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Abstract

In this paper, we aim to see whether transit-oriented development (TOD) in Chinese cities is associated with better air quality. We first identify 37 Chinese cities with existing urban rail transit and/or bus rapid transit (BRT) systems. For each of these cities we generate performance-based TOD indicators – including measures such as urban area coverage, population coverage, street network density and land use mix within station catchment areas – and construct composite TOD indices for each city using those indicators. We also collect daily air quality index (AQI) data from the Ministry of Environmental Protection of China over the entire year 2014 for 152 cities and calculate annual and seasonal average AQIs for each city. Regression models provide some evidence that rail-based TOD is associated with better air quality, after controlling for meteorological, demographic and economic characteristics. BRT-based TOD shows no significant relationship.

Key words: transit-oriented development, air quality, city level, China

1 Introduction

China's urban air pollution, accompanying the nation's rapid economic development and urbanization, has generated increasing concerns (Hao and Wang, 2005; Fang et al., 2009). Among the factors contributing to the severe air quality threats, increasing dependence on private vehicles and growing traffic congestion in cites have become critical. Transit-oriented development (TOD) is often espoused as an effective solution to promoting "green" travel among urban residents and to shaping cleaner cities. However, little empirical research explicitly links urban air quality and TOD. We might expect TOD to be related to better urban air quality because TOD aims to increase the use of public transportation which tends to have lower rates of local pollutants per distance traveled per person than automobiles, to increase walking and bicycling use, and to decrease average trip distances.

While some scholars have explored the relationship between urban air quality and the built environment, they have mainly measured the intra-urban heterogeneity of air pollutant concentrations in specific cities. In this paper, we aim to answer the following questions. Are cities with a higher degree of TOD in China associated with better air quality? Is there a difference in this relationship depending on whether the TOD is rail-based versus bus rapid transit (BRT)-based? We attempt to answer these questions by modeling urban air quality in a sample of Chinese cities as a function of measures of TOD and controlling for other factors, including meteorological conditions, demographic and economic conditions, and urban form. The following section reviews the relevant literature. The third section presents the data collection and modeling strategy. The fourth section presents and discusses the results, and a final section concludes.

2 Literature Review

We focus our literature review on two streams of research directly related to our questions: urban form and air quality and TOD assessment.

2.1 Urban Form and Air Quality

Numerous studies have measured the intra-urban variation of air pollutant concentrations in specific cities to, for example, estimate pollution concentrations and predict exposure. A common technique is land use regression (LUR), in which air quality, measured at different monitoring sites, is regressed on relevant conditions at the monitoring sites. LUR was first developed within GIS by Briggs et al. (1997) to predict traffic-related air pollution (especially NO_2) in European cities as predicted by the road network, traffic volume, land cover and altitude. Briggs et al. (2000) carried out similar research in the UK, while others followed with studies in Germany (Hochadel et al., 2006), New York (Ross et al., 2007), Los Angeles (Moore et al., 2007), and Vancouver (Henderson et al., 2007). Arain et al. (2007) incorporated wind fields into an LUR, showing improvements in the prediction of air pollution and the relative spatial distribution of traffic pollution in the Toronto-Hamilton (Canada) urban airshed.

In a review of LUR models, Hoek et al. (2008) argued for the need to deepen understanding of the relationship between urban form and air quality, urging researchers to expand the scope of the predictor variables, include spatiotemporal components, validate models with personal exposure modeling, and explore model transferability (to other urban areas).

LUR techniques have been applied in China. Chen et al. (2010) examined NO_2 and PM_{10} concentrations in Tianjin and found better predictability of the former than the latter and for heating season versus non-heating season concentrations. Wu et al. (2015) used LUR to examine $PM_{2.5}$ in Beijing, identifying a few key predictors related to road length, vegetation and water land uses and finding more temporal (seasonal, peak/non-peak) than spatial variation. Liu et al. (2015), applying LUR methods to predict NO_2 and PM_{10} concentrations in Changsha, add further temporal refinements, in the form of meteorological factors (temperature, wind, cloud cover); they still find most pollution concentration to be explained by major roads and residential and public facilities land uses. Overall, these LUR analyses of intra-urban variations in pollution concentration in urban China suggest seasonality, meteorology, land uses (including urban greenery), and the road network (and, by implication, traffic) all play a role.

While intra-urban analyses can reveal important predictors of pollution concentration within a metropolitan area, inter-urban analyses can shed light on how differences in factors such as urban form, transportation service provision, climate, etc. might explain pollution variation across urban areas. Examining 45 metropolitan areas in the USA, Stone (2008) found regions with higher sprawl (measured through a composite index) experience more days with ozone exceedances than spatially compact regions. Clark et al. (2011) analyzed concentrations of $PM_{2.5}$, ozone and other criteria pollutants (measured through an air quality index, AQI), finding compactness to be negatively associated with all pollutants and density to be positively associated with $PM_{2.5}$ and AQI. McCarty and Kaza (2015) analyzed the county level in the USA, finding more fragmented urban patterns to be positively associated with higher pollution across a range of pollutant types ($PM_{2.5}$, Ozone and an AQI). Examining NO_2, PM_{10}, and SO_2 concentrations in 249 European urban areas, Cárdenas Rodríguez et al (2016) find that the relationships between urban form indicators and pollutants vary, with urban fragmentation positively associated with NO_2 and PM_{10} and density positively associated with SO_2. Larkin et al. (2016) examined satellite-measured changes in NO_2 and $PM_{2.5}$, from 2000 to 2010, for 830 cities in East Asia, and the relationships between changes in urban characteristics from 2000 to 2010 and found urban expansion positively associated with NO_2; the analysis found a mix of effects between different factors and the two pollutant types, with further heterogeneity across city size categories. The changes in urban characteristics explained more of pollutant changes than baseline (2000) urban characteristics. Most recently, Bechle et al. (2017) examine a global sample of 1300 cities, also using satellite-based measures of NO_2 concentrations, and find that urban contiguity, urban compactness and vegetation have a negative relationship with pollutant concentrations. Hankey and Marshall (2017) reviewed health-related articles in the field and found that there was a consensus on the association between compact growth and improved regional air quality.

Focusing on China, Lu and Liu (2016) use satellite-derived measures of NO_2 and SO_2 and Landsat derived indicators of urban form in geographically weighted regression, finding evidence of negative relationships between both pollutants and urban compactness and poly-centrism; they also find variation in effects across the nation's geography. Most other studies use official AQI data from the Chinese Ministry of Environmental Protection. Xu et al (2017), for example, predict AQI across 31 provincial capital cities, finding a find positive relationship with vehicle population and GDP per capita, but no significant measures of urban form. Yuan et al (2017), examine 157 Chinese cities, finding population density, degree of centering, and street density to be negatively associated with *population-weighted* concentrations of air pollutants (especially $PM_{2.5}$ and PM_{10}; less so for NO_2, CO, SO_2, and O_3). Liu et al (2017) use spatial regression for 289 cities finding a positive relationship between AQI and urbanization, total population, and population density; they also find evidence of pollution spillovers (due to both the population and automobile density of nearby cities). Examining PM_{10} concentration dynamics over time, Liu, Arp, et al. (2017) study 30 cities (using data from 2000, 2007, 2010) (they use satellite-derived pollution measures for the year 2000) and find a positive relationship between pollution and urban compactness and a measure of sprawl (urban elongation); they find a negative relationship between green space and PM_{10}. Zheng and Kahn (2017) also study trends (from 2003-2012), finding decreasing PM_{10} and support for a pollution Kuznets curve (PM_{10} declines as income increases); they do not include indicators of urban form. Finally, and most recently, Zhou et al (2018) examine $PM_{2.5}$ concentrations using spatial regression across 190 Chinese cities and find, among other factors, a positive association with population density and road density.

The growing body of cross-city evidence in China reveals not entirely consistent results on the relationships between urban form and air pollution. This may partly arise from the types of pollutants analyzed, how they are measured, how they are operationalized, the model approach taken, and the urban form indicators and control variables used. Interestingly, none of the studies has explicitly examined TOD and air quality linkages, although some of the urban form indicators may be considered TOD proxies (e.g., compactness, roadway density, population density). Liu, Arp, et al. (2017) find a negative relationship between PM_{10} concentrations and cities' per capita bus fleet, some indirect evidence of possible 'transit-oriented' pollution benefits.

