPG declines with income (but if a household uses coal, coal consumption rises with income). In contrast, consumption of coal gas, the cleanest of these energy sources, increases with income. Coal gas is transmitted through pipes directly into households, while LPG (usually transported in cans) is less convenient and coal is far dirtier.

5.2. City-specific regressions results

We use the UHS data to estimate city specific regressions for household consumption of gasoline, electricity, coal, LPG and coal gas that allow the coefficients to vary by city. Each of these regressions has the same form as those reported in Table 3 but in this case, we now have 222 (74 cities and three explanatory variables) separate coefficient estimates for income, household size and age. Here we provide two salient examples. One is the electricity use equation in Shanghai, estimated using OLS; the other is the private car use equation in Beijing, estimated using Heckman two-step technique.

In Equation (6), we report our estimates based on the Shanghai sample of 1018 households. We have 74 similar regressions for the 74 cities.

$$\text{Log}(\text{Electricity Use}) = \underset{(0.29)}{3.58} + \underset{(0.03)}{0.33} * \text{Log}(\text{Income}) + \underset{(0.02)}{0.10} * \text{Household Size} - \underset{(0.001)}{0.0005} * \text{Age} \tag{6}$$

Table 3. Energy consumption regressions using 2006 micro data

			Heckman two-step		Heckman two-step		Heckman two-step		Heckman two-step		
Dependent variable	log (*ELECQ*)	log (*TAXIQ*)	*CAR_USE*	log (*CARQ*| *CAR_USE=1*)	*COAL_USE*	log (*COALQ*| COAL_USE=1)	*LPG_USE*	log(*LPGQ*| LPG_USE=1)	*COALGAS_USE*	log (*COALGASQ*| *COALGAS_USE=1*)	log(HSIZE)[c]
Model	OLS[a]	OLS[a]	Probit[b]	[a]	Probit[b]	[a]	Probit[b]	[a]	Probit[b]	[a]	OLS[a]
log(*INCOME*)	0.289 (39.21***)	1.929 (54.95***)	0.630 (34.16***)	0.768 (9.40***)	−0.448 (−23.83***)	0.169 (2.17**)	−0.240 (−17.46***)	−0.082 (−2.08**)	0.354 (25.46***)	−0.070 (−0.59)	0.265 (61.36***)
HHSIZE	0.06 (11.77***)	−0.287 (−11.83***)	0.044 (3.39***)		0.153 (11.23***)		0.039 (3.82)		−0.030 (−2.91)		0.025 (8.26***)
AGE	0.0009 (2.62***)	−0.018 (−11.37***)	−0.021 (−23.90***)		0.011 (11.69***)		−0.004 (−6.14**)		0.008 (11.48***)		0.0003 (1.53)
constant	3.988 (51.1***)	−13.642 (−36.75***)	−6.702 (−34.90***)	−2.689 (−2.59**)	2.288 (11.71***)	5.283 (9.39***)	2.389 (16.33***)	3.829 (16.44***)	−3.789 (−25.54***)	5.184 (3.01***)	1.367 (29.83***)
City fixed effects	Yes	Yes	–		–		–		–		yes
Obs	25328	25328	25328		25328		25328		25328		25328
Significance	R^2: 0.22	R^2: 0.234	rho: −0.558 sigma: 1.764 lambda: −0.984		rho: −0.398 sigma: 1.330 lambda: −0.529		rho: 0.961 sigma: 1.314 lambda: 1.262		rho: −0.364 sigma: 0.917 lambda: −0.335		R^2: 0.222

[a] *t*-statistics in parentheses.
[b] z-statistics in parentheses.
[c] for estimating heating.
*indicates significance at the 10% level, **at the 5% level and ***at the 1% level.

Standard errors are reported in parentheses. In this regression, the R-squared is 0.199. We take these regression coefficients and predict the annual electricity consumption for a household living in Shanghai, with an income of 40,000 Yuan, 3 members and a household head aged 45 years. The result is 1494.9 kilowatt hours (kWh). We then multiply this number by the electricity conversion factor in Shanghai (0.8154 tCO_2/mWh), which is γ_2 in Equation (1). This yields a prediction for the standardized household equal to 1.219 tons of carbon dioxide emissions. These steps yield an estimate of γ_2*Electricity [see Equation (1)] for each city.

For private cars, we use the city-specific two-stage Heckman model to predict a standardized household's fuel consumption (fuel consumption taken to be zero when unobserved). In the case of car usage in Beijing, for example, the selection equation is:

$$\begin{aligned}&\text{Prob(Owning a car)} =\\ &f(\underset{(0.861)}{-8.84} + \underset{(0.179)}{0.81} * \text{Log(Income)} - \underset{(0.051)}{0.003} * \text{Household Size} - \underset{(0.003)}{0.015} * \text{Age of household head})\end{aligned} \tag{7}$$

Standard errors are in parentheses. The consumption equation, given the household owns a car, is:

$$\text{Log(Car Fuel Use} \mid \text{Car ownership} = 1) = \underset{(6.599)}{4.52} + \underset{(0.519)}{0.27} * \text{Log(Income)} \tag{8}$$

Standard errors are in parentheses. In the above Heckman two-step estimation, there are 2081 observations. From the first step regression, we predict that the standardized household has a 18.4% probability of owning a car. Using both equations, we predict that the standardized household's expected fuel consumption is 292.2 l/year. We then convert fuel consumption into carbon emissions using standard gas conversion measures.

We follow a similar estimation strategy as the one we use for electricity consumption to quantify the energy consumption impacts from taxi use and housing unit size (indirect measure of heating consumption). The empirical strategy for measuring domestic fuel consumption (coal, LPG and coal gas) is identical to the approach we use for studying private car use. In particular, we use a Heckman two-step technique. Due to the lack of micro data, per-household average energy consumptions from public transit use (bus and subway) are derived from the Statistic Yearbooks.

For the city-specific regressions, we report only the income coefficients in Table 4. Economic growth will surely continue in China; these income coefficients suggest which cities may be particularly likely to increase energy consumption over time.

There are sizable differences in the relationship between household income and energy consumption across cities. The table 4 highlights the cross-city heterogeneity with regards to income effects. Shanghai's income elasticity of private car fuel consumption (conditioning on ownership) is two times larger than the income elasticity in Beijing. The income elasticity of electricity consumption is 0.163 in Beijing, 0.171 in Shanghai and 0.445 in Zibo. Assuming that these year 2006 cross-sectional income elasticities do not change over time, we can use the estimates reported in Table 4 to forecast how ongoing urban growth will affect energy consumption in different Chinese cities. For example, economic development in Zibo will lead to greater electricity consumption than in Beijing.

