A STATISTICAL MODEL OF REGIONAL TRAFFIC CONGESTION IN THE UNITED STATES

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ABSTRACT
Roadway congestion has been a major public policy issue in the United States for many years. There has been an ongoing debate as to whether congestion can be reduced significantly through adding additional roadway capacity, or if adding capacity would only induce traffic growth without any long-term reduction in congestion. The availability of real-time traffic data supports cross-sectional analysis across regions to study factors underlying congestion. In a regression analysis of 74 regions, it is found that more arterial capacity is strongly related to less congestion, but that more freeway capacity is not. The public policy implications are that it is critical that an adequate network of streets be constructed in growing areas rather than relying too much on a system of freeways. In already-congested areas, arterial capacity improvements likely would be more effective at reducing congestion than adding freeway capacity. Otherwise, the regression model suggests that congestion is more a sign of regional success than a problem than can be solved. Only two other independent variables were found to be highly significant in predicting congestion. Higher incomes increase congestion. Higher incomes attract population growth, which also increases congestion.

Keywords: Regional Planning, Congestion, Delay, Induced Travel

INTRODUCTION

Roadway congestion is a huge public policy issue in the United States. When Metropolitan Planning Organizations (MPOs) produce long-term regional transportation plans (RTP), the word "congestion" and the closely related term "delay" appear dozens and sometimes hundreds of times. Environmental Impact Statements (EIS) prepared for roadway projects similarly emphasize congestion and delay. Often, the core metrics in both RTP and EIS documents involve delay and congestion.

One series of research reports has framed the congestion discussion more than any other. Between 1986 and 2012, Lomax and fellow researchers at the Texas Transportation Institute have published a series of 10 reports comparing congestion across U.S. regions. Beginning with the 2001 report, these reports have been titled *Urban Mobility Report* (UMR) (*1*). Whenever each new edition of the UMR has been published, it attracts great media attention – nationally, but especially in the regions that the UMR indicates are the most congested.
Conclusions in the most recent UMR (December 2012) include: "Congestion wastes a massive amount of time, fuel and money. In 2011: ….5 billion hours of extra time… [and] …$121 billion of delay and fuel cost (*2*).

The UMR often has been cited as a justification for adding roadway capacity. However, the UMR itself has argued for a balanced set of approaches. The 2012 report includes multiple strategies including both supply and demand strategies:

- Get as much service as possible from what we have
- Add capacity in critical corridors
- Change the usage patterns
- Provide choices
- Diversity the development patterns
- Realistic expectations (*2*)

There have been many criticism of the UMR including those made an extensive recent critique by Litman (*3*). Litman's criticisms include:

- Using free-flow speeds as the basis for estimating delay is unrealistic in urban areas and even includes using baseline speeds that exceed posted speed limits
- Travel time is valued too highly.
- Induced travel from added roadway capacity is not accounted for.
- The benefits of reduced overall travel time in more compact but congested urban areas are not highlighted.

A debate about roadway capacity and induced travel has continued for many years A recent review of the research literature published on induced travel between 1997 and 2012 concluded: "Thus, the best estimate for the long-run effect of highway capacity on VMT is an elasticity close to 1.0, implying that in congested metropolitan areas, adding new capacity to the existing system of limited-access highways is unlikely to reduce congestion or associated GHG [greenhouse gas] in the long-run" (*4*). This finding does not directly contradict the UMR, which only attempts to measure regional congestion. However, it undermines the policy recommendation that adding roadway capacity will reduce congestion over the long-term.

In addition to the large debate about whether additional roadway capacity can reduce congestion, there are a wide range of more anecdotal assertions made about the relationships about regional congestion. Examples include:

- UMR
    - *Smaller urban areas with a major interstate highway* – Austin, Bridgeport, Salem. High volume highways running through smaller urban areas generate more traffic congestion than the local economy causes by itself.
    - *Geographic constraints* – Honolulu, Pittsburgh, Seattle. Water features, hills and other geographic elements result more traffic congestion than regions with several alternative routes (2).
- Cox
    - Inadequate freeway capacity – especially regions where proposed roads were abandoned after opposition arose
    - Density is a primary cause of congestion (*5*).

Those who argue for increased roadway capacity generally argue that it is economically justified because of the huge costs of congestion. The UMR often is cited in support. However, Dumbaugh uses data to argue that congestion is largely a product of an effective economy. He found a highly-significant positive relationship between congestion and regional Gross Domestic Product (GDP) per capita (*6*).

Here is a brief summary of this debate: Traffic congestion in the U.S. is a big issue. There is uncertainty about the causes. There is uncertainty about the solutions – both in terms of effectiveness and economic value. The primary area where the conversation has advanced in recent years is in the quality of the data. Instead of relying only on models of congestion in each region, as was done with the UMR prior to 2010, INRIX and TomTom now publish data on regional traffic congestion collected from vehicles. This supports much more accurate comparison across regions.

METHODOLOGY

In order to investigate that underlying causes of congestion, the INRIX Index is used as the dependent variable in a regression analysis. INRIX provides this definition of the INRIX Index:

> *The INRIX Index represents the barometer of congestion intensity. For a road segment with no congestion, the INRIX Index would be zero. Each additional point in the INRIX Index represents a percentage point increase in the average travel time of a commute above free-flow conditions during peak hours. An INRIX Index of 30, for example, indicates a 20-minute free-flow trip will take 26 minutes during the peak travel time periods with a 6-minute (30 percent) increase over free-flow* (*8*).

