Environmental Justice in China

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Abstract

Systematic research into social inequalities in the distribution of environmental hazards, though well-established in American sociology, has largely not been conducted using quantitative data from developing countries. In this study we consider whether theory and methods developed to test for and explain environmental inequality in the U.S. can be extended to a major developing country such as China. We argue that, due in part to the state's *hukou* registry system, urban workers in China with an official rural residence may be subject to disproportionate exposure to environmental pollution. We also argue that environmental inequalities in China may be shaped in part by social processes analogous to those which have been held to explain racial differences in pollution exposure in the U.S. In an analysis of the locations and emissions of pollution-producing facilities in China's Jiangsu province, we find that townships with a higher percentage of rural migrants are more likely to be exposed to high levels of air and water pollution. This finding holds even after we control for income and for the presence of "dirty and hard" industries in which rural migrants are most likely to find work.

Keywords: Pollution; Migration; China

1. Introduction

Social scientists have investigated the role of race in shaping pollution exposure and the distribution of pollution-producing facilities in the U.S. for nearly three decades. Consensus on whether race-based environmental inequality exists in the U.S., and if so why, has evaded researchers for much of this time, and the scientific merit of early work in particular has been called into question (Bowen, 2002). Recently, however, data and methods of analysis have diversified and improved, and the findings of researchers have begun to converge. Since the early 2000s, most major studies have found that African-American communities and those of other racial minorities are exposed to more pollution than those of whites, controlling for income, land use, and other potential confounding factors (Downey et al., 2008; Mohai and Saha, 2007; Morello-Frosch and Jesdale, 2006; Morello-Frosch et al., 2001; Pastor et al., 2005). The relationship between race and pollution exposure is complex: there may be significant regional variation in the size—and, in a minority of U.S. metropolitan areas, the direction—of the race effect (Downey et al., 2008). But overall, contemporary studies find

that race matters in determining exposure to pollution, even when income is taken into account.

In this paper we ask whether the theory and methods developed to analyse and make sense of environmental inequality in the U.S. can be extended to a major developing country such as China. The environmental implications of China's economic expansion over the past two decades have been staggering. China is now the world's second largest economy, and its overwhelming reliance on coal has made it the world's largest emitter of greenhouse gasses (Zeng et al., 2008). Urban air quality is so poor that Chinese authorities shuttered factories and power plants throughout the Beijing area in the weeks leading up to the 2008 Olympics, in order to ensure clean air for athletic events. Yet compared to the U.S., research on environmental inequality in China is underdeveloped. Journalism and qualitative research have helped to communicate the depth of the environmental challenges facing all Chinese, from farmers to coal miners to the burgeoning urban middle class (Knup, 1997; Palmer, 2007; Pan, 2001). Yet systematic, quantitative research on who is most affected by pollution in China is in its infancy (Jian, 2005; but see Ma and Schoolman, 2010 and 2009, which we review in greater detail below). Lack of data and the slow diffusion of sociological theory and methods across the Pacific are major reasons why quantitative explorations of the environmental challenges to equality posed by China's fearsome economic transformation have yet to take form.

This paper represents, to the best of our knowledge, the most thorough systematic study to date of environmental inequality in China. We ask two main questions: first, whether environmental inequality exists in China, and second, whether this inequality can be explained purely on the basis of income, or whether—as in the U.S.—other socioeconomic factors might also be found to play a role. In order to answer these questions, we employ methods developed for the U.S. context to analyse an original dataset on the location and emissions of pollution-producing facilities in China's fast-growing Jiangsu province. We find that migrants from the poor countryside are exposed to a disproportionate amount of pollution, even after controlling for other factors, such as the presence of "dirty and hard" industries in which rural migrants are most likely to find work. Moreover, despite the many differences between Chinese and U.S. society, we theorize that environmental inequality in both countries can be understood in part as the outcome of similar processes. For reasons having to do with both impersonal market forces and discriminatory intent, those individuals who occupy the low rungs of the social ladder, whether racial minorities in the U.S. or rural migrants in China, are the ones who bear the brunt of the massive environmental consequences of a changing economy.

In the next section we discuss the development of theory and research into U.S. environmental inequality, and analyse similarities and differences between U.S. and Chinese society in order to derive hypotheses concerning environmental inequality in China. We then introduce our data and methods of analysis, which draw on recent innovations in the use of GIS to analyse the spatial distribution of pollution and pollution-producing facilities. Finally, we present our analyses, discuss our findings, and suggest future directions for the study of environmental inequality in China and other developing countries.

2. Explaining Environmental Inequality

Two main findings have emerged from three decades of research into environmental inequality in the U.S. First, nearly every major study since the early 2000s has found that racial minorities are disproportionately exposed to environmental pollution and hazards, and that this effect persists across income levels. The consensus that has emerged is noteworthy,

given that the first twenty years of research saw significant disagreement. Many early studies did indeed find environmental hazards to be located overwhelmingly in minority and low-income communities (CRJ, 1987; Daniels and Friedman, 1999; GAO, 1983; Goldman and Fitton, 1994; Hamilton, 1995; Hird, 1993; Hird and Reese, 1998; Lester et al., 2001; Perlin et al., 1995; Ringquist, 1997; Zimmerman, 1993). But others found just the opposite: that neither race nor income were significantly associated with proximity to environmental hazards (Anderton et al., 1994; Anderton et al., 1997; Been and Gupta, 1997; Davidson and Anderton, 2000; Greenberg, 1993; Oakes et al., 1996). These "unit-based" studies suffered from methodological shortcomings; most importantly, their measures of pollution exposure largely did not take into account environmental hazards that were near to, but not actually located within, spatial units such as census tracts or zip code areas (Downey et al., 2008; Mohai and Saha, 2006). More recent environmental inequality studies have used either GIS to incorporate distances between spatial units and environmental hazards into measures of pollution exposure (Mohai and Saha, 2006, 2007; Pastor et al., 2001), or sophisticated atmospheric models (Downey et al., 2008; Morello-Frosch and Jesdale, 2006; Morello-Frosch et al., 2001; Pastor et al., 2005) to estimate pollution concentrations over census tracts nationwide. The findings of these studies suggest that race-based environmental inequality has been and continues to be a significant problem in the U.S., even when income is taken into account as a possible confounding variable (but see Downey et al., 2008, for an investigation of regional variation in the effect of race on pollution distribution in U.S. metropolitan areas).[1]

The second main finding to have emerged, based on historical and qualitative research in particular, is that race-based environmental inequality in the U.S. has been the product of both impersonal market forces and prejudicial intent (Brown, 1995; Bryant and Mohai, 1992; Szasz and Meuser, 1997). The complex interplay of urban expansion, industrialization, and racial discrimination in the U.S. is important for this study, because, in our view, the underlying mechanisms may be applicable to the case of China, as well. In the U.S., prior to widespread automobile ownership, industry maximized access to employees and transportation networks by locating facilities in densely populated urban areas. At a time when increases in urban population far outpaced increases in land area, exposure to environmental pollution from industrialization was unequal, but widespread (Fogelson, 2001). Once the automobile and post-war economic growth made mass suburbanization possible, however, whites fled urban cores and kept suburbs closed to minorities through community pressure, discriminatory lending, minimum lot sizes, and opposition to affordable housing (Fishman, 1987; Fogelson, 2005; Jackson, 1985). Minorities, in particular African-Americans, were left to deal disproportionately with the legacy of urban industrialization: brownfields, power plants, highways, and little money for remediation (Bullard, 2000; Checker, 2005; Hurley, 1995; Lerner, 2005). Political marginality and environmental degradation reinforced one another, as polluted areas lost the very middle-class residents whose influence might have kept dirty industrial and waste-management facilities from continuing to locate near minority communities (Mohai and Bryant, 1992). At the same time, low rents on land in polluted areas represented a perverse draw both for new environmentally hazardous facilities and for those who could not afford to live in cleaner communities, adding another layer to the cycle of inequality (Been and Gupta, 1997; Hamilton, 1995; Oakes et al., 1996).

