



# Is economic rebalancing toward consumption “greener”? Evidence from visibility in China, 1984–2006



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## ABSTRACT

**Li, Zhigang, Yuan, Jia, Song, Frank, and Wei, Shangjin**—Is economic rebalancing toward consumption “greener”? Evidence from visibility in China, 1984–2006

The Chinese government has adopted a rebalancing strategy since 2011, shifting from an investment- to consumption-oriented growth model. An aim of this reform is for a “greener” development mode, but relevant empirical evidence is slim. In this study, we propose an innovative methodology to shed light on the environmental externalities of economic rebalancing. First, we use air visibility across China to reflect air quality during 1984–2006. Second, with the daily visibility data, we propose a weekend-effect regression model to difference out city-specific unobserved heterogeneity. Third, we approximate local consumption intensity with the portion of the residential electricity usage in the total electricity usage. To our surprise, the estimates suggest that the pollution intensity of consumption activities has not only been significant, but also exceeded that of production since the mid-1990s. Hence, rebalancing toward consumption is not necessarily more environmentally friendly according to the recent development experience of China. *Journal of Comparative Economics* 42 (4) (2014) 1021–1032. Southwestern University of Economics and Finance, Chengdu, China; University of Macau, Macau, China; University of Hong Kong, Hong Kong Special Administrative Region; Columbia University, USA.

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## 1. Introduction

After over six decades of investment-driven growth, China has become the second largest economy in the world and the most polluted nation, with severe health consequences (Chang et al., 2001; Peng et al., 2002; Brajer and Mead, 2004, 2005; Ebenstein, 2008). In a recent research, Chen et al. (2013) find that the life expectancy of the Chinese in northern China has been reduced by five years due to the severe air pollution. In 2011, Chinese authorities officially announced a rebalancing strategy in its 12th Five-year Development Plan, which marked the start of the transition toward a consumption-driven growth mode. The rationale underlying this reform is to improve the livelihood of people and achieve an environmentally

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friendly growth model. Given the economic scale and the population of China, this change in growth strategy is likely to have profound environmental externalities for China, as well as the rest of the world. However, it is unclear whether consumption-driven growth is necessarily “greener” than the current one.<sup>1</sup> If anything, air quality appears to be a much more serious issue in the major cities of China, especially Beijing and Shanghai, where the economy has effectively rebalanced and is now driven by consumption rather than investment. Unfortunately, relevant empirical evidence is slim.<sup>2</sup>

In this study, we aim to shed light on the environmental externalities of the economic rebalancing. Our evidence cautions the naïve belief of consumption-intensive growth as a “greener” mode. Specifically, two alternative econometric models are considered. The first model estimates a city-year panel-data model of the relationship between air quality and local consumption intensity (approximated by the portion of residential electricity in the total electricity usage). Model estimates suggest that the pollution intensity of consumption activities may have exceeded that of production since the mid-1990s. In other words, rebalancing toward consumption would not alleviate the pollution problem of China. In the second model, we exploit an exogenous variation – people reduce working on the weekend – to utilize the change in the air quality from weekdays to weekends to eliminate city-specific unobserved heterogeneity. The policy change from six-working-day to five-working-day during 1994–1995 further provides another quasi-experimental opportunity to verify the weekend effect model. By exploiting the variations of consumption and production on the weekend, our findings confirm that consumption has been “dirtier” than production in Chinese cities since the mid-1990s. Taken together, the bottom line of the current research findings is that rebalancing is not necessarily environmentally beneficial to China.

Related literature on the pollution of consumption activities is slim, although a large body of studies has examined the association between economic growth and pollution (see [Copeland and Taylor, 2004](#) for a review of the literature). Existing studies have mainly relied on accounting instead of an econometric approach. The Inventory of New York City [Greenhouse Gas Emissions \(2007\)](#) calculated that just under half of the carbon dioxide (CO<sub>2</sub>) emissions in New York City are generated by consumption. In North Carolina, between 35% and 54% of the mercury emissions are by-products of consumption, according to the 1998–1999 Division of Air Quality (DAQ) and Local Program Emissions Inventories. Due to data constraints, evidence for other economies is much sparser and cruder. [Gopalakrishnan \(1997\)](#) suggests that consumption generates at least 34% and as much as 52% of the air pollution in Kolkata (Calcutta), India. [Munksgaarda et al. \(2000\)](#) use a decomposition approach to infer that pollution from consumption can explain most of the pollution increase in the Netherlands since 1960. [Almond et al. \(2009\)](#) provide important evidence showing that the Chinese energy consumption of winter heating has been an important source of air pollution in China. The most closely related work to this study is that by [Davis \(2008\)](#), which estimates the effect of driving restrictions (one week day per week) on air quality in Mexico City, but finds little effect.

In the past, a key hindrance to studying the environmental quality in China is the lack of data. Pollution data that are comparable across different cities of China are available at a highly limited scale to the public. Even if data are available for certain cities, the data quality is unclear given the incentive for local governments to manipulate the data. To address this issue, we propose to use an unconventional indicator, which is air visibility, to reflect the aerosol environment of China. Compared with direct measures of air pollution, air visibility is noisier as it is affected by other non-pollution factors, such as weather conditions. Nevertheless, the close link between visibility and airborne pollutants has been well established in the scientific literature ([Malm, 1999](#)).<sup>3</sup> Moreover, the use of air visibility has several major advantages, without which our study would be infeasible with the official pollution data available. First, observatories that record visibility are spread across China, and cover all of the major cities. Second, visibility records are available for the whole post-reform period of China. Third, visibility is reported daily, which makes it possible to provide more rigorous estimates by eliminating city-specific unobserved confounding factors. Moreover, daily data also allow us to utilize a natural experiment to achieve identification: the weekend policy changed during 1994–1995, from a six-working-day to a five-working-day week.

