I WANT TO RIDE MY BICYCLE: THE RELATIONSHIP BETWEEN BICYCLE INFRASTRUCTURE AND COMMUTING BY CAR IN U.S. CITIES

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**ABSTRACT**

In American cities over the last several years, bicycle ridership and related infrastructure have surged upward as traffic congestion has steadily worsened. Policymakers see additional bicycle-specific infrastructure as a way to decrease the adverse effects of congestion on the road and promote the health and economic benefits that result from bicycle riding. While much scholarship studies the impact of bicycle lanes and trails on bicycle ridership, little research assesses the relationship between the existence of bicycle lanes and trails and rates of commuting by car. Using city-year panel data from 2007, 2009, and 2011, this analysis examines the possible association between bicycle infrastructure per square mile and rates of commuting by car in 51 U.S. cities. While fixed effects models do not provide evidence of a statistically significant relationship between bicycle infrastructure and commuting by car, regular multiple regression suggests a weak negative relationship between these two variables.
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INTRODUCTION

Traffic congestion in American cities has worsened steadily over the last several years. (Hartgen & Fields, 2006). Commuting alone by car remains the norm; in 2011, 86.6% of commuters drove to work and 88.8% of them (about 76% of total commutes) did so alone (U.S. Census Bureau, 2011). Annual rush hour delays for the average driver in urban areas with populations above one million rose by 30 hours from 1982 to 2010, more than tripling from 14 to 44. Outside of rush hour, congestion has also gotten worse, with 40% of delays occurring at non-rush hour times. The estimated cost of congestion based on wasted time and fuel is over $100 billion, or nearly $750 for every commuter in the U.S. (Shrank, Lomax, & Eisele, 2011). At the same time that congestion has worsened, cities have grown. In 2011, urban population growth outpaced that of the suburbs for first time in decades (Frey, 2012).

As a result of the challenges of city driving, commuting by bicycle has come into vogue in urban areas. Cycling is associated with many positive returns, including reductions in obesity, harmful emissions, traffic, and necessary road infrastructure; better health and economic outcomes; increased physical activity; and aggregate- and individual-level savings on car and public transportation costs (Ming Wen & Rissel, 2008; Frank, Andresen, & Schmid, 2004; Cooper, Andersen, Wedderkopp, Page, & Froberg, 2005; Garrett-Peltier, 2010; Horner, 2012; Gotschi & Mills, 2008). de Hartog, Boogaard, Nijland, and Hoek (2010) found that the benefits attributable to shifting from commuting by car to commuting by bicycle (adding 3-14 months to one’s life) outweighed the risks, given the relatively small reductions in life expectancy associated with increased inhalation of air pollution (.8 to 40 days) and the higher probability of being in a traffic accident (5 to 9 days).
As cycling has become increasingly popular, there has been a corresponding growth in bicycle-specific infrastructure, including on-street bike lanes, multiuse and bike paths, and signed bike routes. In some places, bicycle infrastructure miles have more than tripled since 2007, rising from 120 to 374 in Fresno and from 295 to 686 in Albuquerque (Alliance for Biking and Walking, 2012). People tend to feel safer when using dedicated bike facilities, making bicycling a more attractive option (U.S. Department of Transportation, 2010). As such, concurrent with the increase in bicycle facilities, the number of people who bicycle to work soared 67% between 2000 and 2011, from 466,856 to 777,585 (U.S. Census Bureau, 2000; U.S. Census Bureau, 2011).

These dynamics beg the question: has the increase in bicycle infrastructure in cities affected rates of commuting by car? Logically, it would follow that if more people are cycling, fewer must be driving, resulting in less congestion and a diminution of the other harmful effects of car use. Nonetheless, it is possible that those who choose to commute by bicycle would otherwise commute on foot or by public transportation, rather than by car. In examining whether bicycle lanes are a viable option to reduce congestion, decrease harmful emissions, and promote health in cities, I find that there is a very small but statistically significant association between increased bicycle infrastructure and decreased commuting by car. Future researchers should collect more and standardized data as well as include additional variables to control for further omitted variable bias in order to gain a fuller picture of this relationship.

**BACKGROUND**

Federal legislation influences how states and local entities spend transportation funds, shaping policies at all levels of government by stipulating the use of monies for particular
programs. Given the increases in both congestion and bicycle ridership, the relationship between commuting by car and bicycle infrastructure has important implications for the way in which funds should be distributed in the future in order to maximize the positive impact on American cities.

The $286 billion Safe, Accountable, Flexible, and Efficient Transportation Equity Act: A Legacy for Users (2005) (SAFETEA-LU) was enacted in August 2005 and expired on September 30, 2009. This legislation laid the basic federal framework for smart transportation planning, bicycle and pedestrian infrastructure, highway maintenance and improvement, and congestion mitigation. Additionally, the 2009 American Recovery and Reinvestment Act invested substantially in bicycle and pedestrian projects, with $750 million allocated for that purpose in a one-time infusion. Those funds have since been expended. Congress renewed the SAFETEA-LU funding formula several times until the law was finally replaced by the two-year $105 billion Moving Ahead for Progress in the 21st Century Act (MAP-21) in July 2012 (De Zeeuw & Flusch, 2011).

In 2011, less than 2% of SAFETEA-LU’s $40 billion in federal transportation funding went to pedestrian and bicycle programs, distributed across three major programs (De Zeeuw & Flusch, 2011). First, the Surface Transportation Program, a flexible program used largely for highway improvements, sets aside 10% for Transportation Enhancements specifically for cycling and walking projects, including bicycling and walking facilities, historic preservation, environmental mitigation, and “rails to trails” conversion of railway corridors to pedestrian and bicycle trails. Second, the Safe Routes to Schools program funds the construction of safe pedestrian and cycling routes within two miles of schools (De Zeeuw & Flusch, 2011). These routes are intended to encourage children to walk or bike to school since only 12.7% of K-8
children did so in 2009, down from 47.7% of children in 1969 (McDonald, Brown, Marchetti, & Pedroso, 2011). Finally, the Recreational Trails Program funds recreational trail creation, maintenance, and support (De Zeeuw & Flusch, 2011).

SAFETEA-LU (2005) also contained a variety of provisions specifically related to automobile congestion. These include the Real-Time System Management Program, which allows officials to monitor road conditions instantly and share information with the public to alleviate congestion and facilitate travel decision making; road pricing programs; high occupancy vehicle lanes; and the Congestion Mitigation and Air Quality Improvement (CMAQ) program, which provides flexible funding for states and local governments to spend on transportation projects in order to meet Clean Air Act requirements. Additionally, other portions of the legislation provided flexible funding that could be used for congestion reduction purposes.