[1] The overwhelming majority of environmental inequality studies use spatial units such as census tracts and zip codes as units of analysis. This approach implicitly blurs the line between the characteristics of geographic areas and the characteristics of individuals within these areas. While this approach (as we discuss later) is vulnerable to an ecological critique, it remains the best option for our analysis of environmental inequality in China, where individual-level epidemiological and socioeconomic data are often unavailable.

In the U.S., the social characteristic of race has led, in part through the processes described above, to a disproportionate environmental burden for particular groups of people—a burden which cannot be explained by income alone. In China, race is relatively unimportant, as ethnic Han make up 92 percent of the population (Quan 2002). But we would suggest that people associated with rural areas—as identified in recent decades by the official household registry system known as *hukou*—occupy a position in Chinese society that is analogous in many ways to that of racial minorities in the U.S. And we further suggest that the *hukou* system, like race in the U.S., may lead, through broadly similar processes, to a disproportionate environmental burden for particular groups of people in China.

Hukou has been a factor in Chinese society for much of the 20th century, and its effects on income, education, and the life-course parallel in many ways those of race in the U.S. Though a crucial tool of the modern Chinese state, the roots of *hukou* go back over two thousand years, when emperors mobilized a vast bureaucracy to extract revenue from the population (Wang, 2005). The contemporary *hukou* system was established in the 1950s by the post-war communist government, under the tutelage of the Soviet Union, in order to control migration into and out of urban areas, and thus to maintain social stability at a time of wrenching change (Chan and Zhang, 1999). Each individual was required to register in either the city or the village or commune of a parent (typically the mother). Over the next twenty years, privileging urban residents over villagers became a prime consequence of the registry, often with tragic results. During the Great Leap Forward (1958-61), grain allotments skewed toward the cities resulted in the death of over twenty million people, almost all from rural areas (Wang, 2005). By the mid-1960s, the *hukou* registry had facilitated the forced movement of nearly forty million urban residents from their homes in cities to their former villages or the villages of their parents. The remaining urban population, the elite of the nation, "became a truly privileged minority in China for the next three decades and is still heavily subsidized and favored by the state today" (Wang, 2005:47).

The socioeconomic consequences of the *hukou* system have taken on new meaning in recent decades, as tens of millions of Chinese have streamed into urban areas in search of jobs in the export economy. Urban workers with a rural *hukou* constitute an enormous "floating population" whose size, measured at approximately 79 million in 2000 (Liang and Ma, 2004), exceeded 120 million in 2007—one-third the size of the current U.S. population (Zhu, 2007). Rural migrants in China's teeming, modern cities are systematically disadvantaged by the *hukou* system—though the outcomes are perhaps not surprising, if one takes the effect of race in the U.S. as a model. Urban workers with official rural residency have lower wages and returns to education than those with urban residency (Fan, 2001; Knight and Song, 1999; Du et al., 2006). Children of such workers, whose status is rural even if they have been born and raised in the city, go to inferior schools, score lower on competitive exams, and are much less likely to attain a university education (Wu and Treiman, 2004). Rural designation exacerbates the negative effects of gender on income (Huang, 2001). A rural *hukou* harms one's chances of becoming a member of the communist party—an indispensable gateway to the middle class (Wu and Treiman, 2004). Moreover, without legal right to work and live in the city, and with limited access to services, members of the floating population, like undocumented workers in the U.S., are at the mercy of employers and the state. On the other hand, individuals with an official urban residence are guaranteed access to the "subsidized education system, subsidized housing, welfare programs, and community cultural activities," while migrants "have no such entitlements" (Liu, 2005:136). In sum, the *hukou* system "remains the institutional guardian of the deep urban-rural divide that has characterized China since the mid-1950s" (Cheng and Selden, 1994:667).

Like the color of one's skin in the U.S., *hukou* in China is a fundamental and only marginally more malleable aspect of one's identity, with many of the same consequences for

people on the wrong side of the status boundary. Urban workers with a rural *hukou* are more than just poor: they are members of a distinct social class whose lives are constrained by overlapping layers of formal state policy and decentralized personal and institutional discrimination—social constraints which are strikingly similar to those which have long shaped the lives of racial minorities in the U.S. In this study, we consider whether the social similarities between rural migrants in China and racial minorities in the U.S. extend to inequalities in the levels of pollution to which the former are exposed.

Although the precise mechanisms driving race-based inequality in the U.S. cannot be transposed directly to China, existing studies of the *hukou* system give ample reason to expect that among its consequences may be a disproportionate environmental burden for urban workers with rural *hukou*. Individuals with urban *hukou*, across income classes, may be able to gain privileged access to residential areas far removed from polluting facilities, while using their political clout to keep migrants excluded from these cleaner, healthier communities. Improvements to infrastructure, in particular increasing car ownership, may be adding to the ability of those with urban *hukou* to distance themselves from pollution. Moreover, just as in the U.S., the flight of politically influential citizens from polluted urban areas may then contribute to a feedback loop whereby the environmental problems of these areas receive less attention from government, and thus continue to lose socially privileged residents. Both pollution-producing facilities and low-income, socially disadvantaged populations are likely attracted to low rents available in already-polluted areas, further contributing to the cycle of environmental inequalities. Finally, rural migrants occupy a particularly tenuous position with respect to the Chinese state and urban authorities. Like racial minorities in the U.S., the vulnerability of migrants to state action—in the form of harassment, arrest, and expulsion—may further narrow their options with respect to where to live, and also with respect to political reform.

This study is motivated by the possibility that social processes centered on the *hukou* system may be driving environmental inequality in China in ways analogous to processes centered on race in the U.S. Our goal is not to determine the relative importance of different *hukou*-based social processes, but rather simply to investigate whether rural migrants in one part of China are in fact disproportionately exposed to certain forms of environmental pollution. Future research may then see fit to elucidate in greater detail the relative importance of different *hukou*-based processes, such as those outlined above. In this study, our primary hypothesis is that urban areas with large numbers of rural migrants will be found to be exposed to more pollution than those without. Furthermore, we hypothesize that the relationship between *hukou* and pollution exposure will hold even after other factors, such as the propensity of migrants to work in highly polluting industries, are taken into account.

As we note above, there has been little systematic inquiry into environmental inequality in the developing world, let alone in China, using methods developed for the U.S. case. The sole exception, to the best of our knowledge, is an examination of power plant and factory locations in China's Henan province (Ma and Schoolman, 2010). The present study improves upon this earlier work in several crucial ways. First and most importantly, using new data on the geographical distribution of different industries, we address the question of whether a relationship between rural migrants and pollution may simply be a function of the tendency of migrants to work in certain industries, like mining and heavy manufacturing. Second, using previously unavailable data on the actual emissions, as well as locations, of pollution-producing facilities, we test our models against a wide variety of weighted and unweighted dependent variables; this ability to check results across related but analytically distinct outcomes leads, ultimately, to more robust conclusions. Third, we employ spatial regression models to adjust for the possibility of spatial dependency in our data. Fourth, we offer in this study a more fully-realized description of the parallels between the social history

of African-Americans in the U.S. and rural migrants in China—parallels whose possible environmental implications are the subject of the following analysis.

3. Data and Methods

3.1. Pollution Data

Two kinds of data are required for environmental inequality research: data on sources and emissions of pollution, and data on the socioeconomic characteristics of spatial units. Historically, reliable data on pollution in China have been non-existent or not publicly available. Our pollution data come from a 2005 dataset on manufacturing and waste-treatment facilities that has recently been made available by the Environmental Protection Bureau (EPB) of Jiangsu province (the province is the largest administrative unit in Chinese government, after the nation itself). Jiangsu is a microcosm of contemporary China: it is the third-wealthiest province, but there exists a stark divide between its prosperous south, centered on the former national capital of Nanjing, and its poor, rural north. In the absence of nationwide data, Jiangsu's economic dynamism and lingering inequalities make it an ideal venue for a study of how pollution distribution in China may be shaped by social forces.

