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Transportation Research Interdisciplinary Perspectives 2 (2019) 100053

Contents lists available at ScienceDirect

Transportation Research Interdisciplinary Perspectives

journal homepage: https://www.journals.elsevier.com/transportation-research-interdisciplinary-perspectives

Transportation policy profiles of Chinese city clusters: A mixed methods approach☆

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ARTICLE INFO

Article history:
Received 7 July 2019
Received in revised form 29 August 2019
Accepted 1 September 2019
Available online 4 November 2019

Keywords:
Transportation policy
Mixed methods
Time series clustering
Chinese cities

ABSTRACT

Chinese cities have experienced diverse urbanization and motorization trends that present distinct challenges for municipal transportation policymaking. However, there is no systematic understanding of the unique motorization and urbanization trends of Chinese cities and how physical characteristics map to their transportation policy priorities. We adopt a mixed-method approach to address this knowledge gap. We conduct a time-series clustering of 287 Chinese cities using eight indicators of urbanization and motorization from 2001 to 2014, identifying four distinct city clusters. We compile a policy matrix of 21 policy types from 44 representative cities and conduct a qualitative comparison of transportation policies across the four city clusters. We find clear patterns among policies adopted within city clusters and differences across clusters. Wealthy megacities (Cluster 1) are leveraging their existing urban rail with multimodal integration and transit-oriented development, while more car-oriented wealthy cities (Cluster 2) are building urban rail and discounting public transport. Sprawling, medium-wealth cities (Cluster 3) are opting for electric buses and the poorest, dense cities with low mobility levels (Cluster 4) have policies focused on road-building to connect urban cores to rural areas. Transportation policies among Chinese cities are at least partially reflective of urbanization and motorization trends and policy learning needs to account for these distinct patterns in both physical conditions and policy priorities. Our mixed-method approach (involving time-series clustering and qualitative policy profiling) provides a way for government officials to identify peer cities as role models or collaborators in forming more targeted, context-specific, and visionary transportation policies.

1. Introduction

Since the 1990s, China has experienced significant urbanization (Shen et al., 2016; Woetzel et al., 2009) accompanied by spatial suburbanization (Zhou and Meng, 1998). China's urban areas have grown by 350 million people over the past 30 years and continue to add more than 10 million new residents annually (Woetzel et al., 2009; Cherry, 2005). Since the turn of the century, rising household incomes have also led to rapid motorization that has made China the world's largest market for automobiles (Wang and Yuan, 2013). However, these urbanization and motorization transformations have not been distributed equally across China's cities, giving rise to diverse new urban typologies. Each of these urban typologies face different local challenges for municipal policy makers.

Chinese city governments have responded to their urbanization and motorization challenges by formulating and implementing new, innovative urban transportation policy (Wang and Harvey, 2015; Liang, 2014; Wan et al., 2013). As transportation policymaking in China is increasingly driven by these city-level decisions, research into this process in China's cities is growing. Although studies have generated significant understanding of transportation policies in specific urban contexts, much of this scholarship is focused on China's largest megacities (Wang and Yuan, 2013; Ma et al., 2007; Spear, 2006; Wu et al., 1996). These megacities are piloting innovative transportation policies and are often seen as trendsetters for other Chinese cities (Li, 2007; Chun et al., 2019). However, the experiences of the largest, wealthiest cities often do not apply to other cities with different urban forms and travel patterns. Therefore, this study's comprehensive, comparative assessment of how cities with varied levels of urbanization and motorization prioritize different transportation policies is necessary to rectify gaps in the literature and to further inform policymakers and other stakeholders of how transportation policies map to varying local conditions in cities.

The diversity of urbanization and motorization trends across China's cities presents a dilemma for the systematic study of transportation policy at

☆ *Funding:* This work was supported by the MIT Energy Initiative's Mobility of the Future study.
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http://dx.doi.org/10.1016/j.trip.2019.100053

the local level. Considering the unique context of every city in China is impractical. Additionally, city-specific analysis may overlook valuable opportunities for cities to systematically learn from their peers (Dolowitz and Marsh, 1996, 2000; Marsden and Stead, 2011; Marsden et al., 2011). However, the opposite extreme is equally untenable; any one-size-fits-all strategy for city-level transportation policy in China would almost inevitably fail to address the array of urbanization and motorization challenges that face different Chinese cities. Some degree of categorization is necessary in order to reduce the complexity and diversity inherent in the urbanization and motorization of Chinese cities. Our categorization of cities into a manageably small, yet diverse set of clusters will facilitate meaningful comparisons between the local conditions of Chinese cities and the policies that they adopt.

This paper explores the mapping between a city's urbanization and motorization characteristics and their transportation policy priorities for 287 prefectural cities in China from 2001 to 2014.[1] Rather than evaluate the impact of transportation policies on a city, this study blends quantitative and qualitative methods to describe how different local conditions impact prioritization of different transportation policies. The study proceeds in two stages. First, a feature-based time-series clustering is applied to group the cities into four non-overlapping clusters based on their urbanization and motorization trends over the 14-year period. Second, transportation policy profiles are created for each of the four clusters based on qualitative information collected from the city government reports of 44 selected cities. Combining these steps, we examine whether cities that have comparable urbanization and motorization patterns demonstrate similar transportation policy priorities. Our discussion and conclusion describe how these city clusters and their transportation policy profiles could facilitate the identification of peer cities for policy transfer and learning.

2. Literature review

2.1. Classification of cities

There is a long tradition among urban researchers of using cluster analysis to classify cities. Early examples include studies that classified cities using data on occupation type and employment by sector (Harris, 1943; Nelson, 1955; Wilkinson, 1964; Armen, 1972; Britton, 1973; Kass, 1973). Other studies have employed alternative variables for their clustering of cities, including land use data (Frenkel, 2004), dimensions of urban growth and development and socioeconomic status (Jones and Jones, 1970), local prevalence of specific types of restaurants (Neal, 2006), environmental quality and level of environmental awareness (Makra and Sümeghy, 2007), ICT infrastructure and use in local government (Przeybilovicz et al., 2018), and housing market conditions (André and Chalaux, 2018).

There are limited examples of using clustering analysis with transportation indicators to classify cities based on their differing travel patterns. Hook and Replogle (1996) classified Asian cities based on motorization patterns and found four types of cities, including non-motorized transport dominant cities, mixed traffic cities, public transportation dominated cities, and private motor vehicle dominated cities. Case study cities were selected to represent each of these city types and were investigated to illustrate how motorization is influenced by public policies regarding street-space allocation and use, transportation subsidies and transportation system investments. Applying hierarchical clustering to a set of 59 indicators of urban land use, public and private mobility patterns and transport investment, and transport energy use and other externalities, Priester et al. (2013) classified 100 worldwide cities into six categories: hybrid cities, auto cities, transit cities, non-motorized cities, paratransit cities, and traffic-saturated cities. These clusters are then characterized by their key mobility challenges and provide a framework for the selection of case study cities for additional research into megacity mobility cultures.

2.1.1. China's 3-tier city classification

Cities in China are often classified into three tiers based on level of political administration (National Bureau of Statistics of the People's Republic of China). The political three-tier structure classifies the four municipalities directly controlled by the central government (Beijing, Shanghai, Tianjin, and Chongqing) as Tier 1, provincial capitals as Tier 2, and all other cities as Tier 3 (Li, 2007). While useful for some political and administrative purposes, this classification of Chinese cities may fail to account for the multi-dimensional nature of cities and does not reflect diversity among the 250 or so medium and small cities. Other tier structures—usually based on some combination of political configuration as well as gross domestic product (GDP) and population—abound in the media and popular press but there is no consensus on these alternative tier classifications (e.g., Bland and Hernandez, 2016).

2.1.2. Previous clustering analyses in China

While the 3-tier political structure remains one of the most popular and often-cited means of distinguishing Chinese cities, researchers have employed cluster analysis and other empirical techniques (Tian et al., 2002) to classify the differing urban structures and environments of Chinese cities. Early applications of cluster analysis to Chinese cities focused on their differing industrial functions (Zhou and Bradshaw, 1988; Zhang et al., 1990; Zhou and Sun, 1997; Xu and Zhou, 2010). Most of these studies are focused on cities in a single province or region using cross-section analysis (Gan and Chen, 1998; Chen and Yang, 2001; Chen et al., 2002; Ling and Xu, 2003; Xu et al., 2004; Xu and Lian, 2007; Zhang et al., 2007; Yan and Liu, 2009; Zhu and Zhang, 2009). Therefore, their applicability for policy analysis is limited by geographic constraints, their single time point representations of rapidly changing urban environments, as well as their narrow feature set.

