Population Density or Populations Size. Which Factor Determines Urban Traffic Congestion?

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Abstract: A large number of articles have documented that as population density of cities increases, car use declines and public transit use rises. These articles had a significant impact of promoting high-density compact urban development to mitigate traffic congestion. Another approach followed by other researchers used the urban scaling model to indicate that traffic congestion increases as population size of cities increases, thus generating a possible contradictory result. Therefore, this study examines the role of both density and population size on traffic congestion in 164 global cities by the use of Stochastic Impacts by Regression on Population, Affluence and Technology model. We divide 164 cities into the two subgroups of 66 low density cities and 98 high density cities for analysis. The findings from the subgroups analysis indicated a clear-cut difference on the critical role of density in low-density cities and the exclusive role of population size in high-density cities. Furthermore, using threshold regression model, 164 cities are divided into the two regions of large and small population cities to determine population scale advantage of traffic congestion. Our findings highlight the importance of including analysis of subgroups based on density and/or population size in future studies of traffic congestion.

Keywords: traffic congestion; population density; population size; income per capita; urban scaling model; STIRPAT model; threshold regression model

1. Introduction

Traffic congestion in large global cities continues to worsen resulting in high economic cost, lost time, accidents, pollution, and many other negative effects for billions of urban inhabitants [1–4]. Research on the causes and mitigation of traffic congestion has produced a very large number of publications particularly over the last three decades [5,6]. The two best known papers, by Newman and Kenworthy (1989) and Kenworthy and Laube (1999), have found a negative correlation between traffic congestion and population density [7,8]. They also found a positive correlation between density and transit use. In other words, high density in cities may discourage car ownership in favor of using public transportation systems. High-density cities may also require shorter driving distances.

Numerous follow-up studies using aggregate or disaggregate samples of cities have had a significant impact of promoting high–density compact urban development to mitigate traffic congestion and pollution. Using an aggregate sample allows the researcher to analyze the overall pattern of traffic congestion for all cities in one sample without differentiating heterogeneous characteristics such as density, population, and income. An aggregate sample can also be categorized into several disaggregate samples of cities with homogeneous characteristics such as density and population. Analysis of disaggregate samples often yields results that may be more relevant to individual cities with unique characteristics.

As for the key determinant of traffic congestion, a common approach is to use population density of a city while another approach is to use population size. Using density as the key determinant often has revealed a negative relationship between traffic congestion and density of cities [7,8]. In contrast, using population size as the key determinant has often shown a positive relationship between congestion and population size of cities. Similarly, using an aggregate versus disaggregate sample often has provided contradicting evidence on the relationship between traffic congestion and cities. This research attempts to resolve these contradictory results by using both aggregate and disaggregate samples of cities. In other words, both population density and population size are used simultaneously as the key determinants of traffic density.

We used traffic congestion data available from TomTom [9]. TomTom [9] created the traffic index (TI) in 2012 to provide an annual benchmark, making it possible to evaluate congestion levels globally in an objective way. In TI 2017, coverage was extended to 390 cities in 48 countries over six continents. Congestion levels are measured as the percentage of increase in overall travel times compared to non-congested, free-flow travel time. For example, a congestion level of 50% means that overall travel time is 50% greater than free-flow travel time. According to Cohn [10], travel times are calculated on all road segments in the top five functional road classes in each urban area. The overall TI value for a city is the weighted average percentage of extra travel time for drivers in that city over 24 h, 7 days a week for the given calendar period. The TI includes 164 large global cities with complete data on the traffic congestion index, population, income per capita, and population density.

A sample of 164 cities obtained from the TI from TomTom will be divided into two disaggregate samples: (1) 66 U.S.-Canadian low-density cities and (2) 98 high-density cities in 14 countries primarily in Europe. We used a cross-sectional multivariate regression model with population size, population density, and income as independent variables. We also examined the population scaling advantage of traffic congestion between the subgroup of large population size cities versus the subgroup of small population size cities. The threshold regression model was used to divide 164 cities into 46 cities whose population size was larger than the threshold value and 118 cities whose population size was less than the threshold value.

This remainder of this paper is organized into four sections. Section 2 is a brief literature review on urban congestion in relation to vehicle and transit usage. The data and method of analysis are presented in Section 3, followed by an analysis of results in Section 4. Finally, conclusions, implications, and limitations of this research are presented in Section 5.

2. Literature Review

2.1. Aggregate and Disaggregate Analysis of Traffic Congestion

The relationship between urban form and traffic congestion or congestion-generated pollution has been studied extensively over several decades, specifically after the publication of two well-known aggregate studies by [7] and [8]. With an aggregate sample of 46 global cities from several regions including North America., Asia, and Europe, Kenworthy and Laube [8] confirmed the earlier finding that as population density increases, car use declines ($R^2 = 0.838$) and transit use rises ($R^2 = 0.757$). These two papers have prompted numerous follow-up studies using both aggregate and disaggregate samples of cities and have had a significant impact of promoting the concept of high-density compact development to mitigate car use, traffic congestion, and pollution. Representative survey articles include [5,11].

Two methods of analysis have been used in traditional aggregate studies. The first group of articles continue to use population density as the key determining factor in multivariate regression analysis. For example, Karathodorou et al. [12] and Sue [13] have found statistically significant negative density coefficients of −0.229 and −0.064, respectively, for fuel consumption, supporting the earlier findings by Newman and Ken-

worthy [7]. They determined that a 1% increase in density is expected to decrease car fuel consumption by 0.229% and 0.064%, respectively, all else being equal. Ye et al. [14] and Gudipudi et al. [15] also supported the impact of city density on decreased car use and less carbon emissions.

The second aggregate approach uses the urban scaling model, which states that traffic congestion, car use, and pollution emissions may be described by a power-law function [16,17]. For 942 U.S. urban centers, Fragkias et al. [18] established a power function exponent of 1.0 for CO_2 emissions as a function of population size, indicating a constant return to scale. In contrast, Oliveira et al. [19] found that the population size to scale superlinearly (with an exponent of 1.46) represented an increasing return to scale when the U.S. cities were defined as connected urban spaces. Muller and Jha [20] found a sublinear exponent of 0.75 for local air pollution for U.S. metropolitan areas, indicating a decreasing scale trend.

For traffic congestion, Louf and Barthelemy [21] derived a population exponent of 1.27 for a variation of total delay hours due to congestion and 1.262 for excess CO_2 emissions due to congestion for 101 U.S. cities. Barthelemy [22] also established a scale exponent of 1.58 ($r^2 = 0.96$) for total delay from congestion during peak hours as a function of population size of cities. Barthelemy's [22] data on almost 300 urban areas globally came from TomTom in 2016.

Kenworthy and Laube's [8] aggregate study did not explicitly pursue the possibility that driving behavior of people in dense cities may be different from those in less dense cities, even though their data supported this possibility. Their sample of 13 U.S. and 11 European cities clearly showed that the 1990 average density of the European subgroup was about 3.5 times higher at 49.9 persons per hectare and just 14.2 in the North American subgroup. In contrast, the average car use in the North American subgroup is almost 2.5 times higher at 11,155 km per capita and just 4517 for the European subgroup. The difference in driving behavior in cities with different density has been subjected to rigorous quantitative analysis in the context or residential self-selection of driving in disaggregated studies, which we elaborate on next.

