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16. Abstract (Limit: 200 words)

This research project sought to determine whether high-population density or some other aggregate land use characteristic can be used to create beneficial effects on travel behavior at the level of the entire urbanized area. The research also looked at gaining a better understanding of the reasons for variations in travel behavior across large U.S. cities.

This research involved a comprehensive analysis, considering an unusually large number of factors. Researchers also developed a number of ways to describe aggregate "macro" land use in an urbanized area specifically for this study.

The study found that land use, at the aggregate level studied in this project, is not a major leverage point in determining overall population travel choices. Much policy seems to be based on the belief that relatively small changes to land use will have a big impact on travel choices. The findings here imply just the opposite - that even very big, widespread differences in land use have very little impact on travel behavior, in good ways or in bad ways.

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POPULATION AND EMPLOYMENT DENSITY AND TRAVEL BEHAVIOR IN LARGE U.S. CITIES

Final Report

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EXECUTIVE SUMMARY

The primary objective of this report is to determine whether high population density or some other easily measurable aggregate land use characteristic can be used to create beneficial effects on travel behavior, at the level of the entire urbanized area. The more general objective is to understand the reasons for what appear to be substantial variations in travel behavior across large U.S. cities, and the extent to which these variations are due to land use as opposed to demographic, economic, or other factors.

The way this is accomplished is by analyzing a very large number of descriptors of travel behavior (15 variables), land use (11), and other factors (15), measured at the level of the entire urbanized area for 31 of the largest U.S. cities. Three levels of analysis are performed. The first simply calculates average behaviors when people are grouped in different ways; this looks directly at individuals rather than at cities. The second is a regression analysis of the 31 cities, considering average travel behaviors and how they relate to measures of land use and other factors. The third aggregates at yet another level, by grouping cities based on similarities in various land use measures, again analyzing how average travel behaviors differ across groups.

There are two major innovations in this research. The first is the comprehensive nature of the analysis, in terms of the unusually large number of factors that are considered, both in terms of influences on behavior, and the behaviors themselves. By contrast, most research focuses on one or two explanatory factors, while possibly controlling for differences in a handful of others. This creates the undesirable possibility that omitted variables might bias the results, or even that they might have explained the data even better than the variables that were used. Furthermore, most research focuses on one or two behaviors, such as VMT or transit share, and concludes by implication that other travel decisions are similarly influenced. However, it is not clear *a priori* that this is the case.

The second major innovation is that a number of ways of describing aggregate “macro” land use in an urbanized area were developed specifically for this study. For several reasons, simple population density seemed to miss important features of urban land development. This report defines a number of additional descriptors, based on the notion of weighting local density measures by the number of residents or jobs in the local area. In other words, a square mile with 50,000 residents will carry more weight in the calculation than will a square mile with 1,000 residents. This method is used to derive measures of population and job density and concentration, and measures of the density of jobs relative to home locations.

The primary finding of this study is that land use, at least at the aggregate level studied here, is not a major leverage point in the determination of overall population travel choices. On the one hand, certain relationships emerge which correspond to generally held beliefs, for example that high residential concentration increases transit share. On the other hand, aggregate land use characteristics had little or no discernable impact on other measures of travel behavior, such as VMT or total daily travel time. Much policy seems to be based on the belief that relatively small changes to land use will have a big impact on travel choices. The findings here imply just the opposite; that even very big, widespread differences in land use have very little impact on travel behavior, in good ways or in bad.

A particularly important point is that the connections that are often assumed between different travel choices are not generally observed here. Many studies have noted the impact of density on transit share; that impact is also found here. But what is not seen is evidence for the implication that higher transit share must also lead to less driving, shorter commutes, less congestion, etc. None of these effects are observed; indeed, if anything the higher densities that increase transit share tend to *increase* commute times and congestion levels. The benefits of individual travel decisions tend to be dampened at two different levels.

First, individuals do not make different decisions in isolation. The fact that a person decides to shop at a nearby store rather than a more distant one obviously reduces the length of that particular trip, but it does not follow that the person's total travel will be reduced; often time savings in one area will simply be used for additional travel somewhere else. And taking transit to work means one less car on that trip, but doesn't stop the person from taking the car out later for an extra trip that otherwise might have been completed on the way home from work.