2.2 TOD assessment

Relevant research related to TOD assessment focuses on the neighborhood or the station-area level, attempting to assess the "quality" of TOD and, often, its relationship with some outcome of interest. Similar to the air quality research reviewed above, some of these studies focus on variation within a metropolitan area, while others focus on variation across metropolitan areas. Kamruzzaman et al. (2014), for example, use cluster analysis on built environment indicators (e.g., road network, land use mix, employment and residential density) to identify TOD typologies for Brisbane's neighborhoods and "validate" these typologies by showing their significance in predicting mode choices. Examining the Washington (DC) and Baltimore (MD) metropolitan areas, Nasri and Zhang (2014) identify traffic analysis zones as TOD "areas" (binary indicator) based upon relative concentration of residents or jobs, relative mixed use characteristics of the zone, and proximity of the zone to transit; they find some evidence that households in DC's TOD zones have lower vehicle kilometers of travel. Singh et al (2014) use spatial multiple criteria analysis to measure TOD levels, using land use and economic indicators (e.g., residential density, employment density, land use mix, streetscape qualities, number of businesses), to measure areas of high TOD in the City Region Arnhem and Nijmegen (Netherlands). A follow-up paper (Singh et al., 2017) applies a similar approach to measure station-area TOD to derive suggestions for TOD improvements. Higgins and Kanaroglou (2016) apply a latent class model (a probability-based clustering analysis), using eight land use indicators, to derive ten TOD types across 372 stations in the Toronto (Canada) metropolitan area; they find that stations ranking high in TOD-related measures are associated with higher rates of transit, walking, and cycling, and lower household VKT.

Among relevant cross-city comparisons, Papa and Bertolini (2015) develop city-wide TOD measures for 6 European metropolitan areas, using the node-place model (node is a zone's proximity to all other zones; place is a measure of job and resident density) and find a positive relationship between the node index and measures of rail-based accessibility (cumulative, 30-minute reach to jobs and residents). In one of the few cross-city studies focused on the Global South, Rodriguez and Vergel-Tovar (2017) apply factor and cluster analysis, using 35 built environment measures from 81 BRT stations in seven Latin American cities to identify 10 station types, demonstrating variation in passenger demand varies across the types.

While the prospects for TOD in China have been examined in the English-language literature since at least the early 2000s (e.g., Zhang, 2007), little work aims to assess TOD, explicitly. Lyu et al (2016) offer one of the first examples, adapting the node-place approach (e.g., Papa and Bertolini, 2015). They analyze 18 indicators in three dimensions (transit, oriented, and development) for 268 rail stations in Beijing, using principal components analysis and cluster analysis, and identify 6 station types; they do not, however, assess the types relative to particular outcomes of interest (e.g., ridership).

3. Methods

3.1 Data Collection

Our sample consists of 152 major Chinese cities with population over 250,000 persons and with available daily Air Quality Index (AQI) records. Among these cities, 116 have neither urban rail nor bus-rapid-transit (BRT) systems; 37 cities have either urban rail or BRT systems before the end of year 2015, among which seven cities have both systems; 14 cities have only urban rail systems; and, 15 cities have only BRT systems (Figure 1). Data collected for each city includes AQI data, city-level statistics and geo-spatial data.

The daily AQI data for the year of 2014 were collected for each city in the sample from the Ministry of Environmental Protection of China. The daily AQI report contains six types of pollutants: $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO are measured as average per 24h;

O_3 is measured as average per hour. According to the Technical Regulation on Ambient Air Quality Index, an individual air quality index (IAQI) is assigned to the level of each pollutant; the final AQI is the highest of those 6 scores (Ministry of Environmental Protection, 2012). AQI can be easily understood by policy makers and the general public, and it often serves as an important indicator for data interpretation in decision making processes of environmental management (Kumar and Goyal, 2011). Following previous studies (e.g., Fang et al., 2015) and considering that the monitoring sites in China are mostly located in urban areas, we calculated mean AQI values derived from all monitoring sites in a given city to estimate air pollution concentrations for that city:

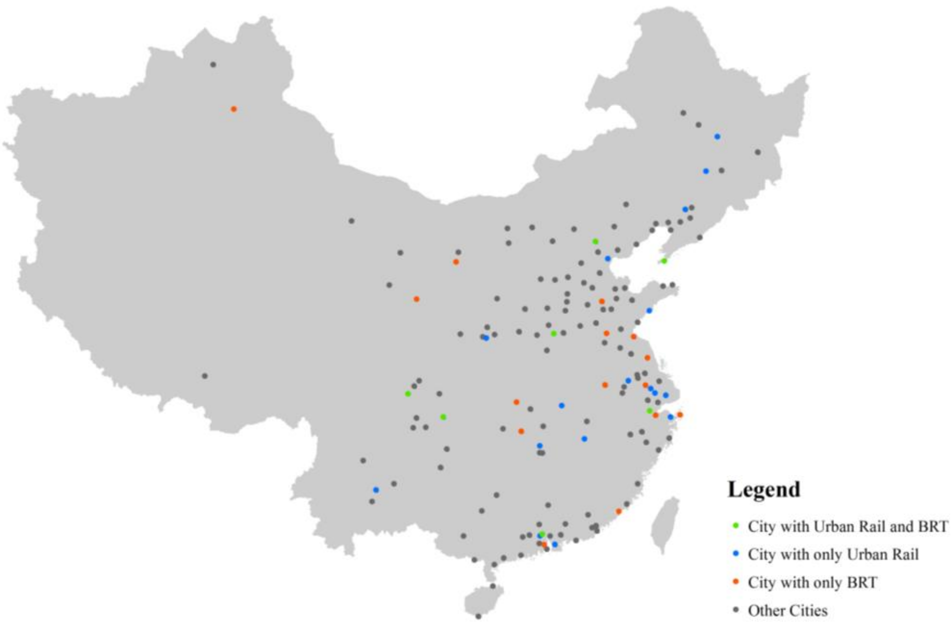
$$IAQI_P = \frac{IAQI_{upper} - IAQI_{lower}}{C_{upper} - C_{lower}} \cdot (C - C_{lower}) + IAQI_{lower} \quad (1),$$

where C_{upper} and C_{lower} indicate the upper and lower breakpoints of the measured concentration C and $IAQI_{upper}$ and $IAQI_{lower}$ are the upper and lower breakpoints of the index, as listed in Table 1.The AQI is:

$$AQI = max\{I_{PM_{2.5}}, I_{PM_{10}}, I_{SO_2}, I_{NO_2}, I_{CO}, I_{O_3}\} \quad (2).$$

Table 1. Air Quality Index (AQI) in China

AQI	**Air quality classification**	**Description**	**Limited maximum concentration (μg/m³)**					
			$PM_{2.5}$	PM_{10}	SO_2	NO_2	CO	O_3
≤50	I	Good	35	50	50	40	2000	160
50-100	II	Moderate	75	150	150	80	4000	200
100-150	III	Lightly Polluted	115	250	475	180	14000	300
150-200	IV	Moderately Polluted	150	350	800	280	24000	400
200-300	V	Heavily Polluted	250	420	1600	565	36000	800
300-400	VI	Severely	350	500	2100	750	48000	1000



400-500	Polluted	500	600	2620	940	60000	1200

Figure 1. 152 Chinese cities with daily AQI record

To control for the various factors related to air pollution concentrations, we collected city-level data within five categories (Table 2): 1) meteorological data – including monthly average precipitation, temperature and wind speed for the year 2014 – were obtained from the National Climate Center; 2) wealth and economic activity data – measured by per capita GDP and secondary industry (i.e., industrial sector) as a percentage of GDP – were obtained from *China City Statistical Yearbook, 2015* (data from 2014); 3) energy data were extracted from *Chinese Urban-Rural Construction Statistical Yearbook 2014*; and 4) characteristics of urban form – including land use, urban green areas and road network – were also obtained from the *Chinese Urban-Rural Construction Statistical Yearbook 2014*. For public transportation data, such as regular bus stop coverage ratio (of the urban area, using a 500-meter radius buffer around each stop), we obtained these for the 152 cities from the Beijing City Lab (http://www. beijingcitylab.org).

Table 2. City-Level Data

Category	Indicators	Data Source
Meteorology	Precipitation	National Climate Center (year 2014 data)
	Temperature	
	Wind Speed	
Socioeconomic and Industry	Secondary Industry as % to GDP	China City Statistical Yearbook, 2015 (year 2014 data)
	Per Capita GDP	
	Urban Populations	China Urban-Rural Construction Statistical Yearbook, 2014
Energy use	Heated Area	
	Gasoline Supply	
	Gasoline Coverage	
Urban Form	Urban Area	
	Urban Green Area	
	Length of Roads	
	Road Area	
	Bus Coverage Ratio	Beijingcitylab.org (year 2013 data)

Apart from the AQI and city-level statistics, for the 37 cities with urban rail and/or BRT, we collected geo-spatial data – including urban rail lines and stations, BRT lines and stations, regular bus stops, urban road network, and points of interest (POIs) – to enable TOD index development. These five types of geo-spatial data were derived from Baidu Map geographical databases (http://map.baidu.com). POIs were classified into residential, government, research and education, medical, retail, entertainment, company, transportation facility, warehouse and green park. In addition, we obtained population distribution data (based on 2010 National Census Data) at 100-meter resolution from the Worldpop database (http://www.worldpop.org.uk).

