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Environmental justice perspective on the distribution and determinants of polluting enterprises in Guangdong, China

Wei Liu [a,f], Jing Shen [b,**], Yehua Dennis Wei [c,d,*], Wen Chen [a,e,f]

[a] Nanjing Institute of Geography and Limnology, Chinese Academy of Sciences, Nanjing, 210008, China
[b] School of Geography and Planning, Sun Yat-Sen University, Guangzhou, 510275, China
[c] Department of Geography, University of Utah, Salt Lake City, UT, 84112-9155, USA
[d] Key Research Institute of Yellow River Civilization and Sustainable Development, Collaborative Innovation Center on Yellow River Civilization, Henan University, Kaifeng, 475001, China
[e] Key Laboratory of Watershed Geographic Sciences, Chinese Academy of Sciences, Nanjing, 210008, China
[f] University of Chinese Academy of Sciences, Beijing, 100049, China

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ABSTRACT

With the rapid urbanization and industrialization, the uneven distribution of polluting enterprises among different socioeconomic groups has become a prominent environmental social problem in transitional China but is rarely recognized. This paper introduces environmental justice theories in industrial location studies. A heuristic analytical framework is proposed to analyze the distribution and determinants of polluting enterprises in Guangdong, China, a highly developed region but with high social and economic inequality. Polluting enterprises are mostly agglomerated in the Pearl River Delta (PRD) region with the rest in the mountainous and hilly non-PRD region. Bivariate local spatial autocorrelation analysis shows the colocation of polluting enterprises and migrants. Our regression results reveal that the county where many migrant residents are concentrated historically appears to attract many polluting firms to enter. However, less firms are found in the county with many highly educated groups and ethnic minorities. Land space planning, environmental regulation, labor costs, and agglomeration economy have driven the distribution of new polluting enterprises, whereas the influences of traffic accessibility and border effect do not work actually. To some extent, the distribution of new polluting enterprises must be recognized as a predictable result of the characteristics of prior demographic distribution.

1. Introduction

Environmental justice (EJ) refers to the equal right for all people to live in a healthy environment free from environmental hazards regardless of their race or socioeconomic status (Cutter, 1995). The discourse of EJ has been expanding in scope far beyond the initial distributive justice in the past three decades, pursuing the outcome equality and procedural equity (Schlosberg, 2013; Agyeman et al., 2016). EJ research originates from the environmental movements in the U.S. in the early 1980s (Banzhaf et al., 2019). It has then spread to Europe (Pasetto et al., 2019), Asia (Ma, 2010; Ortiz-Moya, 2018), Africa (Nieru, 2006), Latin America (Álvarez and Coolsaet, 2018), and has now become a global concern. To date, EJ research has made abundant studies, where many of them focus on distributive EJ (Althor and Witt, 2020). Early studies focus on the relationship between environmental hazardous facilities and ethnic minorities and then expand to the relationship between environmental exposure and socioeconomic status (Ma et al., 2019). The recent discourse of EJ has turned to cultural resistance against hegemonists, aiming to redefine a simple and sustainable form of "good life" (Akbulut et al., 2019). In terms of research methods, EJ studies mainly include qualitative and quantitative methods. These methods are used to study the development of environmental injustice with historical analysis and process analysis (Pellow, 2000; McNair, 2020) and the measurement of EJ with questionnaire analysis (Li et al., 2019), unit analysis (Ma, 2010; Ma et al., 2019), distance analysis (Mears et al., 2019), and environmental modeling (Samoli et al., 2019).

China's EJ research is at the infant stage but the literature on China' EJ is increasing year by year, most of which is distributive EJ research (Ma, 2010; Ma et al., 2019; Huang et al., 2019; Li et al., 2019). With the

* Corresponding author. Department of Geography, University of Utah, Salt Lake City, UT, 84112-9155, USA.
** Corresponding author.;
E-mail addresses: wliu@niglas.ac.cn (W. Liu), shenjing@mail.sysu.edu.cn (J. Shen), wei@geog.utah.edu (Y.D. Wei), wchen@niglas.ac.cn (W. Chen).

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rapid urbanization and industrialization, the uneven distribution of polluting enterprises among different socioeconomic groups has become a prominent environmental social problem in transitional China but is rarely recognized. For a long time, China's rapid and extensive mode of economic development has brought severe environmental degradation and environmental injustice. Today, with China's deep concern for the people's needs of a better life and environmental issues, ensuring EJ is to address the environmental aspects of social contradictions and achieve social fairness and justice in the environmental aspects to some extent. However, few studies have examined the distribution and determinants of polluting enterprises in China from the perspective of EJ.

This paper fills two gaps in existing studies. First, EJ studies are dominantly conducted in developed countries, such as the U.S., and few studies focus on developing countries, such as China. Race-based or income-based EJ theories formed in developed countries cannot be directly applied to China with different historical, social, political, and economic characteristics (Ma, 2010). Second, many studies have explored the drivers of polluting enterprise distribution usually from the perspective of economic geography theories; These studies emphasize the factors of firm strategies and government interventions (Kahn, 2004; Duvivier and Xiong, 2013; Zhu et al., 2014; Kahn et al., 2015; Cai et al., 2016; Zheng and Shi, 2017; Shen et al., 2017, 2019, 2019; Wu et al., 2019; Dou and Han, 2019), but de-emphasize the role of prior socioeconomic determinants in accordance with EJ theories. This paper proposes a heuristic analytical framework to address the distribution and driving forces of polluting enterprises in Guangdong, China, a highly developed region but with high social and economic inequality, by introducing EJ theories in the industrial location studies. This paper aims to examine whether the pre-existing demographic characteristics affect the distribution of polluting enterprises.

The rest of this paper is organized as follows. The next section reviews the existing literature and proposes a heuristic analytical framework. Data and models are then introduced. The empirical results are provided. Some findings are summarized, followed by a discussion of the findings and policy implications.

