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Gearing carbon trading towards environmental co-benefits in China: Measurement model and policy implications

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A B S T R A C T

Given the local effects of co-pollutant emissions, the trading of carbon dioxide emissions between facilities to meet global objectives may improve or worsen local air quality and public health. To gear carbon trading toward maximum environmental co-benefits, a quantitative model based on facility-level carbon dioxide emissions, air pollution dispersion and concentration-response functions is proposed and applied to the Beijing-Tianjin-Hebei region to quantify potential changes of local public health caused by carbon dioxide transactions. The results show that the polluters with the highest Population Health Damage Intensity (PHDI) are medium-sized facilities, because larger facilities either employ more effective pollutant control technologies or are located farther away from densely populated areas. Using this modeling framework, key facilities, sectors and regions can be identified for maximizing the environmental co-benefits from introduction of carbon market and avoiding undesirable environmental damage.

1. Introduction

Carbon markets are important instrument of climate change mitigation, and covered 11% of global energy-related emissions in 2014 (IPCC, 2014; IEA, 2015). The Chinese government has adopted the carbon market as one of its important policies and has rapidly developed it during the last five years (NDRC, 2011; Zhang et al., 2014; Jotzo and Löschel, 2014; NDRC, 2014a,b), with plans to culminate in a nationwide carbon market in 2017 (NDRC, 2016). Unlike developed countries that are focusing mostly on climate change mitigation, China faces the dual challenges of striving to reduce carbon emissions and improve local environmental quality simultaneously. This reflects China's coal-dominated energy mix with substantial share of coal-fired facilities (Wang et al., 2014; Cai and Zhang, 2014). Air pollution has been a major threat to public health in China, resulting in an estimated 1.2 million premature deaths and 25 million disability-adjusted life-years (DALY) lost in 2010 (Yang et al., 2013a).

Carbon markets are designed to reduce the climate mitigation cost. In China, CO_2 emissions often are accompanied by large amounts of other pollutants known as co-pollutants. While the climate effects of CO_2 emissions are global, the environmental effects of co-pollutants are local. In specific localities, CO_2 emission credit transactions between facilities may either improve or worsen air quality, with consequent positive or negative effects on public health. Consider an extreme example: two facilities, A and B, have similar annual CO_2 emissions. They are located, respectively, in an urban area where one million people are affected by co-pollutant emissions and in a desert area with no one living within the range of effects of its pollution. If A buys one ton of CO_2 emissions credit from B in order to expand its use of fossil fuels, the million people living nearby will suffer more co-pollutant emissions than if A's carbon emissions had been capped at the previous level. However, no one will get any air quality co-benefits by virtue of the corresponding reduction of emissions from B. In this context, the total benefit to population health and welfare associated with the carbon transaction is negative. On the other

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hand, the opposite transaction would benefit the people affected by this two-facility carbon trading system.

Unfortunately, the evaluation and assessment of pollution-related health effects of carbon trading have not been fully considered in the pilot emissions trading schemes (ETS) in China (Zhang et al., 2014; Jotzo and Löschel, 2014). They are not even mentioned in the country's ETS strategy document (see NDRC, 2014a,b). Measuring the spatial disparities in environmental co-benefits during carbon trading can be an important step in moving China’s ETS forward. If designed with potential synergies in mind, carbon markets can bring about substantial improvements in local environmental health along with the transaction of carbon emissions.

The purpose of this paper is to propose a method to measure and evaluate the environmental effects of carbon reduction from industrial facilities in China using a quantitative model, and to discuss policy options to improve the environmental benefits of carbon markets in China. Section 2 provides an overview of the environmental effects of reducing CO_2 emissions. Sections 3 and 4, respectively, describe the methods and then use the carbon trading system of the Jing-Jin-Ji region (Beijing-Tianjin-Hebei) as a case study to identify the most important sectors and regions in terms of potential environmental co-benefits. Section 5 proposes policy options for remodeling the ETS of the Jing-Jin-Ji region to obtain CO_2 emission reductions with the highest level of environmental co-benefits.

2. Literature review

Mitigation policies related to CO_2 emissions generally have positive effects on air quality and public health via reduced emissions of co-pollutants such as sulfur dioxide (SO_2), nitrogen oxides (NO_x), and total suspended particles (TSP) (Haines et al., 2010; Harlan and Ruddell, 2011; Nemet et al., 2010; West et al., 2013). Climate policy instruments that mitigate air pollution, improve air quality and provide public health benefits will be favored and accepted by public. For developing countries with serious air pollution problems, the potential for improving air quality and health will be especially large (Markandya et al., 2009; Nemet et al., 2010; West et al., 2013). These air quality co-benefits mean substantial cost savings which can be obtained by reducing CO_2 emissions. In an international review of studies, Bell et al. (2008) argued that measured co-benefits are likely to be underestimated in some cases because a number of important unquantified health and economic results exist. Many studies on the magnitude of air quality co-benefits associated with climate change policy have concluded that these co-benefits are likely to be significant in China (Aunan et al., 2006; Aunan et al., 2004; Mao et al., 2013; Yang et al., 2013b; Haines et al., 2010).

Carbon trading, as one of the important mitigation policies, is likely to have significant impacts on the spatial pattern of CO_2 emissions and co-pollutants emissions. While the warming effects of CO_2 emissions are global, the effects of co-pollutant emissions are local and can be very unequal. The environmental and health effects of CO_2 emissions reduction themselves vary dramatically among locations due to differences in geography, climate and population density (IPCC, 2014; Markandya et al., 2009; Sharon et al., 2009; Smith et al., 2009; GEA, 2012). Spatial differences in co-pollutant emissions add a further dimension of variation to the impacts of carbon trading across locations.

