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Abstract

Relying on a novel satellite dataset, we examine the spatial distribution of air pollution, specifically $PM_{2.5}$, and income across 285 Chinese prefectural and above-level cities. A static spatial dependence analysis reveals the locations of high-value clusters (hot spots) and low-value clusters (cold spots), highlighting a strong negative assosiation between income and air pollution. Then, through dynamic spatial clustering techniques, we study the intertemporal relationship between air pollution and income and find a polarization effect between different regions. Our integrated approach demonstrates how these analyses complement each other in identifying regions where policies to enhance air standards can improve the population's quality of life.

Keywords: Air Pollution, China, Local Indicators of Spatial Association.

JEL classification: C15, O33, P11, P18, Q42

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1 Introduction

In the past few decades, China has experienced a rapid increase in pollution and environmental deterioration as it underwent dramatic economic growth. According to Brauer et al. (2016), most of the population in the country has been exposed to levels of $PM_{2.5}$ air pollution higher than what the World Health Organization (WHO) considers healthy. This issue poses a threat since the Chinese economy is expected to continue growing rapidly, and the deterioration of the environment and air quality will contribute to worsening the general population's health.

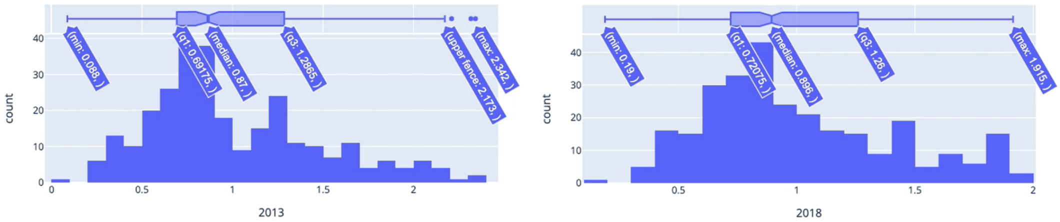
We aim to study the relationship between income and air pollution from a spatial distribution point of view. For this, we rely on a novel dataset by Wu et al. (2022) of 285 Chinese prefectural and above-level cities spanning 2000-2019. We differentiate our work by relying on methods from spatial data analysis to inquire about the evolution of the variables under study along with their spatial dependence, both static and dynamic. Therefore, we obtain results that support Wu et al. (2022) while expanding on these and contributing to the literature by performing additional analyses. These analyses are only possible due to the spatial nature of the methodology employed.

Being a major industrial and economic powerhouse, China has had dramatic rapid urbanization and industrialization in recent decades. These developments have contributed to substantial increases in greenhouse gas emissions (GHG), making China the world's largest emitter of carbon dioxide and other GHGs. Most of the population has been exposed to levels of $PM_{2.5}$ air pollution higher than the WHO considers healthy.

In 2013, the Chinese government introduced the Air Pollution Prevention and Control Action Plan (APPCA program) to mitigate urban air pollution. The main objective of this initiative was to achieve a minimum 10% reduction in PM levels by 2017 compared to the 2012 baseline across all Chinese cities. Notably, the government set a more ambitious reduction target of 25% in heavily polluted regions like Beijing, Tianjin, and Hebei. By 2017, the program demonstrated success by effectively lowering PM_{10} levels in all APPCA program cities by 22.7% from the 2013 baseline.

Even though the APPCA program successfully reduced PM_{10} concentrations, a potential issue is that this policy could shift the distribution of $PM_{2.5}$ concentrations among different income groups in the long run. As shown in Figure 1, the median for $PM_{2.5}$ concentrations before and after 2013 slightly increased. To test for this, we perform a dynamic analysis of spatial dependence and inspect whether there was an actual shift in the distribution of $PM_{2.5}$ amongst various regions and income groups.

Figure 1: Distribution of relative $PM_{2.5}$ across cities in 2013 and 2018



This paper is organized as follows. In section 2 we provide a review of the literature. In section 3 we discuss the different methods and the data employed throughout this work. In section 4 we describe the results obtained. In section 5 we conclude and provide some policy implications.