The structure of the paper is as follows. In Section 2, we first demonstrate the relevance of visibility to air pollution and the empirical methodology. In Section 3, we summarize the data used in the study and the preliminary empirical patterns. In Section 4, the empirical findings are reported and discussed. The last section concludes.

<sup>1</sup> Studies available mainly estimate the reduced-form linkage between aggregate GDP per capita and pollution, without distinguishing between consumption and production ([Groot et al., 2004](#); [Shaw et al., 2004](#); [He, 2005](#); [Shen, 2006](#)).

<sup>2</sup> In theory, consumption- and investment-led growth modes have distinctive environmental implications. [Copeland and Taylor \(1995\)](#) were among the first to point out the importance of distinguishing these two kinds of pollution in economic analysis. They theoretically demonstrate this in a trading context: unlike production, consumption cannot easily migrate to countries with weaker environmental standards. Furthermore, [Hatzipanayotou et al. \(2007\)](#) and [Michael et al. \(2008\)](#) show in theory that the differential pollution intensity of production and consumption affects the design of optimal tax policies. Other relevant studies include that by [Perrings and Ansuategi \(2000\)](#), which study the economic implications of consumption-generated pollution. Abstracting from tax revenue considerations, [Beghin et al. \(1997\)](#) examine the welfare implications of environmental, production, consumption, and trade tax policy reforms. By constructing a reciprocal dumping model with consumption generated pollution, [Kayalica and Kayalica \(2005\)](#) demonstrate that a revenue neutral reform that increases consumption taxes and reduces tariffs is strictly Pareto improving.

<sup>3</sup> Atmospheric researchers have conducted some studies to show the linkage between visibility and air pollutants in several localities of China. [Lee and Sequeira \(2001\)](#) and [Wang \(2003\)](#) provide detailed evidence on the relationship between visibility and airborne pollutants in Hong Kong. [Qiu and Yang \(2000\)](#) examine seasonal patterns of visibility in five cities in north China. [Cheung et al. \(2005\)](#) and [Deng et al. \(2008\)](#) study the relationship between visibility and airborne pollutants in the Pearl River Delta of China. [Rosenfeld et al. \(2007\)](#) use visibility as a proxy for air pollution to study its relationship with precipitation. [Du et al. \(2013\)](#) is another study that uses visibility to reflect air pollution in China.

## 2. Empirical methodology

In this section, we discuss in detail our empirical approach, including the measurement of air quality and consumption intensity, as well as regression models.

### 2.1. Modeling visibility

Air visibility refers to “the greatest distance at which an observer can just see a black object viewed against the horizon sky” (Malm, 1999). It is determined by the density of particles (e.g. black carbon) and gases (mainly nitrogen dioxide (NO<sub>2</sub>)) in the atmosphere. The sources of these aerosol matters can be human-made or natural. They reduce visibility by scattering and absorbing light.<sup>4</sup> Hence, higher level of air pollution means higher particle density and lower air visibility. By following the meteorological literature (e.g., Malm et al., 1994; Watson, 2002; Wang, 2003), the inverse of visibility may be modeled as a linear function of the density of particles and gases. For example, the Interagency Monitoring of Protected Visual Environments (IMPROVE) project models the inverse of visibility as a linear function of sulfate, nitrate, organics, light-absorbing carbon, soil, and coarse mass (Malm et al., 1994). By following this literature and in consideration of our research question, we model the inverse visibility with the following parsimonious form:

$$\frac{K_i}{V_{it}} = (\theta_1 C_{it} + \theta_2 P_{it} + n_{it})^\eta f(w_{it}). \tag{1}$$

The ratio  $k_i/V_{it}$  is the “light extinction coefficient” (as defined in the meteorological literature) at site  $i$  and time  $t$ . The variable  $k_i$  captures the effect of the invariant factors of visibility at site  $i$ , such as the bias of the measurement instrument(s). Visibility is affected by the density of aerosols, and we classify their sources into three categories: consumption (measured by aggregate consumption  $C_{it}$ ), non-consumption economic activities, such as production (measured by  $P_{it}$ ), and nature (represented by  $n_{it}$ ). The parameters  $\theta_1$ ,  $\theta_2$ , and  $\eta$  determine the pollution intensity of consumption, production and other factors. As weather conditions (e.g., humidity) can affect visibility given the same level of pollution, we approximate their effect by using a function  $f(\cdot)$  of the relevant weather conditions  $w_{it}$ . We then multiply this weather effect with the mass of aerosols.

By simple rearrangement, we can rewrite (1) into the following functional form which only uses consumption and total output  $Y_{it}$  ( $=C_{it} + P_{it}$ ) as follows:

$$\frac{K_i}{V_{it}} = ((\theta_1 - \theta_2)C_{it} + \theta_2 Y_{it} + n_{it})^\eta f(w_{it})$$

One could estimate model (1) directly through non-linear regression techniques, but it involves technical complications. Moreover, as  $C$  and  $Y$  are typically highly correlated, multicollinearity issue may generate sensitive estimates. To circumvent these issues, we take the logarithm of both sides of the equation and simplify model (1) as follows (through a first-order approximation based on Taylor expansion):

$$-\ln(V_{it}) = -\ln(K_i) + \eta \ln(\theta_2) + \eta \ln(Y_{it}) + \eta \frac{\theta_1 - \theta_2}{\theta_2} \left(\frac{C_{it}}{Y_{it}}\right) + \eta \frac{n_{it}}{\theta_2 Y_{it}} + \ln[f(w_{it})]. \tag{2}$$