The second, subtler point is that one person's travel decisions, and the factors that influence those decisions, will also affect other people's decisions, often in offsetting ways. For example, if some people cut back on driving, then road capacity will be opened up that others may take advantage of. Or the high-density development that encourages transit use by its residents can adversely impact the travel choices of non-residents. Slow speeds through the neighborhood might induce outsiders to take longer routes or to travel to different, more distant destinations, to avoid the need to pass through it.

To really integrate land use and transportation planning and use them to make cities better places to live and work seems to be one objective that everyone agrees on. But this is not a simple problem. Individual human behavior is complex in itself; add to this the further complications of social, economic, and technological change, and it is easier to see why simple “logical” connections don’t always work as they should. More detailed, empirically validated theories of how and why people make the travel choices that they do is a necessary first step to move beyond simple but incorrect “logic” and on to real understanding.

1 INTRODUCTION

According to widely cited statistics from the Federal Highway Administration (FHWA), vehicle miles traveled per person per day (VMT) varies across large urbanized areas from 15 to 38. There are even larger differences in average urbanized area population density across these cities, from about 1,300 up to 5,400. There is a rough correlation between high VMT and low-density cities. These wide variations in VMT and population density raise the intriguing possibility that there is some set of “low-VMT” land use or transportation policies that some cities are following (perhaps unknowingly) and that others could potentially exploit.

The primary objective of this report is to determine whether high population density or some other easily measurable aggregate land use characteristic can be used to create beneficial effects on travel behavior, at the level of the entire urbanized area. The more general objective is simply to understand the reasons for the large observed variations in travel behavior across cities, and the extent to which these variations are due to land use as opposed to demographic, economic, or other factors.

The way this is accomplished is by analyzing a very large number of descriptors of travel behavior (15 variables), land use (11), and other factors (15), measured at the level of the entire urbanized area for 31 of the largest U.S. cities. Three levels of analysis are performed. The first simply calculates average behaviors when people are grouped in different ways; this looks directly at individuals rather than at cities. The second is a regression analysis of the 31 cities, considering average travel behaviors and how they relate to measures of land use and other factors. The third aggregates at yet another level, by grouping cities based on similarities in various land use measures, again analyzing how average travel behaviors differ across groups.

[The term “urbanized area” is defined in chapter 3. For expository convenience, I sometimes use words like “city” or “urban region” as synonyms for “urbanized area.” For the same reason I generally omit the qualifier “per capita per day;” this should be understood to apply to any descriptor of individual behavior. For example, daily vehicle miles traveled per capita will be abbreviated simply as “VMT”. Chapter 4 includes the exact definition of each variable.]

There are two major innovations in this research. First, this research considers an unusually wide range of possible explanatory variables, ranging from several different land use descriptors, to the transportation system, to economic considerations, and even to historical factors. By contrast, most research focuses on one or two explanatory factors, while possibly controlling for differences in a handful of others. This traditional narrow approach creates the undesirable possibilities that omitted variables might bias the results, or simply that discussion focuses on the factor that happened to be studied, when there might have been others that explained the data even better.

In the same vein, this research also examines a large number of descriptors of travel behavior, and the relationships between them. Most research focuses on one or two descriptors, such as VMT or transit share, and concludes by implication that other travel decisions are similarly positively influenced by high-density land use. However, it is not clear *a priori* that this is the case. For example, suppose hypothetically that residents of dense neighborhoods drive fewer miles simply because they spend most of that time in stop-and-go traffic on congested local streets, with all the air quality and other problems implied by that. Does less VMT really imply less congestion and pollution in this case? This research considers many travel descriptors simultaneously to attempt to better understand the links between them.

The second important innovation is that a number of quantitative methods for describing urbanized area land use were developed especially for this study. Most studies of entire cities use simple overall population density, which for a number of reasons can miss important aspects of how land is developed. Here a number of measures of residential and employment density, and the degree of mixture of the two, were developed based on the concept of calculating overall averages by weighting different subareas based on their population or job counts.

This research looks at 31 of the largest urbanized areas in the US, including all of the top 25. While aggregating data over entire urbanized areas may seem to be a step backward given current trends toward analyzing neighborhoods or even individuals, it is the simplest way to avoid certain biases that are inherent in more disaggregated comparisons. These biases are described in detail in the literature review in chapter 2.