2 Related literature

Many studies exist regarding the relationship between GDP and pollution. One line of research has focused on the so-called "Environmental Kuznets Curve," or EKC, which shows the connection between economic growth and the environment. The classic work by Grossman and Krueger (1991) analyzes the environmental implications of the North American Free Trade Agreement by introducing the EKC. Since then, numerous studies have researched this relationship. In more recent times, Al-Mulali et al. (2015) investigate the linkage between the ecological footprint and GDP of 93 countries and find an inverted U-shaped relationship between these. Churchill et al. (2018) rely on panel data from the late 19th century to 2014 to study the EKC for 20 OECD countries. The authors find that the EKC hypothesis holds for the panel taken as a whole, but when explicitly considered by country, the results are instead mixed.

In the case of China, different authors have also analyzed this association. Relying on a dataset of 73 Chinese cities, Hao and Liu (2016) explore the EKC hypothesis in $PM_{2.5}$ for 2013 and observe that it exists. Jalil and Mahmud (2009) examine the EKC relationship between CO_2 emissions and per capita real GDP. They encounter a one way causality via economic growth to CO_2 emissions, relying on Granger causality tests. In the same vein, Yin et al. (2015) look into the EKC hypothesis for the case of CO_2 emissions by utilizing panel data for the years 1999-2011, finding evidence of its existence. Wang et al. (2016) examine the impacts of economic growth and urbanization on sulfur dioxide emissions through the EKC hypothesis and confirm that there is a relationship between economic growth and sulfur dioxide emissions, but not for urbanization and the latter.

A different strand of the literature concerns the convergence of emissions of different pollutants. These works are influenced by the economic convergence hypothesis, which assumes that countries with low-income tend to grow at a higher rate than their high-income counterparts. Due to this, income levels converge in the long-run. In a similar fashion, it is assumed that pollution declines faster in high-pollution countries relative to low-pollution ones. Therefore, in the long-run, countries converge in their environmental quality. Bulte et al. (2007) and Brock and Taylor (2010) lay the foundations for the theory of environmental convergence. Herrerias (2013) studies the environmental convergence of CO_2 emissions for a set of developing and developed countries, for the period going from 1980 to 2009. By considering the source of emissions, she is able to find the pattern of convergence of emissions more accurately. Although a large number of countries show club convergence, some still diverge. This implies the necessity of implementing environmental policies tuned to each of the clubs, since countries may converge to particular clubs.

A third line of research, where our work is positioned, consists of using spatial analysis to study the economy, pollution, and the interlink between these two. He et al. (2017) perform a geospatial analysis of inequality across various Chinese counties, prefectures and provinces for the period 1997-2010. Utilizing local indicators of spatial autocorrelation, they discern a northward movement of hot spots of economic growth. This shift was influenced by the movement of foreign investors towards the northern regions and the spatial agglomeration, alongside the impact of institutional forces in China. We distinguish our work by performing both static and dynamic analyzes of spatial dependence for a more extended period (2000-2018). Through these methods and data, we can pinpoint to regions and locations where policies to improve local populations' quality of life can be implemented.

Han et al. (2021) explore the interplay between the socioeconomic status of Chinese counties and their prolonged exposure to $PM_{2.5}$ concentrations. The study reveals that populations residing in economically disadvantaged counties are disproportionately vulnerable to the adverse impacts of such exposure. Consequently, this disparity in environmental risk exposure exacerbates socioeconomic inequality and health disparities within these places. By relying on the Directional LISA method, our study finds that regions with similar levels of relative air pollution and income tend to "move" (i.e., cluster) together throughout time.

The current body of literature has yet to yield definitive results concerning the relationship between income and pollution. There remains potential for creating more sophisticated dynamic models that capture the intertwined evolution of economic growth and pollution emissions. Furthermore, there is an opportunity for empirical research to examine alternative theoretical models and uncover new stylized facts in this context.