This model implies the following empirical specification, which can be estimated with a linear least square estimator:

$$-\ln(V_{it}) = \beta_0 + \beta_1 \ln(Y_{it}) + \beta_2 \left(\frac{C_{it}}{Y_{it}}\right) + \beta_3 \left(\frac{1}{Y_{it}}\right) + \beta_4 \ln(humid_{it}) + \beta_5 \ln(temp_{it}) + \beta_6 \ln(wind_{it}) + \alpha_i + \varepsilon_{it}. \tag{3}$$

Here,

$$\begin{aligned} \beta_0 &= -\ln(k_i) + \eta \ln(\theta_2) \\ \beta_1 &= \eta \\ \beta_2 &= \eta \frac{\theta_1 - \theta_2}{\theta_2} \\ \beta_3 &= \eta \frac{n_{it}}{\theta_2} \end{aligned}$$

Eq. (3) reveals how pollution is affected by both economic size and the structure of the economy in terms of consumption share  $C/Y$ . In particular, the coefficient  $\beta_2$  provides a direct measure of the impact of the rebalancing policy. If  $\beta_2$  is positive, then  $\theta_1 > \theta_2$ . In other words, the pollution intensity of consumption is higher than that of production. This thus suggests that even if the economy has shifted from an investment-driven to a consumption-based one, the environment still does not necessarily become greener. We control for three weather conditions – humidity, temperature, and wind speed – which can affect visibility (Malm, 1999). Site-specific fixed effects can be further included into the model. The coefficients are consistently estimated if the error term is uncorrelated with the regressors.

<sup>4</sup> Aerosol refers to particles and the gas together. The light scattering of particles is produced by a wide range of aerosol compositions, whereas the light absorption of particles is only due to elemental carbon. Gas absorption is mainly due to NO<sub>2</sub> and gas scattering is mainly carried out by molecular oxygen and nitrogen. Normally, particles dominate gases in determining visibility (Adams et al., 1990; Eidels-Dubovoi, 2002).

A key issue that hinders the estimation of Model (3) is the lack of information on the consumption intensity at the city-level in China. The Bureau of Statistics only releases the decomposition of GDP at the national level. To address this issue, we propose a proxy in this study: the city-level ratio of residential electricity usage over the total electricity usage. The rationale is straightforward: in a more consumption-intensive economy, spending by residents on electronic products tends to be higher relative to industrial electricity usage. As we do not control for other measures of consumption activities in the regression, such as the usage of private vehicles, the residential electricity usage ratio is actually a proxy for the general consumption-share of an economy.

Another concern of the empirical model is that the analysis and the regression results may be sensitive to the specific functional form of Eq. (3), which is derived from the theory setup. To address this concern, in the following regressions, we also adopt a more flexible functional form to examine the robustness of the results as follows:

$$-\ln(V_{it}) = \beta_0 + \eta \left( \frac{C_{it}}{Y_{it}} \right) + \beta_1 \ln(Y_{it}) + \beta_2 \ln(Y_{it})^2 + \beta_3 \ln(Y_{it})^3 + \lambda_1 \ln(\text{humid}_{it}) + \lambda_2 \ln(\text{temp}_{it}) + \lambda_3 \ln(\text{wind}_{it}) + \alpha_i + \varepsilon_{it} \quad (3a)$$

All the notations here are the same as (3), except that the functional form is more general in the current model. If desired, a higher order of  $\ln(Y_{it})$  can be used to address the flexibility issue. The empirical section will show that the regression results are robust and do not depend on the specific functional form of the regression.

## 2.2. A weekend-effect model

In this section, we propose a simple weekend-effect model, which can be estimated if daily data on visibility are available. This approach has two advantages. First, similar to the fixed-effect model (3), the comparison of weekend and weekday visibilities can difference out site-specific unobserved heterogeneity, such as systematic measurement errors. Second, the estimating of weekend effects can take advantage of the high frequency of data to significantly expand the regression sample size, thus making our estimates more precise.

This approach is illustrated as follows. Suppose that consumption on the weekend increases to  $\lambda_1$  of the weekday level ( $\lambda_1 > 1$ ). In contrast, the total economy on the weekend changes to a share,  $\lambda_2$ , of the weekday level ( $0 < \lambda_2 < \lambda_1$ ).<sup>5</sup> The time index  $t$  indicates day  $t$ . Consider the first case in which  $t$  is a weekend day and  $t - 1$  is the weekday just before the weekend. The first-difference of Eq. (3) gives:

$$-\Delta \ln(V_{it}) = \gamma_0 + \gamma_1 \left( \frac{C_{it}}{Y_{it}} \right) + \gamma_2 \left( \frac{1}{Y_{it}} \right) + \beta_4 \Delta \ln(\text{humid}_{it}) + \beta_5 \Delta \ln(\text{temp}_{it}) + \beta_6 \Delta \ln(\text{wind}_{it}) + \Delta \varepsilon_{it}. \quad (4)$$

where

$$\gamma_0 = \beta_1 \ln(\lambda_2), \quad (5)$$

$$\gamma_1 = \beta_2 \left[ \left( \frac{\lambda_1}{\lambda_2} \right) - 1 \right], \quad (6)$$

and

$$\gamma_2 = \beta_3 \left[ \left( \frac{1}{\lambda_2} \right) - 1 \right]. \quad (7)$$

The model suggests that the change in the air quality on the weekend is affected by the local economic structure well as the change in the weather conditions. Similar to  $\beta_2$  in Model (3),  $\gamma_1$  reflects the effect of consumption on air quality relative to that of production.<sup>6</sup> A positive  $\gamma_1$  suggests that the pollution intensity of consumption is higher than that of production. It also suggests that even if the economy has shifted from an investment-driven into a consumption-based one, the environment still does not necessarily become greener.