Table 4. Income effect estimates based on the household level regressions estimated for each city

Dependent variable	log(elecq)	log(taxiq)	Car_use	log(carq)	log(hsize)	coal_use	log(coalq)	lpg_use	log(lpgq)	coalgas_use	log (coalgasq)
Model	OLS	OLS	Heckman		OLS	Heckman		Heckman		Heckman	
Beijing	0.163	1.432	1.463	0.269	0.218	−0.344	−0.037	−0.447	0.705	0.514	0.068
	(3.631***)	(10.230***)	(8.213***)	(0.518)	(11.158***)	(−1.806)	(−0.180)	(−3.679***)	(0.897)	(4.415***)	(0.650)
Tianjin	0.402	1.499	1.526	0.160	0.416	−1.427	0.519	−0.959	−0.080	0.516	0.058
	(9.811***)	(8.470***)	(6.044***)	(0.281)	(19.992***)	(−7.558**)	(0.840)	(−5.155***)	(−0.358)	(3.018***)	(0.461)
Shijiazhuang	0.321	−0.493	1.894	1.197	0.312	−1.361	0.028	−0.387	−1.889	0.552	−0.097
	(2.605**)	(−1.011)	(3.155***)	(0.796)	(6.087***)	(−2.523**)	(0.015)	(−1.424)	(−0.161)	(1.996)	(−0.313)
Tangshan	0.197	2.227	1.53	−0.053	0.328						
	(2.147**)	(4.043***)	(2.915***)	(0.00)	(6.456***)						
Qinhuangdao	0.138	0.532	1.174	0.753	0.137			−1.095	−0.492	1.023	−0.833
	(1.59)	(1.542)	(2.396)	(1.446)	(4.175***)			(−3.385***)	(−1.506)	(3.296***)	(−0.887)
Handan	0.144	−0.657	1.792	1.184	0.356	−0.3	−1.202	−1.192	0.501	−0.109	0.146
	(0.944)	(−0.986)	(1.486)	(1.077)	(6.546***)	(−0.42)	(−1.093)	(−1.692*)	(0.668)	(−0.129)	(0.521)
Cangzhou	0.333	1.013	0.567	0.341	0.162			−0.444	0.160	0.335	−0.141
	(2.734***)	(1.820*)	(0.879)	(0.605)	(3.139***)			(−0.632)	(0.338)	(0.882)	(−0.233)
Taiyuan	0.08	1.681	1.194	0.984	0.110			−0.225	−0.366	0.093	−0.011
	(1.221)	(3.365***)	(1.929*)	(0.745)	(4.948***)			(−1.108)	(−1.000)	(0.361)	(−0.212)
Shuozhou	0.312	0.476	1.054	0.756	0.038	−1.816	−0.102	−0.934	0.154	1.646	0.478
	(1.857*)	(1.195)	(2.398**)	(1.472)	(0.706)	(−4.031***)	(−0.203)	(−2.630***)	(0.269)	(4.030***)	(1.577)
Huhehaote	0.163	1.173	2.521	2.647	0.221	−0.978	0.448	−0.223	0.177	0.235	−0.118
	(1.636)	(3.398***)	(4.780***)	(2.708***)	(7.348***)	(−2.986***)	(0.744)	(−1.164)	(1.164)	(1.236)	(−0.183)
Baotou	0.167	1.215	0.574	−0.374	0.191	−0.51	−0.204	−0.105	0.007	0.98	−0.372
	(1.488)	(3.253***)	(1.218)	(−0.535)	(5.684***)	(−1.421)	(−0.666)	(−0.442)	(0.041)	(3.788***)	(−1.247)
Wuhai	0.507	0.411	0.719	0.594	0.487	−0.963	−0.026	1.593	0.427	1.604	−0.339
	(1.835*)	(0.804)	(1.712*)	(1.292)	(6.074***)	(−1.803)	(−0.075)	(2.498**)	(1.093)	(1.923)	(−0.361)
Chifeng	0.243	1.354	2.023	1.889	0.247	−0.88	−0.881	−0.619	−0.234		
	(1.487)	(2.375**)	(3.581***)	(2.703***)	(4.507***)	(−1.456)	(−0.431)	(−1.016)	(−0.472)		
Tongliao	0.427	0.696	1.172	1.915	0.325	−1.846	−0.207	0.276	0.102		
	(3.540***)	(2.089**)	(3.082***)	(1.377)	(8.107***)	(−3.529***)	(−1.097)	(0.85)	(0.928)		

(continued)

Table 4. Continued

Dependent variable	log(elecq)	log(taxiq)	Car_use	log(carq)	log(hsize)	coal_use	log(coalq)	lpg_use	log(lpgq)	coalgas_use	log (coalgasq)
Model	OLS	OLS	Heckman		OLS	Heckman		Heckman		Heckman	
Shenyang	0.242	2.004			0.322			−0.733	0.072		
	(3.925***)	(3.945***)			(10.696***)			(−1.834*)	(0.067)		
Dalian	0.344	1.571			0.264			−0.525	0.348	0.744	−0.136
	(6.375***)	(2.905***)			(8.803***)			(−1.775*)	(0.866)	(1.89)	(−0.361)
Liaoyang	0.041	1.675	1.908	0.790	0.247			0.811	0.116	−0.803	0.231
	(0.512)	(2.132**)	(1.551)	(0.488)	(5.762***)			(2.381**)	(0.314)	(−2.288)	(0.538)
Changchun	0.274	2.026	1.454	2.268	0.135	−3.219	4.182	−1.463	−0.095	−0.406	0.271
	(2.814***)	(3.938***)	(2.830***)	(3.058***)	(3.718***)	(−4.001***)	(0.825)	(−2.386**)	(−0.121)	(−0.876)	(2.299***)
Jilin	0.239				0.127			0.007	0.017	0.216	−0.056
	(3.641***)				(5.168***)			(0.031)	(0.012)	(0.682)	(−0.072)
Haerbin	0.373	0.269			0.358			−0.213	−0.139	0.51	0.231
	(4.859***)	(0.648)			(12.992***)			(−0.977)	(−0.865)	(2.002)	(1.719*)
Qiqihaer	0.119	1.14	−0.105	1.270	0.123			0.1	0.166	−0.317	0.074
	(2.471**)	(2.385**)	(−0.127)	(0.715)	(5.649***)			(0.406)	(0.817)	(−0.811)	(0.690)
Daqing	0.219				0.097			−0.454	0.407	0.769	0.299
	(1.379)				(3.881***)			(−1.453)	(0.403)	(1.323)	(1.013)
Mudanjiang	0.346	0.823	1.253	0.677	0.193	−0.879	0.635	−0.142	0.095		
	(3.151***)	(1.697*)	(2.245**)	(0.619)	(5.898***)	(−1.721)	(1.077)	(−0.533)	(0.885)		
Shanghai	0.171	1.34	1.983	0.850	0.485						
	(4.932***)	(6.738***)	(8.036***)	(1.152)	(15.975***)						
Nanjing	0.242	1.388	0.839	−0.201	0.282			−1.143	0.569	1.368	0.548
	(5.548***)	(6.707***)	(2.810***)	(−0.242)	(16.963***)			(−8.306***)	(1.610*)	(9.538***)	(2.322***)
Wuxi	0.279	1.382	2.328	1.618	0.304			−1.332	1.577	1.435	−0.838
	(4.084***)	(4.137***)	(4.884***)	(2.191***)	(7.811***)			(−5.051***)	(0.552)	(5.319***)	(−0.771)
Xuzhou	0.251	1.182	−0.31	−0.695	0.264	−1.174	0.137	−0.836	0.406	1.149	0.126
	(3.674***)	(3.339***)	(−0.473)	(−0.251)	(7.468***)	(−4.481***)	(0.578)	(−3.809***)	(2.308***)	(5.090***)	(0.682)
Changzhou	0.376	0.597	0.321	0.201	0.191	−0.819	0.701	−0.045	0.081	0.113	0.249
	(4.943***)	(2.466**)	(1.306)	(0.679)	(4.728***)	(−1.551)	(1.184)	(−0.2)	(0.668)	(0.5)	(2.240***)

(continued)

