The Chinese Economy, 0: 1–16, 2018

ISSN: 1097-1475 print/1558-0954 online
DOI: 10.1080/10971475.2018.1479597

Examining the Inter-Regional Pollution Spillover: Evidence from Visibility in China

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By utilizing a novel and unique dataset of daily measures of visibility, we propose regression-based new methods that are easy to implement to quantify the long-range spillover of air pollutants. In applying them to China, we find significant externalities of air pollution: an increase in the local pollution intensity by 10% can increase the pollutant intensity of a region 1,000 kilometers away by over 1%.

Keywords: visibility, air pollution, environmental externalities, China

JEL classifications: H8, R1, Q2

INTRODUCTION

The spillover of pollution is known to be a key factor for designing optimal economic policies. Early on, Markusen (1975a, 1975b) shows that the trans-boundary spillover of pollution affects the optimal tax structure (a review of the literature is available by Missfeldt, 1999). To quantify the magnitude of the spillover effect, a large amount of the literature, mainly by atmospheric scientists, has developed two streams of methods. One is to construct models based on the atmospheric theory to simulate the spillover paths under plausible parameters; the other is to use actual measures of pollution concentrations to infer the spillover effects (Rao, Hogrefe, Holloway, and Kallos, 2004). In order to assess the trans-boundary spillover

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effect, both approaches demand significant inputs of resources, either to construct and calibrate structural models or collect data on air pollution for a wide range of physical sites. Arguably, due to the cost constraints, the assessing of actual spillovers still remains the major obstacle in the designing of optimal economic policies (Conconi, 2003).

This study proposes a simple approach that relies on commonly available visibility measures to gauge the significance of the long-range spillover of air pollutants. We employ the Granger-causality in visibility from a pollution source to regions that are potentially affected. In order to address the concern that our estimates may reflect spatial correlation in weather conditions, but not air pollution spillover, we classify our sample according to economic growth rates. We then use the spillover path of low-growth regions as the "control group" to identify the pollution spillover effect. One confounding factor is that the production cycles of different economies may be related, thus generating spatial correlation in their pollution outcomes. Regarding this, we shall examine pollution sources and receptors that are not integrated in production to provide additional evidence.

The key advantages of our methods are that they are easy to implement and may serve as a low-cost substitute of the existing methods: visibility has been commonly monitored and reported at daily frequency in over 8,000 stations around the world for several decades whereas the records of air pollution are much harder to obtain. This is particularly relevant to rapidly emerging economies where systematic collection of data on air pollutants has been lacking.

Moreover, to the best of our knowledge, there is even rarer empirical research to study the air pollution spillover in China. Therefore, another contribution of the study is to add our understanding as well as empirical evidence for the pollution spillover in China. After six decades of rapid industrialization and urbanization, China is already the nation that generates the most pollution (World Bank, 1997, 2001). The health cost of this rising pollution issue is significant (Brajer and Mead, 2004, 2005; Chang, Seip, & Vennemo, 2001; Ebenstein, 2008; Peng et al., 2002). However, data on air pollution in China are highly scarce due to the lack of disclosure of information on air pollution. Typical data are only available for recent years, low in frequency (annually available), and cover limited regions. More important, officially reported pollution data may be misleading. Although the official data report that air quality has been improving in major cities, the amount of pollution perceived by people who live in these cities has not been reduced. The number of "hazy days," which is not in the official pollution-monitoring system, continuously increases over time.

In contrast, visibility data on China contain valuable information on its pollution status. First, visibility has been consistently recorded for over 387 stations since the early 1980s. This period covers almost the whole span of the economic reform of China, thus allowing us to trace the evolving spillover effect onto the surrounding regions. Second, the sites that monitor visibility are evenly distributed across China (Figure 1), thus providing representative estimates of the spillover effects. Third, the visibility data are available at daily frequency. This is necessary to estimate the spillover because it only takes a couple of days for air pollutants to travel hundreds or thousands of miles (Rao et al., 2004). Hence, monthly data may omit much of the spillover effect when our approaches are used.

Our methods suggest significant spillover effects. First, we confirm that a significant amount of air pollutants can spill over into a large area. The emission of the Pearl River Delta (PRD)

FIGURE 1 Weather stations in China (the data sample).

region, which has grown into the most important manufacturing center of China, can significantly affect regions that are a thousand kilometers away. Emission that increases local pollution intensity by 10% can increase the pollutant intensity of a region a thousand kilometers away by over 1%. Our estimated paths of the spillovers of China are generally consistent with the findings of the atmospheric literature when U.S. data are used (Rao et al., 2004).

The structure of this article is as follows. We first discuss our methodology of using visibility to estimate spillover effects. The next section summarizes the features of our data. In the fourth section we provide a report on our empirical findings and the last section concludes the article.