More recently, authors have expanded their analysis to a larger set of Chinese cities and have incorporated dimensions other than economic and industrial functions into their city classification. For example, Heikkila and Xu (2013) perform cross-sectional clustering on a set of key words found in the policy documents (Five-Year Plans) of 286 prefectural cities in China. They grouped cities into seven categories: land use planning, economic development, urban expansion, public management, urban-rural integration, public-private partnerships, and poverty alleviation clusters (Heikkila and Xu, 2013). Guo et al. (2012) employ time-series clustering techniques to characterize the real estate market of 70 Chinese cities into 6 clusters based on housing price data. Despite these notable recent examples, scholarship that categorizes the full spectrum of Chinese cities and incorporates the temporal dimension is lacking. Few of these studies have demonstrated the utility of their classification for the analysis of policymaking at the city-level and none have looked explicitly at the interplay of urbanization and motorization trends over time and across a large number of Chinese cities: dimensions important for understanding differences in transportation policymaking at the local level.

2.2. Mapping transportation conditions and transportation policies

A separate but limited body of literature has explored whether transportation policies reflect the physical, economic, developmental, and transportation conditions of the city in which it is implemented. Using several global megacities as case studies, Akimura (2015) analyzes the relation between micro-scale statistics on cities and transportation (like travel time) and targeted policies (such as car usage restrictions). Akimura (2015) finds that using information to aid in formulating policies is still limited, partly due to the limited supply in transportation related data. A more recent study in China identifies a disconnect between innovative transport policy options and sufficient understanding of China's motorization process and on-the-ground data such as spatial distribution across urban and rural

[1] From 2001 to 2014, the number of prefectural cities changed slightly. Four new cities were established: Bijie and Tongren in Guizhou Province in 2011, Sansha in Hainan Province in 2012, and Haidong in Qinhai Province in 2013. One city, Chaohu in Anhui province, was removed in 2011. Two cities, Xiangfan and Simao, changed their names to Xiangyang and Pu'er around 2010. Hence the total city number in 2014, as shown in the China City Yearbook, was 290, while the number was 287 in 2001. We included only the 287 cities that have the complete records from 2001 to 2014 in our study.

areas (Le Vine et al., 2018). These studies and others like them explore the extent to which data on physical urbanization and transportation contexts influence policy outcomes in particular cities. However, they do not provide a structure for analyzing this relationship across multiple cities with different physical characteristics or different policy types.

2.3. Our contribution

Our approach explicitly investigates the mapping of urbanization and motorization conditions and urban transportation policy priorities across a diverse set of Chinese cities. We combining quantitative clustering analysis with qualitative characterization of transportation policies for cities in each cluster. By building policy profiles of city clusters, we address the common critique that cluster analysis methods may be a useful starting point for further work but often fail to demonstrate applicability for policymaking (Nelson, 1957; Smith, 1965). By using clusters to classify cities, we are able to extend our qualitative understanding of the policy priorities of cities beyond single case studies and distinguish trends across groups of cities that share similar urbanization and motorization challenges. We can then use this method to help policymakers identify peer cities for transportation policy learning or export their policy knowledge to other cities facing similar local challenges.

3. Data and methodology

We adopt a mixed method approach (Teddlie and Tashakkori, 2012) whereby all 287 Chinese prefectural cities are quantitatively categorized based on their urbanization and motorization trends and then qualitatively profiled based on their transportation policy priorities. First, a time-series clustering analysis is applied to the trajectories of 8 indicators of urban wealth, scale, density, road infrastructure investment, and multimodal mobility options from 2001 to 2014. A 4-cluster structure is identified that best balances the variance explained in the data and the interpretability of the resulting classification of each city. Then policy documents are analyzed for selected cities representing each cluster to characterize the transportation policy priorities of each city type.

3.1. Data collection

3.1.1. Urbanization and motorization feature selection

The choice of specific indicators used in this study was informed both by data availability and previous literature. We choose to operationalize urbanization and motorization each by four key indicators, since using too many features in clustering analysis can dilute the interpretability of results. For urbanization, we represent city scale by total urban population and wealth by GDP per capita (Glaeser, 1998; Ingram, 1998). We measure urban form by population density (Cervero and Landis, 1997; Pickrell, 1999), and also include infrastructure investment measured by road area per capita (Rietveld, 1994). For motorization we include automobile ownership per capita (Dargay et al., 2007; Newman and Kenworthy, 1989). To capture travel patterns on other modes, we also include the number of taxis per capita, the number of buses per capita, and subway length per capita (Zhang, 2004). Urbanization and motorization are often highly correlated. For example, a city's wealth, scale, and urban density are associated with road investment (Glaeser, 1998; Ingram, 1998; Rietveld, 1994; Zegras, 2003). The connections between auto ownership, buses, subway lines, urban density, and wealth have also been widely discussed, documented, and debated (Baum-Snow and Kahn, 2000; Cervero and Landis, 1997; Crane, 1996; Newman and Kenworthy, 1989; Pickrell, 1999; Waddell, 2011; Zhang, 2004).

While these eight indicators capture the main aspects of urbanization and motorization according to most literature that looks at cities as the main unit of analysis, we acknowledge that these indicators are not necessarily comprehensive. In choosing indicators we weighed conceptual needs, model sparsity, and data availability (see Appendix A). Since our study covers a span of 14 years and 287 Chinese cities, every additional variable would make the data collection and validation much more challenging. And, in some instances, the ideal measures are simply missing or not consistent.

Each of the indicators identified were extracted and compiled for the 287 Chinese cities from 2001 to 2014 from the China Premium Database from CEIC. We refined and cross-validated the information in the CEIC database by manually comparing outlier values and missing data points by city and year to the fourteen China City Yearbooks and numerous municipal and provincial yearbooks. Subway length was integrated into our database from the website of the China Association of Metros. We report the detailed data processing of the eight variables in Appendix A.

3.1.2. Transportation policy priorities

For a convenience sample of 44 cities, we collect transportation policy priorities. For each city, we download the 2017 Report on the Work of the Government (政府工作报告). These city government reports are official transcripts of oral reports given by the city mayor to the Presidium of the People's Congress, delegates of the People's Congress and members of the Chinese People's Political Consultative Conference each year.[2] These reports provide an overview of the economic and urban development of the city, highlighting specific efforts in the most recent year (in this case, 2016). Each report includes a section on urban and regional planning that includes the state of transportation infrastructure and policy in the city; however, this section of the report is not an exhaustive review of all municipal transportation policies planned or enacted. The mayor can choose what specific aspects to cover and at what level of detail. Therefore, one can view these official annual reports as representing what city government officials see as the policies most critical to their vision for urban development and transportation. Although not all-inclusive, they provide a comparable picture of the policy priorities in each city.

A keyword search[3] on each city government report was conducted and all information regarding transportation policies was extracted. Text segments for each city were then manually categorized and labeled with one of 39 policy types. For consistency and comparability, the types of policies used were common across all cities and a single individual completed all information extraction and document coding. In this way, we use a common data source and systematic process to compile a qualitative matrix of featured transportation policies across 44 Chinese cities. These 39 policy types were then condensed to 21 types by combining similar policies that exhibited similar patterns across cities (such as electric vehicle policy and recharging infrastructure policy) and by eliminating policy types that were only mentioned in one or two cities of the 44 (such as poverty alleviation in the context of transport).

Because this qualitative policy matrix was compiled using the city government report as a single source of information, it has two key limitations. First, there may be "blind spots" in these reports given their focus on public sector transportation policy initiatives and interventions. Such a limitation does not invalidate comparison across cities as long as the omission is systematic, but it does limit the scope of the policy priorities that we can characterize with this single source. Second, no mention of a policy in the document can mean either that the policy does not exist in the city or that the policy exists but is not highlighted by the mayor's office in this year's report. Therefore, while significant meaning can be assigned to policy types that are mentioned in the city government report—namely that the policy is an integral part of the city government's transportation strategy—less meaning can be assigned to the absence of a mention without cross-validation with other data sources. In summary, the policy priorities captured by the city government reports is neither reflective of the full

[2] For example, see Guangzhou's 2017 Report on the Work of the Government (2017年广州市政府工作报告) at http://www.gz.gov.cn/gzgov/s2821/201702/186d97c1fa3246e3bba4cb35acf6ebaa.shtml (in Chinese; updated link accessed on August 24, 2019).

