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Spatial Dynamics of Air Pollution and Income in China

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Abstract

We examine the spatial distribution of air pollution, specifically $PM_{2.5}$ levels, and income across 285 prefectural-level and above cities in China. Our analysis combines static spatial dependence techniques to identify clusters of high pollution (hot spots) and low pollution (cold spots), highlighting a strong negative relationship between income and air pollution, with wealthier regions typically enjoying better air quality. To deepen this understanding, we apply spatial Markov chains to evaluate whether regions are converging over time in terms of air pollution and income levels. This integrated approach not only uncovers spatial patterns but also tracks temporal dynamics, providing insights that can inform strategies to enhance public health, promote environmental equity, and improve overall quality of life.

1 Introduction

China's rapid economic growth in recent decades has been accompanied by a marked increase in air pollution and environmental degradation. According to Brauer et al. (2016), most of the country's population has been exposed to $PM_{2.5}$ air pollution levels exceeding the World Health Organization's (WHO) recommended safety limits. This trend is particularly concerning as China's economy is expected to continue expanding rapidly, further exacerbating environmental decline and negatively impacting public health.

In this study, we examine the spatial dynamics of regional income and air pollution in China. Using a dataset from Wu et al. (2022), which covers 285 prefectural-level and above cities from 2000 to 2018, we analyze how these variables change over time and across space. Unlike previous studies, we employ spatial data analysis techniques to investigate both static spatial dependencies and spatial distribution dynamics, providing a more comprehensive understanding of regional disparities in air pollution and income. By building on and expanding the findings of Wu et al. (2022), our research offers new insights into the spatial persistence and mobility of these disparities, made possible through the integration of spatial methodologies.

China's rapid urbanization and industrialization have played a key role in shaping the spatial distribution of air pollution and income. While driving economic growth, these transformations have also led to severe air pollution, exposing much of the population to $PM_{2.5}$ levels exceeding the levels recommended by World Health Organization (WHO). Understanding the spatial distribution of pollution and income is essential for developing targeted policies to mitigate environmental disparities.

Recognizing the severity of air pollution, the Chinese government introduced the Air Pollution Prevention and Control Action Plan (APPCA) in 2013 to mitigate urban air pollution. The initiative aimed to reduce PM levels nationwide by at least 10% by 2018, using 2012 as the baseline. For heavily polluted regions such as Beijing, Tianjin, and Hebei, the government set a more ambitious target of a 25% reduction. By 2018, the program proved successful, achieving a 22.7% reduction in PM_{10} levels across all APPCA cities compared to the 2013 baseline.

Although the APPCA program effectively reduced PM_{10} concentrations, concerns remain about its long-term impact on the distribution of $PM_{2.5}$ levels across different income groups. To examine this, we use spatial Markov chains to analyze whether there was a significant shift in the distribution of $PM_{2.5}$ and income across the cities under study.

This paper is organized as follows. In section 2 we review the related literature. In section 3 we explain the methods and the data we make use of in this paper. In section 4 we describe the results. In section 5 we discuss the policy implications, and we conclude in section 6.

2 Literature Review

Numerous studies have examined the relationship between economic growth and pollution, with one prominent line of research focusing on the Environmental Kuznets Curve (EKC), a hypothesis that proposes that there is a positive relationship between per capita income and environmental quality at first, until, at a tipping point, the relationship becomes negative. The foundational work of Grossman and Krueger (1991) introduced the EKC while analyzing the environmental impact of the North American Free Trade Agreement (NAFTA). Since then, many studies have investigated this relationship. In more recent times Wang et al. (2024) analyze the mechanisms through which trade protection, measured using trade openness data, impacts the relationship between economic growth and environmental degradation across 147 countries from 1995 to 2018. Kacprzyk and Kuchta (2020) examine the EKC for CO_2 emissions in 161 countries (1992-2012), highlighting GDP measure-dependent inflection points and using nighttime light data as a proxy for economic development.

Several studies have explored this association for the case of China. Zhao et al. (2021) use data from 30 Chinese provinces for the period 1999–2017 and find that financial depth reduces pollution and financial efficiency increases it. Additionally, these two financial development indicators moderate the effects of technical progress and industry structure differently, while an "inverted N"-shaped EKC is confirmed for SO_2 and solid waste. Ding et al. (2019) investigate $PM_{2.5}$ pollution in China's Beijing-Tianjin-Hebei (BTH) region from 1998 to 2016, confirming an inverted U-shaped EKC using satellite data and spatial econometrics. They find that the region remains in the rising phase, with the turning point delayed by spatial effects and likely occurring only after full post-industrialization. Jalil and Mahmud (2009), focusing on CO_2 emissions and per capita real GDP, find evidence of a one-way causality from economic growth to CO_2 emissions based on Granger causality tests. Furthermore, Wang et al. (2016) analyze the effects of economic growth and urbanization on sulfur dioxide emissions, confirming the existence of a relationship between economic growth and sulfur dioxide emissions, but not between urbanization and sulfur dioxide levels.

Another area of research focuses on the convergence of pollution levels across countries or regions, drawing from the economic convergence hypothesis, which posits that lower-income economies tend to grow at a faster rate than wealthier ones, leading to long-term income convergence. In an environmental context, this implies that countries with initially high pollution levels should experience faster reductions, eventually converging toward similar environmental conditions. Bulte et al. (2007) and Brock and Taylor (2010) laid the groundwork for environmental convergence theory. Meanwhile, Borowiec and Papież (2024) examine CO_2 emissions convergence across 38 countries from 1992 to 2019 using the DCCE-MG model to analyze production- and consumption-based emissions. The authors' results show absolute and conditional convergence, with faster convergence in developing countries, though their emissions continue to rise, while developed countries see slower declines. Stringent environmental policies and globalization significantly influence CO_2 convergence in developing countries, whereas GDP effects are ambiguous, and renewable energy and industrialization have no impact.

A third research direction—where our study is situated—focuses on spatial analysis of economic growth and pollution. Li et al. (2014) analyze SO_2 and Chemical Oxigen Demands (COD) emissions in China using county-level data. They identify spatial concentration patterns with Moran's I and examine key economic and industrial drivers through spatial econometric models (SEM and SLM) and find that spatial dependence significantly influences emissions. SEM outperforms SLM, leading to policy recommendations for highly polluted regions. Zhu et al. (2020) study air pollution in China for the years 2011–2017, finding that pollution is more severe in northern provinces and that renewable energy technology innovation (RETI) reduces NO_x and PM_{10} but has no significant effect on SO_2, while spatial spillover effects highlight the need for regionally coordinated air quality policies.