To make Model (4) estimable, we introduce a dummy variable, which is zero for weekdays and one for weekends, and include its full interaction with the residential electricity share and with the inverse of total electricity usage. Formally, we consider the following model, in which  $W_t$  is the dummy variable for the weekend:

$$-\Delta \ln(V_{it}) = \chi_0 + \gamma_0 W_t + \chi_1 \left( \frac{C_{it}}{Y_{it}} \right) + \gamma_1 \left( \frac{C_{it}}{Y_{it}} \right) W_t + \chi_2 \left( \frac{1}{Y_{it}} \right) + \gamma_2 \left( \frac{1}{Y_{it}} \right) W_t + \beta_4 \Delta \ln(\text{humid}_{it}) + \beta_5 \Delta \ln(\text{temp}_{it}) + \beta_6 \Delta \ln(\text{wind}_{it}) + \Delta \varepsilon_{it}. \quad (8)$$

<sup>5</sup> We assume that, on the weekend, consumption activities increase, while production activities are moderated. Therefore, the aggregate economy share change  $\lambda_2$  should be smaller than  $\lambda_1$ .

<sup>6</sup> The sign of  $\gamma_1$  is the same as  $\beta_2$  as  $\lambda_2 < \lambda_1$ .

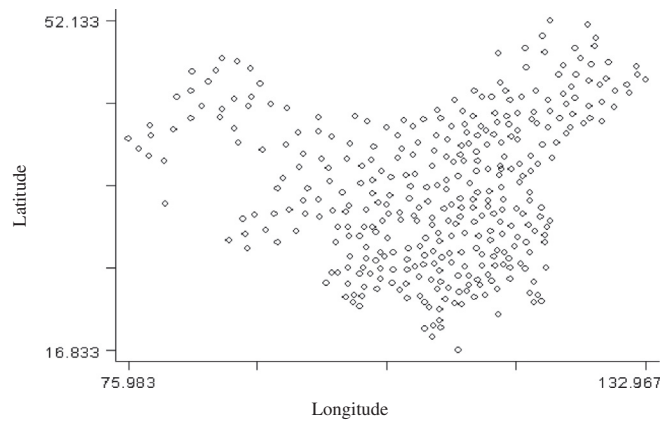


Fig. 1. Sampled observatories spread across China.

To address the concern that regression results may be sensitive to the specific functional form of Eq. (8), we follow (3a) and replace  $1/Y$  with  $\ln(Y_{it})$  to examine the robustness of the results. The empirical section will show that the regression results are robust and do not depend on the specific functional form of the regression.

### 2.3. A natural experiment

The weekend policy in China underwent structural changes in the mid-1990s. China had six working days (Monday through Saturday) until June 1994, when the policy shifted to five and a half working days. Shortly afterwards (May 1, 1995), China further reduced the number of working days to five, and both Saturday and Sunday became the weekend.

This change in the weekend policy offers a quasi-experimental opportunity to identify the causal effect of the weekend on air quality. Specifically, we expect the effect of Saturday on the air quality to be insignificant before 1995, but should become significant after 1995.

## 3. Data and preliminary patterns

Data for this study are separated into two parts: data on the weather conditions and on the local consumption–production structure.

### 3.1. Visibility

The data used in this study are obtained from the National Climatic Data Center maintained by the U.S. Department of Commerce. The data contain daily measures of main weather indicators at 1005 weather stations across China (Fig. 1 plots the location of the stations according to their longitudes and latitudes, thus showing the shape of mainland China). The time periods covered vary for different stations; 357 stations cover the entire period from 1984 to the end of 2006.<sup>7</sup> For each of these stations, we have around 8000 observations over time.

The data contain measures of visibility (miles), temperature (Fahrenheit), dew point (Fahrenheit), and wind speed (knots).<sup>8</sup> All measures are at the observatory level. Table 1 provides the summary statistics of the major weather indicators from 1984 to 2006. Across China, we see large variations in the weather conditions. The air visibility ranges from “invisible” to 47 miles.

Fig. 2 plots the annual averages of visibility across the 357 sites with observations throughout the sample period. The average visibility shows a clear downward trend after mid-1980, as is consistent with the expansion of the economic reform to non-agricultural sectors across China. This visibility decline has been steady: the rate of decline is around 0.3% per year. We have also conducted regressions that control for station fixed effects and weather conditions, including temperature, humidity, and wind speed. The decreasing trend of visibility is slightly steeper with these controls, thus suggesting a more rapid deterioration of the air quality.

In Fig. 3, we further decompose the trend of air visibility by using four sub-regions: northwest (longitude less than 110 and altitude greater than 35), northeast (longitude greater than 110 and altitude greater than 35), southwest (longitude less

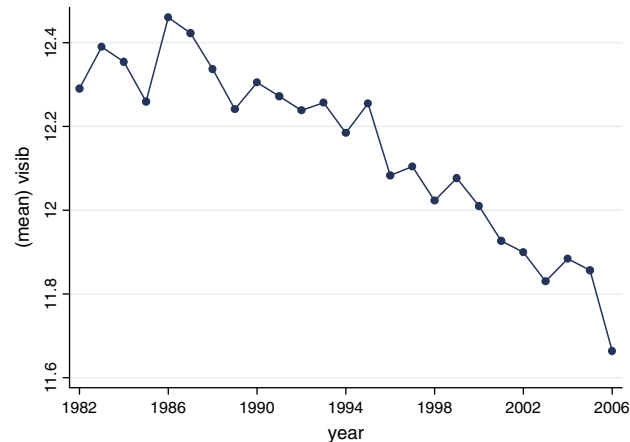
<sup>7</sup> Data available on visibility also cover several years before 1984. We focus on the 1984–2006 period to match the sample coverage of data on electricity.