The 2013 INRIX index ranges from 1 to 36 (highest for the Honolulu region).

A cross sectional regression analysis was done using data from 74 U.S. regions. The regions included in this study are all regions where data are available for both the INRIX Index (the dependent variable) and the TTI Urban Mobility Study (UMR) dataset (the source of some of the independent variables). The regions and codes used in some of the graphics are listed in Table 1.

TABLE 1: Regions Included in Analysis and Codes Used in Graphics

Region	**code**	**Region (continued)**	**code**
Akron OH	Akr	Milwaukee WI	Mil
Albany NY	Alb	Minneapolis-St. Paul MN	Min
Albuquerque NM	ABQ	Nashville-Davidson TN	Nas
Allentown-Bethlehem PA-NJ	All	New Haven CT	HVN
Atlanta GA	Atl	New Orleans LA	NOL
Austin TX	Aus	New York-Newark NY-NJ-CT	NYC
Bakersfield CA	Bak	Oklahoma City OK	Okl
Baltimore MD	Bal	Omaha NE-IA	Oma
Baton Rouge LA	Bat	Orlando FL	Orl
Birmingham AL	Bir	Oxnard CA	Oxn
Boston MA-NH-RI	Bos	Philadelphia PA-NJ-DE-MD	Phi
Bridgeport-Stamford CT-NY	Bri	Phoenix-Mesa AZ	Pho
Buffalo NY	Buf	Pittsburgh PA	Pit
Charleston-North Charleston SC	CHS	Portland OR-WA	Por
Charlotte NC-SC	CLT	Providence RI-MA	Pro
Chicago IL-IN	Chi	Raleigh-Durham NC	Ral
Cincinnati OH-KY-IN	Cin	Richmond VA	Ric
Cleveland OH	Cle	Riverside-San Bernardino CA	Riv
Colorado Springs CO	COS	Rochester NY	Roc
Columbus OH	Col	Sacramento CA	Sac
Dallas-Fort Worth-Arlington TX	Dal	Salt Lake City UT	Sal
Dayton OH	Day	San Antonio TX	SAT
Denver-Aurora CO	Den	San Diego CA	SAN
Detroit MI	Det	San Francisco-Oakland CA	SFO
El Paso TX-NM	ELP	San Jose CA	SJC
Fresno CA	Fre	Sarasota-Bradenton FL	Sar
Grand Rapids MI	Gra	Seattle WA	Sea
Hartford CT	Har	Springfield MA-CT	Spr
Honolulu HI	Hon	St. Louis MO-IL	STL
Houston TX	Hou	Tampa-St. Petersburg FL	Tam
Indianapolis IN	Ind	Toledo OH-MI	Tol
Jacksonville FL	Jac	Tucson AZ	Tuc
Kansas City MO-KS	Kan	Tulsa OK	Tul
Las Vegas NV	LAS	Virginia Beach VA	Vir
Little Rock AR	Lit	Washington DC-VA-MD	Was
Los Angeles-Long Beach-Santa Ana CA	LAX		
Louisville KY-IN	Lou		
Memphis TN-MS-AR	Mem		
Miami FL	Mia		

Note: Codes are generally either the first three letters of the region's central city or the region's primary airport

Candidate independent variables from the hypotheses discussed above include:

- ln(regional population),
- ln(density),
- median household income,
- population per freeway lane mile, and
- population per arterial lane mile.

All these variables would be expected to be positively related to congestion. Other candidate independent variables based on other hypotheses about congestion include:

- transit work mode share (expected negative effect)
- proportion of housing built before 1940 (expected negative effect because of more walkable mixed use), and
- jobs/worker ratio (some of the regions in Table 1 are subregions that export workers, e.g. Riverside CA and Bridgeport CT); ratio is expected to be positively related to congestion).

A significant challenge in modeling congestion is that there are significant correlations between these candidate variables. In order to limit the level of covariance, all of the variables are first transformed as deviations from the means. Correlations between the dependent variable and the independent variables are given in Table 2.

TABLE 2: Covariance in Candidate Variables

	pop	dens	hsd inc	pop/fwy	pop/art	transit	pre-40	job/wrk
INRIX Index	**0.59**	**0.69**	**0.66**	0.17	**0.69**	**0.61**	-0.01	0.15
ln(population)		**0.59**	0.33	0.21	0.33	0.60	0.02	0.09
ln(density)			**0.54**	0.42	**0.60**	**0.76**	0.22	0.05
median hsd inc				0.02	**0.51**	**0.55**	0.12	0.16
pop/freeway lane mile					0.27	0.24	-0.26	-0.02
pop/arterial lane mile						**0.51**	-0.06	-0.04
work transit share							0.37	0.19
pre-1940 housing								0.02

Note: correlations greater than 0.50 shown in **bold**.

As shown in Table 2, the INRIX Index is strongly correlated with 5 of the variables:

- population
- density,
- household income,
- population per arterial lane mile, and
- work transit mode share.