2. Literature review and analytical framework

2.1. Review of studies on the determinants of polluting enterprise distribution

Polluting enterprises are likely to manipulate their production activities in locations with relatively loose environmental regulation (ER) for reducing environmental compliance costs, known as the "Pollution Haven Hypothesis (PHH)" (Grossman and Krueger, 1993). A large body of literature has examined the relationship between ER and polluting industrial distribution to identify the validity of PHH (Jeppesen et al., 2002; Dasgupta et al., 2001; Xing and Kolstad, 2002). However, the consensus on the role of ER in polluting enterprise distribution has not been reached due to the varying geographic scales of analysis and different contexts among regions and countries (Jeppesen et al., 2002; Xing and Kolstad, 2002; Kahn, 2004; He, 2006; Dean et al., 2009; Shen et al., 2017; Wu et al., 2019). The famous "Porter Hypothesis (PH)" points out that appropriate ER stimulates technological innovation, thereby establishing a competitive advantage of enterprise that can offset the increase in environmental cost caused by ER (Porter and Van der Linde, 1995). Some studies have evidenced that polluting firms still tend to stay on regions with relatively stringent ER, thereby highlighting the positive effect of ER (Zhu et al., 2014; Dou and Han, 2019). However, the coexistence of PHH and PH makes the relationship between the distribution of polluting enterprise and ER complicated. Some studies have claimed that the mixed results of ER are caused by the overlook of firm heterogeneities, such as firm scale and ownership type (Zhu et al., 2014), industrial pollution characteristics (Zheng and Shi, 2017), and firm mobility (Dou and Han, 2019). Zhou et al. (2017) believed that enforcement asymmetries of ER exist between small and large firms due to their disparities in tax and employment contributions and bargaining power with the local government. Different polluting industries with varying pollutant emission level implement distinct regulatory strategies, such as closure, transfer, and upgrading (Zheng and Shi, 2017).

In addition to the controversial role of ER, the boundary agglomerations at different geographic scales of polluting firms are specifically observed by researchers (Kahn, 2004; Duvivier and Xiong, 2013; Kahn et al., 2015; Cai et al., 2016; Liu, 2013). The boundary clusters of polluting firms may be an intentional result of the government's manipulation. Certain local governments have been found to strategically implement ER within their jurisdictions and lessen enforcement efforts at borders to drive polluting firms toward such areas (Cai et al., 2016), so as to enjoy complete economic growth but a partial burden of negative environmental externality (Liu, 2013). For polluting firms, locating in boundary areas appears to be benefitable due to the reduction of environmental costs and the proximity to neighboring markets (Kahn, 2004; Cai et al., 2016). However, the incentives for local governments to transfer polluting industries to border areas have weakened with the shift of China's environmental policies (Kahn et al., 2015). Yang and He (2015) showed that the agglomeration effect matters more for the local government compared with the utilization of free rider effects.

Regional differences in place-specific attributes increasingly drive the distribution of polluting enterprises (He et al., 2014). First, the factor endowment hypothesis indicates that polluting industries determine their locations depending on their factor-intensive characteristics. For example, resource-intensive polluting industries tend to agglomerate in regions with sufficient raw material and resources. Second, the new economic geography theories deem that spatial agglomeration is an important location factor for enterprises (Wei et al., 2013). The agglomeration of firms can share skilled labor markets, suppliers, intermediate goods, and specialized business services, thereby allowing for knowledge and technology spillover (Malmberg, 2000). Therefore, locating the polluting firms in regions where the existing industries and local population can provide spillover effects is efficient, which is usually absent in small towns (Yang and He, 2015). Third, regional disparities in locational factors, such as market demands, labor, and transportation costs, significantly affect the distribution of polluting firms (Liu, 2013). By contrast, polluting firms are undesirable in ecologically sensitive regions due to the varying regional environmental policies and regulation instruments (Fan and Li, 2009).

2.2. Review of studies on EJ

EJ researchers have focused on the distribution of pollution and related health risks in the past four decades. They highlight the potential inequality between the benefits and burdens of environmental exploitation among different social groups and appeal to recognize and address such inequality because it can lead to unjust outcomes for specific groups (Cutter, 1995; Pellow, 2000; Schlosberg, 2013; Anguelovski et al., 2018; Ortiz-Moya, 2018; Mears et al., 2019; Rice et al., 2020; Althor and Witt, 2020). EJ is closely connected to social deprived (or disadvantaged) groups, which refer to the population with living standards below the general standards typically characterized by indicators, such as the proportion of population with low income, low education, nonprofessional occupation, and nonowner occupier (Townsend, 1987). However, American EJ studies have not reached a consensus that ethnic minorities are disproportionately exposed to environmental pollution and hazards until 2000 with the new methods of geographic information systems and professional environmental models (Schlosberg, 2013). Thus, race-based environmental injustice becomes the most obvious feature of American EJ problem. EJ studies conducted in Europe seem to reach contradictory results on the socioeconomic determinants of environmental exposures (Wheeler and Ben-Shlomo, 2005; Pasetto et al., 2019; Samoli et al., 2019). Samoli and Stergiopoulou (2019) pointed out that the relationship between the environmental burdens or benefits and socioeconomic determinants depends on the geographic scale of analysis and varies across cities and countries, thereby emphasizing the importance of geographic perspective.

Socioeconomic determinants, such as economic status, geographic location, race or ethnicity, education, age, employment, gender, immigrant, and children, are widely discussed in EJ studies and are often used as social demographic variables in empirical studies (Althor and Witt, 2020). In the context of China, a type of distinct socioeconomic determinant associated with the hukou system is often discussed in a limited number of Chinese EJ studies (Ma, 2010; Ma et al., 2019; Huang et al., 2019). Each individual in China is designed to register as either rural resident or urban resident known as hukou. The hukou system prioritizes urban residents over rural residents in many ways, including welfare programs, housing, education, Medicare, and pensions. The migrants, whose hukous are registered in other places, are treated differently compared with the indigenous (Ma, 2010). The hukou system is originally designed to manage rural–urban migration and is a main historical reason that induces a dual social and economic structure in China; this system has brought increasing inequality between the urban and the rural (Liu, 2005). The migrants and rural residents have been shown to be exposed to high environmental risks, such as air pollution, toxic substances, and polluting firms, but are rarely recognized in China (Ma, 2010; Ma et al., 2019; Huang et al., 2019).

Beyond numerous environmental distributive justice studies, some EJ scholars have focused on the political, economic, and social mechanisms driving the formation of environmental injustice (Pellow, 2000; Mohai et al., 2009; Schlosberg, 2013; Banzhaf et al., 2019). Overall, three models are used to explain the mechanisms in the existing literature. First, some researchers believe that polluting enterprises are intentionally located by decision makers in communities where ethnic minorities or low-income groups gather due to racial discrimination, racial superiority, and beliefs, known as the view of environmental racialism (Schlosberg, 2013). Second, a view of market rationality is deemed by some researchers (Mohai et al., 2009). In detail, polluting enterprises tend to locate in areas with lower environmental costs and compensation costs for the maximum benefits under the market mechanism, probably inducing firm clusters in particular benefitable location. The last perspective focuses on the varying sociopolitical capability among different social groups (Pellow, 2000). The vulnerable groups often reluctantly accept the entrance of polluting enterprises at minimal or zero compensation due to their relatively weaker bargaining power with decision makers. For the wealthier or middle classes, decision makers themselves in many cases utilize their superior social capital and political resource to prevent the entrance of polluting enterprises (Banzhaf et al., 2019).