[3] Key words searched in each document included "transportation" ("交通"), "road" ("路"), and "car"("车").

Table 1
Cluster representation in policy matrix.

Cluster	N in cluster	N selected cities	Proportion of cluster cities represented by selected cities
1	23	13	0.57
2	41	9	0.22
3	134	14	0.10
4	89	8	0.09

transportation space nor of all policies enacted by a given city, but instead captures the transportation policies highlighted by government officials as part of their comprehensive vision for the city and its development.

3.2. Methodology

3.2.1. Time series clustering

There are three major categories of time series clustering methods: raw-data-based, feature-based (Fu et al., 2001; Shaw and King, 1992), and model-based (Baragona, 2001; Beran and Mazzola, 1999; Piccolo, 1990). The choice of the clustering method depends on the specific question of interest and the characteristics of the data (Liao, 2005). Each method requires decisions regarding feature extraction, model specification, and dissimilarity measures.

This study followed a feature-based approach, using the mean value, the average growth (first difference), and the average curvature (second difference) of each variable as the clustering features. The three features were chosen to capture key patterns of the development level and trajectory of each variable over the 14-year period, while excluding nuanced local yearly fluctuations. The mean value, first difference, and second difference are calculated based on the time series of each variable in each city. We opted to use the first difference (average absolute annual growth) rather than percentage growth rate in order to avoid artificially high growth rates of the variables that have very low base values.

There is a tradeoff between the feature extraction and the choice of dissimilarity measure (Liao, 2005). In general, researchers either extract features to reduce the temporal correlation and then apply a conventional dissimilarity measure such as the Euclidean distance or use raw data with a more advanced dissimilarity measure such as the dynamic time warping distance. Given that we have adopted a feature-based approach that has reduced the temporal correlation in the initial time-series data, we employ typical Euclidean distance as the dissimilarity measure.

For the model specification, we employ a Gaussian mixture model (GMM), which is more flexible than the prevalent K-means method, but equivalent when the Gaussian distributions of each cluster have variances σ that go to zero (Kulis and Jordan, 2011). Our GMM clustering approach calculates the probability of a city belonging to a particular cluster and assigns the city's cluster membership to the highest probability. While in most cases, cities are assigned to their cluster with very high probability, a few cities are found to belong to multiple clusters with significant probability. To determine the appropriate number of clusters, we compare model fit using AIC and BIC scores and consider the interpretability and ease of use of the resulting clusters (see Appendix B).

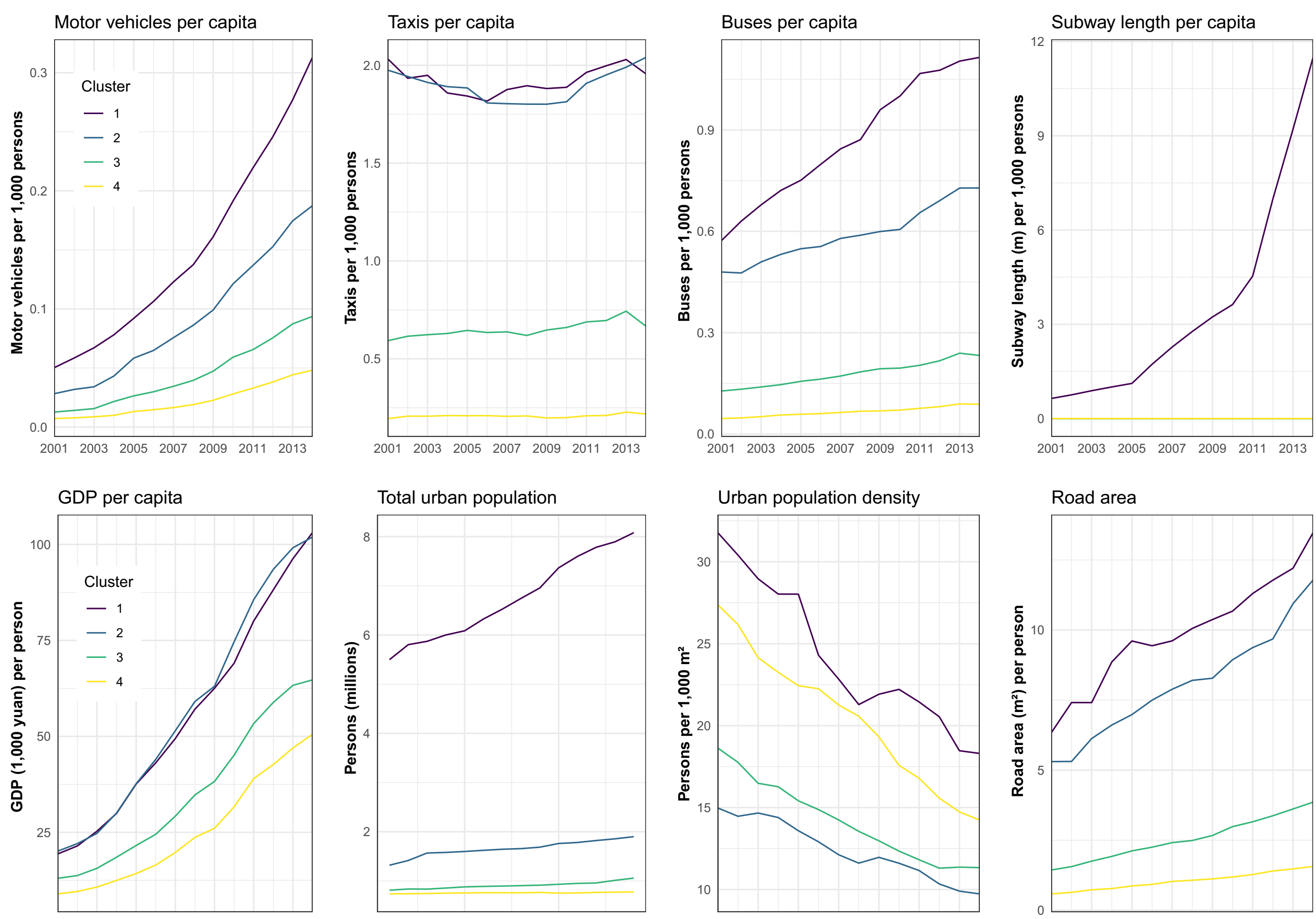

Fig. 1. Trajectories of the four city clusters on the 8 urbanization and motorization indicators.

Table 2
Statistical summaries of the four city clusters.

		Cluster 1	Cluster 2	Cluster 3	Cluster 4
Mean value (over all city-year pairs)	Number of cities	23	41	134	89
	Total urban population (million persons)	6.75*	1.67	0.90	0.76
	GDP (1000 yuan) per person	55.9	56.5*	35.6	24.9*
	Urban density (person/1000 m^2)	24.2	12.6*	14.1	20.6*
	Road area (m^2) per person	9.90	8.05*	2.54	1.05*
	Motor vehicles per 1000 persons	151	92*	45	22*
	Taxis per 1000 persons	1.923	1.895*	0.647	0.207*
	Buses per 1000 persons	0.871	0.591	0.178	0.066
	Subway length (m) per 1000 persons	3.59*	0.000	0.000	0.000
First difference (average yearly growth)	Total urban population (million persons)	0.199	0.042	0.020	0.003
	GDP (1000 yuan) per person	6.437	6.366	3.986	3.188
	Urban density (person/1000 m^2)	−1.036	−0.477	−0.540	−1.014
	Road area (m^2) per person	0.549	0.498	0.185	0.076
	Motor vehicles per 1000 persons	20	12	6	3
	Taxis per 1000 persons	−0.006	0.005	0.006	0.002
	Buses per 1000 persons	0.042	0.019	0.008	0.003
	Subway length (m) per 1000 persons	0.835	0.000	0.000	0.000

Note: Starred (*) features in panel 1 are the most salient differentiators of the cluster.

3.2.2. Policy priority profiling

We categorize the 44 cities for which we collected transportation policy priorities according to the results of the quantitative clustering analysis. These 44 cities are a convenience sample of all 287 Chinese cities included in the clustering. However, they demonstrate adequate coverage and representativeness of the 4 clusters to enable comparative analysis. Our selected cities cover close to 10% of cities in each cluster (Table 1). Furthermore, we find no systematic selection bias in any of the four clusters when comparing the 2014 values of the eight urbanization and motorization indicators used in the clustering analysis across those cities for which we did and did not collect transportation policy priorities (see Appendix C).