3.2 TOD Index Calculation

To approximate the characteristics of TOD in each of cities with urban rail and/or BRT, we developed a set of indicators based on the principles of relevance, objectivity, and comprehensiveness, conditioned on data availability and reliability. The indicator framework consists of two components, namely TOD quantity and TOD quality.

The *quantity* of TOD, which reflects overall supply, is measured by four indicators: line density, station density, land coverage, and population coverage. The former two indicators were calculated as two ratios: the length of rail/BRT lines (km) to built-up urban area (km^2) and the number of rail/BRT stations to built-up urban area (km^2). An 800 meter-radius station service area (hereafter referred to as the 800m-radius buffer) was used to calculate the overall coverage indicator as suggested in the *Guidelines for Planning and Designing of Areas around Urban Rail Transit* released in 2013 by China's Ministry of Housing and Urban-Rural Development.

While the quantity indicators assess the total potential for TOD in the city, the quality indicators aim to measure how well the stations reflect the principles of TOD, in particular integration with land use and other transport networks around the stations. Adapting the "3D" framework proposed by Cervero and Kockelman (1997), the "5D" principles proposed by Zhang (2007), as well as the Guidelines for Planning and Designing of Areas around Urban Rail Transit, we operationalize 13 quality-based indicators, grouped into aspects of density, diversity, design, and accessibility (Cervero et al., 2008). Table 3 summarizes the indicator framework, in which the direction column represents our a priori expectation regarding the indicator's positive or negative relationship with its superior TOD index.

The *density* aspect was measured by three indicators: population density, employment density, and density gradient. Employment density refers to density of major workplaces (i.e., POIs of company and government). The density gradient is for employment only and is approximated as the ratio of employment density in the 400m-radius core to that of the rest station area (Yin and Xue, 2016). These three indicators are assumed to be positively associated with the TOD *density* index.

To measure *diversity*, POIs within the 800m-radius buffer were grouped into six categories: residential, public service, commercial, company, park and other. Shannon's Evenness Index was adopted to calculate the land use mix (H) (Shannon et al., 1949):

$$H = -\sum_{i=1}^{6} p_i \ln p_i \quad (3).$$

In addition, a job-housing imbalance indicator was calculated. In detail, we first generated the ratio of standardized population density against employment density, and then took the absolute value of the difference between this ratio and 1 as job-housing imbalance. Land use mix is presumed to be positively associated with the TOD *diversity* index while the job-housing imbalance is presumed to have a negative association with diversity.

For the *design* aspect, we calculated the density of the road network, expressways, and ground-floor retail, as well as the number of parking facilities within the 800m-radius. Street network density crudely represents less automobile-oriented development, as the denser the street network, the shorter the trip distances, all else equal (Cervero et al., 2007; Jiang et al., 2015). High ground-floor retail density around transit stations represents pedestrian friendly environment. Thus we assume a positive relationship between these two indicators and the TOD *design* index. On the other hand, the *Guidelines for Planning and Designing of Areas around Urban Rail Transit* suggests that urban transit corridors should not overlap with expressways and that the supply of parking facilities should be controlled around rail stations in the central city, hence we assume these two indicators are negatively associated with TOD *design* index. To calculate ground-floor retail density, we first filtered ground-floor retail POIs by type, as coded by Baidu.com, and then counted the number of retail POIs within a 35-m-wide buffer along both sides of road center lines and divided the total by the length of the road network within the buffer areas.

Finally, for the *accessibility* aspect, we used four indicators: the number of bus lines and bus stops within the station area, the distance to the passenger transport terminal, and the distance to municipal public service facilities. The first two capture the feeder bus services around stations and are with positive direction with TOD *accessibility* index. The latter two represent the overall accessibility of urban rail/BRT systems to major facilities on a regional scale. Specifically, they are calculated as the average Euclidean distance from urban rail/BRT stations to every major intercity passenger transport terminal and every major municipal public service facility (e.g. museums, stadiums etc.). The larger these distance values are, the lower the accessibility of the urban rail/BRT systems, thus these are presumed to be negatively associated with the TOD *accessibility* index.

Table 3. Indicator Framework for Assessing City-level TOD

Aspect		Indicators	Direction
TOD Quantity		Line density (km/km^2)	+
		Station Density (unit/km^2)	+
		Urban Land Coverage Ratio (%)	+
		Urban Population Coverage Ratio (%)	+
TOD Quality	Density	Population Density (10k ppl/km^2) [a]	+
		Employment Density(unit/km^2) [a]	+
		Density Gradient [a]	+
	Diversity	Land Use Mix [a]	+
		Job-housing Imbalance [a]	-
	Design	Street Network Density (km/km^2) [a]	+
		Expressway Density (km/km^2)[a]	-
		Ground-floor Retail Density (unit/km) [a]	+
		Number of Parking Facilities (unit) [a]	-
	Accessibility	Distance to Passenger Transport Terminal (km)	-
		Number of Bus Lines (unit) [a]	+
		Number of Bus Stops (unit) [a]	+
		Distance to Municipal Public Service Facilities (km)	-

To derive TOD indexes based on the individual indicators, we adopt the information entropy weighting (IEW) method proposed by Shannon and Weaver (1948), using weights according to the variation degrees among indicators. Specifically, we develop an urban rail TOD quantity index and quality index and then we multiplied the two indexes and divided by 100 to get the urban rail composite TOD index for each city. The BRT composite index was developed using the same scheme. Appendix A presents more detail on the IEW method.

3.3 Temporal and Spatial Regression Modeling

In developing models to predict the mean AQI, we applied a log transformation for several variables, due to a long-tail distribution problem, including: urban area, gasoline supply, and gasoline coverage. Due to the seasonal variation in air pollution, we develop models for different seasons, following a number of previous studies (e.g., Wu et al., 2015; Chen et al., 2010).

Spatial dependence may be problematic in our analysis, either in the form of spatial lag or spatial error. The latter may result from geographic and climate factors with common error terms across regions, while spatial lag may be present since cities' emissions might influence air pollution levels in nearby cities (e.g., Liu et al., 2017). These potential spatial dependencies would violate two assumptions of conventional ordinary least squares (OLS) regression – uncorrelated error terms and independent observations – which would result in biased and inconsistent estimates. Following Anselin (1998), we develop a standard spatial regression scheme (Figure 2).

First, we estimate base OLS models, for annual daily average AQI and seasonal daily average AQIs. To avoid multicollinearity, variables with variance inflation factor (VIF) larger than 5 were removed. Further, stepwise variable selection methods were employed to develop five stepwise OLS models as a common approach to mitigate over-fitting.

Second, we determined a 4-nearest-neighbor spatial weights matrix to capture potential spatial dependencies. Based on the OLS results and the spatial weights matrix, we tested the OLS residuals with the Moran's I method, and performed Lagrange Multiplier tests to determine suitability for spatial modeling.

Third, we specify and estimate Spatial Error Models and Spatial Lag Models for annual and seasonal average AQIs. As mentioned, spatial lag suggests a possible diffusion process - events in one place influence the likelihood of similar events in neighboring places. Thus, a Spatial Lag Model includes a spatially lagged dependent variable:

$$y = (\rho)\, Wy + X(\beta) + \varepsilon \qquad (4),$$

where: Wy represents the spatially lagged dependent variable for the weights matrix W, X represents the matrix for which rows are the explanatory variables, ε represents a vector of error terms, and ρ and β are parameters, with ρ being the simultaneous autoregressive lag coefficient.

Spatial error is indicative of spatially correlated omitted variables, spatially correlated aggregate variables, or spatially correlated errors in measuring variables. A Spatial Error Model includes a spatial autoregressive error term:

$$y=X(\beta) + \varepsilon \tag{5}$$

and,

$$\varepsilon =\lambda(W)\, \varepsilon + u \tag{6}$$

where: W represents the spatial weights matrix, X represents the matrix for which rows are the explanatory variables, ε represents a vector of spatially autoregressive error terms, u represents a vector of i.i.d. (independent identically distributed) errors, and λ and β are parameters in which λ stands for the simultaneous autoregressive error coefficient.

Finally, we compare the different models using model fit tests to help us choose the best model specifications for interpretation.