2.3. Heuristic analytical framework of the determinants of polluting enterprise distribution

Significant studies have explored the drivers of polluting enterprise distribution, usually from the perspective of economic geography theories, which emphasize the factors of firm strategies and government interventions. However, to what extent the pre-existing local demographic characteristics have influenced the siting of polluting enterprises is a perspective rarely adopted by researches. In accordance with EJ theories, another type of environmental stakeholders, that is, the local residents, should be considered apart from local governments and polluting enterprises. The socioeconomic determinants may be another type of factors influencing the distribution of polluting firms.

This paper redesigns a heuristic analytical framework of the determinants of polluting enterprise distribution at the regional level (Fig. 1). We believe that some particular socioeconomic groups are becoming a determinant for polluting enterprise's location, suggesting the environmental injustice issues. The correlation of specific local residents with the siting of polluting firms is complex and mainly depends on their ability and willingness to resist the entry of polluting firms. Slightly similar to American EJ movements, Chinese local residents, usually the wealthier and middle classes, tend to launch mass environmental conflicts and manipulate media power for pushing the government to stop a new polluting project in their district. In addition to the differentiated bargaining power and environmental compensation cost (Pellow, 2000; Mohai et al., 2009), we emphasize the close connection between the employment of polluting enterprises and the rural migrants in the Chinese context. A large number of rural laborers underemployed in collective agriculture have poured into the cities in pursuit of employment under the urbanization in China (Ma, 2010). The migrants are attracted to jobs when a new polluting enterprise is formed, that is, in a case of failing to stop the entry. This condition then attracts many firms for sufficient laborers and cheap labor costs. The disadvantaged groups may accept the entry of polluting firms due to their inability to bear a clean community and tradeoffs between clean environment and other neighborhood amenities, such as access to employment (Banzhaf et al., 2019), known as the process of residential spatial stratification (Schaeffer and Tivadar, 2019).

3. Data and methods

3.1. Description of the study area

Guangdong Province is located in the southernmost part of mainland China (Fig. 2). It is the most developed region with a total gross domestic product (GDP) of 9.73 trillion yuan in 2018, which accounts for 10.6% of the national GDP. This region has a large population of 113 million permanent residents in 2018, which accounts for 8.1% of the national total population. However, the social and economic inequality within Guangdong Province is high although it is the most developed region (Liao and Wei, 2012). The proportion of traditional polluting industries in the industrial structure remains relatively high, thereby putting great pressure on the regional carrying capacity of resources and environment (Shen et al., 2019). Therefore, studying EJ in such a developed region with strong socioeconomic and environmental quality gradients is particularly important, where the agglomeration of polluting enterprises probably and unintentionally exacerbates environmental injustices.

3.2. Data and variable definition

Dependent variable: The list of polluting enterprises is obtained from the official website of the national pollutant discharge license information platform.[1] A total of 8700 polluting enterprises are found in Guangdong Province in accordance with the database obtained in December 2019. Some EJ studies have pointed out that a cyclical cumulative effect is found in the formation of environmental injustice (Pellow, 2000). Specifically, maybe polluting firms first locate somewhere and then attract specific groups (Pastor et al., 2001). We used the 2010 census data of Guangdong Province as the basis to construct the variables of demographic characteristics. A dependent variable Y is set as the number of polluting enterprises established after 2010 within each county to avoid endogenous problem in the models. In accordance with the established year of polluting firms obtained from the business registration information database,[2] we excluded polluting firms established in 2010 and earlier than 2010. A total of 2970 polluting firms established after 2010 are found.

Demographic characteristics: Considering the Chinese context and the availability of data, this paper uses the 2010 census data of Guangdong Province as the basis to construct the variables of demographic characteristics. We construct five demographic indicators, namely, attributes (rural or urban, migrant or indigenous) of hukou

[1] http://permit.mee.gov.cn/permitExt/syssb/xkgg/xkgg!licenseInformation.action.

[2] https://www.qcc.com.

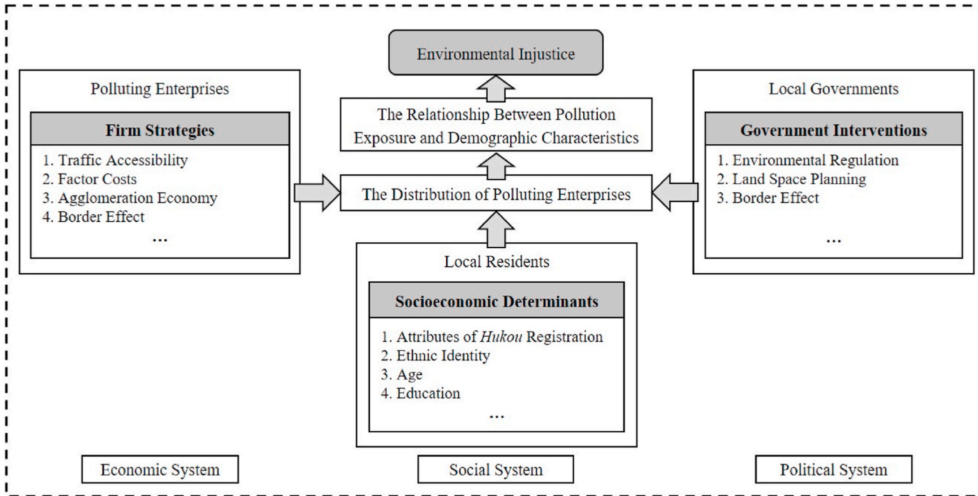

Fig. 1. Analytical framework of the distribution and determinants of polluting enterprises.

