THE EFFECT OF BICYCLE MODE-SHARE ON CONGESTION DELAYS IN U.S. METROPOLITAN AREAS FROM 2005-2010

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Abstract

The United States has one of the most extensive vehicular infrastructure systems in the world. Road networks ranging from highways to local roads are tuned to the needs of the many personal vehicles that are used for commuting and personal trips. Unfortunately, this well-developed system suffers from an oversaturation of the existing infrastructure. Traffic congestion costs society in the form of lost time as well as environmental damage from automobile emissions. In an effort to reduce congestion, some cities have invested bicycling infrastructure to discourage automobile use in favor of cycling. Cycling presents a number of benefits over vehicular commuting. Bicycles take up considerably less space on roads, do not actively contribute to pollution, and provide exercise to commuters. Despite these benefits, U.S. cities have traditionally had low levels of bicycle mode share compared to their international counterparts. Because of this low level of traditional utilization, bicycle commuting has the potential to have a large impact on traffic congestion in metropolitan areas. This analysis examines traffic congestion and bicycle commuting mode share in 99 cities over 5 years to determine to what extent, if any, bicycle mode share can decrease vehicular congestion. By analyzing data from the Texas A&M Transportation Institute as well as the U.S. Census Bureau American Community Survey, a sizeable and in some cases significant reduction in congestion can be observed in cities with higher levels of bicycle mode share. Policy makers can use these findings to advocate for increased investment in bicycle infrastructure and pro-bicycle policies. Through these methods, reductions in congestion can be achieved for a fraction of the cost of increased vehicular infrastructure.
For Megan

Thank you for everything, including putting up with me while writing this.
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1.0 Introduction & Policy Background

Traffic Congestion

Traffic is a problem that nearly everyone has encountered in modern society. It is so much a part of daily life that many radio stations report traffic conditions every ten minutes. Traffic congestion is the result of over saturation of existing infrastructure. There are a limited number of vehicles a road system can handle. Once that limit has been reached vehicle speeds are reduced resulting in longer travel times, increased fuel consumption, and commuter frustration. Traffic congestion results from several cultural trends described below as well as the inherent nature of some road systems.

In the past century the United States population has spread out into suburban areas to find homes. As they spread out, workers increasingly rely on vehicles and public transportation to commute to urban areas. This places increased stress on highways where most people encounter traffic congestion. In addition to the more stereotypical highway congestion, urban arterial roads suffer from high levels of traffic congestion. In the United States, most cities are chronically congested for at least some part of the day resulting in the well-known "rush hour". The total cost of this congestion is very high as congestion increases commuting times for individuals, reduces the efficiency of shipping, and inflicts more wear and tear on roads.

The total costs of traffic congestion are not a straightforward calculation. Congestion costs are an opportunity cost, and therefore depend on the average salary for commuters delayed by traffic. Congestion in low-income areas such as Detroit cost less than congestion in a high-income area such as New York City. Overall though, metropolitan congestion is more expensive than congestion in rural areas, simply because of the higher income and cost of living that comes with urban areas. In addition to opportunity cost, urban areas typically have a higher price for gasoline as well as a higher marginal damage from emissions. This
higher cost for metropolitan areas translates to higher returns for potential congestion reduction.

Metropolitan congestion is a result of unique set of circumstances compared to long distance highway congestion. Populations in metropolitan areas can increase much faster than the infrastructure can be improved. High-rise buildings allow for more people to live in a smaller area but roads and public transportation cannot be as readily expanded. Expressways built within cities can take years to complete and be extremely costly despite their associated benefits (Poole & Samuel 2007). At the same time, increasing the efficiency of public transportation also proves difficult. Construction of new tracks for rail transport is not always possible (e.g., portions of the London Underground cannot be physically expanded) and increasing the availability of buses relies on already limited road infrastructure.

Local residents are only part of the total congestion problem in urban areas. As mentioned above, commuters from suburban areas often rely on personal vehicles for transportation into urban areas. These vehicles not only occupy travel lanes but need secondary infrastructure support such as parking spaces. Commuters looking for parking spaces after arriving at their destination continue to occupy travel lanes, further increasing the level on congestion. The problem comes down to limited supply combined with a constantly increase in demand.

Optimal Congestion and Traffic Reduction Policies

Many commuters would prefer a complete lack of traffic congestion but often it is impossible to achieve. In fact it would be undesirable for planners to completely eliminate traffic at all times. A complete elimination of traffic would mean that peak-period travel (rush hour) would be the maximum free flow capacity for any given roadway. Despite the attractiveness of this situation it would represent and over investment in infrastructure. The
only time that a road would be fully utilized would be a fraction of the time during the day. Money could be spent elsewhere that would give a greater benefit to society. Because of this, there is an optimal level of congestion that planners should aim to achieve and any further reduction is money misspent. Because it can be cheaper to ease congestion then to increase capacity, traffic reduction policies can be an attractive option.

Policy makers have tried a number of measures to reduce the level of traffic congestion. Carpool lanes on highways encourage voluntary reductions in the number of vehicles on the road while tolls attempt to avoid oversaturation of commonly used highways. In urban areas, some cities institute a toll for driving inside cities (London) while others attempt to increase the usage of public transportation (government subsidized public transit). Policy initiatives have also focused on alternative measures, one of which is increased bicycle usage.

The Bicycle Alternative

Theoretically, bicycle usage makes sense as a method for reducing metropolitan traffic congestion. Bikes take up much less space than vehicles and do not require nearly as much infrastructure. Both the costs and size of bicycle facilities are much smaller than their vehicular counterparts (Sælensminde 2004). A single traffic lane can be modified to be a two-way bike lane and one-lane roads can often accommodate a small bike lane. In addition to travel lanes, bicycles do not require large parking spaces. Metropolitan areas typically offer a large number of official bike racks or lockers in addition to improvised parking locations used by bicycle commuters.

The reduction in congestion is only one of the beneficial effects of bicycle commuting. Because bicycle commuting is also a form of exercise, there are potential increases in commuter health and mood (Sælensminde 2004). In addition to personal benefits, bicycle commuters do not produce pollution. Other than the energy needed produce
and maintain a bicycle, there are no emissions of sulfur dioxide, nitrogen oxides, carbon dioxide or other greenhouse gasses (Lindsay 2011). This is especially important for large cities that suffer from bad air quality. Smog and other urban pollution events are in part a result of vehicle emissions. Increased bicycle usage, as a result of reduced vehicle usage, can help alleviate some of these effects. The following section examines the factors affecting bicycle usage as well as some exploration into the practical policy goals.