Table 4. Continued

Dependent variable	log(elecq)	log(taxiq)	Car_use	log(carq)	log(hsize)	coal_use	log(coalq)	lpg_use	log(lpgq)	coalgas_use	log (coalgasq)
Model	OLS	OLS	Heckman		OLS	Heckman		Heckman		Heckman	
Suzhou	0.32	0.927	0.968	0.179	0.416			−1.057	0.945	0.861	−0.935
	(4.264***)	(3.089***)	(2.899***)	(0.245)	(9.257***)			(−3.905***)	(0.671)	(3.221***)	(−0.707)
Nantong	0.213	1.291	3.545	6.984	0.214			−1.124	−0.059	1.741	0.689
	(2.156**)	(2.053**)	(2.282**)	(0.617)	(5.536***)			(−3.401***)	(−0.105)	(3.996***)	(1.749*)
Huaian	0.127	0.869	1.269	0.608	0.242	−1.206	0.408	−0.614	−0.010	1.281	−0.585
	(1.159)	(2.392**)	(2.181**)	(0.597)	(5.290***)	(−4.156***)	(1.172)	(−2.212**)	(−0.062)	(3.913***)	(−0.884)
Yangzhou	0.355	1.342	0.642	−0.139	0.284	−0.601	−0.203	−0.044	−0.107	0.522	0.221
	(3.224***)	(3.468***)	(1.302)	(−0.198)	(5.234***)	(−1.202)	(−0.456)	(−0.149)	(−0.627)	(1.696)	(1.288)
Zhenjiang	0.375	1.438	−0.007	−0.668	0.396	−2.182	−0.153	−0.935	−0.153	1.923	0.162
	(3.895***)	(2.750***)	(−0.008)	(−0.595)	(9.079***)	(−4.894***)	(−0.292)	(−3.089***)	(−0.510)	(4.942***)	(0.590)
Taizhou	0.29	0.431	0.928	0.763	0.254	−1.017	0.462	−0.416	0.306	1.356	0.350
	(2.835***)	(1.551)	(3.182***)	(2.263)	(4.479***)	(−2.912***)	(1.529*)	(−1.609)	(1.192)	(4.090***)	(0.880)
Suqian	0.238	1.473	0.22	−2.082	0.093	−0.43	0.232	0.436	0.019		
	(2.071**)	(4.453***)	(0.458)	(−0.578)	(2.006**)	(−1.836)	(1.504*)	(1.305)	(0.018)		
Hangzhou	0.336	1.228	1.122	−0.453	0.285			−0.512	0.123	0.563	0.357
	(7.124***)	(5.246***)	(3.579***)	(−0.417)	(10.060***)			(−3.047***)	(1.217)	(3.530***)	(1.786*)
Ningbo	0.13	1.231	0.678	0.490	0.217			−0.233	0.085	0.617	0.027
	(2.942***)	(4.391***)	(2.368**)	(0.852)	(8.958***)			(−1.168)	(0.532)	(3.119***)	(0.181)
Wenzhou	0.241	1.362	0.853	−0.081	0.340			−1.692	0.211	2.086	1.613
	(2.984***)	(4.383***)	(5.133***)	(−0.127)	(5.679***)			(−3.741***)	(1.034)	(4.302***)	(0.389)
Jiaxing	0.222	1.381	0.383	−0.317	0.227			−1.222	0.483	0.466	0.349
	(2.463**)	(3.214***)	(1.056)	(−0.521)	(4.645***)			(−2.580**)	(0.926)	(1.102)	(1.243)
Huzhou	0.232	1.313	1.121	0.954	0.321	−0.992	0.675	−1	0.511	1.318	−2.622
	(2.726***)	(3.412***)	(2.991***)	(1.966***)	(7.426***)	(−1.725)	(0.732)	(−2.366**)	(0.644)	(3.440***)	(−0.430)
Shaoxing	0.348	1.445	0.684	1.711	0.326	−1.319	0.341	−1.258	−0.184	1.61	−0.032
	(3.754***)	(2.435**)	(0.471)	(0.607)	(6.775***)	(−3.346***)	(0.688)	(−3.664***)	(−0.300)	(4.102***)	(−0.050)
Jinhua	0.276	1.133	0.128	−0.438	0.256	−1.34	−0.395	−0.935	0.077	1.285	0.282
	(3.316***)	(2.998***)	(0.351)	(−0.962)	(4.802***)	(−3.299***)	(−1.284)	(−1.981**)	(0.693)	(2.686***)	(0.201)

(continued)

Table 4. Continued

Dependent variable	log(elecq)	log(taxiq)	Car_use	log(carq)	log(hsize)	coal_use	log(coalq)	lpg_use	log(lpgq)	coalgas_use	log (coalgasq)
Model	OLS	OLS	Heckman		OLS	Heckman		Heckman		Heckman	
Quzhou	0.2	0.165	1.323	1.477	−0.043	−2.381	−0.525	−0.198	0.197	0.507	0.085
	(2.214**)	(0.422)	(3.180***)	(3.254***)	(−0.620)	(−3.706***)	(−0.433)	(−0.589)	(1.668)	(1.562)	(0.233)
Taizhou	0.326	0.992	1.028	0.922	0.242	−1.281	0.631	−2.094	0.406	1.695	2.347
	(3.100***)	(2.519**)	(2.783***)	(2.234***)	(3.676***)	(−2.207**)	(0.833)	(−3.520***)	(1.172)	(3.186***)	(0.485)
Lishui	0.235	1.676	1.03	0.725	0.202	−0.054	−0.734	−0.276	−0.029		
	(2.536**)	(4.326***)	(3.196***)	(1.859**)	(4.431***)	(−0.138)	(−1.657)	(−0.525)	(−0.133)		
Hefei	0.097	2.597	0.439	2.800	0.225	−1.16	−0.050	−0.693	−0.369	1.081	0.701
	(1.308)	(4.425***)	(0.42)	(1.010)	(6.235***)	(−3.776***)	(−0.189)	(−2.737***)	(−1.488)	(4.151***)	(1.341)
Huainan	0.221	0.922	0.75	−0.230	0.245	−0.922	−0.328	0.363	−0.042	0.305	−0.431
	(2.425**)	(1.598)	(0.686)	(−0.185)	(5.470***)	(−2.872***)	(−1.224)	(1.322)	(−0.171)	(1.062)	(−1.534*)
Fuzhou	0.151	1.275	0.645	0.237	0.250			−0.594	0.174	0.877	0.362
	(2.390**)	(3.781***)	(1.511)	(0.411)	(6.845***)			(−2.112**)	(0.838)	(3.148***)	(1.439)
Xiamen	0.161	0.538	1.638	1.348	0.328	−2.627	5.956	−0.575	0.105	1.162	0.483
	(2.415**)	(1.623)	(3.406***)	(1.443)	(5.836***)	(−4.191***)	(0.422)	(−1.871*)	(0.507)	(3.509***)	(1.108)
Nanchang	0.022				0.205			−0.397	−0.082	0.367	0.118
	(0.197)				(5.044***)			(−1.297)	(−0.524)	(1.29)	(0.501)
Jinan	0.122	0.894	1.494	1.165	0.303	−1.398	0.353	−0.865	0.244	0.954	−1.139
	(1.433)	(4.157***)	(5.489***)	(2.757***)	(8.586***)	(−5.927***)	(1.715*)	(−4.379***)	(2.045***)	(4.666***)	(−0.766)
Qingdao	0.374	2.168	1.56	−1.863	0.275	−1.023	0.224	−0.262	−0.138	0.528	−0.054
	(4.117***)	(4.960***)	(2.666***)	(−0.943)	(8.525***)	(−4.018***)	(0.900)	(−1.295)	(−0.990)	(2.486)	(−0.246)
Zibo	0.445	0.062	0.521	0.500	0.302	−2.06	1.612	−1.163	1.160	0.879	0.155
	(2.112**)	(0.14)	(0.842)	(0.774)	(4.871***)	(−3.002***)	(0.710)	(−2.509**)	(1.083)	(1.892)	(0.047)
Yantai	0.563	−0.135	1.549	1.603	0.198	−1.97	0.903	−0.685	−0.436	0.789	−0.089
	(4.053***)	(−0.28)	(2.338**)	(2.731***)	(4.663***)	(−2.470**)	(0.487)	(−1.662*)	(−0.369)	(1.884)	(−0.162)
Rizhao	0.403	0.951	1.578	1.113	0.190	−1.598	−1.235	−0.587	0.662		
	(2.511**)	(2.236**)	(4.102***)	(2.039***)	(5.014***)	(−3.044***)	(−1.766*)	(−1.519)	(0.591)		
Zhengzhou	0.259	0.975	0.457	−1.476	0.219	−0.876	0.192	−0.298	0.207	0.055	0.171
	(3.951***)	(2.391**)	(0.742)	(−0.770)	(6.540***)	(−3.072***)	(0.769)	(−1.363)	(1.230)	(0.221)	(2.007***)