One group of disaggregate studies continues to use density as the key determinant. These studies use household data to control for observable driving differences between households living in low- and high-density areas [23–26]. For example, Brownstone and Golob [25] found that residential density influences car use. Comparing two households that are similar in all aspects except residential density, a lower density of 1000 housing units per square mile, which is about 40% of the mean value of 2500 housing units, implies a positive difference of 1200 miles per year or 4.8% more miles. Duranton and Turner [26] also found that a 10% increase in "residential density" leads to a 0.7% to 1% decline in driving, when the effects from other variables are held constant. "Residential density" is defined as the density of residents and jobs within a 10-km radius of where a driver lives. Other measures of urban form do not have a measurable effect on driving behavior. Policy implications from these studies suggest that it would be more costly to reduce the driving difference through a densification process than through congestion pricing or increased gasoline taxes.

The second group of disaggregate studies has used population as the key determinant. For example, Chang et al. [27] compared a group of cities with less than 1 million inhabitants to show a strong superliner scale at the exponent of 1.7, while another group of cities with more than 3 million inhabitants showed a linear scale at an exponent of 1.0. Lu et al.'s [28] disaggregate study on pollution concluded that the rate of population growth can aggravate air pollution, but the impact is heterogenous. In mega cities, the rate of population growth can improve air quality, and in small- and medium-size cities, the rate of population growth can aggravate air pollution.

Finally, in an attempt to combine both population size and density to examine the effects on urban CO_2 emissions, Ribeiro et al. [29] proposed a generalized logistic model. The model can generate decreasing or increasing returns to scale, but population size always

has a greater effect on emissions than population density. They also suggested a possible use of the IPAT model, which can use both population size and density simultaneously as predictors.

2.2. Comparison of Transit Capacity and Usage: The U.S. versus Europe

We analyzed the data by separating into two groups: 66 North American (Canada and the United States) cities and 98 other (mostly, European) cities. Separating into two groups in our analysis is based on the expectation that the effect of the independent variable (dense, population, & income) on the dependent variable would be different between the groups.

The primary factor that moderates the effects of independent variables on the dependent variable is public transit system [30]. In general, it is known that there is a strong correlation between population density and transit system usage. However, high density does not necessarily result in increases in transit capacity and transit uses. Well established transit system is expected to mitigate the effects of density, population size, and income on traffic congestion by absorbing the demands for automobile uses. There are sufficient evidences that in the US cities transit capacities and uses are significantly lower than in European cities.

Comparing the differences of transit capacity and transit usage between the 11 metropolitan cities in Europe versus 13 metropolitan U.S cities, Kenworthy and Laube [8] demonstrated a much greater transit dependency of the European cities over the U.S cities. As Table 1 shows, the overall transit capacity measured as transit service kilometers (km) per person was 3.28 times longer at 92 km in the European cities over 28 km in the American cities.

Table 1. Comparing transit capacity and usage between the European and the U.S. cities (1990).

Cities	Transit Service km per Person	Rail Service Intensity (Service km per Urban ha)	Percentage of Total Motorized Passenger km on Transit	Percentage of Workers Using Transit
European (11)	92 km	3651 km	22.6%	38.8%
American (13)	28 km	153 km	3.1%	9.0%
$\frac{\text{European}}{\text{American}}$	3.28 times	23.86 times	7.29 times	4.31 times

Source: Kenworthy and Laube [8].

The transit service km per person includes rail service km as well. The rail service intensity measures as rail service km per urban hectare (ha) shows even a greater difference. The European cities experienced 23.86 times higher intensity at 3651 km over just 153 km in the U.S. cities. As for actual passenger travel using transit systems, the European cities captured even a greater proportion of 22.6% over a tiny 3.1% realized by the U.S. cities, which represented 7.27 times higher transit usage by the European cities. Another transit usage measure is percentage of commuting workers using transit during peak hours. Once again, 38.8% of commuters used transit systems in the European cities over just 9.0% in the U.S. cities representing 4.31 times higher usage in the European cities. In short, the transit dependence of the European cities is much greater than the U.S. cities, whereas the automobile dependence is dominant in the U.S. cities.

A discrepancy in dependency on transit systems between the US and European cities has been widen. For example, Freemark [31] in his comparison analysis with data of 2002–2018 period reported that the transit ridership in the U.S. urban cities had declined by 15% during 2010–2018 while that in the French counterparts had increased by 18% during same period of time. With a few exceptions such as New York, Boston, and Houston, people in the U.S. cities tend to prefer using their own cars instead of using public transit system. Freemark [31] attributes the transit's decline in the U.S. to some factors such as low gas price, cultural influences, and economic differences from European ones. On the contrary, the largest French cities had developed effective tram and bus services. Public transit systems in French cities were designed to serve large and dense cities and a large amount of resources has been invested to develop pedestrian-friendly facilities. As an

additional evidence, Figure 1 shows that there is a clear demarcation between US and Western European cities in terms of transit ridership per capita [32].
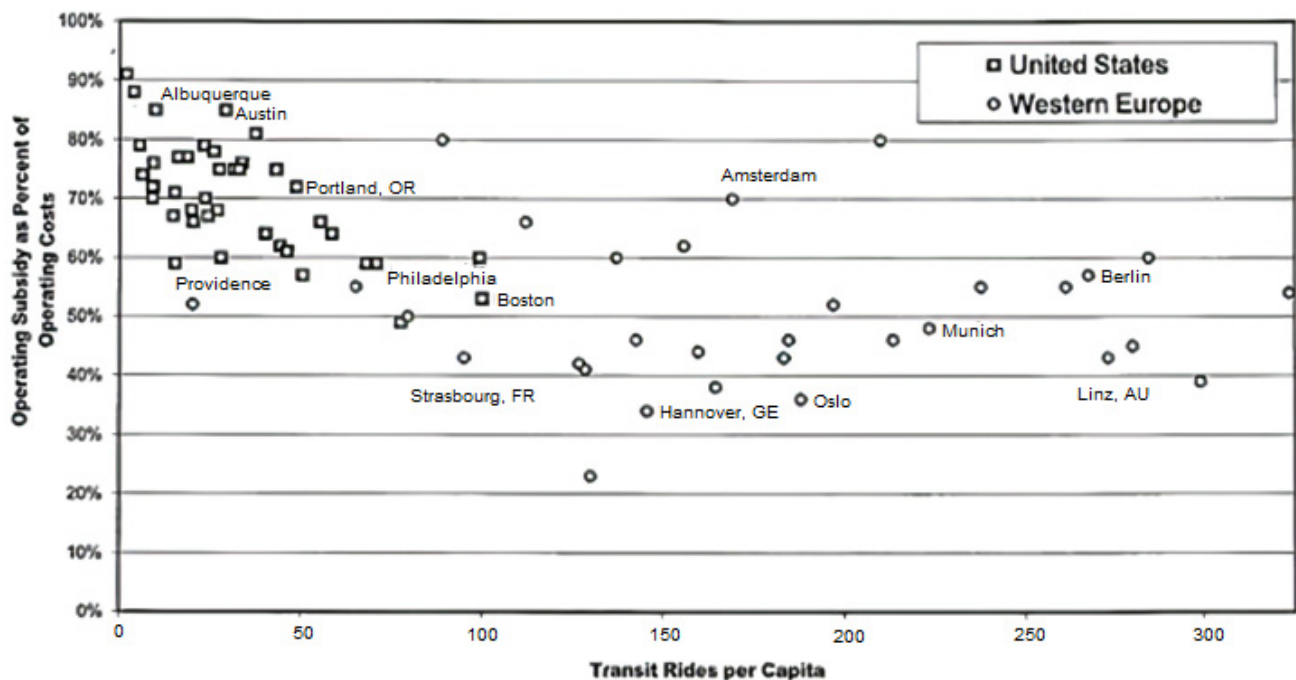

Figure 1. Public operating subsidies and transit ridership levels for selected US and Western European urban areas.

