Scaling Relationship between Traffic Congestion versus Population Size of 164 Global Cities

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Abstract

One of the important unresolved questions on the analysis of urban traffic congestion deals with urban congestion penalty versus advantage. This research with examine whether larger cities experience disproportionately greater traffic congestion by using data available from Tom Tom for 164 global cities. Results from a panel data of multivariate regression from 164 cities indicate that larger cities do experience moderately greater congestions level, supporting urban congestion penalty. However, the degree of congestion penalty increases rapidly, as the population size of cities in subgroups increase.

Implications from these findings will be discussed.

Key words: Urban congestion penalty, Urban congestion advantage, Tom Tom Traffic Index, Population coefficient, Scaling analysis.

1. Introduction

According to the Promise of Smart Mobility report (Viechnicki et al., 2015), the annual cost of traffic congestion in the U.S. was estimated at $121 billion, equivalent to slightly more than 1 percent of all annual US personal consumption. The average American spends about 34 hours every year sitting in traffic. This cost could grow to $186 billion by 2030. The annual cost of traffic congestion in the EU was estimated to be even higher at 1% of the GDP (Christidis and Lbanez Rivas, 2012). During the peak hours, the speed flow of roads in Delhi and Mambai drops to 10-20 km/hour (Alam and Ahmed, 2013). If you include extra cost of gasoline, air pollution, or even lost property value near roadways, the total cost of congestion would multiple ever further.

Congestion is usually associated with large metropolitan areas, where the land is a highly valuable and scarce resource due to the high concentration of people, activities, and services. Therefore, cities usually demand that road networks consume the minimum but necessary land in order for cities to function properly with acceptable traffic congestion.

One of the important unresolved questions in the analysis of congestion deals with scaling relationship between traffic congestion versus population sizes of cities. For example, do larger cities experience disproportionately greater traffic congestion creating longer delay hours? If the answer is in the affirmative, congestion follows urban congestion penalty. On the other hand, the negative answer indicates that congestion follows urban congestion advantage. If, however, larger cities experience proportionately longer total traffic delay hours or constant traffic delay hours per person, then, the situation may be designated as linear or neutral urban congestion.

Results from several past studies (Newman and kenworthy, 1989, Kenworthy and Laube, 1999, Karathodorou, et al., 2010, Sue, 2011) have established less fuel consumption of automobiles in larger and more densely populated cities implying that larger cities may not experience greater degree of traffic congestion suggesting urban congestion advantage. On the other hand, a recent paper (Loaf and Barthelme, 2014) has empirically established a superlinear relationship between population size of cities and roadway congestion in both the U.S. and OECD countries, indicating that larger cities do experience disproportionately greater traffic congestion, following urban congestion penalty.

Another more recent paper (Chang, et al., 2017) supported the earlier finding of urban congestion penalty by Loaf and Bathelemy (2014) for the 101 U.S. cities. However, for the subgroup of largest cities with more than 3 million inhabitants, the superlinear relationship changes into a linear relationship following neutral urban congestion. Furthermore, for the subgroup of cities with less than 1 million inhabitants, the relationship becomes an extreme strong superlinear relationship, following strong urban congestion penalty. In other words, among the largest populated cities, traffic congestion experienced per person remains the same, regardless of population size of cities whereas among the smaller cities, traffic congestion per person increases rapidly as the size of population increases. In summary, the answer to the urban congestion scaling relationship may vary by subgroups of cities with different population sizes.

This paper will examine again the question of whether larger cities experience disproportionately greater traffic congestion by using data available from Tom Tom (2017). There are 164 large global cities with a complete set of traffic congestion index, population, income per capita, and population density. This research will examine the scaling question in the contexts of total group of 164 cities as well as for the five subgroups of cities with different population sizes. To our best knowledge, this may be the first research to analyze traffic congestion level of multiple cities across multiple countries in the world.

Tom Tom created its Traffic Index (TI) in 2012 to provide an annual benchmark which makes it possible to evaluate congestion levels in an objectives way, globally. In TI 2017, the coverage is extended for 390 cities in 48 countries over six continents. Congestion level is measured as a percentage of increase in overall travel times when compared to a non-congested free flow travel time. For example, congestion level of 50% means that overall travel time is 50% greater than free flow travel time. According to Cohn(2014), these travel times are calculated on all road segments within top 5 functional road classes that are located within each urban area. The overall TI value for a city is the weighted average percentage of extra travel time experience by drivers in that city during 24 hours and 7 days a week for the given calendar period.

After this introduction, the paper is organized into four additional sections. The second section will provide a brief literature survey on urban congestion advantage versus penalty. Data and method of analysis to be used will be explained next in the third section, followed by analysis of results in the fourth section. Finally, conclusions, implications, limitations of this research will be presented in the fifth section.