EMPIRICAL METHODOLOGY

In this section, we propose alternative empirical methods to identify the spillover effect of air pollution by using visibility to indicate air quality.

Visibility as a Proxy of Air Pollution

In the literature, researchers have adopted various air pollutant indicators to measure air pollution. Typical indicators include Sulfur dioxide (SO2),[1] nitrogen oxide (NOx), suspended particle matter (SPM), dark matter (fine smoke), carbon oxide (CO), carbon dioxide (CO2), vehicle hydrocarbon emissions, and so on. Readers can refer to Panayotou (2000) and Dinda (2004) for details. In this article, we propose to exploit a rarely used database on air visibility to measure air pollution.

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 NO2) in the atmosphere. The sources of these aerosol matters can be manmade or natural. They reduce visibility by scattering and absorbing light.

Compared with typical pollutant indicators used in the literature, the air visibility data has the following major advantages. First, as air visibility is less technical to measure and is a basic measure of air quality, it is systematically recorded in most areas of the world for a long time span (1950–present). Hence, sample selection, which is a potential issue with studies of the existing literature, may be avoided using the visibility data. Second, for technical reasons, such as the lack of cost-effective measuring devices, important pollutants may be omitted from the data of typical air pollutants. For example, PM2.5, which refers to the particulate matter with 2.5 micrometers or is smaller in size, has important health impacts.[2] However, data on PM2.5 is lacking in many developing countries. Nevertheless, because PM2.5 is the primary cause for the scattering of visible light and the cause of the degradation of visibility (Sloane, Hogrefe, Holloway, and Kallos, 1991), air visibility may help to address this issue.

Despite the advantages, air visibility has seen limited use in the literature, possibly for the following reasons. First, visibility is affected by both manmade pollutants and natural conditions. To address this issue, we shall control for as many weather factors that can affect visibility in our regressions as possible. Generally, we do not find that adding the weather factors have material effects on our estimates. Second, air visibility does not completely capture all harmful pollutants. Hence, our estimates do not perfectly reflect the air pollution as other air pollutant indicators do. Nevertheless, we can advance the literature in this direction with the insufficiently used data on air visibility.

In following the meteorological literature (e.g., Malm, Sisler, Huffman, Eldred, & Cahill, 1994; Wang, 2003; Watson, 2002), 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). We also want to mention that in the literature more and more research begin to employ air visibility as a proxy to measure the air pollution. For example, Rosenfeld et al. (2007) use visibility as a proxy for air pollution to test for its effect on precipitation. Li, Yuan, Song, & Wei (2014) also use air visibility as a proxy for air pollution and measure the relative importance of production and consumption in generating air pollution in China and provide evidence that the pollution intensity of consumption activities has exceeded that of production since the mid-1990s. Du, Li, & Yuan (2014) provide evidence to show that air visibility data can provide more comprehensive information with regard to air pollution as opposed to traditional pollutant measures.

A Granger-Causality Approach

Suppose we are interested in the spillover from pollution in city 0 to another city, *i*. This may be tested with the following simple Granger-causality model which essentially estimates the time-lagged correlation between the air quality in cities 0 and *i*:

$$\Delta \ln (V_{i,t}) = \theta_i + \alpha_i \Delta \ln (V_{0,t1})^{0,t-1} + \beta_i \Delta \ln (V_{i,t1})^{i,t-1} + \Delta X_{0,t} \rho^{0,t}{}_i + \Delta X_{i,t} \lambda^{i,t}{}_i + \varepsilon_{it}. \qquad (1)$$

The visibility in city i at time t is represented by V_{it}. Of interest to us is α_i, the spillover within one period from cities 0 to i. A nonzero α_i implies that when the air pollutant density increases by 1% in city 0, the pollutant density in city i increases by α_i% with a time lag of one period. Note that α_i may vary in city i because, for example, the spillover depends on the distance between cities 0 and i, as we will examine.

Note that we have controlled for the visibility history of city i itself to address the potential confounding effect of past common shocks on both cities. In addition, the model also controls for weather changes in both cities 0 and i, $\Delta X_{0,t}$ and $\Delta X_{i,t}$, such as the log of temperature, humidity, wind speed, terrain, and wind direction.[3] The model may be extended by including more lags of V_{0t} and V_{it} in Equation (1) to capture the pollution spillovers that extend to more than one period of time.

This approach is closely related to the "spatial correlation analysis" in atmospheric science, which infers the scope of spillover by estimating the contemporary and lagged correlations between the time series of pollutants in the source and receptor sites (Civerolo et al., 2003; Lin et al., 2010; Rao et al., 1997; Smith, Sanchirico, & Wilen, 2009). Compared to the approach in the literature, our contributions are two-fold. First, by using visibility, we circumvent the difficulty of obtaining high-frequency air pollution time series data for a wide range of areas. Second, we specifically examine the possible pollution spillover for China and attempt to contribute to our understanding on the spatial pollution externality for the fast-growing Chinese economy.