3. Method and Data

Ribeiro et al. [29] suggested that the well-known environmental principle of *I = PAT* might be used as the analytical model [33–35]. The IPAT (*I = PAT*) model is a multiplicate approach to assess the role of population (*P*), affluence (*A*), and technology(*T*), on environmental impact (*I*). The model is not an equation but rather an identity. The IPAT is still useful in determining which factors (driving forces) are most damaging to the environment.

The IPAT model was extended into the stochastic impacts by regression on population, affluence and technology (STIRPAT) model which enabled to estimate the proportional change in environmental impact per given proportional change in population.

The STIRPAT model is defined as

$$I_i \ = \ aP_i^b A_i^c T_i^d e_i \tag{1}$$

where *a* is *a* constant, *b c*, and *d* are the exponents of *P*, *A* and *T*, respectively, that are to be estimated and *e* is the residual or error term. Subscript *i* denotes the cross-sectional units, namely cities in this paper.

To ease the task of estimating exponents, Equation (1) is converted into is log-log form of Equation (2) by taking the natural log of both sides.

$$lnI_i \ = \ ln(a_i) + b[ln(p_i)] + c[ln(A_i)] + d[ln(t_i)] + e_i \tag{2}$$

The natural log is helpful as it converts non-linear variables to linear ones rendering the results to interpret as percentage change. For example, *b* can be viewed as population elasticity that measures the percentage change in environmental impact resulting from an one percent change in population.

The STIRPAT model has been used to examine the relationship between population size and CO_2 emissions [29,36–40]. The STIRPAT model has also been used to examine the impact of population, income, and/or technology in other areas such as material footprint, human ecological footprint, and environmental efficiency of well-being [41–43].

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

As for the measure for technology, there is no consensus on single measure of technology [44]. According to Cole and Neumayer [37], technology is a broad term which is intended to reflect technological, cultural, and institutional determinants of environmental impact. For example, Uddin et al. [45] have extensively used urbanization ratio measured as percentage of population living in urban areas for technology in their STIRPAT model. Wang et al. [46] also have used urbanization ratio, together with energy intensity for technology factor in their STIRPAT model.

For this study, population density is used to represent technology factor in the STIRPAT model, together with population size of city as P and income per capita of city as A, as shown in Equation (3) as follows.

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

For the estimation of Equation (3), an ordinary least square method of cross-sectional multivariate regression corrected for heteroskedasticity was used. Equation (3) was used to analyze the impact of traffic congestion for the total groups of 164 cities, 66 cities, and 98 cities.

To avoid error caused from the artificial division of population subgroups, this research uses the Hansen's [47] threshold regression model to test the threshold effect of the population size on traffic index. The single threshold regression model contains Equations (4) and (5) as follows:

$$Y_i\ =\ \theta_1 x_i + e_i\ q_i \leq \gamma \tag{4}$$

$$Y_i\ =\ \theta_2 x_i + e_i\ q_i > \gamma \tag{5}$$

where i represents the units of analysis which is a city; Y_i represents the dependent variable of traffic index; x_i represents the explaining variables of population size (P), income per capita (I), and population density (PD); θ_1 and θ_2 represent parameters to be estimated; q_i represents the threshold variable of population size used to split the sample into subgroups; γ represents the threshold quantity; and e_i represents the error term. According to the variables selected in this research, the threshold model is expressed in Equations (6) and (7) as follows:

$$InY_i\ =\ \theta_1[InP_i + InI_i + InPD_i] + e_i\ ,\ (Inq_i \leq In\gamma) \tag{6}$$

$$InY_i\ =\ \theta_2[InP_i + InI_i + InPD_i] + e_i\ ,\ (Inq_i > In\gamma) \tag{7}$$

We, then, combine Equation (6) and Equation (7) using a dummy variable which takes the value of one when the condition in parentheses is met, otherwise it becomes zero. This combined equation is used as the estimation equation of this research. The generalized threshold panel model has been extensively used in the field of energy consumption, renewable energy development, carbon emission, regional technological innovation level on sustainable development [48–53].

For data, the TomTom traffic index was downloaded from [9]. The 2016 TomTom traffic index covered 390 cities in 48 countries. For multivariate analysis, GDP per city as well as GDP per capita per city for 280 cities in the world for 2010 were downloaded from the World Cities Report 2016 by UNHABITAT: http://wcr.unhabitat.org/ (accessed on 20 December 2020). By dividing GDP per city by GDP per capita per city, we obtained population figures for 2010. Population density data were downloaded from the "Demographia World Urban Areas and Population Projections 10th Annual Edition 6.1: 2010.7" at http://www.demographia.com/db-worldua2010.pdf (accessed on 20 December 2020).

We were able to generate data for 164 cities with complete matching data sets of the traffic index, income per capita, population size, and population density for this