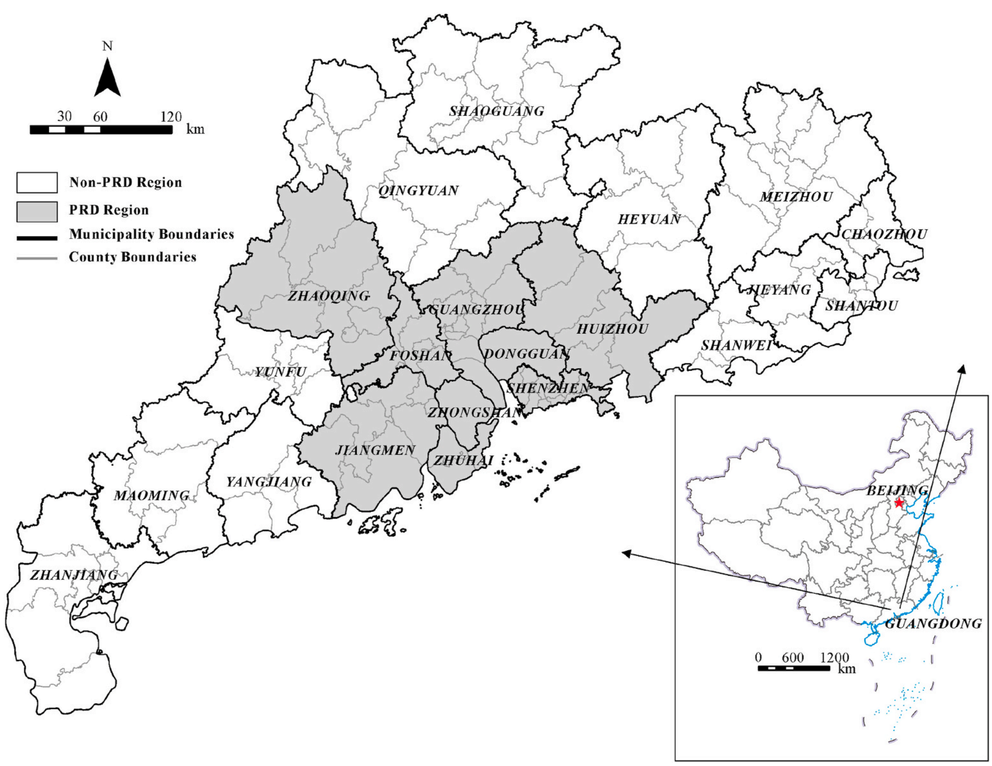

Fig. 2. Location and spatial organization of Guangdong Province.

registration, ethnic identity (Han or non-Han people), age (over 65 years old or not), and education (highly educated or not), to present the characteristics of demographic distribution. The specific definitions of variables are shown in Table 1.

Other determinants

(1) **ER**: In Chinese studies, the stringency of implemented ER is often measured by the level of pollutant emission that is strongly influenced by Chinese governments' environmental policies. (Shen et al., 2017). Some key pollutants have been enforced to be cut down in the government environmental plans since 2004, and the central government has broken down the task of pollutant emission reduction from the top down. The larger the part of pollutant emission reduction task a local district takes on, the stricter ER the local government has to implement, so as to pass the assessment of the superior government. SO_2 has been continuously a key pollutant to be cut down. SO_2-related ER indicators are often used to measure the stringency of ER during a specific period in Chinese empirical studies (Shen et al., 2017, 2019). Therefore, this paper defines the stringency of ER as the ratio of cumulative emission reduction of SO_2 pollutant since 2010 to the SO_2 emission level of 2010. The SO_2 emission data are collected from the statistical yearbooks of Guangdong Province and websites of local governments.

(2) **Land space planning (SP)**: Major function-oriented zoning has been the guideline for optimizing the spatial pattern of regional development in China (Fan and Li, 2009). In accordance with the principle of regional division of labor and regional coordination,

major function-oriented zoning in Guangdong has divided each county into six types. They are national development-prioritized type, national development-optimized type, provincial development-optimized type, national agricultural-function type, provincial ecological-function type, and national ecological-function type. Each type is defined as a dummy variable with values of 6, 5, 4, 3, 2, and 1. The smaller the value, the more important the ecological function the county undertakes and vice versa.

(3) **Traffic accessibility (TA):** This paper uses the density of traffic network to measure TA. The formula is as follows:

$$TA = \frac{NW + EW + RW}{S}, \tag{2}$$

where *NW* is the length of national roads, *EW* is the length of expressways, *RW* is the length of railways, *S* denotes the area of the county, and *TA* measures the TA. The larger the value, the better the accessibility and vice versa. The data of traffic network are obtained from Google Maps.

(4) **Factor costs (FC):** Polluting enterprises in Guangdong Province mostly belong to labor-intensive industries, textile dyeing, papermaking, electroplating, and furniture manufacturing. This paper mainly considers the effect of labor cost, which is measured by the average wage level of each county and is obtained from the statistical yearbooks of Guangdong Province.

(5) **Agglomeration economy (AE):** Spatial agglomeration is an important location factor for enterprises (Wei et al., 2013). This paper assumes that polluting enterprises tend to choose a location where polluting enterprises are historically concentrated to benefit from AE. Thus, the number of polluting enterprises established before 2010 within each county is used to measure the effect of AE.

(6) **Border effect (BE):** The ratio of the number of townships bordering the county boundaries to the total number of townships within the jurisdiction of the county is used to measure the BE. The larger the value, the greater the BE and vice versa.

3.3. Bivariate local spatial autocorrelation

This paper introduces bivariate local spatial autocorrelation to explore the spatial characteristics between the polluting enterprise distribution and the local demographic characteristics with the help of GeoDa software. This method uses bivariate local Moran's I to recognize the four different types of regional disparities, namely, high–high (H–H), low–low (L–L), high–low (H–L), and low–high (L–H) modes. The H–H and L–L modes indicate the spatial agglomeration of similar values, and the H–L and L–H modes indicate the spatial agglomeration of different values. The calculation formula of bivariate local Moran's I is shown below.

$$I_i^{xy} = Z_i^x \sum_{i=1;j=1}^{n} W_{ij} Z_i^y, \tag{3}$$

where Z_i^x and Z_i^y indicate the mean standardization of observed values, and W_{ij} is the spatial weight matrix element that is defined by Queen contiguity weight approach. I_i^{xy} indicates the product of the weighted mean of two variables at location *i*. Two variables at location *i* have a positive correlation if I_i^{xy} is significantly positive. Two variables at location *i* have a negative correlation if I_i^{xy} is significantly negative.

3.4. Negative binomial regression model

The dependent variable is the number of polluting enterprises established after 2010 within each county. Using a count data model to explain and predict the frequency of the phenomenon is rational. Poisson regression models are usually used when the dependent variable is count data. However, the hypothesis that the distribution of dependent variable presents as a Poisson distribution is usually not meet in practice. In other words, the mean is usually unequal to the variance and is often encountered in enterprise location data. Therefore, the negative binomial regression model is often used to account for the overdispersion. The formula of negative binomial regression model is shown below.

$$y_i \sim NB\left[exp\left(\sum_k \beta_k x_{ik}\right), \alpha\right], \tag{4}$$

where y_i is the number of polluting enterprises established after 2010 in the *i*th (i = 1, ..., n) county, *NB* denotes the negative binominal, and x_{ik} indicates the *k*th explanatory variable for county *i*. β_k (k = 0, 1, ..., p) are the estimated coefficients, and α is the parameter of overdispersion.