Endogeneity Issue

The reasons that the lagged correlation analysis of visibility may not reflect the spillover effect are as follows. First, since we directly use visibility, but not air pollutants, the estimated "spillover effect" may reflect the spillover of naturally generated aerosols, but not pollutants.

Second, since the model only controls for the air quality of city 0, the spillovers from other pollution sources into city i are omitted. If these "omitted" spillovers also affect site 0, the estimate of α_i would be biased upward. For example, if site 0 lies between site i and another pollution source 1, then it is possible that the pollutants by source 1 first spread to city 0 and then to city i. This spillover path thus generates a spurious Ganger-causality of visibility from city 0 to i.

Third, the production intensity may vary day by day, for example, due to demand or supply shocks. If the production of firms in different cities is related, such as due to vertical integration, the production shock to one city may spillover to other cities. This spillover in production intensity may reflect on the spatial correlation of air pollution, thus confounding our estimates of the spillover in air pollutants.

To address these identification issues, we propose the following identification tests. First, if the emission from the pollution source is known to have grown over time (e.g., due to economic growth), then it should reflect with strengthened spillover effects. This will be tested.

Furthermore, we propose to use the visibility of the upstream of pollution site 0 as the "control group." In particular, we consider the following model, which replaces site 0 in Model (1) with an upstream site 2:

$$\Delta \ln (V_{i,t}) = \theta_i + \delta_i \Delta \ln (V_{2,t1})^{2,t-1} + \beta_i \Delta \ln (V_{i,t1})^{i,t-1} + \Delta X_{2,t} {\rho^{2,t}}_i + \Delta X_{i,t} {\lambda^{i,t}}_i + \varepsilon_{it}. \qquad (2)$$

If site 2 is clean and the endogeneity issues discussed are not present, we expect δ_i to be insignificant.

DATA

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 1,005 weather stations across China (Figure 1 is a plot of the location of the stations according to their longitudes and latitudes, thus showing the shape of mainland China). The time periods covered vary for the different stations; the 357 stations cover the whole period from 1983 to the end of 2006. For each of these stations, we have over 8,000 observations over time. In fact, visibility data are also available for 1978–1983, but show much larger volatility than the data afterward, so we will be cautious in interpreting the findings when using data before 1983.

The data contain measures on visibility (miles), temperature (Fahrenheit), pressure, dew point (Fahrenheit), wind speed (knots), total precipitation (inches), snow depth (inches), and the indicators for fog, rain, snow, hail, thunder, and tornado. Although we do not directly observe humidity, we approximate humidity by using the difference between temperature and dew point in our empirical exercise. Relative humidity is associated with dew point and temperature.[4] All measures are at the observatory level. Table 1 provides the summary statistics of the major weather indicators from 1983 to 2006 for China. Figure 2 is a plot of the annual averages of visibility across the 357 sites with observations throughout the sample period. The average visibility shows a clear downward trend after the mid-1980s, as is consistent with the spread of the economic reform to the nonagricultural sectors across China. This visibility decline has been steady: the rate of decline was 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.

We further decompose the trend of the air visibility by using four subregions: northwest (longitude less than 110 and altitude greater than 35), northeast (longitude greater than 110 and altitude greater than 35), southwest (longitude less than 110 and altitude less than 35), and

TABLE 1
Summary Statistics of Weather Indicators (1983–2006)

	China
Temperature (Fahrenheit)	52.65 (22.28)
Dew point (Fahrenheit)	38.87 (25.13)
Visibility (miles)	12.51 (5.72)
Wind speed (knots)	4.92 (3.68)
Precipitation (inches)	0.09 (0.35)
Fog or not	0.06 (0.23)
Rain or not	0.32 (0.47)
Snow or not	0.06 (0.24)

Note: Mean and standard deviation (in parentheses) are reported.

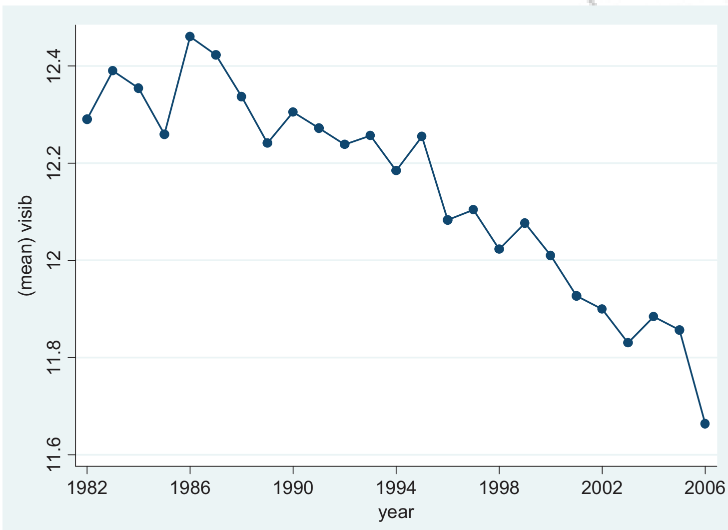

FIGURE 2 National average of air visibility. *Note*: The vertical axis indicates visibility (miles).