analysis. Figures 2–4 display 66 cities in the U.S. and 90 cities in Europe and 8 cities in Australia and Mexico respectively. The location of each city in the map is identified in number. Furthermore, each city has its traffic index listed. For example, Akron in the U.S. is numbered as ① in the map and has its traffic index ranked as T163 among the 164 cities. In addition, Figures 5–8 provide rank distribution of 164 countries in traffic index, density, population and income per capita.
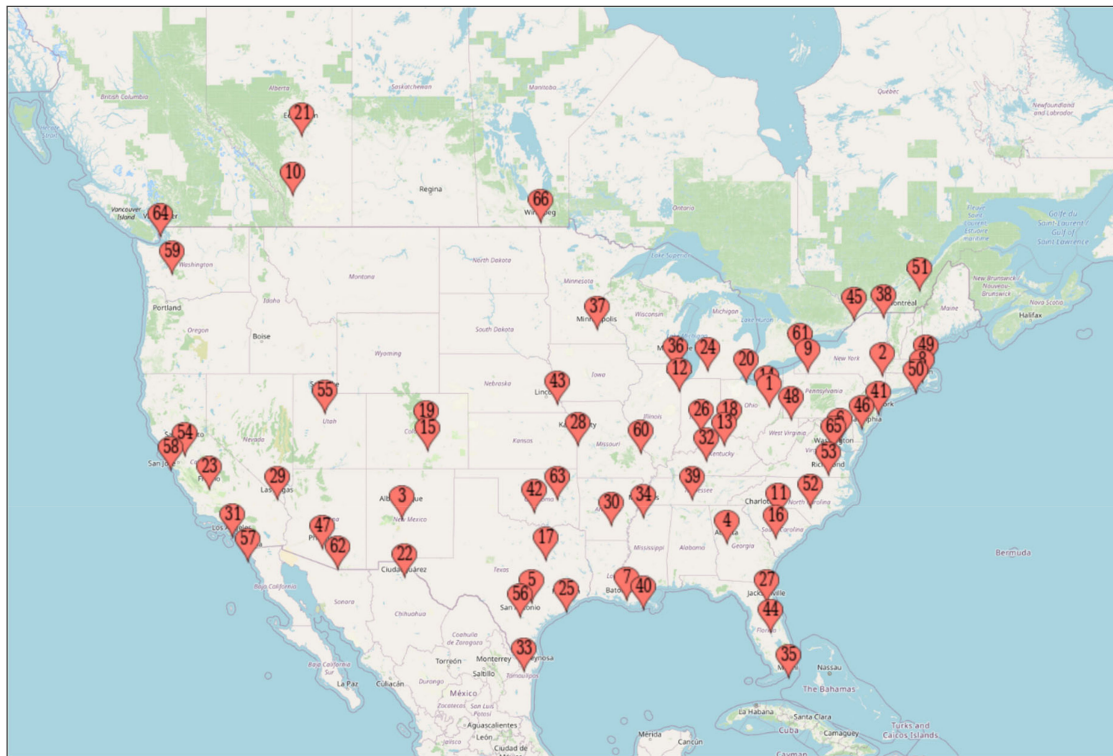

Figure 2. 66 Cities in the U.S. and Canada. 1. Akron(163) 2. Albany(T149) 3. Albuquerque(T140) 4. Atlanta(T68) 5. Austin(T84) 6. Baltimore(T123) 7. Baton Rouge(T78) 8. Boston(T58) 9. Buffalo(T140) 10. Calgary(T115) 11. Charlotte(T135) 12. Chicago(T78) 13. Cincinnati(T149) 14. Cleveland(T156) 15. Colorado Springs(T128) 16. Columbia(T153) 17. Dallas(T128) 18. Dayton(164) 19. Denver(T115) 20. Detroit(T140) 21. Edmonton(T115) 22. El Paso(T135) 23. Fresno(T123) 24. Grand Rapids(T156) 25. Houston(T93) 26. Indianapolis(T159) 27. Jacksonville(T128) 28. Kansas City(T159) 29. Las Vegas(T93) 30. Little Rock(T149) 31. Los Angeles(3) 32. Louisville(T135) 33. McAllen(T113) 34. Memphis(T135) 35. Miami(T41) 36. Milwaukee(T153) 37. Minneapolis(T140) 38. Montreal(T49) 39. Nashville(T100) 40. New Orleans(T100) 41. New York(T22) 42. Oklahoma City(T149) 43. Omaha(T159) 44. Orlando(T115) 45. Ottawa(T58) 46. Philadelphia(T100) 47. Phoenix(T140) 48. Pittsburgh(T123) 49. Portsmouth(T84) 50. Providence(T123) 51. Quebec(T93) 52. Raleigh(T128) 53. Richmond(T159) 54. Sacramento(T108) 55. Salt Lake City(T140) 56. San Antonio(T115) 57. San Diego(T68) 58. San Francisco(T11) 59. Seattle(T25) 60. St. Louis(T153) 61. Toronto(T41) 62. Tucson(T115) 63. Tulsa(T156) 64. Vancouver(T11) 65. Washington(T49) 66. Winnipeg(T93).

Figure 3. 90 Cities in Europe. 1. Amsterdam(T108) 2. Antwerp(T41) 3. Athens(T18) 4. Barcelona(T36) 5. Berlin(T49) 6. Bilbao(T140) 7. Birmingham(T78) 8. Bologna(T93) 9. Bordeaux(T36) 10. Bratislava(T84) 11. Bremen(T100) 12. Bristol(T25) 13. Brussels(T14) 14. Budapest(T108) 15. Cardiff(T68) 16. Cologne(T25) 17. Copenhagen(T100) 18. Dresden(T78) 19. Dublin(T4) 20. Edinburgh(T7) 21. Florence(T78) 22. Frankfurt(T58) 23. Freiburg(T100) 24. Gdansk(T49) 25. Geneva(T20) 26. Ghent(T128) 27. Glasgow(T49) 28. Gothenburg(T100) 29. Graz(T49) 30. Grenoble(T58) 31. Hamburg(T30) 32. Hanover(T49) 33. Helsinki(T140) 34. Karlsuhe(T84) 35. Katowice(T135) 36. Krakow(T14) 37. Las Palmas(T68) 38. Leeds(T78) 39. Leicester(T33) 40. Leipzig(T93) 41. Lille(T108) 42. Lisbon(T20) 43. Liverpool(T41) 44. Ljublijana(T140) 45. Lodz(2) 46. London(T7) 47. Lyon(T49) 48. Madrid(T84) 49. Malaga(T108) 50. Malmo(T128) 51. Manchester(T14) 52. Mannheim(T93) 53. Marseille(T7) 54. Milan(T41) 55. Montpellier(T36) 56. Munich(T41) 57. Nantes(T84) 58. Naples(T30) 59. Newcastle(T33) 60. Nice(T49) 61. Nottingham(T68) 62. Nuremberg(T41) 63. Oslo(T41) 64. Palermo(T4) 65. Paris(T14) 66. Porto(T68) 67. Poznan(T25) 68. Prague(T58) 69. Rennes(T68) 70. Rome(T7) 71. Rotterdam(T123) 72. Rouen(T113) 73. Saint-Etienne(T115) 74. Seville(84) 75. Sheffield(T22) 76. Stockholm(T58) 77. Strasbourg(T58) 78. Stuttgart(T25) 79. Tallinn(T33) 80. Thessalonica(T84) 81. Toulon(T58) 82. Toulouse(T58) 83. Turin(T84) 84. Utrecht(T128) 85. Valencia(T100) 86. Vienna(T36) 87. Warsaw(T18) 88. Wroclaw(T22) 89. Zaragoza(T115) 90. Zurich(T36).