2.0 Literature Review

Factors that Influence Bicycle Commuting

Predicting bicycle usage in metropolitan areas has proven difficult in past research. The prevalence of bicycle transit depends on obvious environmental variables but also more obscure cultural ones. Environmental variables include the geographic makeup of cities (extent of sprawl, hilliness, average commute distance) and weather conditions (average temperatures, average rainfall, and seasonal fluctuations). These variables are impediments to daily cycling but do not address underlying mechanisms that may change a person’s propensity for cycling. Primarily, people make the decision to engage in bicycle commuting because of all the factors that are not inherent to the natural environment but more based on social policies and society’s perception of bicycling (Moudon 2005). Social policies that encourage cycling as well as how easy and safe people perceive cycling to be all affect the longer run decisions to engage in bicycle commuting.

U.S. cities have typically lagged behind their international counterparts in alternative methods of travel. While U.S. travel is dominated by automobile, the European system has a more highly developed rail network (Givoni 2006) as well as a greater traditional level of support for bicycle commuters (Pucher 2000). Even adjacent countries like Canada have higher levels of bicycle commuting despite sharing many similarities with U.S. culture (Pucher 2006). Because of this disparity, research devoted to understanding the effect of
bicycle commuting on vehicular congestion has focused on non-U.S. cities. This has led to
dearth of data and background research on U.S. metropolitan congestion and its relationship
to bicycle commuting mode share\footnote{Mode share refers to the proportion of total commuters that utilize a particular of travel including Automobile, Public Transit, Bicycling, and Walking}.

**Who is Biking**

While bicycling is one of the most accessible means of transportation, there are significant differences between those who choose to commute by bike and those who do not. The cost of other means of transportation, like cars, is a major determinant in bicycle commuting. As the cost of maintaining a car increases from rising gasoline costs and taxes, the levels of bicycle commuting increase as it does in Canada (Pucher 2006). Direct surveys of bicycle commuters have shown that cost is one of the main determinants of bicycle usage, even in the winter season (Bergström 2003). However, U.S. cyclists would seem to be culturally different than other countries, as income across 35 U.S. cities was not observed to be positively correlated with bicycle commuting (Dill & Carr 2003). While the Dill & Carter study may have found this to be the case it is still a logical assumption that income levels would affect overall levels of bicycle usage across the U.S.

Age and gender are additional factor affecting bicycle usage. Because bicycles are a self powered mode of transport it understandable that younger people tend to make up the majority of bicycle commuters (Dill & Voros 2007, Guo et al. 2010). This seems to be less true in Europe (Pucher 2008) where there is more widespread bicycle usage for commuting and utilitarian trips. Gender is often skewed toward male riders for a variety of reasons. It has been observed that female riders prefer off road paths (Garrard 2007). This preference may be an indication of higher level or risk aversion in females and would lead to higher levels of on road male commuters (Dill & Voros 2007).
Race has been shown to also have an impact on bicycle ridership. White commuters make up the majority of all bike trips in 2001 and 2009 (Parkin. 2008, Pucher and Buehler 2011). In addition to bike trips, whites are observed to employ non-motorized transport methods more than non-white commuters (Plaut 2005). Despite the over representation of white bicycle commuters, black bicycle commuters have seen the greatest increase in total bicycle mode share over the past ten years. The reason for this increase is largely undetermined but is most likely related to differences in socioeconomic factors and cultural perceptions of bicycle commuting between races in urban areas.

Geographical Factors

The impediments to bicycle commuting in both short and long run are the natural barriers that people identify. Chief among these barriers is the commuting distance. Several studies have shown that increasing commuting distance has a significant negative effect on bicycle commuting (Parkin 2008; Hunt 2007; Zahran 2008; Stinson & Bhat 2003). Commute distance is of particular interest to U.S. cities because of comparatively greater extent of urban sprawl (Weber & Sultana 2007). This sprawl reduces the overall density of U.S. cities and increases the average distance of the average commute.

In addition to the extent of sprawl, there are land use differences between other countries and the U.S. related to the density of commercial and residential development. The density of commercial development has been shown to be positively correlated with bicycle commuting levels (Guo et al. 2010). In Canada, for instance, cities tend to be more dense with commercial development highly concentrated in city centers compared to the relatively more disperse commercial development in the U.S. This difference in average land use is cited as one of the possible explanations for the disparity in bicycle commuting between the two neighbouring countries (Pucher 2006).
The second most prominent barrier to cycling is the hilliness of a city or average commute. Several methods have been used to account for the effect of slope on commuting preference. A study in the United Kingdom focused on calculating the elevation change from place of residence to place of work (Parkin 2008) while U.S. studies have more generally attempted to characterize perceptions of hilliness in an average commute (Stinson and Bhat 2003). Interestingly, while the effect of hilliness is negative in both countries, the effect in the U.S. is far smaller (Moudon 2005). There has been little speculation but popular theories include the perception that increased hilliness contributes to the "intensity" of bicycle commuting (Heinen 2010). This may be seen as a desirable attribute for U.S. commuters and thus adds to the notion U.S. cyclists are culturally distinct.

Climate Factors

Weather affects levels of bicycle commuting for obvious reasons. Automobiles provide shelter from the elements as well as an increased level of safety in inclement weather. In addition to convenience and safety factors, cars can handle weather much more easily than bicycles. While a car's mechanics are sheltered along with their occupants, bicycle mechanisms are as exposed as their operators. This leads to increased necessary maintenance over the long run. For this reason it is not only the average yearly climate that can affect the decision to engage in bicycle commuting in general but daily weather that can affect decisions more regularly.

In general, warmer weather is associated with increased bicycle usage. Not only average yearly temperature but also seasonal temperature can have a direct effect with some commuters relying on other modes of transportation for winter months (Nankervis 1998, Noland 2006). The reason for this increase level of seasonal commuting can also be partially explained by the extent of winter maintenance on bicycle infrastructure (Bergström 2003). Because the conditions of dedicated bike infrastructure deteriorate in colder months, due to
increase resources dedicated to vehicular infrastructure, it is possible that some of the
decrease is due simply to availability.