southeast (longitude greater than 110 and altitude less than 35). We plot this decomposition in Figure 3. The southeastern region is the most rapidly growing region of China, including the lower Yangtze River Delta (Shanghai, and part of the Zhejiang and Jiangsu provinces) and the PRD (which is part of the Guangdong province). The air visibility of the southeastern region was 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 obtain a more direct illustration of the association between economic growth and the visibility trend, we match the observatories with cities nearby (less than 30 kilometers; the sample is reduced to 91 stations) and plot the log of annual visibility with the log of GDP at the station (city) level (Figure 4). It is clear that visibility has declined as the economy grew.[5]

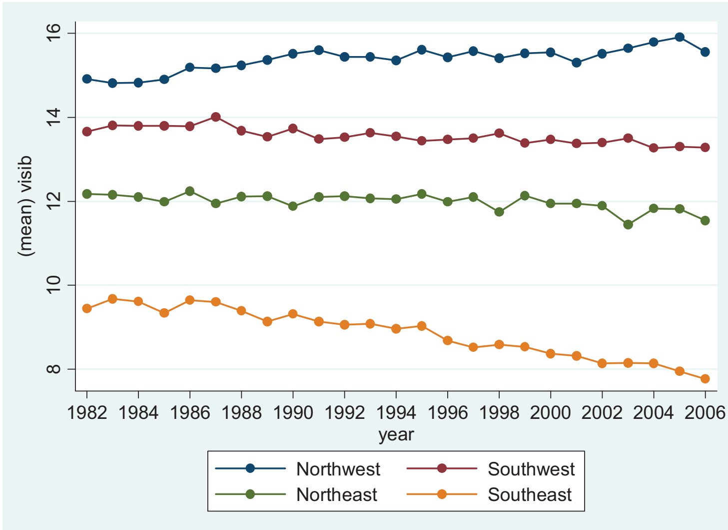

FIGURE 3 Regional average of air visibility. *Note:* The vertical axis indicates visibility (miles).

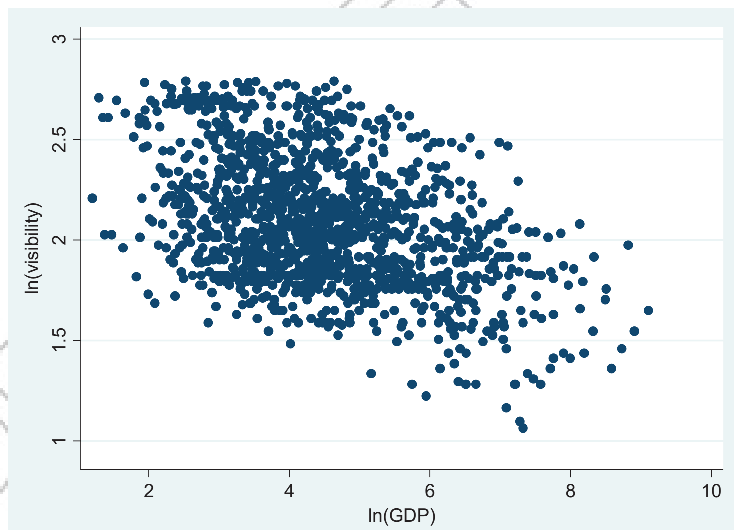

FIGURE 4 Air visibility versus GDP.

In sum, it appears that (1) air visibility has significantly declined in China since its economic reform, and (2), this decline has been mainly driven by the economic growth of China.

EMPIRICAL FINDINGS

Granger-Causality Approach: Spillover from PRD

Located on the south coast of China, the PRD is among the largest of the manufacturing clusters in China (the red circle in Figure 5 indicates the weather stations within the PRD). The PRD includes Shenzhen, the most developed Special Economic Zone of China, and its surroundings regions, such as Dongguan. One of the most densely populated region of China, the PRD covers over 20,000 square kilometers and accommodates over 40 million people. As a whole, the region accounts for around 9% of the GDP of China. The economy of the PRD is dominated by manufacturing.

Given the production scale and density of factories, the PRD is the most polluted region of China. From 1983 to 2006, the air visibility of Shenzhen declined from 12 to below 6 miles (Figure 6). The magnitude of this decline is the greatest in all the cities in China and the current level of visibility is among the lowest in China.