Similarly, Han et al. (2021) explore the relationship between the socioeconomic status of Chinese counties and their exposure to prolonged $PM_{2.5}$ concentrations, finding that economically disadvantaged populations face higher risks from air pollution. This unequal exposure exacerbates socioeconomic and health disparities, reinforcing existing inequalities. Using spatial Markov chains, our research shows that regions with similar levels of relative air pollution or income tend to persist in similar conditions, having a harder time improving than they would if their neighbors were better off, which would help them improve as well. Despite the extensive body of literature on the relationship between income and pollution, results remain inconclusive. There is still significant room for the development of more sophisticated dynamic models capable of capturing the complex interactions between economic growth and environmental degradation. Further empirical research is also needed to test alternative theoretical frameworks and uncover new empirical patterns that can inform both academic discussions and policy interventions.

3 Data and Methodology

In this section, we describe the data used throughout the paper as well as the methodology for its analysis.

3.1 Data

For this work, we utilize a comprehensive panel dataset from Wu et al. (2022), which includes relative $PM_{2.5}$ and relative income data spanning the period from 2000 to 2018. The dataset covers 285 Chinese prefectural and above-level cities. We begin by georeferencing the data with latitude and longitude coordinates and subsequently define the analytical boundaries of each city using Thiessen polygons. We then proceed with the geospatial analysis.

3.2 Spatial Dependence

To study whether there exist clusters in the spatial distribution of a specific characteristic or attribute. We rely on static spatial dependence analysis. The global spatial dependence test evaluates the presence or absence of clustering patterns for the attribute under study. The null hypothesis we test assumes that spatial locations are randomly given, implying that the cities under investigation are independent and do not provide information that is significant. Rejecting the null hypothesis indicates the presence of meaningful clusters relevant to our analysis. The standard method for testing global spatial dependence is Moran's I (Cliff and Ord, 1981), which is expressed as:

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

Here, w_{ij} represents the row-standardized element of the weight matrix, which defines the spatial structure of the data under analysis. x_i denotes the level of air pollution/income in city i, while μ represents the average level of air pollution/income across all cities. In Figure 1 below we can see how spatial dependence is graphically represented.

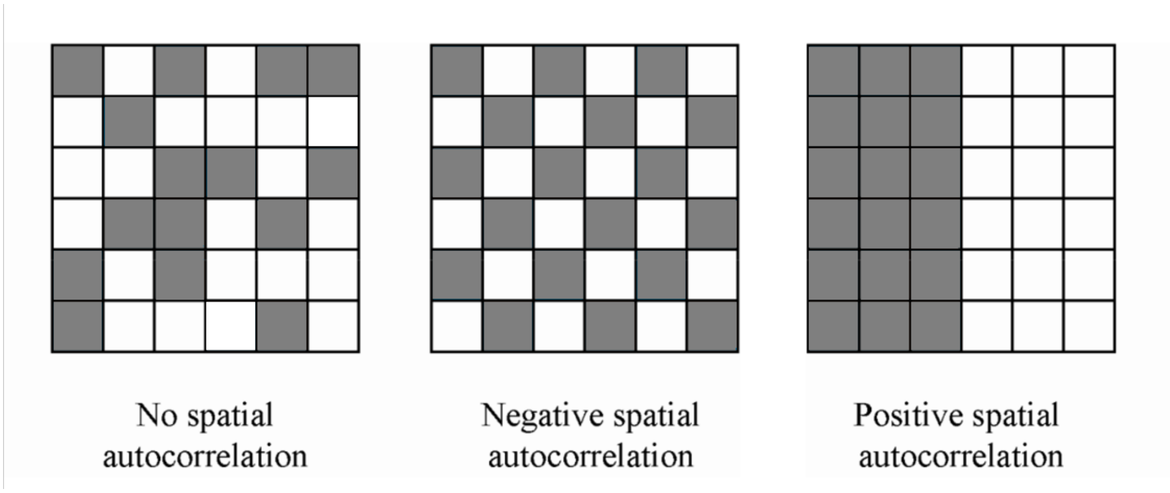

Figure 1: Spatial Dependence

Source: Adapted from Grekousis (2020).

In the weight matrix W, when the spatial weights w_{ij} have positive values ($w_{ij} > 0$), they indicate that there is a relationship between neighboring geographical zones. In contrast, if $w_{ij} = 0$, it means that there is no such relationship. These weights can be defined in several ways, one of which is the "Queen contiguity" method. This approach, inspired by the movement of the queen piece in chess, considers two regions as neighbors if they share a common border or vertex (as illustrated in Figure 2 below). For this study, we adopt this method since it is simple to implement and interpret.

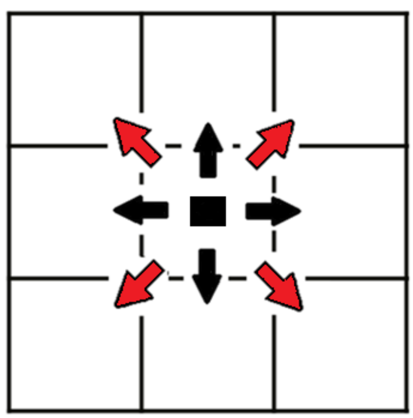

Figure 2: Spatial Contiguity

A method for analyzing spatial association at the local level is through the Local Indicators of Spatial Association (LISA), proposed by Anselin (1995). This method uses the *Local Moran* statistic to identify and assess local spatial patterns, such as "hot spots" (areas with relatively high values), "cold spots" (areas with relatively low values), and spatial outliers (locations with high values surrounded by low values, or vice versa). The Local Moran's I is defined as follows:

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

The notation and variables in this expression are consistent with those used in the Global Spatial Dependence formula for Moran's I.

There may be situations where we have isolated locations or unevenly distributed data points. These cases present a challenge, as it becomes unclear how to define the neighborhood of each data point, making the calculation of spatial weights more complex. To address them, we use the "Thiessen polygons" method. This approach overcomes these challenges by dividing the study area into regular subareas, effectively generalizing the concept of contiguity. It provides clear and precise neighborhood boundaries on maps. Figure 3 illustrates the construction of Thiessen polygons.