**Non-Environmental Factors**

Completely independent of a city's natural environment are the social polices and
cultural perceptions of bicycling. Bicycle trips in the U.S. are predominantly made for
recreational purposes. Only 11% of all trips made by bicycle were associated with
commuting. Comparatively, the majority of bicycle trips in European countries are
motivated by commuting and shopping trips (Pucher 2008). European cities have a distinct
advantage over American cities for several environmental reasons. There are much lower
levels of urban sprawl in European cities compared to their U.S. counterparts (Patachini et
al. 2009). However, controlling for distance reveals the distance of European bicycle trips
are longer than those undertaken by U.S. cyclists (Pucher 2008). Other motivations for
cycling are clearly driving European cyclists to take their comparatively longer trips.

Policies in these European counties encourage the use of bicycles over private cars.
Because of this encouragement, rough estimates of bicycling levels in Europe are 3 to 27
times higher than those in the U.S (Pucher 2008). The high levels of bicycle mode share are
arguably the direct result of social policy. Prior to 1970s, bicycle usage was declining as
overall vehicle ownership rates grown in all industrialized countries (Pucher 2008). In the
1970s, European social planners began focusing on increasing the prevalence of bicycle
commuting and the trend rebounded. This increased emphasis on bicycle infrastructure was a
sustained policy that has led to the high levels of infrastructure and bicycle usage. At the
same time, European cities placed restrictions on automobile usage. The restrictions were
established to address energy, environmental and safety concerns that had arisen from
increased investment in automobile infrastructure. Thirty years of sustained policy
emphasising bicycle usage has led to this great prevalence in bicycle commuting (Pucher 2008).

Responses to Bicycle Investment

Investment in bicycle infrastructure is one of the main methods of promoting bicycle usage throughout the entire world. The argument can be made that the heavy level of investment in European bicycle infrastructure over a sustained time has lead to the high prevalence of bicycle commuting (Pucher 2008). Bicycle infrastructure is a very widely used term that encompasses everything from a bike lane to a shower at a place of business, both of which can be shown to have a positive impact on a person’s decision to commute by bicycle.

Bike lanes and paths are one of the most important parts of bicycle infrastructure. Simply investing in producing more bike friendly travel corridors induces increased bicycle traffic (Sælensminde 2004). This can be attributed to the fact that bicycle riders view riding on dedicated bike lanes and trails as less of an impediment than riding with vehicular traffic (Hunt 2006). Reduction of the perceived impediment is one of the factors central to increasing levels of bicycle commuting. In the Minneapolis-St. Paul area, adding bike paths to bridges coincided with a significant increase in the level of bicycle commuting in part because of the commuters were more easily able to cross geographic divides like the Mississippi river (Barnes 2005).

The presence of bicycle lanes alone, however, is not enough to support commuters. A level of continuity has to be reached in which bicycle commuters can follow a direct route to destinations (Noland 2006, Dill & Voros 2007). Systems with more grid-like structure tend to support bicyclists better than those that have highly congested nodes of intersections. Drawing from the previous example, providing the ability to cross geographic boundaries increases the overall function of a bicycle network and led to increased usage. U.S. cities
may therefore be more naturally adapted for bicycle commuting, as the majority are more planned and grid-like than the much older European counterparts.

Further reductions to impediments can be found in other non-travel lane specific infrastructure. These include safe parking, integration with public transportation, and hygiene facilities at destinations. The presence of safe bicycle parking is a significant factor, with some commuters equating nearly 30 minutes of travel time with the convenience of having secure storage locations (Hunt 2006). Public transportation integration is similarly essential to commuters. The ability to bring a bike on rail or bus systems adds the option for multiple modes of travel and increases the total level of bicycle commuting (Pucher 2006).

Lastly, the presence of showers and changing facilities at places of business are understandably associated with increased bicycle commuting (Abraham 2002). This increase in convenience relates back to perceived ease of engaging in bicycle commuting being a determinant factor. All infrastructure investments increase the perception of convenience and thus the overall bicycle mode share.

**Effect of Bicycle Commuting on Traffic**

With all the factors influencing the levels of bicycle commuting listed it seems it should be easy to increase levels of bicycle usage. The reality is that investments in infrastructure and other social policies can be ineffective in inducing people to switch to bikes from cars. A study done in Stockholm indicated that only 13% of all bicycle commuters listed personal vehicles as their alternative means of transportation (Börjesson 2010). This low cross-elasticity would imply a rise in bicycle commuters would not alleviate traffic congestion, rather it would potentially reduce the burden on other forms of transportation such as public buses and trains. A similar study in Melbourne indicated that only 18% of those who engage in bicycle commuting had access to a private car (Nankervis
However, residents of Stockholm and Melbourne are likely to be substantially different from residents of U.S. Cities.

To gain an accurate picture the level of cross-elasticity has to be evaluated for each area of interest. Stockholm's public transportation system employs busses, trams, light rail, subways, as well as boats making it much more extensive the majority of U.S. systems. Car ownership per capita in U.S. cities with less extensive public transportation would logically be higher indicating a greater potential cross-elasticity. Even if car ownership was similar, cultural factors can influence higher levels of bicycle commuting even in the presence of high levels of car ownership. Germany has one of the highest levels of automobile ownership compared to the surrounding countries but bicycles account for nearly ten percent of all trips (Pucher 2006).

Achievable Policy Goals

Given that investments in bicycle infrastructure and policies promoting bicycle usage may have a limited effect on congestion, it is important to have realistic goals for policy development. Investments in infrastructure have typically not resulted in expected decreases in congestion (Noland 2001). The reason for this is that increased capacity leads to a rebound effect. Increasing the availability of roads makes it easier for people live farther from population centers and increases their reliance on vehicular travel and existing roads. This has led to the concept that building our way out of congestion is not the appropriate policy response to congestion.

Knowing that continued building would not solve the problem, the focus must shift to reducing the congestion on the roads we currently have. Figure 1 below shows how speed is affected by congestion when capacity is fixed. As is evident in the graph, there are diminishing marginal returns to decreasing congestion past a specific level of service, meaning that an optimal solution exists where some congestion exists at a manageable level.
Efforts to reduce congestion within this fixed capacity allow policy makers to increase the speed at which vehicles travel and move the equilibrium for any given infrastructure closer to a free-flow state.