SAFETEA-LU’s replacement, MAP-21 (2012), does not fundamentally alter the existing transportation framework. However, it does reduce significantly the amount of funds that must be spent specifically on bicycle and pedestrian facilities, with a possible drop of 33-66%, depending on how states choose to allocate these dollars (Hall, 2012). In terms of congestion control and in contrast to SAFETEA-LU, MAP-21 provides funding for transportation projects that reduce congestion generally but leaves it up to the states to decide whether these funds are best spent on projects such as highway improvement programs, recreational trails, safe routes to school, bicycling programs, or road improvements. In the absence of strong federal guidance, the removal of spending requirements may lead state and local governments to divert those monies away from bicycle infrastructure.

MAP-21 also combined the bicycling and pedestrian programs Recreational Trails, Transportation Enhancements, and Safe Routes to Schools into the new Transportation
Alternatives program, to be distributed via a competitive process (Hall, 2012). In combination with the overall decrease in available funds, the threat of fund redistribution away from bicycling and walking programs, and the introduction of new entities eligible to receive funds, this policy change may stymie bicycle infrastructure projects. It is important to note that lawmakers have disproportionately targeted bicycle and pedestrian funds for rescission. For instance, in 2010, Transportation Enhancements and CMAQ funding made up 7.3% of state Departments of Transportation funding but comprised 44% of funds rescinded that year (Alliance for Bicycling and Walking, 2012). In fact, 21% of total Transportation Enhancements funding has been rescinded since 1992 (Alliance for Bicycling and Walking, 2012).

States and localities enact a variety of policies to make cycling a more attractive option for commuters, including public information activities; publicly available bicycle maps; bicycle master plans; “complete streets” policies, where all users of streets must be accommodated; advisory committees; bicycle-friendly legislation, including passing distance laws; bicycle parking spaces; “share the road” campaigns; and statewide rides; among others. Even so, states spent only 1.6% of federal transportation dollars on bicycling and walking from 2006-2010, or just $2.17 per capita (Alliance for Bicycling and Walking, 2012).

Clearly, federal, state, and local policy play a large role in determining the trajectory of transportation planning. For cities that wish to reduce their congestion due to excessive automobile traffic, it seems logical to assume that investing in bicycle infrastructure would cause people who ordinarily drive to work to take advantage of the opportunity to commute by bicycle. But it is also possible that those who use bicycle infrastructure are substituting for walking to work or taking public transportation, in which case there would be no correlation. Currently,
there is no demonstrated link between bicycle infrastructure and commuting by car; this paper explores that relationship.

**Literature Review**

Understanding why people choose to commute by car is integral to the study of any policy intended to mitigate congestion. Commuting to work by car is the default in the United States; the National Household Transportation Survey (NHTS) reports that, from 1969-2009, the percentage of people commuting to work in privately-owned vehicles remained steady at around 90%, with 151 million people commuting to work by privately-owned vehicle in 2009. Car commuters rarely cycle to work; only 1% of commuters who usually drove alone commuted by bicycle on the day recorded. (U.S. Department of Transportation, 2009).

Much of the extant research on bicycle infrastructure and commuting focuses on the former’s effect on commuting by bicycle rather than on other modes. Research suggests that cycling levels and the miles of available bicycle paths and lanes are positively correlated. Using data from 90 of the 100 largest U.S. cities, Buehler and Pucher (2012) found that cities with more bicycle paths had significantly higher bicycle commuting rates. Nelson and Allen (1997), using a cross-sectional dataset of 18 U.S. cities, found that the addition of one mile of bicycle paths or lanes per 100,000 residents was associated with a .069% increase in the number of commuters who cycle to work. A cross-sectional analysis of data from 35 cities across the U.S. expanded upon Nelson and Allen’s work, finding that adding a mile of bicycle lanes per square mile in cities was correlated with an increase of approximately 1% in the bicycle commuting rate (Dill & Carr, 2003).
Evidence suggests that increasing funding for bicycle infrastructure is associated with an increase in the number of cyclists on the roads (Garrard, Rose, & Lo, 2008; Pucher & Buehler, 2007; Pucher & Buehler, 2008). Gotschi and Mills’s (2008) cross-country study found a positive relationship between metropolitan investment in bicycling and the level of bicycle travel.

Researchers have also found that car commuting choice is associated with a number of individual-level characteristics. In 2011, researchers analyzing the NHTS found an inverse relationship between car ownership and levels of walking and bicycling (Pucher, Buehler, Merom, & Bauman, 2011). Dargay and Hanly (2007) found that working part time and living in a single-person household were negatively related to commuting by car, and that households containing more than one adult and/or self-employed individuals were more likely to commute by car. Women make up 44% of car commuters while men make up 56% (U.S. Department of Transportation, 2009). Environmentally conscious households tend to drive 450 fewer miles per year than less “green” ideologically inclined households (Kahn & Morris, 2009). In addition, living in an urban or diverse land use area is negatively correlated with commuting by car (Winters, Friesen, Koehoorn, & Teschke, 2007).

Cyclist commuters also tend to share some common demographic features. Male cyclists far outnumber female cyclists, with 76% of trips made by men. Researchers found that, in cities, men accounted for all of the growth in cycling from 2001 to 2009 (Pucher, Buehler, & Seinen, 2011). Women tend to prefer off-road paths over on-road lanes or roads with no bike facilities (Garrard et al., 2008). Plaut (2005) found that those who choose to bike or walk to work tend to be younger and better educated. Kahn and Morris (2009) found that living in a “green” voting district is associated with choosing more environmentally friendly commuting options, including the use of a bicycle to get to work.
The literature is unclear as to the relationship between income and commuting choices. Plaut (2005) found income and car commuting to be positively associated. However, Krizek, Barnes, and Thompson (2009), using census data from 1990 and 2000 in the Minneapolis-St. Paul area, found income to be positively correlated with bicycle commuting for those with annual incomes below $15,000 or over $50,000. Dill and Carr (2003), meanwhile, found no association between income and cycling rates.

Geographic considerations also seem to have an influence on commuting choices, but once again, some research findings are contradictory. Bergstrom and Magnussen (2003) found that, in winter, there is a 47% decrease in bicycle trips and 27% increase in car trips, and Winters et al. (2007) found the number of days with freezing temperatures to be negatively related to cycling.\(^1\) In contrast, Yang, Roux, and Bingham (2011) found that people walk and cycle to work, school, and other destinations less in the southern United States in general, which has a warmer climate than the rest of the country.