After organizing the selected cities by cluster, the 39 policy priorities were refined and condensed into 21 types by eliminating policy types with fewer than three mentions across all 44 cities—examples include transportation policies targeting poverty or social capital and management of e-hailing services—and combining similar policy types—such as clean energy (electric) car policies and electric car recharging infrastructure. This condensed list was then compared for the cities within each cluster and then across clusters to map the transportation policy priorities of different Chinese cities.

One potential limitation of this comparative analysis is the temporal mismatch between the two data sources. The quantitative clustering analysis was based on time series data from 2001 through 2014 while the transportation policy priorities were collected from city government reports released at the beginning of 2017. While we must recognize the temporal gap between the two datasets, we claim that it does not pose a serious threat to the validity of our results.[4] We can expect that clustering based on a 14-year time series provides reasonable projections of near future urbanization and motorization trends. Furthermore, our policy profiles are based on transportation policy interventions that often take years to move from planning (in response to these trends) to implementation.

4. Results

4.1. China city clusters

As presented in the methodology section above, we conducted a time-series clustering analysis from 2001 to 2014 on the mean, first difference, and second difference of our eight indicators of urbanization and motorization discussed in Appendix A. Based on model fit statistics presented in Appendix B, we determined four clusters that best categorize the 287 Chinese cities in our dataset:

1. Large, wealthy cities with heavy rail ($N = 23$),
2. Low-density, wealthy cities with auto-oriented mobility patterns ($N = 41$),
3. Low-density, medium-wealth cities with moderate mobility ($N = 134$), and
4. High-density, low-wealth cities with lower mobility levels ($N = 89$).

Fig. 1 plots the central trajectories of the four clusters on each of the eight urbanization and motorization indicators and Table 2 summarizes the key characteristics of each cluster by indicator.

Cluster 1 characterizes 23 cities by their large urban population, the presence of heavy rail systems, and the rapid growth of these two features (Table 2). Cluster 1 cities are the richest cities with rapid GDP growth during the period; they have the highest urban density, but density has declined rapidly from 2001 to 2014 as the urban area sprawled (supported by heavy road investment). While Cluster 1 cities are distinguished by their urban rail systems, these cities had the highest overall mobility levels across all modes—the largest number of buses, taxis, and private automobiles per capita. In fact, the number of automobiles per capita and buses per capita grew reasonably rapidly in Cluster 1 cities over the 14-year period. Lastly, we see that the rapid growth of scale, wealth, infrastructure, automobiles, and subway lines has not leveled off by 2014, implying that the major cities have not yet reached their saturation point in terms of urbanization and motorization.

The 41 cities in Cluster 2 are low-density, wealthy cities with an auto-oriented mobility pattern. While Cluster 2 cities have high GDP per capita, their total urban population numbers are moderate. In contrast to Cluster 1 cities, which grew in both wealth and population, Cluster 2 cities grew only in wealth, but not in scale (Table 2). Cluster 2 cities also have the lowest average urban density over the 14-year period, with a negative first difference indicating increasing sprawl accompanied by significant investment in road infrastructure. Finally, Cluster 2 cities are characterized by their auto-oriented mobility pattern. The numbers of private automobiles per capita grew rapidly between 2001 and 2014, averaging 12% growth per year; furthermore, the number of taxis per capita is as high as that seen in Cluster 1 cities (Note: Starred (*) features in panel 1 are the most salient differentiators of the cluster). These auto levels far outstripped the availability of public transit, with the number and growth of buses per capita being moderate and no existence of subway lines.

The 134 cities in Cluster 3 could be considered the most "common" cities in China, having moderate levels across almost all eight indicators of motorization and urbanization. These are low-density, medium-wealth cities that have moderate mobility levels across many different modes.

[4] This temporal gap may be of particular importance when considering Cluster 2 cities, such as Qingdao, that have opened urban rail lines (a key characteristic of Cluster 1 cities) since 2014 (see Discussion).

Cluster 4 characterizes 89 cities by their high-density, low GDP per capita, and low mobility levels. The most striking pattern of Cluster 4 cities is the contrast between their low levels and growth of GDP per capita and their high urban densities (Table 2). Associated with low urban wealth, road investment in Cluster 4 cities showed the lowest levels and slowest growth. This suggests that Cluster 4 cities have maintained higher densities because lack of wealth and investment in road infrastructure has prevented significant sprawl. This pattern is exactly opposite what is seen in Cluster 2 cities, where urban areas suburbanized to lower density over the 14-year period accompanied by considerable road infrastructure investment. Regarding mobility patterns, Cluster 4 cities show the lowest numbers of buses, taxis, and private automobiles per capita with private automobiles showing the highest average growth.

4.2. Transportation policy priorities across city clusters

In this section, we summarize the transportation policy priorities for each of the four clusters of Chinese cities identified above. As presented in Section 3.2.2, we compare qualitative information about 21 policy types gathered from the 2017 city government reports of selected cities within each cluster. Appendix D includes the detailed qualitative matrices. Here, we synthesize clear patterns within and across clusters (Table 3).

Building policy profiles for city clusters, we find that cities with different urbanization and motorization trajectories also have distinct transportation policy priorities. This demonstrates the potential utility of our quantitative clusters for comparative analysis of transportation policies as well as the identification of potential peer cities with similar policy priorities for knowledge sharing and policy learning.

We find that Cluster 1 cities—distinguished by high wealth, large urban populations, and the existence of urban rail—are expanding their rail infrastructure and implementing complementary policies such as multimodal integration and transit-oriented development (TOD). Wealthy, low-density, auto-oriented Cluster 2 cities are developing their first urban rail lines, are investing significant resources in expanding and optimizing bus systems, and are implementing public transit discounts to reverse previous trends of auto-oriented travel patterns. Cluster 3 cities—with moderate GDP per capita, fairly low density, and average mobility levels across all modes—have opted for clean energy buses rather than urban rail development. Finally, Cluster 4 cities with low GDP per capita, low mobility levels, but high density in their urban cores, have transportation policies focused on connecting this urban core to rural areas on the periphery of the city and to other cities in the region.

While the policy profiles in Table 3 look at within-cluster patterns among cities with similar urbanization and motorization trends, cross-cluster comparison also demonstrates that cities with different urbanization and motorization trends exhibit differences in their transportation policy priorities. Our clustering results and policy profiles provide a framework to help contextualize municipal transportation policies to the local urban form and travel patterns of different Chinese cities, and may serve as a guide for academics conducting in-depth case studies of city-level transportation policymaking or for city officials in China looking to collaborate with and learn from the transportation policies being implemented by other cities in the country.

Table 3
Transportation policy profiles of our China city clusters.

	Key urbanization and motorization features	Transportation policy priorities
Cluster 1	Large, dense, wealthy megacities with heavy rail	Expanding existing urban rail Improving and expanding bus services Improving multimodal connectivity through transfer hubs, including non-motorized forms of transport Connecting land use and transport planning with transit-oriented development Continued investment in urban expressways
Cluster 2	Low-density, wealthy cities with auto-oriented mobility patterns	Developing new urban rail Improving and expanding bus services Public transport discounts (to develop PT mode share)
Cluster 3	Low-density, medium-wealth cities with moderate mobility	No urban rail development, so focus is on improving and expanding bus services Particular emphasis on clean energy (electric) buses Significant ongoing investment in additional parking spaces as well as urban and rural roads
Cluster 4	High-density, low-wealth cities with lower mobility levels	Focused on (road) development to connect the urban core to rural areas on the periphery Prioritize interconnection with other cities in the region (via road, rail, and air)

5. Discussion

Transportation policy in China is increasingly dictated at the local level and recent scholarship has accordingly delved into the municipal transportation policymaking process. Yet much of this scholarship focuses on China's largest megacities, which are trendsetters for innovative transportation policymaking. While these megacities warrant significant study since they house a large portion of the country's urban population, our clustering analysis suggests that the challenges faced by China's largest megacities are not representative of the urbanization and motorization trends facing the majority of China's cities. While Beijing and Shanghai may indeed be appropriate peer cities from which other Cluster 1 (and perhaps Cluster 2) cities might learn and adopt policy, cities with drastically different urban form and travel patterns may struggle to contextualize policies that are successful in these large, wealthy cities.