Rao et al. (2013) estimated the extent and distribution of outdoor air pollution exposures associated with climate policies, and confirmed the importance of population exposure and pollution distribution. The Global Energy Assessment (2012), coordinated by the Institute for Applied Systems Analysis, observed that the human exposure risks from particulate matter pollution resulting from energy use are divergent in different cities worldwide. Carbon trading will impact emissions of both CO_2 and co-pollutants at the facility level (IPCC, 2014; Driscoll et al., 2015). The World Bank (2015) concluded that carbon markets could induce carbon leakage, or relocation of carbon-intensive activities, with attendant environment impacts at the facility level. Studies in the United States have shown that the disparities in environmental justice – the extent to which vulnerable populations are disproportionately impacted by environmental harm – can be induced by changes in the spatial pattern of point emission sources (Mohai and Saha, 2006; Pastor et al., 2013; Pollock and Vittas, 1995). Muller (2012) found that the co-pollutant damage per ton CO_2 in the United States varies considerably across source types and locations, and that a large fraction of the welfare improvement from emissions reductions could come from a small percentage of pollution sources.

Most studies focused on the environmental effects of carbon trading in China have been carried out at the macro- or meso-level, and have been based on the average quantitative relationship between co-pollutant and CO_2 emissions with little consideration given to the population exposure (Sun et al., 2014). Beijing ETS policymakers explicitly expect a carbon trading scheme to provide positive effects in air quality by pollutants reduction (BMCDR, 2013), and positive environmental effects have been discussed related to the Guangdong ETS (Cheng et al., 2015) and Shanghai ETS (Zhou, 2015). Spatial variations associated with differences in the relationship between co-pollutant and CO_2 emissions and with differences in population exposure have not been analyzed, however.

The works of Boyce and Pastor (2012, 2013) and Pastor et al. (2013) provide an entry point to explore the spatial differences in the co-benefits of reductions in CO_2 emissions from industrial facilities. These studies used population-weighted measures of co-pollutant damages based on exposure modeling (or, more simply, on the product of co-pollutant emissions multiplied by the number of people living within a 2.5 mile radius of a facility) as a ratio to CO_2 emissions to evaluate the spatial disparities of environmental co-benefits. Taking a similar approach, in this study we develop a comprehensive model that combines facility CO_2 and co-pollutant emissions, facility-specific fate and transport of co-pollutants, and concentration-response functions to measure the potential environmental co-benefits of carbon trading in the Chinese context.

3. Methodology

3.1. Description of the Jing-Jin-Ji region

The Jing-Jin-Ji region is made up of two Municipalities Directly Under the Central Government’s control (MDUCG), that is, Beijing and Tianjin, and the province of Hebei (Fig. 1). This region covers 216,760 km^2 and was inhabited by 107.70 million people at the end of 2012 (National Statistics Bureau, 2013). It is emerging as a large regional carbon market, against the background of the Jing-Jin-Ji integration strategy launched by Chinese president Xi Jinping (Encyclopedia, 2015), the inter-regional carbon emissions trading cooperative agreement signed in 2013 (Sina News, 2013), and the integration of the emission units of Chengde City, Hebei Province, into the Beijing ETS in 2014 (He, 2014). The Jing-Jin-Ji region is also one of China's three most important regions needing stricter air pollution controls (the other two are the Yangtze River delta region and the Pearl River delta region), according to the *Air Pollution Control Action Plan* issued by China State Council (2013).

In light of the emerging Jing-Jin-Ji ETS, we use this region as the spatial boundary for our analysis. Because this region suffers from serious smog-related air pollution, an urgent need exists to develop the best methods to measure the environmental impacts

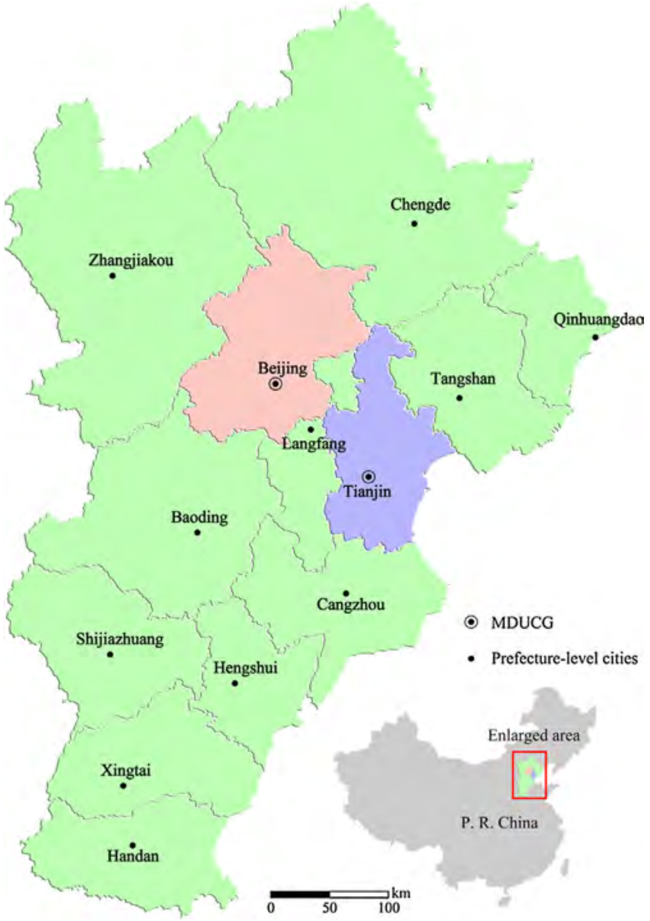

Fig. 1. Map and inset vicinity map of the Jing-Jin-Ji (Beijing-Tianjin-Hebei) region in China. Note: MDUCG, Municipalities Directly Under the Central Government.

of carbon trading, to understand how to maximize environmental co-benefits of an ETS, and to minimize any negative effects on the local environment.

3.2. Calculation of CO_2 emissions

The CO_2 emission calculations used here comply with the *Guidelines for Calculating and Reporting CO_2 Emissions of Organizations in Beijing (2013)* (Beijing Municipality, 2013). The CO_2 emissions of individual facilities were calculated by summing emissions from the combustion of fossil fuels and those from the industrial processes (clinker production, lime production and iron and steel production) (Eq. (1)).