(continued)

Table 4. Continued

Dependent variable	log(elecq)	log(taxiq)	Car_use	log(carq)	log(hsize)	coal_use	log(coalq)	lpg_use	log(lpgq)	coalgas_use	log (coalgasq)
Model	OLS	OLS	Heckman		OLS	Heckman		Heckman		Heckman	
Luoyang	0.127	1.268	1.28	1.201	0.315	−0.945	0.704	−0.554	0.089	0.747	1.318
	(1.314)	(3.527***)	(2.845***)	(2.305***)	(6.934***)	(−3.033***)	(2.240***)	(−1.727*)	(0.450)	(2.237)	(0.471)
Wuhan	0.246	2.823	1.779	0.628	0.269	−1.425	−0.106	−0.39	0.051	0.91	−0.685
	(5.273***)	(5.385***)	(2.882***)	(0.380)	(8.347***)	(−4.245***)	(−0.143)	(−2.158**)	(0.320)	(4.638)	(−0.951)
Changsha	0.345	1.206	1.226	0.215	0.322	−1.538	0.805	−0.98	−0.088	1.06	0.718
	(5.948***)	(4.120***)	(3.336***)	(0.346)	(10.448***)	(−4.916***)	(1.003)	(−3.860***)	(−0.577)	(5.001***)	(2.167***)
Guangzhou	0.185	1.853	0.935	0.511	0.333			−1.357	0.922	1.007	0.476
	(2.213**)	(4.645***)	(1.963**)	(0.584)	(6.615***)			(−3.870***)	(0.679)	(3.298***)	(0.915)
Shenzhen	0.275	1.581	0.144	0.078	0.158			−1.275	0.515	2.16	0.064
	(4.076***)	(2.691***)	(0.682)	(0.147)	(3.364***)			(−2.439**)	(0.781)	(3.567***)	(0.196)
Zhuhai	0.098	1.711	1.416	1.860	0.085			1.839	0.098	−0.341	−0.570
	(1.001)	(3.263***)	(3.761***)	(1.750**)	(1.747*)			(1.585)	(0.494)	(−0.518)	(−1.342)
Nanning	0.167	0.829	0.653	0.492	0.316	−1.796	2.628	−1.292	−0.085	2.161	−0.822
	(2.916***)	(3.300***)	(2.232**)	(1.097)	(9.342***)	(−3.884***)	(1.044)	(−2.712***)	(−0.350)	(3.491***)	(−0.380)
Haikou	0.256	1.388	1.145	−0.391	0.294			−0.546	0.134	1.456	0.486
	(3.917***)	(5.474***)	(4.332***)	(−0.437)	(5.875***)			(−1.842*)	(0.931)	(4.305***)	(1.845**)
Chongqing	0.229	1.255			0.336						
	(4.134***)	(1.705*)			(7.458***)						
Chengdu	0.291	1.635	1.915	2.726	0.340			−1.5	0.147	1.442	0.156
	(8.148***)	(6.881***)	(6.694***)	(1.300)	(12.646***)			(−3.574***)	(0.302)	(3.612***)	(2.412***)
Mianyang	0.287	2.458	2.837	1.288	0.296						
	(3.775***)	(3.610***)	(2.349**)	(0.998)	(6.634***)						
Guiyang	0.203	1.868	1.344	0.276	0.358	−0.859	0.314	−0.813	0.162	0.909	0.454
	(3.138***)	(5.220***)	(3.588***)	(0.090)	(10.284***)	(−3.374***)	(0.984)	(−2.896***)	0.371	(3.707***)	(1.140)
Kunming	0.307	1.077	0.599	−0.144	0.315	−0.025	−0.113	−0.576	0.176	0.355	0.027
	(5.270***)	(4.538***)	(2.531**)	(−0.322)	(8.327***)	(−0.105)	(−0.334)	(−3.668***)	(1.674*)	(2.343)	(0.354)
Xi'an	0.395	1.238	1.134	−0.222	0.300	−1.659	0.075	−1.651	0.924	1.706	0.069
	(5.133***)	(2.894***)	(1.677*)	(−0.094)	(8.616***)	(−5.612***)	(0.136)	(−6.504***)	(1.918***)	(6.720***)	(0.307)

(continued)

Table 4. Continued

Dependent variable	log(elecq)	log(taxiq)	Car_use	log(carq)	log(hsize)	coal_use	log(coalq)	lpg_use	log(lpgq)	coalgas_use	log (coalgasq)
Model	OLS	OLS	Heckman		OLS	Heckman		Heckman		Heckman	
Lanzhou	0.249	0.322			0.218	−1.116	−0.208	−0.382	−0.182	0.127	0.006
	(3.051***)	(0.553***)			(6.831***)	(−2.581**)	(−0.279)	(−1.855*)	(−1.066)	(0.62)	(0.031)
Xining	0.285	1.419			0.140	−1.281	0.873	0.24	0.073	1.664	−2.106
	(2.423**)	(2.323**)			(5.254***)	(−4.680***)	(1.008)	(0.796)	(0.165)	(2.687***)	(0.265)
Yinchuan	0.167	0.473	0.804	0.341	0.137	−0.334	−0.206	−0.652	0.641	0.703	0.225
	(2.045**)	(1.641)	(2.019**)	(0.625)	(6.053***)	(−1.298)	(−0.448)	(−2.973***)	(0.997)	(2.605)	(0.445)
Wulumuqi	0.349	0.965			0.136			−0.002	−0.340	0.494	−0.200
	(3.068***)	(1.684*)			(5.441***)			(−0.007)	(−1.398)	(2.196)	(−1.187)

Note: When estimating city-level regressions for car use, coal, LPG and coal gas, we did not employ Heckman two-step estimations when the use rate of the corresponding energy type is <5% or >95% in a city. For the former case, we set the corresponding energy use in that city to be zero; for the latter case, we use OLS estimations. *t*-statistics are reported in parentheses.

5.3 China's greenest cities based on the household CO_2 metric

We convert the standardized household's energy consumptions, predicted by the city-specific regressions, into carbon emissions using various conversion factors. Combining the components in Equation (1) then enables us to rank China's 74 major cities with respect to total carbon emission per standardized household. The results are shown in Table 5. The first nine columns in Table 5 report our sectoral estimates for this standardized household in each of the 74 cities. The units are tons of CO_2.

China's major cities' household carbon emissions are dramatically lower than in USA. Glaeser and Kahn (2010) report that in the cleanest cities (San Diego and San Francisco), a standardized household emits around 26 tons of CO_2 per year.[6] Shanghai's standardized household produces 1.8 tons of carbon and Beijing's standardized household produces 4.0 tons. Even in China's brownest city, Daqing, a standardized household emits only one-fifth of the carbon produced by a standardized household in America's greenest cities.[7] Table 5 presents our ranking in order from Greenest to Brownest. The top 10 cities are: Huanian, Suqian, Haikou, Nantong, Nanchang, Taizhou, Zhengjian, Shaoxing, Xining and Xuzhou. The bottom 10 sorted from worst to relatively cleaner are: Daqing, Mudanjiang, Beijing, Qiqihaer, Yingchuan, Shenyang, Haerbin, Dalian, Baotou and Liaoyang.