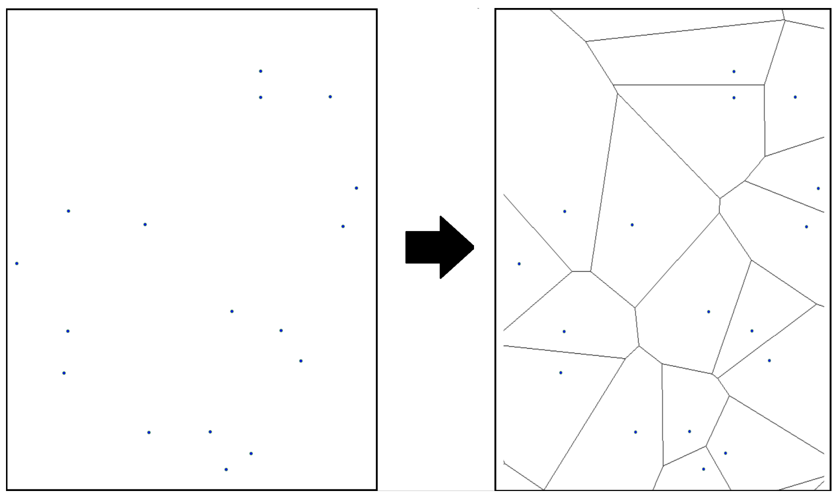

Figure 3: Thiessen Polygons

3.3 Spatial Markov Chains

A Markov chain is a mathematical system that describes a sequence of states or events, where the probability of transitioning between states depends only on the current state and not on past ones. This property, known as the Markov property, ensures that the system is memoryless, meaning that past states have no direct influence on future states beyond the present one. Markov chains are widely used in probability theory, statistics, and various applied fields, including economics, physics, and biology. They are often represented using a transition matrix, which defines the probabilities of moving from one state to another, enabling structured analysis of system behavior over time. Markov chains are particularly useful for modeling stochastic processes where outcomes evolve over discrete time steps.

Figure 4 shows a simple two-state Markov chain with states A and B, where the arrows represent transitions between the states, and the transition probabilities are shown in the matrix. The transition matrix in the image provides the probability of moving from one state to another: for example, the probability of staying in state A ($P(A|A)$) is 0.19, while the probability of transitioning from A to B ($P(B|A)$) is 0.81. Similarly, the probability of remaining in B ($P(B|B)$) is 0.50, and the probability of transitioning from B to A ($P(A|B)$) is also 0.50.

Spatial Markov chain extends the traditional Markov chain framework by incorporating spatial dependencies into the transition process. While a standard Markov chain models state transitions based solely on the current state, a spatial Markov chain considers the influence of neighboring locations or spatial contexts when determining transition probabilities. This means that the probability of moving from one state to another does not depend only on the present state but also on the spatial structure or regional characteristics of the system. Spatial Markov chains are particularly useful in contexts where spatial autocorrelation and neighborhood effects play a crucial role in system dynamics. This difference makes spatial Markov chains more suitable for capturing spatial heterogeneity and spatial dependence, which traditional Markov chains ignore.

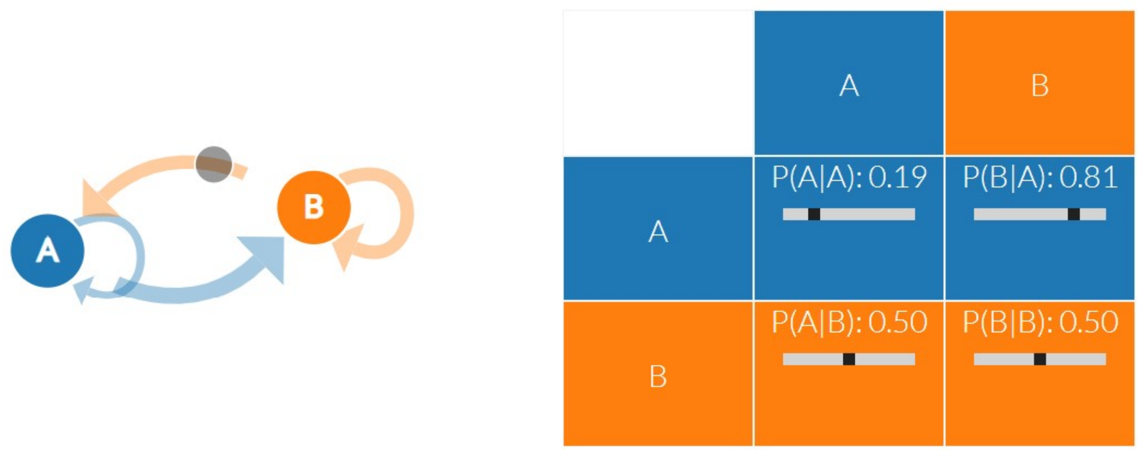

Figure 4: A sample Markov Chain

4 Results

To identify each city's neighbors, we construct Thiessen polygons on the map (shown in Figure 5) using Queen contiguity. This reveals a "core-periphery" pattern: cities at the center tend to have higher $PM_{2.5}$ concentrations, while those in the outer ring exhibit lower concentrations. In contrast, high-income cities are predominantly found in the outer ring. This pattern raises an important question: do spatial dependence and clustering influence the distribution of cities with similar pollution levels?

4.1 Spatial Dependence Analysis

We use the Local Moran statistic to examine the presence of local clusters and spatial outliers for 2000 and 2018. The results for the year 2000 are presented in Figure 6. In part (a) of this figure, the analysis shows high spatial dependence (Moran's $I = 0.79$), with most observations concentrated in the top-right (High-high) and bottom-left (Low-low) quadrants. In part (b), we observe that hot spots (cities with high pollution levels surrounded by similarly polluted cities) are mainly located toward the center of the map. In contrast, cold spots are found in the outer regions, following the previously identified "core-periphery" pattern. These clusters, colored in red and blue, are statistically significant (p-value < 0.05). Most highly polluted cities are concentrated in central and middle-to-eastern China, while less polluted cities are located out of this cluster.

