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THE DECOMPOSITION AND DYNAMICS OF INDUSTRIAL CARBON DIOXIDE EMISSIONS FOR 287 CHINESE CITIES IN 1998–2009

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Abstract. 85% of China's GHG emissions are attributed to urban economic activities, and this share is expected to rise given China's fast urbanization process. This paper provides estimates of city-level industrial CO₂ emissions and their growth rates for all 287 Chinese prefecture-level and above cities during the years 1998–2009. We decompose the CO₂ emission changes into scale, composition and technique effects. The decomposition results show that these three effects differ significantly across the three tiers of cities in China. The scale effect contributes to rising CO₂ emissions, while the technique effect leads to declining CO₂ emissions in all cities. The composition effect leads to increasing CO₂ emissions in the third-tier cities, while it reduces CO₂ emissions in the first and second-tier cities, due to the relocation of energy-intensive industries from the latter to the former type of cities. Based on these decomposition results, we identify the separate channels through which the inflow of FDI and the environmental regulations affect city-level CO₂ emissions. The decomposition framework in our paper can help policy makers and scholars to better understand Chinese cities' trade-offs between economic growth and environmental goals.

Keywords. Chinese cities; Decomposition; Industrial carbon dioxide

1. Introduction

Urban energy use significantly contributes to climate change. According to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), urban areas account for between 67% and 76% of global energy consumption and generate about three quarters of global carbon emissions (Creutzig

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et al., 2013). This share is even larger in China where 85% of carbon emissions are attributed to urban economic activities, and this share will likely increase as China's urban population is projected to grow by 240 million over the next 35 years (Liu, 2015).

Industrialization and urbanization have gone hand in hand during China's rapid economic development. In the past three decades China has been the 'The World's Factory' (e.g. 40% of the world's clothes are 'Made in China'¹), largely driven by the fast growth of export-oriented, labor- and energy-intensive industries in cities. In urban areas the industrial sector emits much more carbon dioxide than the residential sector. In 2011, China's industrial sector consumed about 71% of the country's total energy, while in the USA, the manufacturing sector's share reached a peak of 41% in 1951, and declined to 32% in 2013.^{2,3}

While cities play an important role in shaping China's CO₂ emissions, the patterns and dynamics of city-level CO₂ emissions in China remain largely unexplored due to data unavailability. Some studies examine the provincial level CO₂ emissions across China, but they do not perform disaggregate analysis at the city level (Wang *et al.*, 2014; Xu and Lin, 2015). A city-level study by Zheng *et al.* (2010) estimates household carbon emissions across 74 Chinese cities, and ranks those cities with respect to a standardized household's carbon emissions. They find that based on this criterion, even in the dirtiest city (Daqing), a standardized household produces only one-fifth the emissions compared to those in America's greenest city (San Diego). However, such patterns may flip if we look at the industrial carbon emissions in those cities. A recent report by the PBL Netherlands Environmental Assessment Agency estimates that the emitted CO₂ per GDP (corrected for purchasing power parity) in China reached 650 kg CO₂/1000 USD, which is almost twice as much as that of the USA (330 kg CO₂/1,000 USD).⁴

The first purpose of our paper is to conduct an accounting style decomposition of city-level industrial carbon dioxide emissions growth into three separate effects: the scale, composition and technique effects. In line with Copeland and Taylor (2004), these three effects work together to determine the total energy consumption, and thus CO₂ emissions, for a city's industrial sector. Scale refers to the output located in a city while composition refers to a city's industry mix and the vintage of its capital stock. Technique represents energy consumption per unit of economic activity. We do such decomposition work for Chinese prefecture-level and above cities during the period of 1998–2009. China has 287 prefecture-level and above cities, which vary significantly in population size and productivity level. Following the city classification method in OECD (2005), we group them into three tiers based on city size and economic development stage: 4 first-tier cities (Beijing, Shanghai, Guangzhou and Shenzhen), 31 second-tier cities including capital cities across all provinces in China and 252 third-tier cities (all the other prefecture-level cities). This decomposition exercise helps us better understand how cities behave differently according to the dynamics of their industrial carbon dioxide emissions.

The second goal of our paper is to gain a better understanding of the environmental consequences of the influx of FDI and environmental regulations. We do this by examining their impacts on the scale, composition and technique effects for the industrial CO₂ emission growth path. The relationship between FDI and a city's (local and global) pollution is ambiguous, depending on two competing forces (Copeland and Taylor, 2004). The first is the raw scale of capital investment such as heavy machines and construction equipment in factories. This should lead to a positive effect of FDI on CO₂ emissions ('pollution haven' hypothesis). On the other hand, FDI may help a city to upgrade the quality of its capital stock and such technique effect may translate into lower energy consumption and CO₂ emissions. The optimistic case would be more likely if new capital is significantly cleaner than older durable capital. Therefore the decomposition analysis will help us determine whether the scale or the technique effect dominates the impact of FDI inflow on the industrial CO₂ emissions trend in urban China.

Where firms locate is both a function of the natural advantages of different geographic areas and of the regulatory policies and incentives offered by different local governments. Local governments who are aware of this strategic dynamic must decide whether to enforce regulations and pay the price of losing some mobile dirty jobs or to enjoy the environmental gains of deindustrializing. A strand of the literature on environmental regulation has documented that differential enforcement of pollution regulation

encourages industrial migration to areas featuring laxer regulation (Kahn, 1997; Becker and Henderson, 2000; Greenstone, 2002; Kahn and Mansur, 2013). In the richer first-tier and some of the second-tier cities, Chinese local governments are starting to enforce stricter environmental regulations (Zheng and Kahn, 2013). Based on our decomposition results, we are able to explore how typical environmental regulations affect a city's industrial pollution via these three channels – losing dirty firms (both scale and composition effects) or encouraging incumbent firms to improve their technology (technique effect).

The remainder of this paper is organized as follows: Section 3.2.1.2 surveys the relevant literature. Section 3.2.1.3 presents the decomposition analysis of CO₂ emissions across cities in China. Section 4 investigates the impacts of FDI and environmental regulations on the changes in CO₂ emissions and its decomposed parts. Section 5 concludes.

2. Survey of Related Literature

2.1 Scale, Composition, Technique Effects and the Decomposition Methodology

A change in energy consumption, pollution and carbon dioxide emissions can be decomposed into three channels: the scale effect, the composition effect and the technique effect (see Copeland and Taylor, 1994, 2003; Grossman and Krueger, 1995; Antweiler *et al.*, 2001; Managi *et al.*, 2009). The scale effect measures the effect on pollution of an increase in the economy size that results from income-driven growth in production. Other things being equal, a positive scale effect means that rising industrial output will drive up CO₂ emissions. Managi *et al.* (2009) find a positive effect of trade openness on CO₂ emissions for non-OECD countries, providing suggestive evidence of the scale effect from trade-driven increases in industrial production. The second is the composition effect, which measures the impacts of a change in industrial composition. This effect could be positive or negative, depending on the abundance of resources and the strength of environmental policy of the economy. For instance, a shift in an economy from relatively clean service industries towards relatively dirty ones such as steel and cement production is considered a composition effect and will lead to an increase in energy consumption and CO₂ emissions. Moreover, the composition effect may also be positive if more stringent environmental regulations increase costs and drive out polluting firms. A recent study by Zheng and Kahn (2013) shows that the rising costs and tighter environmental standards – especially for carbon dioxide and sulfur dioxide emissions – in the large Chinese cities have pushed those heavily polluting manufacturers to shut down their factories or to relocate them to other places with laxer environmental regulations.