4. Empirical results

4.1. Spatial pattern of polluting enterprises

Polluting enterprises in Guangdong Province are mostly agglomerated in the Pearl River Delta (PRD) region with the rest in the mountainous and hilly non-PRD (NPRD) region (Fig. 3a). The count of polluting enterprises in each county varies largely with a coefficient of variation (C.V.) of 1.89. The firms in the PRD region and the top 10 counties account for approximately 74.9% and 47.3% of the total, respectively. Similar to Fig. 3a, new polluting enterprises established after 2010 are mainly concentrated in the PRD region (Fig. 3b). This

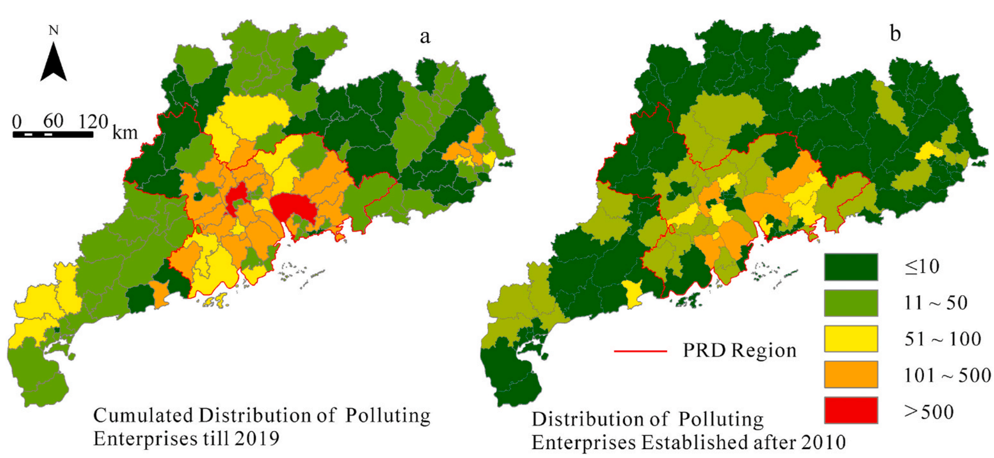

Fig. 3. Distribution of polluting enterprises in Guangdong Province.

finding indicates that the PRD region is still the main destination for polluting enterprises although the Guangdong government has implemented the policy of industrial transfers to non-PRD region since 2005. Newly established polluting enterprises are few in the urban districts of Guangzhou, Shenzhen, Foshan, and Zhuhai due to the policy of "tuierjinsan" industrial restructuring, that is, the tertiary industries replace the secondary industries in urban district.

4.2. Demographic characteristics of Guangdong

Table 1 summarizes the descriptive statistics of variables. The demographic characteristics vary largely among counties in Guangdong. The migrants are mainly concentrated in the PRD region, and the spatial pattern varies largely among counties. The percentage of rural residents remains relatively high in the NPRD region and Dongguan, thereby representing lower level of urbanization to some extent. The percentage of ethnic minorities in most counties is below 2.0, except for several counties in the north hilly NPRD region with more than 55%. The percentage of population over 65 years old in the NPRD region is relatively higher than that in the PRD region. The percentage of highly educated population in the PRD region is relatively higher than that in the NPRD region. The central urban district of each municipality usually shows a relatively high proportion.

4.3. Correlations of polluting enterprise location and demographic characteristics

Table 2 presents the Pearson correlations of indicators. The number of newly established polluting enterprises shows positive correlations with the percentage of the migrants ($r = 0.368$, $p < 0.01$) and the percentage of the rural residents ($r = 0.129$, not significant). It shows a weak correlation with the percentage of ethnic minorities ($r = 0.030$, not significant) and shows negative correlations with the percentage of elderly residents ($r = -0.327$, $p < 0.01$) and the percentage of the highly educated groups ($r = -0.037$, not significant). Some interesting correlations are found on the demographic indicators. The percentage of migrants shows negative correlations with the percentage of rural residents ($r = -0.353$, $p < 0.01$) and with the percentage of elderly residents ($r = -0.852$, $p < 0.01$). It shows positive correlation with the percentage of highly educated population ($r = 0.625$, $p < 0.01$), thereby indicating that the more the migrants, the more urbanized a county, and attracts highly educated groups and the migrants.

Fig. 4 reveals the characteristics of significant local spatial agglomeration between the number of newly established polluting firms and different demographic variables. The right section of Fig. 4 shows the quadrant distributions of bivariate local Moran scatter, and the left section shows the corresponding spatial patterns of bivariate local Moran cluster. In Fig. 4a, H–H and L–L clusters constitute the main types of agglomeration. Counties belonging to the H–H classification tend to be concentrated in the PRD region, whereas the counties within the L–L cluster are shown to be highly concentrated in the eastern and western parts of Guangdong, thereby providing evidence of colocation of the polluting firms and the migrants. For the rural residents (Fig. 4b), L–H clusters constitute the main types and are mainly located in the eastern and western parts of Guangdong. For the ethnic minorities (Fig. 4c), L–L clusters constitute the main types and are mainly located in the eastern and western parts of Guangdong. For the elderly residents (Fig. 4d), H–L and L–H clusters constitute the main types of agglomeration. H–L clusters are concentrated in the PRD region, whereas L–H clusters are concentrated in the northwest and eastern parts of Guangdong. For the highly educated residents (Fig. 4e), L–H clusters constitute the main types in the PRD region, and L–L clusters constitute the main types in the NPRD region.

Table 1
Variable definition and descriptive statistics.