Figure 4. 8 Cities in Central America, South America, and Australia. 1. Adelaide(T68) 2. Brisbane(T58) 3. Gold Coast(T68) 4. Melbourne(T30) 5. Mexico City(1) 6. Perth(T68) 7. Santiago(T4) 8. Sydney(T11).
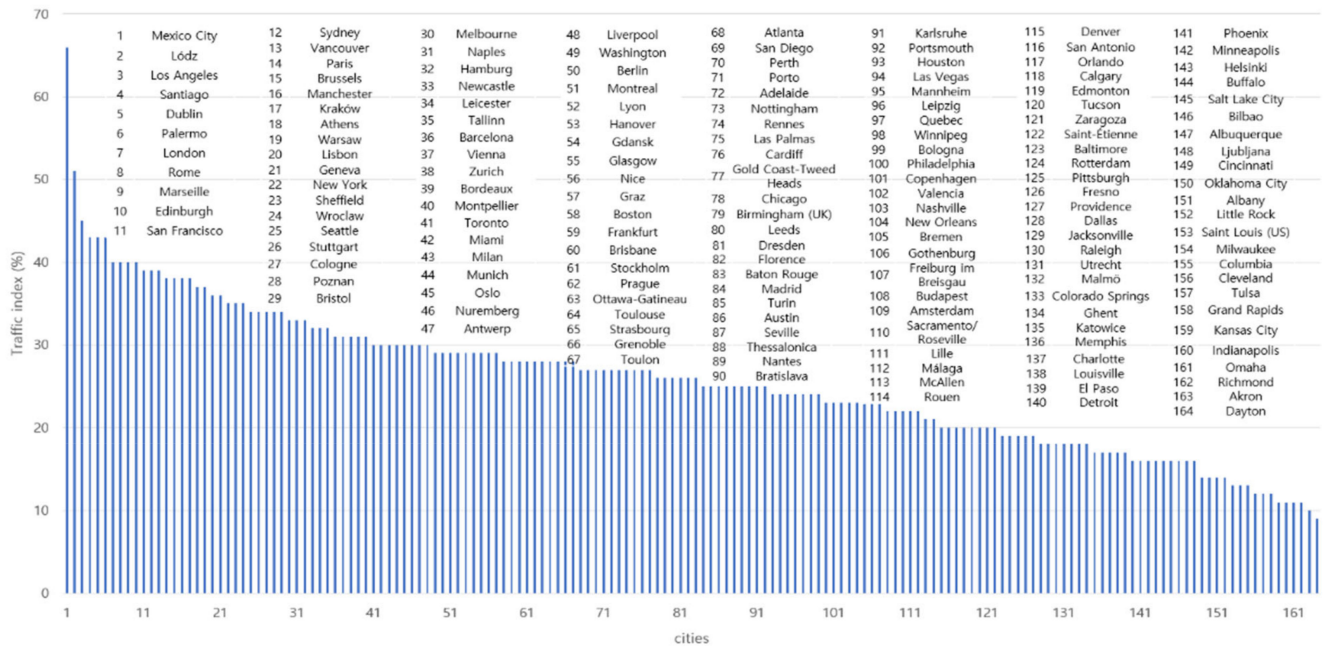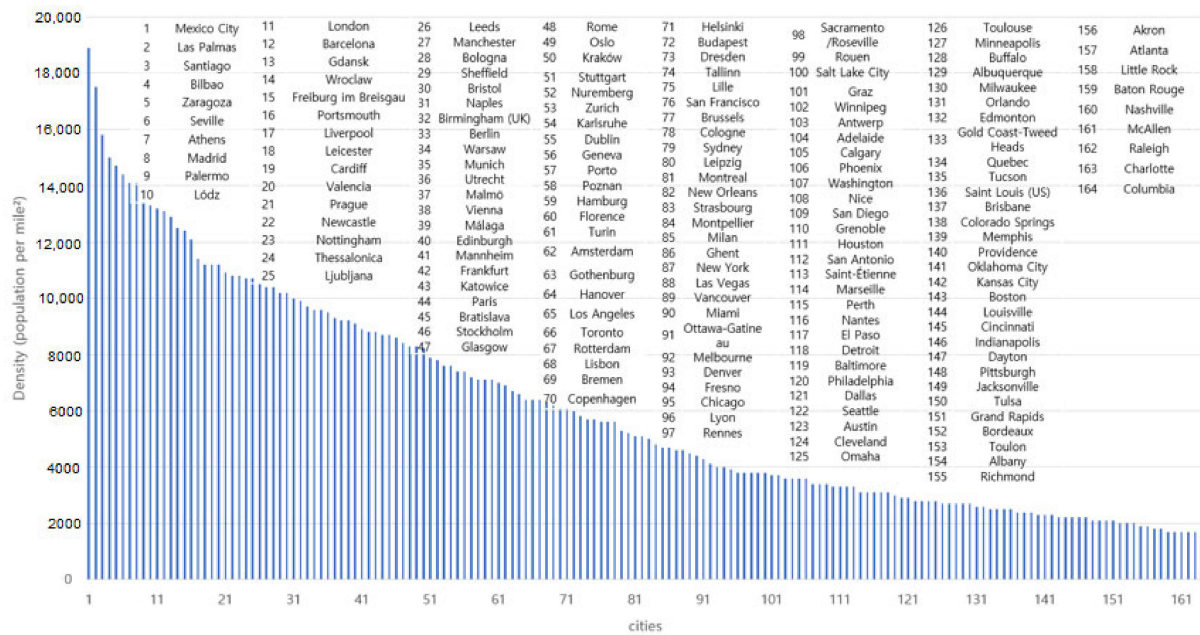

Figure 5. Rank Distribution of Traffic Index.
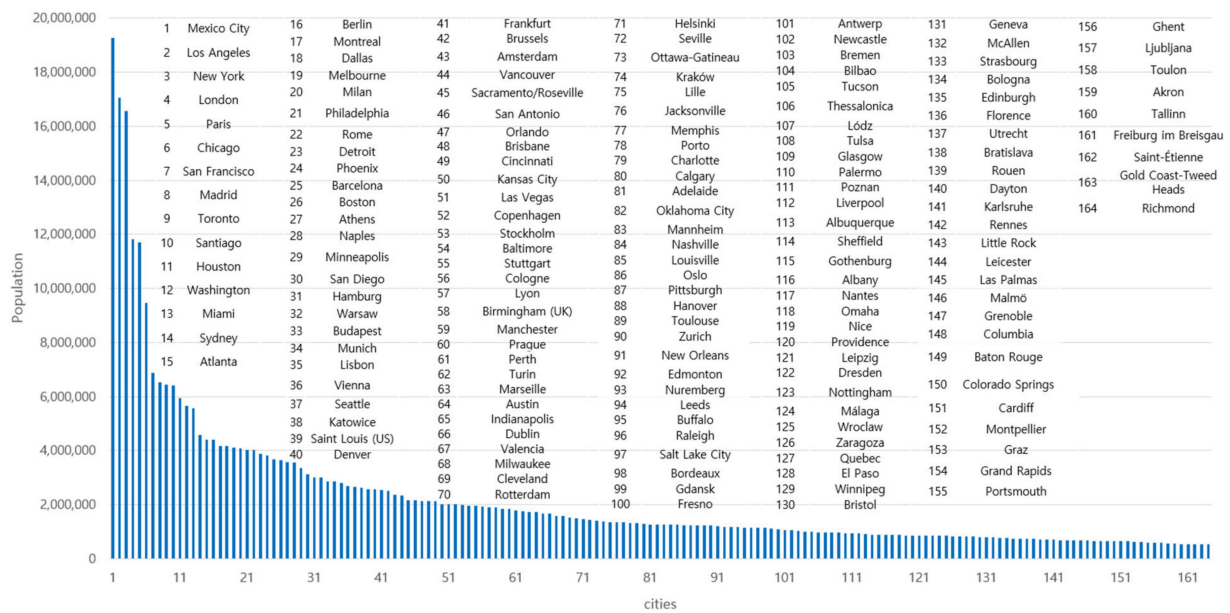
Figure 6. Rank Distribution of Density.