Safety on the roads is another important determinant of commute mode choice. Dill and Voros (2007) found that the majority of respondents to a phone survey on bicycling attitudes wanted to cycle more and cited the lack of bike lanes or trails as the second biggest reason for why they did not. Jacobsen (2003) found an inverse relationship between levels of cycling and walking and the likelihood of being struck by a motorist. This suggests that the more cyclists and walkers there are on the road, the more likely it is that motorists will be alert to the associated dangers and risks and modify their behavior accordingly. A review of existing bicycle infrastructure research found that bicycle-specific infrastructure is associated with the lowest risk of bicycle injuries and crashes; that sidewalks and multi-use trails are associated with the highest risk; and that major roads are more hazardous than minor roads (Reynolds, Harris, Teschke,\(^1\) While the Bergstrom and Magnussen survey was conducted in Sweden, which has harsher winters than most of the...
The National Bicycling and Walking Study found that dedicated cycling lanes help to foster a feeling of safety among cyclists and may be necessary in order to realize substantial increases in bicycle ridership (U.S. Department of Transportation, 2010). More specifically, researchers found a strong correlation between bikeway network size and bicycle commuting. Dill and Voros (2007) found that people listed “too much traffic” as the biggest reason why they did not cycle more often, and Tilahun, Levinson, and Krizek (2007) found that individuals would cycle up to 23 minutes out of their way to use an off-road bike lane rather than a road with traffic and side parking.

Commute length may play a role in commuting choices as well. Over the last several decades, commutes have lengthened in both distance and time (U.S. Department of Transportation, 2009). Plaut (2005) found that people are more likely to commute by car when their commutes are longer. Similarly, Cervero and Duncan (2003) found that people with shorter commutes are more likely to cycle to work.

The literature suggests that other assorted factors may be important for this analysis. Specifically, gasoline prices are negatively related to the number of trips by car and positively related to the number of trips by public transportation, foot, and bike (Buehler, 2010). Additionally, Lintanakool, Dijst, and Schwanen, (2006) found that the availability of public transportation options is negatively related to car commuting. Areas with shorter travel times due to compact infrastructure tend to have higher commuter cycling rates (Zahran, Brody, Maghelal, Prelog, & Lacy, 2008). Diversity in the land use due to mixed residential areas and commercial properties is also related to more cycling to work (Cervero & Duncan, 2003).

The studies cited above are correlational. This paper improves upon the existing literature by using fixed effects to control for characteristics within cities that do not change over time and
for characteristics common to all cities that do change over time. This analysis also studies a different dependent variable: commuting by car. There is little research on the tradeoff between commuting by car and commuting by bike or on whether increased bicycle infrastructure causes individuals to substitute driving to work with riding a bike.

**Conceptual Framework and Hypothesis**

Figure 1 shows factors that, as discussed in the literature review, are related to the dependent variable, commuting by car, and key independent variable, miles of bicycle infrastructure per square mile. These can be broken down into two main categories: individual-level factors and city-level factors. The individual-level characteristics that have an impact on whether one commutes by car are primarily demographic and include gender, age, race, poverty status, education, household size, family composition, car ownership, and income. Individual determinants of commute choice also include the length of one’s commute (since people with shorter commutes are more likely to not drive to work) and political inclination (more liberal, environmentally conscious individuals are more likely to commute by bicycle).

City-level factors that influence commute-mode decisions include the availability of bicycle infrastructure, population size, city size, the existence of bicycle-friendly policies, transportation funding levels, safety, and gas prices. A city’s weather and geography also play roles, with factors like cold and hot weather days, precipitation levels, steepness of the roads (or bike paths), and concentration of residential, commercial, and other properties in a central location influencing commute choices. Additionally, commuting choices are related to the range of available commuting alternatives (i.e., driving, taking public transportation, walking, riding a
bicycle, etc.). Higher congestion levels may also discourage driving and promote alternative transportation options.

**Figure 1: Factors Affecting the Decision to Commute by Car**

I hypothesize that the relationship between commuting by car and bicycle infrastructure is negative, with fewer people commuting by car when there is an increase in bicycle infrastructure. With the addition of bicycle-friendly routes, more people may choose to bicycle to work instead of driving, since bicycle infrastructure promotes doing so. Yet, it is possible that there is no relationship between bicycle infrastructure and commuting and that, instead, those who choose to use new bicycle infrastructure would have biked anyway or are substituting commuting by bike for commuting by public transportation or foot. The substitution of commuting to work via public transportation or walking with commuting by bicycle may be particularly likely in large cities since, due to congestion, rates of commuting by car tend to be
lower than the national average and point-to-point commuting by bicycle is often faster and more convenient than commuting on foot or by public transportation.

**DATA AND METHODS**

This analysis uses a city-year panel dataset constructed using data from several different sources. Data on the dependent variable, percentage of commuters travelling by car, is available through the American Community Survey (ACS), a continuous Census Bureau survey that samples a portion of the U.S. population annually and contains a wide range of information related to respondents’ demographic characteristics. Federal and state officials use these data to allocate government resources. The ACS includes single-year, three-year, and five-year estimates that represent data collected over differing periods of time. To ensure an apples-to-apples comparison for the city-years of interest, this analysis uses one-year estimates, the data for which are collected over 12 months in areas with populations over 65,000.

Very little data exist for the key independent variable, miles of bicycle infrastructure, and what data there are were not collected by a government agency. There is one reasonably reliable source: the Alliance for Bicycling and Walking (ABW), which operates a biannual benchmarking project funded by the Centers for Disease Control and Prevention, American Association of Retired Persons, and Planet Bike. These data are available for 2007, 2009, and 2011 and include city-level information on infrastructure and transportation spending for the 51 largest U.S. cities in a given year. They are collected through two surveys that reach out to city staff, state Departments of Transportation, metropolitan planning organizations, and advocacy organizations. The dependent variable for the regressions, bicycle lane miles per square mile, was created by dividing each city-year’s estimated number of miles of bicycle infrastructure by
the city’s square miles as collected by the ABW survey to ensure an apples-to-apples comparison.²

My initial sample size was 153: 51 cities for three years. In 2007, ABW was unable to obtain data from nine of the 51 cities, bringing the sample size down to 144. Also, in 2007 ABW collected data from Amarillo, Texas but did not collect data from that city in any other years, therefore it was excluded from the final dataset because in order to be included in my fixed effects models, I require at least two data points for each city. The final sample size is 143 city-year observations.

All monetary variables, including median household income and state average annual gas price, were inflation adjusted to 2011 dollars using the average Consumer Price Index for a given calendar year as determined by the U.S. Department of Labor Bureau of Labor Statistics.

This analysis uses Ordinary Least Squares (OLS) regression with city and year fixed effects. The fixed effects specification controls for static unobserved characteristics unique to a particular city as well as for time-varying unobserved characteristics common to all cities in a given year. This technique reduces the potential for omitted variable bias in the model’s parameter estimates. Per the discussion in the literature review and conceptual framework, the time varying control variables summarized in Table 1 below are plausibly correlated with miles of bicycle infrastructure and the rate of commuting by car. These variables are included in the model to in order to further reduce omitted variable bias.