We suggest that our mixed method approach to identifying transportation policy profiles among city clusters in China could help policymakers in all Chinese cities identify appropriate peer cities and facilitate policy learning among cities facing similar transportation and urbanization challenges. To illustrate how our results might facilitate policy learning for government officials in Chinese cities, we provide two brief hypothetical examples: Qingdao and Nanchong.

Qingdao is categorized as a Cluster 2 city—with high income, high taxi and auto mode share per capita, and no urban rail—in our time series clustering from 2001 to 2014. Had the time series data extended through 2016, Qingdao may have been categorized instead as a Cluster 1 city given that the first section of urban rail opened in December 2015. Despite this time-gap between the end of the clustering analysis and the 2017 city government reports used to characterize the policy landscape, we find that Qingdao is similar in its transportation policies to its Cluster 2 counterparts; it continues to expand its urban rail infrastructure and improve its bus service, while promoting public transit mode share through discounts (see Table A4). Unlike Cluster 1 cities, Qingdao does not mention policies such as multimodal transfers and TOD that can complement ongoing urban rail investment. City government officials in Qingdao who are rapidly investing in urban rail infrastructure may benefit from the example of Cluster 1 megacities and their use of complementary policies to better leverage urban rail infrastructure. However, recognizing that Qingdao has developed with more auto-oriented urban form and mobility patterns, Qingdao may also want to learn from and collaborate with Urumqi, the only Cluster 2 city to mention TOD, to contextualize transit-oriented land use development (and multimodal integration) for cities with more similar urbanization and motorization patterns.

Nanchong is a Cluster 4 city characterized by low GDP per capita, high density in the urban core, and low mobility levels across modes. Compared with other Cluster 4 cities with similar urbanization and motorization trends, Nanchong appears to prioritize transportation, mentioning more transportation-related policies than any other city in Table A6. Furthermore, Nanchong is the only city in its cluster to mention electric buses, which are a key component of the policy profile of Cluster 3 (rather than 4) cities. Based on these results, city government officials in Nanchong may choose to look to Cluster 3 cities for inspiration on clean energy bus policies. Having contextualized these policies to the denser urban form of Cluster 4 cities, Nanchong may itself serve as a trendsetter for other Cluster 4 cities that want to make sustainable transportation more of a policy priority. Our mixed method approach could help city government officials in Nanchong not only identify other Chinese cities from which to learn relevant policies, but also might encourage them to export their policies and teach other cities what they learn.

While we apply our mixed method approach to cities in China, this type of study could easily be expanded to cities in other countries around the world. Using time series clustering analysis to define clear patterns in urbanization and motorization trends across cities can provide a framework for analysis of transportation policy across a manageable and distinct set of cities. This type of framework may be particularly important as an increasingly diverse group of cities around the world begin innovating and learning from one another how to shape more sustainable urban transportation systems.

6. Conclusions

This study uses a mixed method approach to explore the mapping between transportation and motorization trends and transportation policy priorities at the city level. In the context of China, we demonstrate the utility of this approach for creating a framework for policy learning among cities facing different local challenges. We use time-series clustering analysis to quantitatively identify patterns in the heterogeneous trajectories of urbanization and motorization for 287 Chinese cities from 2001 to 2014. Our time-series clustering identifies four types of Chinese cities characterized by different levels of urban wealth, scale, density, road investment, and multimodal mobility options. Compared to the traditional 3-tier political classification of cities in China, our 4-cluster structure better represents the variation in urbanization and motorization trends across cities. Our quantitative analysis suggests that China's largest megacities (Tier 1 and Tier 2 cities, which mainly make up our Cluster 1) may not be representative of the urbanization and motorization challenges facing most of China's cities. In addition to China's megacities, our 4-cluster structure explicitly captures three distinct patterns of urbanization and motorization among China's Tier-3 cities. Using official mayor reports of selected cities, we then qualitatively profile each city cluster by their transportation policy priorities. We find that the cities in different clusters (i.e., with different transportation and motorization trends) exhibit different transportation policies. We then discuss how this mapping could provide a framework to enable policy learning.

While we illustrate the potential utility of our mixed method approach for exploring the municipal transportation policymaking across cities clustered by their different urbanization and motorization trends, we also acknowledged specific limitations to our method and data. First, the clustering method in this study does not allow cities to change their cluster membership during the 14-year period. Advanced methods (such as those used by Campbell et al., 2013) could be applied to allow for dynamic cluster membership. Second, the city government reports that form the basis of our policy profiles do not include an exhaustive list of all transportation and mobility policy in each city. Therefore, the absence of a policy in our analysis does not necessarily mean that the policy does not exist; it only means that the city government did not choose to highlight the policy in its annual report. To corroborate and complement the transportation policy priorities presented here, future work could collect additional primary policy data from sources other than the city government reports, including interviews with transportation policy-makers from city governments. Finally, there is a temporal mismatch between the policy documents collected for the profiles and the most recent year available in the clustering time series data. As more recent data is released re-running the time series clustering with additional years could close this gap, but we suspect that this is unlikely to have a large effect on the clustering results which already account for trends over 14 years.

In addition to work to address these limitations of data and methods, there are two other areas of future work that are suggested by this study: generalizability and utility for decision-makers. First, the policy profiles presented in this study are based on primary policy information from a relatively small subset of cities, which while representative of all cities in the cluster in terms of motorization and urbanization indicators may not be representative in terms of their transportation policy priorities. Furthermore, even though clear patterns exist within each cluster and across clusters, there remains significant heterogeneity in which policies are highlighted by each individual city government report. Future work is needed to validate the generalizability of our policy profiles beyond the cities we selected for policy analysis compared to others in their cluster. Such an exercise might randomly select additional cities from each cluster, hypothesize their potential policy profiles based on our results, and then confirm or deny the hypotheses by comparing to the actual city government reports. Second, this study concludes with a hypothetical case study for how the results might inform policy learning among Chinese cities with different urbanization and motorization patterns. However, the utility of our mixed method approach for decision-makers remains an area for future work. Focus groups or a more structured policy learning exercise with transportation policy-makers from city governments within and across clusters would help to explore the applicability of our results for identifying peer cities and facilitating contextualized policy learning.

While future research is needed to corroborate and complement the work presented here, this paper presents a novel mixed method approach to understanding the transportation policy priorities across cities. By using the results of a quantitative, time-series clustering analysis of 287 Chinese cities, we explore similarities and differences among cities classified based on their urbanization and motorization trends. Combining these clusters with in-depth, qualitative review of city government reports shows that cities similar in terms of their urban form and travel patterns (physical characteristics) also have similar transportation policy priorities. This finding has significant implications for policy learning among Chinese cities. Our results suggest that transportation and mobility policies piloted in Chinese megacities may not fit the unique urbanization and motorization trends faced by many other Chinese cities. Instead, policy learning may be better facilitated among different clusters of Chinese cities that are similar in terms of their urban form, travel patterns, and policy profiles. Our mixed method approach provides a potential way for government officials in Chinese cities to identify peer cities in terms of physical characteristics and policy profiles for transportation policy learning. Furthermore, our mixed method approach that combines time series clustering and qualitative policy analysis to build city typology profiles could be readily applied in other contexts, particularly other large and rapidly developing countries with heterogeneous urban areas.

Declaration of competing interest

The authors declare no conflicts of interest.

Appendix A. Feature selection for the clustering analysis

The time span for this study characterizes the most relevant motorization and development period of Chinese cities and represents a 14-year period in which relatively consistent and completed data is available across all Chinese cities. However, in some cases features that have been shown to be important indicators of urban form or travel patterns are unavailable. For example, we considered using mode shares in each city as features in our clustering analysis. However, a complete mode share database for all Chinese cities across 14 years does not exist. Similarly, we chose not to use urbanization rates even though it seemed an obvious choice because there is no consistent measurement of urbanization rates across cities and over the years in question. In addition to the data availability, we are cognizant of the sparsity of the clustering model feature set; we only include variables that are clear and consistent indicators of motorization and urbanization.