In many cases these 5 candidate variables also are strongly correlated with each other. When regression is done with independent variables that are highly correlated, multiple problems can result including coefficients with high standard errors and low significance, and coefficients with the wrong sign or implausible magnitudes (9).

Two steps were taken to remove this multicollinearity problem. First, the 2 most highly-correlated variables were dropped from the regression model: transit work mode share and density. While density often is mentioned as a cause of congestion, it is highly correlated with population per arterial lane mile. This arterial capacity measure is also a density measure and is more central to this study than population per square mile. A sensitivity analysis is presented later in this paper with the population density variable in the model and the roadway variables excluded.

With these two variables excluded, the only high correlation between the independent variables shown in Table 2 is a correlation of 0.51 between population per arterial lane mile and median household income. Median household income also is strongly correlated with ln(population). These correlations with income were addressed by transforming the income variable by dividing median household income by ln(population). The covariance matrix for the 6 independent variables used in the initial model are shown in Table 3. The correlations range from 0.25 to 0.34. The multicollinearity issue has been addressed successfully.

TABLE 3: Covariance in Model Variables

	ln(pop)	income	pop/fwy	pop/art	pre-40	job/wrkr
INRIX Index	0.59	0.34	0.17	0.69	-0.01	0.15
ln(population)		-0.25	0.21	0.33	0.02	0.09
med hsd inc/ln(pop)			-0.10	0.34	0.10	0.08
pop/freeway lane miles				0.27	-0.26	-0.02
pop/arterial lane miles					-0.06	-0.04
pre-1940 housing						0.02

Note: The INRIX Index is the dependent variable.

The definitions of the independent variables and the data sources are:

Population – Regional population is taken from the 2010 UMR data (2). The UMR data are used to assure consistency with the other UMR-based measures discussed below, e.g. population per freeway lane mile. The variable form is ln(population/1000). 2010 UMR data were used because not all of the variables were available in the 2012 UMR data.

Median household income – Median household income data are taken from the American Community Survey for the 5-year period 2009-2013 (7). It is transformed by dividing by ln(population) to reduce collinearity as described above.

Freeway lane miles – Freeway lane miles data are from the UMR data (2). The model variable is population in thousands per arterial lane mile.

Arterial lane miles– Arterial lane miles data are from the UMR data (2). The model variable is population in thousands per arterial lane mile.

Proportion of housing build before 1940 – Many researchers studying transportation- lane use interactions have noted that housing built prior to 1940 typically is in walkable neighborhoods with small blocks, and that most housing built since then (at least until recently) is in suburban areas with less street connectivity, and often without sidewalks. Researchers have found statistically significant relationships between this variable and travel behavior. These data are from the American Community Survey for the 5-year period 2009 to 2013 (7).

Jobs/worker ratio – The jobs/worker ratio data are calculated from the 2009-2013 American Community Survey (7). Taking data for all workers who work outside the home, the numerator is the number of jobs commuted to inside the region, and the denominator is the number of workers commuting from inside the region. This variable was included to account for sub-regions like Riverside-San Bernardino-Ontario California. This region is in the dataset but includes many bedroom communities within the greater Los Angeles region. In the dataset, this region-has the smaller jobs/worker ratio – 0.87. It would be expected that this out-commuting would shift traffic (and related congestion) to outside the sub-region.

Summary statistics for these variables are shown in Table 4.

TABLE 4: Summary Statistics for Independent and Dependent Variables

	minimum	maximum	mean	standard dev
INRIX Index	1.00	35.60	9.45	7.29
ln(population)	6.38	9.85	7.47	0.77
med hsd inc/ln(pop)	5583	12103	7647	1310
pop/freeway lane mile	0.69	3.82	1.58	0.57
pop/arterial lane mile	0.32	1.37	0.57	0.16
pre-1940 housing	0.00	0.35	0.12	0.10
jobs/workers ratio	0.87	1.12	1.01	0.04

PRELMINARY REGRESSION MODELS

The regression results for the 74-region cross-sectional congestion model with the 6 independent variables listed in Table 4 are shown in Table 5.

Table 5: Regression Model Results with 6 Independent Variables

Regression Statistics	
Multiple R	0.850
R Square	0.723
Adjusted R Square	0.698
Standard Error	4.036
Observations	74

ANOVA

	df	*SS*	*MS*	*F*	*Signif F*
Regression	6	2845.41	474.24	29.11	7.09E-17
Residual	67	1091.49	16.29		
Total	73	3936.90			

	Coef.	*Std Err*	*t Stat*	*P-value*	*Low 95%*	*Up 95%*
Intercept	9.45	0.47	20.14	0.00000	8.51	10.39
ln(population)	5.10	0.72	7.05	0.00000	3.66	6.55
med hsd inc/ln(pop)	0.00184	0.00043	4.25	0.00007	0.00098	0.00270
pop/freeway lane mile	-0.47	0.90	-0.53	0.60052	-2.27	1.32
pop/arterial lane mile	19.26	3.80	5.06	0.00000	11.67	26.85
pre-1940 housing	-3.19	5.06	-0.63	0.53087	-13.30	6.92
jobs/workers ratio	14.79	11.06	1.34	0.18558	-7.28	36.86

In the model in Table 4, there are 3 independent variables with statistical significance at greater than the 99.99% confidence level:

- ln(population),
- transformed income, and
- population per arterial lane mile.