The third one is the technique effect, which relates to the change in the production technique of a given industry. All else being equal, if the manufacturers in an industry adopt more efficient environmentally friendly production methods and improve management quality, it will induce a negative technique effect, thus reducing energy consumption and CO₂ emissions per unit of economic activity within this industry. Shapiro and Walker (2015) find that the observed decrease in nitrogen oxide emissions (NO_x) in the USA during the period of 1990–2008 is more attributable to falling pollution per unit of output within industries at a more disaggregated level, suggesting the existence of a technique effect in those industries. A study focusing on China by Zhang (2012) finds that the changes in input mix, sector energy intensity, fuel mix and carbon intensity of fuels can offset the increasing trade-induced carbon emissions in twenty-six sectors including agriculture, mining, manufacturing and service industries. His analysis provides some evidence that the technique effect contributes to mitigating pollution emissions arising from the energy consumption by trade-oriented sectors.

The decomposition of energy consumption, pollution and CO₂ emission changes into scale, composition and technique effects can be found in several studies. Some of them rely on the Divisia index method (Lin and Chang, 1996; Viguier, 1999). Another avenue makes use of structural decomposition analysis (SDA) based on input-output tables. This line of decomposition methods is based on regression analysis

performed on aggregate data, and is often referred to as a 'top-down' approach. Twenty years ago, Grossman and Krueger (1995) introduced scale, composition and technique effects into the trade and the environment literature by developing a bottom-up approach, which relies on disaggregated emission and economic activity data.

Many studies have applied this 'bottom-up' approach to investigate the air-pollution dynamics using both cross-country and within-country data. For example, using data of sulfur dioxide concentrations across 293 cities in 44 countries from the Global Environment Monitoring Project over the period 1971–1996, Antweiler *et al.* (2001) decompose the pollution impacts of free trade into scale (GDP), composition (capital-labor endowment ratios), and technique effects. They regress pollution concentrations on representative variables of the above three effects. They attempt to distinguish between the pollution impacts of income changes brought on by international trade from those created by factor accumulation. Their empirical results show a positive scale effect, a negative technique effect and a negative composition effect. The composition effect caused by trade is found to vary across countries depending on relative income and factor endowments. Dean (2002) applies this decomposition framework to estimate the effect of trade openness on water pollution at the provincial level in China from 1987 to 1995. She estimates a two-equation model in which trade has both a direct effect on environmental quality through a composition effect and an indirect effect through an induced technique effect. She finds that the inflow of pollution-intensive industries aggravates environmental damage in China, but openness tends to reduce the environmental costs through stronger regulation as trade-induced income increases. Shapiro and Walker (2015) recently explained the decline of air pollution in the USA between 1990 and 2008 by utilizing this bottom-up decomposition approach. Following this decomposition methodology, this paper examines the change in CO₂ emissions in the context of China for a large number of cities and with more disaggregated sub-sectors in Section 3.2.1.3.

2.2 *The Impact of FDI and Environmental Regulation on Industrial CO₂ Emissions*

The decomposition framework allows scholars to better understand the dynamics and the underlying mechanisms of industrial CO₂ emissions at a geographic level (national, state/provincial, or city). In this paper we focus on two underlying forces, FDI and environmental regulation, and examine how they affect the three decomposition effects, thus shaping CO₂ emissions dynamics. Existing studies show mixed empirical findings on their effects since they examine different samples in different study periods. Moreover, current studies lack of a clean identification strategy to separate the different channels. Our analysis attempts to improve upon the literature by explicitly looking at their impacts on all three decomposition effects. We first survey the related literature.

2.2.1 *FDI*

Previous studies have highlighted the role played by the influx of FDI on local environmental quality in China. *Ex ante*, there are two different possible channels associated with urban FDI inflows. One possibility is that cities experiencing increased FDI inflows become dirtier as the scale of industrial production increases and the composition of industries tilts towards dirtier heavy manufacturing. In a system of cities where foreign investors can choose between many cities within a developing country, they may seek out cities with laxer environmental regulation. This is a pollution haven effect (Copeland and Taylor, 2004). The empirical analyses by He (2006, 2009) show that pollution (which should be positively correlated with CO₂ emissions) and FDI are positively correlated in China as FDI increases industrial output and pushes up carbon emissions.

The other possibility is that FDI reduces energy consumption and thus CO₂ emissions in a city because such new capital from western countries helps to modernize the capital stock, leading to a technique

effect. Zheng *et al.* (2010) use data across 35 major Chinese cities for the years 2003–2006 and report a negative correlation between a city's FDI influx and its ambient air pollution levels. Wang and Jin (2007) find that foreign firms exhibit better environmental performance than state-owned and privately owned firms as they adopt cleaner techniques in production.

Therefore we predict that the impact of the inflow of FDI on pollution varies across cities depending on whether the technique effect can outpace its scale effect, and the direction of its composition effect. We will use our decomposition results to explicitly test this hypothesis in Section 4.

2.2.2 Environmental Regulations

The current literature argues that local officials' incentives and efforts to regulate pollution vary across different regions and cities in China. Van Rooij and Lo (2010) show that the more developed cities in coastal China have more stringent environmental regulations. Zheng *et al.* (2014) also find that people in richer cities in China are willing to pay more for the clean environment and this incentivizes their local leaders to pursue more stringent environmental regulations. In China, as in the rest of the world, regulators rely on two types of environmental regulation: one is a standards-driven administrative intervention such as stipulation of scrubber installment (Xu *et al.*, 2009); the second relies on economic incentives including pollution levy (Wang and Wheeler, 2005; Lin, 2013) and more recently local cap and trade markets (Auffhammer and Gong, 2015).

Stringent environmental regulations will cause regulated firms to bear compliance costs, and this will push them to either improve their production technology (technique effect), or locate to regions with laxer regulations, known as the pollution haven hypothesis (scale and composition effects). The empirical studies of US manufacturing provide evidence that manufacturing firms tend to move to less regulated areas (Henderson, 1996; Berman and Bui, 2001a, 2001b; Greenstone, 2002). In China, mayors of big coastal cities face incentives leading them to drive dirty firms out of their cities, whereas the city mayors in under-developed areas welcome them because of the investment, job opportunities and fiscal revenue brought by those energy-intensive manufacturers. The recent literature shows that the city mayors in inland China face incentives to accept large firms' heavy pollution in return for the generation of local tax revenue, jobs and economic growth (see Yu *et al.*, 2013; Jiang *et al.*, 2014). Moreover, relocation of dirty firms due to tight pollution regulation has been found to take place both across regions and within regions in China. For instance, Guangdong province is subsidizing polluting firms in the Pearl River Delta to relocate to the northern part of the province and Jiangsu province drives those firms to the north-Jiangsu (*Subei*) area. These moves reflect the provincial governments' strategy to green the big city by moving dirty industrial activities further from the major population centers and to narrow income gaps across cities by spreading wealth to the poor underperforming areas (Zheng and Kahn, 2013; Cai *et al.*, 2016). Again, our decomposition results will help us look into the above channels, which may be different across different tiers of cities.