Figure 1 shows the per-household carbon dioxide emissions in each of the 74 cities on a GIS map. High levels of carbon emissions are particularly common in the north, which reflects the cold temperatures and government heating policy. Coastal cities also have higher emissions, perhaps because they are somewhat more developed. Daqing, China's oil capital, has dramatically higher carbon emissions than any other city.

The provision of centralized heating in north cities contributes a lot to the regional differences in residential carbon emissions. Eight of the 10 greenest cities in our sample are located just south of the centralized heating border in the coastal provinces. These cities are not entitled to the centralized winter heating services and their summers are not exceptionally hot. To further illustrate the role centralized heating system plays, we do a simple discontinuity comparison here. We identify three pairs of cities. Each pair has similar income levels and winter temperatures, and spatially the two cities are relatively close but on both sides of the heating cut-off line. In addition, we choose the city pairs to be on the eastern part of China (on both sides of the Huai River) rather the western part (the Qingling Mountain) because the climate changes more dramatically on different sides of a major mountain than a river. The three pairs are: Rizhao (north) and Huaian (south); Qingdao (north) and Zhenjiang (south); Zhengzhou (north) and Nantong (south). In each of the three pairs, the former city has a higher emission level than the latter by 48.9, 53.3 and 37.2%, respectively. Since we do not know the prices for heating in north cities, and we do not have (decentralized) heating information in south cities either (some households there use electricity for heating, but we cannot separate this from their total electricity use), we are unable to perform a more rigorous discontinuity design and analysis.

6 Glaeser and Kahn's standardized US urban household has an income of \$62,500. Obviously, this is a much higher income level than for the standardized Chinese urban household.

7 This type of data is not available for the countries other than the US, so we are unable to make further comparisons.

Table 5. Overall 2006 green city ranking

Rank	City	Electricity	Coal	LPG	Coal gas	Car	Taxi	Bus	Rail	Heating	Total CO_2	Standard error
1	Huaian	0.879	0.098	0.082	0.016	0.120	0.011	0.023			1.230	0.090
2	Suqian	0.865	0.218	0.117		0.000	0.006	0.026			1.231	0.073
3	Haikou	0.983	0.007	0.176	0.015	0.000	0.006	0.065			1.252	0.124
4	Nantong	1.062		0.036	0.164	0.000	0.007	0.012			1.281	0.080
5	Nanchang	0.978		0.141	0.048	0.000	0.007	0.130			1.305	0.138
6	Taizhou	1.069	0.041	0.076	0.016	0.094	0.006	0.005			1.307	0.142
7	Zhenjiang	1.098	0.067	0.036	0.064	0.030	0.009	0.027			1.331	0.118
8	Shaoxing	1.170	0.048	0.066	0.052	0.002	0.006	0.021			1.365	0.115
9	Xining	0.878	0.250	0.020	0.012	0.000	0.019	0.175		0.016	1.371	0.198
10	Xuzhou	0.946	0.070	0.046	0.112	0.172	0.010	0.040		0.006	1.401	0.172
11	Shuozhou	0.594	0.255	0.046	0.060	0.083	0.016	0.015		0.357	1.426	0.113
12	Yangzhou	1.123	0.033	0.063	0.083	0.113	0.009	0.019			1.443	0.325
13	Quzhou	1.115	0.030	0.189	0.068	0.006	0.007	0.037			1.452	0.278
14	Luoyang	0.905	0.155	0.127	0.027	0.040	0.010	0.038		0.189	1.491	0.169
15	Chengdu	1.243	0.016	0.005	0.232	0.007	0.012	0.007			1.522	0.097
16	Nanning	1.079	0.001	0.220	0.002	0.117	0.009	0.097			1.524	0.073
17	Mianyang	1.157		0.001	0.209	0.153	0.012	0.027			1.558	0.135
18	Changzhou	1.224	0.009	0.106	0.053	0.131	0.010	0.041			1.574	0.100
19	Jinhua	1.154	0.046	0.167	0.002	0.233	0.008	0.016			1.626	0.094
20	Huzhou	1.330	0.014	0.194	0.008	0.026	0.007	0.059			1.638	0.100
21	Lishui	1.308	0.018	0.197		0.110	0.005	0.013			1.651	0.108
22	Ningbo	1.328	0.004	0.213	0.011	0.058	0.006	0.050			1.670	0.142
23	Chongqing	1.396			0.229	0.000	0.014	0.039	0.004		1.681	0.342
24	Zhuhai	1.197		0.345	0.002	0.026	0.010	0.148			1.726	0.027
25	Wuxi	1.461		0.071	0.123	0.023	0.010	0.060			1.748	0.044
26	Zhengzhou	0.984	0.185	0.053	0.109	0.000	0.006	0.057		0.363	1.757	0.071
27	Taizhou	1.359	0.008	0.256	0.004	0.117	0.007	0.009			1.761	0.157
28	Hefei	1.360	0.069	0.101	0.064	0.000	0.044	0.138			1.776	0.064
29	Lanzhou	0.573	0.029	0.047	0.067	0.000	0.016	0.077		0.976	1.785	0.081
30	Shanghai	1.219		0.007	0.235	0.130	0.014	0.118	0.074		1.796	0.066
31	Guangzhou	1.315		0.213	0.052	0.056	0.008	0.127	0.055		1.827	0.138
32	Rizhao	1.060	0.092	0.065		0.222	0.013	0.060		0.318	1.831	0.102
33	Zibo	0.998	0.169	0.119	0.024	0.034	0.021	0.062		0.441	1.870	0.120
34	Jiaxing	1.286		0.187	0.009	0.373	0.007	0.028			1.890	0.088
35	Huainan	1.008	0.144	0.056	0.085	0.480	0.063	0.058			1.895	0.091
36	Nanjing	1.293	0.003	0.097	0.051	0.318	0.009	0.096	0.032		1.899	0.045
37	Hangzhou	1.650	0.006	0.132	0.026	0.000	0.006	0.087			1.907	0.045
38	Wuhan	1.526	0.016	0.133	0.092	0.065	0.011	0.069	0.003		1.915	0.100
39	Yantai	0.969	0.142	0.069	0.067	0.017	0.019	0.022		0.629	1.934	0.066
40	Wulumuqi	0.509		0.027	0.086	0.000	0.024	0.177		1.128	1.951	0.091
41	Handan	0.998	0.029	0.008	0.222	0.004	0.013	0.068		0.633	1.974	0.215
42	Guiyang	1.433	0.201	0.016	0.118	0.141	0.010	0.073			1.993	0.076
43	Qingdao	1.205	0.248	0.060	0.067	0.000	0.020	0.053		0.388	2.041	0.123
44	Xi'an	0.871	0.072	0.037	0.101	0.605	0.018	0.104		0.246	2.055	0.101
45	Changsha	1.204	0.028	0.193	0.044	0.505	0.021	0.088			2.083	0.095
46	Shenzhen	1.491		0.261	0.012	0.263	0.010		0.112		2.149	1.601
47	Kunming	1.003	0.033	0.068	0.106	0.814	0.005	0.138			2.167	0.133
48	Jinan	1.099	0.373	0.062	0.030	0.084	0.017	0.085		0.436	2.185	0.060
49	Tangshan	0.865			0.232	0.405	0.017	0.058		0.625	2.203	0.076
50	Cangzhou	0.868		0.185	0.020	0.023	0.029	0.014		1.087	2.226	0.080

(continued)