² City size in square miles as reported in the 2000 Census was used for the the 2007 and 2009 ABW Surveys while city size in square miles as reported in the 2010 Census was used for the 2011 ABW Survey. The boundary lines and metropolitan areas of several cities changed significantly and so are included as a control.
The equation for the regression can be expressed as:

\[
commutecarrate_{it} = \beta_0 + \beta_1 b i kelanespermile_{it} + \beta_2 \text{population}_{it} + \\
\beta_3 \text{citysize}_{it} + \beta_4 \text{weather}_{it} + \beta_5 \text{economic factors}_{it} + \beta_6 \text{safety}_{it} + \\
\beta_7 \text{public transit}_{it} + \beta_8 \text{congestion}_{it} + \beta_9 \text{ideology}_{it} + \\
\beta_{10} \text{commute characteristics}_{it} + \beta_{11} \text{demographic characteristics}_{it} + \alpha_i + \gamma_t + \\
u_{it}
\]

The alpha term represents city fixed effects and the gamma term represents year fixed effects. The \(i\) subscript refers to the “\(i^{th}\)” city and the subscript \(t\) refers to the “\(t^{th}\)” year.

Many of the determinants of commute mode choice are difficult to measure and were therefore operationalized using proxies. To operationalize weather, I include the number of days with greater than .1 inches of precipitation. Economic determinants of commute choice are operationalized using state average gas price. To control for ideological factors that could influence commute mode choice, I include a measure from the League of Conservation Voters that ranks members of Congress from 0 to 100 based on environmental and conservation-related voting records. While congressional districts do not correspond exactly to city boundary lines, this measure approximates the ideological makeup of a particular area. To control for safety-related considerations, I include measures of bicycle fatalities per year and property crime rates. To control for the availability of public transit, I use a measure of the public transit miles travelled per year divided by the population. To control for congestion, I include a measure of the ratio of the travel time during the peak period to the time required to make the same trip at free-flow speeds. I also include a variety of demographic characteristics to account for their possible influences on the dependent and key independent variables.
<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Definition*</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage Commuting by Car</td>
<td>The percentage of the commuting population who commute by car</td>
<td>ACS</td>
</tr>
<tr>
<td>Miles of Bicycle Infrastructure Per Square Mile</td>
<td>Miles of on-street bike lanes, multiuse and bike paths, and signed bike routes divided by city square miles</td>
<td>ABW</td>
</tr>
<tr>
<td>Population</td>
<td>City population in 100,000s</td>
<td>ACS</td>
</tr>
<tr>
<td>City Size</td>
<td>Size of each city in miles squared in 1,000s</td>
<td>ABW</td>
</tr>
<tr>
<td>Days with greater than .1 inch of precipitation</td>
<td>The number of days per year where precipitation was greater one-tenth of one inch</td>
<td>National Oceanic and Atmospheric Administration</td>
</tr>
<tr>
<td>Environmentalism</td>
<td>Score of how members of Congress vote on environmental and conservation issues with 100 as the most supportive and 0 as the least</td>
<td>League of Conservation Voters</td>
</tr>
<tr>
<td>Property Crime Rate</td>
<td>Rate of crime including burglaries, larceny, and motor vehicle theft</td>
<td>Federal Bureau of Investigation**</td>
</tr>
<tr>
<td>Bicycle Fatalities</td>
<td>Number of bicycle deaths per year</td>
<td>ABW</td>
</tr>
<tr>
<td>State Average Gas Price</td>
<td>Average price of gas within a state, inflation adjusted to 2011 dollars</td>
<td>Energy Information Administration</td>
</tr>
<tr>
<td>Miles of Public Transportation Travelled Per Person</td>
<td>Total miles of public transportation traveled divided by population</td>
<td>National Transit Database</td>
</tr>
<tr>
<td>Congestion</td>
<td>The ratio of the travel time during the peak period to the time required to make the same trip at free-flow speeds</td>
<td>Texas Transportation Institute</td>
</tr>
<tr>
<td>Proportion of Commuters who Walk</td>
<td>Proportion of commuting population who walk to work</td>
<td>ACS</td>
</tr>
<tr>
<td>Mean Commute Time</td>
<td>Mean length of commute in time</td>
<td>ACS</td>
</tr>
<tr>
<td>Male Proportion of Population</td>
<td>Proportion of the population that is male</td>
<td>ACS</td>
</tr>
<tr>
<td>Nonwhite Proportion of Population</td>
<td>Proportion of population that identifies as nonwhite, including black, asian, native american, pacific islander, and multiple races</td>
<td>ACS</td>
</tr>
<tr>
<td>Average Household Size</td>
<td>Average number of people in a household</td>
<td>ACS</td>
</tr>
<tr>
<td>Proportion of Households with a Child under 18</td>
<td>Proportion of households that include a child under the age of 18</td>
<td>ACS</td>
</tr>
<tr>
<td>Median Household Income</td>
<td>Median income of households inflation adjusted to 2011 dollars</td>
<td>ACS</td>
</tr>
<tr>
<td>Median Household Income Squared</td>
<td>Median income of households inflation adjusted to 2011 dollars squared</td>
<td>Calculation</td>
</tr>
<tr>
<td>Percentage High School Graduates</td>
<td>Percentage of the over 25 population who have graduated from high school</td>
<td>ACS</td>
</tr>
<tr>
<td>Percentage Bachelor's Degree or Higher</td>
<td>Percentage of the over 25 population who have a Bachelor's degree or higher</td>
<td>ACS</td>
</tr>
</tbody>
</table>

* All variables are continuous

** Data for Chicago, Honolulu, Kansas City, and Tuscon were collected directly from Police Department websites
DESCRIPTIVE STATISTICS

Table 2 shows descriptive statistics for the variables used in the analysis and Table 3 shows a correlation matrix for the same set of variables. As shown in Table 2, the mean of the dependent variable of interest, the percentage of commuting by car, is 79.7 with a minimum of 26.7 in New York City in 2011 and a maximum of 94.1 in Oklahoma City in 2007. The key independent variable, miles of bicycle infrastructure per square mile, has a mean of 1.5 with a minimum of 0 in El Paso, San Antonio, and Jacksonville (2009) and a maximum of 5.6 in San Francisco (2011). While the 51 largest American cities in a given year are used in this analysis, city size and population vary widely, as do climatic conditions. City size ranges from 35.67 square miles (Miami) to 757 square miles (Jacksonville). Population is as low as 239,124 in New Orleans in 2007 in the wake of Hurricane Katrina and as high as 8,391,881 in New York City in 2009. Public transportation miles travelled per person are as low as 0 (several observations) and as high as 4,398 (Oakland, 2007), with a mean of 646.5.