The emission factors by fuel type are from the Department of Climate Change (2014), which reports emission factors of the GHG inventory in the *Second National Communication on Climate Change of the People's Republic of China* (NDRC, 2013) and detailed emission factors for various industries in different regions in terms of different energy types.

$$E = \sum M_{fuel} \times F_{fuel} + E_p \tag{1}$$

where E is CO_2 emissions of a facility, M_{fuel} is energy use of a specific fuel,F_{fuel} is the CO_2 emission factor for a specific fuel, and E_p represents CO_2 emissions from industrial processes.

3.3. Population health damage intensity measurement

We link a facility CO_2 emission model (Wang et al., 2014) and facility-specific fate and transport model of co-pollutant emissions with a concentration-response model to build a composite model that allows us to quantify the local public health benefit of CO_2 reduction (Fig. 2). Three air pollutants emitted from industrial facilities are considered, namely SO_2, NO_x and TSP, which are the main official indicators for air pollutants from facilities and have relatively sound data quality. Population Health Damage Intensity (PHDI) is defined as the ratio of population health damage to CO_2 emissions:

$$PHDI_{facility} = \sum_i (PD_i/E_{CO_2}) \times 1000 \tag{2}$$

$$PD_i = \int_0^{MDi} TM \times ITM_{i,x} \times POP_x dx \tag{3}$$

$$ITM_{i,x} = \alpha_i \times CP_{i,x} \tag{4}$$

where $PHDI_{facility}$ is a unitless indicator for making relative comparisons of the PHDI of individual facilities; E_{CO_2} is the facility's CO_2 emissions; PD_i is the number of premature deaths as a result of emissions from pollutant i from the facility; i indexes the three pollutants, SO_2, NO_x and TSP; TM is the total mortality of the region, from National Health and Family Planning Commission of China (2014);. $ITM_{i,x}$ is the increase of total mortality associated with increase of pollutant i at distance x; α_i is the association factors of outdoor air pollution (i) with mortality, based on parameters from Cao et al. (2011); x is distance from the facility; $CP_{i,x}$ is the concentration of the pollutant i at distance x; POP_x is the population at distance x, calculated based on a GIS spatial analysis platform with high-resolution grid population data; and MD_i is the maximum of range of effects of SO_2, NO_x and TSP emissions of the facility defined by the China national standard (*Guidelines for Environmental Impact Assessment-Atmospheric Environment (HJ2.2-2008)* (CMEP, 2008) as the maximum distance at which the concentration of pollutant i emitted by the facility reaches 10% of the ambient air quality standard (CMEP, 2012). The pollution concentrations resulting from emissions of each facility are modeled by SCREEN3. SCREEN3 is developed by U.S. Environmental Protection Agency (1995). It is a single-source Gaussian plume model that contains a full range of meteorological conditions, including wind speeds, to simulate maximum ground-level concentrations. SCREEN3 is the screening model that is recommended by China's national standards for preliminary assessments of environmental effects (CMEP, 2008).

A large body of literature has shown that point-source emissions from industrial facilities have immediate and direct effects on air quality and the health of nearby residents (see, for examples, Boyce and Pastor, 2012, 2013; Mohai and Saha, 2006; Pastor et al., 2013; Pollock and Vittas, 1995). To estimate health impacts, we use facility-specific pollution concentration distributions calculated by the SCREEN3 model along with the spatial distribution of the population and mortality data to evaluate the population health damage caused by each specific facility. This method makes a direct link between specific facilities and public health damage. It should be noted, however, that some people suffer the effects of cumulative exposure caused by pollution from multiple facilities.