The Jiangsu EPB dataset contains two kinds of data. First, it identifies, based on a nationwide database from the China State Environmental Protection Agency (SEPA) that ranks over eighty thousand facilities by their emissions of sulfur dioxide (SO_2), smog, ammonia nitrogen (NH_3-N), and waterborne organic compounds (COD[2]), the names and host administrative units of facilities whose summed emissions constitute 85 percent of the total amount of each pollutant emitted in Jiangsu. Second, it gives the actual emissions of the four pollutants for each facility on the list. The resulting dataset describes the emissions of the manufacturing facilities, power plants, and waste treatment facilities which together represent the 647 most significant sources of pollution in Jiangsu. SEPA's use of these four pollutants as ranking criteria reflects scientific consensus on their consequences for human health[3] and the fact that they are byproducts of a wide variety of industrial processes.

Precise geographical coordinates of sources were not reported in the published dataset, and we used several digital map databases in order to determine the coordinates for each facility. In this way we were able to determine precise coordinates for 541 facilities, or 83.6 percent of all pollution sources on the list. For 100 facilities, we generated approximate coordinates.[4] We dropped 6 sources for lack of location information. Our final dataset thus contains data for 641 major sources of pollution in Jiangsu province.

3.2. Socioeconomic Data for Spatial Units

[2] COD, or "chemical oxygen demand," is a widely-used measure of water pollution by organic compounds from wastewater treatment and manufacturing.

[3] The U.S. Clean Air Act requres the EPA to set National Ambient Air Quality Standards for six common air pollutants, including sulfur dioxide and nitrogen oxides, a key component of smog.

[4] For 85 sources we generated approximate coordinates by using either the facility's street address, when it could be found online, or the geocenter of the facility's host village, a sub-unit of the township. These imputed coordinates fully satisfied the research need: street address gives a very precise location; and the average village unit in China is 17.5 times smaller than the average township. For 15 pollution sources for which neither street address nor village was available, we used the geocenter of the host township, an alternative which we believed preferable to dropping the source altogether.

China has five levels of administrative division: 1) province level (34); 2) prefecture level (333); 3) county level (2,862); 4) township level (41,363); 5) village level (703,786).[5] The choice of unit of analysis can have significant implications for the outcomes of spatial analyses, and many studies of environmental inequality in the U.S. do not give adequate consideration to this aspect of research design (Baden et al., 2007; Noonan, 2008; Noonan et al., 2009). We used the township as our spatial unit of analysis for two reasons. First, as we explain below, our focus in this study is on urban areas in China, and specifically on the question of whether rural migrants to urban areas are disproportionately exposed to certain kinds of pollution. The China Census classifies townships and villages as either urban or rural, but not counties or prefectures. Therefore, using county or prefecture as the unit of analysis would not have permitted us to address our main research question, because we would not have been able to identify urban areas for our study.[6] Second, detailed socioeconomic data are available for townships, but not for the village level.

Data for Jiangsu townships were collected from the China Census 2000 (CC 2000), the Statistical Yearbook of Jiangsu 2000 (SYJ 2000), and annual reports of local governments. For Jiangsu province, data were available for 1802 township units, including urban (1446), rural (272) and virtual units (84)[7]. We use only urban townships as units of analysis, because, as can be seen in Figure 1, which depicts township boundaries and pollution sources in Jiangsu, there is little doubt that rural areas are exposed to much less industrial pollution than urban areas.[8] The more interesting question, and the one which motivates our study, is whether all urban areas are equally likely to contain, or to be near to, major sources of pollution—and, by extension, whether all individuals in urban areas are equally likely to suffer from pollution's ill effects.

[Figure 1 about here]

3.3. Dependent Variables: Pollution Exposure by Township

We give each spatial unit—the townships of Jiangsu province—a buffer of five miles; the result is that each township is associated with a containment area that is mathematically similar to its actual borders. (We also performed the following analyses with shorter buffers and smaller containment areas and obtained similar results.) After constructing the containment areas, we test the ability of primarily township-level socioeconomic characteristics to predict three different dependent variables: 1) the number of pollution-producing facilities located within each containment area; 2) the per capita amount of major pollutants (SO_2, smog, NH_3-N, and COD) emitted within each containment area; 3) the per capita amount of these same pollutants, with the emissions of each contributing facility

[5] The numbers in parentheses mark the total units nationally at each level as of the end of 2009.

[6] It may have been theoretically possible to use counties as the units of analysis, and then to include a control for the percentage of urban area (i.e. townships) contained within each county. But this approach would have been quite complicated, and if the control had not been good enough, the result would have been a biased estimate of the effect of rural migrant populations on pollution in urban areas.

[7] Urban townships refer to "Zhen" and "Jie Dao". Rural townships refer to "Xiang". Some areas (and associated population) are not classified in the formal Nation – Province – Prefecture – County – Township – Village administrative division. For statistical purpose, they are named as "Xu Ni" townships (i.e. virtual units).

[8] Jiangsu, a coastal province, differs in this respect from inland Henan province, which was the subject of an earlier study (Ma and Schoolman 2010).

weighted by the facility's distance from the geocenter of the township in question[9]. Our research design adopts key methodological innovations characteristic of recent studies of environmental inequality in the U.S. First, by using buffers to create containment areas around our spatial units, we avoid treating administrative entities which are close to, but which do not actually contain, environmental hazards, as *ipso facto* different from true host units. Second, by incorporating distance-based weights into the third set of dependent variables, we allow for the fact that pollution sources located within the containment areas of small host units are likely, due to increased proximity, to impact residents more severely than those located within the containment areas of large host units. As we discuss in our conclusion, it would have been useful to be able to conduct our analyses using both townships and village-level units, and then to compare results across different units of analysis. But until detailed socioeconomic data are available for the "village" level of Chinese geography, analyses based on township-level data provide a suitable foundation for systematic research into environmental inequality in China.

3.4. Independent Variables

3.4.1. Independent Variable of Main Interest

Percentage of Rural Migrants in Township Population (MIGRANTS). Our model is primarily intended to test the hypothesis that the population of rural migrants in urban areas predicts pollution exposure in these areas, controlling for other factors. China Census 2000 reports the total migrant population of townships but does not differentiate between migrants with a rural *hukou*—members of the "floating population" discussed above, who largely work in low-skill, low-wage jobs—and the much smaller number of members of the urban elite who, with an urban *hukou*, have simply changed cities in search of high-skill, high-wage employment (Fan, 2001; Knight and Song, 1999). However, rural migrants are much less likely than city-to-city migrants to gain a university education (Wu and Treiman, 2004), and the Census does distinguish between migrants who are college-educated and those who are not. Therefore, we take as our measure of rural migrant populations in urban areas the difference between the total migrant population in each township and the number of migrants with an education level of college or above (i.e. the urban elite).

3.4.2. Control Variables

The set of control variables in a study such as ours implicitly determines the counterfactual world against which the actual distribution of environmental hazards or pollution is compared (Noonan, 2008). The counterfactual in our study is one in which the distribution of pollution-producing facilities—and their emissions—is associated not with *hukou*, but with the distribution of individuals whose income and education, independent of place of birth, render them more likely to live in close proximity to these kinds of facilities. The control variables in our model are therefore intended to represent, first, key aspects of this counterfactual, and second, forms of environmental inequality other than that centered on *hukou*. Socioeconomic measures of income and race are common to nearly all studies environmental inequality (e.g.