Variable	Definition	Data source	Min.	Max.	Mean	Median	S.D.	N	Unit
Y	The number of polluting enterprises established after 2010 within each county	The website of http://permit.mee.gov.cn and https://www.qcc.com	0	483	23.95	8	54.41	124	/
Migrant	The percent of population whose *hukou* registered in other counties	2010 census data of Guangdong Province	0.36	89.89	20.04	8.06	23.71	124	%
Rural	The percent of population whose *hukou* registered as rural residents	2010 census data of Guangdong Province	14.64	96.17	69.95	77.39	18.27	124	%
Minority	The percent of population of non-*Han* ethnic groups	2010 census data of Guangdong Province	0.00	59.92	2.32	0.76	7.34	124	%
Elderly	The percent of population over 65 years old	2010 census data of Guangdong Province	0.78	12.57	8.04	8.54	2.72	124	%
H-educated	The percent of highly educated population	2010 census data of Guangdong Province	0.70	40.04	7.79	4.59	7.38	124	%
ER	the ratio of cumulative emission reduction of SO2 pollutant since 2010 to the SO_2 emission level of 2010.	Statistics yearbooks of Guangdong Province and websites of local governments	21.12	96.93	75.37	77.43	17.70	124	%
SP	A dummy variable for each county, and 6, 5, 4, 3, 2, 1 accordingly represents a type of major-function oriented zone	Major-function oriented zoning of Guangdong Province in 2012	1	6	4.07	4	1.68	124	/
TA	The density of traffic (national road, express way, railway) network	Google map	0.00	2.68	0.31	0.17	0.39	124	km^{-1}
FC	The average wage level of each county	Statistics yearbooks of Guangdong Province	4.08	12.88	6.76	6.39	1.56	124	¥10000
AE	The number of polluting enterprises established before 2010 within each county	The website of http://permit.mee.gov.cn and https://www.qcc.com	1	526	41.39	18	75.25	124	/
BE	The ratio of the number of townships bordering the county boundaries to the total number of townships within each county	Calculated by the author	0.00	1.00	0.48	0.50	0.23	124	/

Table 2
Pearson correlation coefficients of indicators.

	Y	*Migrant*	*Rural*	*Minority*	*Elderly*	*H-educated*	*ER*	*SP*	*TA*	*FC*	*AE*	*BE*
Y	1	0.368**	0.129	0.030	−0.327**	−0.037	0.042	0.278**	0.086	0.018	0.656**	−0.135
Migrant		1	−0.353**	0.078	−0.852**	0.625**	0.419**	0.696**	0.578**	−0.117	0.365**	−0.056
Rural			1	0.089	0.168*	−0.785**	−0.170*	−0.410**	−0.568**	−0.010	0.047	0.035
Minority				1	−0.047	0.007	−0.006	−0.073	−0.006	−0.019	0.119	0.050
Elderly					1	−0.467**	−0.456**	−0.736**	−0.392**	0.082	−0.309**	−0.009
H-educated						1	0.357**	0.530**	0.724**	−0.090	0.017	−0.024
ER							1	0.352**	0.335**	−0.013	0.161*	0.110
SP								1	0.535**	−0.144	0.314**	−0.030
TA									1	−0.063	0.106	0.029
FC										1	−0.002	−0.146
AE											1	−0.090
BE												1

**,* means significant at 0.01 and 0.05 level (single tailed) respectively.

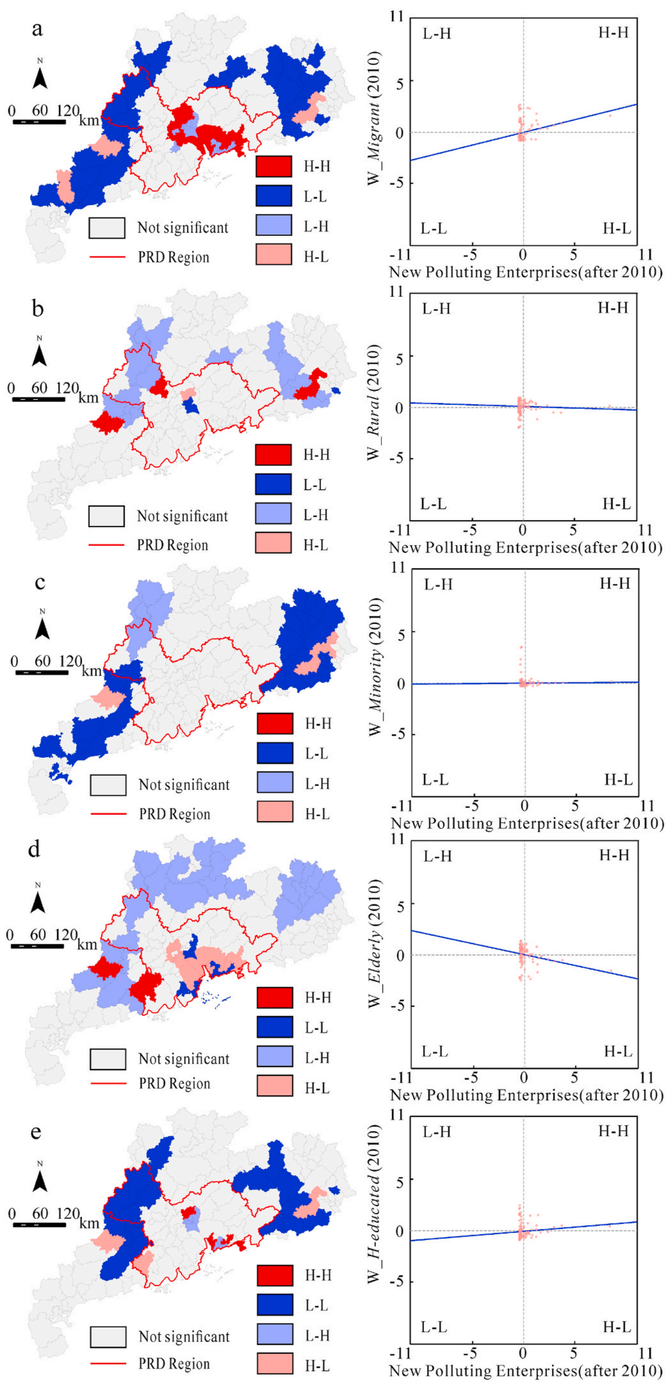

Fig. 4. Local spatial of agglomeration between the number of newly established polluting enterprises and different demographic variables.

4.4. Model regression results

The regression model was calculated on Stata 15 software. The variance inflation factor (VIF) values among independent variables are all smaller than 10, thereby indicating an absence of severe multicollinearity among the data (Table 3). Considering the great differences between the PRD and NPRD regions, two subregion models are additionally calculated to reveal the differentiated effects of prior demographic characteristics. All α parameters in three models are significant and not zero, indicating that the dependent variable does not obey the Poisson distribution and proving the rationality of using the negative binomial regression model.