3 Decomposition of Carbon Dioxide Emissions in Chinese Cities

3.1 Decomposition Framework

Following the recent literature (e.g. Shapiro and Walker, 2015), we decompose the change in a city's industrial CO₂ emissions into scale, composition and technique effects. Let x_{kit} be the output measure (we use value-added in this paper) for industry i in city k in year t , e_{kit} be the CO₂ emission intensity per unit of output. Then, CO₂ emissions for city k in year t , P_{kt} , is given by

$$P_{kt} = \sum_i x_{kit} \cdot e_{kit} \quad (1)$$

Let X_{kt} be the total output for all industries in city k in year t and θ_{kit} the output share of industry i in city k in year t . Then Equation (1) can be rewritten as follows:

$$P_{kt} = X_{kt} \cdot \sum_i \theta_{kit} \cdot e_{kit} \quad (2)$$

or in vector notation:

$$P = X\theta'e \quad (3)$$

where θ and e are $M \times 1$ vectors that include the each industrial activity's output share and its pollution intensity, respectively, and M is the number of industries in a given city.

By total differentiation of Equation (3), the change in CO₂ emissions can be decomposed into the following expression:

$$\Delta P_{kt} = \Delta X_{kt} \cdot \sum_i \theta_{kit} \cdot e_{kit} + X_{k,t-1} \cdot \sum_i \Delta \theta_{kit} \cdot e_{kit} + X_{k,t-1} \cdot \sum_i \theta_{ki,t-1} \cdot \Delta e_{kit} \quad (4)$$

In Equation (4), the first term of RHS is the scale effect, measuring the impact of the increased size of total output on CO₂ emissions, holding industrial composition and emission intensities of all industries constant. The second term is the composition effect, measuring how the change in the industrial composition affects CO₂ emissions, holding the scale and emission intensities constant. The last term is the technique effect, capturing the effect of the changes in emission intensities on CO₂ emissions, holding the scale and composition effects constant.

3.2 Data Issues

To conduct the decomposition analysis, we need to econometrically estimate three key parameters in Equation (4): X_{kt} , θ_{kit} , e_{kit} . In this paper, we consider 44 sub-sectors (See Appendix A) across 287 prefecture-level-and-above cities in China during the time period of 1998–2009.⁵ The finer level of industrial disaggregation can help us to better understand the changes in industrial composition and how such changes matter for our decomposition results (Sinton and Levine, 1994; Fisher-Vanden *et al.*, 2004). The terms X_{kt} and θ_{kit} can be estimated by using the industrial production data from the database of Annual Survey of Industrial Firms (ASIFs) (for the manufacturing sector)⁶ and from the China's Urban Statistical Yearbooks (for construction and service sectors).

3.2.1 Data Sources

We now list the data sources we use to construct our database of CO₂ emissions by city and industry for the 1998–2009 period in China. This emissions database is combined with production and energy data to carry out our decomposition exercise.

3.2.1.1 Output data. In this analysis, we measure carbon dioxide emission intensity by CO₂ emissions per unit of value added instead of gross output. The reason is that double counting problem inherent in the gross output measure may lead to inconsistent aggregation at the sector level (Ma and Stern, 2008). The value added at the sub-sectoral levels in the manufacturing sector is calculated by aggregating the firm-level value added data. The firm-level data are collected from the Annual Survey of Industrial Firms (ASIFs) dataset released by National Bureau of Statistics (NBS) from 1998 to 2009. All the value added data are converted to constant 1998 prices. The value added for the construction and service industries and their related sub-sectors are collected from China's Urban Statistical Yearbooks in the corresponding years.

3.2.1.2 Energy consumption data. Energy consumption data come from the provincial energy balance tables published by NBS in the corresponding years, which provides us with the quantities of various types of energy consumptions at the provincial level for six relatively aggregated sectors.⁷ Those tables report each sector-province's energy consumption information for 20 types of energy, including 17 kinds of fossil fuels, 2 secondary energy types (heating power and electricity), and 1 other energy category.⁸ In this analysis, we only consider the CO₂ emissions generated from end-use energy consumption. For example, we count the CO₂ emissions from the consumption of goods and services which are produced using electricity but we will not count the CO₂ emissions from the generation of electricity itself.

3.2.1.3 CO₂ emission factors. CO₂ emission factors for different types of energy are collected from the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Following most of the literature, we use these factors to convert energy consumption data into CO₂ emissions figures.

3.2.2 Calculating the Scale and Composition Effects

The value-added of the whole industrial sector in city k in year t (X_{kt}) is calculated by aggregating the value-added of all industries in city k in year t , $X_{kt} = \sum_i x_{kit}$. The share of sub-sector i in city k in year t (θ_{kit}) is calculated as $\theta_{kit} = \frac{x_{kit}}{X_{kt}}$.

3.2.3 Calculating the Technique Effect

The key task in this decomposition exercise is the estimation of the CO₂ emission intensity (e_{kit}) at the more disaggregated sector level (44 sub-sectors) across 287 cities. First, we calculate total CO₂ emissions for the six more aggregated sectors at the provincial level by summing up the products of each fossil fuel type's consumption quantity and its corresponding CO₂ emission factor across all types of fossil fuels.⁹ Then, we obtain CO₂ emission intensities at the provincial level for these six relatively aggregated sectors by dividing a sector's CO₂ emissions in a province by the corresponding value added number. Finally, we infer the city- and sub-sector-specific CO₂ emission intensity by multiplying the provincial- and sector-specific emission intensity with a 'conversion factor'.

We construct our conversion factor based on the underlying assumption that TFP is negatively related to energy use and thus emission intensity at the firm level. A broad set of studies support our assumption. Based on the model of Melitz (2003), Kreckemeier and Richter (2014) illustrate that firm heterogeneity can affect environmental performance. As pollution is incorporated as a joint output of production, more efficient input use turns out to have lower emission intensity, so the firm heterogeneity argument implies that firm productivity is negatively related to emissions intensity. Bloom *et al.* (2010) empirically show that more productive firms associated with higher management quality are likely to increase the efficiency of input uses, thus leading to lower greenhouse gas emissions. Another line of studies in the trade and productivity literature argues that the correlation between TFP and energy use and emissions involves technology adoption. Bustos (2011) studies new technology adoption by heterogeneous firms and refines the Melitz model. According to her model, decreasing trade costs allow high productivity firms to upgrade technology since they benefit more from lower variable costs. Cui *et al.* (2012) consider environmental pollution and technology choice into a trade model with heterogeneous firms. Their model predicts that only the productive firm has the profitable incentive to adopt emission saving technology and to export. Based on the above studies, to keep it simple but without loss of generality, we construct the conversion factor which is the inverse ratio of city- and sub-sector-specific TFP over the provincial-sector-specific TFP. Martin (2011) and Shapiro and Walker (2015) also build their empirical analysis on a similar assumption. The apparent advantage here is that we have all the TFP measures needed for calculating those conversion factors coming from ASIFs dataset and China's Urban Statistical Yearbooks.¹⁰