3 Methods and Data

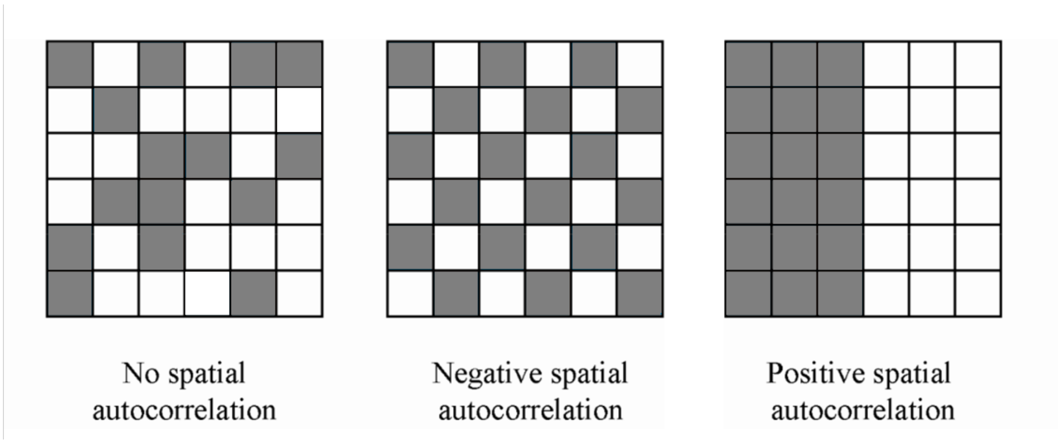
In this study, we rely on a panel dataset containing data on relative $PM_{2.5}$ levels along with relative income from Wu et al. (2022) for the period spanning 2000-2018. We then georeference the data, incorporating latitude and longitude variables, allowing us to perform the spatial analysis. All these data are for 285 Chinese prefectural and above-level cities.

We employ spatial dependence analysis to check the existence (or lack thereof) of clusters in the spatial distribution of a given characteristic or attribute. A global dependence test seeks if a pattern of clusters in the spatial distribution for an attribute is present or not. In this test, the null hypothesis consists in detecting if there is randomness in the spatial location we are studying (i.e., are the cities under study independent from each other and do they provide no significant information). If the null hypothesis is rejected, this implies that we can find clusters that are important for our study. The "gold standard" for testing global spatial dependence is Moran's I (Cliff and Ord, 1981). This test can be expressed as:

$$I = \sum_i \sum_j w_{ij} \left(x_i - \mu\right) \left(x_j - \mu\right) / \sum_i \left(x_i - \mu\right)^2 \tag{1}$$

where w_{ij} is the row-standardized element of the weighted matrix, outlining the spatial structure of the data we analyze. Additionally, x_i indicates the level of air pollution in city i, and μ shows the average level of air pollution. Figure 2 below shows a graphical depiction of spatial dependence.

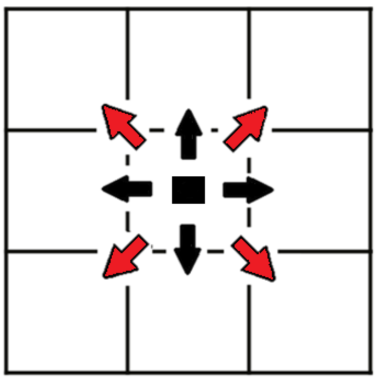
Figure 2: Spatial Dependence



Source: Adapted from Grekousis (2020).

When the spatial weights w_{ij} of the weighted matrix W take positive values (i.e., $w_{ij} > 0$), it denotes a relationship among neighbors in a geographical zone. Meanwhile, if $w_{ij} = 0$, there is a lack of such a relationship. These weights can be specified in various manners. One such way is the so-called "Queen contiguity" (referring to the movement of the queen piece in chess), in which two regions are considered neighbors if they share a common border or vertex (shown in Figure 3 below). In this work, we rely on this interpretation due to its ease of implementation and interpretation.

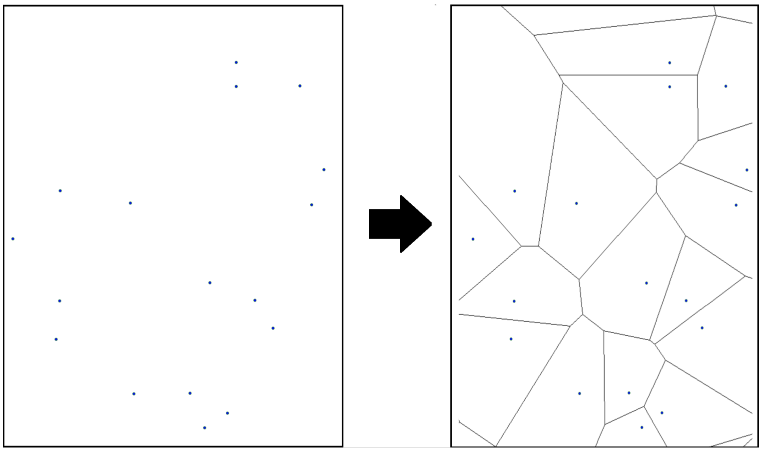
Figure 3: Queen Contiguity



In certain instances, we may encounter isolated locations or uneven distributions of data points. This situation poses a problem since it is not clear what the neighborhood of each data point is, complicating the computation of the spatial weights. In order to avoid these issues, we rely on the so-called

"Thiessen polygons."[1] These polygons allow us to work around these issues by dividing the areas into regular subareas. Additionally, it serves by generalizing the concept of contiguity, providing clear delineations of neighborhood boundaries on maps. Figure 4 below provides a visual explanation of the construction of Thiessen Polygons.