<sup>8</sup> Relative humidity is associated with the dew point and temperature. At a given barometric pressure, independent of temperature, the dew point indicates the mole fraction of water vapor in the air, and therefore determines the humidity. A high relative humidity indicates that the dew point is closer to the current air temperature. If the relative humidity is 100%, the dew point is equal to the current temperature. Although we do not directly observe humidity, we approximate humidity with the difference between the temperature and the dew point in our empirical exercise.

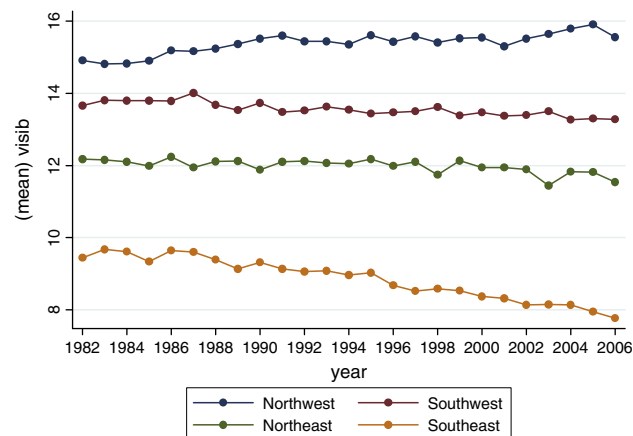
**Table 1**

Summary statistics of weather indicators (1984–2006). Source: Authors' calculation and National Climatic Data Center, USA.

	Mean	Obs.
Temp (Fahrenheit)	54	5,321,283
Dew point (Fahrenheit)	40	5,298,367
Visibility (miles)	12	5,307,245
Wind speed (knots)	5	5,302,431
Max wind speed (knots)	10	5,238,136



**Fig. 2.** Average of air visibility declined in China. Note: The vertical axis indicates visibility (miles).



**Fig. 3.** Visibility trends vary by region. Note: The vertical axis indicates visibility (miles).

than 110 and altitude less than 35), and southeast (longitude greater than 110 and altitude less than 35). The southeastern region is the most rapidly growing region of China, which includes the lower Yangtze River Delta (Shanghai, and part of the Zhejiang and Jiangsu provinces) and the Pearl River Delta (which is part of the Guangdong province). The air visibility of the southeastern region is the lowest among the four regions even at the beginning of the reform. Moreover, it has decreased the most rapidly ever since (by about two miles from 1982 to 2006). In sharp contrast, the air quality has actually improved in the northwestern region.

To have a more direct illustration of the association between economic growth and the visibility trend, we match the observatories with cities nearby (less than 30 km; the sample is reduced to 91 stations) and plot the log of annual visibility with the log of the GDP at the station (city) level (Fig. 4). It is clear that visibility is lower when the economic size is larger.<sup>9</sup>

<sup>9</sup> Note that some stations censor visibility above 20 miles (i.e. visibility was reported as 20 miles when the actual visibility is greater). An OLS estimation of the visibility-GDP elasticity can be downwards biased by this censoring.

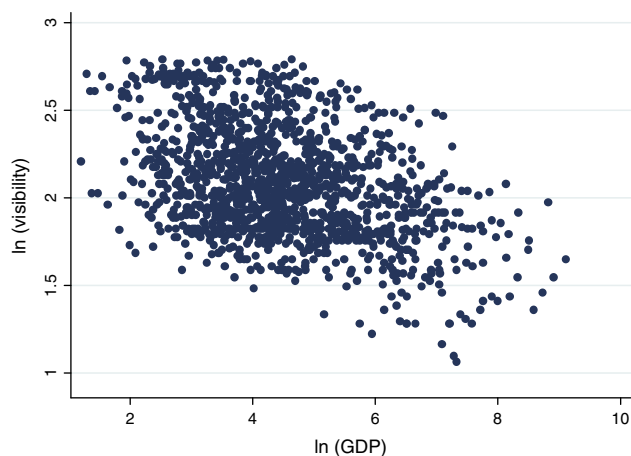


Fig. 4. Air visibility is negatively correlated with local GDP.

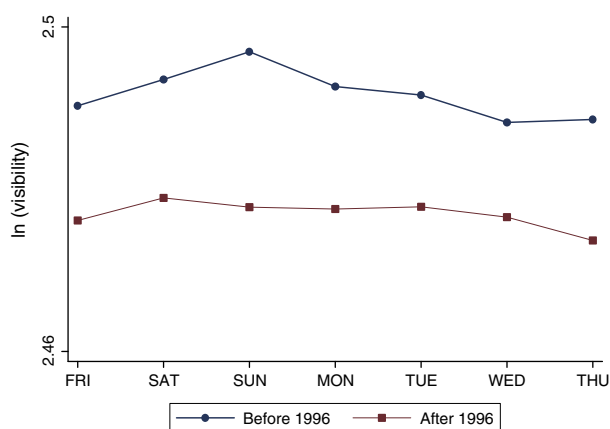


Fig. 5. Weekend effects before and after 1996. Note: Each point is the simple average of the log value of visibility for the corresponding day of the week during the sample period.

Finally, in Fig. 5, we plot the simple average of the log value of visibility for each day of the week before 1996 and after 1996, respectively. It suggests two patterns as expected. First, the average visibility in China declined after 1996 compared with that before 1996. This is consistent with what Fig. 2 shows. Second, the two lines also illustrate the weekend effect in China. Before 1996, because the weekend was only Sunday, therefore we observe that the visibility significantly improved on Sunday. After 1996, because of the change of weekend policy, the visibility peak moved to Saturday. Although this figure is only based on the simple average of the visibility across all years and regions, it still reveals the basic weekend effect. More detailed analysis will be conducted in the Section 4.2.