[9] We also tested an alternative specification with log total emissions (and weighted emissions) as dependent variables while including log total population as a control; however, this alternative specification does not change our main results. We have thus chosen to report per capita measures as indicators of pollution exposure, which we believe more effectively convey the average exposure for individuals within a given unit. But results from the alternative specification are available upon request.

Anderton et al., 1997; Davidson and Anderton, 2000; Mohai and Saha, 2006, 2007), while measures of education, though highly correlated with those of income, are also to be found in the majority of studies (Mohai and Saha, 2007; Jerrett et al., 2001). Bowen (2002) cites the presence of a control for percent industrial and manufacturing employment as a crucial characteristic of "high-quality" environmental inequality research, and we include such a control in our study, as well as a more general control for the number of working-age adults. Following the lead of several recent studies, we also employ a control for density (Anderton et al., 1997; Noonan et al., 2009). We limit our study to urban areas, and a dichotomous control for urban/rural land use would therefore be redundant. We also do not include a control for population, as our dependent variable of per capita pollution implicitly takes into account the population of each township (but see our earlier footnote on an alternative specification, which does use population as a control). We operationalize each of our controls as follows:

Percentage of employment in "dirty and hard" industries (INDUSTRY). This variable captures the impact of industrial structure on township pollution by describing the percentage of township residents employed in mining, manufacturing, and electricity generation. Most facilities from the SEPA dataset are in the pollution intensive sectors for which we use "mining, manufacturing and electricity generation" as a proxy. By controlling for employment in highly polluting industries, we are able to test whether, if rural migrants are indeed associated with increased pollution, the effect is simply due to the fact that migrants who work in pollution-producing facilities are also likely to live near them.

Percentage of Ethnic Minorities in Township Population (MINORITY). The Chinese government recognizes 55 official ethnic minorities, but together they make up only about 8 percent of the population. More importantly, racial tension is far less of an issue in China than in the U.S. (Quan, 2002). Nevertheless, we include the percentage of racial minorities in each township as a control in order to compare its effect with the theoretically much more important effect of race on environmental inequality in the U.S.

Log of County-Level Per Capita Disposable Income (INCOME). Data on income at the township level were not available. Instead, we use the log of urban per capita disposable income at the county level as an indicator of income for all urban townships within each county. A recent study suggests that the majority of income inequality at the provincial level is primarily due to inequality between counties rather than within counties (Gustafsson and Li, 2002). Thus, while not ideal, we believe that using county-level per capita income as an indicator of township-level income should not pose a serious problem to the analysis.

Log of Distance to the Nearest River (RIVER). Township proximity to a main river may be an important factor in determining facility location, because many industries require access to freshwater for cooling purposes and waste disposal. The log of the distance between the township's center and the nearest river is intended to control for this effect. This variable has not been employed in previous studies of environmental inequality, but may capture a physical feature of urban areas that is non-trivial where relatively high-polluting industries are concerned.

Other Township-Level Controls. We also control for the population density of each township (DENSITY), measured in thousands of persons per square kilometer, the percentage of residents with a high-school education (EDUCATION), and the percentage of working-age (15-64) persons (LABOR) in the population.

Regional-Level Variation (PREFECTURE). Many studies of environmental inequality point to the potential for regional differences and suggest the introduction of a control for such factors (Bowen et al., 1995; Bowen, 2001; Downey et al., 2008; Pastor et al., 2004; Yandle and Burton, 1996;). The thirteen prefectures of Jiangsu province are certainly ripe for such variation. Province-level planners may implement different industrial location policies in different prefectures. Officials may be more aggressive in promoting environmental protection in some prefectures than in others. Differences may also exist in resource availability (water, energy, or labor) and production across prefectures. We generate a dummy variable for each of Jiangsu's thirteen prefectures[10] in order to account for regional characteristics which are not captured by other independent variables. Standard procedure with dummy variables is to omit one region as a reference category; however, this practice is less informative when little knowledge exists of the selected reference (Haisken-DeNew and Schmidt, 1997; Kennedy, 1986; Suits, 1984). The approach taken here follows Kennedy (1986) and uses the provincial average as the reference category. The coefficient of a regional dummy thus has a straightforward interpretation: the extent to which each region is more or less pollution intensive than the provincial average, *ceteris paribus*.

Table 1 reports summary statistics for all variables. The number of pollution sources per township includes all sources of pollution that are located within each township's containment area. Per capita emissions of each pollutant are calculated for the same containment areas.
[Table 1 about here]

3.5. Model and Hypothesis

Recent research suggests that spatial dependency in data can significantly influence analyses of environmental inequality (Chakraborty, 2011; Havard et al, 2009; Jerrett et al, 2001; Mennis and Jordan, 2005). When spatial autocorrelation is found to be present in the residuals of OLS models, simultaneous autoregressive (SAR) models can be used to reduce bias and improve efficiency in estimators. Diagnostic tests performed for our data after initial OLS regressions found greater evidence for spatial error autocorrelation than for spatial lag[11]; however, we elected to run both spatial error and spatial lag regressions. Major results were robust across all regressions (OLS, spatial error, and spatial lag); in this study we discuss the

[10] Nanjing (Capital of Jiangsu Province), Wuxi, Xuzhou, Changzhou, Suzhou, Nantong, Liangyungang, Huaiyin, Yancheng, Yangzhou, Zhenjiang, Taizhou, and Suqian. We have included, as Supplementary Figure 1, an additional map of Jiangsu where prefectures are labeled by name.

[11] There are primarily two types of spatial dependence: *spatial error* – the error terms across different spatial units are correlated and *spatial lag* – the dependent variable in spatial unit *j* is affected by the independent variables in both spatial unit *j* and *k*. Spatial error is indicative of omitted covariates that would affect inference if left unattended and spatial lag is suggestive of a possible diffusion mechanism – events in one spatial unit would increase the likelihood of similar events in neighbour units. The assumption of uncorrelated error terms in OLS regressions is violated under both cases so that the estimates are inefficient. In addition, the assumption of independent observations is also violated with *spatial lag*. As a result, the estimates are even biased. The Moran's I test is highly significant across all regressions suggesting a *spatial error* type of dependence.

results of the spatial error models[12]. However, we also report OLS results for comparison. The econometric model is specified as follows:

$$POLLUTION_i = \beta_0 + \beta_1 MIGRANTS_i + \beta_2 INDUSTRY_i + \beta_3 MINORITY_i + \beta_4 INCOME_i + \beta_5 DENSITY_i + \beta_6 EDUCATION_i + \beta_7 LABOR_i + \beta_8 RIVER_i + \sum \alpha_j PREFECTURE_{ij} + \varepsilon_i$$

For each dependent variable (four pollution types, both weighted and unweighted), we include results both with and without the *INDUSTRY* control variable, in order to show the robustness of the effect of rural migrant populations on pollution once the tendency of migrants to work in highly polluting industries is accounted for.

Our primary hypothesis is that pollution in urban townships is positively associated with the percentage of township residents who are rural migrants—that is, with the percentage of residents who, despite working in an urban area, have their official residence, or *hukou*, in a rural area. We expect that, due to the social mechanisms outlined above, the effect of rural migrants on township pollution will remain, even after controlling for confounding factors such as the role of heavy industry in a township's economic base.

4. Results and Discussion

4.1. Results

Table 2 gives the results of regressions of the number of pollution sources. Table 3 and Table 4 provide the results of regressions of actual emissions. Results of regressions of weighted emissions are shown in Table 5 and Table 6. All significance tests are two-tailed.

Overall, the analyses provide support for our primary hypothesis that rural migrants in Jiangsu province are disproportionately exposed to industrial pollution in urban areas. When all control variables are included, the effect of the percentage of rural migrants in the population—those who have their *hukou* in rural areas but who have migrated to the city in search of work—on township pollution levels is positive and significant across all dependent variables, with the exception of SO_2. Townships with a higher percentage of rural migrants are close to more major sources of pollution, and are exposed to higher levels of smog, organic pollutants (as measured by COD), and NH_3-N, even when other factors are taken into account. In particular, the effect of the percentage of rural migrants does not lose significance—though it tends to decrease in magnitude—when a key confounding variable, the percent of township residents employed in dirty, hard industries, is added to the regression model.