Figure 4: Construction of Thiessen Polygons



A method of spatial association at the local level proposed by Anselin (1995) is that of Local Indicators of Spatial Association (LISA). In it, the Local Moran statistic assesses local spatial patterns through "hot spots" (displaying relatively high patterns), "cold spots" (relatively low values), and spatial outliers (high values surrounded by low values or vice-versa). The Local Moran's I is given by the expression:

$$I_i = \frac{(x_i - \mu)}{\sum (x_i - \mu)^2} \sum_j w_{ij} (x_j - \mu) \tag{2}$$

the notation and variables in this expression are the same as those given by equation 1.

3.1 Directional LISA

To analyze the spatial co-evolution of income and air pollution distribution throughout time (i.e., whether these attributes form clusters or not), we make use of the method by Rey et al. (2011). This indicator connects two different periods of cross-sectional LISA, showing moving vectors and allowing us to

[1]These are also known as Voronoi diagrams or tessellations in the literature.

observe the joint movement of cities and their neighbors' income and air pollution. The Directional LISA[2] for city i at time t is given by:

$$I_{i,t} = \frac{(x_{i,t} - \mu)}{\sum(x_{i,t} - \mu)^2} \sum_j w_{ij}(x_{j,t} - \mu) \tag{3}$$

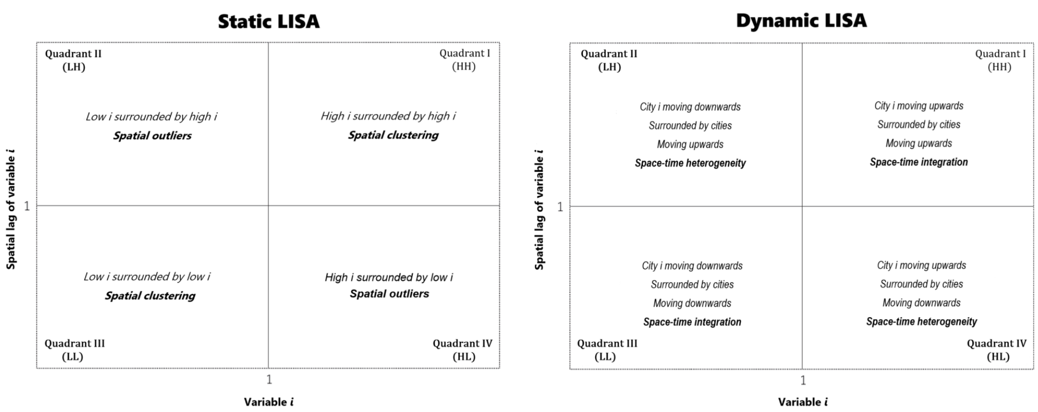
where $x_{i,t}$ is the variable of interest for city i at time t and $w_{i,j}$ has the same interpretation as in equation 1.

The hypothesis testing is given by the following criteria:

$$H_0 : h_{i,t+k} = h_{ip,t+k}$$
$$H_1 : h_{i,t+k} \neq h_{ip,t+k}$$

where $h_{i,t+k}$ refers to the height and direction of the vector from year t to year $t+k$, and h_{ip+k} alludes to the expected direction and height of the vector based on the null hypothesis of random spatial permutations, implying space-time independence. Consequently, the null hypothesis affirms that there is independence in the movements between cities and their neighbors. In Figure 5 we present a graphic comparing the static and dynamic LISA.

Figure 5: Comparison Between Static and Dynamic LISA



Source: Adapted from Aginta (2022).