Population (Total urban population)

This study uses total urban population as the population indicator, which manifests the scale of a city. Although used prevalently, the precise definition of population is complicated due to the dichotomy of locals vs. migrants and agricultural vs. non-agricultural populations in China. At least five population variables are often used, including 1) census-based total population, 2) year-based total population, 3) registered population, 4) registered urban population, and 5) registered non-agricultural population. However, none of the five variables serve our purpose perfectly. The census-based total population is not appropriate because the national government conducted a census only once every ten years. The year-based total population, provided by the CEIC database, is infeasible because it has on average 80 missing data points for each year. This is unsurprising because the statistics of migrants is particularly difficult to acquire. Registered population, registered urban population, and registered non-agricultural population are not adequate because any registered population variables exclude the migrants, which account for a sizeable portion of the total population, especially in major cities such as Beijing and Shenzhen. The ideal measure is the total urban population, which includes both locals and migrants, but excludes the residents living in the rural area.

To construct a better proxy for total urban population, we combined the information from year-based total population, registered population, and registered urban population and used the following formula:

$$\text{Total urban population} = \text{Registered urban population} \times \frac{\text{Year based total population}}{\text{Registered population}}$$

The underlying assumption is that the ratio of the total to the registered population is the same between the urban area and the entire region. This assumption is clearly not perfect, but the constructed proxy variable is more fitting than any of the five original variables and strikes a balance between feasibility and relevance.

GDP per capita (urban GDP/total urban population)

Associated with the population variable, we used urban GDP rather than total regional GDP to measure the economic status of a city. The urban GDP variable is collected from the 14 China City Yearbooks. This variable is of high quality because it contains nearly no missing data points from 2001 to 2014. The GDP per capita variable is constructed as the ratio of urban GDP to total urban population.

Urban density (total urban population/urban built area)

The urban density variable is constructed as the ratio of total urban population to the built area. China City Yearbooks include three area variables (built areas, administrative areas, and urban areas) that measure the size of cities; and we opted for the built area. The built area reflects the real scale of urban development. The administrative area is inappropriate because this variable never changed except for the rare cases when new cities were established or old cities were removed even though the Chinese cities had grown significantly in the 14 years. While seemingly relevant, the urban area does not pertain to our study because it only changed when the central government commanded that the central urban district incorporated adjoining rural districts. When this happened, urban area changes were sudden and dramatic, rarely reflecting the incremental development patterns of the cities.

Road area per capita (total road area/total urban population)

The road area variable was collected from the CEIC database and cross-validated by inspecting relevant yearbooks. Thirteen errors were found in the CEIC database. Among the thirteen data points, the CEIC and the yearbooks shared twelve consistently. We removed these data points and replaced them by linear imputation. For instance, both the CEIC database and the yearbooks show that Ankang city in Shannxi province had the road area of 3.48 km squared in 2005, 0.93 km squared in 2006 and 4.50 km squared in 2007. The data point in 2006 was a clear mistake. We removed these data points and replaced them by linear imputation. The final road area per capita is constructed as the ratio of road area to total urban population.

Automobile per capita (automobile numbers/total registered population)

This variable is most pertinent to our study, but also the most challenging to be collected, partially due to the convoluted terminology of all kinds of vehicles and also due to the varying data availability in yearbooks. As to the terminology, a provincial yearbook reports the number of total motor vehicles, which include five major categories: total automobiles, motorcycles, tractors, trailers, and others. Among the five categories, the total automobiles and motorcycles account for 90% of the total vehicle number. Within the category of automobiles, there are three types: passenger automobiles, freight automobiles, and others. The passenger automobiles and the freight automobiles are further segmented into three sizes: large, medium, and small. The other automobiles include three-wheel and four-wheel slow-speed automobiles. Although prevalently used, this terminology is not consistent across all the provinces. Some provinces only reported their total motor vehicles without further details. In about one third of the provincial yearbooks, no motor vehicle information at the city level was provided. In this case, we delved into the city level yearbooks for 14 years to collect motor information, increasing the effort significantly.

The validation of the motor variable is much more complex than the other variables. This is because the motor variable compiled by the CEIC is a mix of the total motor vehicle and the total automobile number, and this is a mistake in the CEIC database, probably due to the inconsistency of the terminology across city yearbooks. We cross-validated and corrected the CEIC dataset by identifying the illogical data points and replacing them with the information from provincial or city yearbooks. In total, we removed thirty-one outliers in the CEIC database after inspecting tens of corresponding city yearbooks. We substituted the data points of three provinces[5] in the CEIC database after scanning over 42 provincial yearbooks. The motor indicator in our final database represents the number of automobiles in one city each year. Our revision clearly improved the data accuracy, but some mistakes may still exist.

As an additional note, we used total registered population as the denominator instead of total urban population because the automobile numbers reported in the statistical yearbooks refer to the automobiles owned by the total registered population. The same is true for the bus number per capita and taxi number per capita indicators discussed below.

Bus per capita (bus numbers/total registered population)

Similar to the road area variable, the variable measuring the number of buses is included in the CEIC database and the China City Yearbooks, and the collection and validation are relatively easy. After validating the CEIC database, twelve data points were removed due to illogical fluctuations, and five cities' bus numbers were replaced by using the data from the China City Yearbooks.

Taxi per capita (taxi numbers/total registered population)

Similar to the bus variable, twelve erroneous data points of taxi numbers in the CEIC database were removed and four cities' taxi numbers were substituted with the information from the China City Yearbooks.

Subway length per capita (subway line length/total urban population)

This variable was collected from the website of China Association of Metros.

Appendix B. Gaussian model specifications and selection of number of clusters

After we chose to use the Gaussian mixture model, we had to determine how flexible the Gaussian distribution variance matrix should be and how many clusters we should use. To answer these two questions, we compared the AIC and BIC scores of the models, which vary by the flexibilities of the Gaussian distributions and the number of clusters, as shown in Fig. A1. Gaussian distribution could be flexible to different degrees as it takes the form of a diagonal, spherical, or full variance matrix. As shown, the models with spherical variance matrix are inferior to the other two types due to the consistently

[5] Yunnan, Hunan, and Shanghai. They were replaced due to the data error in CEIC

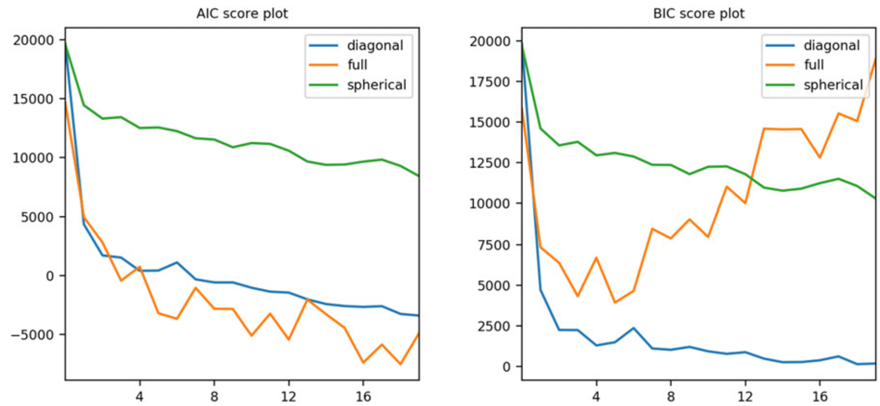

Fig. A1. AIC (left) and BIC (right) scores of clustering models ($N = 2$ to 20)

high AIC and BIC scores. The comparison between the models with a full variance matrix and those with a diagonal variance matrix is not consistent between AIC and BIC. In terms of the AIC scores, the models with the full variance matrix perform slightly better than those with the diagonal variance, while they do significantly worse in terms of the BIC scores.[6] To maintain a relatively parsimonious model and a simple computation process, we opted for the model with the diagonal variance matrix for our clustering analysis.

As for the cluster numbers, Fig. A1 cannot provide conclusive results. The AIC and BIC scores of the models with the diagonal variance matrix decline very modestly when the number of clusters is larger than four. The statistical results do not suggest any superior cluster number, and the choice of the cluster number depends on the research objective and result interpretability. We examined the results of five and six clusters, but they did not reveal more interesting results than four clusters. Since a larger number of clusters reduces the interpretability of the result, we decided on four clusters.

After deciding on four clusters, we ran the estimation hundreds of times to identify a robust clustering result with the minimum AIC and BIC. These repetitive calculations were necessary to approximate the global optimum since the EM algorithm[7] can only identify a local optimum. The clustering method and the EM algorithm both present limitations and do not guarantee a completely stable result. In fact, even after extensively repeated estimations, one or two cities could change their cluster membership. Within the time-series clustering framework, we did not exhaust the potential of the method. For instance, with the clustering result, researchers could readily analyze the associations between automobile growth and socio-economic factors, and how they differ across the four clusters. Some simple linear transformations based on our Gaussian mixture model could help answer this question.