### 3.2. Consumption share of local economy

In order to estimate model (3) for the pollution effect of consumption relative to production, we need information on the consumption share of the local economy, which is measured by  $C/Y$ . Here  $C$  is the consumption and  $Y$  is the total local GDP. However, this information is not available to the public. The National Bureau of Statistics only releases information on the consumption of GDP at the national level. To address this issue, as discussed in Section 2.1, we propose to approximate the consumption share of the local economy with the ratio of residential to total electricity usage, which is available from the Urban Statistics Yearbooks. To be specific, we use the residential electricity to proxy the consumption  $C$ , and the total electricity usage, which includes both the residential electricity usage and industrial electricity usage, to proxy the total output  $Y$ . The advantage of using this proxy is as follows. (1) The electricity data at the city-level are readily available for the 1984–1990 and 1996–2006 periods. (2) The measurement of electricity usage is more transparent than that of aggregate production and consumption, and easier to compare over time. Hence, electricity has become an important measure for researchers of the Chinese economy to gauge the actual growth trends (Rawski, 2001). (3) With electricity measures, we do not need to adjust for the effect of inflation, which could be demanding given the poor quality of Chinese data (Young, 2003). Although

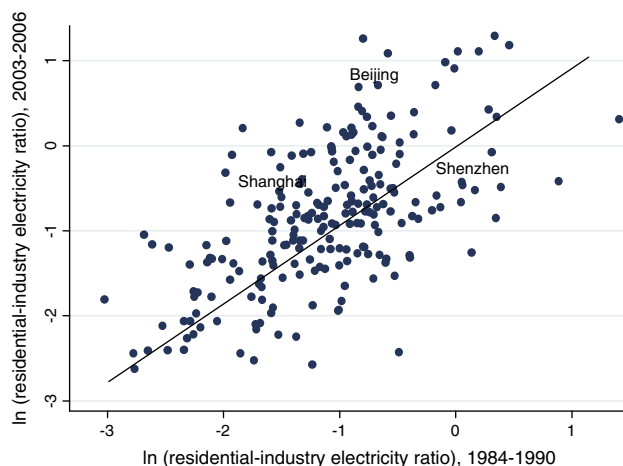


Fig. 6. Residential share of electricity usage is generally stable over time.

the use of electricity to proxy economic activity has greatly addressed the issue of the lack of reliable data, the electricity data themselves are still far from being perfect. For example, electricity data at the city-level between 1990 and 1996 are not provided in the Urban Statistics Yearbooks. In many cases, although the total electricity data at the city-level are provided, the corresponding residential electricity usage data are missing. In the end, we have gone through all of the Urban Statistics Yearbooks and obtained the electricity data for 539 cities for the time periods from 1984 to 1990 and 1996 to 2006.

To examine the stability of the residential share of electricity usage over time in Chinese cities, we use Fig. 6 to plot the logarithm of the average residential-industry electricity usage ratio for two periods, 1984–1990 versus 2003–2006. The sample covers most of the major cities in China. The residential shares of electric usage are generally stable over time for the cities in the sample, as shown by the positive correlation between the ratios of the two periods. Moreover, as labeled in the chart, the data points that correspond to the two most important cities of China, Beijing and Shanghai, are above the fitted regression line. This suggests that the residential-industry electricity usage ratios of these two cities have increased over time. This is expected, as these two cities have started to rebalance their growth model toward consumption much earlier than other cities in China. In contrast, Shenzhen, which was only a small village before the reform started in 1978 and then became the most important production and exporting hub of China, saw a decline in the residential-industry electricity usage ratio.

#### 4. Empirical findings

We first present the estimates of the relationship between city-level visibility and residential-total electricity ratios. We then estimate the weekend-effect model of visibility.

##### 4.1. Evidence from city-year panel regressions

We aggregate the visibility data to annual frequency (by taking medians), as the electricity data are reported annually. Based on Model (3), we use the negative logarithm of the median visibility at the site level as the dependent variable, which should be positively correlated with air quality.<sup>10</sup> We conduct the estimation for two sub-periods, 1984–1990 and 1996–2006, respectively, because the pollution intensity of consumption and other economic activities may have changed over time.

Columns 1 and 2 of Table 2 report the pooled ordinary least squares (OLS) estimates for the two sub-periods. We find that the total electricity usage is positively associated with air pollution, and the magnitude is very similar in both sub-periods. In contrast, the pollution intensity of consumption relative to that of production has significantly increased over time. Before 1990,  $\beta_2$  was insignificant, but became positive and statistically significant after 1996. This means that the pollution intensity of consumption has outweighed that of production after 1996.

In Columns 3 and 4, we include year-specific fixed effects to the foregoing estimations. This may address year-specific changes, such as the change of classification standards for residential and total electricity usage. Encouragingly, we find that controlling for the year-specific factors has little effect on our earlier estimates.

In Columns 5 and 6, we further add city-specific fixed effects and find that both the effects of economic size and structure become insignificant in the two sub-periods. This could be so for two reasons. One is that the pollution effects of economic activities are actually insignificant. A more plausible reason is that within-city variations in both the industry and residential electricity usage are small relative to the noise term. This, coupled with our small sample size, reduces the statistical power

<sup>10</sup> We have also tried to aggregate the visibility data to a monthly level and the results are qualitatively the same.