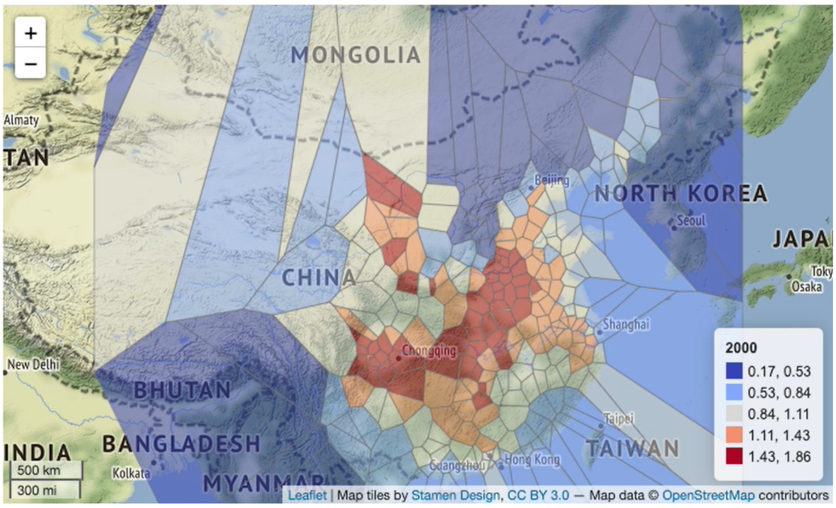
4 Results

We begin by constructing Thiessen polygons in the map (Figure 6) to clearly delimit each city's neighbors. From this, we observe a "ring-like" pattern

[2]Throughout this work, we will use the terms "Directional" and "Dynamic" LISA interchangeably.

where the cities in the center tend to have higher concentration levels of $PM_{2.5}$, and the outer-ring cities have lower concentrations than the rest. This situation naturally begs the question of whether spatial patterns of dependence play a role in this apparent clustering of cities with similar pollution levels.

Figure 6: Spatial distribution of $PM_{2.5}$ in 2000 using Thiessen Polygon



To identify the presence of local clusters and local spatial outliers for 2000 and 2017, we rely on the Local Moran statistic. The results for the year 2000 are shown in Figure 7. In part (a), we see that there is a high spatial dependence (Moran's I is 0.79), with most of the observations concentrating in the High-High (HH) and Low-Low (LL) quadrants. In part (b) of Figure 7, we observe that the concentration of hot spots (cities with high levels of pollution, surrounded by cities also with high pollution levels) are located towards the center of the Thiessen polygon.

Meanwhile, the cold spots are located towards the outer parts, following the "ring-like" pattern encountered before. These clusters, highlighted in red and blue, are statistically significant (p-value < 0.1). Finally, in part (c) of Figure 7, we show the geographic position of the cities on the Chinese map, with their respective $PM_{2.5}$ levels.[3] We see that, just as with the Thiessen polygons, most of the highly polluted cities are concentrated towards the center/middle-to-east of China, with less polluted cities outside of this cluster.

[3] It is worth noting that parts (a) and (b) are not directly correlated or matched in a one-to-one manner with the map in part (c). We plot them together to understand the results and their geographical positioning visually.

Figure 7: $PM_{2.5}$ Spatial Dependence (2000)

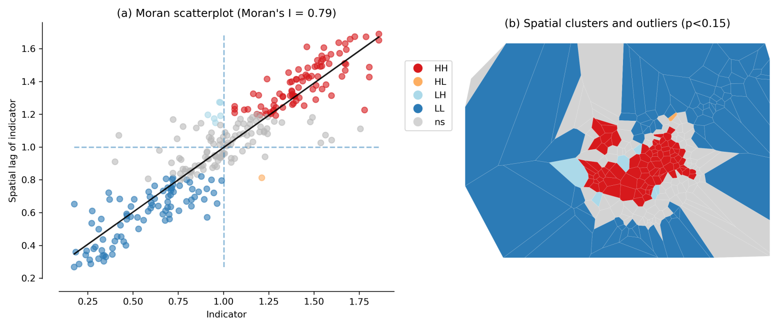
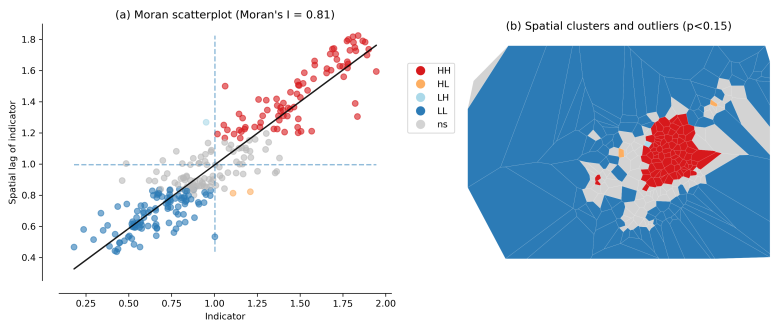


Figure 8 shows the same results but for the year 2017. Once again, we find a high level of spatial dependence (Moran's I is 0.83) and the statistically significant ring structure (p-value < 0.15) from before. The map in part (c) suggests that in the period spanning from 2000, many cities in the center of China with high concentrations of $PM_{2.5}$ have improved. In the meantime, those to the center-east have slightly worsened (those at the tail-end increasing from 1.859 to 1.915 *relative* $PM_{2.5}$).