Table 5. Continued

Rank	City	Electricity	Coal	LPG	Coal gas	Car	Taxi	Bus	Rail	Heating	Total CO_2	Standard error
51	Suzhou	1.424	0.016	0.068	0.077	0.718	0.008	0.033			2.344	0.167
52	Wenzhou	2.057		0.286	0.001	0.000	0.015	0.051			2.410	0.090
53	Wuhai	0.536	0.632	0.045	0.017	0.089	0.014	0.093		1.008	2.435	0.155
54	Qinhuangdao	0.841	0.096	0.076	0.089	0.253	0.017	0.096		0.977	2.447	0.157
55	Taiyuan	0.939	0.027	0.012	0.237	0.027	0.013	0.086		1.107	2.449	0.171
56	Fuzhou	2.124		0.201	0.025	0.060	0.006	0.054			2.470	0.076
57	Huhehaote	0.747	0.105	0.066	0.073	0.014	0.034	0.077		1.468	2.584	0.115
58	Xiamen	2.035	0.001	0.152	0.021	0.326	0.007	0.171			2.713	0.069
59	Tongliao	1.448	0.063	0.162		0.000	0.058	0.019		0.972	2.722	0.073
60	Shijiazhuang	1.110	0.044	0.091	0.099	0.000	0.019	0.048		1.313	2.724	0.069
61	Jilin	0.983		0.198	0.016	0.000	0.030	0.204		1.512	2.944	0.126
62	Chifeng	0.873	0.161	0.085		0.025	0.020	0.031		1.802	2.998	0.089
63	Tianjin	1.551	0.063	0.014	0.070	0.553	0.018	0.087	0.017	0.690	3.063	0.071
64	Changchun	0.914	0.010	0.003	0.126	0.004	0.024	0.056	0.006	1.938	3.080	0.069
65	Liaoyang	0.962		0.139	0.024	0.173	0.026	0.028		1.885	3.237	0.052
66	Baotou	0.698	0.102	0.054	0.053	0.174	0.021	0.072		2.134	3.309	0.084
67	Dalian	0.904		0.015	0.191	0.000	0.040	0.071	0.007	2.143	3.371	0.068
68	Haerbin	1.157		0.027	0.236	0.000	0.021	0.057		2.009	3.508	0.285
69	Shenyang	0.974		0.009	0.099	0.000	0.028	0.082		2.337	3.528	0.060
70	Yinchuan	0.675	0.019	0.059	0.036	0.338	0.034	0.095		2.287	3.543	0.146
71	Qiqihaer	0.765		0.054	0.115	0.000	0.018	0.041		2.620	3.614	0.085
72	Beijing	1.558	0.145	0.049	0.084	0.650	0.018	0.138	0.049	1.306	3.997	0.192
73	Mudanjiang	1.047	0.136	0.081		0.353	0.040	0.017		3.154	4.827	0.107
74	Daqing	0.998		0.233	0.003	0.000	0.026	0.137		3.719	5.115	0.056
	Mean	1.122	0.093	0.102	0.077	0.135	0.016	0.067	0.036	1.228	2.177	0.134

The units are tons of carbon dioxide per-household per year.

The Chinese centralized heating system is coal-based and highly subsidized. Most of the heat is derived from coal-fired heat-only boilers or combined heat and power generators, which are inefficient in energy usage compared to electric, gas and oil heating systems in industrial countries (Wang et al., 2000; Jiang, 2007). If China's home heating system were to be dramatically changed, perhaps using far less carbon intensive energy sources, then this could certainly change the rankings of cities.

The results reported in Table 5 are measured in tons of carbon dioxide per household. We use an estimate of $35 per ton as the marginal social cost of one ton of carbon dioxide. This is a conservative estimate relative to the Stern report (2008), which suggests a cost of carbon dioxide that is twice this amount. This value lies in the middle of the range reported by Metcalf (2007).[8]

8 It is relevant to note that carbon tax policy proposals have suggested taxes per ton of carbon dioxide roughly in this range. Metcalf (2007) proposes a bundled carbon tax and a labor tax decrease. As shown in his Figure 6, he proposes that the carbon tax start at $15 per ton (as per year 2005 dollars) now and rise by 4% a year. Under this proposal, the carbon tax per ton of carbon dioxide would equal $60 per ton (as per year 2005 dollars) by 2050.

Given our estimates of the spatial differences in household carbon emissions across China's cities, we find that moving the average household from the greenest city to the brownest would cause a social externality of \$136.5 [$35 \times (5.1-1.2)$] per year. This is roughly 2.5% of a year's income. If the northern cities substitute away from coal for home heating, or if the richer cities invest more in subways or other forms of transit, this gap could narrow.[9] Conversely, increases in income could cause some of the differences in consumption to widen. We will explore these possibilities in Section 7.

We acknowledge that our rankings may overstate how accurately we can distinguish the 'greenest' city from the city that finishes in 'second place'. Given the relatively large sizes of standard errors associated with each city's standardized household's emission estimates, it is hard to assert that Daqing and Mudanjiang are exactly the two 'dirtiest' cities in China, or Huaian and Suqian are the 'greenest'. It is more appropriate to say that the first two cities are in the dirtiest 10% while the latter two are in the greenest 10%, respectively.

A city's carbon emission is just one indicator of its 'greenness', but it is the component of greenness that seems most likely to have an impact outside the city and country of residence. Zheng et al. (2010) use hedonic methods to rank China's major 35 cities. A major component in their quality of life index calculation is city air quality, measured by small particulate matter, PM_{10}. We calculate the correlation between the 35 cities' PM_{10} levels and our per-household carbon emission. These two sets of rankings have a positive correlation coefficient of 0.33. In the colder northern cities, people burn coal to produce home and office heating creating both particulates and carbon dioxide emissions.

5.4. Understanding cross-city differences in carbon emissions

Table 6 reports the correlation between our carbon emissions estimates and city-level attributes including population, population growth, income, temperature and urban form. Population is positively correlated with emissions from use of taxis, buses and electricity. Unsurprisingly, larger cities tend to be more transit-oriented and less dependent on cars. Population density is associated with lower levels of emissions from taxi use and buses. An increase of 1000 people per square kilometer (about 19% of the sample standard deviation) on average is associated with a reduction of carbon dioxide emissions per household of 0.424 ton from use of taxis and 0.837 ton from the use of buses. Just as in USA, compact development leads to lower carbon emissions.

There is a positive correlation between city-level income and carbon emissions, even holding individual income constant. Higher income cities have higher emissions from electricity, driving and subways but lower emissions from taxis. One explanation for the link between city-level income and emissions for a standardized household is that there is mis-measurement in individual income and that city-level income is correlated with unobserved household prosperity. A second explanation is that higher income cities have built infrastructure that is complementary with greater use of energy. When we

9 Northern cities should be aware of the local ambient pollution problems caused by household coal use. After the horrific deaths in the great 1952 London Fog, the city banned home coal use. While households have little incentive to curb their greenhouse gas emissions, the cost of local pollution (caused by coal burning) provides a direct incentive to consider encouraging substitution to cleaner fuels.

Table 6. Explaining cross-city variation in the standardized household's carbon production

	Electricity	Heating	Car	Taxi	Rail	Bus	Total
Log(*CINCOME*)	0.439	1.065	1.420	−1.377	3.188	−0.455	0.440
	(3.40***)	(1.08)	(1.88*)	(−4.96***)	(2.00*)	(−1.22)	(3.24***)
Log (*POP*)	0.067	−0.028	−0.083	0.153	0.535	0.491	0.054
	(1.95*)	(−0.13)	(−0.36)	(1.79*)	(1.08)	(4.47***)	(1.46)
JAN_TEMP		−0.111					−0.033
		(−4.41***)					(−8.8***)
JULY_TEMP	0.031						
	(2.64***)						
DENSITY			0.257	−0.424	−0.66	−0.837	
			(0.61)	(−2.75***)	(−0.7)	(−4.01***)	
Constant	−5.898	−11.72	−17.822	10.085	−41.273	0.238	−4.291
	(−5.06***)	(−1.22)	(−2.21**)	(3.41***)	(−2.58**)	(0.06)	(−3.08***)
Observations	74	35	74	74	10	73	74
R^2	0.436	0.394	0.05	0.27	0.91	0.317	0.598

The dependent variable is measured in tons of carbon dioxide emission of standardized household. The unit of analysis is one of the 74 cities. *t*-statistics are reported in parentheses.
*Indicates significance at the 10% level, **at the 5% level and ***at the 1% level.