The other 3 variables are not statistically significant at the 95% confidence level. The coefficients for 2 of the variables - pre-1940 housing and jobs/workers ratio - have the expected signs. The other variable, population per freeway lane mile, not only is not statistically significant, but the sign of the estimated coefficient is negative. As freeway capacity is in the denominator, a negative coefficient suggests that more freeway capacity causes more congestion. There is no evidence in these data that freeway capacity helps to reduce regional congestion.

The model presented above includes 3 very strong independent variables and 3 weak independent variables. The regression analysis was redone with only the 3 highly-significant independent variables. The results are shown in Table 6.

Table 6: Regression Model Results with 3 Independent Variables

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.844
R Square	0.713
Adjusted R Square	0.701
Standard Error	4.018
Observations	74

ANOVA

	df	*SS*	*MS*	*F*	*Signif F*
Regression	3	2806.902	935.6341	57.9595	6.1E-19
Residual	70	1130.003	16.14289		
Total	73	3936.905			

	Coef.	*Std Err*	*t Stat*	*P-value*	*Low 95%*	*Up 95%*
Intercept	9.45	0.47	20.24	0.00000	8.52	10.38
ln(population)	5.19	0.70	7.37	0.00000	3.79	6.59
med hsd inc/ln(pop)	0.00192	0.00042	4.62	0.00002	0.00109	0.00275
pop/arterial lane mile	18.38	3.60	5.10	0.00000	11.19	25.56

Comparing the models in Tables 5 and 6, the adjusted R-squared for the 3-variable model, 0.701, is higher than the adjusted R-squared for the 6-variable model, 0.698. This suggests that the additional 3 variables add little, if any, explanatory power. Therefore, the 3 not-significant variables were dropped from further analysis.

The 3-variable model carried forward includes the population per arterial lane mile variable and does not include a population density variable. Two sensitivity analyses were done by substituting first a) population per square mile and then b) ln(population per square) for the arterial capacity variable. In both cases, the density variable is highly significant. However, the overall model fit in both cases is poorer than with the arterial capacity variable. The adjusted R-squared is 0.616 with density and 0.631 with ln(density The 3-variable model including population per arterial lane mile is the better model of regional congestion (adjusted R-squared = 0.0701).

Figures 1 and 2 are scatter plots of the model outputs vs. the INRIX Index labeled with the codes for each region In Table 1, with Figure 2 showing detail for the less congested regions.