Figure 8: $PM_{2.5}$ Spatial Dependence (2017)



From the results above, we ask ourselves, what is the income for these cities? Do we observe cities with high income having lower or higher pollution levels? To answer this, we do the same local spatial dependence analysis but for relative income. The results are presented in Figures 9 and 10. Figure 9 shows that Moran's I is still positive but lower than before, at 0.34. This implies that despite spatial dependence being present, it is not as strong as in the case of $PM_{2.5}$. In part (b) of this Figure, we see that contrary to the $PM_{2.5}$ case, the hot spots are located in the outer ring, while the cold spots are in the center.

Figure 10 once again paints a similar picture. Although spatial dependence is slightly higher than before (Moran's I is 0.37), it is not as strong as for $PM_{2.5}$. Nevertheless, for 2017, we still find cold spots in the center and hot spots on the outer sides of the ring. This suggests that cities with higher income levels (with respect to the mean) tend to have lower concentrations of $PM_{2.5}$ and vice versa.

Figure 9: Spatial Dependence for Relative Income (2000)

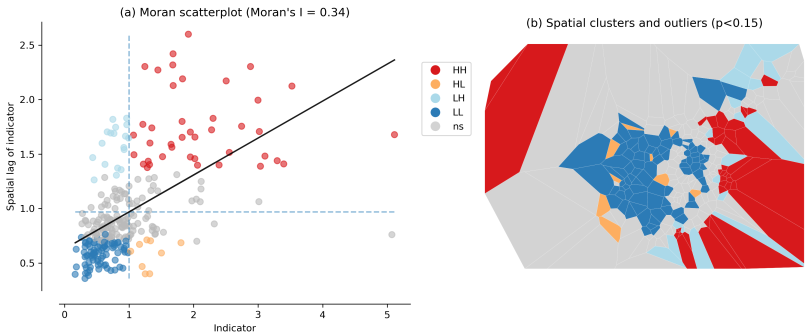
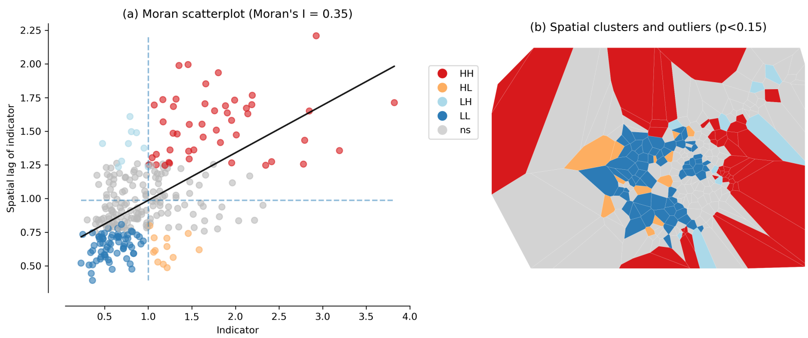


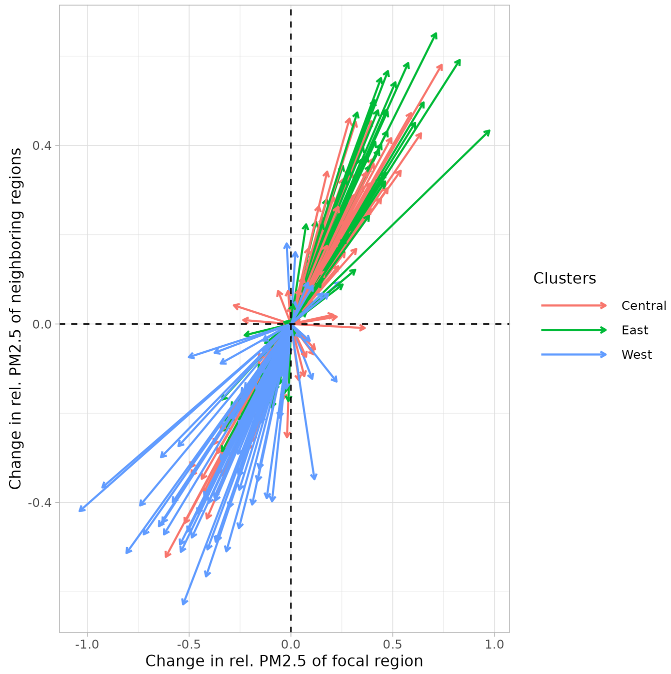
Figure 10: Spatial Dependence for Relative Income (2017)