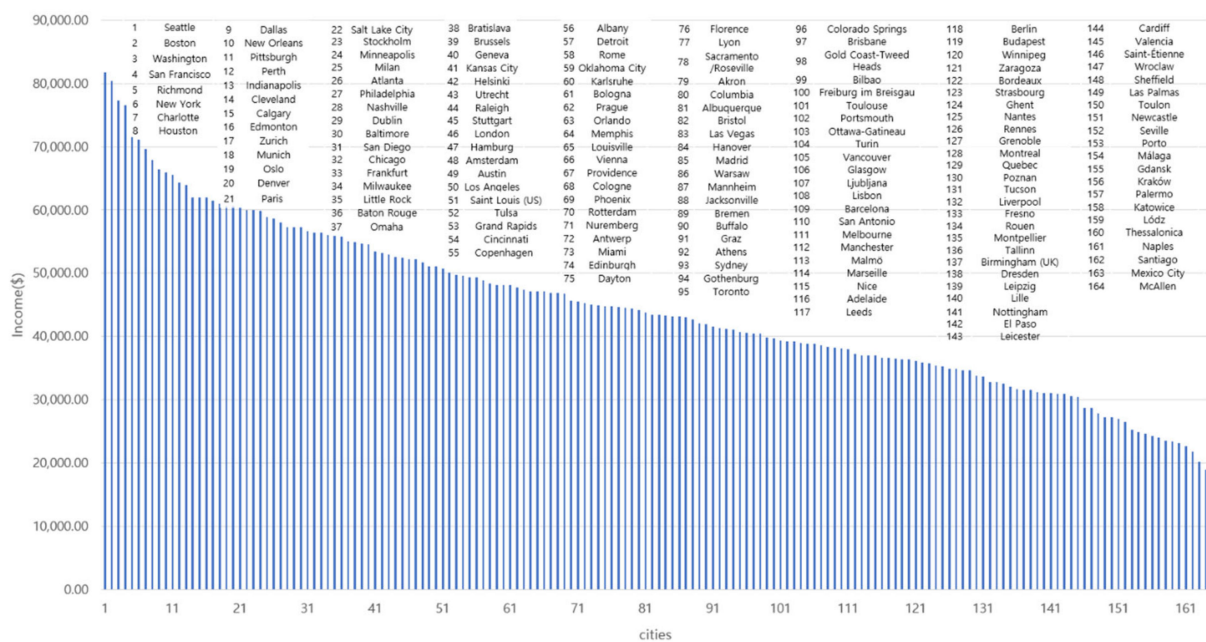**Figure 7.** Rank Distribution of Population.

Figure 8. Rank Distribution of Income.

The 164 cities were then further divided into two groups: (1) 66 U.S.-Canadian cities and (2) 98 cities in 14 mostly European countries including Germany, United Kingdom, France, Spain, Poland, Australia, Italy, Netherlands, Belgium, Norway, Switzerland, Ireland, and Mexico. The population density of 66 cities was estimated at 3139 persons per square mile, while the density of 98 cities was higher at 8169 persons, as shown in Appendix A Table A1.

The averaged traffic index for the 98 cities was again higher at 29.3 over 20.5 for the 66 cities. As for income per capita, the average for the 66 cities was higher at $52,048 over $39,636 for the 98 cities. Finally, the averaged population size for the 66 cities was again higher at 2.598 million over 1.994 million for the 98 cities.

4. Analysis of Results

The correlation analysis of both dependent variable (traffic index) and three independent variables (population, income, and density) is shown in Table 2. The results indicated that statistically significant correlation between population size and population density did not exist.

Table 2. Correlations among Variables.

	In_Traffic Index	In_Density	In_Population	In_Income
In_Traffic Index	1.000	-	-	-
In_Density	0.556 **	1.000	-	-
In_Population	0.351 **	0.123	1.000	-
In_Income	−0.257 **	−0.409 **	0.27 **	1.000

** Correlation is significant at the 0.05 level (2-tailed).

The results of the multivariate regression of the STIRPAT model on traffic congestion index shown in Table 3 indicate that all three variables generated statistically significant coefficients at less than 1% level for the aggregate group of 164 cities with a density coefficient of 0.242, a population coefficient of 0.155, and an income coefficient of −0.20. These coefficients indicate that a 1% increase in population density is expected to increase traffic congestion by 0.242%, while the effects from population and income are held constant for the 164 cities. A 1% increase in population is expected to increase traffic congestion by 0.155%. In other words, the impact from density is greater than the impact from population

size for the 164 cities. However, a 1% increase in income is expected to reduce traffic congestion by −0.2%, holding the effects from population and density constant.

Table 3. Multivariate Regression of Traffic Index by Aggregate Group of 164 Cities, Disaggregate Groups of 98 Cities and 66 Cities.

Variable\Group	Aggregate Group (164 Cities)	Disaggregate Group 1 (66 Cities)	Disaggregate Group 2 (98 Cities)
ln_Density	0.242 ***	0.311 ***	−0.004
	(0.039)	(0.077)	(0.042)
ln_Population	0.155 ***	0.207 ***	0.155 ***
	(0.027)	(0.039)	(0.035)
ln_Income	−0.200 **	−0.140	−0.137
	(0.083)	(0.142)	(0.103)
Constant	1.050	−0.972	2.632
	(0.963)	(1.553)	(1.014)
R^2	0.412	0.472	0.208
Observation	164	66	98

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

The results of the same multivariate regression of the STIRPAT model on traffic congestion for the two disaggregate subgroups displayed a substantial difference. For the 98 high density cities primarily from Europe, only the population coefficient met less than the 1% level of statistical test of significance at 0.155 which was identical to the population coefficient of whole 164 cities at 0.155. The density coefficient displayed a marginal value of −0.004, while the income coefficient was −0.137.

In contrast, the 66 low density cities in the US-Canada had both density and population coefficients meeting the statistical test of significance at less than the 1% level, while their income coefficient failed to meet the statistical test of significance. In fact, the impact of density and population became greater at 0.311 and 0.207 respectively, compared to the coefficients for whole 164 cities. On the other hand, the income coefficients realized a negative value of −0.140 while feeling to meet the statistical test of significance.

In short, the results from the aggregate group of 164 cities and the first disaggregate group of low density 66 cities indicated that density was the key determinant whereas the second disaggregate group of high density 98 cities indicated that population was the exclusive determinant for traffic congestion, as shown in Figure 9.

In order to pursue now the question of urban scaling of traffic congestion [18–22,27], population size of cities for whole 164 cities were analyzed by the use of threshold panel regression [54]. The results as shown in Table 4 indicate that the optimal number of threshold was just one with the threshold value of ln14.675 or the population size of 2.138 million inhabitants. In other words, the aggregate group of 164 cities was divided into Region 1 or 46 cities with more than 2.138 million population and Region 2 of 113 cities with less than 2.138 million population.