2. Literature Survey

The first pioneering paper by of Newman and Kenworthy established a negative correlation between high population density cities and lower annual fuel usage per capita, suggesting urban congestion advantage. Many other papers (Kenworthy and Laube, 1999, Mindali et al., 2004; Bento et al., 2005; Brownstone and Golob, 2009; Small and Van Dender, 2007; Karathodorou, et al., 2010; Coevering and Schwanen, 2006; Su, 2011) have pursued this topic, some in support of, while other not in support of Newman and Kenworthy. A comprehensive study examining the relationship between population size of cities and traffic congestion appeared recently (Loaf and Barthelemy, 2014). Incorporating the concept of polycentric cities, they have empirically derived a superlinear population coefficient at 1.27 for total traffic delay hours from the 2010 data for 91 urban areas in the US. Superlinear population coefficient of 1.27 means population coefficient of 0.412 if traffic delay hours per driver were to be used as dependent variably ($2^{1.27} = 2.412$).

In a more recent paper (Chang, et al., 2017), they also derived a superlinear population coefficient of 1.375 from using a panel data of multivariate regression on 101 U.S. cities during the period of 1982 to 2010, which supported the earlier finding on urban congestion penalty by Loaf and Barthelemy. Superlinear population coefficient of 1.375 translates into population coefficient of 0.594, if traffic delay hours per driver were used as dependent variable ($2^{1.375} = 2.594$). However, for the small group of cities with more than 3 million inhabitants, they discovered population coefficient at 1.046 which is closer to a linear, not superlinear relation. In summary, they have discovered that population coefficient varies depending on the subgroups of cities with different population sizes.

2. Data and Method

For data, Tom Tom Traffic Index (2016) was downloaded from Tom Tom International B.V. : https://www.tomtom.com/en_gb/trafficindex/ For 2016, Tom Tom Traffic Index covered 390 cities in 48 countries throughout the world. For multivariate analysis, GDP per city as well as GDP per capita per city for 280 cities in the world for the year of 2010 were downloaded form World Cities Report 2016 by UNHABITAT : http://wcr.unhabitat.org/ By diving GDP per city by GDP per capita per city, we obtained population figures for the year of 2010. Population density data was downloaded from the 'Demographia World Urban Areas and Population Projections 10^{th} Annual

Edition 6.1: 2010.7', by Demographia at http://www.demographia.com/db-worldua2010.pdf

We were able to generate a total of 164 cities with matching complete sets of data of traffic index, income per capita, population and population density for this analysis. And then, the total group of 164 cities was divided in to the first subgroup of top 9 cities with more than 6.4 million inhabitants, the second subgroup of top 12 cities with more than 5.6 million inhabitants, the third subgroup of top 25 cities with more than 3.65 million inhabitants, the fourth subgroup of top 50 cities with more than 2 million inhabitants, and finally the fifth subgroup of top 100 cities with more than 1 million inhabitants. The smallest city from the total group of 164 cities is Richmond in the U.S. which has 511,149 inhabitants.

For the total group of 164 cities and five subgroups, a simple power function model to determine the scaling relationship of TI scores as a function of population size of cities in 2016 is applied. The formula for the individual power function model is:

$$Y_i = a \, P_i^b \tag{1}$$

where Y is the TI score for city, a is a constant, P is the population size of city, and i indexes the individual city. The exponent b determines the scaling relationship between Y and P.

Taking the natural logarithm of Eq. (1), the estimation equation is:

$$InY_i = Ina + blnP_i + \varepsilon_i \tag{2}$$

A general form of Eq. (2) has been used extensively to empirically test the scaling relationship between socio-economic activity measures and the population size of urban centers (Bettencourt, et al., 2007, 2010). Equation (2) was used to run cross-sectional ordinary least square estimations corrected for hetroskedasticity for the group of 164 cities. For the five other subgroups, the same cross-sectional ordinary least square estimation was made.

Next, Eq. (1) was expanded to include other control variables. For that purpose, the wellknown environmental principle of I = PAT, where I stands for the environmental impact from population (P), affluence (A) and technology (T) was used (Ehrlich and Holdren, 1972; Holdren and Ehrlich, 1974). More specifically, a more refined STIRPAT model known as Stochastic Impacts by Regression on Population, Affluence, and Technology was used (Dietz and Rosa, 1994, 1997; York, Rosa and Dietz, 2003a, 2003b).

The STIRPAT model has been used to examine the relationship between population size and CO_2 emissions (Shi, 2003; Cole and Neumayer, 2004; Martinez-Zarzoso, Bengochea-Morancho and Morales-Lage, 2007; Poumanyvong and Kaneko, 2010; Martinez-Zarzoso and Maruotti, 2011). In addition, the STIRPAT model has been used to examine the impact of population, income and/or technology in such other areas as material footprint, human ecological footprint and environmental efficiency of well-being (Dietz, Rosa and York, 2007, 2009; Steinberger, Krausmann and Eisenmenger, 2010; Fischer-Kowalski et al., 2011).