A wide range of data on travel behavior, land use, demographic and economic factors, the highway system, and the population and land use histories of the cities were derived from a variety of sources. As mentioned earlier, many of the land use measures were developed specifically for this research. The ideas behind these measures and the formulas describing how they were calculated are outlined in chapter 3. This chapter also describes the central travel behaviors of interest, how they are defined and measured, and the relationships between them. The sources and definitions of the other data are in chapter 4.

There are three broad types of analysis in this research. First is a simple discussion of how the different travel behaviors vary with a number of different possible influences such as city size, block population density, and so on. This analysis, in chapter 5, uses all of the travel behavior data simply lumped together rather than broken out by individual city. The point here is just to get a general sense of the sizes and nature of the variations in behavior, to provide a baseline for understanding the variations across cities.

The differences between individual cities are analyzed in chapter 6. This is a regression analysis, where the values for the different travel behaviors for the 31 cities are regressed against various combinations of a long list of possible influencing factors. Another perspective is how the different behaviors influence each other; for example how transit share affects VMT or how commute time affects total daily travel time.

The very broad outcome of this analysis is that while some travel choices, such as transit share, can be very well explained, some of the more important ones, such as VMT and total daily travel time, appear almost entirely random. That is, while there are fairly large variations across the cities in the average value of these variables, it is often difficult to trace these variations to specific influences. This result likely has to do with measurement error resulting from the relatively small sample sizes available for many of the cities. For some variables, this measurement error can become the dominant source of observed variation, making it hard to discern the true sources.

Given the difficulty in finding relationships among variables at the level of individual cities, one last analysis, in chapter 7, groups cities together on the basis of similarities in land use factors and examines differences between these groups of cities. This is a sort of middle point between the analyses in the two previous chapters. For example, cities might be grouped together based on their residential density, or their job concentration (it won't be the same grouping in each case), and the differences between, say, high and low residential density cities can then be studied with somewhat more confidence.

Ultimately the results of all these analyses are somewhat ambiguous. If one wanted to see a link between land use and travel behavior, there is certainly some evidence that supports such a link. If one believes that no such link exists, there is also plentiful evidence that could be taken to support this point of view. At the very least, it seems clear that the strong, inevitable link between high density, mixed use development and reduced auto travel that is implied by much of the literature is actually at best a weak, occasional link when considered at the larger level of the entire urbanized area. While there are large variations in factors such as VMT and daily travel times across cities, little of this variation appears to be due to land use differences, even when using the most optimistic of the possible conclusions.

2 THE LITERATURE ON LAND USE AND TRAVEL

There are two important competing theories of the link between travel behavior and land use. The standard theory, that is, the one that is typically cited when the subject is discussed is, in a greatly simplified form, that people wish to accomplish certain tasks or participate in activities and will travel the minimum distance and time necessary to do so. Adherents of this "travel minimization" theory assert that the reason people drive so many miles is that modern American cities are so spread out that it is impossible to participate in the desired activities with less auto travel. A secondary component of this theory is that people would rather walk or ride transit if those modes were competitive with auto; thus another reason people drive so much is because low-density land uses make these alternative modes uncompetitive.

This theory is distinct from the commonplace notion that people wish to minimize the time necessary to complete any given trip. Once a destination is chosen, it is reasonable to think that a person will usually use the quickest route to get there; indeed, traffic forecasting models are based on this hypothesis. The travel minimization hypothesis, however, goes further by implying that even the destination choice and the number of trips are based on a desire to minimize travel time or distance. That is, generally people should prefer not to travel at all unless it is "necessary," and when they do travel they should prefer the closest "suitable" destination for what they want to do. The implication is that any policy that eliminates or shortens a trip will reduce the total amount of travel correspondingly.

The competing theory of land use and travel behavior asserts that people have a time budget for travel. The idea here is that people desire to spend a certain amount of time traveling each day (on average) and that the number of miles they cover will be determined by the speed at which they can travel, not by land use. In this theory high-density areas generate fewer miles of travel in large part because speeds are lower, so people cannot cover as many miles in the amount of time they are willing to spend. An often-overlooked element of this theory is that people have both an upper bound (which seems logical) *and a lower bound* on how much time they want to spend traveling on an average day. The other effect of land use is the same as the standard theory; that time spent in other modes will be part of the total travel time budget and thus mean less time spent in cars. To the extent that land use influences mode choice, it will influence total auto mileage and time.