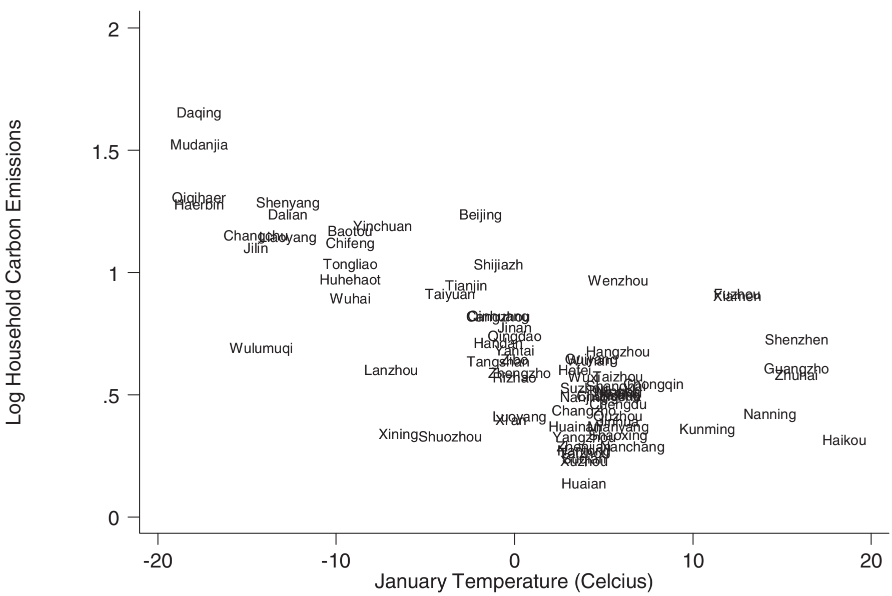

Figure 2. The cross-city relationship between winter temperature and household carbon emissions.

form our projected energy use in a richer China, we will combine both the income effects suggested by the individual regressions and the city-level income elasticities.

Figure 2 shows the strong correlation between January temperature and carbon emissions, which reflects both the natural tendency of colder places to require more heat and the home heating rules that provide subsidized heating only to northern cities. A 1 SD increase in January temperature (8.66°) is associated with a 0.29 ton decrease in carbon dioxide emissions. The temperature effect of January comes primarily from its impact on household heating emissions—one degree higher in January temperature corresponds to 0.111 ton less CO_2 emissions from heating. However, if the northern cities charge residents marginal cost of winter heating and install temperature controllers in people's homes, people will be able to control their household heating consumption. Given the fact that the current centralized heating system is subsidized by the government, we expect that carbon emissions of northern cities may decrease if current heating system is replaced by one that charges marginal cost.

6. The potential consequences of China's regional development programs

Unlike USA, China's government pursues a well-defined set of regional development strategies. If successful, these efforts will impact carbon emissions of the targeted regions and the whole country. There are at least three significant programs that are intended to bolster the growth of particular regions. The Western Development Program launched in 1999 gives infrastructure aid and support for industrial adjustment to western and inland provinces. The program attempts to help heavy and defense industries convert to consumer goods production (Chow, 2002, 174). Secondly, a revitalization program is taking place in China's Northeast (Liaoning, Jilin and Heilongjiang provinces). This region was a center of heavy industry during the Mao years. Since then, like the American Rustbelt, the Chinese northeast has struggled with high unemployment, aging industry and infrastructure and social welfare bills (Saich, 2001, 149). While the Western Development Program targets both urban and rural areas, the Northeast Revitalization Program focuses on reinventing the declined cities. A third program is targeted at the development of Beijing–Tianjin–Bohai Sea region. This program intends to expedite the development of this northern mega-region to catch up to the Yangtze and Pearl River Deltas in the south. The 2008 Olympics caused a massive public investment in infrastructure and environmental improvement. Centralized political power will surely continue to attract physical and human capital to the region (Ades and Glaeser, 1995).[10]

To assess the carbon production consequences of these programs would require a detailed model of how each of these programs will influence the spatial distribution of Chinese urban growth. Such a model and its required data are unavailable as of now. However, to begin to address this topic, we calculate the regional household carbon emissions factor by taking population-weighted averages of our urban household carbon production measures reported in Table 5. The weighted average of residential emissions in the Western region is 1.9 tons per household relative to 2.3 tons in the rest of the country. The weighted average residential emissions in the cities impacted by northeastern regional development are 3.5 tons per household. Emissions are 2.0 tons per household outside that region. Finally, the weighted average emissions in the cities

10 There is the fourth regional development program called 'Rise of Central China', aiming to support the development of central provinces. However, very few real policies came out since the launch of this program.

inside the Beijing–Tianjin–Bohai Sea region are 2.9 tons per household, as opposed to 2.1 tons outside that region. The Northeast Revitalization Program and the development program of Beijing–Tianjin–Bohai Sea region seem to be trying to bolster growth in areas that have particularly high levels of carbon emissions. The Western Development Program is encouraging the developments in the areas with slightly low levels of carbon emissions.

These results, although primitive, highlight how the environmental costs of regional policies can be incorporated into a type of 'green accounting' for estimating the full consequences of spatial policies. Such externalities need to be put in the context of other policy objectives. Without detailed modeling of each of the three programs, it is hard to tell the potential net effect of regional development policies. Our estimates just suggest that there can be significant environmental consequences of regional development programs.[11]

7. Future carbon emissions

China is changing so rapidly that current Chinese emissions only offer the vaguest sense of what emissions will be like 20 years in the future. In this admittedly speculative section, we use our income elasticity estimates to project household carbon emissions across Chinese cities 20 years in the future. We make the same assumptions about incomes and population levels in 2026. The assumptions are from authoritative research institutes in China: (i) Chinese urban per capita incomes will increase 200% over 20 years, which would occur if urban incomes grew at a 5.6% annual real rate. (source: Institute of Quantitative & Technical Economics, Chinese Academy of Social Sciences) and (ii) Chinese urbanization rate will increase from 43.9% in 2006 to 62% in 2026, thus urban population growth is about 40% over 20 years. (source: China Academy of Science)

We then use our China-specific data to estimate emissions for 2026. To do this, we create a composite CO_2 emission measure that includes our predicted emissions for every household in the UHS, including emissions from fuel, subways, cars and so forth. We then perform the following regression:

$$\begin{aligned} \text{Emissions} = {} & a_i * \text{Log(Income)} + b_i * \text{Household Size} + c_i * \text{Age} \\ & + \text{d} * \text{Log(City Population)} + \text{e} * \text{anuary Temperature} \end{aligned} \tag{9}$$

Coefficients a_i, b_i and c_i all differ by city. We first use this equation to predict the standardized household's carbon emissions in each of the 74 cities in 2006. We then

11 Such hidden cost may be further increased if urbanization leads to more reliance on local and regional energy sources. Fossil fuels are predominantly in the north, which has 90% of the oil and 80% of the coal reserves of China. Hydropower remains the vast majority of renewable power (roughly 17% of the total electricity) generated in China. Roughly two-thirds of the hydropower is located in the south west region of China. In contrast to the distribution of fossil and hydro energy, the east and south coastal areas have very little energy resources. Of course, the northern part of the country has some potential in increasing its small but growing share of renewable energy. Wind power is concentrated in the northern provinces and the east and south coasts. The seasonal fluctuation of wind power are complementary to hydropower, but the geographical distribution of land areas with rich wind power potential is to a large extent different from that of the demand for power. In addition, international energy trade may help reduce the northern cities' carbon footprint. If the northern cities can import natural gas from Russia to substitute their coal use to a significant level, the geography of urban carbon foot print will be different.