Although the STIRPAT model had not been used in the analysis of traffic congestion in the past, the use of the STIRPAT model conceptually may be appropriate. The reason is that TI scores like CO_2 emission or other environmental and ecological measures are greatly influenced by such underlying elements as population size, income level and technology. Another reason for the use of STIRPAT model is the ready availability of necessary data.

Representing income per capita (I) for affluence and population density (PD) for technology, Eq. (2) was expanded into Eq. (3) as follows:

$$InY_i = lna + b(InP_i) + c(In\ I_i) + d\ (InPD_i) + \varepsilon_i \tag{3}$$

For the estimation of Eq. (3), ordinary least square method of cross-sectional multivariate regression corrected for hetroskedasticity was used.

4. Analysis of Results

The results of bivariate cross-sectional analysis of traffic congestion indexes of 164 cities as a function of population size of cities generated the population coefficient of 0.123. The population coefficient indicated that 1% increase in population size of city would result in 0.123% increase in traffic congestion index. The coefficient met the statistical test of significance at 1% level. In other words, larger cities would encounter disproportionately higher traffic index implying higher traffic congestion.

Running the same regression analysis for the subgroup of 9 largest cities with more than 6.4 million populations, the population coefficient dramatically increased to 0.424, although it did not meet the test of significance. The subgroup of top 25 cities with more than 3.67 million populations generated a statistically valid coefficient of 0.326, however. Next subgroup of 50 cities with more than 2 million populations also generated a statistically valid coefficient of 0.287. Finally, the subgroup of 100 cities with more than 1.08 million populations again generated a statistically valid coefficient of 0.192. These results of five subgroups indicate that as the focus of analysis moved from the total group of 164 cities to the subgroups of top 9 cities with largest populations, population coefficients increased continuously from 0.123 to 0.424. The results from the subgroups indicate that a strong diseconomy of scale operates. In other words, the larger the population size of cities, the higher becomes the level of traffic congestion. However, the rate of increase for respective population coefficients was not even. The rate of increase was faster from the total group of 164 cities to top 50 cities, followed by a moderate increase from top 50 to top

12 cities, and ending with a very rapid increase from top 12 to top 9 cities, as shown in Figure 1. For examples, the largest cities like Mexico City, Los Angeles, and New York displayed the highest traffic index among top 9 cities, as shown in Appendix Table1.

When the bivariate regression is expanded to multivariate regression by adding two additional control variables of income per capita and population density of city, the results shown in Table 2 indicate that all three variables generated statistically valid coefficients for the total group of 164 cities. Namely, population coefficient of 0.117, density coefficient of 0.248, and income coefficient of -0.178 were generated. The population coefficient of 0.117 was slightly reduced from 0.123 from the bivariate regression. This means that 1% increase in population size would result in 0.117% increase in the level of traffic congestion, while the effects from income and density were held constant. On the other hand, 1 % increase in income would reduce the level of traffic congestion by -0.178%, while the effects from population and density were held constant for the group of 164 cities. The density would also have similar effect on traffic congestion level as population in that 1% increases in density would increase the level of traffic congestion by 0.248%.

When the same multivariate regression was conducted for the subgroup of top 9 cities, only the population coefficient generated a statistically valid measure of +0.445, whereas both density and income yielded coefficients did not meet the statistical test of significance. The population coefficient of +0.445 was slightly higher than +0.424 obtained from the bivariate analysis for the subgroup of top 9 cities. This means that only the size of population displayed a valid positive impact of increasing traffic congestion level for the subgroup of top 9 cities, supporting the result from bivariate regression.

For the subgroup of top 12 and top 25 cities, only the population coefficients again met the statistical test of significance. The population coefficients from the subgroups of top 12 and top 25 cities decreased to 0.306 and 0.299 respectively. For the subgroup of top 50 and top 100 cities, coefficients from both populations and density met the statistical test of significance. Population coefficients from the subgroups of top 50 and top 100 cities continued their decline to .0202 and 0.144 respectively, as shown in Table 2. These coefficients were again somewhat lower in values compared to population coefficients from bivariate analysis. However, density coefficients from the subgroups of top 50 and top 100 cities remained clustered at 0.227 and 0.216 respectively. These values were similar to the density coefficient of 0.246 estimated for the total group of 164 cities.

In short, the increasing trend of population coefficients from the multivariate analysis was again evident as the analysis moved from the total group of 164 cities to subgroup of top 9 cities. Furthermore, the influence of population was pervasive in that in every subgroup analysis, the population coefficients met the statistical test of significance. The increasing trend of population coefficients illustrated in Figure 2 clearly shows that as the population size of cities increases, the worse becomes the level of traffic congestion. In contrast, impact from income per capita was evident only for the total group of 164 cities. The impact from population density was more evident in increasing traffic congestion level for the total group and two subgroups of top 100 and top 50 cities, but not for the remaining subgroups of cities with larger population sizes.