These theories are very different in both what sorts of policies are likely to have impacts, and what are likely to create benefits. That is, if people want to travel less, then policies that make that possible will be both effective and in people's interest. If they have a minimum time budget, then the same policies might have little or no impact. For example, if there were more shopping opportunities close to home, people might occasionally take advantage of them, but the time they save might simply be applied to making additional trips. And to the extent that higher density might lead to lower local speeds, people could be worse off in that it would take them longer to access the vast majority of opportunities that are outside the neighborhood.

This report will not answer the question of which of these theories is right, although it will point out situations where facts appear to support one point of view more than the other. The long discussion of the literature in this chapter is not here because this report will resolve or even address all the issues that are raised. It is here for three main reasons. First, to illustrate in some detail the point that the issues that are studied in this research are not in fact nearly as clear and well understood as they are commonly believed to be. Second, to provide some background on how these questions are typically approached, and some standard results. Finally, to provide some detail on why, from a methodological standpoint, questions about the relationship between land use and travel behavior are hard to answer, and to hint at some future directions.

2.1 Travel Minimization

There is a long literature in the travel minimization tradition, with apparently unanimous agreement that higher density land use is associated with less VMT, and more use of non-auto modes. Even opponents by and large concede this point; their skepticism is more focused on the size and reasons for the impact. In particular, they question the extent to which the undeniable *correlation* between high-density land use and low auto travel is actually due to a *causal* relationship between the two, as opposed to demographics, or income, or other factors that are correlated with both.

Studies in this tradition tend to fall into three categories: simulations, comparisons of cities, and comparisons of different neighborhoods within the same city or region. Simulations are not helpful for our purposes here because the traffic forecasting models on which they are based inherently assume certain travel-land use relationships to exist. However the question we are asking is *whether* they exist . Thus this review will focus more on the latter two types, that is, studies based on data.

Probably the most famous comparison of cities is that done by Newman and Kensworthy (1989, 1999). They compared a number of large cities from around the world and found that several measures of auto use declined exponentially with density. Their early results provoked strong responses (e.g., Gordon and Richardson 1989), based in part on their evidence, and probably to a large extent on the implicit moral judgements underlying the analysis (Gordon and Richardson decry “Maoist planning practices”). Pickrell, in his excellent (although perhaps excessively harsh) literature review , criticizes the methodology of Newman and Kensworthy’s original work:

> … none of these results explicitly recognizes the critical influence of differences in income, household size, gasoline prices, and automobile taxation. Differences in these variables can be particularly large in international comparisons of residential density, as are differences in the historical timing of different cities’ development and thus in the transportation technology that influenced land use during periods of their most rapid growth. (Gomez-Ibanez, et al., page 423)

NK (1999, page 78) give the results of a subsequent analysis that does control for differences in income and gas prices; half of the difference between cities disappears. They then assert that the remaining differences are due to land use; the other issues of taxation, demographics, and history are still ignored. Another reasonable question, given the extremely high levels of congestion in many European and Asian cities, is whether VMT per person is constrained by the impossibility of physically fitting any more cars onto the available road space, and by the low speeds implicit in such crowding. If the low driving rates are a matter of physical constraint rather than choice, the outcome seems less desirable.

History is a particularly interesting factor in explaining differences. Evidence from the Twin Cities (Barnes and Davis 1999) and in the present research hints at the possibility that travel habits might be relatively persistent over the life of a given person. In particular, people who have not learned to drive by the time they reach adulthood seem less likely to ever learn. In the Twin Cities, a large part of the overall increase in driving between 1970 and 1990 was due to older people (especially older women) who did not drive being replaced in the population by younger people who did.

Given that higher incomes and car ownership have arrived somewhat later in other parts of the world than in the U.S., it seems not unlikely that substantial fractions of the populations of many countries still fall into the “never learned to drive” category. In addition to directly pulling down the average driving rate, these non-drivers create a larger market for transit and other options, which in turn helps to make these modes more viable for others. It seems likely that driving rates in other countries may rise closer to those in the U.S. as non-drivers become a less numerous part of their populations.