The geographic location of the PRD makes it an ideal place to test its spillover effect. Since the PRD lies on the south coast, the number of potential "omitted pollution cities" is significantly reduced because to the south of the PRD is the ocean. It is still possible,

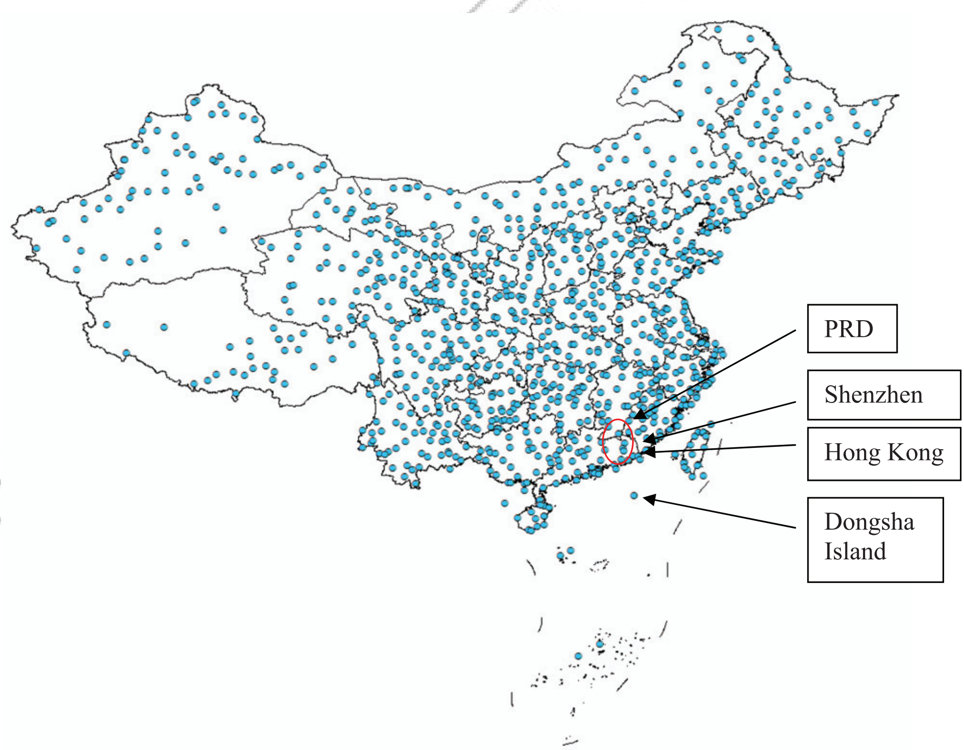

FIGURE 5 The empirical setting 1—Shenzhen, Hong Kong, and Donsha Island.

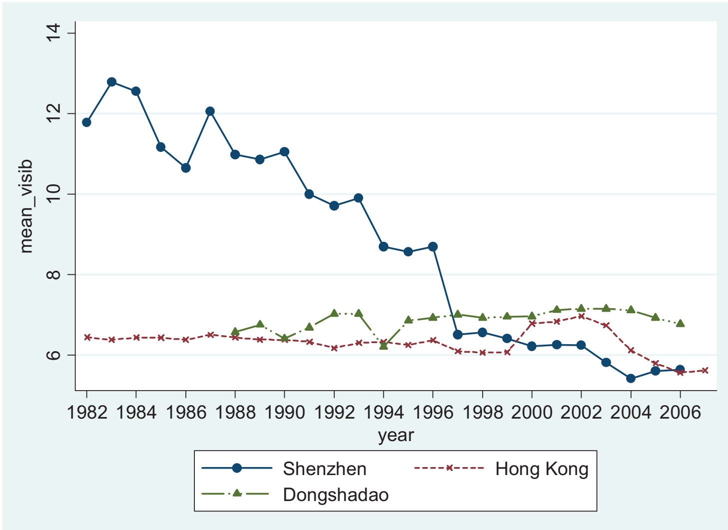

FIGURE 6 Visibility at Shenzhen, Hong Kong, and Dongsha Island.

however, that the emissions from other "dirty" cities along the south coast may generate an "omitted city bias." To address this concern, we propose two alternative control cities. One is Hong Kong, which is located just to the south of Shenzhen (around 20 miles from the center of Hong Kong). Moreover, Hong Kong specializes in the service industry and had few manufacturing industries in our sample period. Alternatively, there is an island named Dongsha that is around 200 miles to the south of the PRD region. This island has few residents and no industry. Both Hong Kong and Dongsha Island are at the "upstream" of the PRD because most of the sites that may be affected by the PRD are located to its north.

In sharp contrast to the rapidly declining visibility of Shenzhen, both Hong Kong and Dongsha have been stable during our sample period (Figure 6). Hence, we may use the effect of the latter sites on other sites in China as the control group for the effect by Shenzhen.