As shown in Figure 2, the population coefficient from multiple analyses for the subgroup of top 9 cities at 0.445 is 3.8 times higher than the population coefficient from the total group of 164 cities at 0.117. The rate of increase again varies among subgroups the most rapid increase was observed for the subgroups of top 50, 25 and 9 cities. In contrast, the population coefficient from bivariate analysis for the subgroup of top 9 cities at 0.424 is 3.4 times higher than the population coefficient of 0.123 for the total group. The most rapid rates of increase occurred at the subgroups of top 100, 50, and 9 cities, as shown in Figure 1.

5. Conclusions

Key findings from this research can be summarized as follows. First, results from a panel data of multivariate regression indicate that larger cities, in general, encounter a moderately higher Traffic Index by Tom Tom, suggesting a higher level of traffic congestion for the total group of 164 cities. This finding supports the earlier finding on urban congestion penalty reported by Loaf and Barthelemy (2014). They reported the value of population coefficient to be equivalent of 0.594, while our population coefficient was lower at 0.117.

Second, results from a panel data of multivariate regression for the five subgroups of cities varying in population sizes from top 9 cities to top 100 cities generate significantly different values of population coefficients, similar to what was reported earlier by Chang, et al. (2017). However, population coefficients increased from 0.117 for the total group to 3.8 times higher at 0.445 for the subgroup of top 9 most populous cities. In contrast, Chang, et al., (2017) reported earlier that population coefficient of total delay hours for the total group of 101 cities declined, not increased, as the analysis moved to the subgroups of most populated cities with more than 3 million inhabitants, reversing the increasing trend found in this research.

Third, positive impact from population density was evident in the analysis of the total group of 164 cities as well as for the two subgroups of top 100 and top 50 cities. However, impact of income per capita was statistically valid only for the total group of 164 cities. In general, income coefficients were negative in value suggesting that richer cities would enjoy somewhat reduced traffic congestion.

In summary, findings of this research do support urban congestion penalty experienced by larger cities. However, the degree of urban congestion penalty varies by the subgroups of cities with different population sizes. In this research, the degree of urban congestion penalty increases rapidly, as the population size of cities tin subgroup increases.

What are some policy implications? First of all, those 12 or so largest populated cities with more than 5 million inhabitants face special challenge of controlling their traffic congestion due to urban congestion penalty coming from the scale disadvantage of large population. As the number of population is expected to increase, the task of managing traffic congestion in the future will grow even more challenging. As the size of population grow 1%, the congestion level experienced by drivers will increase from 0.338% to 0.424%. These large cities will need to mobilize many of congestion reduction strategies such as more effective use of public transit, ridesharing, congestion pricing, cycling, walking and many others. These cities include not only those mega cities like Mexico City, Los Angeles, and New York, but also somewhat smaller cities like Washington, D.C., Houston and Toronto.

As for the remaining 140 cities with less than say 5 million inhabitants, they will be subjected to more moderate urban congestion penalty. However, congestion level of these cities may also be influenced by population density as well. This research found that 1% increase in population density would increase traffic density by 0.216 to 0.227% among these smaller cities. Traffic congestion level may also be lowered, as the level of income per inhabitant increases in these cities. In summary, comparing the progress of traffic congestion and projecting future congestion targets and strategies, individual city needs to define its peer group of cities carefully by considering population size as well as density and income per capita.

There are several limitations to this research. Traffic index scores we used available from Tom Tom are not replicable in that details of their scoring systems in use are not available to the public. In addition, the score data are provided for 2016 only. Although Tom Tom scores cover many cities in multiple countries around the world, a majority of 164 cities we used is concentrated in North America and Europe. For example, there were only 6 cities for Australia, 2 cities from Austria, 1 city each from Mexico and Chile. Also, there may be other control variables which impact the congestion level in addition to income and density we have used.

Some of these limitations may provide productive topics for future research. In conclusions, realizing that urban congestion advantage and penalty is based on a complex dynamics of multiple relationships, the findings from this research represent a beginning toward a better understanding of this important issue.

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Tom Tom Traffic Index 2016, Tom Tom International B.V. 2017: https://www.tomtom.com/en_gb/trafficindex/https://www.tomtom.com/en_gb/trafficindex/

Table 1. Analysis of Population Scale on Traffic Congestion Indexes by Six Subgroups of Cities (2016).

	Population Scale	Constant	R^2
164cities	0.123*** (0.036)	-1.932 (3.177)	0.075
100cities	0.192*** (0.050)	0.397 (0.729)	0.141
50cities	0.287*** (0.088)	-1.083 (1.344)	0.215
25cities	0.326** (0.134)	-1.716 (2.093)	0.25

12cities	0.338 (0.200)	-1.931 (3.177)	0.203
9cities	0.424 (0.235)	-3.340 (3.771)	0.244

***** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level**

Table 2. Cross-sectional Analysis of Population Scale on Traffic Congestion Indexes by Six Subgroups of Cities (2016).