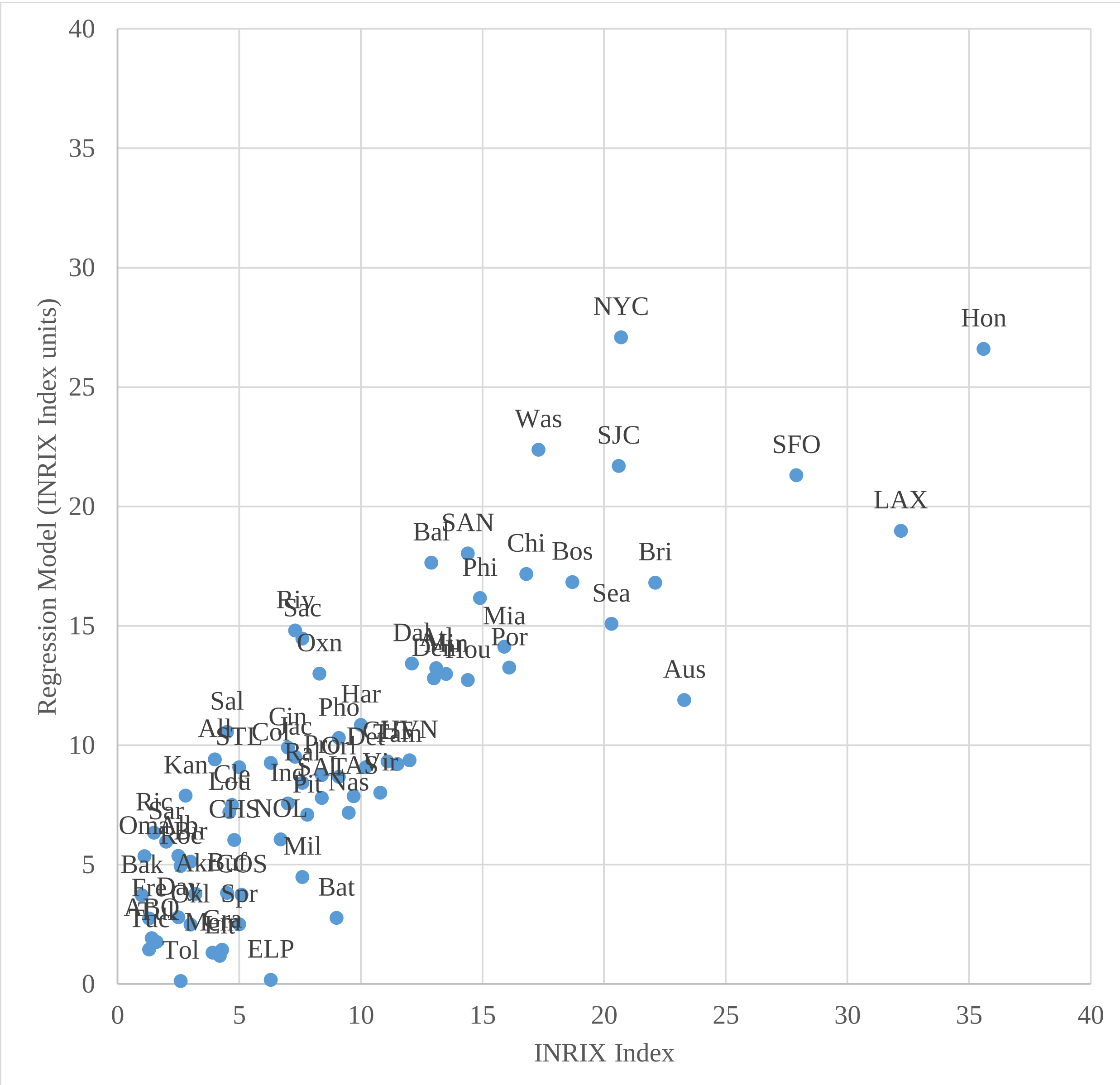

FIGURE 1: 3-Variable Regression Model Outputs vs. INRIX Index (using regional labels in Table 1)

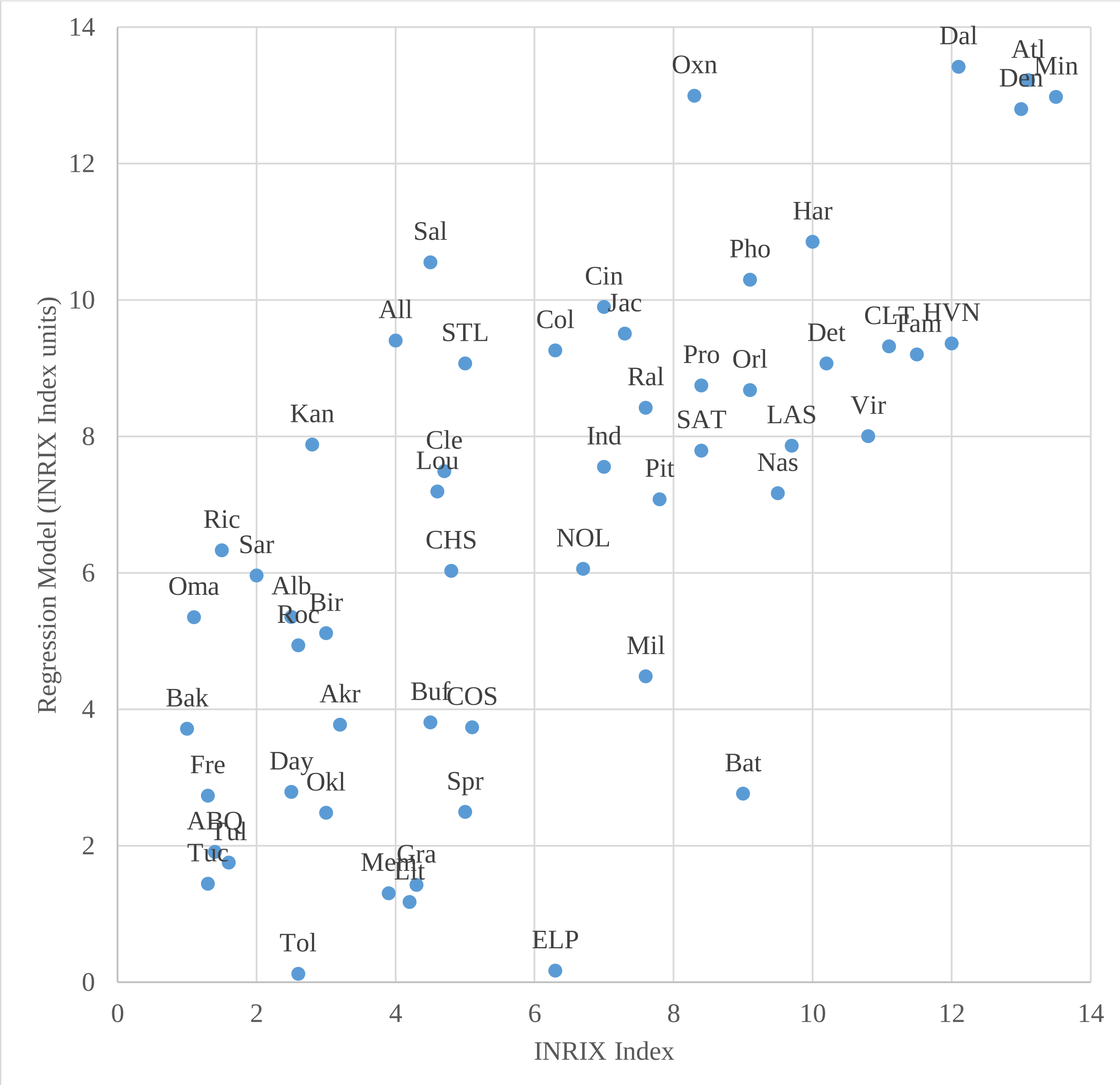

FIGURE 2: 3-Variable Regression Model Outputs vs. INRIX Index Detail (using regional labels in Table 1)