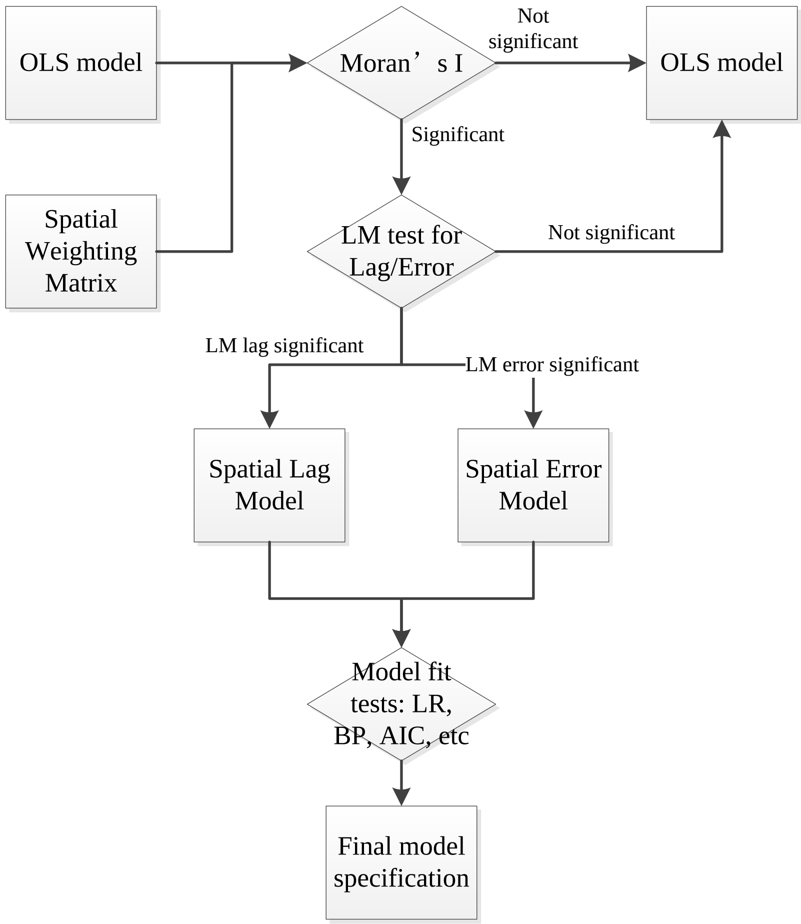


Figure 2. Spatial Regression Modeling Flow

4. Result and Findings

4.1 Descriptive Statistics

As shown in Table 4, air quality among cities in the year 2014 is worst in the winter, reaching a peak average of 125.4, and best in the summer, with an average of 88.0. This pattern follows the findings of Wu et al. (2015). The seasonal variations in meteorological variables are also intuitive: summers are hotter and rainier while winters and springs are windier. In terms of energy and industry, over 50% of our sample cities provide their citizens with central heating. For general urban form indicators, average road area coverage, at 14.7%, is almost four times higher than the average urban green space coverage (3.9%), which might represent urban policies implicitly catering to residents' expanding demands for automobiles. Average bus coverage reached 69%; all of the cities have relatively extensive regular bus services.

Table 4. Statistics of Variables (N=152)

Variable			Mean	S.D.	Min	Max
Daily Average AQI		Annual	102.2	20.5	66.5	175.7
		Spring	97.5	21.3	56.1	176.7
		Summer	88.0	15.6	57.5	129.8
		Fall	95.4	20.8	56.6	170.1
		Winter	125.4	34.8	67.2	251.3
Meteorology	Daily Average Precipitation (1 mm)	Annual	75.7	40.0	13.8	205.1
		Spring	71.6	59.2	10.3	237.2
		Summer	148.5	84.1	13.1	569.8
		Fall	63.1	32.9	14.3	181.5
		Winter	19.4	18.2	0.7	65.3
	Daily Average Temperature (0.1°C)	Annual	154.2	44.8	44.6	246.6
		Spring	162.9	36.9	64.3	257.6
		Summer	255.2	23.4	158.5	296.6
		Fall	166.5	51.4	53.3	261.0
		Winter	31.9	73.6	-168.8	178.9
	Daily Average Wind Speed (0.1m/s)	Annual	21.8	5.0	12.3	48.4
		Spring	24.3	5.9	13.3	51.0
		Summer	20.3	4.0	12.7	39.3
		Fall	20.3	5.2	11.0	47.7
		Winter	22.4	6.0	10.0	55.7
Energy and Industry	Heated Area (km²)		29.3	66.5	0.0	567.9
	Central Heating Provision (dummy)		0.51	0.50	0.00	1.00
	Gasoline Supply (ton)		48.0	116.0	0.0	665.0
	Gasoline Coverage (thousand person)		54.0	135.0	0.0	1101.0

	Secondary Industry as % to GDP	50.0	8.7	19.9	75.5
Urban Form	Urban Area (km²)	220.2	311.3	24.1	2915.6
	Urban Population (10k)	170.5	207.8	25.0	1859.0
	Population Density (10 thousand/km²)	0.8	0.3	0.2	2.2
	Urban Green Area (km²)	8.0	9.4	1.0	80.2
	Urban Green Coverage (%)	3.9	0.7	1.2	7.0
	Road Area (km²)	14.9	15.7	1.3	81.1
	Road Area Coverage (%)	14.7	5.2	3.4	41.3
	Length of Roads (km)	1488.0	1570.7	134.0	8107.0
	Road Network Density (km/km²)	7.4	2.8	1.7	18.8
	Bus Coverage Ratio	0.69	0.15	0.22	0.97

Table 5 enables some preliminary comparisons between the TOD-ness of China's urban rail and BRT systems. First of all, urban rail systems cover slightly more urban land 20.7% and more population 14% than BRT systems (17.6% and 13.2%, respectively). Regarding TOD quality, interestingly the overall Job-housing imbalance is high in BRT catchment areas, suggesting BRT station areas are more distributed in employment centers. For the design aspect, areas around BRT stations are not as pedestrian friendly as those around urban rail stations, as street network density is low at 4.2 km/km^2, compared with 5.0 km/km^2; and ground-floor density is low at 4.8 unit/km, compared with 8.5 unit/km around urban rail stations. On the other hand, areas around BRT stations are much more automobile friendly, with higher expressway density and more parking facilities. Also, BRT systems in China have fewer feeder bus services as indicated by the lower number of bus lines and stops compared with urban rail systems. In sum, in terms of both quantity and quality of TOD, BRT systems measure lower than urban rail systems in China.

Table 5. TOD performance indicators for Urban Rail and BRT Cities

Dimension		Indicator	Urban Rail Cities (N=24)				BRT Cities (N=23)			
			Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Quantity		Rail Line density (km/km^2)	0.19	0.14	0.03	0.66	0.18	0.23	0.00	1.01
		Rail Station Density (unit/km^2)	0.13	0.08	0.03	0.41	0.35	0.35	0.02	1.29
		Urban Land Coverage Ratio (%)	20.7	10.4	4.5	54.5	17.6	12.3	2.8	48.6
		Urban Population Coverage Ratio (%)	14	6.7	2.9	26.2	13.2	9.8	2.6	39.3
Quality	Density	Population Density (10k/km^2)	0.87	0.24	0.52	1.35	0.61	0.33	0.17	1.05
		Employment Density (unit/ km^2)	17.3	4.4	9.0	28.2	25.9	8.1	8.1	36.4
		Density Gradient	1.26	0.17	0.99	1.68	1.85	0.82	0.79	4.58
	Diversity	Land Use Mix	0.58	0.08	0.29	0.71	0.67	0.04	0.04	0.76
		Job-housing Imbalance	0.26	0.22	0	0.85	0.87	1.29	0.00	2.64
	Design	Street Network Density (km/km^2)	5.0	0.8	3.8	6.7	4.2	1.2	1.2	5.5

	Expressway Density (km/km^2)	0.13	0.13	0.00	0.46	1.14	0.91	0.00	2.10
	Ground-floor Retail Density (unit/km)	8.5	2.8	5.1	14.4	4.8	1.9	1.2	7.3
	Number of Parking Facilities (unit)	0.7	0.5	0.2	2.1	1.3	0.6	0.0	2.3
Accessibility	Distance to Passenger Transport Terminal (km)	8.7	6.8	2.1	29.1	14.5	9.9	0.7	33.3
	Number of Bus Lines (unit)	12	4.1	7.0	22.2	9.8	5.2	1.2	21.1
	Number of Bus Stops (unit)	6.9	2.1	4.0	11.8	6.0	2.4	1.4	9.4
	Distance to Municipal Public Service Facilities (km)	3.2	2.0	0.9	7.7	6.6	5.3	0.7	19.1

Table 6 presents the estimated TOD Index for each city, sorted highest to lowest by the urban rail TOD composite index and the BRT TOD composite index. By these measures, Shanghai, Beijing, Guangzhou and Shenzhen have the highest urban rail TOD indexes among 24 urban rail cities. This finding is consistent with these four first tier cities being the pioneers of urban rail construction and TOD development experiments in China. Next come cities that were later in developing their rail systems, but also stand out in TOD quality, perhaps because they could more easily shape urban form, such as: Nanchang, Chengdu, and Tianjin. Regarding BRT cities, due especially to the relatively poor performance for the quality index, which only averages 20.0 compared with 45.4 for the urban rail cities, the BRT composite index is very low, averaging only 4.9 (compared to 14.9 for rail). Yet, the composite index still demonstrates variation. Zhengzhou, Changzhou, Changde, Xiamen, Zaozhuang stand out as the first tier group among the 23 BRT cities; these cities rely on BRT systems as their main mode of public transportation and thus, perhaps have made more effort to better shape their urban structure along BRT corridors. Cities like Beijing, Chongqing, Chengdu seem to be using BRT more as supplement to their public transportation system, resulting in lower BRT TOD scores.