Baseline Estimates

We first estimate the baseline model (1) to test the spillover from Shenzhen into each of the remaining sites in mainland China. Figure 7 is a plot of the estimates of α_i (one-day spillover) for these sites against their straight-line distances to Shenzhen (by using data from 1996 to 2006) together with a locally weighted regression line. The nonparametric regression line is generated by using the lowess command of STATA by using a bandwidth of 0.8. The figure shows that the spillover is reduced with distance, but appears sizable for sites within 1,000 kilometers of Shenzhen. In particular, when the air pollution density increases by one unit in the PRD, the air pollutant density of a site that is 1,000 kilometers away from the PRD would increase by approximately 0.1 unit. This pattern is similar to the findings for ozone spillover in the eastern United States which used a "spatial correlation analysis" per Civerolo et al. (2003).

The spillover effect shown in Figure 7 may underestimate the spillover effect because the air pollutants may take longer than one day to reach distant sites. To illustrate this, in Figure 8, we plot the fitted spillover-distance link for one, two, and three lagged days. The spillover effect is the strongest for the first day, but significantly reduced in the following days. This is consistent with the findings on ozone by Rao et al. (2004): "results from the case study in the United States … suggest that O3 levels in a region from Virginia to Maine can potentially be affected by emissions in the Pittsburgh area within one day".

Evidence on Causality

We then conduct our identification tests to show that the Granger-causality in visibility is caused by the spillover of pollutants, but not other confounding factors. First, we plot the spillover-distance effects for three sample periods: 1978–1985, 1986–1995, and 1996–2006 in Figure 9. It is clear that the spillover line shifts upward over time. This is consistent with the increasing pollution level in the PRD due to its rapid agglomeration following the reform and opening up of China. If the spillover-distance pattern was due to natural weather conditions, it should not have changed so dramatically within such a short time span.

Could this spillover curve be due to airborne water content but not pollutants? We then plot the "spillover" of humidity against distance for the three subperiods, in Figure 10. Unlike visibility, humidity shows little signs of spillover: the spillover-distance gradients are generally flat and show no signs of strengthening over time. This may further strengthen our claim that the lagged correlation of visibility is due to air pollutants.

Last but not least, we estimate the spillover-distance curves with Hong Kong or Dongsha Island as the "pollution sources" (Figures 11 and 12). If endogeneity problems are present,

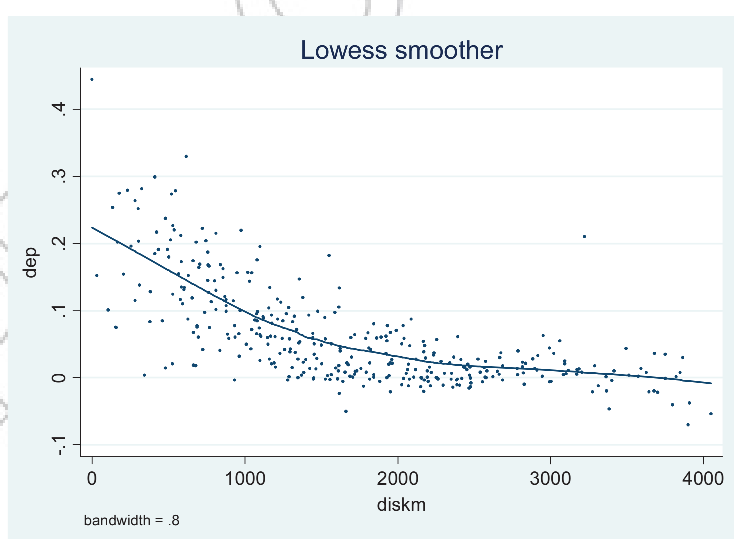

FIGURE 7 The spillovers of Shenzhen (1996–2006; one-day lag effect). *Notes:* The y-axis is representing the spillover effect or the estimates of α_i.