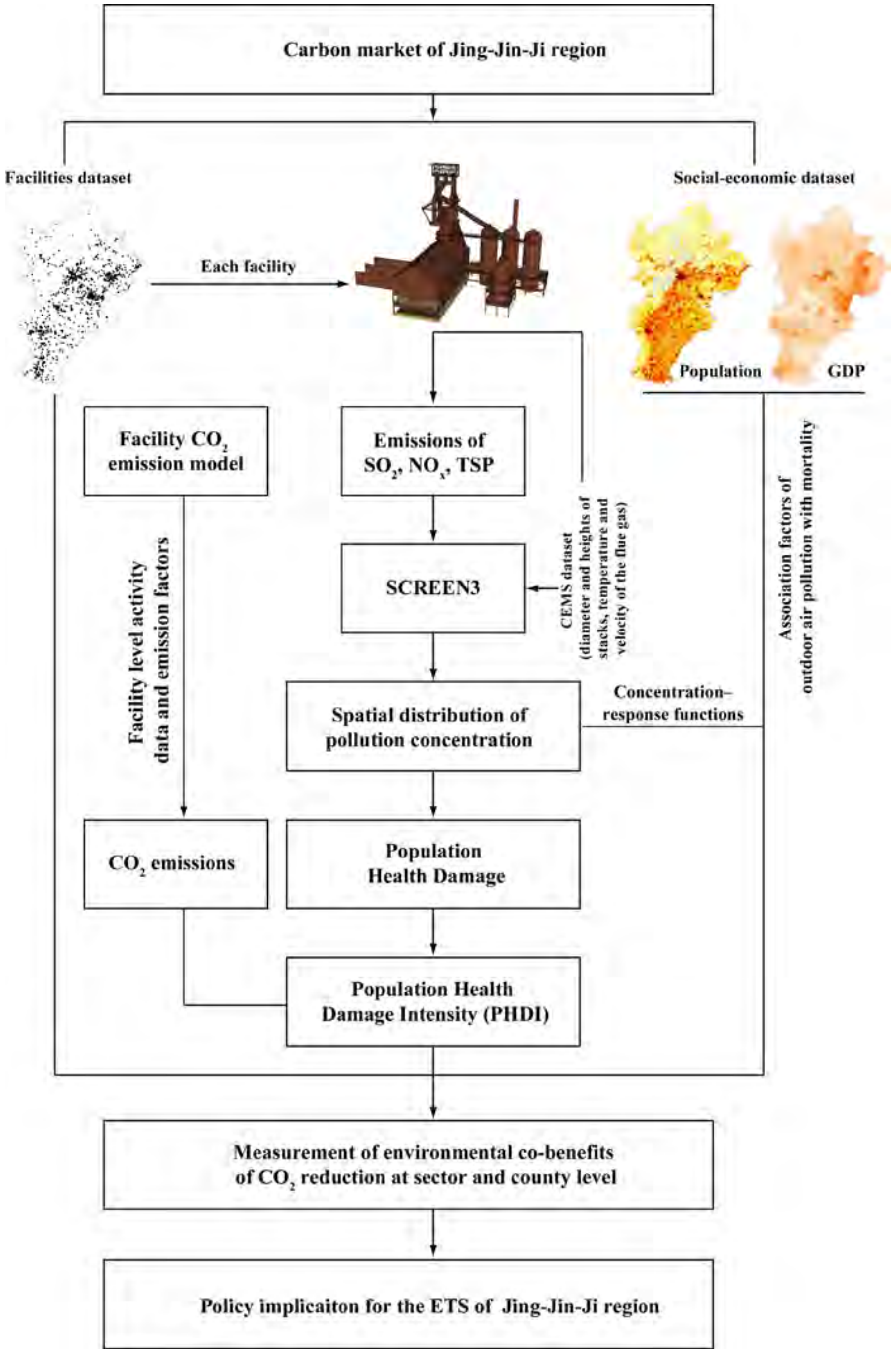

Fig. 2. Schematic diagram of the environmental effects of the CO_2 emission mitigation model. Note: Jing-Jin-Ji region, Beijing-Tianjin-Hebei region; ETS, emission trading system; GDP, Gross Domestic Product.

4. Data

4.1. Facility data

Pollution data for industrial facilities in the Jing-Jin-Ji region were obtained from the China industrial facility database (Wang et al., 2014) and updated information from environmental statistical data and our survey. This data include fossil fuel consumption, geographic coordinates (latitude and longitude), administrative properties, addresses, products, production technology, kiln/boiler information and co-pollutant (SO_2, NO_x, and TSP) emission data. The data are for the year 2012, and emissions cover the full year for each facility (Table 1). We checked the accuracy of the position of facilities by field investigation and by using high-resolution imagery in Google Earth to confirm visually that the coordinates of facilities with large emissions were correct. A comparison of the aggregated pollutant emission data of the Jing-Jin-Ji region from our facility data with official national statistical data (CMEP, 2013) shows that emissions as reported in our aggregated data are slightly lower than those in the latter (with SO_2, NO_x, and TSP 6%, 5%, and 8% lower, respectively). Overall, this suggests that our facility-level data can be regarded as reasonably sound.

The diameter and height of stack, along with the temperature and velocity of the flue gas, for each facility (information used in the SCREEN3 model) are obtained from the Continuous Emission

Table 1
Information on the selected facilities in 2012.

Indicators/Regions		Jing-Jin-Ji region	Beijing	Tianjin	Hebei
Facilities	Number of facilities	2,111	211	334	1,566
	Share of regional total	16%	24%	17%	16%
CO_2	CO_2 emissions (10^4 tons)	90,567.41	4,041.78	10,050.53	76,475.10
	Share of regional total	98%	97%	98%	98%
SO_2	SO_2 emissions (10^4 tons)	126.86	4.39	19.01	103.46
	Share of regional total	89%	78%	95%	88%
NOx	NOx emissions (10^4 tons)	142.18	8.07	25.15	108.96
	Share of regional total	96%	97%	97%	96%
TSP	TSP emissions (10^4 tons)	84.12	1.70	4.74	77.68
	Share of regional total	80%	62%	86%	80%

Monitoring System (CEMS) of these facilities (Bo et al., 2014). If a facility lacked an installed CEMS, these parameters are obtained from other facilities with similar production capacity in the same industrial sector.

We selected the facilities with annual emissions of no less than 10,000 tons, which is the threshold for inclusion in the Beijing ETS (BMCDR, 2013). We consider only direct emissions since these are directly related to the co-pollutant emissions. Descriptive statistics for the selected facilities are provided in Table 1.

The CO_2, SO_2, NO_x, and TSP emissions of the 2111 selected facilities accounted for 98%, 89%, 96%, and 80%, respectively, of the respective total emissions of the Jing-Jin-Ji region. This implies that managing the carbon market of the Jing-Jin-Ji region would bring significant effects to the spatial distribution of both CO_2 and co-pollutant emissions.

4.2. Other data

County-level social and economic data were obtained from the statistical yearbooks of the three provincial regions in the Jing-Jin-Ji region (Administration of Hebei Province, 2013; Beijing Bureau of Statistics, 2013; Tianjin Bureau of Statistics, 2013). The average area of counties in the Jing-Jin-Ji region is $1218\,km^2$. A high spatial resolution population dataset ($30'' \times 30''$ globally, and $0.7\,km^2$ in the Jing-Jin-Ji region), LandScan (East View Geospatial, 2016), is used for our population exposure analysis. LandScan, developed by Oak Ridge National Laboratory, is the finest resolution global population distribution dataset available, and has been widely used for spatial analysis (Bhaduri et al., 2007; Dobson et al., 2000; Fu et al., 2010; Huang, 2012). While the spatial distribution of population is inconsequential in mitigation of CO_2 emissions, it is important when considering the more localized effects of co-pollutant emissions. These data pertain to the year 2012.