Much of the other literature in this field focuses around comparing different parts of a metropolitan area. Some of this compares averages from different neighborhoods, while another approach examines the behavior of individual households in various land use settings. A well-done example of this is Cervero and Gorham (1995). They look at a two sets of neighborhoods in San Francisco and Los Angeles, the first being neighborhoods with what they call a "transit" design and the other with an "auto" design. Unlike many other studies, they go to some lengths to ensure that each neighborhood from one set is matched with a neighborhood from the other set with similar characteristics in terms of income, access, and other factors. They then examine the work trip mode choice in the two sets.

Their work is aimed more directly at the physical layout of the neighborhood rather than the density per se. To the extent that they examine density as a stand-alone variable, the effect is not particularly strong. In Los Angeles County, increasing the density of a transit neighborhood from 2 to 30 dwelling units per acre (about 3,000 to 45,000 per square mile) increased transit share of commute trips from 7% to 23%, while the increase in an auto neighborhood was from 5% to 13%. It is not clear whether they controlled for the quality of transit service in this regression.

The results in this work are typical of the literature in two ways. First, links between population density and transit use are considerably more common than links to other measures of travel behavior. Second is that it takes a very large increase in density to generate a relatively small change in behavior. For example, a common result is that significant reductions in auto travel occur only when densities rise above 10,000 per square mile, which is nearly the upper bound of existing density in most cities, including Minneapolis-St. Paul. As another example, Schimek (1996) found that increasing residential density in U.S. urban areas from its 1990 average of 3,600 to 5,400 (50% higher) would reduce auto travel by less than 3% once household and neighborhood characteristics are controlled for. This is supported by Barnes and Davis (2001) who found that in the Twin Cities an increase in density of 1,000 per square mile (an increase of 10% to 100% depending on location) would be expected to reduce auto travel by about 1%, when controlling for differences in job access.

The most common objection to this literature is that travel choices are influenced by many factors, and many studies do not adequately control for these other influences. Thus behavioral differences are attributed to land use when they might really be arising because of, say, income differentials. Low-income people tend to travel less overall and use non-auto modes more. Thus any neighborhood with a high concentration of low-income people (or students, or elderly, or other low-travel groups) would generate less auto travel regardless of land use. However, low-income people tend to be more concentrated in high-density areas (and high-income people in low-density areas); thus if income is not explicitly considered, travel differences that are due to income could be mistakenly attributed to density. Ruth Steiner (1994) discusses this at length in her survey of the literature.

Another factor that is seldom controlled is speed of auto travel. This is an important point in distinguishing between the two theories of behavior. It is probably not considered in travel-minimization type studies because it should not be an issue according to this theory. In the theory, people should travel the distance necessary to reach their desired destinations; the amount of time it takes to get there (and the speed at which they travel) should not matter. However, in time budget theory, speed should be almost the only thing that matters. Thus controlling for speed, and studying it explicitly, should be a way of distinguishing the relative merits of the two theories.

The failure to explicitly consider speed is symptomatic of a more general problem in this field, which is that studies typically examine a single travel decision, such as work trip mode choice, in isolation. While it may seem trivially obvious that a trip by bus is replacing a trip by car, evidence suggests that the relationship is not so clear cut. For example, if one person in a one-car household takes the bus to work, then the car is available for the other person to make trips in during the day. Thus in this case the total amount of driving may not be reduced. The relationship between different travel decisions (and even by different people) is underexamined in this literature.

A final important factor that is usually not considered explicitly is location. Evidence from the Twin Cities indicates that access to regional opportunities influences the amount of time people spend traveling. People who live on the edges of metropolitan areas, far from the major job concentrations, have longer commutes and more total travel time than those who live in more central locations. This is true regardless of the density of the home location. Of course, outlying areas tend to be low density; thus the possibility arises that behavioral differences that are due to inconvenient location will be mistakenly attributed to density or other land use factors.

The importance of location leads to another important criticism of the methodology of comparing neighborhoods. This is that people choose where they will live within a city; that is, the sample is self-selected. In general, people who care about being able to ride the bus or walk to the store will try to live in places where they can do these things; people who don't care will be more likely to live in the less expensive suburbs. There is a very strong possibility that much of the auto travel reductions associated with high-density areas are an artifact of the people that chose to live there (and of the people that chose to live in low density, auto oriented suburbs).