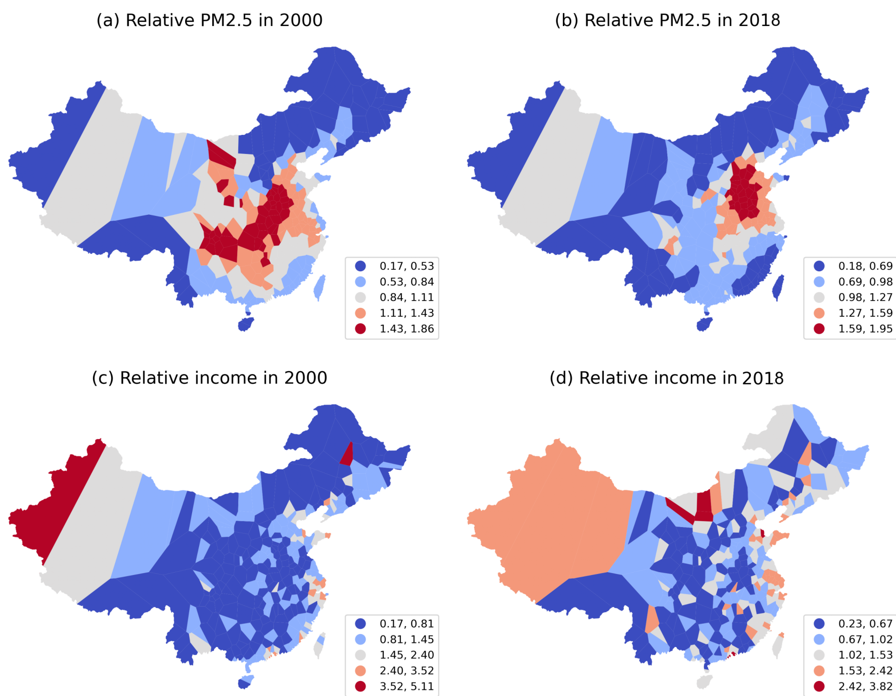

Figure 5: Spatial Distribution of $PM_{2.5}$ and GDP per Capita

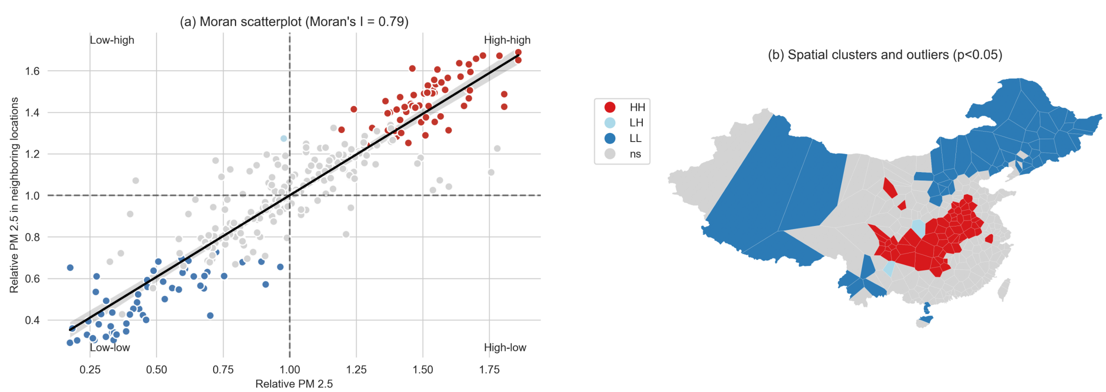

Figure 6: $PM_{2.5}$ (2000)

Figure 7 presents the results for the year 2018. As for the case of the year 2000, we observe a high level of spatial dependence (Moran's $I = 0.82$) and the statistically significant core-periphery structure (p-value < 0.05) identified previously. The map indicates that, over the period since 2000, many central Chinese cities with high concentrations of $PM_{2.5}$ have shown improvement. Meanwhile, cities in the center-east have experienced a slight increase in pollution levels, with relative $PM_{2.5}$ rising from 1.859 to 1.915 in the most affected areas.

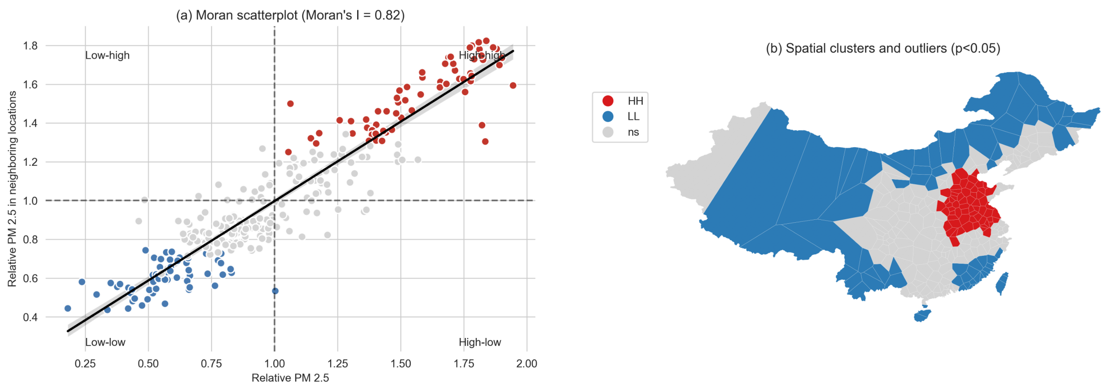

Figure 7: $PM_{2.5}$ (2018)

The results above prompt us to ask: What are the income levels of these cities? Do cities with higher income tend to have lower or higher pollution levels? To address this, we conduct the same local spatial dependence analysis, now instead focusing on relative income. The findings are presented in Figures 8 and 9. Part (a) of Figure 8 tells us that Moran's I is positive but significantly lower than in the case of $PM_{2.5}$, with a value of 0.33. This indicates that while spatial dependence exists, it is much weaker for income than for pollution levels. Part (b) of the figure reveals a reversal in the spatial pattern: unlike $PM_{2.5}$, high-income hot spots are found in the outside, while low-income cold spots are concentrated in the center.

A similar pattern is observed in Figure 9. While Moran's I increased slightly, to 0.36, the spatial dependence remains weaker than for the $PM_{2.5}$ case. For 2018, we again see cold spots in the center and hot spots along the outer parts. These results suggest that higher-income cities (relative to the mean) tend to have lower $PM_{2.5}$ concentrations, whereas lower-income cities are associated with higher pollution levels.

From the analysis, we observe that even though the Moran's I value is consistently positive and significant for the years under study, it does not provide information on the evolution of income and pollution in different cities in China over time. This is due to two main reasons: 1) The Moran's I statistic assesses spatial dependence at a single point in time but does not capture changes or dynamics in the variables under study, and 2) other factors, such as regional context (i.e., the influence of neighboring regions/cities), may play an important role in shaping income and pollution dynamics. Therefore, in the following section, we rely on spatial Markov chains, a spatially explicit method that allows us to incorporate spatial effects in understanding regional distribution dynamics.