Demographics also vary across city-years, with median income in 2011 dollars as low as $25,193 (Detroit, 2011) and as high as $83,497 (San Jose, 2007). The proportion of the population that identifies as nonwhite has a low of .05 (El Paso, 2011) and a high of .85 (Detroit, 2007) with a mean of .33. With respect to education, the percentage of the population with just a high school degree ranges from 11.7 in Seattle (2007) to 36.8 in Philadelphia (2007), with an aggregate mean of 24.3. The percentage of the population with a Bachelor’s degree or higher is

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3 Data for Annual Bicycle Fatalities were not available for 2011 and so were interpolated by assuming a linear continuation of the trend from 2007 and 2009. Data for Environmentalism were not available for Washington, DC because their elected Congressperson is a non-voting delegate and so were imputed by regressing my environmentalism measure on the other controls in the model for the available observations. I then used the resulting coefficient values to predict a value for Washington, DC. The predicted value was beyond the scope of the League of Conservation scale (i.e. over 100) and so I top coded those observations to 100. Additionally, data on Environmentalism were not available for San Francisco because, as Speaker of the House, Congressperson Nancy Pelosi was not required to vote. As such, I use an alternate variable of her lifetime average score as calculated by the League of Conservation Voters.
as low as 11.8 in Detroit (2007) and as high as 56.2 in Seattle (2011), with an aggregate mean of 31.7.

Commute characteristics also vary. The proportion of commuters who walk to work has a mean of .04, a low of 0 (Jacksonville, 2011), and a high of .14 (Boston, 2011). Mean commute time in minutes is as low 17.3 minutes (Omaha, 2007) and as high as 39.8 (New York, 2007), with an aggregate mean of 24.7.

Table 3 shows a correlation matrix of the variables used in this analysis. The correlation between the independent variable of interest and the dependent variable is -0.34. This relationship is statistically significant at the 99% level and indicates that there is a negative relationship between cities’ bicycle infrastructure per square mile and the rate of commuting by car, as hypothesized. This relationship is only correlational and the fixed effects and regular regressions in the next section explore this relationship in a more sophisticated fashion.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage Commuting by Car</td>
<td>79.7</td>
<td>26.7</td>
<td>94.1</td>
<td>14.9</td>
</tr>
<tr>
<td>Miles of Bicycle Infrastructure Per Square Mile</td>
<td>1.5</td>
<td>0.0</td>
<td>5.6</td>
<td>1.2</td>
</tr>
<tr>
<td>City Characteristics</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population (in 100,000s)</td>
<td>9</td>
<td>2</td>
<td>84</td>
<td>13</td>
</tr>
<tr>
<td>City Size (1,000 mi$^2$)</td>
<td>0.21</td>
<td>0.04</td>
<td>0.76</td>
<td>0.16</td>
</tr>
<tr>
<td>Days with greater than .1 inch of precip</td>
<td>56.0</td>
<td>5.0</td>
<td>123.0</td>
<td>28.1</td>
</tr>
<tr>
<td>Environmentalism</td>
<td>71.9</td>
<td>0.0</td>
<td>100.0</td>
<td>37.2</td>
</tr>
<tr>
<td>Property Crime Rate</td>
<td>0.05</td>
<td>0.02</td>
<td>0.07</td>
<td>0.01</td>
</tr>
<tr>
<td>Bicycle Fatalities</td>
<td>2.1</td>
<td>0.0</td>
<td>26.0</td>
<td>3.0</td>
</tr>
<tr>
<td>State Average Gas Prices</td>
<td>2.32</td>
<td>1.90</td>
<td>3.12</td>
<td>0.27</td>
</tr>
<tr>
<td>Miles of Public Transportation Travel</td>
<td>646.5</td>
<td>0.0</td>
<td>4,397.8</td>
<td>905.2</td>
</tr>
<tr>
<td>Congestion</td>
<td>1.2</td>
<td>1.1</td>
<td>1.4</td>
<td>0.1</td>
</tr>
<tr>
<td>Individual Characteristics</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion of Commuters who Walk</td>
<td>0.04</td>
<td>0.00</td>
<td>0.14</td>
<td>0.03</td>
</tr>
<tr>
<td>Mean Commute Time</td>
<td>24.7</td>
<td>17.3</td>
<td>39.8</td>
<td>4.0</td>
</tr>
<tr>
<td>Male Proportion of Population</td>
<td>0.49</td>
<td>0.46</td>
<td>0.52</td>
<td>0.01</td>
</tr>
<tr>
<td>Nonwhite Proportion of Population</td>
<td>0.33</td>
<td>0.05</td>
<td>0.85</td>
<td>0.18</td>
</tr>
<tr>
<td>Average Household Size</td>
<td>2.6</td>
<td>2.1</td>
<td>3.2</td>
<td>0.2</td>
</tr>
<tr>
<td>Proportion of Households with a Child under 18</td>
<td>0.27</td>
<td>0.16</td>
<td>0.39</td>
<td>0.05</td>
</tr>
<tr>
<td>Median Household Income (in 1,000s)</td>
<td>48.2</td>
<td>25.2</td>
<td>83.5</td>
<td>10.5</td>
</tr>
<tr>
<td>Median Household Income Squared</td>
<td>2430.8</td>
<td>634.7</td>
<td>6971.8</td>
<td>1086.7</td>
</tr>
<tr>
<td>Percentage High School Graduates</td>
<td>24.3</td>
<td>11.7</td>
<td>36.8</td>
<td>5.1</td>
</tr>
<tr>
<td>Percentage Bachelor's Degree or Higher</td>
<td>31.7</td>
<td>11.8</td>
<td>56.2</td>
<td>9.4</td>
</tr>
</tbody>
</table>