As shown in Figures 1 and 2, the model generally matches the INRIX Index well. However, the model value of Honolulu, 27, is considerably lower than the INRIX Index for Honolulu, 36. The Honolulu region has the largest population per arterial lane mile of any of the 74 regions in the dataset (i.e. the least arterial capacity per person). Both the fit with Honolulu and the overall model fit are improved by transforming this variable into a steeper relationship. Two alternative formulations of the 3-variable model were tested:

- Quadratic: Honolulu model 31, adjusted R-squared 0.724 (vs. 0.701 for the linear form)
- Cubic: Honolulu model 34, adjusted R-squared 0.732

Care must be taken in overfitting the model to a single point, so the linear model presented in Table 5 will be retained as the recommended model. However, these alternative regression models reinforce the conclusion that arterial capacity is a critical factor in regional congestion.

The underlying workings of the 3 variables in the model are illustrated using the most congested region Honolulu (INRIX Index 36, model 27) and an uncongested region Tucson (INRIX Index 1 and model 1). The regression intercept is 9.45, i.e. the model predicts a congestion index of 9 for a region with mean values for all of the independent variables. Each region has a population of about 1 million which reduces the model estimate by about 3. Therefore, the effects from the other 2 independent variables add up to -5 for the Tucson region and +21 for the Honolulu region. As shown in Figure 3, in both cases the income and arterial capacity variables work together. Tucson has lower income and more arterial capacity than average, and Honolulu has higher income and less arterial capacity than average. In both cases, the arterial capacity variable is much more important than the income variable. In the quadratic and cubic models, the arterial effect for Honolulu is even stronger.

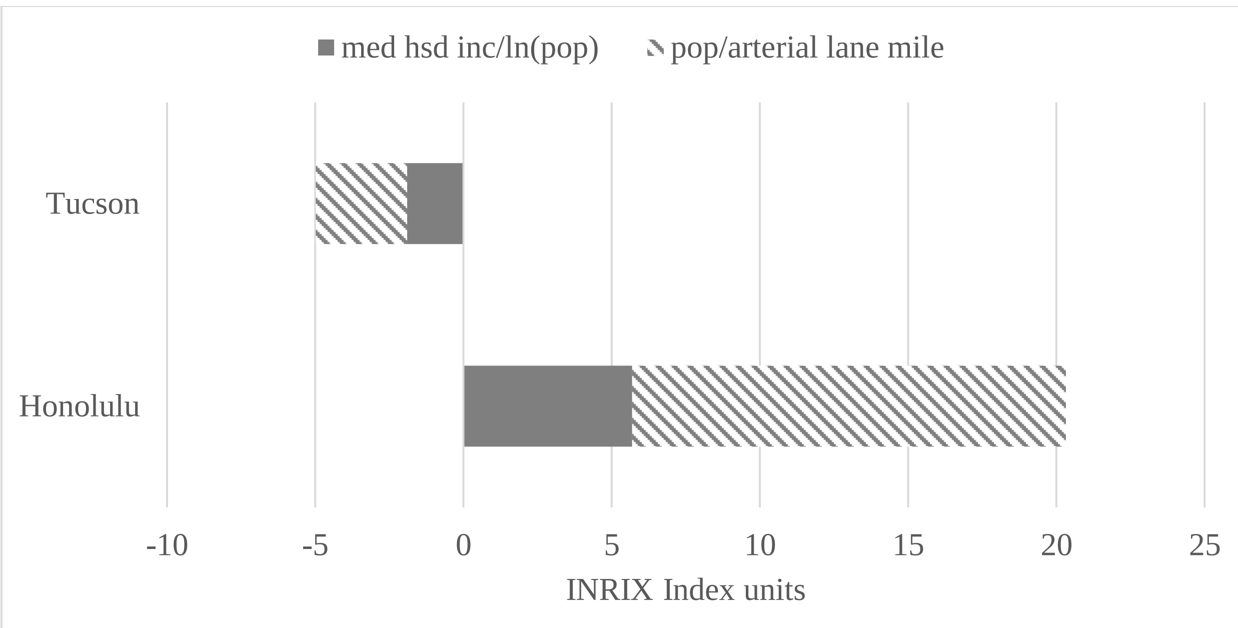

FIGURE 3: Comparison of Independent Variable Effects in Two Regions

COMPARISON OF AGGREGATE MODEL TO A DISAGGREGATE MODEL OF REGIONAL CONGESTION

As shown in Table 2, the correlation between the INRIX Index and a single regional aggregate variable is as high as 0.691 (population per arterial lane mile). The correlation of the 3-variable linear model outputs with the INRIX Index is 0.844. The correlation with the 3-variable including the cubic arterial capacity variable is 0.862. These correlations are high compared to many statistical results in social science.

How does the fit of the aggregate model compare with the fit of the model based on disaggregate roadway segment data? There is one such model – the model underlying the Texas Transportation Institute’s Urban Mobility Study (UMR). The UMR computes multiple performance measures including the Travel Time Index (TTI). At first glance, the TTI Index appears to be essentially the same value as the INRIX Index although it is expressed differently:

Travel Time Index (TTI) – The ratio of travel time in the peak period to travel time at free-flow conditions. A Travel Time Index of 1.30 indicates a 20-minute free-flow trip takes 26 minutes in the peak period (*2*).