For the number of pollution sources, smog, COD, and NH_3-N, the magnitude of the effect of rural migrants on pollution is comparable to that of reliance on dirty, hard industries. For instance, each additional percentage point of rural migrants in the population of townships is associated with .1193 more major sources of pollution ($p < .01$, Table 2) and 2.2857 more kilograms (weighted) of smog per capita ($p < .01$, Table 5). Similarly, each additional percentage point of township residents employed in mining, manufacturing, and electricity generation is associated with .1063 more sources of pollution ($p < .01$, Table 1) and 3.141 more kilograms (weighted) of smog per capita ($p < .01$, Table 5). As we discuss in greater detail below, the fact that the effect of rural migrants on township pollution remains significant and substantial, even when employment in dirty industry is included in the models,

[12] Results from spatial lag regressions are available upon request. Due to the size of the weighting matrix, all spatial autocorrelation tests and spatial regressions were performed with State/SE 12.0 on a 64-bit machine (with 8 gigabytes memory).

suggests that migrants are not disproportionately exposed to pollution simply because they tend to work in the dirtiest industries. It is notable, however, that the association of migrants with SO_2, while quite large in Model 1, decreases dramatically and loses significance once the *INDUSTRY* control is added. It would thus appear that rural migrant exposure to pollution caused by burning fossil fuels (the main source of SO_2) is largely the result of their employment in these facilities.

The effects of control variables differ across the four pollutants but are largely consistent across the actual and weighted emissions of each pollutant. The effect of population density, though generally significant, is very small. Once all controls are added to the models, the effect of income is significant, positive and very large for SO_2 and smog, but not significant for COD and the weighted NH_3-N. The uneven impact of income may be a residue of the fact that precise income statistics for townships were not available, and so we used county income in its place. A somewhat surprising result is that the effect of the ethnic minorities control variable is significant and quite large for both unweighted and weighted emissions of organic pollutants (COD). As race is traditionally not seen as a major source of tension in Chinese society, much less of environmental inequality, this result suggests the need for future research into whether ethnic minorities in urban areas may be disproportionately exposed to organic pollutants—and if so, why this might be the case.

[Table 2 about here]

[Table 3 about here]

[Table 4 about here]

[Table 5 about here]

[Table 6 about here]

4.2. Discussion and Future Research

We have argued that environmental inequality is not a contingent effect of industrialization, but rather a predictable consequence of the way that social class structures channel the environmental consequences of development toward the most vulnerable populations. We have also suggested that social forces leading to race-based environmental inequality in the U.S. provide a template for thinking about how status distinctions embedded in other cultural frameworks may operate to perpetuate existing social hierarchies into the environmental realm. The results of our analyses, by examining the web of social factors affecting the distribution of pollution in one of China's most dynamic provinces, provide support for the idea that, with respect to pollution exposure, the state-sponsored *hukou* system may be playing the role that racial classification has historically played in the American context.

The culture, institutions, and political traditions of China could hardly be more different from those of the U.S. Yet the results of our analyses lend support to the idea that people with an official "rural" designation could, over time, suffer an environmental fate analogous to that of African-Americans and other racial minorities. The most intriguing finding of this study is that a relationship between pollution and rural migrant populations in Jiangsu exists even when employment in heavy, dirty industry is taken into account. The persistence of this relationship suggests that rural migrants and high levels of pollution do not hang together simply because of where the former are likely to work. Rather, we would argue that social mechanisms may be in play which have been implicated in the evolution of American race-based environmental inequality. Most members of the "floating population" likely can only afford to live in the most polluted areas of modern Chinese cities, even when they do not actually work in the industries causing the pollution. As happened with African-Americans, social prejudice may be keeping cleaner, healthier, more desirable Chinese communities closed to people bearing the stigma of a rural *hukou*. The construction of new factories, power plants, and waste treatment facilities may be being taking place largely in

areas occupied by low-status social groups partly because the land is less expensive, but also because the political opposition is less viable. Any of these factors, or all of them, could be in play, as well as social processes unique to the Chinese context. As members of China's burgeoning middle class use their newfound wealth, and newly bought cars, to move away from pollution, members of the floating population are likely have little choice but to live with it and even move to it—when pollution does not come to them first. Indeed, the results of our study suggest that this dynamic may have already taken root in Jiangsu.

The findings of this study make clear the need for future research into environmental inequality in China. There are many directions that future research might take. First, although we have based our hypotheses on theorized pathways through which the inequalities characteristic of Chinese society might find their way into the environmental realm, our findings do not in themselves speak to which, if any, of the pathways that we have discussed are in fact responsible for the inequalities that we have found. Studies of environmental inequality in the U.S., both quantitative and qualitative, have leveraged increasingly detailed data to examine how inequalities develop over time. As data on environmental hazards in China, as well as socioeconomic data generally, improve in resolution and become more widely available, we expect that researchers will be able to address many of the topics that have historically occupied studies in the U.S. For instance, researchers may want to investigate the role of legal and cultural institutions in determining where in urban areas rural migrants are able to live, and whether the siting of environmental hazards near communities of rural migrants is purely a response to market forces or whether there is also prejudicial intent. Second, the spatial units that we use in this study—townships—are larger, on average, than either census tracts or zip codes. Thus, our findings are vulnerable to an ecological critique: that pollution exposure over a geographic area does not mean that individuals within this geographic area are all being exposed to the same amount of pollution. This is an important critique, and we agree that it would be preferable to be able to test our results across a wider variety of spatial units, and in particular at the village level. But when it comes to investigating a social problem as pressing as environmental inequality, we would argue that, where data is concerned, the perfect should not be the enemy of the good. The data that we have used is the most detailed that is currently available for any Chinese province. We hope that the findings of the current study might spur greater interest in the topic of environmental inequality in China, and that greater interest might result in more comprehensive data being made more quickly available.

4. Conclusion

The first reports on environmental inequality in the U.S. were published over thirty years ago. But research into environmental inequality in China, let alone in other parts of the developing world, is in its early stages. The main finding of this study is that townships in Jiangsu province with large populations of rural migrants are disproportionately exposed to industrial pollution, even after taking into account possible confounding factors. This finding agrees with theories of the relationship between social status and environmental burden that have arisen from studies of environmental inequality in the U.S. Peter Hessler, a former Peace Corps volunteer and trenchant observer of modern China, recently wrote that "to drive across China was to find yourself in the middle of the largest migration in human history—nearly one-tenth of the population was on the road, finding new lives away from home" (2010:33). As China continues to grow and change, the need will only increase for research into how the most vulnerable members of Chinese society are coping with the epochal transformation of

their nation. Researchers have a role to play, not only in chronicling the present, but also, by exposing inequality and injustice to light, in helping to change the future for the better.