Table 6. TOD Index for Urban Rail and BRT Cities

City	Rail TOD Index			BRT TOD Index		
	Quantity	Quality	Composite	Quantity	Quality	Composite
Shanghai	99.5	72.4	72.1	-	-	-
Beijing	70.3	48.4	34.0	5.0	22.7	1.1
Guangzhou	48.3	58.5	28.2	32.8	22.0	7.2
Shenzhen	38.5	60.8	23.4	-	-	-
Wuhan	44.9	45.8	20.5	-	-	-
Nanchang	28.8	59.2	17.1	-	-	-
Dalian	46.3	36.8	17.1	1.3	16.2	0.2
Chengdu	33.4	48.6	16.2	4.2	23.9	1.0
Tianjin	31.4	50.0	15.7	-	-	-
Wuxi	35.6	36.4	12.9	-	-	-
Kunming	26.3	44.9	11.8	-	-	-
Ningbo	35.8	32.8	11.7	-	-	-
Hangzhou	27.7	42.0	11.6	20.2	19.3	3.9

Xi'an	23.2	48.0	11.1	-	-	-
Chongqing	25.9	40.0	10.3	0.7	20.9	0.2
Nanjing	42.3	20.6	8.7	-	-	-
Shenyang	18.6	38.5	7.2	-	-	-
Foshan	10.4	58.8	6.1	-	-	-
Zhengzhou	10.3	57.8	6.0	63.7	19.5	12.4
Suzhou	14.8	37.0	5.5	-	-	-
Changsha	12.5	39.1	4.9	-	-	-
Changchun	12.8	34.5	4.4	-	-	-
Harbin	3.9	42.0	1.6	-	-	-
Qingdao	1.7	36.1	0.6	-	-	-
Changzhou	-	-	-	50.8	21.4	10.9
Changde	-	-	-	57.8	17.9	10.3
Xiamen	-	-	-	35.3	25.1	8.9
Zaozhuang	-	-	-	46.2	17.6	8.1
Zhoushan	-	-	-	25.9	22.1	5.7
Lianyungang	-	-	-	30.1	19.0	5.7
Zhongshan	-	-	-	32.7	15.9	5.2
Yichang	-	-	-	33.8	14.1	4.8
Jinan	-	-	-	23.6	20.1	4.7
Urumqi	-	-	-	20.6	20.8	4.3
Yinchuan	-	-	-	13.8	25.8	3.6
Yancheng	-	-	-	15.3	23.1	3.5
Hefei	-	-	-	14.0	21.9	3.1
Shaoxing	-	-	-	15.9	15.7	2.5
Lanzhou	-	-	-	4.3	14.7	0.6
Mean	31.0	45.4	14.9	24.9	20.0	4.9
S.D.	21.7	11.5	14.6	18.1	3.3	3.5
Min	1.7	20.6	0.6	0.7	14.1	0.2
Max	99.5	72.4	72.1	63.7	25.8	12.4

4.3 Model Results

The Moran's I test rejects the null hypothesis that residuals are randomly distributed spatially for all OLS models, with and without the stepwise variable selection procedure. Lagrange Multiplier diagnostics also suggest significant spatial dependence. Therefore, we specified and estimated five Spatial Error Models and five Spatial Lag Models.

In terms of model fit, the Spatial Regression models reflect a reasonably strong explanatory power (0.55 to 0.69), better than the OLS models. The spatial error models seem to outperform the spatial lag models (except for the summer model), as shown in Table 7. Based on the Moran's I test and Breusch-Pagan test (BP test) for regression residuals' spatial dependencies (Table 8), with 95% confidence, the annual lag model and winter lag model could not pass the Moran's I test and the summer lag model failed to pass the BP test, suggesting unsolved residual heteroskedasticity in these three models. On the contrary, the five spatial error models all pass the Moran's I test and BP test. Therefore, we conclude that the spatial error model is more appropriate in this case. Our final model estimates presented below are based on the spatial error model (Appendix B and C includes model results from the 5 OLS and spatial lag models).

Table 7. Modeling Fit of Spatial Regression Models

		Annual	Spring	Summer	Fall	Winter
Spatial Error Models	Pseudo R2	0.685	0.707	0.549	0.583	0.666
	Log Likelihood	-586.667	-587.045	-571.834	-610.369	-671.245
	Akaike Inf. Crit.	1207.33	1208.09	1175.67	1252.74	1376.49
Spatial Lag Models	Pseudo R2	0.679	0.706	0.565	0.565	0.647
	Log Likelihood	-587.887	-587.13	-569.13	-613.571	-675.434
	Akaike Inf. Crit.	1209.77	1208.26	1170.26	1259.14	1384.87

Table 8. Moran' I and BP Test Result for Spatial Regression Models

		Annual	Spring	Summer	Fall	Winter
Spatial Error Models	Moran's I for residuals	0.858	0.94	-0.716	0.107	1.595
	p value for Moran's I	0.195	0.174	0.763	0.457	0.055
	BP Test (df = 14)	11.378	4.575	20.521	17.361	16.161
	p value for BP Test	0.656	0.991	0.083	0.183	0.304
Spatial Lag Models	Moran's I for residuals	1.813	1.171	-1.034	0.839	2.307
	p value for Moran's I	0.035	0.121	0.849	0.201	0.011
	BP Test (df = 14)	14.565	9.383	29.712	19.695	11.66
	p value for BP Test	0.409	0.806	0.005	0.103	0.634

In the five Spatial Error Models, the simultaneous autoregressive error coefficients (Lambdas) are significant (Table 9). Variation in AQI is partially explained by omitted autoregressive error upon the spatial weight matrix constructed. Overall the directions and magnitudes of the coefficients are mostly consistent across the five models (except for secondary industry as a % of GDP and population density in summer model), although the significance varies across seasons. Meteorological features have strong relationships with AQI. Coefficients of average daily precipitation and wind speed are found with consistent directions as suggested by, for example, Lu and Liu (2016) and Zheng and Kahn (2017). Due to potential seasonal variations, however, meteorological variables are not significant in all models.

As for energy and industry factors, not surprisingly, central heating provision has a significant relationship with AQI, probably since central heating in China still relies heavily on coal burning. This finding is different from that of Liu, Arp, et al. (2017) who only study 30 cities, but over time. Meanwhile, secondary industry as % GDP and gas supply are each only significant in one of the five models, and their magnitudes and directions are also not consistent among five models. The secondary industry result is distinct from the spatial error models of Liu et al. (2017).

Regarding urban form indicators, population density reveals, for the most part, a positive relationship with AQI, although it is only significant in the spring and fall models. This is in line with Clark et al. (2011)'s finding for 111 US urban areas as well as with Liu et al (2017) and Zhou et al (2018) for Chinese cities. In contrast, Yuan et al. (2017) find a negative relationship of population density and population-weighted concentrations of PM_{10}, $PM_{2.5}$, and O_3. Log of urban constructed area is significant and positively correlated with AQI. This suggests that air pollution is more highly concentrated in regions with large urban areas, a finding consistent with Lin et al. (2013)'s research on the relationship between PM2.5 concentrations and urban areas in China from 2001-2010 and with one of Liu, Arp et al's (2017) models; this result differs from Liu et al (2017) who find no significant relationship for urban land. Green space coverage is found to be negatively related with AQI, which is consistent with findings of Liu, Arp et al. (2017). Road area coverage has a positive relationship with AQI in fall, winter, and the annual models, consistent with Zhou et al. (2018), and possibly indicating that building more roads in cities may lead to more motorized traffic and associated air pollution.

Finally, turning to the TOD indices, the rail TOD index is significant and negatively associated with AQI in all models, except the summer model. All else equal, cities with more TOD-ness around their rail transit stations have lower air pollution, possibly due to reduced motorized transportation and its associated pollutants. A higher value of the rail TOD index might be related to urban form indicators identified by others to be associated with lower pollution in Chinese cities, such as urban centering (Yuan et al., 2017) and more polycentric urban forms (Lu and Liu, 2016). These results do not hold, however, for the BRT TOD Index. This may be due to the fact that the current TOD around BRT systems is generally poorer in terms of both quantity and quality, such that these systems have lower possibilities to impact trip-making in relevant ways (e.g., fewer and/or shorter motorized trips).