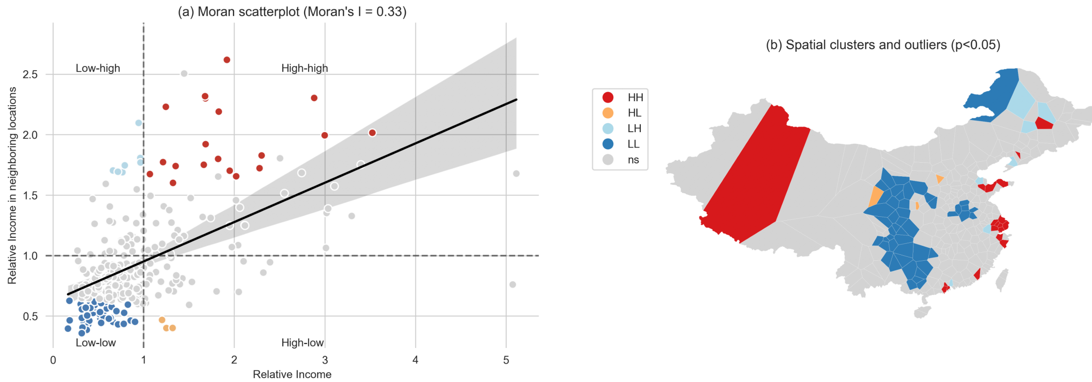

Figure 8: GDP per Capita (2000)

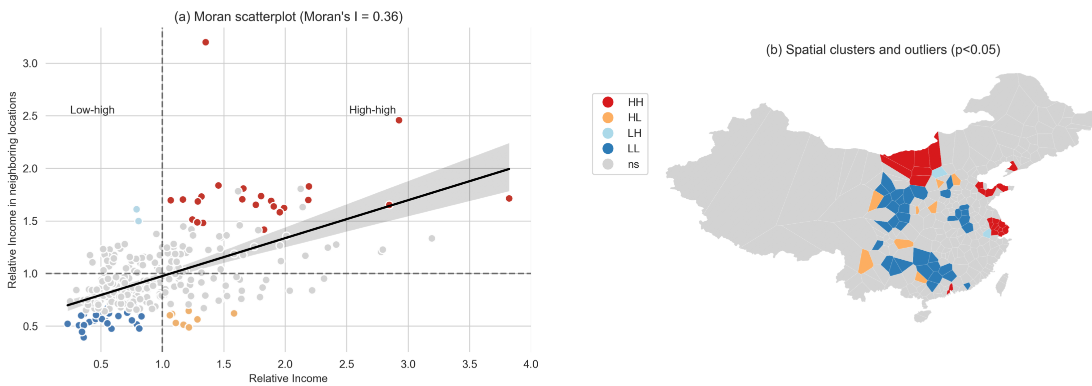

Figure 9: GDP per Capita (2018)

4.2 Spatial Markov Chains Analysis

As mentioned before, spatial Markov chains allow us to quantify the probabilities of transitioning from a state (e.g., income or $PM_{2.5}$ levels) based on the current state of a city/region and the states of neighboring locations. From this type of analysis, we can gain a better understanding of whether cities are undergoing improvements or not, based on their own performance and that of their neighbors over time. In Figure 10 below, we see six matrices showing the evolution of $PM_{2.5}$ for the period from 2000 to 2013: "Global", which refers to the traditional Markov chain (i.e., it does not include spatial lags), and five matrices with "Spatial Lag" 1 to 5 (representing neighbors with low to high air pollution, respectively). For the global matrix, we observe that during this period, a city with low pollution (state 0) has a 96.9% probability of remaining in the same state, while it has a 3% chance of transitioning to a slightly higher pollution level (middle-low level). At the other extreme, a city with high pollution (state 4) has a 97.1% probability of remaining in the same situation and only a 2.9% likelihood of slightly reducing to state 3 (middle-high level of pollution).

Meanwhile, when considering the effects of neighbors, we see that if a low-pollution city is surrounded by other low-pollution cities, it has a 97.9% chance of remaining in the same state and a 2.1% probability of transitioning to a middle-low pollution level. Conversely, if a highly polluted city has low-pollution cities as neighbors, its likelihood of remaining in the same state is 93.4%, while the probability of transitioning to a middle-high pollution level is 4.4%, to a middle-level pollution state is 1.1%, and to a middle-low pollution state is also 1.1%. It has a 0% probability of becoming a low-pollution city. At the other extreme, a city with low pollution surrounded by highly polluted cities has a 94% chance of not worsening, a 5.2% probability of slightly increasing its pollution to a middle-low level, and a 0.9% probability of reaching a middle pollution level. Similarly, cities surrounded by middle-low to middle-high pollution levels (Spatial Lag 2 to 4) have varying probabilities of either remaining in the same state or transitioning to different pollution levels.

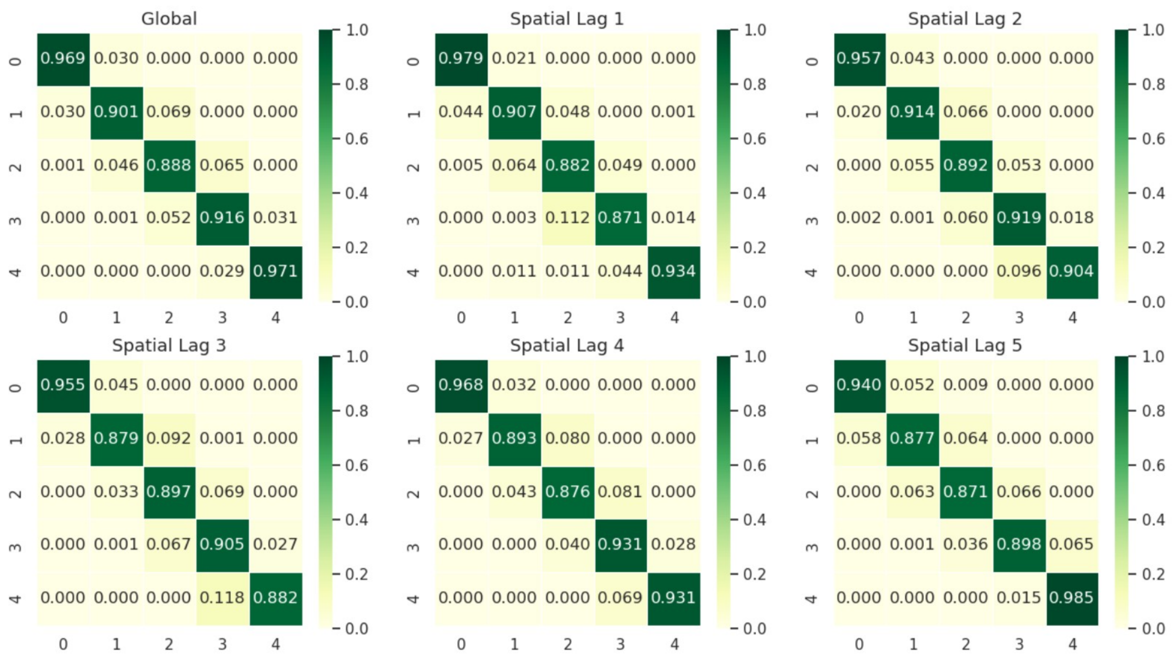

Figure 10: $PM_{2.5}$ (2000-2013)