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Supplementary Table 1: Data Appendix – Variable Definitions and Sources

Variable	Definition	Source
POLLUTION	Number of pollution sources / Per capita emission of *SO_2, SMOG, COD, NH_3-N (kg)*	Jiangsu EPA, 2005
MIGRANTS	Percentage of rural migrants (%)	China Census 2000 with Maps, China Data Center
INDUSTRY	Percentage of employment in "dirty & hard" industry (%)	China Census 2000 with Maps, China Data Center
MINORITY	Percentage of minorities (%)	China Census 2000 with Maps, China Data Center
INCOME	Log of per capita disposable income (Yuan)	Annual County Reports, 2004 and 2005
DENSITY	Population density (1,000 person/km^2)	China Census 2000 with Maps, China Data Center
EDUCATION	Percentage of senior high-school educated (%)	China Census 2000 with Maps, China Data Center
LABOR	Percentage population of age 15 – 64 (%)	China Census 2000 with Maps, China Data Center
RIVER	Log of distance to nearest river (meter)	China Census 2000 with Maps, China Data Center
PREFECTURE	Dummies for 13 prefectures (1/0)	China Census 2000 with Maps, China Data Center

Table 1. Summary Statistics

	Mean	Std. Dev.	Min	Max
Dependent Variables*				
Number of pollution sources	5.827	6.886	0.0	36.0
*Per capita emission of SO_2***	305.5	1097.7	0.0	26575.7
Per capita emission of SMOG	77.0	241.5	0.0	5110.4
Per capita emission of COD	40.7	90.7	0.0	1329.9
Per capita emission of NH_3-N	4.0	9.0	0.0	120.2
Independent Variables				
Percentage of rural migrants	13.3	12.1	0.4	68.5
*Percentage of employment in "dirty & hard" industry****	25.3	19.1	0.1	90.6
Percentage of minorities	0.4	0.8	0.0	21.5
Per capita disposable income (Yuan)	9.3	0.3	8.6	9.8
Population density (1,000 person/km^2)	4390.6	10845.2	34.6	84167.3
Percentage of senior high-school educated	17.2	13.8	3.9	71.9
Percentage of population of age 15 - 64	71.7	4.5	59.1	87.5
Distance to nearest river	8.0	1.3	0.1	10.4

*For containment areas with a buffer width of 5 miles around the borders of each township.
**All per capita emissions statistics are in kilograms per resident.
***Mining, Manufacturing and Power Production.
Data Sources: CC 2000; Annual reports of local governments, 2004-2005.

Table 2 – Spatial Regression Results for Number of Pollution Sources

Dependent:	**Number of Pollution Sources**			
	Model 1		Model 2	
Independent:	OLS	Spatial Error	OLS	Spatial Error
MIGRANTS	0.1657**	0.1656**	0.1193**	0.1193**
INDUSTRY			0.1062**	0.1063**
MINORITY	-0.1343	-0.1338	-0.1756	-0.1757
INCOME	1.5538	1.5845	-1.4838	-1.5005
DENSITY	0.0000	0.0000	0.0000	0.0000
EDUCATION	0.0664**	0.0663**	0.0847**	0.0848**
LABOR	0.1162	0.1168	-0.0215	-0.0217
RIVER	-0.2837**	-0.2840**	-0.2205*	-0.2206**
Prefectures				
NANJING (125)[#]	0.4864	0.5	1.8054**	1.8098**
WUXI (132)	7.1969**	7.1861**	6.7245**	6.7299**
XUZHOU (167)	-1.1752*	-1.1643*	-1.9395**	-1.9445**
CHANGZHOU (89)	4.4080**	4.3976**	4.6796**	4.6834**
SUZHOU (153)	0.9299	0.9119	0.8410	0.8472
NANTONG (124)	-0.7938	-0.7983*	-0.4040	-0.4026
LIANYUNGANG (68)	-2.0338**	-2.0217**	-2.6998**	-2.7062**
HUAIYIN (83)	-0.7009	-0.6899	-0.4340	-0.4359
YANCHENG (147)	-2.8577**	-2.8491**	-2.2201**	-2.2205**
YANGZHOU (92)	-1.0305*	-1.0284*	-1.4428**	-1.4427**
ZHENJIANG (90)	-1.0218*	-1.0289*	-0.9686*	-0.9663*
TAIZHOU (92)	-1.2416**	-1.2442**	-1.0504*	-1.0507*
SUQIAN (83)	-0.4503	-0.4359	-1.4661*	-1.4759*
Constant	-18.0886	-19.5709	17.0357	16.7073
N of Obs.	1445		1445	
R-squared	0.5794		0.6037	
Mean VIF	3.19		3.37	
Lamda		0.0614		-0.0267
Log likelihood		-4212.0581		-4169.08
Spatial error:				
Moran's I (z-score)		1067.738**		974.342**
Lagrange multiplier		42.496**		35.343**
Robust Lagrange multiplier		47.905**		38.719**
Spatial lag:				
Lagrange multiplier		0.116		0.000
Robust Lagrange multiplier		5.525*		3.377

*significant at $p < 0.05$; **significant at $p < 0.01$; # numbers in parentheses are sample sizes of prefectures

Table 3 – Spatial Regression Results for SO_2 and Smog

Dependent:	**SO2 Emission**				**SMOG Emission**			
	Model 1		Model 2		Model 1		Model 2	
Independent:	OLS	Spatial Error	OLS	Spatial Error	OLS	Spatial Error	OLS	Spatial Error
MIGRANTS	11.0521**	11.0558**	2.9205	2.9186	3.2032**	3.2037**	1.7084*	1.7084*
INDUSTRY			18.1737**	18.1695**			3.3408**	3.3406**
MINORITY	12.6943	12.3678	6.6217	6.5302	-2.7193	-2.7487	-3.8356	-3.8496
INCOME	1176.492**	1179.115**	669.4752**	671.2568**	307.812**	308.0161**	214.6089**	214.7648**
DENSITY	-0.0104**	-0.0104**	-0.0091**	-0.0091**	-0.0025**	-0.0025**	-0.0023**	-0.0023**
EDUCATION	0.9342	0.9247	3.9877	3.9811	0.2482	0.2475	0.8096	0.8090
LABOR	8.8745	8.8110	-13.8342	-13.8377	0.5715	0.5654	-3.6029	-3.6050
RIVER	-21.2821	-21.2080	-10.5945	-10.5759	-10.0041**	-9.9976**	-80.394*	-8.0366*
Prefectures								
NANJING	-210.394**	-245.3282**	10.9238	-24.2764	-43.6103*	-43.6127*	-2.9262	-2.9422
WUXI	-552.6153**	-588.6257**	-639.5328**	-675.0784**	-133.706**	-133.8022**	-149.6838**	-149.7473**
XUZHOU	723.8605**	689.7224**	605.5704**	571.2311**	163.5059**	163.5569**	141.761**	141.8071**
CHANGZHOU	-347.3942**	-382.3004**	-305.5578**	-340.7295**	-99.6513**	-99.6516**	-91.9606**	-91.9850**
SUZHOU	-651.9362**	-686.9319**	-675.9234**	-711.2833**	-175.3816**	-175.383**	-179.7911**	-179.8153**
NANTONG	-34.2454	-68.7887	31.0845	-3.8080	-13.4237	-13.3954	-1.4143	-1.4040
LIANYUNGANG	469.0856**	435.4671**	362.0716**	327.9671**	133.0442**	133.1381**	113.3722**	113.4436**
HUAIYIN	372.8363**	337.0993**	421.1834**	386.2145**	157.408**	157.3131**	166.2955**	166.2597**
YANCHENG	93.4398	57.4644	202.6498**	167.5333**	28.9658**	28.8553*	49.0414**	48.9950**
YANGZHOU	94.8891	59.4769	22.2572	-12.7749	1.0421	0.9885	-12.3096	-12.3327
ZHENJIANG	-123.9	-158.6088*	-119.0708	-154.0764*	-30.5250	-30.5109	-29.6372	-29.6384
TAIZHOU	-97.6176	-131.7526*	-65.7999	-100.5006	-31.1136	-31.0536	-25.2646	-25.2361
SUQIAN	588.3143**	555.9927**	423.1432**	389.5407**	150.05**	150.2561**	119.6871**	119.819**
Constant	-10808.09**	-10736.83**	-5172.708**	-5220.17**	-2678.408**	-2636.624**	-1642.475**	-1622.399**
N of Obs.	1439		1439		1439		1439	
R-squared	0.1651		0.2340		0.1710		0.2077	
Mean VIF	3.33		3.50		3.33		3.50	
Lamda		-0.0432		-0.0284		-0.0156		-0.0127
Log likelihood		-11326.285		-11264.377		-9336.5816		-9304.0035
Spatial error:								
Moran's I (z-score)		1695.138**		1513.789**		1773.131**		1673.945**
Lagrange multiplier		104.702**		83.421**		114.561**		102.013**
Robust Lagrange multiplier		59.671**		37.417**		68.326**		53.852**
Spatial lag:								
Lagrange multiplier		45.111**		48.097**		46.292**		48.964**
Robust Lagrange multiplier		0.08		2.092		0.057		0.803