Appendix C. Cluster representativeness of selected cities

Table A1
Descriptive statistics for the urbanization indicators (2014) for cities selected for policy analysis and those not included, by cluster.

		Total Urban Population	GDP per capita	Urban density	Road area per capita
Cluster 1	Average (all)	8.081	103.067	18.307	13.472
	Average (selected)	6.972	98.407	20.590	15.920
	Average (not selected)	9.805	110.316	14.755	9.665
	t.test 1	$t = -1.0627$	$t = -0.84862$	$t = 1.1126$	$t = 1.2185$
		$p = 0.3103$	$p = 0.4071$	$p = 0.2826$	$p = 0.2415$
	t.test 2	$t = -0.69673$	$t = -0.40452$	$t = 0.38898$	$t = 0.4227$
		$p = 0.4907$	$p = 0.689$	$p = 0.7009$	$p = 0.6764$
Cluster 2	Average (all)	1.899	101.935	9.732	11.785
	Average (selected)	2.574	135.494	9.240	17.619
	Average (not selected)	1.710	92.497	9.871	10.144
	t.test 1	$t = 1.6675$	$t = 1.9479$	$t = -0.49617$	$t = 1.6265$
		$p = 0.121$	$p = 0.0768$*	$p = 0.6259$	$p = 0.1398$
	t.test 2	$t = 1.3208$	$t = 1.528$	$t = -0.41007$	$t = 1.2452$
		$p = 0.2122$	$p = 0.1546$	$p = 0.6877$	$p = 0.2435$
Cluster 3	Average (all)	1.056	64.714	11.333	3.859
	Average (selected)	1.280	69.392	11.518	4.065
	Average (not selected)	1.030	64.164	11.312	3.835
	t.test 1	$t = 1.4154$	$t = 0.63872$	$t = 0.21268$	$t = 0.62981$ $p = 0.5353$
		$p = 0.1764$	$p = 0.5323$	$p = 0.8334$	
	t.test 2	$t = 1.2713$	$t = 0.57373$	$t = 0.19484$	$t = 0.57477$ $p = 0.5717$
		$p = 0.2223$	$p = 0.5745$	$p = 0.8473$	
Cluster 4	Average (all)	0.776	50.533	14.238	1.565
	Average (selected)	0.892	32.837	21.011	1.132
	Average (not selected)	0.763	52.549	13.486	1.613
	t.test 1	$t = 1.6179$	$t = -2.1526$	$t = 2.2083$	$t = -1.6384$
		$p = 0.1397$	$p = 0.05861$*	$p = 0.06016$*	$p = 0.1374$
	t.test 2	$t = 1.4836$	$t = -1.9699$	$t = 2.0072$	$t = -1.4988$
		$p = 0.1725$	$p = 0.07991$*	$p = 0.08135$	$p = 0.1703$

Note: t.test 1 has null hypothesis that the average for selected cities is equal to the average for not selected cities in the cluster; t.test 2 has null hypothesis that the average for selected cities is equal to the average for all cities in the cluster; * = statistically significant difference at the 10% level.

6 This discrepancy is because BIC scores penalizes the complexity of models much more than AIC

7 Expectation-maximization algorithm is commonly used in the models with latent variables. In our study, the latent variables are clusters.

Table A2
Descriptive statistics for the motorization indicators (2014) for cities selected for policy analysis and those not included, by cluster.

		Auto per capita	Taxi per capita	Bus per capita	Subway lines per capita
Cluster 1	Average (all)	0.313	1.956	1.115	11.495
	Average (selected)	0.339	1.759	1.150	11.608
	Average (not selected)	0.273	2.262	1.061	11.319
	t.test 1	$t = 0.92488$	$t = -0.49209$	$t = 0.28996$	$t = 0.077478$
		$p = 0.3684$	$p = 0.6282$	$p = 0.7756$	$p = 0.939$
	t.test 2	$t = 0.32844$	$t = -0.70211$	$t = 0.10248$	$t = 0.034913$ $p = 0.9724$
		$p = 0.7455$	$p = 0.4908$	$p = 0.9193$	
Cluster 2	Average (all)	0.187	2.040	0.728	0
	Average (selected)	0.212	2.342	1.023	0
	Average (not selected)	0.180	1.955	0.646	0
	t.test 1	$t = 0.91439$	$t = 0.68438$	$t = 2.0268$	–
		$p = 0.3785$	$p = 0.5097$	$p = 0.0693$*	
	t.test 2	$t = 0.72673$	$t = 0.53313$	$t = 1.5753$	–
		$p = 0.4823$	$p = 0.6058$	$p = 0.1449$	
Cluster 3	Average (all)	0.094	0.667	0.233	0
	Average (selected)	0.096	0.661	0.207	0
	Average (not selected)	0.093	0.667	0.236	0
	t.test 1	$t = 0.20405$	$t = -0.052975$	$t = -0.90387$	–
		$p = 0.8408$	$p = 0.9584$	$p = 0.3779$	
	t.test 2	$t = 0.18382$	$t = -0.047844$	$t = -0.81762$	–
		$p = 0.8565$	$p = 0.9624$	$p = 0.4246$	
Cluster 4	Average (all)	0.048	0.218	0.088	0
	Average (selected)	0.044	0.198	0.068	0
	Average (not selected)	0.049	0.220	0.090	0
	t.test 1	$t = -0.61778$	$t = -0.41334$	$t = -1.1701$	–
		$p = 0.5538$	$p = 0.6891$	$p = 0.2682$	
	t.test 2	$t = -0.56412$	$t = -0.37921$	$t = -1.0789$	–
		$p = 0.5882$	$p = 0.7136$	$p = 0.3063$	

Note: t.test 1 has null hypothesis that the average for selected cities is equal to the average for not selected cities in the cluster; t.test 2 has null hypothesis that the average for selected cities is equal to the average for all cities in the cluster; * = statistically significant difference at the 10% level; –- = not applicable.

Table A3
Policy matrix for representative cluster 1 cities

	Nanjing	Wuxi	Suzhou	Shenyang	Guangzhou	Shenzhen	Foshan	Dongguan	Zhongshan	Harbin	Chongqing	Chengdu	Kunming
Completed urban rail lines	X	X	X	X	X	X		X		X	X	X	X
Planned/ongoing urban rail construction	X	X	X	X	X	X	X	X	X	X		X	X
Multimodal (transfer) hubs	X	X	X		X	X		X					
Transit-oriented development					X		X	X	X				
Increase public transit mode share	X	X					X						X
Public transport discount													
New or optimized bus routes	X	X	X	X	X	X	X	X	X	X	X		X
"bus metropolis"				X	X					X			X
Clean energy buses	X	X	X	X						X		X	
Clean energy cars and/or charging infrastructure					X	X	X		X				X
Public bike share	X	X					X	X					X
Bike lanes and greenways												X	X
Non-motorized transport				X	X			X				X	
Intelligent transportation system	X		X	X			X	X	X			X	X
Traffic demand management (TDM) / signage				X			X	X	X			X	X
Urban roads/expressway	X	X	X	X	X	X	X		X	X	X	X	X
Additional parking spaces	X			X			X			X			X
Rural roads										X			
Intercity highway	X								X				
Intercity (high-speed) railway	X				X			X		X	X		X
Airport							X	X		X	X		X

Table A4
Policy matrix for representative cluster 2 cities

	Changzhou	Urumqi	Jinan	Qingdao	Weihai	Karamay	Daqing	Zhuhai	Dalian
Completed urban rail lines									
Planned/ongoing urban rail construction	X	X	X	X				X	X
Multimodal (transfer) hubs					X				
Transit-oriented development		X							
Increase public transit mode share	X								
Public transport discount			X	X	X			X	
New or optimized bus routes		X	X	X	X	X	X	X	
“bus metropolis”		X							
Clean energy buses			X	X	X			X	X
Clean energy cars and/or charging infrastructure			X						
Public bike share			X						
Bike lanes and greenways								X	
Non-motorized transport			X	X					
Intelligent transportation system		X	X	X	X			X	X
Traffic demand management (TDM)/signage			X					X	X
Urban roads/expressway	X	X	X	X	X		X	X	
Additional parking spaces				X	X				
Rural roads							X		
Intercity highway		X					X		
Intercity (high-speed) railway	X	X	X		X	X	X		
Airport	X	X			X	X	X	X	X

Appendix D. Policy matrices by city cluster

Cluster 1

Cluster 1 cities are characterized by high urbanization and motorization trends across all modes and are particularly distinguished by the existence of urban rail systems by 2014 (see.