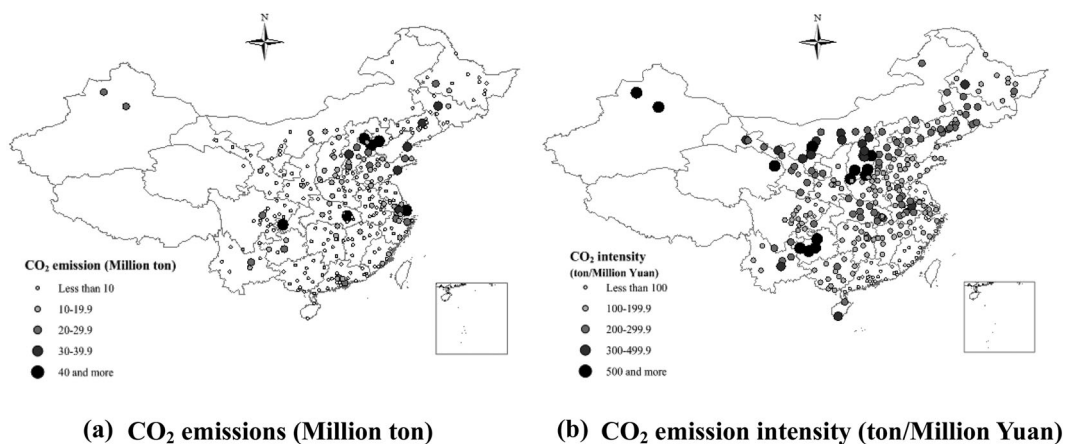


Figure 1. Average Annual CO₂ Emissions and Emission Intensity in 287 Cities during 1998 and 2009.

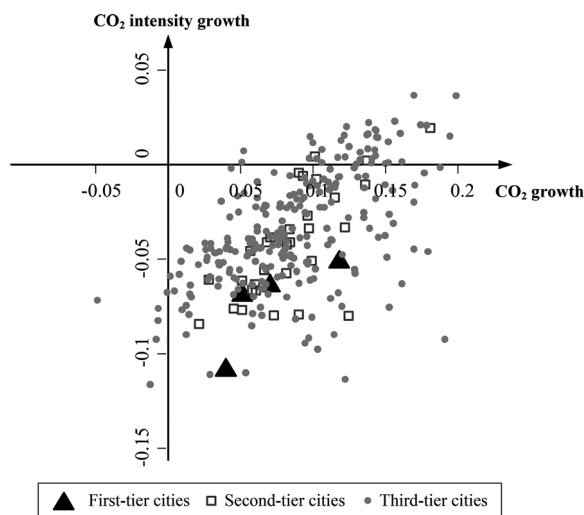


Figure 2. Annual Industrial CO₂ Emissions Growth and CO₂ Emission Intensity Growth in 287 Cities.

3.3 Decomposition Patterns

Based on the estimates of X_{kit} , θ_{kit} , e_{kit} , we employ Equation (4) to conduct the decomposition. We are able to calculate the CO₂ emission numbers (in levels), and its growth rates (in differences), as well as the three decomposed effects within the differences, by sub-sector by city by year. We are also able to aggregate those numbers to provincial and national levels.

Figure 1(a) illustrates the average annual industrial CO₂ emissions in 287 cities during this 12-year period. We can see significant spatial variation. Large cities, especially the four first-tier cities, emit the most CO₂. Figure 1(b) shows the average annual CO₂ emissions per value added (in Yuan). This CO₂ emission intensity also varies a lot across different cities. However, Figure 2 clearly shows that this

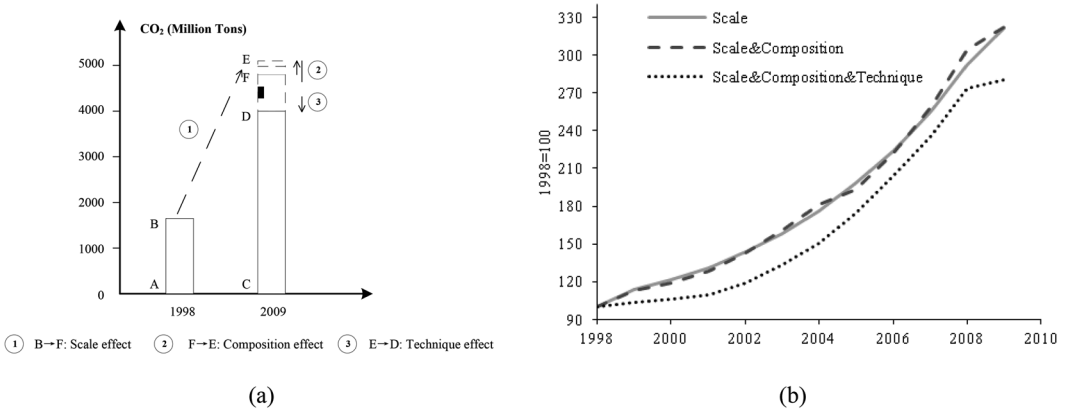


Figure 3. Decomposition Results for Industrial CO₂ Emissions at the National Level.

intensity has a clear declining trend over time in most cities, attributed to both composition and technique effects. According to our calculation, two first-tier cities, Shanghai and Beijing, rank at the very top places in terms of total CO₂ emissions because of the size of their economies; Urumqi and Xining are among the highest CO₂ emission intensity cities due to the large share of heavy industries in their economies. The annual industrial CO₂ emissions per capita for all cities during the sample period is 2.5 tons, which is 3.4 times as many as the annual residential CO₂ emissions per capita (Zheng *et al.*, 2010). The industrial sector dominates the urban CO₂ emissions in China.

Figure 2 depicts the positions of the 287 cities in terms of their annual growth rates in both total industrial CO₂ emissions (*X* axis) and CO₂ emission intensities (*Y* axis). The annual growth rate of industrial CO₂ emissions during this 12-year period is 9.3% for all cities, and 7.4%, 8.9% and 9.4% for the first-tier, second-tier and third-tier cities, respectively. These figures are lower than a recent all sector forecasting exercise by Auffhammer and Carson (2008) based on population projections, which did not account for recent policy intervention and other potential local determinants. Our estimates at the disaggregated city level show that, a large portion of cities locate in the fourth quadrant, enjoying a decline in CO₂ emission intensity (composition and technique effects) but experiencing rising industrial CO₂ emissions due to the sizable scale effect. The first-tier cities are all in the fourth quadrant, and they are among the cities with the fastest declining CO₂ emission intensity. Most of the second-tier cities are also in the fourth quadrant, and they locate at the upper right of first-tier cities, which indicates a relatively higher CO₂ emission growth rate but a slower CO₂ emission intensity decline compared to the first-tier cities. A large share of the third-tier cities are also in the fourth quadrant, while a small number of cities locate in the first quadrant with growth in both CO₂ emission and its intensity. Shizuishan and Yinchuan (both in Ningxia Province) are the top two cities in terms of total CO₂ emission growth and CO₂ emission intensity growth because of their large share of energy-intensive industries; Beijing ranks at the top in terms of total CO₂ emissions decline, thanks to its successful and ongoing transformation to service industries and the vast technical innovations.