For the second period, shown in Figure 11 and spanning the years 2013–2018, the spatial Markov chains indicate that for cities in state 0 (low-pollution), if their neighbors belong to Spatial Lag 1, their likelihood of remaining in the same state is 98.6%, while the probability of transitioning to state 1 (middle-low pollution) is only 1.4%. Likewise, cities in state 4 (high-pollution) with the same spatial-lag neighbors will remain in their respective state with a 100% probability. In other words, high-pollution cities surrounded by low-pollution cities during this period had a 0% probability of improving. In contrast, for cities in state 0, having highly polluted neighbors meant an 89.1% chance of remaining in the same situation and a 10.9% probability of transitioning to state 1 (middle-low pollution).

On the other hand, cities in state 4 with highly polluted neighbors had a 98.6% probability of not improving and only a 1.4% likelihood of reaching state 3 (middle-high pollution). These findings suggest that in the period after the APPCA was implemented, cities, on average, had greater difficulty in reducing their pollution levels. When we consider the entire period (2000–2018), shown in Figure

12, we observe that the values along the main diagonal of the matrices (representing the likelihood of remaining in the same state) are higher than the off-diagonal values (representing the probability of transitioning to a different state). Additionally, the matrix values fall between those of the pre- and post-2013 periods, implying that they represent an average of both periods.

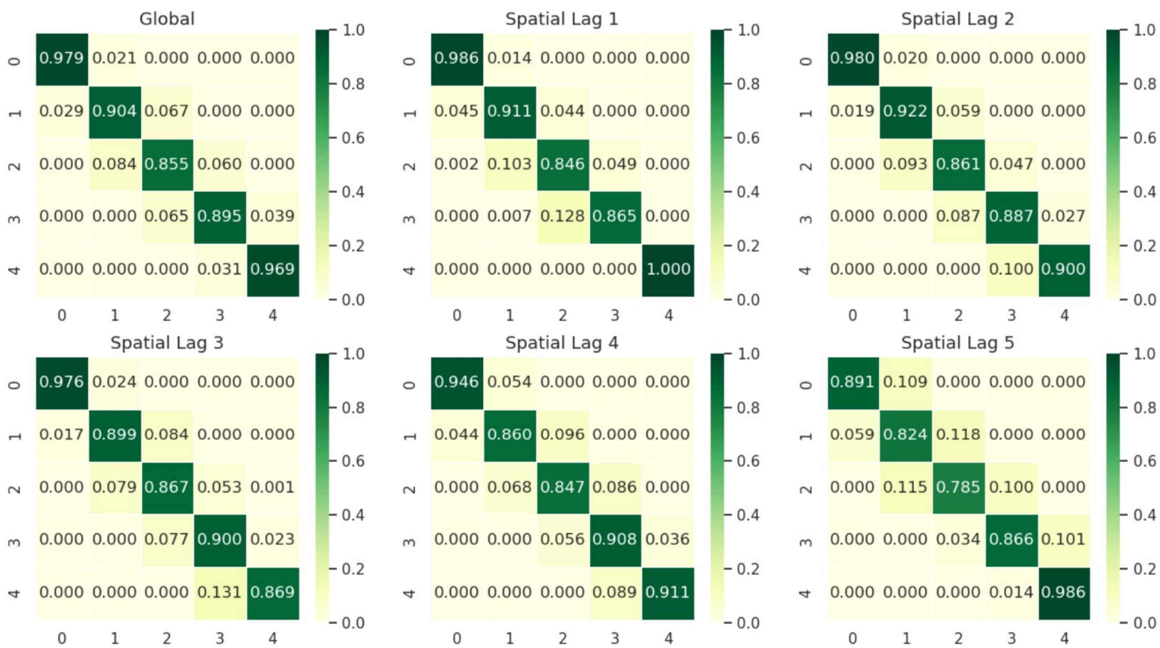

Figure 11: $PM_{2.5}$ (2013-2018)

In Figure 13 below we see that for the case of income (GDP per capita), cities with low income (state 0) that have low-income neighbors (Spatial Lag 1) have a 96.6% probability of remaining poor, while they have a 3.4% chance of improving their condition to state 1 (middle-low income). Meanwhile, high-income cities (state 4) with low-income neighbors have an 85.9% likelihood of remaining rich, with a 14.1% chance of transitioning to middle-high income. On the flip side, for cities in state 0, having Spatial Lag 5 (high-income) neighbors implies a 2.9% probability of transitioning to a higher income state, whereas the probability of remaining in the same situation is 90.2%. High-income cities surrounded by other high-income cities have a 97.7% probability of maintaining their status quo, while they will only reduce their income to middle-high in 2.2% of cases.

For the second period (shown in Figure 14), the likelihood of a state 0 city remaining in the same state when surrounded by low-income neighbors is 99.3%, with a transition probability of only 0.7%. On the opposite end, a high-income city in this context would remain so with an 88% probability and transition to middle-high income with a 12% probability. For cities with high-income neighbors, a low-income city would improve to middle-low income with a 5.7% probability and remain poor in 94.3% of cases. In contrast, a high-income city surrounded by other high-income cities would remain in the same state with a 97.7% probability and only worsen to middle-high income with a 2.2% probability.

As in the previous $PM_{2.5}$ analysis, when considering the entire period (2000–2018), the results average out when compared to the two periods separately, as shown in Figure 15. Once again, we observe that the off-diagonal values of all matrices are lower than the main diagonal values, indicating that a city is more likely to remain in its current state than to either improve or decline.