Figure 1: Level of Service/Speed for levels of Congestion on fixed Infrastructure

To reduce the level of congestion and increase speeds on existing infrastructure, non-vehicular modes have to be explored. Massive increases in public transportation infrastructure are similar to investments in vehicular infrastructure in that they have extremely high costs and have limits on their total capacity for improvement. However, increasing the accessibility of alternative transportation methods can reduce the pressure on the system overall without creating the incentive to overuse the system that is currently in place. There is no increase in overall vehicular capacity when bicycle infrastructure is built. It can also be implemented in stages to gradually reduce congestion if it is shown that small increases in bicycle mode-share can have an impact on vehicular congestion.

If this is indeed the case, then policies can gradually increase their support for bicycle mode share until an optimal level of traffic congestion is achieved. This can have an

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extremely high level of cost effectiveness compared to vehicular infrastructure investment because of the lower cost of bicycle infrastructure. This lower cost could theoretically allow for greater reductions in congestion because the benefit threshold for justifying increased support of bicycle mode share is much lower than for support of vehicular mode share. Overall, it is a potential policy scheme of building vehicular infrastructure to meet capacity and then tuning the level of congestion with comparatively lower cost investment in bicycle mode share.

3.0 Data

Traffic Data

Traffic data is collected by a multitude of agencies in different jurisdictions and with different levels of detail. In addition to data collected by the government, there are private organizations that collect traffic data for computer modelling and projecting traffic patterns. The University of Texas A&M Transportation Institute (TTI) releases an annual Mobility report that synthesises many of these observations into a unified data set. A large portion of the TTI data is derived from the private company INRIX. INRIX collects data on vehicle speed and location from commercial and industrial vehicles to track traffic patterns. The products it offers include real-time traffic information to private consumers as well as system-wide analyses to address traffic policy issues. TTI supplements INRIX data with usage data from the U.S. Department of Transportation and state agencies to compile estimates for usage and traffic volume.

The TTI 2011 Urban Mobility Report contains information related to traffic in over one hundred urban areas between 1982 and 2010. The urban areas included in this dataset are metropolitan statistical areas (MSA, e.g. Dallas-Fort Worth-Arlington). Relevant variables that have been collected include population, number of travellers (both during peak
usage and total commuters), total lane-miles, total daily vehicle miles of travel, and a large number of associated delay/cost calculations. Descriptive statistics are presented below.

**Bicycle Usage and Data**

Bicycle usage data is captured in the American Community Survey (ACS). This yearly survey, run by the U.S. Census Bureau, provides community level data on demographics as well as commuting and financial data. Summary files for this data is available from 2005 through 2011. Mode share, the primary means of conveyance for commuting, is captured within this survey and is divided between walking, bicycle, transit, and automobile. The survey provides one year, three year, and five-year estimates with increasing precision. For the purpose of this analysis, the one-year estimates were selected to allow for more of the traffic data to be utilized. The one-year estimates are rated to populations of at least 65,000, which is lower than the lowest metropolitan area contained in the traffic data set.

**Descriptive Statistics**

Below, Table 1 contains descriptive statistics for several of the variables in the compiled dataset. Other variables are available but are less relevant for understanding urban arterial traffic congestion. Data is on a MSA level scale, from 2005-2010. Demographic and mode share data are taken from the ACS, Traffic data is taken from the TTI. There are a total of 99 cities in the complete dataset. For most variables, data is either complete or only missing a small number of observations from the ACS. Missing data is concentrated to the earliest ACS in 2005 when the process was still being refined as well as cities that were dropped in later years.
Table 1: Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs.</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Skew</th>
<th>Median</th>
<th>Min</th>
<th>Max</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population</td>
<td>591</td>
<td>1996597</td>
<td>2601116</td>
<td>3.889</td>
<td>1095693</td>
<td>221478</td>
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<td>Male</td>
<td>591</td>
<td>980546</td>
<td>1271454</td>
<td>3.824</td>
<td>539341</td>
<td>106257</td>
<td>9243998</td>
<td>9137741</td>
</tr>
<tr>
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<td>591</td>
<td>1016050</td>
<td>1330061</td>
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<td>555264</td>
<td>115221</td>
<td>9825798</td>
<td>9710577</td>
</tr>
<tr>
<td>Caucasian</td>
<td>590</td>
<td>1390296</td>
<td>1589867</td>
<td>3.396</td>
<td>761448.5</td>
<td>141204</td>
<td>11693277</td>
<td>11552073</td>
</tr>
<tr>
<td>African American</td>
<td>590</td>
<td>278893</td>
<td>461537</td>
<td>3.826</td>
<td>128884.5</td>
<td>321</td>
<td>3398915</td>
<td>3398594</td>
</tr>
<tr>
<td>Total Commuters</td>
<td>584</td>
<td>938047</td>
<td>1208949</td>
<td>3.779</td>
<td>515292</td>
<td>83554</td>
<td>9080260</td>
<td>8996706</td>
</tr>
<tr>
<td>Public Transport</td>
<td>584</td>
<td>65373</td>
<td>273948</td>
<td>8.508</td>
<td>10572</td>
<td>497</td>
<td>2763305</td>
<td>2762808</td>
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<tr>
<td>Bike</td>
<td>584</td>
<td>4768</td>
<td>7417</td>
<td>3.188</td>
<td>1924</td>
<td>0</td>
<td>50141</td>
<td>50141</td>
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<tr>
<td>Male Bike</td>
<td>584</td>
<td>3639</td>
<td>5767</td>
<td>3.496</td>
<td>1476.5</td>
<td>0</td>
<td>41561</td>
<td>41561</td>
</tr>
<tr>
<td>Female Bike</td>
<td>584</td>
<td>1129</td>
<td>1781</td>
<td>2.687</td>
<td>401.5</td>
<td>0</td>
<td>9898</td>
<td>9898</td>
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<tr>
<td>Arterial Miles of Travel per Commuter per Day</td>
<td>591</td>
<td>18.6</td>
<td>4.485</td>
<td>0.529</td>
<td>17.9</td>
<td>8</td>
<td>32.9</td>
<td>24.9</td>
</tr>
<tr>
<td>Hours of Delay per Commuter per Year</td>
<td>591</td>
<td>29.17</td>
<td>14.933</td>
<td>1.159</td>
<td>26</td>
<td>6</td>
<td>89</td>
<td>83</td>
</tr>
</tbody>
</table>