Therefore a TTI of 1.30 would appear be equivalent to an INRIX Index value of 30. Both numbers would indicate that congested travel times are 130% of uncongested travel times. However. There appear to be differences between the two indices as is discussed below. In the most recent UMR editions, INRIX data are incorporated into the UMR model. Therefore, in order to get a clean comparison of UMR with INRIX, it is necessary to use earlier UMR congestion estimates. This requires going back to the 2008 UMR. 2008 is several years earlier than the 2013 INRIX Index numbers. However, traffic volumes have been relatively flat in most regions during this time period, so regional congestion likely was similar in both years. (For the U.S. as a whole, the Federal Highway Administration estimates that the highest year for vehicle miles traveled over the period 2005-2014 was 2007, and that the total VMT for the other years was within 2% of the 2007 level.) (11)

The UMR estimates delay on each roadway segment for peak and off-peak travel periods, and for the peak and off-peak directions. It then sums these segment-by-segment estimates of recurring delay and incident-related delay (11). Compared to the INRIX Index values, the UMR TTI values generally are higher, especially in regions with lower INRIX Index scores. For example the 2008 UMR TTI for the Tucson region is 24. Even after integrating INRIX data into the UMR, the 2012 UMR TTI for the Tucson region is 16 (vs. an INRIX Index value of 1 as discussed above). It appears that there is a fundamental difference in the way the two indices are conceptualized. The INRIX Index compares congested travel times to uncongested travel times as actually measured during off-peak travel times. It appears the UMR may be comparing modeled congested travel times to a hypothetical state where there are no traffic signals at all. In regions like Tucson that are heavily reliant on arterials, the calculated TTI is consistently high relative to the INRIX Index. The correlation between the 2008 UMR TTI and the INRIX Index is only 0.656. Figure 4 shows the 2008 UMR vs. INRIX Index scatter plot.

The correlation with the INRIX Index has increased to 0.824 in the 2010 UMR and increased again to 0.839 in the 2012 UMR. However, even with inclusion of the “dependent” INRIX Index variable as part of the UMR model, the correlation between the TTI and the INRIX Index is no better than for the 3-variable aggregate model presented above (0.844 for the linear model and 0.862 for the cubic version). This suggests both that the aggregate model is fairly good, and that there are limitations in the disaggregate approach.