Now we turn to our decomposition results. We first look at the national level numbers. Figure 3(a) illustrates the decomposition results for total industrial CO₂ emissions at the national level. We first look at the changes between the initial and end years. Arrow ① shows that, if we had held the composition of industries and the production technology constant ($\Delta\theta = 0$, $\Delta e = 0$) during this 12-year period, what the size of the total industrial CO₂ emissions would be (the column length between C and F). This scale effect equals to a 221% increase (37 billion tons). Arrow ② measures the composition effect. It is positive,

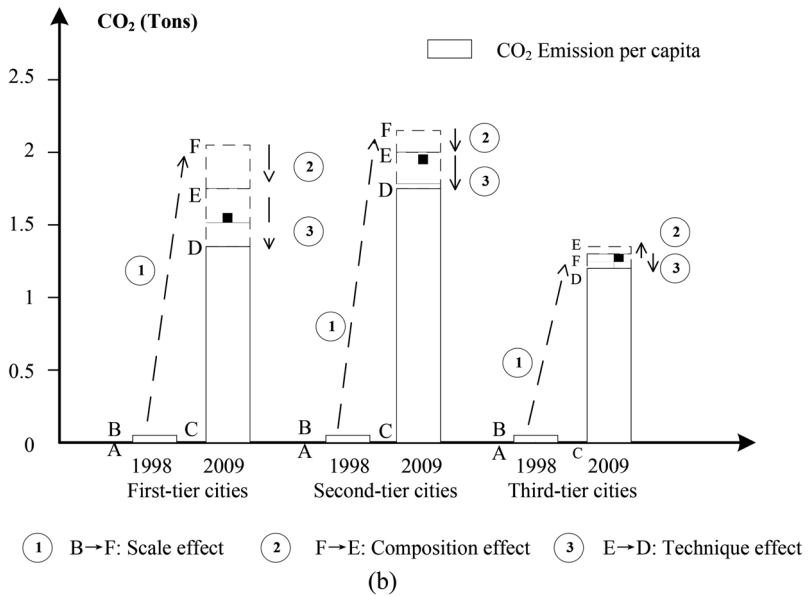
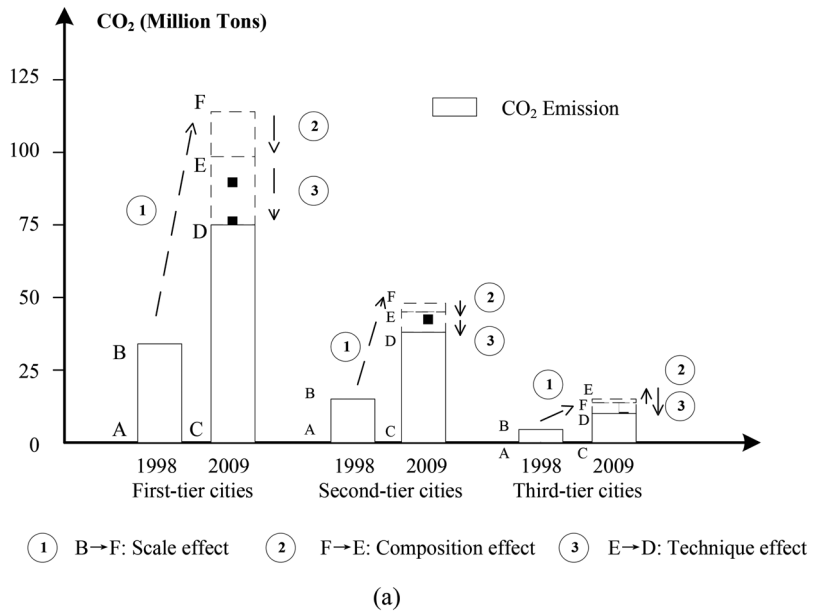


Figure 4. The Decomposition Results of CO₂ Emission across Three Tiers of Cities: 1998 versus 2009.

but the size is small (1.3%, 22 million tons in total and 3.03 tons per value-added million Yuan) due to the mix of negative composition effects in some cities but positive effects in other cities. The column length between C and E is what the CO₂ emissions would be if every industrial activity still used the production techniques from 1998, which combines the scale and composition effects. Arrow ③ indicates the technique effect, which reduces CO₂ emissions. Its size is much larger than that of the composition effect, with contributing to a 41% decrease (690 million tons in total and 97.5 tons per value-added million Yuan) in CO₂ emissions from China's urban industrial sector.

Figure 3(b) plots these three effects at the national level in each of the 12 years. The solid line depicts the pure scale effect (the would-be CO₂ emissions in each year if all industries keep the same shares and the same production technology as those in 1998). The middle dashed line plots what CO₂ emissions would be in each year if every industrial activity used the original production technique in 1998 (the combination of both scale and composition effects). The gap between the middle dashed and the solid lines shows that the composition effect has led to a smaller change in CO₂ emissions between 1998 and 2007 with somewhat rising CO₂ emissions in the last two years. The bottom dashed line depicts CO₂ emissions when considering all three decomposed effects, so this measures the real CO₂ emissions in every year. The gap between this line and the middle dashed line reveals that the technique effect always works to reduce carbon dioxide emissions over time.

For the purposes of this paper we are more interested in the city-level industrial CO₂ emissions dynamics. Figure 4(a) shows some interesting patterns in these dynamics. We find the three effects play different roles at the three tiers of cities. The scale effect contributes to the rise of CO₂ emissions in all three tiers of cities. The absolute value of this effect is the largest for the first-tier cities and the smallest for the third-tier cities. The technique effect universally leads to the reduction of CO₂ emissions for all three tiers, indicating that all cities have enjoyed the improvements in both production technology and management quality. At the same time, the composition effect on CO₂ emissions is mild. We find that the composition effect contributes to the rising CO₂ emissions in the third-tier cities, while it reduces CO₂ emissions in the first-tier and second-tier cities. Figure 4(b) shows the dynamic change in CO₂ emission per capita across different tiers of cities between 1998 and 2009. We find that second-tier cities have higher levels of CO₂ emissions per capita than the other two. The decomposition patterns using CO₂ emissions per capita across these three groups of cities are quite similar to those using total CO₂ emission illustrated in Figure 4(a). Our decomposition results suggest that there may be a relocation of those energy-intensive industries from the first-tier and second-tier cities to those third-tier medium- and small-sized cities. In this sense, larger cities enjoy less CO₂ emissions at the expense of the increasing emissions in medium- and small-sized cities, so the domestic 'pollution haven' does exist. Yet this effect appears to be small.

We further examine CO₂ emissions changes over time across these three tiers of cities, respectively (See Appendix B). The results show that the increased CO₂ emissions in the first-tier cities over the past decade is more attributable to the scale effect, but the composition change towards cleaner industries and the technique improvement helps to offset the otherwise much higher CO₂ emissions. The second-tier cities have experienced similar patterns of these three decomposed effects on the change in CO₂ emissions but the contribution of composition effect on emission reduction is smaller than in the first-tier cities. In the third-tier cities only the technique effect works to reduce CO₂ emissions, but both the scale and composition effects work to increase emissions.

4. The Impacts of FDI and Environmental Regulations on Scale, Composition and Technique Effects

Using the results from Section 3.2.1.3, we are able to examine the impacts of FDI and environmental regulations on these three decomposed effects, and thus gain a better understanding of the underlying mechanisms why such impacts are heterogeneous across cities.

Table 1. Cross-City Variations in FDI, Industrial Electricity Price and Waste Water Treatment Fee.

	(1)	(2)	(3)	(4)
	The ratio of FDI to GDP	Industrial electricity price (RMB/KWH)	Industrial waste water treatment fee (RMB/ton)	Environmental Regulation Index (ERI) (1998–2009)
First-tier cities	0.85%	0.46	1.14	0.37
Second-tier cities	0.58%	0.34	0.83	0.31
Third-tier cities	0.29%	0.35	0.52	0.26

4.1 FDI Measures and Proxies for Environmental Regulation Intensity

4.1.1 FDI and Its Instrumental Variable

We use the ratio of annual foreign direct investment (FDI) in a city's total GDP as the proxy for a city's participation in global trade, which of course is a strong assumption. The city-level data sets on FDI and GDP are from the China's Urban Statistical Yearbooks in the corresponding years. Column (2) in Table 1 illustrates the average ratios of FDI in total GDP for three tiers of cities, respectively. The first-tier cities have received much more FDI compared to the other two tiers of cities.