Table 7. Predictions of CO_2 emissions per Standard Household in the year 2026

City	CO_2 emission in 2026 (tons)	City	CO_2 emission in 2026 (tons)	City	CO_2 emission in 2026 (tons)
Beijing	5.250	Wuxi	2.425	Jinan	4.931
Tianjin	5.272	Xuzhou	1.601	Qingdao	4.720
Shijiazhuang	5.282	Changzhou	2.083	Zibo	5.234
Tangshan	4.439	Suzhou	2.250	Yantai	4.103
Qinhuangdao	5.018	Nantong	1.574	Rizhao	5.331
Handan	5.473	Huaian	1.595	Zhengzhou	5.851
Cangzhou	5.776	Yangzhou	1.808	Luoyang	6.110
Taiyuan	4.496	Zhenjiang	1.634	Wuhan	2.921
Shuozhou	4.701	Taizhou	1.555	Changsha	2.656
Huhehaote	6.526	Suqian	1.461	Guangzhou	2.711
Baotou	6.681	Hangzhou	2.738	Shenzhen	3.062
Wuhai	8.136	Ningbo	2.263	Zhuhai	2.546
Chifeng	7.361	Wenzhou	3.708	Nanning	2.289
Tongliao	8.050	Jiaxing	2.267	Haikou	2.171
Shenyang	4.249	Huzhou	2.260	Chongqing	2.629
Dalian	4.461	Shaoxing	1.899	Chengdu	2.367
Liaoyang	4.694	Jinhua	2.040	Mianyang	1.853
Changchun	5.863	Quzhou	1.907	Guiyang	2.542
Jilin	6.184	Taizhou	2.474	Kunming	2.056
Haerbin	6.672	Lishui	2.292	Xi'an	4.123
Qiqihaer	5.976	Hefei	2.381	Lanzhou	3.705
Daqing	7.973	Huainan	1.841	Xining	6.627
Mudanjiang	6.474	Fuzhou	3.572	Yinchuan	4.702
Shanghai	2.361	Xiamen	3.592	Wulumuqi	3.429
Nanjing	2.238	Nanchang	1.946		

predict for each city in 2026, the predicted emissions for a household with three members earning 120,000 Yuan, or 17,500 dollars in today's currency (a 200% increase from 40,000 Yuan), assuming that the city's population has also risen in the manner discussed above. The predicted 2026 per-household carbon emissions are listed in Column (3) in Table 7. They essentially predict household energy use assuming that China in 20 years will look essentially like a richer and more urbanized version of China today. All cities have higher emission levels in 2026. On average, per-household carbon emission grows by a mere 26% from 2006 to 2026. Combined with the projected 40% increase in urban population, a richer China in 2026 will have a modest 76% ($1.4*1.26 = 1.76$) increase in its GHG emissions from urban households (assuming constant average household size and with given infrastructure and urban form as at 2006).

But there are good reasons to be skeptical about that optimistic projection, which essentially assumes that China in 2026 will look like a richer version of China today, not a poorer version of USA. This is of course a strong assumption. Glaeser and Kahn (2010) calculated the emissions for a household that earns 62,500 dollars, which is about 10.66 times richer (by nominal exchange rate) than the Chinese household investigated in this study. The median city in their United States sample had household carbon emissions that are 20 times higher than the median city found here in China. To explain this difference with income alone, the income elasticity of carbon emissions would have to be 1.3, which is far higher than any of our estimates within China, or Glaeser and Kahn's estimates within USA.

Under the assumption that the energy consumption Engel curves we estimate are stable over time, then all else equal, the carbon footprint for rich Chinese households today is a leading indicator of what future richer Chinese middle class households will emit. Under this assumption, the aggregate carbon impact of rising per-household income in China will be modest. If China's middle class in the future starts to use energy like the poorer Americans today, then global emissions will rise quite significantly. The wide range between those alternatives suggests the potential large impact that different investments in Chinese infrastructure will have on the world's carbon emissions.

8. Conclusion

China's economic growth has profound environmental implications. Past research has examined the greenhouse gas implications of this growth using an Environmental Kuznets Curve framework either with national panel data (see Schmalensee et al., 1998) or with regional aggregate data. Auffhammer and Carson (2008) create a panel data set for 30 Chinese provinces covering the Years 1985–2004. They also find that the relationship between greenhouse gas emissions and per capita income is increasing and is concave.

In this article, we find that some of the patterns of carbon emissions within China replicate findings that hold in the US and elsewhere. If economic growth takes place in compact, public transit friendly, cool summer, warm winter cities, then the aggregate carbon emissions will increase less than if economic growth takes place in 'car dependent' cities featuring hot summers, cold winters and where electricity is produced using coal-fired power plants.

Recognizing that diverse cities differ with respect to these characteristics, we have used individual and institutional data to measure household carbon emissions across a sample of 74 Chinese cities. We have found that the 'greenest' cities based on this criterion are Huaian and Suqian while the 'dirtiest' cities are Daqing and Mudanjiang. However, even in China's brownest city, Daqing, a standardized household emits only one-fifth of the carbon produced by a standardized household in America's greenest city (San Diego).

The cross-city differential in the carbon externality is 'large'. At $35 per ton of damage from carbon dioxide, moving a standardized household from Daqing to Huaian would reduce the externality by roughly $136.5 per year, which is reasonably high relative to household per capita income of 40,000 Yuan, or about 5800 dollars. This differential is mainly generated by cross city differences in climate, centralized heating policy, regional electric utility emissions factors and urban form. Unlike USA, China is pursuing major regional growth initiatives. Our results highlight the presumably unintended adverse carbon consequence of encouraging growth in the North.

Our study relies on cross-sectional data, and changes over time may not resemble differences at a point in time. New technologies may radically reduce the carbon emissions associated with certain types of energy production. Alternatively, China may invest more in infrastructure, like highways, that complement heavy energy use. China will surely grow richer, and the country is likely to use more energy. But the actual impact on carbon emissions, which may be either modest or large, will depend on infrastructure and new technologies.

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Appendix A

Cross-checking the carbon dioxide emission estimates

We conduct several cross-checks on the reliability of our bottom–up CO_2 emission estimates. As discussed in Section 4, we create a standardized household, defined by the mean characteristics (income, household size and age of household head) of the total Chinese sample, and estimate its carbon emissions if it lived in 74 different cities. We compare this ranking to an alternative approach. In this second approach, we predict each household's carbon dioxide emissions in the city in which it lives and then we calculate the city specific average emissions. The two versions of the carbon dioxide rankings have a high correlation coefficient of 0.71. The magnitudes of the two series are similar. On average, the 'standardized household' estimate is about 20% larger than the city average number.

We have also compared our 74 city ranking with rankings that could be constructed using aggregate data from Statistic Yearbooks. We use that data source to calculate per-household electricity consumption (in KWh) and home size (in square meter, from which per-household heating consumption can be derived). Based on such aggregate data, we estimate per-household carbon emissions from electricity and heating by city. The 'standardized household' version and the aggregate version for electricity CO_2 emissions by city have a positive correlation coefficient of 0.60. On average, the former is 17% higher than the latter. The two versions for heating CO_2 emissions have a very high correlation coefficient of 0.98, due to that per household floor area consumptions in the two versions are quite similar. On average, the former is slightly 6% larger than the latter. Unfortunately, there is no aggregate data for the energy uses from private car, taxi and domestic fuel uses, so we are unable to do the cross-checks for these energy types.