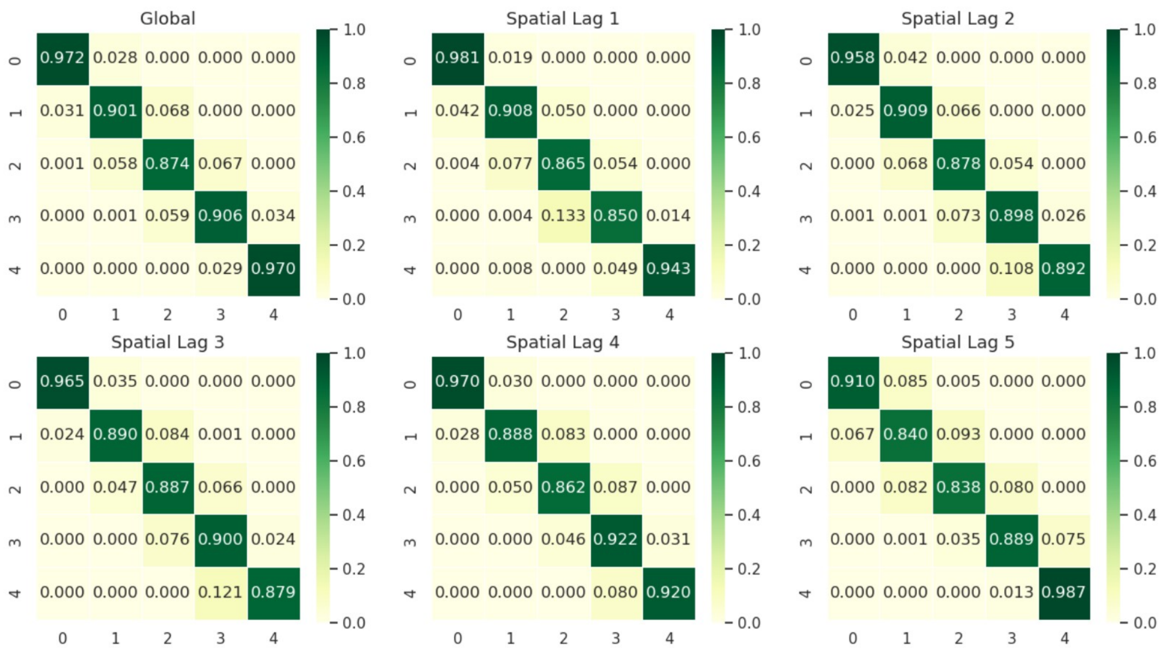

Figure 12: $PM_{2.5}$ (2000-2018)

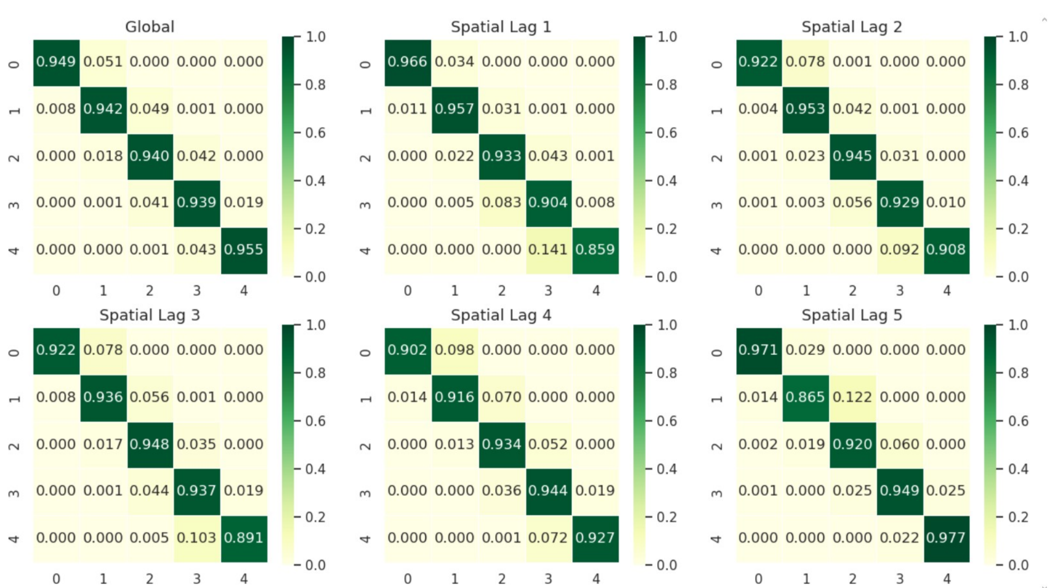

Figure 13: GDP per capita (2000-2013)

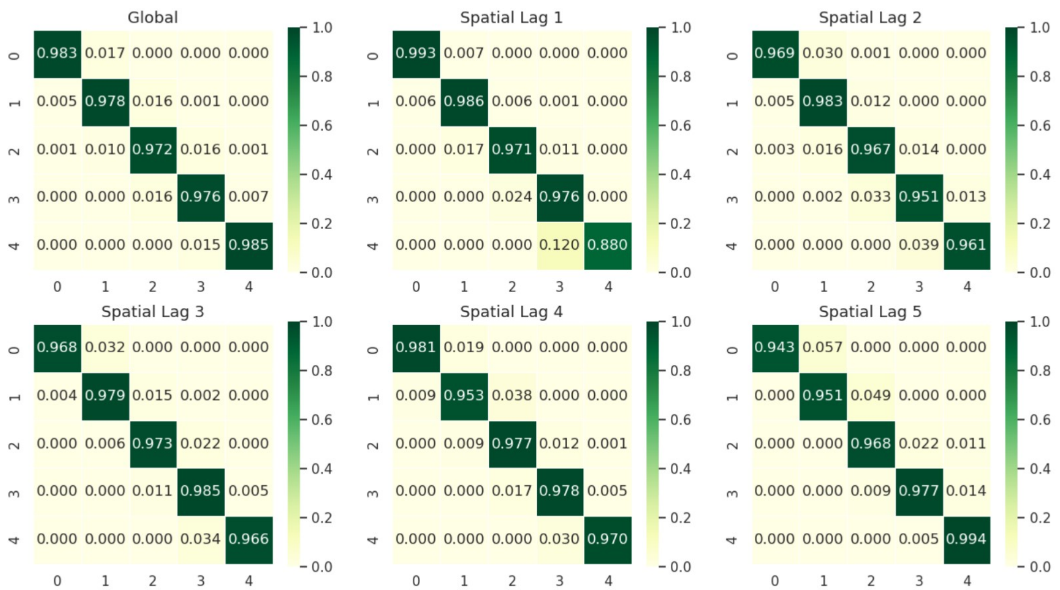

Figure 14: GDP per capita (2013-2018)