All three independent variables generated statistically significant coefficients at less than the 1% level for the income and density coefficients and less than 5% level for the population coefficient from the Region 1. However, only the density and population coefficients from the Region 2 met the statistical test of significance at less than the 1% level.
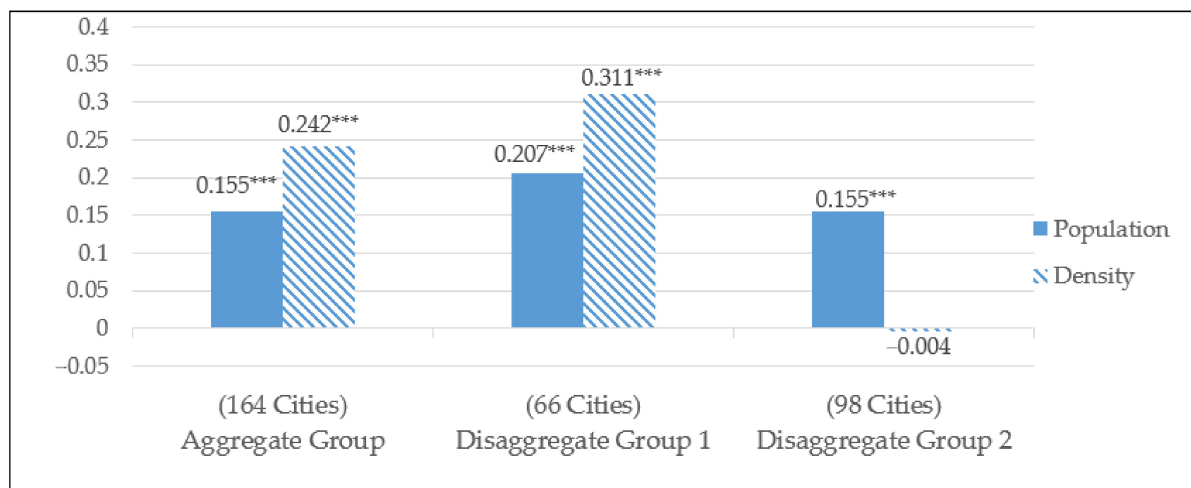
Figure 9. Density and Population Coefficient from Multivariate Regression from an Aggregate Group of 164 Cities, and Disaggregate Groups of 98 Cities and 66 Cities. *** Significant at 1% level.

Table 4. Threshold Multivariate Regression of Traffic Index for Aggregate Group of 164 Cities.

	ln_Traffic Index	Coef.	Std. Err.	z	P > z	95% Conf. Interval	
Region 1 (46 Cities)	ln_Density	0.227	0.040	5.620	0.000	0.148	0.307
	ln_Population	0.149	0.062	2.410	0.016	0.028	0.270
	ln_Income	−0.349	0.100	−3.470	0.001	−0.545	−0.152
	In_cons	2.845	1.312	2.170	0.030	0.273	5.417
Region 2 (118 Cities)	ln_Density	0.327	0.094	3.480	0.001	0.143	0.511
	ln_Population	0.209	0.080	2.630	0.009	0.053	0.365
	ln_Income	0.165	0.159	1.040	0.300	−0.147	0.477
	In_cons	−4.447	2.404	−1.850	0.064	−9.159	0.266

Number of Threshold = 1.

Comparing the population coefficient for the 46 large population cities at 0.149 to that of 118 smaller population cities at 0.209 supported a moderate scale advantage for the subgroup of large population size cities. To explain, a 1% increase of population size in the larger population city subgroup (Region 1) generated only 0.149% increase of traffic congestion, while a 1% increase of population size in the smaller population size subgroup would generate 0.209%, supporting the urban scale advantage in traffic congestion, as shown on Figure 10.

It is interesting to note that the density coefficient also displayed urban scale advantage in that a 1% increase in density generated smaller increase of congestion at 0.277% in the large population city subgroup overcome small population city subgroup at 0.327%. The same urban scaling advantage did exist on income in that a 1% increase in income generated a larger reduction of congestion at 0.349% in the large population city subgroup over −0.2% for the aggregate group of 164 cities. Finally, between density and population, density played somewhat greater impact to traffic congestion in large population subgroup as well as in small population subgroup, supporting the earlier finding from the whole 164 cities.
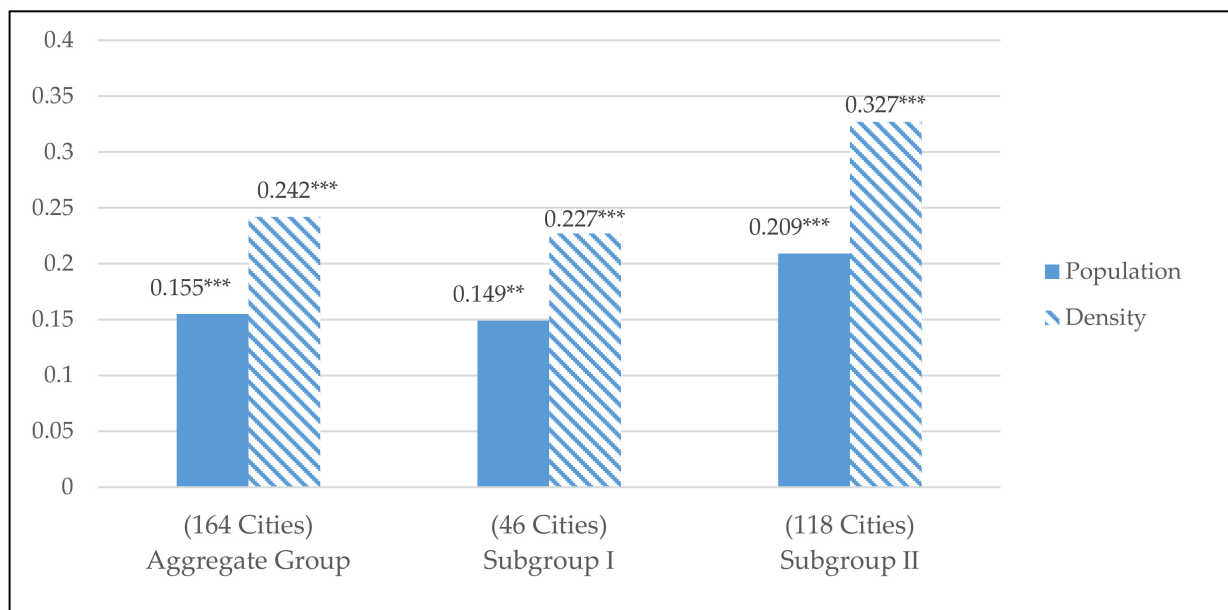
Figure 10. Density and Population Coefficient from Threshold Multivariate Regression for Aggregate Group of 164 Cities, and Population Subgroups of 118 Cities and 46 Cities. *** Significant at 1% level. ** Significant at 5% level.

5. Conclusions

The key findings of this research can be summarized as follows. First, the results of multivariate regression on traffic congestion using the STIRPAT model for the aggregate group of 164 cities from 16 countries generated the most influential factor to be density with its coefficient at 0.242 over the population coefficient at 0.156. On the other hand, the income coefficient at −0.20 reduced congestion as income per capita in cities increased. All three coefficients met the statistical test of significance.