Table 2). Laying out the transportation policy profile of a subset of these Cluster 1 cities, we see that these high urbanization and motorization levels are accompanied by active policymaking and huge investments across all modes of transportation (Table A3). In line with the subway per capita physical characteristic used in the clustering analysis, Cluster 1 cities are the only cities to highlight completed urban rail lines in their city government reports. Furthermore, 12 of the 13 cities highlight planned or ongoing expansion of these existing urban rail systems.[8]

In addition to massive investment in urban rail, every single selected city from Cluster 1 highlights the purchase of new buses, the addition of new bus lines (on dedicated infrastructure), and the optimization or increased frequency on current bus routes. Multiple cities use the term “bus metropolis” to highlight their strategy of expanding bus-based public transit infrastructure in addition to urban rail lines. They also have a much greater focus on multimodal transfer hubs between rail, bus, and non-motorized or “slow” or “green” modes of transport. Cluster 1 cities have the highest mention of public bike share systems and the prioritization of non-motorized transport. Furthermore, Cluster 1 cities are the only cities (with the exception of Urumqi in Cluster 2) to mention transit-oriented development (TOD) and therefore to recognize the key connection between transportation and land use.

While there is a clear focus on public transit expansion as well as increasing mode share for public transit and non-motorized transport, almost every single city from Cluster 1 also mentions significant investment in new urban expressways, roads, and bridges in their government reports.

Cluster 2

Cluster 2 cities are wealthy, medium-sized cities that have lower density and more auto-oriented mobility patterns than their Cluster 1 counterparts. While the presence of subway lines per capita (by 2014) was a key differentiator of Cluster 1 cities from Cluster 2 cities in the clustering analysis, it is clear that the transportation policy priorities of Cluster 2 cities includes development of new urban rail systems (Table A4).

While no city mentioned completed urban rail lines, most (7 out of 9) highlighted planned or ongoing urban rail construction in their 2017 city government reports. However, the policy priorities of these cities suggest that many are as focused on improving and expanding bus services as they are on urban rail development. All but one city (Dalian) mentioned new or optimized bus routes. Taken together, this suggests that Cluster 2 cities are focused on improving public transit mode share through new infrastructure development. Interestingly, the only 4 cities in the qualitative policy matrix that mention public transport discounts are all in Cluster 2, suggesting that infrastructure investment is being complemented by other policies to improve public transit mode share. Despite continued investment in urban roads, this suggests that Cluster 2 cities are looking to move away from existing auto-oriented mobility patterns to foster greater public transit mode share. Notably, this push for new public transit infrastructure is not complemented by discussion of multimodal integration or TOD as seen in Cluster 1.

Weihai, Karamay, and Daqing do not mention planned or ongoing urban rail construction, instead focusing public transit investment on new and optimized bus routes. While supplemental searches of additional policy documents suggest that Weihai and Daqing have released plans for urban rail for 2020 and 2030, these cities are outliers to the overall trends discussed above for other Cluster 2 cities.

Cluster 3

Cluster 3 cities are low-density, medium-wealth cities with moderate mobility. This cluster represents the largest number of Chinese cities (N = 134), which are distinguished by their moderate-to-low levels across all urbanization and motorization indicators (see.

Table 2). From the relative sparseness in Table A5, we see that these cities only have a moderate focus on transportation in their 2017 city government reports. Unlike Cluster 1 and Cluster 2 cities, cities in Cluster 3 make no mention of either ongoing or planned urban rail construction. Instead, the public transit focus is on expanding and optimizing bus routes. Of all clusters, Cluster 3 cities have the greatest focus on clean energy buses, with 10 out of the 14 representative cities highlighting ongoing or planned procurement of electric buses.

[8] A reminder that the matrices collected from our government reports do not represent an exhaustive list of all policies adopted by these cities; instead, they represent the policies that are highlighted by each city's mayor. So while no Cluster 1 city highlights discounts for public transportation in their city government report, we know that many of these cities do have such policies.

Table A5
Policy matrix for representative cluster 3 cities.

	Rizhao	Linyi	Zigong	Yuxi	Weifang	Tieling	Lianyungang	Yangzhou	Dandong	Jinzhou	Jining	Mudanjiang	Anshan	Jiamusi
Completed urban rail lines														
Planned/ongoing urban rail construction														
Multimodal (transfer) hubs														
Transit-oriented development														
Increase public transit mode share							X	X						
Public transport discount														
New or optimized bus routes	X		X				X	X						
"bus metropolis"								X						
Clean energy buses	X				X	X	X	X	X	X	X		X	X
Clean energy cars and/or charging infrastructure	X			X			X				X			
Public bike share	X										X			
Bike lanes and greenways				X			X							
Non-motorized transport	X													
Intelligent transportation system	X		X					X					X	
Traffic demand management (TDM) /signage	X						X	X	X					
Urban roads/expressway		X				X		X			X	X		X
Additional parking spaces	X		X				X	X	X	X	X	X	X	X
Rural roads		X	X	X	X	X	X	X		X				
Intercity highway	X	X	X								X			
Intercity (high-speed) railway		X		X							X		X	
Airport		X									X			

Table A6
Policy matrix for representative cluster 4 cities.

	Suihua	Qujing	Bazhong	Ya'an*	Baoshan	Yibin	Zhaotong	Nanchong
Completed urban rail lines								
Planned/ongoing urban rail construction								
Multimodal (transfer) hubs								
Transit-oriented development								
Increase public transit mode share								
Public transport discount								
New or optimized bus routes					X	X	X	X
"bus metropolis"								
Clean energy buses								X
Clean energy cars and/or charging infrastructure	X							X
Public bike share								
Bike lanes and greenways								
Non-motorized transport								
Intelligent transportation system								
Traffic demand management (TDM)/signage								
Urban roads/expressway	X							
Additional parking spaces					X			
Rural roads	X	X	X		X		X	X
Intercity highway	X	X	X		X	X	X	X
Intercity (high-speed) railway	X	X	X		X	X	X	
Airport	X	X	X		X	X	X	X

*Ya'an had only one reference to transportation in the city government report, stating the goal to become the "West Sichuan transportation hub".

While the 2017 city government reports in Cluster 3 highlight clean energy bus systems, they also show competitive investment in car-oriented (rather than public-transit-oriented) infrastructure. Cluster 3 cities have the highest mention of additional parking facilities compared to cities in the other clusters, with 10 out of the 14 representative cities referring to recent, ongoing, and/or planned parking space development. In addition, Cluster 3 cities also mention the construction of rural and urban roads. The relative focus between these two competing investment interests could have significant impact on how the motorization and urbanization in these cities continue to develop.

Although the within-cluster patterns discussed above are clear, there is also significant variation among the representative cities in Cluster 3. In particular, three cities—Linyi, Yuxi, and Mudanjiang—appear to be outliers from the general trend of (clean energy) bus-focused public transport development in the other Cluster 3 cities. These cities do not highlight bus investment (in terms of new routes or new fleets) in their 2017 government reports, instead Linyi and Mudanjiang focus exclusively on urban and rural road development while Yuxi mentions clean energy cars (private electric passenger vehicles) and bike lanes.

Cluster 4

Cluster 4 cities are smaller, lower-income cities with dense urban cores and relatively low mobility patterns across all modes (Table 2). Overall, transportation policy is less of a priority among these cities compared to cities in other clusters as evidenced by very few transportation policies being highlighted in the city government reports (Table A6). While some of these cities (about half) highlight efforts to optimize existing (mixed-traffic) bus routes within the urban core, their transportation policy priorities are much more focused on interconnections with the rural areas on the periphery of their urban core and with other cities in the region. For example, 6 of the 8 cities mention construction of significant lengths of rural roads (2500–8000 km in the past 5 years), with most cities planning to construct more. In addition to rural roads, 7 cities mention construction of expressways/highways and 4 mention the development of intercity rail to help connect the city with economic opportunities in other cities and parts of the region. Another key piece of the transportation policy profile of these cities is the construction of new, domestic airports to help solidify the city's position as a regional transportation hub.

While not highlighted in Table A6, it was also observed that cities in Cluster 4 mentioned PPPs as a potential way to finance new transport and other infrastructure projects more than cities in other clusters (potentially to supplement their more limited municipal resources).

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