Sample Size: 143
| Table 3. Correlation Matrix: Percentage Commuting by Car and Miles of Bicycle Infrastructure Per Square Mile* |
|--------------------------------------------------|--------------------------------------------------|--------------------------------------------------|--------------------------------------------------|
| Percentage Commuting by Car | Miles of Bicycle Infrastructure Per Square Mile | Days with greater than 1 inch of precipitation | City Size |
| Population | Environment | State Average Gas Price | Property Crime Rate | Bicycle Facilities | Miles of Public Transit per Person | Proportion of Commuters who Walk | Mean Commute Time | Proportion of Population Nonwhite | Homeownership Rate | Average Household Income (in 1,000s) | Median Household Income Squared | Percentage Bachelor's Degree or Higher |
| 1.0000 | -0.3441*** | 1.0000 | -0.3064*** | -0.5923*** | 1.0000 |
| City Size | 0.1492*** | -0.3758*** | -0.0882 | 1.0000 |
| Population | -0.402*** | 0.0082 | 0.075 | 0.3085*** | 1.0000 |
| Environmental | -0.365*** | 0.0063 | 0.2081** | -0.0929 | 0.183** | 1.0000 |
| State Average Gas Price | -0.1328* | 0.1049** | -0.2603** | -0.1615* | 0.0063 | 0.0063 | 1.0000 |
| Property Crime Rate | -0.2644*** | -0.2490*** | 0.3182*** | 0.0571 | -0.397*** | -0.0742 | -0.0770 | 1.0000 |
| Bicycle Facilities | -0.2523*** | 0.0062 | -0.063 | 0.274** | 0.6263*** | 0.1174 | 0.0706 | -0.237*** | 1.0000 |
| Miles of Public Transit per Person | -0.7414*** | 0.181** | 0.2338** | -0.3748*** | 0.1531* | 0.3091*** | 0.156* | -0.0572 | 0.0262 | 1.0000 |
| Congestion | -5.4254*** | 0.1708*** | 0.0241 | -0.1284 | 0.3780*** | 0.2884*** | 0.3254*** | -0.3492*** | 0.1900** | 0.4753*** | 1.0000 |
| Proportion of Commuters who Walk | -0.8648*** | 0.2794** | 0.352** | -0.4256*** | 0.2706** | 0.3033*** | 0.1562* | -0.2081** | 0.0978 | 0.6234*** | 0.4480** | 1.0000 |
| Mean Commute Time | -0.7206** | 0.2035** | 0.1459* | -0.1089 | 0.6681*** | 0.4121*** | 0.1077 | -0.3863*** | 0.4013** | 0.5586*** | 0.6655*** | 0.5545*** | 1.0000 |
| Male Proportion of Population | -0.2341*** | 0.2278*** | -0.4487*** | 0.1525* | -0.0599 | -0.1484* | 0.0929 | -0.1184 | 0.0623 | -0.2415*** | 0.0659 | -0.2537*** | -0.2063** | 1.0000 |
| Nonwhite Proportion of Population | -0.3295*** | -0.1515* | 0.4749** | -0.2437*** | -0.0162 | 0.3819*** | 0.1124 | 0.1644** | -0.1172 | 0.3252*** | 0.2122* | 0.3648*** | 0.2689*** | -0.5096** | 1.0000 |
| Average Household Size | 0.2874*** | -0.0776 | -0.5104*** | 0.2084** | 0.2163** | 0.0040 | -0.0001 | -0.3838*** | 0.2408*** | -0.3015*** | 0.0110 | -0.3088*** | 0.1333 | 0.1082 | -0.1202 | 1.0000 |
| Proportion of Households with a Child under 18 | 0.6083*** | -0.234*** | -0.4729*** | 0.3457*** | 0.0480 | -0.1872** | -0.1068 | -0.2352*** | 0.1389* | -0.56*** | 0.0119** | -0.6384*** | -0.2116* | 0.1783*** | -0.4082*** | 0.7361*** | 1.0000 |
| Median Household Income (in 1,000s) | -0.2355*** | 0.2108** | -0.2454*** | -0.0785 | 0.0509 | 0.0218 | 0.2251*** | -0.4409*** | 0.0059 | 0.1690*** | 0.3115*** | 0.1580* | 0.1451* | 0.4607*** | -0.1281 | 0.0465 | 0.0246 | 1.0000 |
| Median Household Income Squared | -0.2811*** | 0.2155*** | -0.2191*** | -0.1134 | 0.0139 | 0.0344 | 0.2287*** | -0.4335*** | -0.0124 | 0.1562* | 0.2995*** | 0.1681** | 0.155* | 0.4409*** | -0.0721 | 0.0726 | 0.0174 | 0.9858*** | 1.0000 |
| Percentage High School Graduates | 0.2695*** | -0.3705*** | 0.2689*** | 0.0840 | -0.0033 | -0.0286 | -0.0385 | 0.2703*** | 0.0078 | -0.2328*** | -0.2478*** | -0.1173 | -0.0555 | -0.4765*** | 0.2848*** | 0.1325 | 0.1303 | -0.6471*** | -0.6058*** | 1.0000 |
| Percentage Bachelor's Degree or Higher | -0.4572*** | 0.2699*** | 0.1115 | -0.1839*** | -0.0075 | 0.0819 | 0.0801 | -0.1339 | -0.0824 | 0.4211*** | 0.2977*** | 0.3944*** | 0.1001 | 0.2935*** | -0.0626 | -0.5083*** | -0.5081*** | 0.6683*** | 0.622*** | -0.8106*** | 1.0000 |

* Significant at p<.10, ** p<.05, ***p<.01

| Sample size=143 | Table 3. Correlation Matrix: Percentage Commuting by Car and Miles of Bicycle Infrastructure Per Square Mile* | 19 |
Regression Results

Table 4 presents estimated regression coefficients for three different regression models. Robust standard errors are reported in parentheses immediately below each coefficient. The column marked “Model 1” contains the results from a model that contains a full set of controls but does not use fixed effects. The column marked “Model 2” shows results from a model using city fixed effects. The column labeled “Model 3” shows results from a model using city and year fixed effects. The control variables are grouped into city- and individual-level characteristics. As explained in the Data and Methods section, the control variables account for time varying characteristics that may be correlated with the dependent and/or key independent variable.

The availability of many different measures of the same basic variables required a determination as to which was the most sensible to include. I estimated models using alternative measures for several broad categories. The final model allows me to capture the dynamics for which I wish to control in the most parsimonious way.4

---

4 I estimated models using several different measures of climate, commute characteristics, demographics, and safety and then evaluated their relative statistical significance, magnitude, and effect on the key independent variable coefficient. For climate, I estimated models including heating degree days, cooling degree days, days with one inch of snow or more, days with .1 inch of precipitation or more, and days with .5 inch of precipitation or more. For commute characteristics, I estimated models including measures of the proportion of the population with a variety of commute time lengths in minutes, including under 10, 10-14, 15-19, 20-24, 25-29, 30-34, 25-44, 45-59, under 30, over 60, and mean commute time. For availability of public transit, I estimated models including the proportion of commuters who take public transit and the number of transit miles traveled per person. For education, I estimated models using several different measures, including percentage of the population 25 and older with less than a high school degree, high school degree only, some college, associate’s degree, bachelor’s degree, post-graduate degree, high school or higher, and bachelor’s degree or higher. In terms of household composition, I estimated models using average household size and average family size as well as proportion of married households, proportion of single person households, proportion of households with a child six or younger, and proportion of households with a child 18 or younger. In terms of demographic controls, I estimated models using several different race and poverty measures. For safety measures, I evaluated models including property crime rates and violent crime rates as well as annual bicyclist fatalities. The final variables in the model were included based on their influence on the coefficient for the key independent variable relative to the other options available. In other words, I included all variables whose omission would have induced bias in the coefficient of interest.
Table 4. OLS and Fixed Effects Regression Results