Second, the results from the same STIRPAT analysis for the disaggregate group of 66 low-density US-Canadian cities supported the results from the aggregate group with even higher density coefficient at 0.311 and a population coefficient at 0.207, both meeting the statistical test of significance. However, the income coefficient with a value of −0.140 failed to meet the statistical test of significance.

Third, the results of traffic congestion from the other disaggregate group of 98 high-density cities primarily from Europe generated that population coefficient at 0.155 was the only influential factor for traffic congestion. The density and income coefficients failed to meet the statistical test of significance. Besides, the density coefficient carried a very low value of 0.004.

Fourth, the use of threshold panel regression enabled the division of whole 164 cities into two regional subgroups of 46 larger population cities and the remaining 118 smaller population cities. Comparing the population coefficients between the subgroup of 46 larger population size cites and the subgroup of 118 smaller population-size cities, the same 1% increase in population resulted in 0.149% and 0.209% increase of traffic congestion respectively. Put it another way, the larger city would generate about 35% less traffic congestion from the same 1% increase of population size, compared to the smaller city.

Fifth, as for the difference of impact among the three variables, the large population subgroup of 46 cities displayed the order of impact from income at −0.349, followed by density at +0.227 and population at 0.149. The smaller population subgroup of 118 cities displayed the order of impact from density at +0.327 followed by population at +0.209.

In short, combining the use of STIRPAT model and threshold panel regression, we have analyzed traffic congestion in the aggregate group of 164 cities together with four disaggregate groups of 66 low-density cities, 98 high-density cities, 46 large population cities and 118 small population cities. Among the three independent variables of density, population,

and income, statistically significant impact exercised by income was limited only in the two case of the aggregate group and the disaggregate group of large population cities. Therefore, focusing on the relative impact between remaining variables of density and population, population exercised the primary impact to congestion only in one case of the 98 high-density cities. In the remaining four cases, density has exercised greater impact over population to determine the level of traffic congestion.

These findings from the aggregate group indicate that traffic congestion in cities is influenced by varying density and population sizes. The findings from the disaggregate samples highlighted a clear difference in the critical role of density in low-density cities and the exclusive role of population size in high-density cities. Further threshold analysis by population-based subgroups in the aggregate group established the existence of both a population and density scale advantage to traffic congestion.

This study has several implications for researchers and city planners. For evaluation and planning of traffic congestion, individual cities may want to begin their analysis with an aggregate sample of cities and use all three determinants of density, population, and income since this research established statistically significant coefficients for all three factors. Next, if a disaggregate analysis between cities with low versus high density is possible, then a high-density city may wish to focus on analyzing a disaggregate group of high-density cities and use population and other determinants, because an additional increase of density in highly compact cities may have little impact on traffic congestion as suggested by Kenworthy and Laube [8] and many others. In contrast, the population scale advantage of congestion indicates that cities with a larger population may experience proportionately less congestion.

A low-density city, however, may wish to focus on a disaggregate group of low-density cities and use density as the primary determinant together with population and other variables. This research estimated that the size of the density coefficient was nearly 82 percent larger than the population coefficient from the 64 low-density cities (0.351/0.193). However, this study also indicates that using both density and population as determinants is preferred, as both variables met the statistical test of significance.

In summary, the use of aggregate analysis where high- and low-density cities are combined may generate both density and population coefficients, which may not always be appropriate to evaluate traffic congestion for individual cities with either low or high density. In other words, the results from an aggregate study with a large cross-country sample needs to be verified with appropriately designed disaggregate studies before developing specific policy implications for an individual city or country. Furthermore, empirical findings of population scale advantage on traffic congestion provide valuable supporting evidence to earlier studies of urban scaling of traffic congestion [21,22,27].

This study has several limitations that provide opportunities for future studies. Due to the unavailability of relevant data, this study was unable to account for several other possible determining factors for traffic congestion. These other factors may include automobile density, percent of the commuting population, traffic control systems, traffic regulations, road conditions, weather, and many other factors that vary across cities in multiple countries. The use of the TomTom traffic index may be another limitation in that the index cannot be verified by other data sources.

Despite these limitations, this research has established the role of both population density and population size of cities as important determining factors in traffic congestion. Equally important is that it is essential to use disaggregate samples based on density and/or population in future studies of traffic congestion.

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Appendix A

Table A1. Traffic Index, Population, Income and Density for the Total Group of 164 Cities.

Rank of Population	City	Traffic Index (%)	Population (2010)	Income per Capita (in $)	Density (Population per m²)
1	Mexico City	66	19,255,921	20,215.63	18,900
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	13,200
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	14,100
9	Toronto	30	6,418,623	40,672.78	6400
10	Santiago	43	6,393,830	21,815.31	15,800
11	Houston	24	5,920,500	67,964.36	3300
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
25	Barcelona	31	3,675,206	38,232.79	13,100
26	Boston	28	3,639,144	80,446.39	2200
27	Athens	37	3,563,607	41,327.19	14,100
28	Naples	33	3,552,568	22,693.61	10,000
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

Table A1. *Cont.*

Rank of Population	City	Traffic Index (%)	Population (2010)	Income per Capita (in $)	Density (Population per m²)
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
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	10,400
60	Prague	28	1,829,843	47,763.9	10,900
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	11,200
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	14,400
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	10,500
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	12,900
100	Fresno	19	1,081,742	32,741.63	4000

Table A1. *Cont.*

Rank of Population	City	Traffic Index (%)	Population (2010)	Income per Capita (in $)	Density (Population per m²)
101	Antwerp	30	1,053,725	45,242.08	3600
102	Newcastle	32	1,050,561	26,967.74	10,800
103	Bremen	23	1,025,580	42,069.64	6200
104	Bilbao	16	997,311	39,892.96	15,000
105	Tucson	20	980,263	33,647.09	2500
106	Thessalonica	25	957,946	23,153.73	10,700
107	Lódz	51	956,156	23,413.22	13,300
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	13,400
111	Poznan	34	934,001	33,721.75	7100
112	Liverpool	30	929,014	32,751.69	11,400
113	Albuquerque	16	887,077	43,740.28	2700
114	Sheffield	35	880,236	27,884.3	10,200
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	10,800
124	Málaga	22	834,023	24,858.77	9200
125	Wroclaw	35	832,974	28,682.28	12,500
126	Zaragoza	20	825,837	36,155.34	14,700
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	10,200
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	10,400
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	11,200
145	Las Palmas	27	658,957	27,249.89	17,500
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	11,200
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	12,100

Table A1. *Cont.*

Rank of Population	City	Traffic Index (%)	Population (2010)	Income per Capita (in $)	Density (Population per m²)
156	Ghent	18	576,408	35,359.67	4700
157	Ljubljana	16	567,097	38,662.37	10,700
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	12,400
162	Saint-Étienne	20	520,667	28,743.96	3300
163	Gold Coast-Tweed Heads	27	519,630	40,495.97	2500
164	Richmond	11	511,149	71,732.51	1900
Average	164 Cities (Total)	25.8	2,236,921	44,631.82	6145
	66 Cities (U.S.-Canada)	20.5	2,598,129	52,048.61	3139
	98 Cities (Remaining countries)	29.3	1,993,658	39,636.83	8169

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