4.1 Directional LISA

In the previous section, we found a negative relationship between income levels and concentrations of $PM_{2.5}$. This relationship, though, was in a static sense. We would like to know whether this relationship also holds intertemporally and, if so, where in China. Therefore, we rely on the Directional LISA method discussed in section 3.1. Doing this will allow us to analyze the spatial co-evolution between $PM_{2.5}$ and income throughout time.

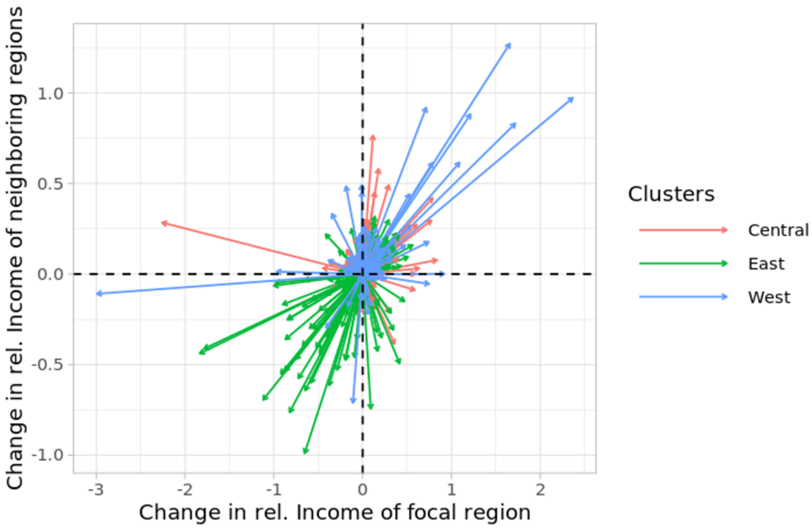
Figure 11: Standardized Directional LISA for $PM_{2.5}$ (2000-2017)



In Figure 11, we plot the directional LISA for $PM_{2.5}$ comprising the years 2000-2017. We proceed to divide the cities in China into three regions: East, West, and Central. The arrows point to the quadrant to which each city is moving, with the color representing the region where each belongs. Additionally, we standardize the plot so that all arrows depart from the origin. For this period, there is a clear divide between East and West (with the central region being more ambivalent).

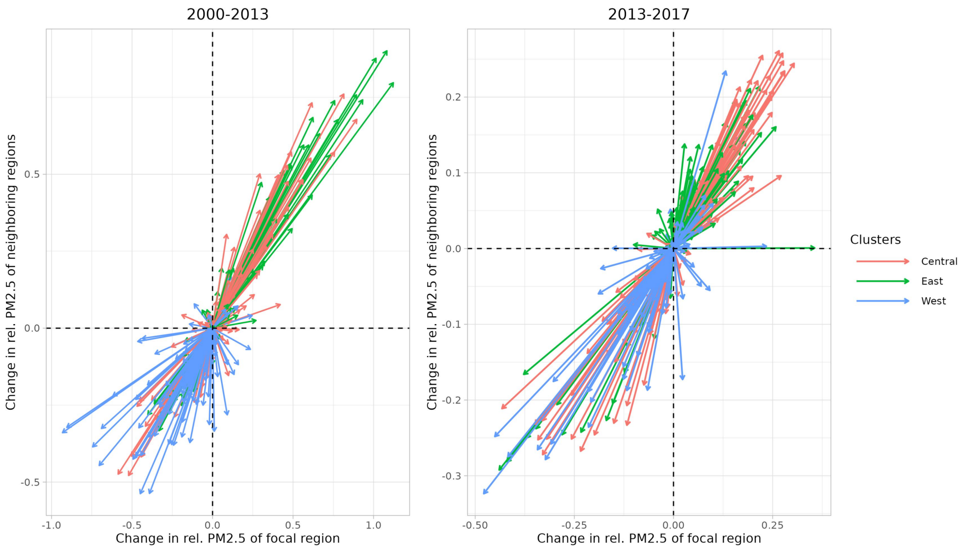
In Figure 12, we observe the results for relative income. Similar to the case of $PM_{2.5}$, a polarization-like effect occurs, in which the East and West regions move in opposite directions (cities with high levels of income move upwards, surrounded by cities moving upwards and vice-versa). Just as in the static case, this suggests that cities with high (low) income levels tend to have lower (higher) air pollution levels and neighbors similar to them.