5. Results and discussion

5.1. PHDI at the facility level

Table 2 presents data on variations in PHDI across the facilities which are partitioned into three groups on the basis of their CO_2 emissions. A total of 506 facilities (24%) had zero PHDI, meaning that their modelled maximum emitted pollution concentrations are lower than 10% of the ambient air quality standards (or there are no people living where the concentrations attributable to their emissions are above this threshold). The facilities with the highest average values of PHDI – that is, the highest population health damages per ton of CO_2 – are not the largest CO_2 emitters. Instead the highest values of PHDI generally are found among medium-size emitters (100,000–500,000 tons). Medium-sized facilities exhibited the highest average PHDI (and also the lowest coefficient of variation, the ratio of the standard deviation to the mean), while large facilities have lowest average PHDI. This may occur because large facilities can employ more effective pollutant control technologies, or because they are spatially located farther from densely populated areas. Small- and medium-sized facilities often have implemented relatively few pollution control measures, reflecting financial constraints and limited pollution management know-how. When these facilities are located in or near densely populated areas, their environmental effects can be substantial.

Fig. 3 presents a scattergram of the relationship between CO_2 emissions and PHDI (the ratio of health damage to CO_2 emissions) of facilities. The fifteen facilities with the highest PHDI (>100) all have CO_2 emissions below 300,000 tons/year, with a mean of 55,612 tons. These are labeled “worst polluters” in the figure. Facilities that emit large amounts of CO_2 and have a high PHDI deserve special attention from policymakers, since they rank high in both quantity of emissions and damage per ton of emissions. We identified 28 large CO_2 emitters, defined as having annual emissions above 500,000 tons, with PHDI above 10. These are identified in the figure as facilities with high potential of environmental co-benefits.

These findings imply that carbon emissions reductions in different facilities will bring about quite different public health co-benefits. Carbon trading under the ETS among facilities with large discrepancies in their PHDI therefore could yield environmental health outcomes inferior to those that would occur with equivalent across-the-board emissions reductions without trading. On the other hand, with careful consideration an appropriate policy design could achieve substantial health co-benefits by focusing on emissions reductions among the facilities with high potential of environment improvement.

Table 2
Statistical analysis of PHDI of facilities in different scale in the Jing-Jin-Ji region.

Scale of facilities		Number	Average CO_2 emissions (thousand tons)	PHDI	
Scale	CO_2 emissions range (thousand tons)			Average	Coefficient of variation
Large	>500	284	2792.28	3.91	2.50
Medium	100-500	297	227.09	9.58	1.85
Small	<100	1530	29.56	7.05	4.22

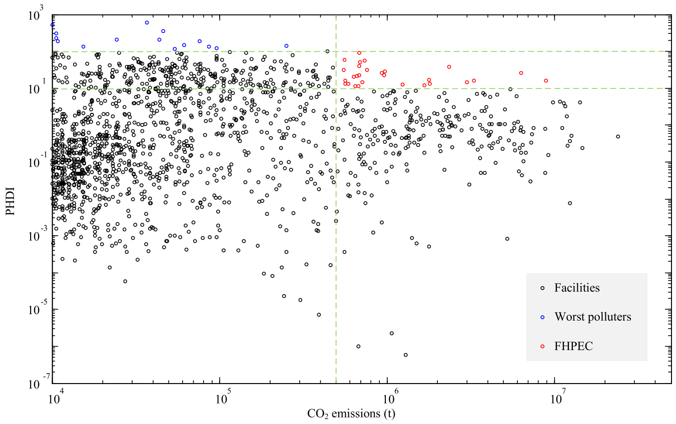

Fig. 3. Scattergram of CO_2 emissions and Population Health Damage Intensity (PHDI) of facilities. Note: FHPEC = facilities with high potential of environmental co-benefits.

5.2. Spatial distribution of CO_2 emissions and PHDI facilities

Fig. 4 maps the spatial distribution of CO_2 emissions and PHDI, showing a noticeable clustering of facilities in specific urban areas. While almost all cities have at least some facilities with high CO_2 emissions and high PHDI (>10), these are clustered in Tianjin, Beijing, Shijiazhuang and Tangshan, areas with a high density of population and a large number of facilities.

We further explore the spatial characteristics of the PHDI by means of a kernel density model, a non-parametric method used to estimate the probability density function of a variable (ESRI, 2015). We use this to calculate the magnitude of PHDI per unit area, so as to identify hotspots and the spatial distribution gradient of the PHDI of facilities. The results (Fig. 5) show that the Tianjin metropolitan area, especially Tianjin proper, is the most important hotspot for PHDI. A large number of facilities in Tianjin proper emit a large quantity of pollutants, and the population density is quite high (Tianjin Bureau of Statistics, 2013).

Other important PHDI hotspots include the central parts of Baoding, Beijing, Qinhuangdao, Shijiazhuang, and Tangshan. The latter two, as well as Tianjin, Handan, and Xingtai, ranked as five of the ten most polluted cities in China in 2013 (Baike, 2013).

Although the clustering of CO_2 emissions itself generates no significant environmental results, since the harms from CO_2 are global rather than localized, the clustering of facilities with high PHDI is consequential. The many people who live in the areas affected by the clustering of facilities suffer from cumulative exposure to pollutants generated from multiple sources.

5.3. Intersectoral comparison

Table 3 shows the CO_2 emissions and PHDI of six major industrial sectors and others. The average PHDI of facilities in the