The data show a high level of positive skew. This is due in part to the nature of the analytical question that examines traffic patterns in larger cities. This severity of this skew is greatly reduced when values are converted into log scales (Population, Total Transport Trips, Arterial Miles of Travel per Commuter per Day, Hours of Delay per Commuter per Year) as well as proportions (Demographic date and Trip Mode shares) for the regression analysis. Despite the modifications made to the data, several variables retained a substantial degree of skew requiring robust standard errors to be used for the entirety of the analysis.³

The average city size is 1,996,597 made up predominately of women and Caucasians on average. There is an average of 938,047 commuting related trips being made each day and the public transportation mode share (65,373) is more then ten times the number of bicycle mode share (4768) on average. There is a large amount of variation in the

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³ Using robust standards errors corrects for heteroskedasticity, the violation of the standard assumption in OLS that the error terms are normally distributed.
commuting data, standard deviations tend to be greater than the averages themselves which is indicative of the positive skew that exists within the data.

The dependent variable, Hours of Delay per Commuter per Year has an average of 29.17 and a standard deviation of 14.93 hours. The range is quite large, with the more congested cities achieving nearly 90 hours of yearly delay per commuter and the least congested achieving only 6. Compared to the other data there is a lower level of positive skew in the measure of Hours of Delay per Commuter per Year. The dependent variable was chosen for two reasons. First, Annual Hours of Delay was a variable constructed by the TTI that measures the delay a commuter experiences that would not have occurred if traffic were in a free flow state. Because of this the variable is independent of measures of distance (i.e., 100 miles of free flow traffic equals no delay while an hour to travel 1 mile would be a significant delay). Second, Hours of Delay per Commuter per Year is more salient to congestion reduction measures than other available measures. Travel times are a combination of distance from destination and the congestion. Policy makers are unable to decrease the former but can decrease the latter. Finally, directly measuring congestion time lost gives a more accurate assessment of the impact of bicycling.

Figure 2 below depicts the proportion of bicycle mode share compared to the average hours of delay experienced by commuters. From the graph it is clear that there are factors affecting congestion that are masking the effect of bicycle commuting. There is a distinct difference between city sizes, with larger cities averaging more congestion, but there are distinct clusters that could indicate a negative effect of increased mode share if fixed effects are included. Smaller cities actually do see an overall decrease in the level of congestion with increased levels of bicycle commuting, but the effect is muted by the broad range of the proportion of cycling in this graph. There are clearly more dramatic effects for individual clusters of smaller cities.
4.0 Proposed Models

The models in this analysis will regress the average number of hours of congestion-related delay that each consumer experiences in a given year against a number of explanatory variables. Measures of mode share as well as other controlling factors including basic demographics and city characteristics are used to isolate the effect of bicycle mode-share within the model. Fixed effects are used to account for any possible variation with cities or years that is impractical to measure or to include in this study. Below is the basic model that is used for this analysis.

\[ D_{CY} = B_0 + B_1 \times BMScy + B_2 \times Exp_1 \times CY + \ldots + B_Y \times Exp_Y \times CY + \eta_C + \eta_Y + \epsilon \]

Where \( D_{CY} \) is the delay experienced by the average computer per year for City \( C \) in Year \( Y \), \( BMScy \) is the total bicycle commuting mode-share measured for city \( C \) in year \( Y \), \( Exp \)
1 through Exp Y are the additional explanatory variables for each city/year combination, and \( \eta \) is the fixed effect for either the city \( C \) or year \( Y \).

The models below include the percentage of total bike trips to measure the direct effect of bicycle commuting on traffic. The natural log of total number of trips is included to control for cities with uncharacteristically large or small trip levels for their percentage of total bike trips. Percentage transit trips is being used to control for the level of utilization of each city's transit system as well as control for cities with highly developed transit. Higher transit utilization would lead to less traffic and including this control will help isolate the effect of bike trips.

Table 2: Regression Models

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Annual Delay per Commuter (hours)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model</td>
</tr>
<tr>
<td>Independent Variables</td>
<td>1  2  3  4  5  6</td>
</tr>
<tr>
<td>Percentage Bike Trip</td>
<td>B1  B1  B1  B1  B1  B1</td>
</tr>
<tr>
<td>Percentage Transit Trips</td>
<td>B3  B3  B3  B3  B3  B3</td>
</tr>
<tr>
<td>Percent Caucasian</td>
<td>B4  B4  B4  B4  B4  B4</td>
</tr>
<tr>
<td>Percent African American</td>
<td>B5  B5  B5  B5  B5  B5</td>
</tr>
<tr>
<td>Percent Male</td>
<td>B6  B6  B6  B6  B6  B6</td>
</tr>
<tr>
<td>Medium City Indicator</td>
<td>B7  B7  B7  B7  B7  B7</td>
</tr>
<tr>
<td>Large City Indicator</td>
<td>B8  B8  B8  B8  B8  B8</td>
</tr>
<tr>
<td>Very Large City Indicator</td>
<td>B9  B9  B9  B9  B9  B9</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>-   -   -   -   - One Way Two-Way</td>
</tr>
</tbody>
</table>

Demographic information includes the percent of the population that identifies as Caucasian or African American as well as the percentage of the population that is male. Race can be a useful indicator as males have been observed to bike more then women for a number of reasons listed above. Medium, Large, and Very Large city indicators are based on population thresholds used by the TTI Mobility report. These are included to determine if there are any threshold level effects of population on bicycle commuting. The final two
models include one and two-way fixed effects to isolate the effect of bike trips from difficult to observe city and yearly variances. Rather then including data on weather for individual cities the two way fixed effects model should capture regional climate as well a yearly changes for in climate as a whole. Measures of city hilliness are also absent as they should not change from year to year. This is in addition to the fact that past study has not shown a direct link between hilliness and determination of mode share in U.S. Cities. Correlation coefficients for the independent variables are shown in Table 3.