	Population	Density	Income per capita	Constant	R^2
164cities	0.117*** (0.031)	0.246*** (0.040)	-0.178** (0.081)	1.321 (1.016)	0.356
100cities	0.144*** (0.042)	0.216*** (0.059)	-0.136 (0.115)	0.731 (1.627)	0.336
50cities	0.202*** (0.073)	0.227** (0.093)	0.011 (0.158)	(-)1.851 (2.586)	0.341
25cities	0.299*** (0.094)	0.037 (0.161)	-0.037 (0.249)	1.943 (4.051)	0.392
12cities	0.306** (0.118)	-0.189 (0.327)	-0.548 (0.425)	6.196 (7.351)	0.441
9cities	0.445* (0.189)	0.147 (0.171)	-0.086 (0.228)	5.534 (9.960)	0.642

***** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level**

Figure 1. Bivariate Population scale of Traffic Congestion Index for six subgroups of cities

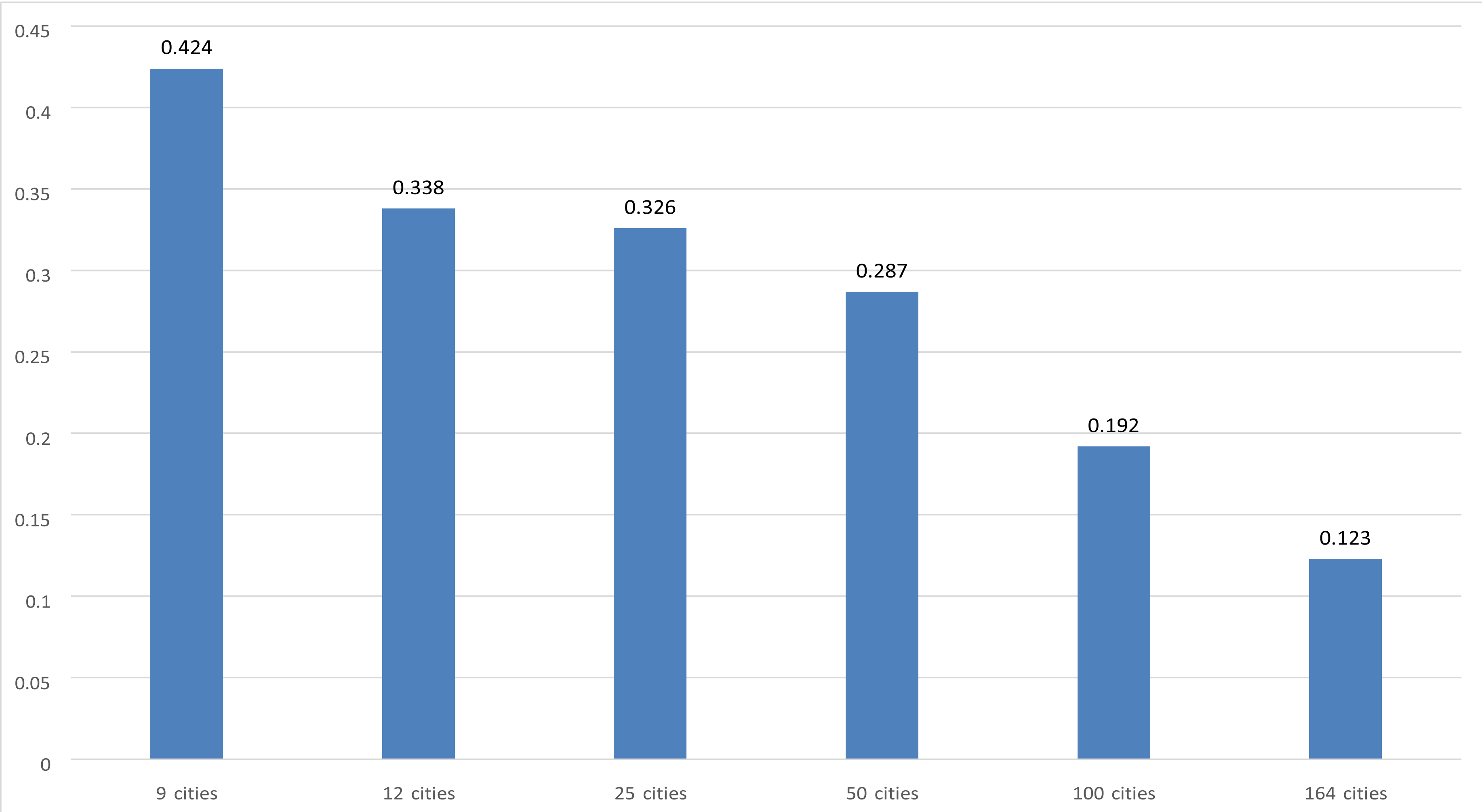
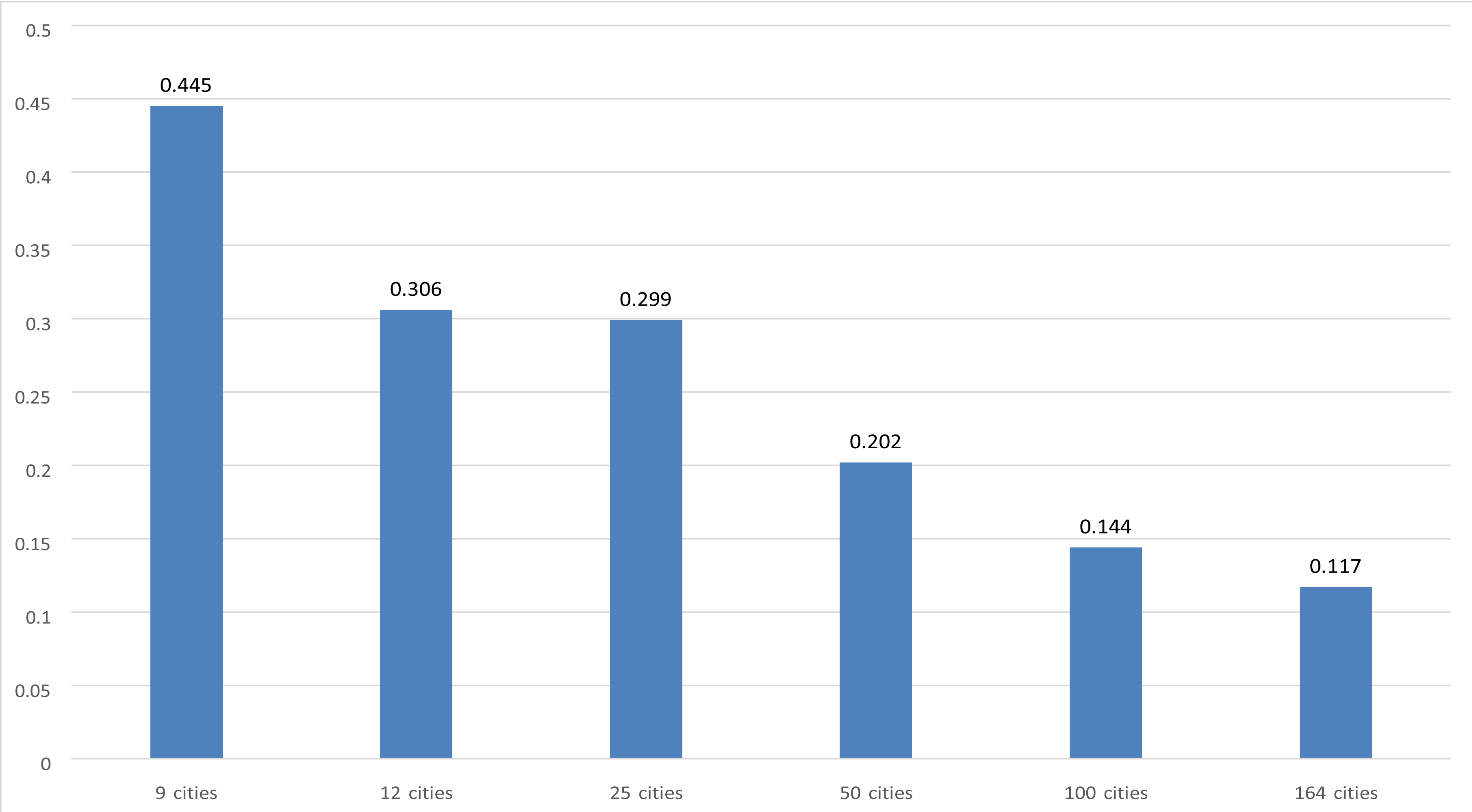


Figure 2. Multivariate Analysis of Population scale of Traffic Congestion Index for six subgroups of cities


0.5
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0.445
0.306
0.299
0.202
0.144
0.117
9 cities
12 cities
25 cities
50 cities
100 cities
164 cities

Appendix 1. Traffic Congestion Index, Population, Index, and Density for 164 Large Global cities