More generally, studies of individual neighborhoods do not address the issue of how the land use in a given neighborhood influences the behavior of people who do not live there. If the ultimate objective is reducing the amount of auto travel in the region as a whole, then this is an important point. If all that is happening is that people who would have used transit anyway are concentrated in one area rather than dispersed throughout the region, then there will be little or no effect on overall auto travel. Or, mixing jobs into residential areas rather than concentrating them along freeways might mean more walking to work for local residents, but additional driving for (probably the vast majority) employees coming from outside the neighborhood. The important question is not whether high density reduces auto travel in that neighborhood; it's whether it leads to a net reduction over the urbanized area as a whole.

The largest problem from the point of view of the theoretical issue of this paper is that none of the evidence presented to support a density/VMT link is inconsistent with the travel time budget theory. That is, travel time budget theory would also predict lower VMT in high-density areas, because of lower speeds, more convenient location, and demographic and economic differences. From the evidence presented in the literature so far, it is impossible to know whether VMT is lower in high-density areas because people want to minimize the distance they travel, or because low speeds prevent them from traveling farther without exceeding their travel time budgets. To answer this question requires finding evidence that is consistent with one theory but not the other.

2.2 Travel Time Budgets

The general idea of travel time budgets is that people have an inherent upper and a lower bound on how much time they wish to spend traveling each day on average. There are individuals who are willing to spend much more or less, but when large groups are averaged, the range is fairly small. People may go outside their preferred range if constrained in some way (a broken leg, or a faraway but very desirable job), but if unconstrained they will gravitate on average to a range of times of about 60-80 minutes per day. Various factors, such as demographic and economic characteristics, and perhaps land use, may affect where in this range an individual will fall, but the range itself is relatively firm.

Some research is based on comparisons of the same city at different points in time. The classic example is a sequence of works by Zahavi and others around 1980 comparing travel times in the Twin Cities in 1958 and 1970, and Washington, D.C in 1955 and 1968. These papers found that time per traveler in both cities remained very nearly constant during these times, even though both cities grew substantially both in population and land area. This research was extended to 1990 in the Twin Cities by Barnes and Davis, who found average travel times just 3% higher than 1958.

Two other recent works examine travel times in other cities. Levinson and Kumar (1994, 1995) examine Washington, D.C. data from 1968 and 1988 and find that while total travel time per traveler appeared to have increased by about 15%, that commute times had remained constant over the period. Purvis (1994), studying the San Francisco area, reports that daily time per traveler increased 15.8% from 1965 to 1981, then declined 5.5% by 1990.

Other studies compare different cities, or neighborhoods within the same city. A good example of the latter is Ewing, et al. (1994), who finds that residents of a distant, low-density suburb of West Palm Beach spent almost two-thirds more time per person than comparable households in a “traditional” city. Barnes and Davis find that adult travelers in the most distant parts of the Twin Cities metropolitan area travel about 80 minutes per day, compared with 68 in the central cities. Both of these studies note the substantial differences in accessibility between the low-travel central regions and the high-travel outlying areas. Rutherford, et al. (1997) find that neighborhoods in Seattle varied considerably in VMT, but that there was almost no variation at all (from 86 to 91 minutes) in travel time.

A particularly interesting work (Schafer and Victor 1997, Schafer 1998) compares daily travel times in a large number of cities with widely varying transportation, land use, and cultural factors, ranging from the U.S. to Europe to developing Asia all the way to villages in rural Africa. They find that daily travel times across this extraordinarily wide range of urban situations varies only within a range from about 60 to 90 minutes a day, and that there seems to be no systematic difference between the different parts of the world. For example, the African villages, while almost entirely pedestrian based, did not generate different daily travel times than cities in developing Asia, which were not on average different from Japan or Europe or the U.S.

While 60 to 90 minutes may seem like a large range, it must be remembered that these numbers are drawn from many unconnected surveys; differences in methodology such as what travel is counted, how carefully the information is checked, and so on, can substantially affect how averages turn out. For example, in the Twin Cities, eliminating trips that left the metropolitan area reduced the average time per traveler from 90 minutes to 75. A few cases of a family of four piling in the car and driving ten hours to their vacation destination can make a surprisingly big difference, and so can a few coding errors that make some trips 1,000 minutes long; similar corrections or lack thereof make it difficult to directly compare results from different surveys.