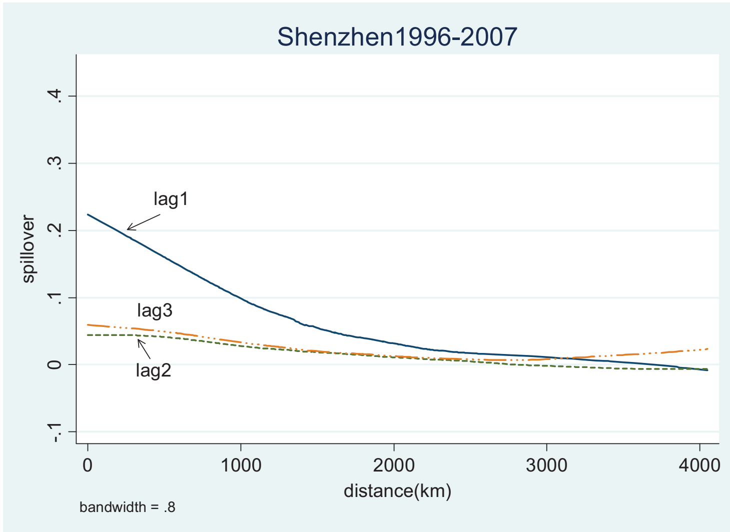

FIGURE 8 The spillovers of Shenzhen (1996–2006; one-, two-, and three-day lag effects). *Notes:* The y-axis is representing the spillover effect or the estimates of α_i. Lag1 represents the spillover after the one-day lag, lag 2 represents the spillover after the two-day lag, and lag 3 represents the spillover after the three-day lag.

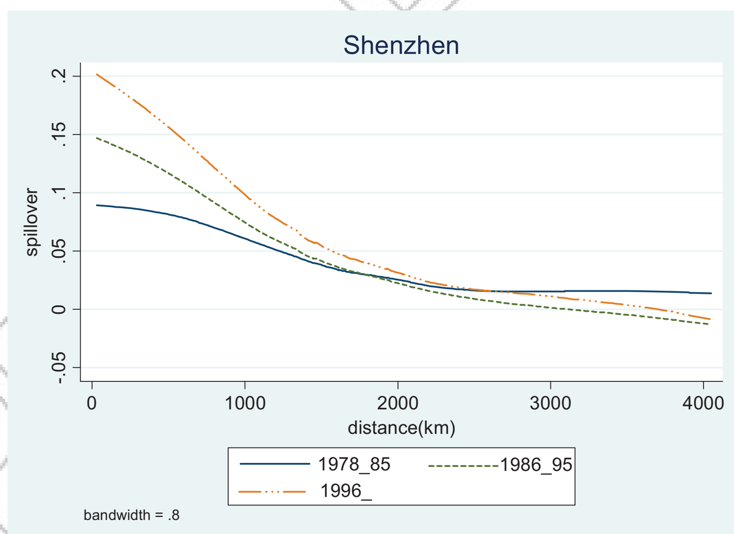

FIGURE 9 The spillover curves of Shenzhen (1978-2006; one-day lag). *Notes:* The y-axis is representing the spillover effect or the estimates of α_i.

they may have also affected Hong Kong and Dongsha Island, which are not far away from Shenzhen. We do not find this to be the case for Hong Kong: the spillover-distance curve for Hong Kong is flat, in sharp contrast to that of Shenzhen. Interestingly, the visibility of

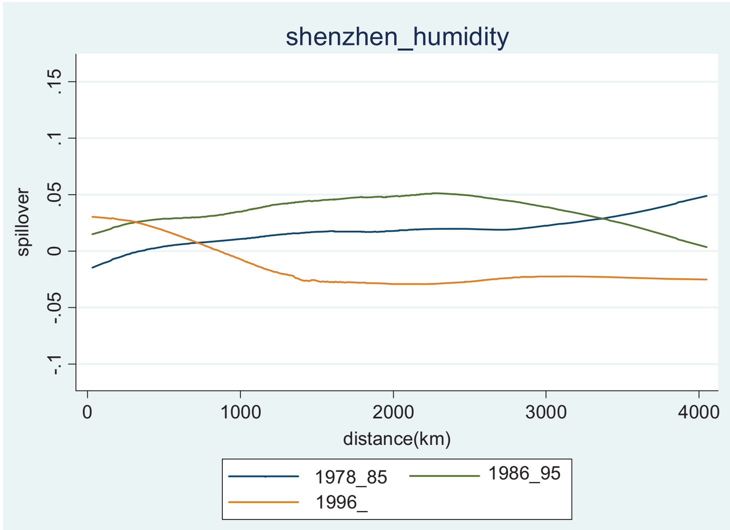

FIGURE 10 The “spillover” of humidity (Shenzhen; one-day lag). *Notes:* The y-axis is representing the spillover effect or the estimates of α_i.