Table 9. Spatial Error Model Result

	AQI				
(Coefficient)	Annual	Spring	Summer	Fall	Winter
Meteorology					
Average daily precipitation	-0.150**	-0.051	-0.032*	-0.052	-0.678*
	(0.067)	(0.042)	(0.018)	(0.058)	(0.272)
Average daily temperature	0.147**	0.124*	0.117*	0.004	0.089
	(0.070)	(0.073)	(0.064)	(0.067)	(0.076)
Average daily wind speed	-0.743**	-0.553**	-0.233	-0.727**	-1.304***
	(0.267)	(0.244)	(0.289)	(0.295)	(0.398)
Energy and Industry					
Central Heating Provision	10.484***	9.234***	-	-	14.559**
	(4.129)	(4.008)			(7.206)
Log of Gasoline Coverage	1.073	0.485	0.799	1.618*	0.814
	(0.797)	(0.786)	(0.736)	(0.931)	(1.379)
Second Industry as % GDP	0.070	-0.006	0.190*	-0.059	0.111

	(0.108)	(0.106)	(0.101)	(0.128)	(0.189)
Urban Form					
Population Density	3.996	6.172*	-3.762	8.155*	4.058
	(4.112)	(4.069)	(3.831)	(4.835)	(7.192)
Log of Urban Area	4.113**	3.441**	3.050*	5.609***	7.057**
	(1.687)	(1.636)	(1.565)	(1.944)	(2.883)
Green Space Coverage	-2.794**	-3.644***	-0.240	-0.342	-5.209**
	(1.385)	(1.369)	(1.289)	(1.628)	(2.412)
Road Area Coverage	0.410*	0.145	0.299	0.552*	0.808*
	(0.245)	(0.242)	(0.227)	(0.285)	(0.425)
Street Network Density	-0.597	-0.162	-0.633	-1.089*	-1.065
	(0.477)	(0.472)	(0.441)	(0.558)	(0.831)
Bus Coverage Ratio	-6.837	-5.928	-1.318	-7.187	-13.494
	(6.155)	(6.067)	(5.849)	(7.183)	(10.653)
Rail TOD Index	-0.342**	-0.335**	-0.159	-0.485***	-0.477*
	(0.143)	(0.140)	(0.134)	(0.167)	(0.247)
BRT TOD Index	0.140	0.080	0.226	0.003	0.645
	(0.367)	(0.360)	(0.343)	(0.431)	(0.637)
Constant	73.354***	76.354***	36.147	65.562***	124.876***
	(18.838)	(19.975)	(22.315)	(20.682)	(27.140)
Lambda	0.779***	0.813***	0.720***	0.767***	0.781***
Observations	152	152	152	152	152
Pseudo R2	0.685	0.707	0.549	0.583	0.666
Log Likelihood	-586.667	-587.045	-571.834	-610.369	-671.245
sigma2	110.04	107.794	93.979	151.643	334.445
Akaike Inf. Crit.	1207.33	1208.09	1175.67	1252.74	1376.49
Wald Test (df = 1)	310.196***	442.647***	180.358***	273.825***	315.606***
LR Test (df = 1)	78.961***	87.897***	55.538***	92.661***	93.170***

Note: *p<0.1, **p<0.05, ***p<0.01.

4.4 Limitations

This study still has several limitations. First, in the absence of high-resolution employment data, we used the number of company and government POIs as a proxy, which may bias the employment density estimates used. Second, some of the relationships revealed in this study are muddled by the use of average AQIs as the only dependent variables in our models. Seasonal patterns are different between secondary (e.g., O3) and more primary (PM) pollutants and some may be more traffic-related (e.g., NO2). Future studies might examine individual pollutants separately. Finally, the considerable variation in results across different studies in China to date warrants further examination, to better understand the sources of such variation and the policy implications.

5. Conclusion

This study adds to the growing body of research on air quality and urban form in China, by examining city-level relationships with a focus on the potential impacts of transit-oriented development (TOD). A TOD performance indicator system reflecting the quantity and quality dimensions was developed and composite TOD indexes were estimated for 37 Chinese cities with either urban rail or bus-rapid-transit (BRT) systems. These metrics suggest that, firstly, the rail-based TOD performs better than that of BRT-based TOD (in general, better quality and quantity of TOD). Second, all else equal, the rail TOD index correlates negatively with air pollution concentrations measured by annual and seasonal average AQIs (except for the summer average AQI). The BRT TOD index show no significant impact after controlling for spatial autocorrelation.

Our findings have several potential policy implications. First, aiming at ameliorating air pollution, Chinese cities should consider rail-based TOD as part of their environment management efforts. As of the end of 2017, urban rail has been put into service in 34 Chinese cities with a total of 5,022 km of lines. Many more cities will likely soon be home to urban rail systems thanks to the central government's recent policy on loosening the minimum population requirement threshold for initiating urban rail development in a local city (Xinhuanet, 2016). In pursuing air quality objectives, those cities should not only increase the supply of urban rail systems, but also focus on improving TOD around the stations. Second, the rail TOD index proposed in this paper could be adapted as an indicator to guide urban planning and monitor TOD progress in Chinese cities. The index captures both the quantity and quality aspects of TOD for a target city and allows benchmarking and peer learning among cities. The indicator framework provides a foundation upon which improvements can be made for better measuring TOD, understanding its impacts on urban quality of life, and identifying pertinent policy actions.

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References

Arain, M.A., Blair, R., Finkelstein, N., Brook, J.R., Sahsuvaroglu, T., Beckerman, B., Zhang, L. and Jerrett, M., 2007. The use of wind fields in a land use regression model to predict air pollution concentrations for health exposure studies. Atmospheric Environment, 41(16), pp.3453-3464.

Bechle, M.J., Millet, D.B. and Marshall, J.D., 2017. Does Urban Form Affect Urban NO2? Satellite-Based Evidence for More than 1200 Cities. Environmental Science & Technology, 51(21), pp.12707-12716.

Briggs, D.J., Collins, S., Elliott, P., Fischer, P., Kingham, S., Lebret, E., Pryl, K., van Reeuwijk, H., Smallbone, K. and Van Der Veen, A., 1997. Mapping urban air pollution using GIS: a regression-based approach. International Journal of Geographical Information Science, 11(7), pp.699-718.

Briggs, D.J., de Hoogh, C., Gulliver, J., Wills, J., Elliott, P., Kingham, S. and Smallbone, K., 2000. A regression-based method for mapping traffic-related air pollution: application and testing in four contrasting urban environments. Science of the Total Environment, 253(1), pp.151-167.

Cárdenas Rodríguez, M., Dupont-Courtade, L., Oueslati, W. 2016. Air pollution and urban structure linkages: Evidence from European cities. Renewable and Sustainable Energy Reviews, 53, pp. 1-9.

Cervero, R. and Kockelman, K., 1997. Travel demand and the 3Ds: density, diversity, and design. Transportation Research Part D: Transport and Environment, 2(3), pp.199-219.

Cervero, R. and Day, J., 2008. Suburbanization and transit-oriented development in China. Transport Policy, 15(5), pp.315-323.

Chen, L., Bai, Z., Kong, S., Han, B., You, Y., Ding, X., Du, S. and Liu, A., 2010a. A land use regression for predicting NO 2 and PM 10 concentrations in different seasons in Tianjin region, China. Journal of Environmental Sciences, 22(9), pp.1364-1373.

Clark, L.P., Millet, D.B. and Marshall, J.D., 2011. Air quality and urban form in US urban areas: evidence from regulatory monitors. Environmental science & technology, 45(16), pp.7028-7035.

Fang, C., Liu, H., Li, G., Sun, D. and Miao, Z., 2015. Estimating the impact of urbanization on air quality in China using spatial regression models. Sustainability, 7(11), pp.15570-15592.

Fang, M., Chan, C.K. and Yao, X., 2009. Managing air quality in a rapidly developing nation: China. Atmospheric Environment, 43(1), pp.79-86.

Hankey, S. & Marshall, J.D. Urban Form, Air Pollution, and Health. Curr Envir Health Rpt (2017) 4: 491. https://doi.org/10.1007/s40572-017-0167-7

Hao, J. and Wang, L., 2005. Improving urban air quality in China: Beijing case study. Journal of the Air & Waste Management Association, 55(9), pp.1298-1305.

Henderson, S.B., Beckerman, B., Jerrett, M. and Brauer, M., 2007. Application of land use regression to estimate long-term concentrations of traffic-related nitrogen oxides and fine particulate matter. Environmental science & technology, 41(7), pp.2422-2428.

Higgins, C.D. and Kanaroglou, P.S., 2016. A latent class method for classifying and evaluating the performance of station area transit-oriented development in the Toronto region. Journal of Transport Geography, 52, pp.61-72.

Hochadel, M., Heinrich, J., Gehring, U., Morgenstern, V., Kuhlbusch, T., Link, E., Wichmann, H.E. and Krämer, U., 2006. Predicting long-term average concentrations of traffic-related air pollutants using GIS-based information. Atmospheric Environment, 40(3), pp.542-553.