Rank of Population	City	Traffic Index(%)	Population (2010)	Income per capita (in $)	Density (population per mile²)
1	Mexico City	66	19,255,921	20,215.63	18900
2	Los Angeles	45	17,053,745	51,053.36	6400
3	New York	35	16,539,429	71,109.83	4600
4	London	40	11,793,530	52,237.95	13200
5	Paris	38	11,693,219	60,450.15	8700
6	Chicago	26	9,461,104	56,441.72	3900
7	San Francisco	39	6,848,028	76,564.96	5600
8	Madrid	25	6,507,502	43,229.84	14100
(subgroup1)9	Toronto	30	6,418,623	40,672.78	6400
10	Santiago	43	6,393,830	21,815.31	15800
11	Houston	24	5,920,500	67,964.36	3300
(subgroup2)12	Washington	29	5,636,185	77,356.4	3400
13	Miami	30	5,564,641	45,055.92	4400
14	Sydney	39	4,555,516	41,163.05	5300
15	Atlanta	27	4,377,197	58,611.71	1800
16	Berlin	29	4,374,708	36,532.48	9700
17	Montreal	29	4,169,714	34,588.1	5100
18	Dallas	18	4,145,124	66,430.82	2900

19	Melbourne	33	4,105,858	37,940.97	4100
20	Milan	30	4,060,624	58,845.9	4700
21	Philadelphia	23	4,024,830	58,040.46	2900
22	Rome	40	4,008,095	48,383.29	8300
23	Detroit	16	3,863,924	48,862.76	3100
24	Phoenix	16	3,817,117	46,708.03	3600
(subgroup3)25	Barcelona	31	3,675,206	38,232.79	13100
26	Boston	28	3,639,144	80,446.39	2200
27	Athens	37	3,563,607	41,327.19	14100
28	Naples	33	3,552,568	22,693.61	10000
29	Minneapolis	16	3,348,859	59,931.46	2700
30	San Diego	27	3,095,313	56,602.03	3400
31	Hamburg	33	2,984,966	52,203.59	7100
32	Warsaw	37	2,981,198	43,220.62	9600
33	Budapest	22	2,846,464	36,383.2	6000
34	Munich	30	2,844,749	60,969.98	9600
35	Lisbon	36	2,797,612	38,308.21	6300
36	Vienna	31	2,683,251	47,076.79	9200
37	Seattle	34	2,644,466	81,820.3	2800
38	Katowice	17	2,628,207	23,544.08	8800
39	Saint Louis (US)	13	2,559,926	50,708.89	2500

40	Denver	20	2,551,341	60,606.95	4000
41	Frankfurt	28	2,517,805	56,430.53	8800
42	Brussels	38	2,485,480	54,631.33	5600
43	Amsterdam	22	2,360,958	51,664.7	6900
44	Vancouver	39	2,312,497	38,896.62	4500
45	Sacramento /Roseville	22	2,149,127	44,583.68	3800
46	San Antonio	20	2,142,508	38,053.07	3300
47	Orlando	20	2,134,411	47,411.67	2600
48	Brisbane	28	2,108,348	40,495.97	2400
49	Cincinnati	14	2,107,074	49,612.88	2200
(subgroup4)50	Kansas City	11	2,009,344	53,458.74	2300
51	Las Vegas	24	1,995,215	43,392.82	4600
52	Copenhagen	23	1,989,871	49,396.2	6100
53	Stockholm	28	1,964,829	59,970.73	8600
54	Baltimore	19	1,957,901	57,239.36	3000
55	Stuttgart	34	1,954,756	52,425.89	7900
56	Cologne	34	1,903,154	46,880.74	5600
57	Lyon	29	1,894,945	44,700.19	3800
58	Birmingham (UK)	26	1,884,199	31,555.11	9900
59	Manchester	38	1,841,382	37,290.18	10400

60	Prague	28	1,829,843	47,763.9	10900
61	Perth	27	1,781,132	64,368.88	3100
62	Turin	25	1,747,614	39,019	7000
63	Marseille	40	1,722,236	37,015.14	3100
64	Austin	25	1,716,283	51,069.08	2800
65	Indianapolis	11	1,658,600	63,942.48	2200
66	Dublin	43	1,650,202	57,273.71	7400
67	Valencia	23	1,570,517	30,441.55	11200
68	Milwaukee	13	1,555,908	56,077.22	2700
69	Cleveland	12	1,510,163	62,025.09	2800
70	Rotterdam	19	1,484,830	45,676.02	6400
71	Helsinki	16	1,455,677	53,154.43	6100
72	Seville	25	1,421,045	26,445.16	14400
73	Ottawa-Gatineau	28	1,386,544	39,189.63	4300
74	Kraków	38	1,351,831	24,237.5	8200
75	Lille	22	1,349,194	31,022.56	5700
76	Jacksonville	18	1,345,596	42,674.77	2100
77	Memphis	17	1,324,829	47,111.74	2400
78	Porto	27	1,300,285	25,300.07	7200
79	Charlotte	17	1,298,931	69,592.61	1700
80	Calgary	20	1,271,737	61,957.94	3600
81	Adelaide	27	1,253,097	36,662.65	3600
82	Oklahoma city	14	1,252,987	48,159.32	2300
83	Mannheim	24	1,240,964	42,997.92	8900