When examining the impact of FDI on energy and environmental indicators, a typical challenge a researcher faces is the endogeneity arising from possible reverse causality. If those Chinese cities with more energy-intensive industries impose more regulations and if FDI flows to less regulated areas, then FDI will be pushed to less energy-intensive cities and the OLS estimate will be biased toward finding that FDI lowers CO₂ emissions. Conversely, if some cities are clean as they impose more regulation, the OLS estimate will be biased toward finding that FDI increases CO₂ emissions (Keller and Arik, 2002). Therefore, we use an IV strategy to overcome this endogeneity issue. Following Zheng *et al.* (2010), we take advantage of the regional favoritism exhibited by China's government to construct the instrumental variables. Cities on the coast, especially those close to major ports, receive favorable 'open-door' development policies from the central government and this encourages greater FDI to flow to these cities. Therefore, we use a city's distance to the closest major port as IV for our FDI measure. This variable is time-invariant so we can only use this to explain the spatial variation in FDI inflows.

4.1.2 Proxies for Environmental Regulations

To measure local officials' effort in regulating pollution associated with CO₂ emissions, we develop an Environmental Regulation Index (ERI) by combining two observable regulation tools at the city level. One is related to the differentiated industrial electricity pricing across cities. In China, as a legacy of communism, the central government has used its power to control energy prices (Tan and Frank, 2009). However, recently the central government is increasingly willing to allow energy prices to fluctuate and decentralize the energy pricing power to the local level, which enables local governments to use energy prices as a policy tool to attract or regulate energy- and pollution-intensive industries. We collect the price of electricity for industrial usage across provinces from China's Price Yearbooks in the corresponding years.¹¹ As shown in Column (3) of Table 1, there is big variation in the electricity price across the three tiers of cities. The other is the industrial sewage treatment fee that firms have to pay. Lan *et al.* (2011) use this measure to proxy for the stringency of local governments' pollution regulation. The data on

industrial sewage investment is collected from China's Urban Statistical Yearbooks in the corresponding years. Column (4) in Table 1 illustrates the industrial sewage treatment fees in the unit of RMB/ton. The data reveals that first-tier cities in China are likely to put more investment on industrial sewage treatment than the other two groups of cities.

Calculating *ERI* begins with transforming two city-level environmental regulation indicators, electricity price changes (*EPC*) and industrial waste water treatment fee (*IWWTF*), to two standardized and comparable performance scores ranging from 0 to 1 ($SCORE_{EPC}$ and $SCORE_{IWWTF}$), respectively. *ERI* for city k is then calculated by averaging the two standardized scores of these two indicators in city k :

$$ERI_k = (SCORE_{EPC,k} + SCORE_{IWWTF,k})/2 \quad (5)$$

In Equation (5), $SCORE_k = (Z_k - L)/(H - L)$, in which H is the highest level of the indicator, L is the lowest level of the indicator and Z_k is the value of the indicator for city k .

Column (5) in Table 1 presents the *ERI* across cities. It is found that first-tier cities have higher *ERI* values than that of the other two groups of cities, which is consistent with the statistics of the two individual indicators in Column (3) and (4).

4.2 Estimation Results

We examine the effects of these local factors on the change in carbon dioxide emissions and its three decomposed components using China's city-level data between 1998 and 2009 via a reduced form approach. Equation (6) is in the form of first-difference because the three decomposed effects are with respect to the changes in CO₂ emissions. The first-difference specification also enables us to drop out city-level time-invariant unobservables. We also include regional fixed effects to control for region-specific trend in CO₂ emissions changes.

$$\Delta Y_k = \alpha_0 + \alpha_1 \cdot \Delta \ln(FDI_k) + \alpha_2 \cdot ERI_k + \mathbf{X} \cdot \boldsymbol{\beta} + r_k + \varepsilon_k \quad (6)$$

We have four versions of the dependent variable ΔY_k , including the total changes in CO₂ emissions from 1998 to 2009, as well as three decomposed components in city k ; ΔFDI_k is the change in the share of total GDP for city k between 1998 and 2009; ERI_k is city k 's environmental regulation index; \mathbf{X} is vector of control variables including the changes in GDP, share of secondary industry in GDP and share of tertiary industry in GDP; r_k is regional fixed effects¹² and ε_k is the error term.

Table 2 reports the OLS estimation results and Table 3 provides those with FDI being instrumented with the distance to the closest port. Firstly, we look at the estimated coefficients of the change in our FDI measure (FDI to GDP ratio) using OLS. The coefficient is negative and significant at the 1% level, suggesting that the inflow of FDI pulls down energy intensity and thus CO₂ emissions. Specifically, a 10% increase in the FDI to GDP ratio contributes to a 1.74 percentage point decrease in CO₂ emissions. As for the three decomposed effects, the estimated coefficient of the change in the FDI measure the technique effect is significantly negative, while the estimates on the other two effects are insignificant. These suggest that the inflow of FDI works on pollution emission more through the technique effect than the scale effect. This justifies why we find the optimistic result that FDI helps a city to reduce CO₂ emissions (and corresponding energy consumption). The underlying reasons may be that FDI brings in cleaner capital, technology and better management skills. As the IV estimation results suggest (see Table 3), the inflow of FDI reduces CO₂ emissions, but with larger magnitudes in terms of its impact on the total CO₂ emission change and the change of the technique component compared with OLS estimates. A 10% increase in the FDI to GDP ratio leads to a 6.89 percentage point decrease in total CO₂ emissions and a 4.31 percentage point decrease in CO₂ emissions due to the technique effect. This finding is consistent with our statistical analysis in Table 1 that the cities with more FDI also impose more regulation on the environment.

Table 2. Effects of FDI and Environmental Regulations on CO₂ Emissions and the Three Decomposed Effects (OLS)

	(1) ΔCO ₂ emissions	(2) Scale effect	(3) Composition effect	(4) Technique effect
ΔLog(<i>FDI</i>)	-0.174*** (0.045)	-0.009 (0.036)	-0.005 (0.011)	-0.053** (0.022)
<i>ERI</i>	-1.981*** (0.473)	-1.191*** (0.338)	-0.262** (0.114)	-0.527** (0.205)
ΔLog(<i>GDP</i>)	1.698*** (0.210)	2.278*** (0.143)	-0.117** (0.0513)	-0.422*** (0.093)
Δ <i>Secondary Industry GDP Share</i>	0.055*** (0.010)	0.032** (0.008)	0.030*** (0.00251)	-0.011 (0.016)
Δ <i>Tertiary Industry GDP Share</i>	0.002 (0.013)	0.0158* (0.009)	0.005 (0.00318)	-0.019*** (0.006)
Constant	-0.217 (0.299)	-0.725*** (0.212)	0.023 (0.0714)	0.442*** (0.128)
Region fixed effects	Yes	Yes	Yes	Yes
Observations	186	186	186	186
R ²	0.603	0.721	0.641	0.329

Note: Standard errors are reported in parentheses, which are clustered by province. **p* < 0.10, ***p* < 0.05, ****p* < 0.01.