**Table 2**  
Regressions at city-year level.

	1984–90	2003–06	1984–90	2003–06	1984–90	2003–06
Intercept	–2.07** (.179)	–3.39** (.251)				
ln(Y)	.108** (.012)	.174** (.015)	0.111** (0.012)	0.173** (0.0151)	0.001 (0.003)	0.003 (0.004)
(C/Y)	–.093 (.091)	.381** (.122)	–.132 (.099)	0.387** (0.122)	–0.017 (0.026)	0.032 (0.033)
(1/Y)	40.9** (15.5)	–422.3 (133)	47.0** (15.96)	275.7 (469.8)	–4.22 (4.94)	51.79 (78.81)
Year dummies	No	No	Yes	Yes	Yes	Yes
City dummies	No	No	No	No	Yes	Yes
Num. of Obs.	1808	944	1808	944	1808	944
R-squared	.33	.40	.34	.44	.81	.86

Note: (1) The dependent variable is negative log of visibility. (2) All regressions control for the log of temperature, humidity, and wind speed. (3) All regressions use the nonlinear least square estimator. (4) Robust standard errors clustered over site are reported in the parenthesis.

\*  $p < 0.1$ .  
\*\*  $p < 0.01$ .

**Table 3**  
Robustness check with flexible functional form.

	1984–90	2003–06	1984–90	2003–06	1984–90	2003–06
ln(Y)	–0.0788 (0.0765)	0.242 (0.186)	–0.0697 (0.0771)	0.256 (0.181)	0.118 (0.0629)	0.432** (0.156)
ln(Y) 2	0.00887* (0.00394)	–0.00290 (0.00749)	0.00848* (0.00397)	–0.00349 (0.00729)	–0.00570 (0.00317)	–0.0216** (0.00786)
(C/Y)	–0.113 (0.0894)	0.389** (0.128)	–0.102 (0.0911)	0.391** (0.129)	–0.0130 (0.0501)	0.0615 (0.0638)
Year dummies	No	No	Yes	Yes	Yes	Yes
City dummies	No	No	No	No	Yes	Yes
N	1808	944	1808	944	1808	944
adj. R <sup>2</sup>	0.332	0.392	0.332	0.393	0.823	0.844

Note: (1) The dependent variable is negative log of visibility. (2) All regressions control for the log of temperature, humidity, and wind speed. (3) All regressions use the nonlinear least square estimator. (4) Robust standard errors clustered over site are reported in the parenthesis.

\*  $p < 0.1$ .  
\*\*  $p < 0.01$ .

of our estimation. To address this issue, in the following section, we shall provide further evidence through the weekend-effect model, which utilizes the high-frequency feature of the data.

One concern of the research is that the above regression results may critically depend on the specific functional form of Eq. (3). Therefore, we also conduct a robustness check by employing a more general setup of the visibility function as denoted by Eq. (3a). Table 3 shows the regression results when we include only the first order term of  $\ln(Y_{it})$  and both the first and the second order terms of  $\ln(Y_{it})$ , respectively. The first and also the most important observation is that the regression results in Table 3 have the same signs and significance as Table 2. In other words, the regression results in Table 2, which follow the theory setup, are robust and do not come from the specific functional form of the regression. Second, the results in Table 3 confirm that the impact of the consumption intensity was insignificant before 1996, but became significantly positive after 1996.<sup>11</sup>

#### 4.2. Evidence from weekend effects

We then turn to the weekend-effect model, which can address the potential confounding effect of unobserved heterogeneity at the site-level, as discussed in Section 2.2. As the measures of consumption–production structure is at annual frequency, we first calculate the first difference of daily visibility and then obtain the annual average of the daily visibility change for the working days, Saturday and Sunday, respectively, for each site. This aggregation also reduces the noise in the visibility data due to the averaging. In alternative regressions, we also consider a fixed-effect version of model (8), in which

<sup>11</sup> As alternative robustness checks, we also examine the robustness of our empirical estimates to outliers in the consumption–output ratio, by excluding 5% or 10% of observations with the largest or smallest consumption–output ratios. This has little effect on our estimates reported in the paper.

**Table 4**  
Weekend-effect model estimates: first-difference approach.

	(a)		(b)		(c)	
	1984–95	1996–06	1984–90	2003–06	1984–90	2003–06
Saturday	-.110 (.092)	-.328** (.087)	-.794 (.705)	-1.64** (.655)	-.744 (.707)	-1.77** (.691)
Sunday	-.506** (.098)	-.004 (.086)	-1.21* (.581)	-.444 (.602)	-1.21* (.531)	-.342 (.633)
Sat. $\times$ (C/Y)			2.33 (1.91)	2.91* (1.55)	1.96 (1.87)	3.17** (1.48)
Sun. $\times$ (C/Y)			1.38 (1.26)	1.53 (1.38)	1.24 (1.25)	1.37 (1.37)
Num. of obs.	25,700	23,522	3613	3276	3607	3264
R-squared	.08	.09	.118	.153	.122	.151

Note: (1) In the above regressions, (a) is the regression without interaction terms; (b) is the regression following the model setup using Eq. (8); (c) is the regression using the more general format to examine the robustness of the regression. (2) Temperature, humidity, and wind speed are controlled for in all the regressions. Control variables in the last two columns also include C/Y, 1/Y, and the interactions of 1/Y with Saturday and Sunday dummies. (3) Coefficients reported have been scaled up by 100 times. (4) Robust standard errors clustered over site are reported in the parenthesis.

\*  $p < 0.1$ .  
\*\*  $p < 0.01$ .

we first calculate the average of daily visibility by working days, Saturday and Sunday, and then explicitly control for site-year specific fixed effect.

Table 4 summarizes the estimates of the weekend-effect model. We first regress  $-\Delta \ln(V_{it})$  on the dummy indicators for Saturday and Sunday without including measures of consumption and other economic activities (Columns 1 and 2). The coefficients of the weekend dummies thus indicate the average weekend effects.<sup>12</sup>

Our estimates confirm that air quality improves on the weekends. Specifically, we conduct estimations before and after 1996, respectively, to examine the effect of the weekend policy change in 1995. The estimates confirm our hypothesis. Before 1996, the air quality of Saturday was not significantly different from that of Friday. On Sunday, however, the density of air pollutants declined by about 0.5%, and this effect is statistically significant (Column 1). In contrast, after 1996, the Saturday effect became statistically significant, while the Sunday effect disappeared. This suggests that air quality improved on Saturdays and remained at about the same level on Sundays (Column 2). As the dependent variable  $-\Delta \ln(V_{it})$  measures the air quality difference between the two adjacent days, the insignificant Sunday effect suggests that the air quality of Sunday is not much different from that of Saturday after 1996. The quasi-experimental evidence thus provides strong support for the causal effect of weekends on air quality.