Table 3: Correlation Coefficients Independent Variables

<table>
<thead>
<tr>
<th></th>
<th>ln(Pop)</th>
<th>Percent Male</th>
<th>Percent White</th>
<th>Percent African American</th>
<th>ln(Total Commuters)</th>
<th>Percent Public Transport</th>
<th>Percent Bike</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(Population)</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion Male</td>
<td>-0.005</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion Caucasian</td>
<td>-0.277</td>
<td>-0.055</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion African American</td>
<td>0.135</td>
<td>-0.410</td>
<td>-0.466</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(Total Commuters)</td>
<td>0.934</td>
<td>-0.007</td>
<td>-0.314</td>
<td>0.201</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion Public Transport</td>
<td>0.556</td>
<td>-0.060</td>
<td>-0.231</td>
<td>0.001</td>
<td>0.577</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Proportion Bike</td>
<td>-0.100</td>
<td>0.317</td>
<td>0.127</td>
<td>-0.343</td>
<td>-0.126</td>
<td>0.151</td>
<td>1</td>
</tr>
</tbody>
</table>

Prior to standardizing the variables in either a log scale or percentage of total population or trips there was an extremely high level of correlation between independent variables. After standardization that correlation has largely disappeared. There is a very large correlation between the log of total population and the log of total commuters, as would be expected. As the population of a city increases the number of requisite commuting related trips also must increase holding employment relatively constant. For this reason the total population of the city is excluded from the regression equations. The total commuters variable is expected to capture this aspect of individual cities reasonably well as population is not the main focus of this analysis.
5.0 Results

Results from the regressions are displayed in Table 4 below. The first and most basic model is not statistically significant overall and explains less than 1% of the variation in the model. The more complex OLS models (2-4) are all statistically significant (F< 0.000). The level of explained variation in these models ranges from 56.6% to 58.3%. The fixed effects models (5 & 6) were both statistically significant (F< 0.000). The one-way fixed effect model (City-level fixed effects) explains 55.7% of the variation in the model and the correlation between the fixed effects and fitted values is -0.9399 indicating non-random fixed effects. The two-way fixed effects model (City/Year fixed effects) explains only 30.4% of the variation in the model and the correlation between the fixed effects and fitted values is -0.0071 indicating random fixed effects. The correlation of fixed effects to fitted values in the one-way fixed effects model indicates that fixed effects are having a significant effect on the log of Annual Hours of Delay per Commuter.
Table 4: Regression Results

<table>
<thead>
<tr>
<th>Ind. Variables</th>
<th>Model</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>5B</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage Bike Trip</td>
<td></td>
<td>-6.084†</td>
<td>0.482</td>
<td>1.349</td>
<td>0.370</td>
<td>-15.516**</td>
<td>-5.451</td>
<td>-3.988</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(3.426)</td>
<td>(2.615)</td>
<td>(2.888)</td>
<td>(2.483)</td>
<td>(5.937)</td>
<td>(5.461)</td>
<td>(5.441)</td>
</tr>
<tr>
<td>ln(Trips Commuters)</td>
<td></td>
<td>0.422***</td>
<td>0.397***</td>
<td>0.302***</td>
<td>-0.463*</td>
<td>-0.046</td>
<td>0.346</td>
<td>0.346</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.018)</td>
<td>(0.020)</td>
<td>(0.041)</td>
<td>(0.198)</td>
<td>(0.172)</td>
<td>(0.254)</td>
<td>(0.254)</td>
</tr>
<tr>
<td>Percentage Transit Trips</td>
<td></td>
<td>0.505</td>
<td>0.651</td>
<td>0.861</td>
<td>-3.139</td>
<td>-3.761*</td>
<td>-2.516</td>
<td>-2.516</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.595)</td>
<td>(0.637)</td>
<td>(0.615)</td>
<td>(2.053)</td>
<td>(1.876)</td>
<td>(1.95)</td>
<td>(1.95)</td>
</tr>
<tr>
<td>Percent Caucasian</td>
<td></td>
<td>-0.308*</td>
<td>-0.331*</td>
<td>0.189</td>
<td>0.152</td>
<td>0.242</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.135)</td>
<td>(0.137)</td>
<td>(0.178)</td>
<td>(0.205)</td>
<td>(0.178)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent African American</td>
<td></td>
<td>0.443*</td>
<td>0.393*</td>
<td>-2.024*</td>
<td>-0.327</td>
<td>1.299†</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.175)</td>
<td>(0.185)</td>
<td>(0.859)</td>
<td>(0.958)</td>
<td>(0.765)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent Male</td>
<td></td>
<td>3.917</td>
<td>3.679</td>
<td>4.442</td>
<td>3.054</td>
<td>5.272</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.485)</td>
<td>(2.537)</td>
<td>(2.916)</td>
<td>(2.912)</td>
<td>(3.275)</td>
<td></td>
<td></td>
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<tr>
<td>Medium City Indicator</td>
<td></td>
<td>0.015</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.055)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Large City Indicator</td>
<td></td>
<td>0.143*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.066)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Very Large City Indicator</td>
<td></td>
<td>0.232*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.104)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(Arterial LMT/Commuter/Day)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.249***</td>
<td>(0.195)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.027)</td>
<td>(0.249)</td>
<td>(1.146)</td>
<td>(1.277)</td>
<td>(2.482)</td>
<td>(2.913)</td>
<td>(3.219)</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td></td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>City/Year</td>
<td></td>
</tr>
<tr>
<td>Probability &gt; F</td>
<td></td>
<td>0.076</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000***</td>
</tr>
<tr>
<td>R²</td>
<td></td>
<td>0.0064</td>
<td>0.5664</td>
<td>0.5833</td>
<td>0.5881</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Within</td>
<td></td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.1211</td>
<td>0.2883</td>
<td>0.3396</td>
</tr>
<tr>
<td>Between</td>
<td></td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.5571</td>
<td>0.0557</td>
<td>0.3006</td>
</tr>
<tr>
<td>Overall</td>
<td></td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.5179</td>
<td>0.0421</td>
<td>0.3037</td>
</tr>
<tr>
<td>corr(u_i, Xb)</td>
<td></td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.9399</td>
<td>-0.7037</td>
<td>-0.0071</td>
</tr>
</tbody>
</table>

† = p < 0.1  * = p < 0.05  ** = p < 0.01  *** = p < 0.001

Demographic Results

Models 3-6 contain information on basic demographics for each city-year pair. For the non-fixed effects models (3 & 4) the relative proportion of Caucasians and African Americans were both statistically significant (p < 0.05). In these OLS models, the effect of an increase of one percentage point of the proportion of Caucasians was a decrease Annual
Hours of Delay per Commuter (decrease of 0.308% and 0.331% respectively). The effect of an increase of one percentage point of the proportion of African Americans had the opposite effect, increasing the Annual Hours of Delay per Commuter (increase of 0.443% and 0.393% respectively).