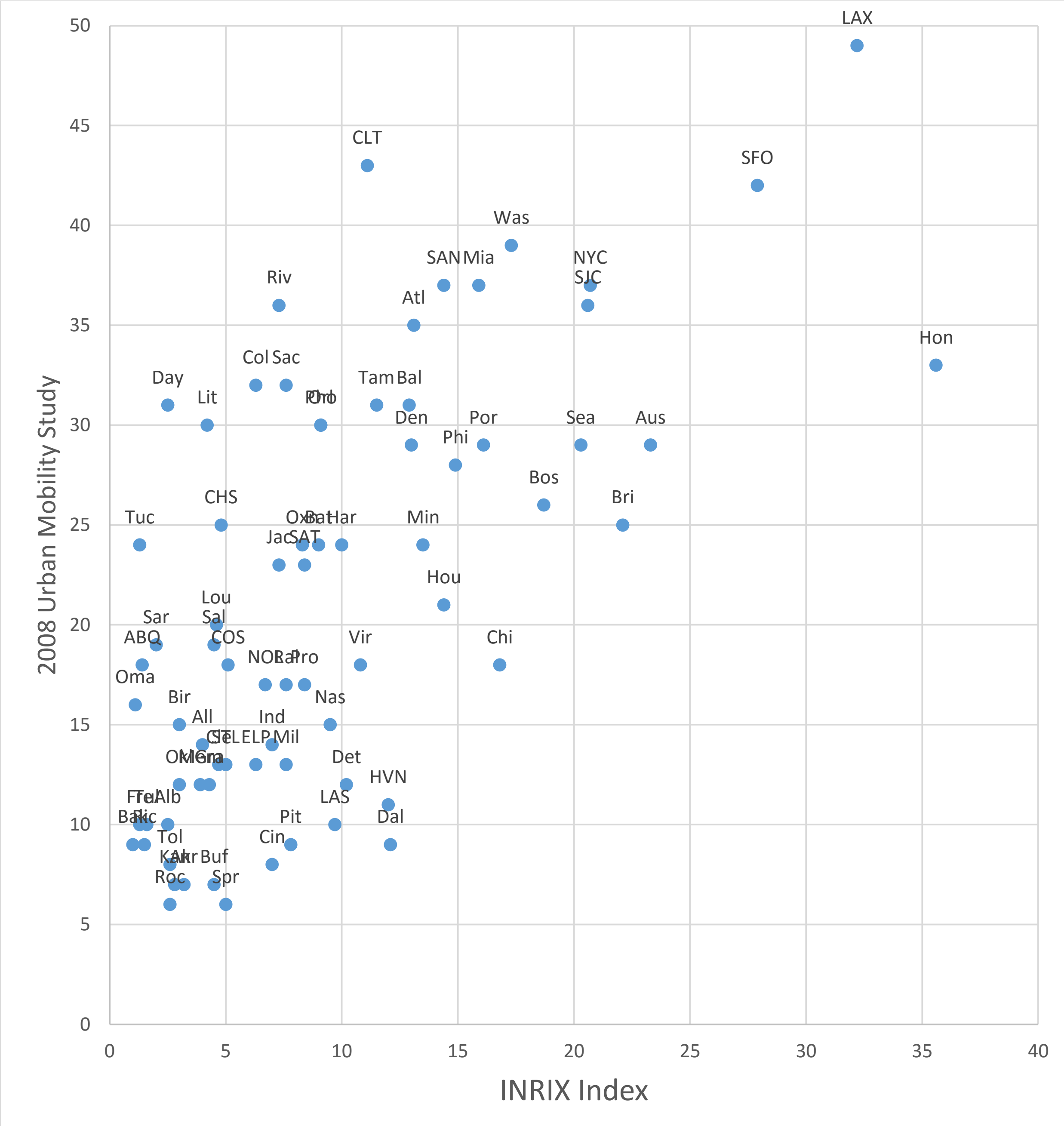

FIGURE 4: 2008 UMR TTI vs. INRIX Index (using regional labels in Table 1)

DISCUSSION

It would be logical to assume that adding up calculated delay across thousands individual roadway segments would be much more accurate than using an aggregate model with only 3 regional values. However, this assumes that delay on each roadway segment can be estimated accurately with models that treat roadway segments independently. These are called “static” models in contrast to “dynamic” models that account for interactions between roadway segments. Static models require much less computing time than dynamic versions and also converge nicely to consistent results. These are the reasons why static models are generally used instead of dynamic models However, it is well known that static models are poor at estimating congestion delay, particularly for freeway links. Here is an excerpt from *Dynamic Traffic Assignment: A Primer* that describes the limitations of static models:

> “*In a static model, inflow to a link is always equal to the outflow: the travel time simply increases as the inflow and outflow (volume) increases. The volume on a link may increase indefinitely and exceed the physical capacity (in vehicles per hour) of the link, as represented by a volume-to-capacity (V/C) ratio > 1…* ***The drawback of using V/C is that it does not directly correlate with any physical measure describing congestion (e.g., speed, density, or queue*** *[emphasis added] Traffic initially becomes congested (e.g., queuing occurs) at the end of a link because link inflow is greater than link outflow... “*
>
> *This phenomenon brings forth the question of congestion spill-back, which is not represented in a static model. At the moment that the link inflow becomes equal to the outflow (as described above), the congestion then continues to spread upstream into whichever upstream links are feeding traffic into the congested link. The outflows of these links are thus reduced, and the process repeats as described above. This queue spillback process also describes how a long queue (congested traffic) can be represented over a sequence of links in a dynamic traffic model.” [but not in static models]* (*10*)

This spillback delay cannot be estimated accurately with static models (12).

Along with the INRIX Index, INRIX also publishes a list of the most congested corridors (*8*). All of the over 200 corridors shown for the U.S. appear to be freeway corridors. These most congested freeways all experience many hours of the type of traffic “spillback” discussed in the excerpt above. In contrast arterial roadways can have relatively slow average speeds, but queues are broken up by traffic signals, and there are many more opportunities for drivers to leave one facility and shift to another roadway. Extreme congestion in the U.S. is more of a freeway phenomenon than an arterial one. Without accounting for spillback, estimated delays on these freeway links are wrong. Adding together thousands of inaccurate estimates for individual links will not result in an accurate total estimate.

CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER WORK

Regional Transportation Plans (RTP) and roadway Environmental Impact Statements (EIS) routinely show large reductions in future congestion from adding freeway capacity. These performance measures are based on static models that fail to account for spillback on freeways. In the regression model presented above, additional freeway capacity does not reduce regional congestion.

More arterial capacity strongly reduces congestion in the model. The public policy implications are that it is critical that an adequate network of streets be constructed in growing areas rather than relying too much on a system of freeways. In already-congested areas, arterial capacity improvements likely would be more effective at reducing congestion than adding freeway capacity.

Otherwise, the regression model suggests that congestion is more a sign of regional success than a problem that can be solved. Higher incomes increase congestion. Higher incomes attract population growth which also increases congestion.

The critical role of arterial capacity in reducing regional congestion suggests that research is needed into how the quality of the arterial network contributes to congestion relief (in addition to the simple quantity variable included in the regression model). In Figure 1, the model underestimates congestion in some highly-congestion regions including the Austin and Los Angles regions; but overestimates congestion in other congested regions including the New York City and Washington DC regions. Are there measurable differences between the New York City and Washington DC arterial networks vs. the Austin and Los Angeles arterial networks that make the first pair more effective than the second pair? Inclusion of local streets into the analyses also would be useful.

This paper has been focused on congestion because of its emphasis in transportation planning, and because of the availability of consistent data across regions. However, other travel metrics are at least as important, including total travel time, and the availability of transportation alternatives. Higher regional population and higher income may increase congestion, but they also can support shorter average trip lengths and more travel choices. These benefits may offset the costs of added congestion. More research is needed in these areas.

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