We then turn to the effect of local economic structure by estimating the complete Model (8), which includes residential electricity share, the inverse of total electricity usage, and their interactions with the weekend dummies.

The regression results are presented in Columns 3 and 4 in Table 4. Our estimates confirm the pattern from the city-level OLS regressions: the pollution intensity of consumption became more significant over time relative to that of production. In particular, for the 1984–1990 period, the coefficient of the interaction between the weekend dummy and the residential electricity share,  $\gamma_1$ , is insignificant (Column 3). In contrast,  $\gamma_1$  is estimated as 2.91 and statistically significant for the 1996–2006 period (Column 4). The difference between the coefficients  $\gamma_1$  in the third and fourth columns is not significantly different. Nevertheless, it is useful to know that, given the same model specification,  $\gamma_1$  turns significantly positive after 1996. As discussed in Section 2.2, a significant positive  $\gamma_1$  implies  $\theta_1 > \theta_2$ . In other words, the pollution intensity of consumption is higher than that of production after 1996, which is a key finding of this study.

To address the concern that the above results may depend on the specific function form derived from the theory model, we further check the robustness of the above results by conducting the regression using more general function forms. The regression results are in Columns 5 and 6 in Table 4, and they are similar to those in Columns 3 and 4. This suggests that the estimation results are not sensitive to the choice of function form.

We further consider a fixed-effect version following model (3) to examine the robustness of the regression results (Table 5). The first two columns are the regression results with no interaction terms and the last two columns are the regression results with interaction between weekend indicators and residential electricity share. The first two columns of Table 5 show similar results as those of the first-difference specification (Table 4). Before 1996, air quality improved on Sunday; after 1996, air quality improved both on Saturday and Sunday. The last two columns in Table 5 also provide similar message as the Columns 3 and 4 of Table 4 do. The coefficient of the interaction term,  $\beta_2$ , is positive for the period after 1996 and negative for the 1984–1990 period, although they are not statistically significant. Nevertheless, this pattern is consistent with what we found using the first-difference model.

<sup>12</sup> We exclude days with rain, snow, or fog to reduce their confounding effect. All regressions control for daily variations of the temperature, humidity, and wind speed. The exclusion of the three measures of weather conditions does not significantly affect our estimates, though. This strengthens our claim that air pollutants underlie the weekly visibility cycles. Moreover, we have also tried to add year-specific fixed effects and the estimates do not change much.

**Table 5**  
Weekend-effect model estimates: fixed effect approach.

	(a)		(b)	
	1984–95	1996–06	1984–90	2003–06
Saturday	–.387 (.359)	–.821** (.360)	–.248 (.875)	–1.52* (.878)
Sunday	–.702* (.363)	–.236 (.359)	–.368* (.892)	–.671 (.825)
Sat.*(C/Y)			–.460 (2.26)	1.42 (1.91)
Sun.*(C/Y)			–.591 (2.62)	1.40 (1.97)
Num. of Obs.	3613	3276	3613	3264
R-squared	.93	.93	.93	.93

Note: (1) In the above regressions, (a) is the regression without interaction terms; (b) is the regression following the model setup using Eq. (3). (2) Temperature, humidity, and wind speed are controlled for in all the regressions. (3) Coefficients reported have been scaled up by 100 times. (4) Robust standard errors clustered over site are reported in the parenthesis.

\*  $p < 0.1$ .  
\*\*  $p < 0.01$ .

The above result is that the weekend effect can be very different contingent on economic development. For example, the weekend air quality could be worse in big cities because people may drive more on the weekends, such as in Beijing and Shanghai. This also explains why the pollution intensity of consumption increased over time, as the automobile market of China grew rapidly after joining the World Trade Organization (WTO) in 2001, and by 2010, China was already the largest auto market in the world.

## 5. Conclusion

Under the background of economic rebalancing toward consumption-driven growth in China, this study introduces a new methodology to empirically assess the impact of economic structure on the environment. By using visibility as an indicator of air quality, we circumvent the difficulty of limited data on the environmental quality in China. The high-frequency nature of the data further enables us to exploit two institution-based exogenous variations to achieve identification. One is the weekend policy, which should weaken production activities, but increase consumption. The other is a policy change introduced in 1994–1995, which changed the working schedule from six to five working days across China. We then develop the standard panel-data and weekend-effect models, which directly estimate the relative pollution intensity of consumption with that of production.

Is rebalancing bringing forth a “greener” China, then? Not necessarily, according to our empirical evidence. Even though there is no evidence that consumption generates more air pollution than production in the 1980s, we find that the pollution intensity of consumption has exceeded that of production since the mid-1990s. This finding is robust to the choice of functional form and also confirmed by both empirical models. Hence, a policy implication of our study is that it may not be realistic to count on the rebalancing strategy alone to address the environmental issues of China. Policies that target pollution-intensive consumption activities are necessary, such as raising the user costs of driving and imposing more stringent standards on the gasoline quality. Moreover, as consumption activities are much less mobile than investment and production activities, the pollution level of a rebalanced economy may persist for a longer period of time (Copeland and Taylor, 1995). In this sense, the burden of environmental issues on policy making may not be moderated as the rebalancing moves forward.

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