Table 3. Effects of FDI and Environmental Regulations on CO₂ Emissions and the Three Decomposed Effects (Using IV for FDI)

	(1) ΔCO ₂ emissions	(2) Scale effect	(3) Composition effect	(4) Technique effect
ΔLog(<i>FDI</i>)	-0.689*** (0.241)	-0.076 (0.435)	0.024 (0.045)	-0.431* (0.231)
<i>ERI</i>	-1.729*** (0.623)	-0.899** (0.405)	-0.269** (0.113)	-0.435 (0.332)
ΔLog(<i>GDP</i>)	1.533*** (0.281)	2.298*** (0.243)	-0.109** (0.053)	-0.502*** (0.155)
Δ <i>Secondary Industry GDP Share</i>	0.057*** (0.014)	0.055*** (0.020)	0.030*** (0.002)	0.001 (0.010)
Δ <i>Tertiary Industry GDP Share</i>	-0.010 (0.018)	0.019 (0.016)	0.005 (0.003)	-0.019** (0.009)
Constant	0.018 (0.495)	-0.425 (0.482)	-0.063 (0.091)	0.669** (0.300)
Region fixed effects	Yes	Yes	Yes	Yes
Observations	186	186	186	186
R ²	0.591	0.738	0.627	0.420

Note: Standard errors are reported in parentheses, which are clustered by province. **p* < 0.10, ***p* < 0.05, ****p* < 0.01.

Table 4. Effects of FDI and Environmental Regulations on CO₂ Emissions in Different Cities (Using IV for FDI)

	(1) ΔCO ₂ emissions	(2) Scale effect	(3) Composition effect	(4) Technique effect
First- and second-tier cities				
ΔLog(<i>FDI</i>)	-1.173 (0.940)	-1.174 (0.815)	-0.090 (0.121)	0.140 (0.192)
<i>ERI</i>	-3.453* (2.090)	-1.394 (1.768)	0.116 (0.270)	-1.473*** (0.503)
Third-tier cities				
ΔLog(<i>FDI</i>)	-0.656** (0.265)	-0.082 (0.349)	-0.024 (0.049)	-0.567** (0.226)
<i>ERI</i>	-1.425** (0.643)	-1.050*** (0.338)	-0.291** (0.115)	-0.145 (0.474)

Note: Standard errors are reported in parentheses, which are clustered by province. Other specifications are same with those of Table 3. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table 3, as expected, the Environmental Regulation Index has a negative impact on industrial carbon emissions. If we look into the three decomposed effects, we can see that stringent environmental regulation works through all three channels – the scale of production drops, the industrial composition shifts towards cleaner industries, and the production technology and management quality also increase (a significant negative technique effect). The magnitudes of the three coefficients suggest that the scale effect dominates this process. The observed composition effect due to the enforcement of environmental regulations is consistent with those in previous studies in the USA such as Berman and Bui (2001a,2001b) and Henderson (1996). As the instrumental variable strategy here is less than perfect due to the lack of time series variation in the instrument, these results should be taken as suggestive.

The estimated coefficients on the other control variables are also consistent with our expectations. Cities with higher GDP growth experience a larger increase in CO₂ emission mainly due to the increases in economic scale, which dominates the changes from cleaner industry composition and more efficient production technology. The growth in the share of secondary industry is found to increase the cities' CO₂ emission through scale and composition effect, while the growth of tertiary industry helps to decrease CO₂ emission by improving production technology.

We are also interested in whether the effect of FDI and environment regulation on CO₂ emissions varies across these three tiers of cities. We estimate Equation (6) separately for the first, second-tier cities and third-tier cities, and the regression results are provided in Table 4. It shows that the change in FDI had insignificant effect on CO₂ emissions in the first and second-tier cities, while it tends to decrease CO₂ emissions in the third tier cities mainly through the technique effect. A possible explanation is that the first- and second-tier cities already have advanced technologies (in our study period) so the marginal effect of FDI is weak; while its marginal effect is much larger in the third tier cities where production technologies stand at a lower level. Stringent environmental regulation is found to contribute to the declining CO₂ emission in all three groups of cities. This mitigation effect is mostly attributed to the technique effect in the first- and second-tier cities, while to the scale and composition effects in the third-tier cities. Our results indicate that the environmental regulation in the first- and second-tier cities helps to promote the adoption of greener production technology, but it constrains the scale expansion and the receipt of dirty industries (relocating from the first and second-tier cities) in the third-tier cities.

5. Conclusions

In 2007, China became the largest greenhouse gas emitter in the world. 85% of China's GHG emissions are attributed to urban economic activities, and this share will continue to increase with China's rapid urbanization process. This paper enriches our understanding of city-level industrial CO₂ emissions in China and its dynamics by decomposing CO₂ emission changes into scale, composition and technique effects over the past decade (all 287 prefecture-level-cities in 1998–2009).

The paper first reviews the literature on the decomposition analysis and several local determinants that shape such dynamics. We then use city-level data in China to decompose the changes in industrial CO₂ emissions into the scale, composition and technique effects. Our estimates show that the industrial CO₂ emissions per capita are about 3.4 times larger than the residential CO₂ emissions per capita in China's urban sector and the industrial CO₂ emissions have been increasing by 9.3% annually during this 12-year period. The decomposition analysis shows that the three effects play different roles in the three tiers of cities. The scale effect contributes to the rise of CO₂ emissions in all cities. On the other hand, the technique effect universally leads to the reduction of CO₂ emissions in all three tiers of cities, indicating that all cities have enjoyed the improvements in both production technology and management quality towards energy efficiency. The composition effect on CO₂ emissions is mild – it contributes to the rising CO₂ emissions in the third-tier cities, while it reduces CO₂ emissions in the first-tier and second-tier cities. These patterns suggest that there may be a relocation of those energy-insensitive industries from the first-tier and second-tier cities to those third-tier medium- and small-sized cities. In this sense, larger cities enjoy less CO₂ emissions at the expense of the increasing emissions in medium- and small-sized cities.

Our decomposition results facilitate us to provide some suggestive evidence as to how FDI inflow and environmental regulations drive the change in CO₂ emissions and its decomposed three effects. It is found that the inflow of FDI pulls down energy intensity and thus CO₂ emissions by generating significant technique effect (and the other two effects are insignificant), so it brings in cleaner production technology and better management quality. The environmental regulations help cities to reduce their industrial CO₂ emissions through all three channels –the economy scale shrinks, the industrial composition shifts towards cleaner industries and the energy-efficient technologies and management skills also improve.

Our empirical results clearly indicate that shifting towards less-energy-intensive industries (composition effect), exploiting 'clean' fuel inputs and fostering technology transfers (technique effect), matter for China in curbing carbon dioxide emissions during its ongoing urbanization and industrial progress. The Chinese government has pledged to wean its economy away from reliance on fossil fuels as it grows. In November 2014, China and the US unveiled new pledges on greenhouse gas emissions. The deal commits China to reducing greenhouse gas emissions after a peak in 2030 (and ideally sooner). China also aims to have non-fossil fuels make up 20% of its primary energy consumption by 2030. It is the first time China, the world's largest emitter by far in absolute terms (roughly 28% of the world's CO₂ emissions in 2014), has agreed to set a ceiling, albeit an undefined one, on overall emissions. To achieve this goal, the central government in China will come up with ways of incentivizing local officials to go green, and city mayors will make their own trade-off between their economic growth (scale), and environmental goals (economic restructure and technology improvements). The decomposition framework in our paper can help policy makers and scholars to observe such trade-offs and the underlying rationales.