The regression results affirm that the pre-existing demographic characteristics certainly affect the distribution of new polluting enterprises established after 2010 in Guangdong, especially when other determinants are considered. In accordance with Model 1 in Table 4, Migrant is a significant ($\beta = 0.027$, irr $= 1.027$, $p < 0.01$) positive predictor of the number of new polluting firms established after 2010. Specifically, for every one-unit increase in the percentage of migrants, the predicted log count of polluting firms increases by 0.027, and the incidence rate increases by a factor of 1.027. This result indicates that the migrants are disproportionately exposed to environmental risks caused by polluting firms. While Minority ($\beta = -0.041$, irr $= 0.960$, $p < 0.05$) and H-educated ($\beta = -0.104$, irr $= 0.901$, $p < 0.01$) are significant negative predictors of the number of new polluting firms. Rural and Elderly are positive but insignificant predictors of the number of new polluting firms. In the two subregion models, the demographic variables show different effects on new polluting firm location from Model 1. Migrant and Elderly turn to have negative but insignificant effects on the location choice of new polluting enterprises in Model 2, and Minority turns to be positive but not significant predictor in Model 2. It is also worth mentioning that H-educated is a significant negative predictor of the number of new polluting firms in the three models. This result indicates that the highly educated population are less exposed to the environmental risks induced by polluting firms no matter in the PRD or NPRD region.

Our results show that some other determinants drive the distribution of polluting enterprises. In terms of government interventions, SP is a significant positive predictor of the number of new polluting enterprises in the three models, indicating that the county with many economic-oriented functions attracts many polluting enterprises to enter. ER negatively affects the location choices of polluting enterprises, especially has a significant negative effect in Model 1. The result indicates that polluting enterprises still tend to seek a “Pollution Haven” in Guangdong. In terms of firm strategies, AE is a positive predictor on the distribution of new polluting firms, especially has a significant positive effect in Model 1, indicating that newly established polluting firms tend to locate in the county where polluting firms are historically agglomerated. TA is positive but not significant in the three models. The

Table 3
VIF values among independent variables.

Variables	*Migrant*	*Rural*	*Minority*	*Elderly*	*H-educated*	*ER*	*SP*	*TA*	*FC*	*AE*	*BE*
VIF	6.01	3.51	1.07	6.21	5.30	1.36	3.20	2.56	1.10	1.35	1.09

Table 4
Negative binomial regression results.

Dependent variable	Number of new polluting firms					
	Guangdong		PRD region		NPRD region	
Independent variables	Model 1		Model 2		Model 3	
	β	irr	β	irr	β	irr
Migrant	0.027*** (0.010)	1.027*** (0.011)	−0.020 (0.028)	0.980 (0.027)	0.061** (0.029)	1.063** (0.031)
Rural	0.007 (0.010)	1.007 (0.010)	1.018 (0.020)	1.018 (0.021)	0.001 (0.018)	1.001 (0.018)
Minority	−0.041** (0.019)	0.960** (0.018)	0.326 (0.209)	1.385 (0.289)	−0.043** (0.020)	0.958** (0.019)
Elderly	0.045 (0.095)	1.046 (0.099)	−0.099 (0.240)	0.905 (0.217)	0.102 (0.117)	1.107 (0.130)
H-educated	−0.104*** (0.032)	0.901*** (0.028)	−0.087* (0.052)	0.917* (0.048)	−0.206** (0.099)	0.814** (0.080)
ER	−0.011** (0.005)	0.989** (0.005)	−0.005 (0.012)	0.995 (0.011)	−0.010 (0.006)	0.990 (0.006)
SP	0.323*** (0.091)	1.381*** (0.126)	0.516*** (0.200)	1.675*** (0.336)	0.224* (0.118)	1.251* (0.148)
TA	0.472 (0.407)	1.604 (0.652)	0.679 (0.601)	1.971 (1.184)	2.241 (1.533)	9.409 (14.426)
FC	−0.056 (0.063)	0.946 (0.060)	0.224 (0.141)	1.251 (0.176)	−0.171** (0.081)	0.843** (0.068)
AE	0.003** (0.001)	1.003** (0.001)	0.002 (0.002)	1.002 (0.002)	0.003 (0.008)	1.003 (0.008)
BE	−0.152 (0.462)	0.859 (0.397)	−0.275 (0.810)	0.759 (0.615)	−0.283 (0.565)	0.753 (0.425)
c	1.780 (1.710)	5.932 (10.146)	−0.547 (4.232)	0.579 (2.450)	2.691 (2.459)	14.741 (36.253)
Observations	124		50		74	
α	0.881***		0.858***		0.721***	
LR test	1866.14***		1139.13***		506.97***	
Log likelihood	−453.628		−210.432		−234.942	

Notes: irr means incident rate ratio; number in () is standard error; ***, **, * means significant at 0.01, 0.05, and 0.10 level respectively.

Table 5
Two-step negative binomial regression results.

Dependent variable	Number of new polluting firms					
	Guangdong		PRD region		NPRD region	
Independent variables	Model 4		Model 5		Model 6	
	β	irr	β	irr	β	irr
Two-step_NB						
Migrant	0.029** (0.011)	1.029** (0.011)	−0.019 (0.029)	0.982 (0.028)	0.061** (0.029)	1.063** (0.031)
Rural	0.008 (0.010)	1.008 (0.010)	0.019 (0.021)	1.019 (0.021)	0.001 (0.018)	1.001 (0.018)
Minority	−0.041** (0.019)	0.960** (0.018)	0.295 (0.245)	1.343 (0.330)	−0.043** (0.020)	0.958** (0.019)
Elderly	0.052 (0.097)	1.054 (0.102)	−0.100 (0.240)	0.905 (0.218)	0.102 (0.118)	1.108 (0.130)
H-educated	−0.101*** (0.032)	0.904*** (0.029)	−0.088* (0.053)	0.916* (0.049)	−0.205** (0.099)	0.814** (0.081)
ER	−0.016 (0.013)	0.984 (0.012)	−0.008 (0.020)	0.991 (0.018)	−0.010 (0.015)	0.989 (0.014)
res_ER	0.005 (0.013)	1.006 (0.013)	0.005 (0.023)	1.005 (0.023)	0.001 (0.015)	1.001 (0.015)
SP	0.334*** (0.095)	1.396*** (0.133)	0.546** (0.241)	1.727** (0.416)	0.224* (0.121)	1.252* (0.152)
TA	0.511 (0.419)	1.619 (0.662)	0.706 (0.614)	2.026 (1.243)	2.232 (1.561)	9.319 (14.547)
FC	−0.051 (0.064)	0.950 (0.061)	0.227 (0.142)	1.255 (0.178)	−0.170** (0.082)	0.844** (0.069)
AE	0.003** (0.001)	1.003** (0.001)	0.002 (0.002)	1.002 (0.002)	0.003 (0.008)	1.003 (0.009)
BE	−0.073 (0.506)	0.930 (0.470)	−0.221 (0.846)	0.801 (0.678)	−0.280 (0.575)	0.756 (0.435)
c	1.806 (1.714)	6.086 (10.433)	−0.549 (4.243)	0.578 (2.451)	2.706 (2.505)	14.976 (37.517)
Observations	124		50		74	
α	0.880***		0.857***		0.721***	
LR test	1861.94***		1131.72***		504.98***	
Log likelihood	−453.552		−210.405		−243.942	
First step						
IV	2.810*** (0.501)		2.836*** (0.504)		5.456*** (1.519)	
Control variable	YES		YES		YES	
F test	25.23***		31.13***		11.21***	
Partial-R^2	0.184		0.450		0.153	

Notes: irr means incident rate ratio; number in () is standard error; ***, **, * means significant at 0.01, 0.05, and 0.10 level respectively.

influence of FC is negative except in Model 2, especially statistically significant in Model 3. BE does not work as expected and is statistically insignificant overall.