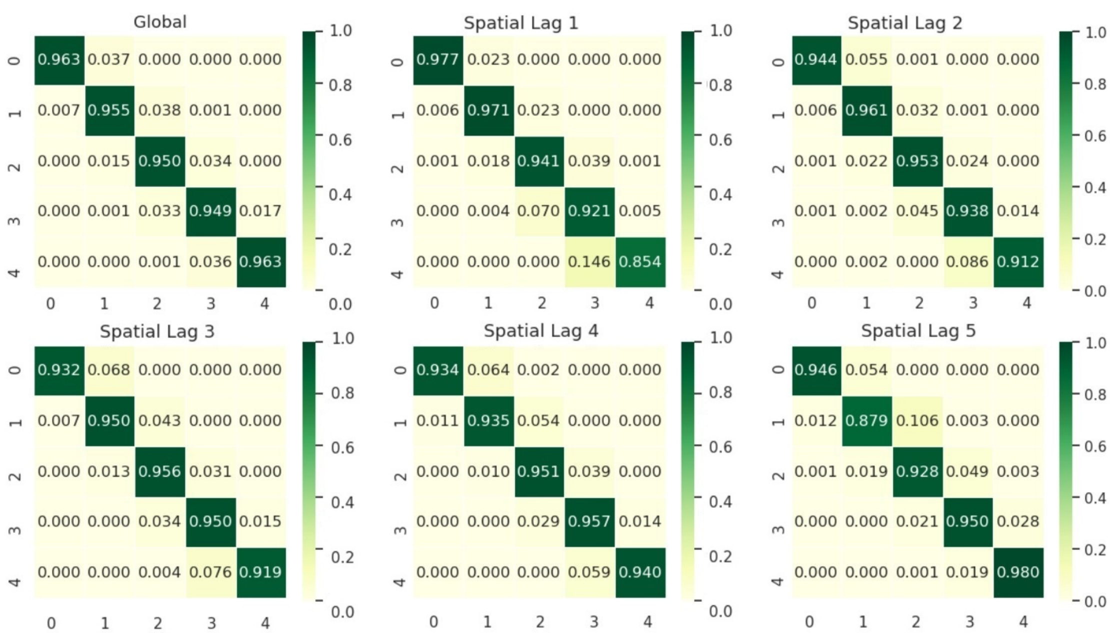

Figure 15: GDP per capita (2000-2018)

5 Discussion

The analyses in the previous section reveal a persistent pattern in income and $PM_{2.5}$ pollution levels across cities over the study period. Spatial context plays a crucial role in these transitions, as cities with low income and high pollution levels are more likely to remain in their initial states when surrounded by similar neighbors. This suggests that regional disparities in both economic and environmental conditions are reinforced by spatial clustering. Notably, after 2013, conditions appear to have worsened on average, suggesting declining mobility and increasingly entrenched inequalities. These findings highlight the importance of considering spatial dependencies when analyzing long-term trends in economic growth and environmental quality.

At the same time, proximity to wealthier or less-polluted cities can, on average, lead to greater mobility, underscoring the importance of spatial spillovers. Cities with middle-income and moderate pollution levels exhibit more dynamic transitions, but their trajectories depend largely on their spatial surroundings. This suggests that neighboring conditions can either facilitate or hinder economic growth and air quality. The results emphasize the interconnectedness of regional dynamics and the significant influence of spatial interactions on economic and environmental outcomes.

The results highlight the need for spatially targeted policies that address both income immobility and environmental sustainability. In terms of income, leveraging spillover effects from wealthier neighbors could foster upward mobility and help break the cycle of poverty in low-income clusters. High-income cities should focus not only on maintaining their economic level but also on implementing strategies that uplift surrounding lower-income areas, thereby reducing regional disparities. Meanwhile, middle-income cities could benefit from targeted support, such as industrialization incentives or infrastructure investments, to stimulate growth and prevent stagnation. By addressing these spatial economic dynamics, policymakers can promote more equitable development and create opportunities for long-term prosperity across different regions.

At the same time, policies must also target $PM_{2.5}$ pollution to ensure environmental sustainability across regions. High-pollution clusters should introduce stricter emission controls and encourage the adoption of clean technologies, while regions at risk of spillover pollution should implement green buffers and proactive air quality monitoring to mitigate environmental damage. Middle-pollution cities should prioritize reducing pollution levels by investing in cleaner industries and implementing sustainable urban planning measures. Low-pollution areas, in turn, should implement policies that help preserve their air quality through long-term sustainable practices. By addressing pollution at different levels and recognizing the spatial interconnections between regions, policymakers can create a more effective strategy for improving environmental quality while ensuring economic resilience.

6 Conclusion

In this study, we focus on China from 2000 to 2018, examining how spatial dependence influences economic and environmental conditions. We break this period into two subperiods—2000–2013 and 2013–2018—to assess potential changes before and after the implementation of the Air Pollution Prevention and Control Action Plan (APPCA) in 2013. The presence of spatial dependence suggests that a city's income and pollution levels are strongly influenced by its neighboring regions, reinforcing persistent regional disparities. By incorporating spatial Markov chains, our analysis extends traditional transition models to account for local spatial interactions, providing a more comprehensive understanding of how clusters of high or low pollution and income persist. These findings underscore the importance of considering spatial relationships when designing policies to reduce inequality and environmental degradation.

The results indicate high (> 0.5) and significant (p-value < 0.05) spatial dependence across all periods, confirming that income and pollution levels are not randomly distributed but rather influenced by regional spillovers. Furthermore, the persistence of cities in their respective states—whether in high or low pollution or high or low income categories—suggests low mobility during the study period. This finding raises concerns about the effectiveness of past policy interventions, particularly the APPCA, which may have had unintended consequences, potentially reinforcing existing disparities instead of mitigating them. Understanding these long-term spatial dynamics is essential for developing policies that effectively promote both economic mobility and environmental sustainability in China.

Despite the advantages of spatial Markov chains in capturing spatial dependencies, this approach has certain limitations. Notably, it does not provide a visual or geographic representation of how transitions are spatially distributed, making it difficult to directly identify which specific cities or regions are driving these patterns. Future research could address this limitation by integrating complementary methods, such as spatial econometric models or geographically weighted transition analyses, to provide a more explicit spatial representation of regional dynamics. Combining these approaches would offer deeper insights into the mechanisms driving spatial disparities and enhance the development of targeted, evidence-based policies that address both economic inequality and environmental challenges.

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