In the fixed effects models (5 & 6) the effect of the relative proportion of Caucasians was no longer significant while the effect of proportion of African Americans is only significant in the one-way fixed effects model ($p < 0.05$). In the one-way model a one-percentage point increase in the proportion of African Americans resulted in a 2.02% decrease in the Annual Hours of Delay per Commuter. In the two-way fixed effect model the effect of an increase in the proportion of African Americans was only marginally significant but was positive.

The proportion of males in the sample was not significant for any of the models. Despite the lack of significance the effects were large and positive across all the models.

**City Size Results**

The fourth model distinguishes between cities based on their size. The coefficients on large and very large cities were statistically significant ($p < 0.05$). As would be expected, the effect of a larger city is an increase in the Annual Hours of Delay per Commuter. Large cities have 0.143% more Annual Hours of Delay per Commuter than small cities while very large cities have 0.232% more Annual Hours of Delay per Commuter than small cities.

**Mode Share Results**

Mode Share results includes the variable of interest, the proportion of commuter trips made by bicycle transit trips per day, as well as total number of commuter trips per day and the proportion of commuter trips made by public transit. The effect of the proportion of bicycle trips was varied over the 6 models. In the simple model, the effect of the proportion
of bike trips was large and negative but only marginally significant. For the remainder of the OLS models, the effect of the proportion of bicycle trips was small, positive, and not significant. Thus the basic modes do not shed very much light on the effect of bicycle mode share proportion on the Annual Hours of Delay per Commuter.

For the fixed effects models, the effects of proportion of bicycle mode share are both negative. For the one-way fixed effects model the effect is large, negative, and highly statistically significant (p < 0.010). The result of a 1-percentage point increase in the proportion of bicycle mode share results in a 15.52% decrease in Annual Hours of Delay per Commuter. This would be a significant increase in the proportion of bicycle mode share as it ranges from 0-5.6% in the dataset. The coefficient two-way fixed effects model is smaller compared to the fixed effect model, negative, but not statistically significant.

**Sensitivity Analysis**

Based on the strong results in model 5 a small sensitivity analysis was conducted to test the overall robustness of the model. Arterial Vehicle Miles of Travel (AVMT) was selected as an explanatory variable that could potentially alter the results. AVMT is the closest measure of vehicle usage available in the data set. Theoretically, if including AVMT in the regression model reduces the effect of bicycle mode share then it is likely that bicycle mode share does not have as significant or sizeable effect on hours of delay experienced by the average commuter. This explanatory variable was logged to control for the skew in AVMT across cities and included in model 5 as it displayed the highest level of significance and a considerable effect on delay per consumer.

The results of this additional explanatory variable are included in table 4 as model 5b. The effect of AVMT was modest, positive, and significant indicating that a one percent increase in AVMT per commuter per day leads to a 1.25 percent increase in the hours of delay experienced per commuter per year. The effect of bicycle mode share is stunted in this
model compared to model 5 and is no longer significant, but is still negative. The size of the
coefficient is still much larger than those in other models but the lack of significance brings
up the question of endogeneity. While the effect of bicycle mode share in model 5 may be
artificially high, the size of the effect in model 5B is still relevant the policy discussion and
could be confirmed with further research.

6.0 Discussion

The results of the regression analysis presents evidence that supports the congestion
reducing effects of increasing bicycling mode share as well as some evidence indicating it
has no discernable effect. This analysis remains mostly at a high level, but the results of
Models 1, 5, and 6 indicated a negative effect on congestion of increases to bicycle mode
share. These models were both the most basic (Model 1) and the most complex (5 & 6) of all
the models run. Model 1 indicates that overall there is a negative association between bicycle
ridership and annual delay per commuter. This effect is marginally significant, not meeting
the threshold for true significance, but illustrates the basic concept that alternative mode
shares are associated with reduced congestion times.

The addition of demographic/city size details in the Models 2, 3, and 4 had the
surprising effect of reversing the overall impact of bicycle mode share. This would present
the puzzling situation where bicycle mode share actually increased the average delay per
commuter on highway and arterial roads. While there is a logical mechanism for a reduction
of delay, there is little evidence that a delay would increase. These two mode shares do not
occupy the same streets; bikes are rarely allowed on arterial streets and almost never allowed
on freeways, so adding bicycles could not be seen as competing with the available
infrastructure. Moreover, while this may be seen as presenting contradictory results, the
magnitude of the effects has to be taking into account. While Model 5 was the only model to
present statistically significant results, the magnitude of the coefficients indicating positive
effects were much smaller then those indicating negative effects. It is much more likely that these effects are statistically the same as zero, while the effects predicted in Models 1, 5, and 6 would be more likely to be significant given a more precise data set.

Returning to the more salient portions of the analysis, Models 5 & 6 build upon the basic association in Model 1 by accounting for numerous fixed effects that were impossible or impractical to quantify in this analysis. These effects include the overall climate of the cities in question as well as the variability of their terrain, progressive nature of their culture, and extent of public transportation. With these effects taken into account, Model 5 predicts a sizeable reduction in traffic due to increases in bicycle mode share. Model 6 accounts for two way fixed effects to try to determine the effect of time on the delay per commuter. In this case, the effect of bicycle mode share is reduced, but still higher in magnitude then the majority of the other models. Despite the fact that Model 5 was the only model where the effect of bicycle mode share was significant, all three salient models indicated sizeable negative effects that would lead to beneficial results for city planners.

Caveats/Limitations

While the results of the initial analysis seem somewhat significant, there remain several limitations to the analysis that must be addressed. The first and most obvious limitation is due to the precision of the data used. The ACS survey data is made available on a yearly basis but its consistency is not as reliable as would be desired. The one-year estimates are designed to give a rough picture of the overall trends in metropolitan areas with a population greater then 65,000 for this type of analysis. Three-year and five-year data releases are much more precise and should be used in more in-depth studies. At the time of this paper’s writing, there were substantially more one-year estimates (ACS began in 2005) then three of five-year estimates, which necessitated their selection. Because of the large degree of variation in the data, the standard errors are relatively large. More precise data
derived from longer averages would allow for a more precise measurement of the effect of bicycle mode share.