Hoek, G., Beelen, R., De Hoogh, K., Vienneau, D., Gulliver, J., Fischer, P. and Briggs, D., 2008. A review of land-use regression models to assess spatial variation of outdoor air pollution. Atmospheric environment, 42(33), pp.7561-7578.

Kamruzzaman, M., Baker, D., Washington, S. and Turrell, G., 2014. Advance transit oriented development typology: case study in Brisbane, Australia. Journal of Transport Geography, 34, pp.54-70.

Larkin, A., van Donkelaar, A., Geddes, J.A., Martin, R.V. and Hystad, P., 2016. Relationships between Changes in Urban Characteristics and Air Quality in East Asia from 2000 to 2010. Environmental science & technology, 50(17), pp.9142-9149.

Li, M. and Long, Y., 2015. The coverage ratio of bus stations and spatial pattern evaluation in Chinese major cities. Urban Planning Forum, 2015(6), pp.33-40

Lin, G., Fu, J., Jiang, D., Hu, W., Dong, D., Huang, Y. and Zhao, M., 2014. Spatio-temporal variation of $PM_{2.5}$ concentrations and their relationship with geographic and socioeconomic factors in China. International journal of environmental research and public health, 11(1), pp.173-186.

Liu, H., Fang, C., Zhang, X., Wang, Z., Bao, C. and Li, F., 2017. The effect of natural and anthropogenic factors on haze pollution in Chinese cities: A spatial econometrics approach. Journal of Cleaner Production, 165, pp.323-333.

Liu, W., Li, X., Chen, Z., Zeng, G., León, T., Liang, J., Huang, G., Gao, Z., Jiao, S., He, X. and Lai, M., 2015. Land use regression models coupled with meteorology to model spatial and temporal variability of NO_2 and PM_{10} in Changsha, China. Atmospheric Environment, 116, 272-280.

Liu, Y., Arp, H.P.H., Song, X. and Song, Y., 2017. Research on the relationship between urban form and urban smog in China. Environment and Planning B: Urban Analytics and City Science, 44(2), pp.328-342.

Lu, C. and Liu, Y., 2016. Effects of China's urban form on urban air quality. Urban Studies, 53(12), pp.2607-2623.

Lyu, G., Bertolini, L. and Pfeffer, K., 2016. Developing a TOD typology for Beijing metro station areas. Journal of Transport Geography, 55, pp.40-50.

McCarty, J. and Kaka, N., 2015. Urban form and air quality in the United States. Landscape and Urban Planning, 139, pp. 168-179.

Ministry of Environmental Protection of the People's Republic of China, 2012. Technical Regulation on Ambient Air Quality Index (In Chinese). MEP, Beijing. http://kjs.mep.gov.cn/hjbhbz/bzwb/dqhjbh/jcgfffbz/201203/W020120410332725219541.pdf

Moore, D.K., Jerrett, M., Mack, W.J. and Künzli, N., 2007. A land use regression model for predicting ambient fine particulate matter across Los Angeles, CA. Journal of Environmental Monitoring, 9(3), pp.246-252.

Nasri, A. and Zhang, L., 2014. The analysis of transit-oriented development (TOD) in Washington, DC and Baltimore metropolitan areas. Transport policy, 32, pp.172-179.

Papa, E. and Bertolini, L., 2015. Accessibility and transit-oriented development in European metropolitan areas. Journal of Transport Geography, 47, pp.70-83.

Rodriguez, D.A. and Vergel-Tovar, E., 2017. Urban development around bus rapid transit stops in seven cities in Latin-America, *Journal of Urbanism*, in press.

Ross, Z., Jerrett, M., Ito, K., Tempalski, B. and Thurston, G.D., 2007. A land use regression for predicting fine particulate matter concentrations in the New York City region. Atmospheric Environment, 41(11), pp.2255-2269.

Shannon, C.E. and Weaver, W., 1949. The mathematical theory of communication. University of Illinois press.

Singh, Y.J., Fard, P., Zuidgeest, M., Brussel, M. and van Maarseveen, M., 2014. Measuring transit oriented development: a spatial multi criteria assessment approach for the City Region Arnhem and Nijmegen. Journal of Transport Geography, 35, pp.130-143.

Singh, Y.J., Lukman, A., Flacke, J., Zuidgeest, M. and Van Maarseveen, M.F.A.M., 2017. Measuring TOD around transit nodes-Towards TOD policy. Transport policy, 56, pp.96-111.

Stone, B., 2008. Urban sprawl and air quality in large US cities. Journal of Environmental Management, 86(4), pp.688-698.

Wu, J., Li, J., Peng, J., Li, W., Xu, G. and Dong, C., 2015. Applying land use regression model to estimate spatial variation of $PM_{2.5}$ in Beijing, China. Environmental Science and Pollution Research, 22(9), pp.7045-7061.

Xinhuanet. The Threshold of Urban Rail Transport Construction Would Be Lowered. 2016 (In Chinese). http://news.xinhuanet.com/politics/2016-05/16/c_128984816.html. Cited July 2017.

Xu, L.J., Zhou, J.X., Guo, Y., Wu T.M., Chen, T.T., Zhong, Q.J., Yuan, D., Chen P.Y., Ou, C.Q., 2017. Spatiotemporal pattern of air quality index and its associated factors in 31 Chinese provincial capital cities. Air Qual Atmos Health, 10, pp. 601–609

Yin, Z. and Xue, Q., 2016. Comparative research on compactness of metro station areas in Hong Kong and Shenzhen. City Planning Review, 3, p.013.

Yuan, M., Song, Y., Huang, Y., Hong, S. and Huang, L., 2017. Exploring the Association between Urban Form and Air Quality in China. Journal of Planning Education and Research, p.0739456X17711516.

Zhang, M., 2007. Chinese edition of transit-oriented development. Transportation Research Record, (2038), pp.120-127.

Zheng, S. and Kahn, M.E., 2017. A New Era of Pollution Progress in Urban China? Journal of Economic Perspectives, 31(1), pp. 71-92.

Zhou, C., Chen, J. and Wang, S., 2018. Examining the effects of socioeconomic development on fine particulate matter (PM 2.5) in China's cities using spatial regression and the geographical detector technique. Science of the Total Environment, 619, pp.436-445.

Appendix A – IEW Process for Developing TOD Indexes

Step 1. Decision matrix construction

The data matrix $X=(x_{ij})_{m\times n}$, comprising m cities and n indicators, is assembled, where x_{ij} is the value of the j^{th} indicator of the i^{th} city.

Step 2. Normalization of the decision matrix

As different indicators have varying dimensions and units, they were made dimensionless to get a quantitative index value of the same degree x'_{ij}. The calculation is made as:

$$X'_{ij}=\frac{X_{ij}-X_{j\min}}{X_{j\max}-X_{j\min}} \tag{1}$$

or

$$X'_{ij}=\frac{X_{j\max}-X_{ij}}{X_{j\max}-X_{j\min}} \tag{2}$$

where the indicators meeting the requirements of a positive relationship with TOD levels (shown in Table 1) are calculated with Eq. (1), while the indicators meeting the requirements of a negative relationship with TOD levels are calculated with Eq. (2).

Step 3. Calculation of the entropy value of each indicator

The entropy value H_j of the j^{th} indicator is:

$$H_j=-\frac{1}{\ln m}\sum_{i=1}^{m}p_{ij}\ln p_{ij} \qquad (3),$$

where:

$$p_{ij}=\frac{X'_{ij}}{\sum_{k=1}^{m}X'_{kj}} \qquad (4).$$

$$i=1,2,\cdots,m;\ j=1,2,\cdots,n$$

If $p_{ij}=0$, then $\ln p_{ij}$ is set as 0.