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient (Robust Standard Errors)</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variable</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percentage of Population Commuting by Car</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Key Independent Variable</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Miles of Bicycle Infrastructure Per Sq. Mi</td>
<td>-1.09***</td>
<td>0.16</td>
<td>0.25</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.36)</td>
<td>(0.15)</td>
<td>(0.15)</td>
<td></td>
</tr>
<tr>
<td><strong>City Level Controls</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Days with Greater than 1 inch of Precipitation</td>
<td>0.02</td>
<td>-0.01</td>
<td>-0.01</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td></td>
</tr>
<tr>
<td>City Square Miles (in 1,000s)</td>
<td>6.94***</td>
<td>9.62***</td>
<td>9.54***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.09)</td>
<td>(2.94)</td>
<td>(2.77)</td>
<td></td>
</tr>
<tr>
<td>Population (in 100,000s)</td>
<td>-0.31***</td>
<td>0.50***</td>
<td>0.41**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.18)</td>
<td>(0.19)</td>
<td></td>
</tr>
<tr>
<td>Environmentalism</td>
<td>-0.01</td>
<td>0.01</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td></td>
</tr>
<tr>
<td>State Average Gas Price</td>
<td>-0.17</td>
<td>-1.27**</td>
<td>-8.42***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.09)</td>
<td>(52)</td>
<td>(2.15)</td>
<td></td>
</tr>
<tr>
<td>Property Crime Rate</td>
<td>-53.70**</td>
<td>45.32*</td>
<td>51.53**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(25.86)</td>
<td>(23.60)</td>
<td>(24.37)</td>
<td></td>
</tr>
<tr>
<td>Annual Bike Fatalities</td>
<td>-0.06</td>
<td>0.03**</td>
<td>0.04***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td></td>
</tr>
<tr>
<td>Public Transit Miles Traveled Per Person</td>
<td>-0.001**</td>
<td>-0.003**</td>
<td>-0.003**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td>Congestion</td>
<td>19.27***</td>
<td>3.18</td>
<td>0.13</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(5.50)</td>
<td>(4.02)</td>
<td>(4.55)</td>
<td></td>
</tr>
<tr>
<td><strong>Individual Level Controls</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion of Commuters who Walk</td>
<td>-187.00***</td>
<td>-26.36***</td>
<td>-21.30**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(58.08)</td>
<td>(9.44)</td>
<td>(8.73)</td>
<td></td>
</tr>
<tr>
<td>Mean Commute Time</td>
<td>-1.11***</td>
<td>-0.41**</td>
<td>-0.58***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(0.18)</td>
<td>(0.19)</td>
<td></td>
</tr>
<tr>
<td>Male Proportion of Population</td>
<td>97.13**</td>
<td>7.29</td>
<td>2.21</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(45.34)</td>
<td>(20.00)</td>
<td>(19.11)</td>
<td></td>
</tr>
<tr>
<td>Nonwhite Proportion of Population</td>
<td>2.68</td>
<td>8.53</td>
<td>8.73</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.33)</td>
<td>(7.94)</td>
<td>(7.94)</td>
<td></td>
</tr>
<tr>
<td>Average Household Size</td>
<td>3.34</td>
<td>-3.04**</td>
<td>-2.86**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.37)</td>
<td>(1.35)</td>
<td>(1.56)</td>
<td></td>
</tr>
<tr>
<td>Proportion of Households with a Childer under 18</td>
<td>32.02**</td>
<td>-4.41</td>
<td>-4.61</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(15.45)</td>
<td>(10.14)</td>
<td>(9.79)</td>
<td></td>
</tr>
<tr>
<td>Median Household Income (in 1,000s)</td>
<td>0.15</td>
<td>0.19</td>
<td>0.32</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.19)</td>
<td>(0.14)</td>
<td>(0.18)</td>
<td></td>
</tr>
<tr>
<td>Median Household Income (in 1,000s) Squared</td>
<td>-0.003</td>
<td>-0.002</td>
<td>-0.003*</td>
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</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td>Percentage High School Graduates</td>
<td>-0.19</td>
<td>0.34**</td>
<td>0.30**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.21)</td>
<td>(0.12)</td>
<td>(0.12)</td>
<td></td>
</tr>
<tr>
<td>Percentage Bachelor's Degree or Higher</td>
<td>-0.25</td>
<td>-0.19</td>
<td>-0.25**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
<td>(0.12)</td>
<td>(0.12)</td>
<td></td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>44.83***</td>
<td>69.04***</td>
<td>91.83***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(22.11)</td>
<td>(16.04)</td>
<td>(15.22)</td>
<td></td>
</tr>
<tr>
<td><strong>City Fixed Effects</strong></td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td><strong>Time Fixed Effects</strong></td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>143</td>
<td>143</td>
<td>143</td>
<td></td>
</tr>
<tr>
<td><strong>R-Squared</strong></td>
<td>0.9874</td>
<td>0.9995</td>
<td>0.9996</td>
<td></td>
</tr>
</tbody>
</table>

Robust standard errors are in parentheses
* Significant at p<.10, ** p<.05, ***p<.01
Model 1 indicates that, for each additional mile of bicycle infrastructure per square mile, the percentage of commuters who travel by car decreases by 1.09 percentage points. This finding is statistically significant at the 0.01 level. The coefficients in Models 2 and 3 are imprecisely estimated, as indicated by their low t-values and large standard errors, and are smaller in magnitude than that in Model 1.

Focusing on Models 2 and 3, the city fixed effects dummies explain almost all of the variation in the dependent variable. When the percentage of commuters by car is regressed only on the city fixed effects, the city dummy variables account for over 99% of the variation in percentage of commuters by car, leaving less than 1% to be explained by bicycle infrastructure per square mile and all of the additional control variables. Ultimately, due to the small sample size and limited range of years of data available, there is very little within-city variation in the dependent variable over time, and the fixed effects dummies capture almost all of the variation that exists. This suggests that the non-fixed effects regression results may be more reliable, since they leave a larger portion of the variation in the dependent variable to be explained by the covariates in the model. However, the amount of variation left unexplained in the regular regression model is quite low as well, with a regression including just the control variables and no fixed effects dummies explaining 98.6% of the variation in the dependent variable.