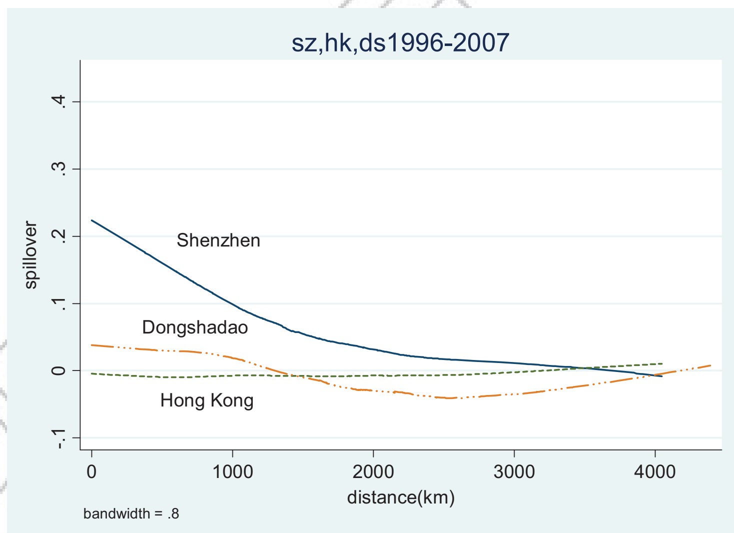

FIGURE 11 The spillover curves of Shenzhen, Hong Kong, and Dongsha Island (1996–2006; one-day lag). *Notes:* The y-axis is representing the spillover effect or the estimates of α_i.

Dongsha Island shows some positive lagged effect on other sites within 1,000 kilometers. This might reflect the presence of “omitted sites” bias, but its magnitude is significantly less than the estimated spillover from Shenzhen.

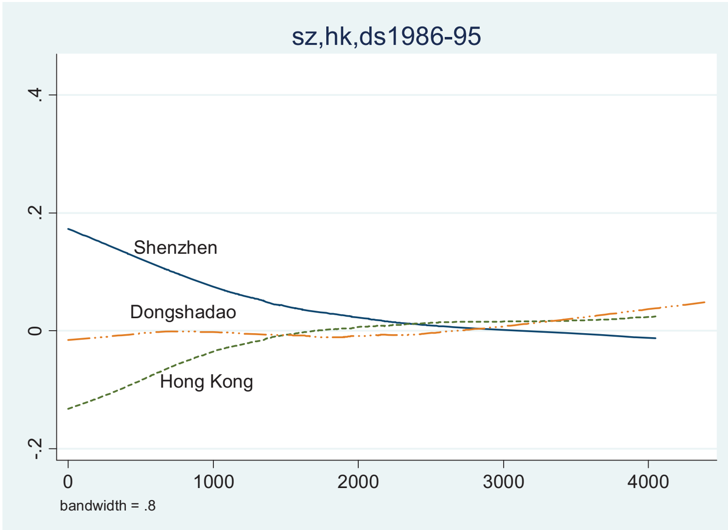

FIGURE 12 The spillover curves of Shenzhen, Hong Kong, and Dongsha Island (1986–1995; one-day lag). *Notes:* The y-axis is representing the spillover effect or the estimates of α_i.

CONCLUSION

After several decades of fast economic growth, the environment in China has deteriorated badly. There have been many discussions on how China should handle the environmental pollution (Chen and Warren, 2011; Song, 2015). By applying econometric methods onto daily visibility data from 300 sites across China in the past three decades, we find evidence that the air pollutants of China have strong spillover effects. In particular, we find that the spillover from major pollution sources of China remain significant for regions more than 1,000 kilometers away. Moreover, the magnitude of the spillover has significantly increased over time due to rapid economic growth.

It is interesting to compare our estimates with those of existing studies. The decay path of spillover over distance is comparable to findings in the United States, which use direct measures of pollution through spatial correlation analysis (Civerolo et al., 2003). Sigman (2002) examines water pollution by using data measured by monitoring stations that are close to country borders. She finds no evidence that water pollution significantly affects the water quality of the other nation downstream. In this regard, our study contributes with new evidence to the slim trans-boundary pollution literature.

In the article, we assume that the spillover effect between city 0 and city i remains constant. However, the relationship could be time variant and more complex because there might be a very complicated chemical process in the atmosphere in which many potential factors might not be controlled for in the current research. Further modification on the model to address these issues will be left for future research.

ACKNOWLEDGMENTS

We are indebted to the coeditor of this journal, Prof Ni Jinlan, and the two anonymous referees for helping us to substantially improve the article. All errors are our own.

NOTES

1. Stern (2005) employs a database of SO_2, which documents and imputes the Global Sulfur Emissions at the country level from 1850–2003.
2. Cohen et al. (2005) estimates that "… fine particulate air pollution (PM(2.5)), causes about 3% of mortality from cardiopulmonary disease, about 5% of mortality from cancer of the trachea, bronchus, and lung, and about 1% of mortality from acute respiratory infections in children under 5 yr, worldwide." (doi:10.1080/15287390590936166)
3. Due to the data limitation, in the regression we cannot control for terrain and wind direction.
4. Relative humidity is associated with 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 level 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.
5. Note that some stations censor visibility above 20 miles (i.e., visibility was reported as 20 miles when the actual visibility is greater). An ordinary least squares (OLS) estimation of the visibility-GDP elasticity may be biased downward due to this censoring.

FUNDING

The first author acknowledges the financial support of FDCT/064/2014/A from the Macau Science and Technology Foundation.

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