4.5. Endogeneity issues

The performance-based ER indicators may induce endogeneity issues as reported in environmental pollution and regulation literature. The two-stage least squares (2SLS) estimation derived from the instrumental variable (IV) method is widely used to solve the endogenous problem in the classic linear econometric models, which cannot be directly used in our count data regression models. We followed Hilbe's (2011) two-step negative binomial regression approach to solve the certain endogeneity.[3] On the choice of IV, this paper selects the number of public transport vehicles per 10,000 people in each city in 2010 as the IV of ER. Its logic basis is as follows: firstly, the development of public transportation could affect the stringency of environmental regulation by reducing the travel of private vehicles and pollution emissions. Secondly, the number of polluting enterprises established after 2010 cannot affect the number of public transport vehicles in 2010.

As shown in Table 5, the regression results of first step show that our IV significantly affect the ER and the results of F test mean that the selected IV is reasonable and effective. In accordance with the regression results of second step, the coefficients of res_ER are not significant, thereby indicating an absence of severe endogenous issues caused by the ER variables in the models. And the significance and sign of coefficients of demographic variables are consistent with Table 4 except for a slight change in the coefficients value. The results show that after eliminating the possible endogeneity of ER, the prior demographic distribution still affect the new polluting firm distribution.

5. Conclusion and discussion

5.1. Summary of findings and discussion

Numerous EJ studies have been conducted in developed countries, whereas studies on developing countries, such as China, have been rarely reported. With the rapid urbanization and industrialization, the uneven distribution of polluting enterprises becomes a prominent environmental social problem in transitional China but is rarely recognized. This paper analyzes the distribution and determinants of polluting enterprises from the perspective of EJ in Guangdong, China, a highly developed region with high social and economic inequality. Polluting enterprises are mostly agglomerated in the PRD region rather than in the non-PRD region. Bivariate local spatial autocorrelation analysis shows the colocation of polluting enterprises and the migrants, which is consistent with the existing literature (Ma, 2010; Ma et al., 2019; Huang et al., 2019).

We propose a heuristic analytical framework and conduct an empirical test of the determinants of polluting enterprise distribution. The factors of firm strategies and government interventions widely and deeply discussed in the existing literature (Kahn, 2004; Duvivier and Xiong, 2013; Zhu et al., 2014; Kahn et al., 2015; Cai et al., 2016; Zheng and Shi, 2017; Shen et al., 2017, 2019, 2019; Wu et al., 2019; Dou and Han, 2019) and socioeconomic determinants are considered in accordance with EJ theories (Pellow, 2000; Mohai et al., 2009; Banzhaf et al., 2019; Althor and Witt, 2020). Our negative binomial regression results and two-step negative binomial regression results reveal that the county where many migrant residents are concentrated historically seems to attract many polluting firms to enter. Less firms are found in the county with many highly educated groups and ethnic minorities. SP, ER, FC and AE drive the distribution of new polluting enterprises, whereas the influences of TA and BE do not work actually.

To some extent, the distribution of new polluting enterprises must be recognized as a predictable result of the characteristics of prior demographic distribution. In the Chinese context, the special socioeconomic determinants associated with hukou play a crucial role in the environmental injustice formation; this condition is different from the race-based or income-based EJ theories formed in developed countries (Pellow, 2000; Mohai et al., 2009; Banzhaf et al., 2019).

5.2. Policy implications

On the basis of the above analysis, environmental injustice may be an unavoidable problem in liberalized market economy if proper corrections are not effectively made. We propose two methods to address environmental injustice in China. The first method is to achieve institutional justice. On the one hand, the Chinese government needs to further deepen the reform of the hukou system and ensure that the migrant and rural groups enjoy fair social security and welfare during the process of "New Urbanization." On the other hand, major function-oriented zoning has become a basic national policy for optimizing the spatial pattern of regional development. At present, increasing efforts should be exerted to improve the mechanism of "the polluters pay and the protectors benefit" for achieving EJ between the development-oriented region and ecology-oriented region. Introducing the value orientation of EJ in the decision-making process is necessary to achieve procedural justice, ensure the effective participation of vulnerable groups in the decision-making process, and establish an effective environmental right litigation mechanism for the public (McNair, 2020). The second method is to reduce environmental pollution from the source by developing ecological technology and ecological economy, thereby reducing environmental injustice in addition to achieving institutional justice. Ecological advantages are transformed into economic advantages by developing and utilizing clean new energy, developing green technology to promote clean production, and developing ecological products. The last point is that we must be wary of ecological or green gentrification in the process of urban ecological restoration in many Chinese cities (Anguelovski et al., 2018; Rice et al., 2020). The disadvantaged group living in polluted environment shall not encounter the second social injustice.

5.3. Prospects of future research

We propose two research prospects to move forward in both theoretical and empirical works. First, the increasing important socioeconomic determinants should be taken into account in the prevalent environmental pollution and regulation studies. And more attention should be paid to EJ studies in developing countries due to distinct socioeconomic contexts. Second, future empirical researches can further analyze the interactions of different environmental stakeholders to better interpret environmental injustice formation and mechanism.

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CRediT authorship contribution statement

Wei Liu: Conceptualization, Data curation, Methodology, Writing – original draft, Software. **Jing Shen:** Resources, Data curation, Writing – review & editing. **Yehua Dennis Wei:** Resources, Writing – review & editing, Supervision. **Wen Chen:** Resources, Writing – review & editing.

[3] The first step is to use endogenous variable (*ER*) to perform OLS estimation on IVs and other control variables to obtain the corresponding residual; and the second step is to use dependent variable to perform negative binomial estimation on *ER*, the first-step residual, and other control variables (excluding IVs).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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