*significant at $p < 0.05$; **significant at $p < 0.01$

Table 4 – Spatial Regression Results for COD and NH_3-N

Dependent:	**COD Emission**				**NH3-N Emission**			
	Model 1		Model 2		Model 1		Model 2	
Independent:	OLS	Spatial Error	OLS	Spatial Error	OLS	Spatial Error	OLS	Spatial Error
MIGRANTS	1.8719**	1.8712**	1.3022**	1.3021**	0.1490**	0.1488**	0.1174**	0.1173**
INDUSTRY			1.2998**	1.2997**			0.0721**	0.0720**
MINORITY	-28.6818**	-28.6713**	-29.053**	-29.0519**	-1.5672**	-1.5645**	-1.5878**	-1.5866**
INCOME	54.7279**	54.7686**	17.5787	17.6111	6.6889**	6.7232**	4.6273*	4.6558*
DENSITY	-0.0011**	-0.0011**	-0.0010**	-0.0010**	-0.0001**	-0.0001**	-0.0001**	-0.0001**
EDUCATION	1.3365**	1.3364**	1.5599**	1.5598**	0.0504	0.0503	0.0628*	0.0627*
LABOR	-1.1514	-1.1488	-2.8388*	-2.8385*	-0.1458	-0.1449	-0.2395*	-0.2389*
RIVER	-1.7055	-1.7073	-0.9325	-0.9325	-0.3102	-0.3107	-0.2673	-0.2675
Prefectures								
NANJING	1.6031	1.5834	17.6902	17.6836	-0.8118	-0.8227	0.0810	0.0727
WUXI	10.1864	10.1787	4.3889	4.3793	-2.1592*	-2.1689*	-2.4809*	-2.4879*
XUZHOU	9.0446	9.0681	-0.3245	-0.3134	-0.6536	-0.6392	-1.1736	-1.1631
CHANGZHOU	55.0141**	54.9911**	58.3078**	58.3018**	4.6538**	4.6411**	4.8365**	4.8287**
SUZHOU	-41.4623**	-41.5061**	-42.5594**	-42.5714**	-2.2721*	-2.2943*	-2.3330*	-2.3461*
NANTONG	-6.9317	-6.9448	-2.1808	-2.1829	-1.1736	-1.1792	-0.9100	-0.9134
LIANYUNGANG	-13.5187	-13.5053	-21.6807	-21.6699	-0.6636	-0.6496	-1.1166	-1.1057
HUAIYIN	6.9331	6.9834	10.1824	10.1893	1.2439	1.2929	1.4542	1.4636
YANCHENG	-10.7941	-10.7504	-2.9978	-2.9959	-0.2418	-0.2257	0.1909	0.1977
YANGZHOU	3.9023	3.9201	-1.1814	-1.1805	6.2781**	6.2843**	5.9960**	5.9992**
ZHENJIANG	7.0250	7.0052	7.6401	7.6355	-1.6846	-1.6936	-1.6504	-1.6556
TAIZHOU	-10.8612	-10.8764	-8.5254	-8.5244	-0.7632	-0.7673	-0.6336	-0.6351
SUQIAN	14.7058	14.7056	2.2449	2.2635	2.3704	2.3843	1.6788	1.6925
Constant	-397.0486*	-409.0972*	17.8685	18.1648	-45.4034**	-48.7594*	-22.3768	-23.5516
N of Obs.	1441		1441		1441		1441	
R-squared	0.2105		0.2315		0.1425		0.1490	
Mean VIF	3.32		3.50		3.32		3.50	
Lamda		0.0280		0.0138		0.0588		0.0367
Log likelihood		-8371.534		-8352.169		-5104.0398		-5098.5584
Spatial error:								
Moran's I (z-score)		909.31**		791.47**		965.441**		897.949**
Lagrange multiplier		30.424**		23.028**		34.298**		29.645**
Robust Lagrange multiplier		31.241**		21.632**		44.531**		38.228**
Spatial lag:								
Lagrange multiplier		3.500		3.710		12.249**		10.537**
Robust Lagrange multiplier		4.316*		2.314		2.016		1.954

*significant at $p < 0.05$; **significant at $p < 0.01$

Table 5 – Spatial Regression Results for Weighted SO_2 and Smog

Dependent:	Weighted SO2 Emission				Weighted SMOG Emission			
	Model 1		Model 2		Model 1		Model 2	
Independent:	OLS	Spatial Error	OLS	Spatial Error	OLS	Spatial Error	OLS	Spatial Error
MIGRANTS	11.5469**	11.5513**	3.6401	3.6367	3.6928**	3.6927**	2.2857**	2.2857**
INDUSTRY			17.6503**	17.6393**			3.1410**	3.1410**
MINORITY	-12.2876	-12.8407	-18.7239	-18.9546	4.4782	4.4812	3.3328	3.3302
INCOME	1248.627**	1253.486**	753.2514**	757.7011**	292.5479**	292.5337**	204.3923**	204.41**
DENSITY	-0.0144**	-0.0144**	-0.0132**	-0.0132**	-0.0034**	-0.0034**	-0.0032**	-0.0032**
EDUCATION	-3.0330	-3.0494	-0.0395	-0.0552	-0.5473	-0.5472	-0.0145	-0.0146
LABOR	28.5915*	28.4821*	6.7017	6.6875	4.0185	4.0192	0.1231	0.1226
RIVER	-28.3261	-28.1955	-17.8468	-17.798	-13.3615**	-13.3621**	-11.4967**	-11.4962**
Prefectures								
NANJING	-120.1429	-120.4305	95.0542	94.3117	-24.3314	-24.3324	13.9645	13.9640
WUXI	-545.8245**	-547.9844**	-629.7166**	-631.3225**	-131.0768**	-131.0695**	-146.006**	-146.0143**
XUZHOU	803.1509**	804.3427**	686.5048**	687.852**	166.6662**	166.6637**	145.9082**	145.9127**
CHANGZHOU	-444.6863**	-444.9279**	-403.5194**	-404.1852**	-112.8329**	-112.8344**	-105.507**	-105.5072**
SUZHOU	-748.2121	-748.6635	-770.845**	-771.9541**	-176.6894**	-176.6919**	-180.7171**	-180.7177**
NANTONG	-166.9908*	-166.4664*	-99.2048	-99.1208	-40.1478	-40.1513*	-28.0848	-28.0818
LIANYUNGANG	662.829**	664.983**	558.058**	559.9536**	167.5544**	167.548**	148.9097**	148.9176**
HUAIYIN	411.0891**	409.6325**	457.0143	456.8427**	166.3533**	166.3639**	174.526**	174.518**
YANCHENG	54.5745	52.6579	159.4461	158.8757	17.9756	17.9873	36.6382	36.6290
YANGZHOU	74.4875	73.4765	3.2773	2.9350	-11.2729	-11.2675	-23.9453	-23.9497
ZHENJIANG	-189.5002*	-189.3433*	-184.9062*	-185.1353*	-35.2287	-35.2310	-34.4111	-34.4099
TAIZHOU	-50.4607	-49.2747	-19.8167	-19.2934	-18.8064	-18.8122	-13.3531	-13.3481
SUQIAN	680.0935**	684.4305**	518.6591	521.9269**	154.8923**	154.8756**	126.1639**	126.1814**
Constant	-12711.46**	-11950.54**	-7224.026**	-6891.764**	-2749.745**	-2753.875**	-1773.217**	-1769.731**
N of Obs.	1439		1439		1439		1439	
R-squared	0.1326		0.1714		0.1468		0.1684	
Mean VIF	3.32		3.50		3.32		3.50	
Lamda		-0.0642		-0.0531		0.0015		-0.002
Log likelihood		-11720.339		-11687.425		-9646.2609		-9627.8121
Spatial error:								
Moran's I (z-score)		199.559**		189.273**		672.391**		686.12**
Lagrange multiplier		1.452		1.305		16.534**		17.206**
Robust Lagrange multiplier		0.328		0.701		4.537*		4.292*
Spatial lag:								
Lagrange multiplier		5.869*		6.797**		14.299**		15.715**
Robust Lagrange multiplier		4.745*		6.194*		2.302		2.802