84	Nashville	23	1,239,565	57,311.23	1700
85	Louisville	17	1,235,708	47,104.17	2200
86	Oslo	30	1,225,202	60,611.41	8300
87	Pittsburgh	19	1,223,423	65,591.38	2100
88	Hanover	29	1,222,773	43,258.58	6600
89	Toulouse	28	1,217,316	39,352.55	2700
90	Zurich	31	1,206,312	61,496.19	7600
91	New Orleans	23	1,189,866	65,883.89	5100
92	Edmonton	20	1,169,701	61,957.94	2600
93	Nuremberg	30	1,166,976	45,539.94	7800
94	Leeds	26	1,166,267	36,564.48	10500
95	Buffalo	16	1,135,509	41,937.14	2700
96	Raleigh	18	1,130,641	52,516.23	1700
97	Salt Lake City	16	1,125,301	59,997.28	3800
98	Bordeaux	31	1,121,983	35,859.6	2000
99	Gdansk	29	1,091,850	24,647.37	12900
(subgroup5)100	Fresno	19	1,081,742	32,741.63	4000
101	Antwerp	30	1,053,725	45,242.08	3600
102	Newcastle	32	1,050,561	26,967.74	10800
103	Bremen	23	1,025,580	42,069.64	6200
104	Bilbao	16	997,311	39,892.96	15000
105	Tucson	20	980,263	33,647.09	2500
106	Thessalonica	25	957,946	23,153.73	10700

107	Lódz	51	956,156	23,413.22	13300
108	Tulsa	12	948,014	50,150.1	2100
109	Glasgow	29	947,808	38,793.74	8400
110	Palermo	43	935,921	23,983.38	13400
111	Poznan	34	934,001	33,721.75	7100
112	Liverpool	30	929,014	32,751.69	11400
113	Albuquerque	16	887,077	43,740.28	2700
114	Sheffield	35	880,236	27,884.3	10200
115	Gothenburg	23	877,149	41,114.96	6700
116	Albany	14	870,710	49,349.38	2000
117	Nantes	25	870,045	35,281.28	3100
118	Omaha	11	865,350	55,089.85	2800
119	Nice	29	845,186	36,935.75	3400
120	Providence	19	842,700	46,882.64	2300
121	Leipzig	24	837,610	31,192.13	5200
122	Dresden	26	836,995	31,540.9	5800
123	Nottingham	27	835,625	31,018.8	10800
124	Málaga	22	834,023	24,858.77	9200
125	Wroclaw	35	832,974	28,682.28	12500
126	Zaragoza	20	825,837	36,155.34	14700
127	Quebec	24	820,529	34,588.1	2500
128	El Paso	17	804,122	30,984.07	3100
129	Winnipeg	24	803,601	36,342.14	3700
130	Bristol	34	795,480	43,403.14	10200

131	Geneva	36	785,022	54,529.92	7400
132	Mcallen	21	774,768	18,937.26	1700
133	Strasbourg	28	758,724	35,761.87	5000
134	Bologna	24	745,254	48,110.43	10400
135	Edinburgh	40	727,619	44,885.33	9100
136	Florence	26	723,164	44,815.39	7100
137	Utrecht	18	716,648	52,927.46	9500
138	Bratislava	25	715,455	54,881.97	8700
139	Rouen	21	698,385	32,486.72	3800
140	Dayton	9	696,726	44,823.93	2200
141	Karlsruhe	25	686,938	48,127.25	7600
142	Rennes	27	671,929	34,897.79	3800
143	Little Rock	14	671,459	55,966.19	1800
144	Leicester	32	660,817	30,950.14	11200
145	Las Palmas	27	658,957	27,249.89	17500
146	Malmö	18	656,834	37,027.86	9300
147	Grenoble	28	649,285	34,839.83	3300
148	Columbia	13	646,877	44,153.68	1600
149	Baton Rouge	26	645,639	55,743.22	1700
150	Colorado Springs	18	645,626	40,548.24	2400
151	Cardiff	27	640,632	30,532.13	11200
152	Montpellier	31	635,897	32,078.6	4800
153	Graz	29	608,420	41,510.68	3700

154	Grand Rapids	12	602,622	49,789.09	2100
155	Portsmouth	25	577,191	39,255.57	12100
156	Ghent	18	576,408	35,359.67	4700
157	Ljubljana	16	567,097	38,662.37	10700
158	Toulon	28	547,702	27,216.78	2000
159	Akron	10	541,781	44,418.32	1900
160	Tallinn	32	530,760	31,661.92	5700
161	Freiburg im Breisgau	23	527,581	39,673.2	12400
162	Saint-Étienne	20	520,667	28,743.96	3300
163	Gold Coast-Tweed Heads	27	519,630	40,495.97	2500
(subgroup6)164	Richmond	11	511,149	71,732.51	1900