Figure 12: Standardized Directional LISA for rel. income (2000-2018)



Additionally, we analyze the evolution of $PM_{2.5}$ before and after the 2013 Air Pollution Prevention and Control Action Plan (APPCA program) implemented by the government. Doing so lets us see if said program altered the clustering tendency we observed for the whole period. The left panel of Figure 13 presented below shows that the polarization effect between the East and West regions, previously shown in Figure 12, persisted until 2013. In the right panel, we can see that from 2013 onward, this trend mostly reversed: the West region started to improve while the East got worse. The Central region also, in its majority, moved downwards.

Figure 13: Standardized Directional LISA before and after 2013



5 Discussion

By "spatializing" the data and making use of spatial analysis methods, we can identify clusters that present both similarities in location and attributes with respect to air pollution and income. This is in contrast to the approach by Wu et al. (2022), who rely on a distribution dynamics approach to find long-run relationships between these variables.

The dynamic clustering analysis in the previous section reveals a growing polarization between the eastern and western regions of China, indicating distinct patterns of development and environmental dynamics. However, when splitting the period into two (before and after 2013), we see a shift post-2013, suggesting unintended consequences possibly stemming from implementing the Atmospheric Pollution Prevention and Control Action (APPCA) program. These findings highlight the complexity of addressing environmental challenges, particularly in relation to reducing $PM_{2.5}$ pollution levels. Moreover, the analysis of diffusion patterns suggests a negative correlation between pollution levels and income distribution, emphasizing the need for targeted interventions to mitigate environmental inequalities while promoting sustainable development.

The significance of finding these clusters relies on the fact that it allows for policy coordination at that level. The static approach, through the Local Moran statistic, provides information on spatial dependence and whether there is a diffusion process taking place amongst neighboring cities or regions. Complementing this, the dynamic approach shows whether these cities and regions, along with their neighbors, are converging towards similar levels of pollution and income. When considered together, these approaches help to pinpoint the locations where more effort needs to be taken by providing an analytical and visual representation of the data.

On the policy side, collaborating with Japan and other neighboring countries can be beneficial for China. Japan's successful experience in addressing air pollution during its high economic growth period in the 1950s and 1960s presents valuable lessons for China. Given their geographical proximity and shared concerns about air quality, fostering joint cooperation is important. By working together, these nations can effectively tackle environmental challenges while also encouraging regional economic growth.

6 Conclusions

In this work, we analyzed the pollution-income relationship for cities in China using data on relative income and $PM_{2.5}$. After georeferencing this data, we relied on spatial analysis methods and found a "ring-like" pattern where cities at the center tended to have higher concentration levels of $PM_{2.5}$, and the outer-ring ones had lower concentrations than the rest. This linkage is inverted when considering relative income, suggesting that spatial patterns of dependence may be causing this clustering of cities with similar income-pollution levels. We then proceeded to detect hot spot and cold spot clusters, with a very high (> 0.5) and significant (p-value < 0.1) spatial dependence. All this further confirmed the ring pattern of clusters found before.

Finally, through a dynamic LISA analysis, we studied the intertemporal association between pollution and income for the whole period and before and after the APPCA program in 2013. The former showed that for the years 2000-2017, there was a polarization between different regions: the western region increased its income while improving its air pollution, while the east region headed in the opposite direction. The latter, instead, painted a different picture. While presenting a similar behavior up to 2013, afterward, the tendency reverted.

Future research could focus on analyzing the relationship between income and air pollution for a longer time frame. Additionally, using a larger dataset that includes more cities from the western region would allow us to corroborate the present results. Furthermore, a more detailed analysis and understanding of the impact of the APPCA program on the $PM_{2.5}$ levels would allow the development of programs that better address the issue of air pollution.

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