Exploratory analysis showed that the inclusion of population size in the models accounts for nearly all of the high R-Squared values. Population size is strongly correlated with the percentage of the population commuting by car and is almost certainly also correlated with the number of bicycle infrastructure miles per square mile, so it would not be appropriate to exclude it from this analysis, as doing so would produce omitted variable bias. Nonetheless, its inclusion
in the model accounts for almost all of the variation in the percentage of commuters who drive, leaving very little to be explained by the other variables. Therefore, I estimated regular regression models without population as a covariate, without population weights, and without population as a covariate and population weights. The results of these alternate specifications with respect to the magnitude and significance of the coefficient on the key independent variable are very similar to those in Model 1. This reveals that, when the main driver of the high R-Squared value of the non-fixed effects regression is excluded, the coefficient on the key independent variable is still small but statistically significant, indicating that results are not being driven solely by the limited variation in the dependent variable.

The controls are grouped into city-level and individual-level variables. Table 5 shows results from joint significance tests for each group of variables, indicating that they are highly jointly significant. All three models show that city size is positively correlated with commuting by car and that the number of public transit miles traveled per person is negatively correlated with commuting by car, both of which are to be expected. In terms of individual-level determinants of commute mode, the proportion of commuters who walk and mean commute time are statistically significant and negatively related to commuting by car in all models.

<table>
<thead>
<tr>
<th>Table 5. Joint Significance Test Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>City Level Controls</td>
</tr>
<tr>
<td>Individual Level Controls</td>
</tr>
</tbody>
</table>

* Significant at p<.10, ** p<.05, ***p<.01
Overall, these results yield three interesting findings. First, city size in square miles, public transportation miles traveled per person, proportion of commuters who walk, and mean commute time are statistically significant correlates of commuting by car in all models. Thus, commuting options and city-level characteristics appear to have the strongest relationship with commute mode choice. Second, arguably, Model 1 most usefully assesses the relationship between the dependent variable and key independent variable because there is such limited variation in the fixed effects models from which to estimate a relationship. Third, Model 1 shows a statistically significant negative relationship between bicycle infrastructure and commuting by car, as hypothesized.

**DISCUSSION**

The purpose of this study was to determine whether or not there is a relationship between bicycle infrastructure and commuting by car in large American cities. Logically, one might think that increasing the availability of bicycle-specific travel options would reduce the percentage of people who drive to work, but it is unclear whether people who choose to bicycle to work would otherwise drive.

All three models show a relationship so small as to be negligible between bicycle infrastructure and the rate of commuting by car. Only one regression shows a statistically significant and negative relationship between bicycle infrastructure and the rate of commuting by car. The models incorporating city and year fixed effects show a weak positive relationship that is not statistically different from zero. Model 1, using regular OLS regression, shows a somewhat less weak and statistically significant negative association, whereby the addition of one mile of
bicycle infrastructure per square mile is associated with a one percentage point reduction in the percent commuting by car. This is quite a small change, as the mean percent commuting by car is 80 and the mean number of miles of bicycle infrastructure per square mile is 1.5. Thus, increasing the existing bicycle infrastructure by 67% is associated with 1% decrease in commuting by car.

For the fixed effects models, it should be remembered that city and year fixed effects control for the vast majority of the variation in the dependent variable, leaving very little to be explained by the independent variable of interest. Thus, the regular OLS model may capture better the relationship between commuting by car and bicycle infrastructure, since there is slightly more variation left to be explained. Also, excluding the key driver of the high R-Squared value, thereby freeing up more variation in the data, had very similar results. Importantly, even though the relationship is statistically significant in Model 1, it is still miniscule.

There are also significant limitations to this analysis. Data on the independent variable of interest, miles of bicycle infrastructure per square mile, are available only from one source and only for three years. These data are also not available for all cities in all three years, further limiting variation in the dependent variable over time. Data from more cities and over a longer time period would offer richer variation in the dependent variable and key independent variable to be explored in subsequent research and therefore would provide a more complete picture of the true relationship between bicycle infrastructure and commuting by car. These data are also reported by city governments and so are not collected in a standardized fashion. Having data collected in a uniform way would improve future inquiries in this area.
Moreover, there is the distinct possibility of omitted variable bias in this analysis. While the fixed effects models mitigate a great deal of potential bias, there are other possible influences on commute mode choice that were not included in these models and could be explored in future research. One such variable is the availability of bikeshare programs, in which an individual pays a fee to collect a bicycle from a station and returns that bicycle to any other station within the service area, with additional pricing based on use time. These programs have changed the landscape of bicycle use in cities by providing a new convenient, fast, and inexpensive non-motorized point-to-point transport option. Specifically, in 2009, the city of Paris found that 28% of respondents to a survey about their bikesharing program indicated that they were less likely to use personal vehicles in 2008 due to the availability of bikes. This figure increased to 46% in 2009 (DeMaio 2009). Bikesharing programs are spreading rapidly throughout the nation, and including a measure of availability could improve similar models in future analysis.

Additionally, types of bicycle infrastructure, government policies, and program funding levels may affect commute mode choices. New infrastructure innovations include bike boxes, which favor cyclists at red lights; cycle tracks, or lanes for cyclists separated from vehicle traffic by physical barriers; and contra flow bike lanes, which allow cyclists to travel in either direction on one-way streets (Pucher, Dill, & Handy, 2010). In addition, bicycle-transit integration, such as having bike racks on buses and allowing bikes on trains, could be an important control variable for future research, since people may be more willing to take public transit to work rather than drive if they can cycle to stations (Krizek & Stonebraker, 2011). Complete streets policies, safe routes to schools, bike to work days, and public information campaigns aimed at cyclists and drivers could promote greater awareness of transportation alternatives as well as
encourage safe driving and cycling (Alliance for Bicycling and Walking, 2012). The policies and programs above are probably positively related to the presence of bicycle infrastructure and negatively related to percentage of the population commuting by car, therefore the omission of these variables from the models likely exerts downward bias on the coefficient for the key independent variable. The inclusion of variables controlling for program funding levels would mitigate this downward bias and provide a more accurate causal estimate of the relationship studied here.

Ultimately, the policy implications of this research are limited. There is a relationship between bicycle infrastructure and commuting by car in some, but not all, models. Moreover, this relationship is negligible in magnitude. Because there is modestly more variation to exploit in the dependent variable, the regular OLS regression model in which there is a statistically significant relationship is perhaps the most credible of the three models run. This analysis provides suggestive evidence that there might be such a relationship and that cities seeking to encourage non-motorized commute to work choices might consider investing more heavily in bicycle infrastructure. With further research and the collection of more and more accurate data, policymakers will be better able to more comprehensively evaluate options for the most efficient use of public funds in order to encourage particular commute mode choices.