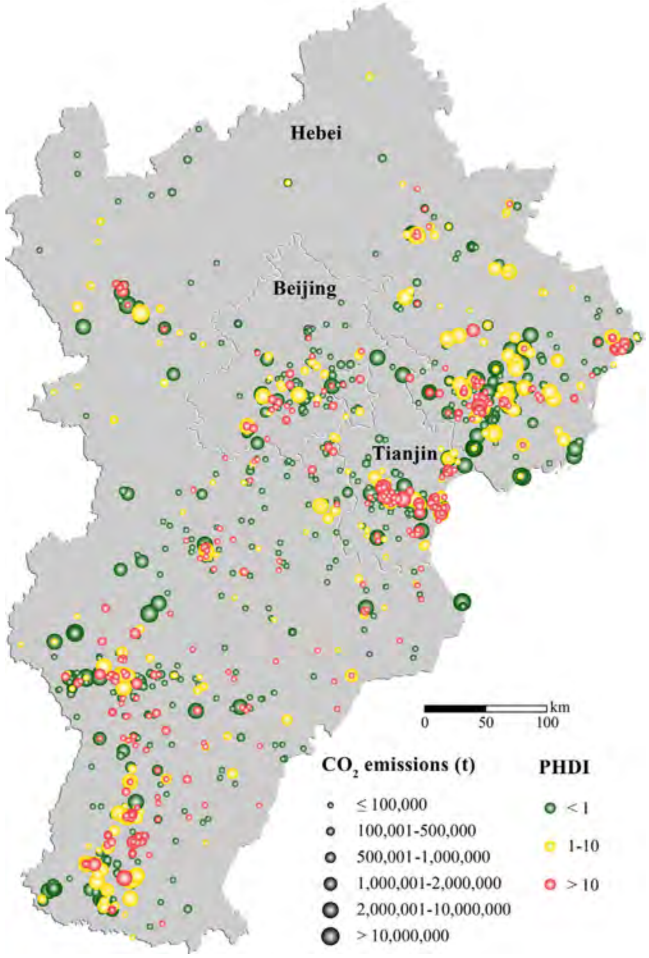

Fig. 4. Spatial distribution of CO_2 emissions and Population Health Damage Intensity (PHDI) of facilities in the Jing-Jin-Ji (Beijing-Tianjin-Hebei) region. Note: Bubble size represents the magnitude of CO_2 emissions, while bubble colors represent the magnitude of PHDI.

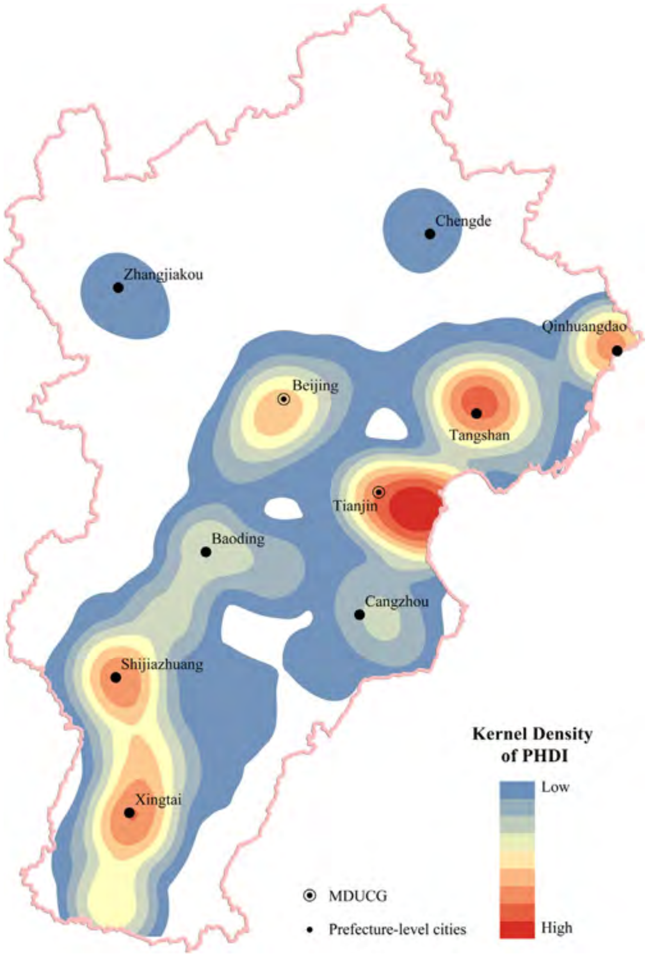

Fig. 5. Kernel density of Population Health Damage Intensity (PHDI) in the Jing-Jin-Ji (Beijing-Tianjin-Hebei) region. Note: MDUCG = Municipalities Directly Under the Central Government.

Table 3
Sectoral distribution of the selected enterprises in the Jing-Jin-Ji region.

Sector	Number of facilities	CO_2 emissions (Million tons)	PHDI	
			Average	Coefficient of variation
Smelting and Pressing of Ferrous Metals (SPF)	270	344.11	4.71	2.09
Thermal power (THP)	117	282.27	1.43	2.77
Processing of Petroleum and Coking (PPC)	86	106.97	15.19	3.26
Manufacture of Non-metallic Mineral Products (MNM)	402	74.30	8.65	3.59
Production and Supply of Heat (PSH)	390	27.50	3.92	3.09
Manufacture of Raw Chemical Materials and Chemical Products (MRC)	231	23.68	9.46	4.45
Other (ELS)	615	46.86	7.82	3.14

Note: "Other" is the total of other industrial sectors whose CO_2 emissions are less than 2% of the total. PHDI = Population Health Damage Intensity (see text).

sectors indicates intersectoral differences in the environmental co-benefits provided by reducing carbon emissions. The coefficient of variation indicates the extent of inter-facility variations within sectors.

The iron and steel (SPF) sector has the largest share of industrial CO_2 emissions, accounting for 38% of the total CO_2. The thermal power sector (THP) ranks second; it is dominated by coal-fired power plants (there were only six natural gas-fired facilities in the total of 117 power plants) and is responsible for nearly 31% of the total. Together these two sectors account for more than two-thirds of total CO_2 emissions, and hence they will be the main players in the carbon market. The relatively low average PHDIs (4.71 and 1.43 for the SPF and THP sectors, respectively) of these two sectors, however, means that CO_2 emissions reductions at these facilities generally will yield fewer air quality co-benefits per ton than reductions in most other sectors, and the relatively low coefficients of variation for these sectors indicate that intrasectoral differences in this respect are relatively small.

The Processing of Petroleum and Coking (PPC) sector has the highest PHDI. The PPC sector accounts 12% of total CO_2 emissions, and its average PHDI is 15.19 with a coefficient of variation of 3.26. This means that CO_2 emissions reductions in this sector would have especially large co-benefits, and that these would be exceptionally great at the worst facilities in this sector.

The Manufacture of Raw Chemical Materials and Chemical Products (MRC) sector also has a high PHDI level (9.46), and the highest coefficient of variation among all the sectors. This sector includes a variety of small facilities used for the production of nitrogen fertilizer (based on coal), inorganic base, and other inorganic salts. Its CO_2 emissions account for 3% of the total.