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Notes

1. Source: China Textile Industry Development Report 2010–2011. Published by China Textile & Apparel Press, 2011.
2. ‘Consumption of Energy by Sector (2011)’, National Bureau of Statistic of China, accessed October 14, 2014, <http://www.stats.gov.cn/tjsj/ndsj/2013/indexeh.htm>
3. ‘Consumption & Efficiency’, U.S. Energy Information Administration, accessed October 14, 2014, <http://www.eia.gov/consumption/>
4. See ‘Trends in Global CO₂ Emissions 2014 Report’, available on http://edgar.jrc.ec.europa.eu/news_docs/jrc-2014-trends-in-global-co2-emissions-2014-report-93171.pdf
5. We refer to the aggregation in two levels, industries and sector. In China, the whole economy is often divided into three industries, the primary, secondary and service industries. The secondary industry includes three sectors, Mining, Manufacturing, Electric Power-Gas-and-Water (EGW), and Construction Sector. The service industry includes three sectors, Transportation, Storage, Post and Telecommunication Services Sector (TSPTS), Wholesale, Retail, and Accommodation, Catering Sector (WRTCS), and Others Service Sector. The sectors of Mining, Manufacturing, and EGW are further disaggregated into 6, 30 and 3 sub-sectors, respectively.
6. See Brandt *et al.* (2012).
7. See footnote 5 for details.
8. Other energy includes those such as wind and solar energy that does not generate pollution emissions.
9. We convert the two secondary energy types, electricity and heating power, into the corresponding fossil fuels that generate them on the basis of the provincial energy balance tables.
10. The calculation of TFP for manufacturing firms is done according to the method in Brandt *et al.* (2012). For non-manufacturing firms we consider labor productivity as an alternative of TFP due to data limitations.
11. China’s Price Yearbooks provide annual the price of electricity at the provincial level for different kinds of usage such as industrial use and residential use.
12. Cities are divided into seven regions: North China, Northeast China, East China, Central China, South China, Southwest China and Northwest China.

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Appendix A

List of 44 Sectors/Subsectors

No.	Name of industry sector	No.	Name of industry sector
1	Agriculture, forestry, animal husbandry and fishery, water conservation	23	Chemical fiber
2	Coal mining and dressing	24	Rubber production
3	Petroleum and natural gas mining	25	Rubber production
4	Ferrous metals mining and dressing	26	Nonmetal mineral production
5	Nonferrous metals mining and dressing	27	Smelting and pressing of ferrous metals
6	Nonmetal minerals mining and dressing	28	Smelting and pressing of nonferrous metals
7	Others mining and quarrying	29	Metal production
8	Agricultural and sideline products processing	30	Equipment in common use
9	Food manufacturing	31	Special purpose equipment
10	Soft drinks manufacturing	32	Transport equipment
11	Tobacco processing	33	Electric equipment and machinery
12	Textile industry	34	Telecommunications, computer and other electronic equipment
13	Garments and apparel industry	35	Instruments, meters, cultural and clerical machinery
14	Leather, furs, down and related production, shoes manufacturing	36	Handicraft article and other manufacturing
15	Timber processing, bamboo, cane palm fiber and straw production	37	Waste resources and materials recovering
16	Furniture manufacturing	38	Production and supply of electricity and heating power
17	Papermaking and paper production	39	Production and supply of gas
18	Printing and record medium reproduction	40	Production and supply of water
19	Cultural and educational, arts and crafts, sports and entertainment	41	Construction sector
20	Petroleum processing, coking and nuclear fuel processing	42	Transportation, storage and postal services sector
21	Raw chemical materials and chemical production	43	Wholesale, retail and accommodation, catering sector
22	Medical and pharmaceutical production	44	Other service sectors

Note: #1 sector belongs to the primary industry, #2–7 are mining sectors, #8–37 are manufacturing sectors, #38–40 are electric power-gas-and-water sectors, #42–44 sectors belong to service industries.

Appendix B

Decomposition Effects of CO₂ Emissions for Three-Tier Cities from 1998 to 2009

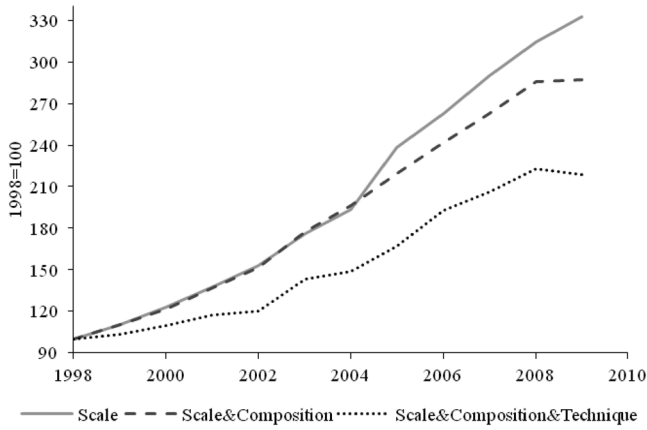


Figure A1. Decomposition Effects of CO₂ Emission for First-Tier Cities from 1998 to 2009.

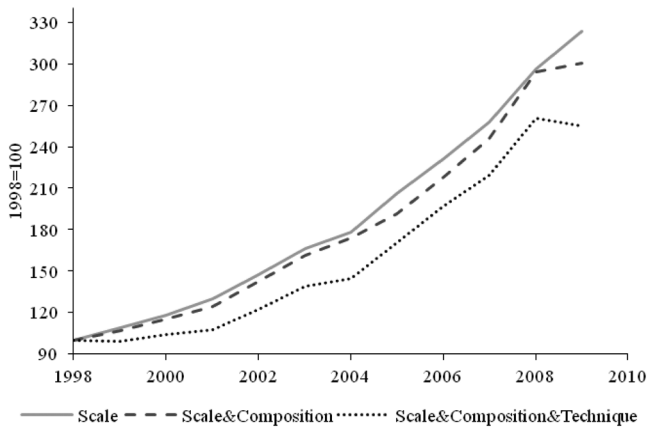


Figure A2. Decomposition Effects of CO₂ Emission for Second-Tier Cities from 1998 to 2009.

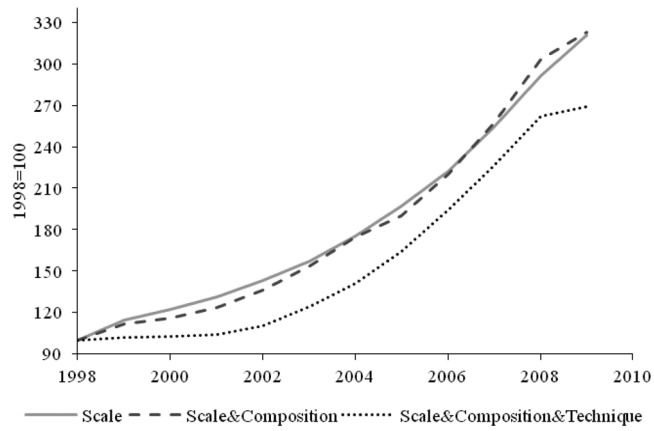


Figure A3. Decomposition Effects of CO₂ Emission for Third-Tier Cities from 1998 to 2009.