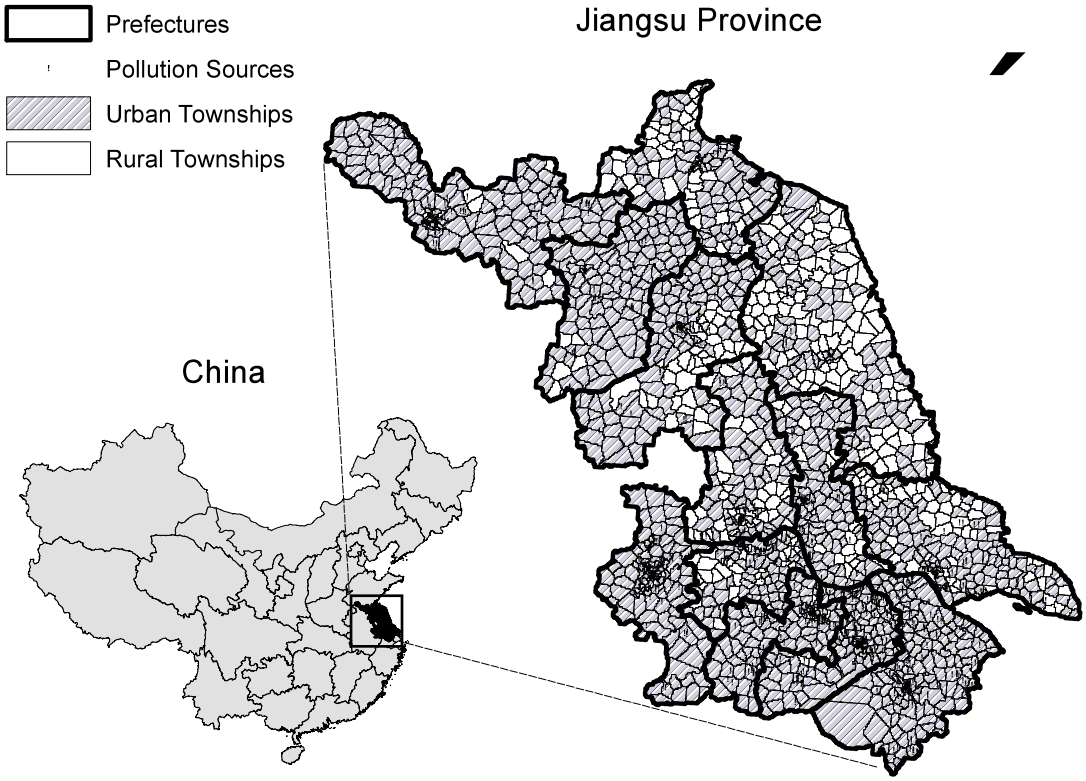
*significant at $p < 0.05$; **significant at $p < 0.01$

Table 6 – Spatial Regression Results for Weighted COD and NH_3-N

Dependent:	**Weighted COD Emission**				**Weighted NH3-N Emission**			
	Model 1		Model 2		Model 1		Model 2	
Independent:	OLS	Spatial Error	OLS	Spatial Error	OLS	Spatial Error	OLS	Spatial Error
MIGRANTS	2.3633**	2.3621**	1.7175**	1.7178**	0.1757**	0.1752**	0.1277**	0.1276**
INDUSTRY			1.4737**	1.4742**			0.1095**	0.1094**
MINORITY	-28.0655**	-28.0589**	-28.4863**	-28.4851**	-1.3362	-1.3332	-1.3675	-1.3670
INCOME	3.3264	3.5202	-38.7895	-38.9504	4.5074	4.5797	1.3768	1.4047
DENSITY	-0.0015**	-0.0015**	-0.0014**	-0.0014**	-0.0001**	-0.0001**	-0.0001**	-0.0001**
EDUCATION	0.7884*	0.7878*	1.0416**	1.0421**	0.0083	0.0081	0.0271	0.0270
LABOR	1.6808	1.6834	-0.2322	-0.2331	0.1114	0.1127	-0.0308	-0.0304
RIVER	-1.8726	-1.8734	-0.9963	-0.9969	-0.6999**	-0.7004**	-0.6348**	-0.6349**
Prefectures								
NANJING	24.3418*	24.2942*	42.5797**	42.6127**	0.2356	0.2159	1.5912	1.5839
WUXI	11.1526	11.0878	4.5799	4.6306	-3.2854**	-3.3083**	-3.7739**	-3.7815**
XUZHOU	-6.0705	-5.9981	-16.6922	-16.7436	-0.7829	-0.7553	-1.5725	-1.5628
CHANGZHOU	48.4262**	48.3712**	52.1603**	52.1914**	3.3669**	3.3442*	3.6445**	3.6375**
SUZHOU	-28.6012*	-28.6976*	-29.8450**	-29.7928**	-1.6938	-1.7329	-1.7862	-1.7977
NANTONG	6.5178	6.5010	11.9039	11.9108	-0.1685	-0.1765	0.2319	0.2294
LIANYUNGANG	-20.0127	-19.9336	-29.2660	-29.3288*	-0.8086	-0.7880	-1.4964	-1.4853
HUAIYIN	-7.8417	-7.7774	-4.1580	-4.1758	1.2162	1.2445	1.4900	1.4968
YANCHENG	-21.6337*	-21.5867*	-12.7950	-12.7973	-1.0144	-0.9917	-0.3574	-0.3530
YANGZHOU	-6.0563	-6.0436	-11.8197	-11.8189	6.4053**	6.4128**	5.9769**	5.9788**
ZHENJIANG	14.8726	14.8373	15.5699	15.5869	-1.5100	-1.5248	-1.4582	-1.4624
TAIZHOU	3.6443	3.6411	6.2925	6.2833	-0.1367	-0.1400	0.0602	0.0599
SUQIAN	-1.2909	-1.1848	-15.4177	-15.5203	2.2119	2.2487	1.1618	1.1769
Constant	-136.8708	-141.4331	333.5197	328.2843	-40.4433	-43.7278	-5.4781	-5.8202
N of Obs.	1441		1441		1441		1441	
R-squared	0.1952		0.2195		0.1104		0.1203	
Mean VIF	3.32		3.50		3.32		3.50	
Lamda	0.0261		-0.0168		0.058		0.0178	
Log likelihood	-8458.4182		-8436.3109		-5430.1403		-5422.0851	
Spatial error:								
Moran's I (z-score)	949.099**		812.55**		789.816**		734.702**	
Lagrange multiplier	33.146**		24.272**		22.95**		19.841**	
Robust Lagrange multiplier	35.141**		24.132**		33.575**		29.084**	
Spatial lag:								
Lagrange multiplier	3.706		3.538		1.153**		1.117**	
Robust Lagrange multiplier	5.701*		3.399		11.778		10.359	

*significant at $p < 0.05$; **significant at $p < 0.01$

Figure 1. Pollution Sources in Jiangsu Province



Data sources: CC 2000; authors' collection.

Supplementary Figure 1. Prefectures in Jiangsu Province