The Manufacture of Non-metallic Mineral Products (MNM) sector accounts for 8% of total CO_2 emissions and has a PHDI of 8.65. Cement, lime and glass production facilities dominate this sector, with relatively heavy emissions of NO_x and TSP. Constrained by transportation costs, these facilities which produce building material are largely located nearby the consuming locations (human settlements).

Fig. 6 shows the distribution of facilities in these sectors across the three constituents of the Jing-Jin-Ji region, Beijing, Tianjin and Hebei. In the PPC sector, where the potential for public health co-benefit per unit CO_2 emissions is highest, coking facilities make up 74% of the facilities and emit 97% of the sectors CO_2 emissions. All but one of the coking facilities are located in Hebei Province. Therefore, this should be the most important sector related to carbon trading management in terms of environment effects for Hebei Province.

In the MRC sector, facilities in Beijing, Tianjin and Hebei produce 2.42%, 23% and 75% of the emissions, respectively, with average PHDIs of 28.08, 23.95 and 6.15. Beijing has phased out many obsolete plants, so the high value of PHDI in Beijing in MRC sector implies that the facilities are located in densely populated areas.

In the MNM sector, facilities in Beijing, Tianjin and Hebei produce 8%, 3%, and 89% of the emissions, respectively. The average value of PHDI in the MNM sector in Tianjin is almost twice of that in this sector in Beijing. Integration of the currently separated Beijing and Tianjin carbon markets could be favorable for achieving maximum air quality and public health co-benefits in these two regions, whose economic development and air quality are closely related, as stated earlier in the Jing-Jin-Ji integration strategy (Encyclopedia, 2015) and *Air Pollution Control Action Plan* (China State Council, 2013). This will be possible, however, only if the policy takes PHDI variations into account.

5.4. Variations at the county level

Fig. 7 depicts average CO_2 emissions and PHDIs for facilities at the county level for the 178 counties in the Jing-Jin-Ji region. The PHDI, CO_2 emissions and per capita GDP vary substantially, as shown in the figure. Most counties with large CO_2 emissions are located in the upper left zone, which indicates that economic conditions are linked to CO_2 emissions via industrial activity.

Considerable heterogeneity can be observed in the average PHDI across counties in the region. Counties in the lowest quartile of per capita GDP (below 20,757 RMB/person/year) are regarded as the economically most vulnerable group. Counties in the fourth quartile of average PHDI (higher than 8.00) are those where the

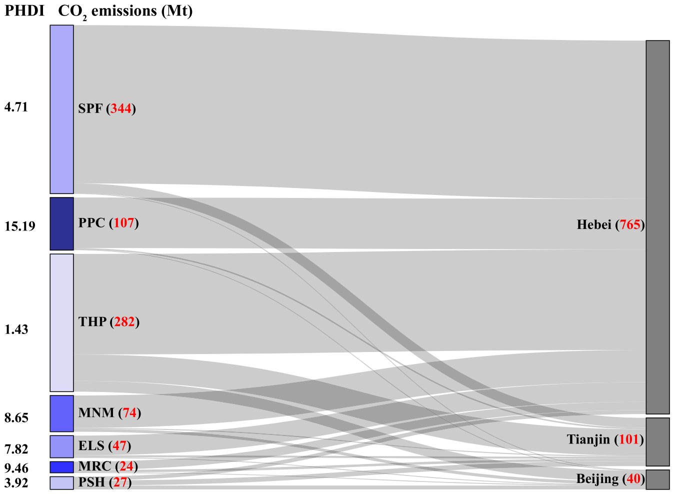

Fig. 6. CO_2 emissions and Population Health Damage Intensity (PHDI) in sectors and provinces in the Jing-Jin-Ji (Beijing-Tianjin-Hebei) region. Note: Minor differences between totals and the sum of their individual components were caused by rounding. Red numbers in the brackets indicate the CO_2 emissions (Mt). The number in the left side is the PHDI of sectors, while the colors of the cylinders in the left represent the level of PHDI from high to low by black blue to light blue. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

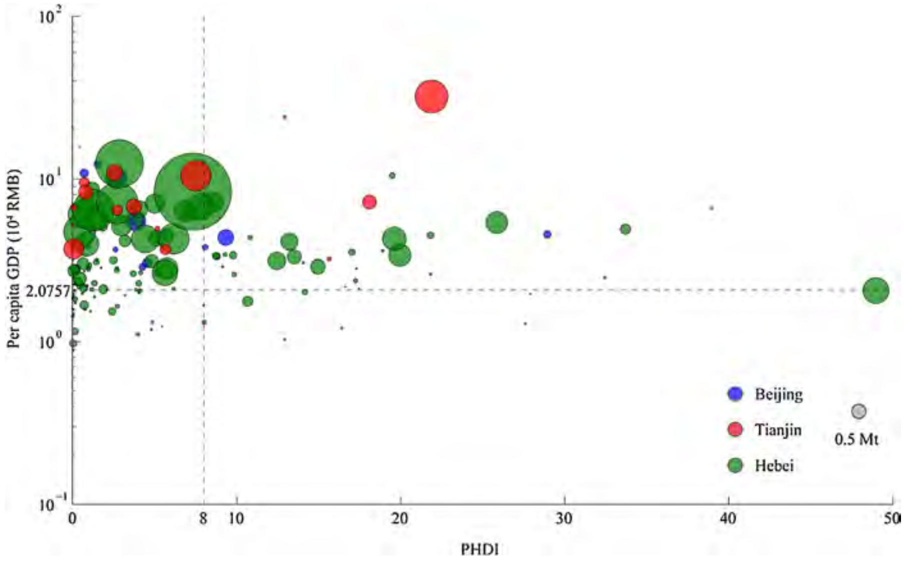

Fig. 7. County level per capita Gross Domestic Product (GDP) and Population Health Damage Intensity (PHDI) in the Jing-Jin-Ji region. Note: Bubble size represents the magnitude of CO_2 emissions, while the colors represent each county's region.

environmental co-benefits per unit of CO_2 emission reduction are greatest. Counties with greater economic vulnerability and higher PHDI need special attention from policymakers, because economically vulnerable people are likely to be less able to cope with the effects of pollution.