A second limitation to this study is the construction of the independent variables relative to the dependent variable. The mode share variables were used in the model as proportions of total transportation trips. This choice was made to normalize the level of bicycle usage across all city sizes but makes interpretation more difficult. The coefficient on bicycle usage has to be interpreted as the change that a one-percentage point increase in bicycle mode share has on annual hours of delay per commuter. Because of the relatively low level of bicycle mode share in most cities, a one-percentage point increase is massive in some cases. Therefore evaluation has to be done by other means, such as doubling the value of bicycle mode share for cities of interest or looking at an increase in standard deviations.

Extrapolation is also an issue for this data analysis. It seems logical that the initial effect of bicycle ridership would be quite pronounced. Transportation theory tells us that each vehicle added to a roadway adds to congestion time at an increasing rate. Because of this, removing cars from the road should initially have a larger effect with diminishing marginal returns as congestion levels begin to ease. The effect of bicycle mode share in Model 5 is quite high, but if it is held constant then increases in bicycle mode share would consistently reduce congestion. Not only is this illogical but it is most likely impossible. Because of this, the analysis applies mostly to marginal increases in bicycle mode share as opposed to constant direct effects.

**Policy implications**

Despite these limitations this analysis shows an observable, negative impact of bicycle mode share on the average delay per commuter on arterial roads and highways. The findings of this analysis result in two new ideas that can be used to effectively support bicycle infrastructure investment in the U.S. First, it appears that U.S. cities are different
than their foreign counterparts when it comes to mode share and its effect on congestion. Second, the effect of increased bicycle ridership can have significant effects on congestion in the lower percentages of total mode share. Because bicycle ridership can significantly impact the delay experienced by consumers cities can implement relatively modest programs to have large impacts on congestion in their area.

One of the largest obstacle preventing increased levels of bicycle investment can be the low level of observed impact bicycle infrastructure has in some countries. While some countries enjoy high levels of bicycle mode share, others have struggled to achieve meaningful increases. This problem can be due to a number of factors that reduce the motivation to use bicycles as an alternative to cars. This can result from a high standard of public transit that substitute for bicycle mode share, natural physical obstacles including weather and distance, and a relatively low level of cross elasticity between bicycle and vehicular mode share. The outcome is that increases in bicycle mode share do not coincide with reductions in congestion. However this analysis has shown that there may be something fundamentally different about U.S. cities or citizens. Increases in bicycle mode share actually do have an impact on congestion in U.S. metropolitan areas. Because of this, international examples may not be applicable to the policy discussion and could result in an underinvestment in bicycle infrastructure in the U.S.

An additional obstacle to policies that promote bicycle infrastructure is the objection that bicycle mode share will never reach meaningful levels. There is a common misconception that bicycle mode share would need to reach a threshold to begin to reduce traffic congestion. However, this analysis shows that low levels of bicycle mode share can have meaningful effects on traffic congestion without meeting some arbitrary threshold. Increasing bicycle mode share in the lower ranges, between 1 and 5 percent of total transportation trips, can lead to significant reductions in the delay people experience because
of congestion. While this analysis does not give support to the concept of an uncongested bicycle utopia, it supports the promotion of bicycle usage as one of many policies to reduce congestion.

The prospect of eliminating congestion may seem like the ultimate goal for civil engineers but the complete elimination of congestion would imply an over investment in vehicular infrastructure. As was shown in the policy background, there is an optimal level of congestion for any given roadway that minimizes potential for over investment while simultaneously limiting the amount of congestion. Investments in bicycle infrastructure may never increase to mode share levels comparable to vehicular mode share, but it has the potential to get us closer to the optimal level of congestion for an area. Moreover, the sheer amount of time, money, and land that goes into the construction of a major road compared to bicycle infrastructure makes any investment in bicycle infrastructure more attractive. If there are diminishing marginal returns to bicycle infrastructure investment then overinvestment would be comparatively cheaper than roadway construction projects.

**Future research**

As was stated previously, there are a number of limitations in this study. Data constraints made interpretation of the results difficult to generalize and applicable to specific areas of congestion within each metropolitan area. Future researchers could collect a more robust data set to make up for these shortcomings. Ideal data would include congestion data for local and collector roads in addition to arterial roads and highways. In addition to a greater extent of traffic data, more resolution in commuting data, in the form of more accurate mode share measurements, could potentially increase the reliability of the results. Utilizing ACS data from future averages could allow for more precise mode-share evaluation.
In terms of the theory behind this analysis, there still remain several questions that future research can address. First, there is the question of what truly makes U.S. commuters different from their international counterparts. While this analysis does indicate that increases in bicycle mode share lead to a reduction in congestion, their needs to be more in depth analysis about what motivates U.S. commuters to use bicycles. Previous studies have suggested that hilliness and other environmental factors affecting non-U.S. riders are less of a concern domestically, but do not suggest many positive motivations. Analysis of cities both within the U.S. and abroad for total levels of bicycle ridership could identify the factors that increase bicycle mode share in the U.S.

Another potential question is the effect infrastructure investments have on bicycle ridership. This analysis shows a decrease in congestion as a result of increased bicycle mode share but it does not address the most effective method of increasing mode share. There are a number of new policy measures and investments that are designed to increase bike mode share in several U.S. cities, ranging from increased construction of bike lanes to the implementation of bike sharing systems. Analysis of these policy measures and their effect over time is going to be essential to increasing mode share and thereby reducing congestion.

7.0 Conclusion

This analysis has attempted to demonstrate the effect bicycle mode share can have on the total hours of delay experienced by commuters per year. Data collected from both public and private sources indicate that increasing the proportion of bicycle mode share reduces the delay experienced on highways and arterial roads. This analysis can be used to support increasing the level of bicycle infrastructure investment and development in an effort to incrementally reduce congestion on more traditional roadways. Additional studies to confirm the best methods of promoting bicycle mode share as well as isolating the characteristics that make U.S. cyclists unique would complement these results in the ongoing policy discussion.


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