Step 4. Calculation of the imbalance coefficient of each indicator

Deviation in the coefficient G_j of the j^{th} indicator, is:

$$G_j=1-H_j\ . \qquad (5).$$

Step 5. Calculation of the weight of each indicator

In general, the higher the deviation degree of the indicator, the lower the information entropy of the indicator, and the greater the indicator weight. Weight W_j

of the j^{th} indicator is:

$$W_j = \frac{G_j}{\sum_1^n 1 - G_j} \tag{5}$$

Step 6. Calculation of the index value for each city

The evaluation index V_i of the i^{th} city is:

$$V_i = \sum_{j=1}^{n} W_j X'_{ij} \times 100 \tag{7}$$

Step 7. Combining the quality index and the quantity index

As we differentiate the TOD levels between quantity and quality, the methods above can be used to acquire quantity index V_i^s and quality index V_i^q in the i^{th} city. Finally, these two indices are combined to obtain the TOD composite index V_i' with a scale of 0-100, for the i^{th} city:

$$V_i' = \frac{V_i^s \times V_i^q}{100} \tag{8}$$

Appendix B Model Result of OLS Model, Stepwise OLS Model and Spatial Lag Model

Table. OLS Model Result

	AQI				
(Coefficient)	Year	Spring	Summer	Fall	Winter
Meteorology					
Average daily precipitation	-0.348***	-0.170***	-0.104***	0.051	-0.455**
	(0.070)	(0.035)	(0.016)	(0.057)	(0.193)
Average daily temperature	0.236***	0.209***	0.223***	-0.132***	0.104*
	(0.053)	(0.055)	(0.056)	(0.041)	(0.053)
Average daily wind speed	-0.927***	-0.502*	0.101	-0.716**	-1.848***
	(0.281)	(0.268)	(0.286)	(0.323)	(0.424)
Energy and Industry					
Central Heating Provision	13.420***	19.730***	-	-	23.389***
	(4.631)	(4.023)			(8.419)
Log of Gasoline Coverage	-1.273	-1.995	-0.576	0.803	-4.685**
	(1.228)	(1.279)	(1.022)	(1.506)	(2.189)
Second Industry as % GDP	0.012	0.173	0.120	-0.164	0.151
	(0.165)	(0.171)	(0.137)	(0.201)	(0.305)
Urban Form					
Population Density	-0.360	5.171	-10.793**	9.461	4.686
	(5.810)	(5.849)	(4.786)	(6.983)	(10.794)
Log of Urban Area	2.753	3.858	1.497	2.929	7.897
	(2.671)	(2.722)	(2.219)	(3.185)	(4.774)
% of Green Space	-4.874**	-4.047*	-0.476	-1.149	-9.572**
	(2.071)	(2.153)	(1.727)	(2.556)	(3.791)
% of Road Area	0.601	0.453	0.661**	1.030**	1.189*
	(0.385)	(0.402)	(0.316)	(0.453)	(0.700)
Street Network Density	0.276	0.746	0.336	-1.230	0.439
	(0.720)	(0.747)	(0.586)	(0.845)	(1.321)
Bus Coverage Ratio	11.382	4.843	13.661*	8.348	16.139
	(9.443)	(9.599)	(7.906)	(11.330)	(17.494)
Rail TOD Index	0.011	0.007	0.157	-0.260	0.012
	(0.223)	(0.230)	(0.187)	(0.270)	(0.411)
BRT TOD Index	0.131	0.716	0.046	-0.081	1.175
	(0.609)	(0.625)	(0.509)	(0.739)	(1.112)
Constant	104.098***	65.038***	34.231	106.730***	160.145***
	(23.233)	(24.581)	(22.960)	(27.147)	(38.493)
Observations	152	152	152	152	152
R2	0.470	0.477	0.351	0.232	0.383
Adjusted R2	0.416	0.423	0.290	0.160	0.320

Residual Std. Error	15.680	16.188	13.120	19.102	28.662
F Statistic	8.673***	8.915***	5.739***	3.214***	6.082***
Moran's I for residuals	7.929***	7.602***	6.273***	10.267***	8.964***
LM lag (df = 1)	74.880***	86.526***	66.029***	106.490***	89.941***
LM err (df = 1)	58.403***	53.716***	36.489***	98.672***	74.566***
Note:	*p<0.1	**p<0.05	***p<0.01		

Table. Stepwise OLS Model Result

	AQI				
(Coefficient)	Year	Spring	Summer	Fall	Winter
Meteorology					
Average daily precipitation	-0.364***	-0.174***	-0.108***	-	-0.418**
	(0.066)	(0.035)	(0.015)		(0.179)
Average daily temperature	0.225***	0.202***	0.220***	-0.137***	0.112**
	(0.051)	(0.053)	(0.052)	(0.030)	(0.050)
Average daily wind speed	-0.958***	-0.595**	-	-0.602**	-1.923***
	(0.259)	(0.252)		(0.302)	(0.394)
Energy and Industry					
Central Heating Provision	12.522***	18.928***			24.479***
	(4.409)	(3.838)			(7.920)
Log of Gasoline Coverage	-	-1.845	-	-	-4.701**
		(1.241)			(2.104)
Second Industry as % GDP	-	-	-	-	-
Urban Form					
Population Density	-	-	-11.319***	10.047	-
			(4.192)	(6.320)	
Log of Urban Area	-	3.396	-	3.495*	8.630**
		(2.127)		(1.898)	(3.672)
% of Green Space	-5.128***	-3.401	-	-	-9.028**
	(1.959)	(2.077)			(3.639)
% of Road Area	0.714***	0.728***	0.457**	1.061**	1.378***
	(0.260)	(0.272)	(0.205)	(0.428)	(0.475)
Street Network Density	-	-	-	-1.228	-
				(0.810)	
Bus Coverage Ratio	13.975	-	15.807**	-	-
	(8.550)		(7.150)		
Rail TOD Index	-	-	-	-	-
BRT TOD Index	-	-	-	-	-
Constant	109.393***	85.588***	39.150***	98.602***	178.318***
	(12.821)	(16.621)	(13.819)	(15.858)	(23.999)
Observations	152	152	152	152	152
R2	0.462	0.463	0.332	0.213	0.372
Adjusted R2	0.436	0.433	0.309	0.180	0.337
Residual Std. Error	15.406	16.055	12.937	18.869	28.300
F Statistic	17.674***	15.394***	14.533***	6.539***	10.609***
Moran's I for residuals	8.193***	8.364***	6.198***	10.487***	9.426***
LM lag (df = 1)	74.961***	91.416***	63.642***	106.700***	93.661***

LM err (df = 1)	62.471***	65.182***	35.581***	102.88***	82.524***
Note:	*p<0.1	**p<0.05	***p<0.01		

Table. Spatial Lag Regression Model Result

	AQI				
(Coefficient)	Year	Spring	Summer	Fall	Winter
Meteorology					
Average daily precipitation	-0.135***	-0.045*	-0.047***	-0.010	-0.114
	(0.052)	(0.024)	(0.013)	(0.038)	(0.134)
Average daily temperature	0.126***	0.101***	0.115***	-0.023	0.063*
	(0.039)	(0.037)	(0.042)	(0.027)	(0.036)
Average daily wind speed	-0.506**	-0.344*	-0.120	-0.394*	-0.852***
	(0.198)	(0.179)	(0.212)	(0.219)	(0.293)
Energy and Industry					
Central Heating Provision	6.543**	8.397**	-	-	11.686*
	(3.259)	(2.766)			(5.704)
Log of Gasoline Coverage	0.217	-0.454	0.052	1.283	-0.356
	(0.851)	(0.847)	(0.759)	(1.008)	(1.469)
Second Industry as % GDP	0.023	0.020	0.145	-0.064	0.068
	(0.115)	(0.113)	(0.102)	(0.135)	(0.205)
Urban Form					
Population Density	1.412	4.302	-5.500	8.252*	2.944
	(4.027)	(3.873)	(3.562)	(4.669)	(7.251)
Log of Urban Area	4.230**	4.068**	2.781*	5.079**	7.147**
	(1.852)	(1.802)	(1.651)	(2.129)	(3.202)
% of Green Space	-3.906***	-4.058***	-0.745	-1.224	-7.171***
	(1.435)	(1.425)	(1.281)	(1.710)	(2.546)
% of Road Area	0.504*	0.255	0.412*	0.746**	0.996**
	(0.267)	(0.266)	(0.235)	(0.303)	(0.470)
Street Network Density	-0.324	0.189	-0.618	-1.151**	-0.596
	(0.499)	(0.495)	(0.435)	(0.566)	(0.886)
Bus Coverage Ratio	-1.725	-2.475	2.433	-1.238	-5.961
	(6.541)	(6.358)	(5.882)	(7.581)	(11.736)
Rail TOD Index	-0.256*	-0.228	-0.080	-0.423**	-0.376
	(0.155)	(0.152)	(0.139)	(0.181)	(0.276)
BRT TOD Index	0.117	0.191	0.135	-0.023	0.709
	(0.422)	(0.414)	(0.378)	(0.494)	(0.747)
Constant	15.230	9.577	-6.098	1.029	32.488
	(16.972)	(16.848)	(17.540)	(19.060)	(26.996)
Rho	0.689***	0.721***	0.629***	0.716***	0.708***
Observations	152	152	152	152	152
Pseudo R2	0.679	0.706	0.565	0.565	0.647
Log Likelihood	-587.887	-587.130	-569.130	-613.571	-675.434
sigma2	117.972	114.846	94.686	163.108	369.701
Akaike Inf. Crit.	1209.77	1208.26	1170.26	1259.14	1384.87
Wald Test (df = 1)	184.166***	224.551***	105.837***	195.640***	200.188***

LR Test (df = 1)	76.521***	87.727***	60.946***	86.257***	84.791***
Note:	*p<0.1	**p<0.05	***p<0.01		