In Fig. 7, two dashed lines demarcate counties on these bases, indicating where PHDI = 8.00 and where per capita GDP = 20,757. Eight counties (Dingzhou, Julu, Laishui, Longyao, Ningjin, Ren, Xinhe, and Zaoqiang), all in Hebei province, are located in the right-bottom zone, identifying them as both economically vulnerable and as locations with high potential public health co-benefits from CO_2 emissions reductions. Two of these (Julu and Xinhe) are also national poverty counties (CPAD, 2012). Most of these counties currently have relatively low average CO_2 emissions per facility. Policies related to the carbon market should be carefully designed to avoid encouraging facilities located in these counties to emit significantly more CO_2–an important concern in light of excess capacity of the vast majority of the facilities in the energy-intensive sectors in Jing-Jin-Ji region (MIIT, 2015)—because this would not only worsen the local health conditions and reduce the total health benefits in the entire Jing-Jin-Ji region but also result in a deterioration in the environmental equity of the region. The circle to the extreme right in Fig. 7 represents Dingzhou county, which has the highest average PHDI (48.98) as well as substantial average CO_2 emissions (17.72 Mt) and low per capita GPD (20,572 RMB/person). This county deserves extra attention from policymakers because of its relatively serious environmental and economic situation.

6. Conclusions and policy implications

China has announced plans to develop a national ETS in the near future (NDRC, 2014a,b, 2016). When implemented, this will be the world's largest system, twice the size of the European Union ETS. The initial creation of several regional ETSs, such as that of the Jing-Jin-Ji region, will lay the basis for a national ETS; and the development of regional ETSs will provide needed information and experience for the design and implementation of the national ETS.

One important issue, rarely discussed and evaluated in this context, is the air quality effects of an ETS. This is especially important in China. Whereas the effects of GHGs are global, the environmental and health effects of co-pollutants are more localized. Therefore, designing a carbon market while ignoring environmental co-benefits may exacerbate environmental conditions in some localities that already face serious air pollution burdens with negative effects on public health and welfare, and sacrifice the positive effects that will accrue if the co-benefits are well addressed in the policy design.

To analyze how the carbon market could capitalize on opportunities for environmental co-benefits, this paper uses the Jing-Jin-Ji region as a study case. We construct Population Health Damage Intensity (PHDI), a facility-level indicator of the public health co-benefits per unit of CO_2 emissions, to evaluate the environmental co-benefits of CO_2 emission mitigation in a carbon market. We identify facilities and sectors whose PHDIs are highest and with the greatest potential of producing environmental co-benefits in light of both their PHDIs and total emissions. Our spatial results show that the Tianjin proper is the most important hotspot, with a clustering of a large number of facilities with substantial emissions and high PHDI. The largest environmental co-benefits per unit of CO_2 emissions reduction will be achieved in the MNM (Manufacture of Non-metallic Mineral Products), MRC (Manufacture of Raw Chemical Materials and Chemical Products) and PPC (Processing of Petroleum and Coking) sectors. At the county level we also find wide variation in average PHDI in the Jing-Jin-Ji region. Eight counties are recommended for particular attention owing to their combination of relatively poor economic conditions and high PHDIs. Our evaluation and analysis suggest that modest adjustments to the ETS in the Jing-Jin-Ji region could achieve readily obtainable public health benefits. Support for carbon emissions reduction policies can be enhanced by emphasizing near-term benefits for the jurisdictions implementing the policies, rather than focusing exclusively on long-term global benefits (Boyce, 2016). Stressing the policy's immediate health benefits in the Jing-Jin-Ji region is likely to enhance acceptance for the ETS among the public. Here we offer three suggestions for policy design with these benefits in mind.

First, trading directions should be geared carefully. In other words, the buying of emission allowances (or offset credits) should be strictly restrained for high-priority emitters, i.e., key facilities (such as the worst polluters and facilities with high potential of environmental co-benefits), hotspots (such as Tianjin City proper), low-income counties with substantial pollution burdens, and specific sectors with high PHDI (such as the PPC sector). An example of such a policy design is the Regional Clean Air Incentives Market (RECLAIM) program in southern California, in which trading in NOx and SOx pollution permits is restricted by the designation of zones. Facilities in Zone 1 (the more polluted coastal area) cannot buy permits from facilities in Zone 2 (South Coast Air Quality Management District, 2015).

In addition, tighter emission reduction targets could be established for these emitters compared to their counterparts. An alternative is the establishment of an "exchange rate" that makes the price for one permit for the high-priority emitters higher than the price for lower-priority emitters (Muller and Mendelsohn, 2009). More generally, policies related to the carbon market should encourage polluters in these areas to accomplish reductions as rapidly as possible.

Second, the environmental impacts of carbon trading should be carefully monitored and assessed, and the stringency of environment regulations should be increased if necessary. If systematic evaluation finds worsening air pollution and public health in specific localities associated with carbon trading, additional environmental policies, such as stricter air pollution standards, or not allowing production expansion in hotspots, should be implemented to complement the carbon market.

Third, financial support should be directed to vulnerable counties in the catchment area of the carbon market, such as Dingzhou, which face a high risk of further deterioration of environment welfare and public health. Government investment or subsidies should be used for household and public health protection measures. Financial support is also needed to encourage the technology improvement and pollution control measurement in these vulnerable areas.

Our model, calculated in terms of a relatively simple measure, PHDI, provides a tractable method for using data for the evaluation and comparison of the changes in localized environmental co-benefits associated with carbon trading. Future studies should employ rigorous investigation of the actual impacts as carbon markets are implemented and possibly more sophisticated measures of environmental co-benefits of CO_2 emission mitigation.

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