In general this research is not aimed at identifying sources of variation in average daily travel times. This leads some to the belief that the travel time "budget" is a number fixed in stone; that any deviation disproves the theory. However, even the early work of Zahavi noted that money and poor job access can be important constraints, especially among lower income people. A more general approach recognizes that the travel time budget is somewhat pliable, that factors such as household income and access to jobs can affect the average amount of time that an individual will travel in a day. Because of these factors, average daily travel times could vary from one location to another within a city, from one city to another, and even within the same city over time.

Barnes and Davis identify three major sources of variation in the Twin Cities. First, adults spend more time traveling than children (under age 18) by about 70 minutes a day to 50. Workers are more likely to travel on a given day than are non-workers, but on the days they travel, the difference between them is only about 5 minutes. Finally, as noted above, residents of outlying areas with poor job access have longer commute times, which correspond almost one-for-one with longer total daily travel times. The first two of these are directly supported by the evidence in the present research. The last is not directly supported, since no evidence is available on job access for the individuals in the data, but the link between longer commutes and more daily travel time is found.

An important point is that observed travel time budgets apply to all modes, *on the days when people actually travel*. If people travel on a higher fraction of days rather than staying at home, this will lead the observed travel time *per person* (rather than per traveler) to rise. Barnes and Davis find that a substantial part of the increase in auto travel in the Twin Cities from 1958 to 1990 was due to this. In particular, rising travel rates among women and lower income people had a large, although probably one-time impact.

Another important point is that if more people use modes other than the auto, then the observed *auto* travel time per day will be lower, even if total travel time is not. Barnes and Davis find that the central cities of Minneapolis and St. Paul generate about five minutes less vehicle (auto) time per person compared with inner ring suburbs, although total time per traveler was nearly identical in the two locations. The difference was due to central city residents being more likely to use non-auto modes, and being slightly less likely to travel at all.

2.3 Role of this Research

The present research adds to the literature described above in a number of ways. Most importantly, it avoids the biases created by a disaggregate analysis by comparing travel behaviors across entire urbanized areas. While this may seem less sophisticated than modeling the behavior of individual travelers, a strong case can be made that it is methodologically more reliable. As discussed above, studies of individual travelers and the characteristics of their neighborhoods are subject to several sources of bias inherent in the implicit assumption that neighborhoods exist in isolation from the cities that surround them.

As noted earlier, the most famous comparison of cities is Newman and Kensworthy (1999). The present work improves upon their analysis in several ways. First, a very wide range of possible explanatory factors is considered; there is no inherent bias toward land use as the most important factor. Second, variations in governmental, cultural, and historical factors are minimized since all the cities studied here are in the United States; thus the specific influence of the physical structure of the city can be seen more clearly. Third, a large number of different travel choices are analyzed, rather than just one or two. This makes it possible to examine how, say, changes in transit share influence total VMT, and how total VMT is related to travel times.

Finally, this research improves upon almost all of the existing literature by explicitly breaking VMT into its components of speed and travel time. This is important in understanding the reasons why VMT is lower in dense areas. If it is because people are able to accomplish their desired activities with less travel, then it is a good thing. If, however, it is just because speeds are low and people cannot travel farther without exceeding their desired time budgets, then it may be a bad thing. While this paper does not develop a formal theory of travel preferences and behavior, there is an ongoing theme of identifying behavioral facts that tend to support one or the other of the travel minimization and travel time budget hypotheses.

3 LAND USE AND TRAVEL: THEORETICAL ISSUES

This chapter addresses a couple of theoretical points that are important for understanding the relationship between the land use of an urbanized area and the travel choices made by its residents.

The first issue is to develop methods to quantitatively describe the “land use” of an urbanized area in ways that correspond to intuition about what kinds of factors should matter. Simple density is probably not a particularly good way to describe land use of a large and heterogeneous area, because it is too dependent on where the boundary is drawn and because it is determined by total land area even if some of the land is sparsely or not at all populated. People who live in dense areas face certain choices; the presence of sparsely populated land somewhere else in the region probably does not affect these choices very much. To account for this, ways of measuring density are developed which assign more weight to more heavily occupied areas.

The second issue is understanding the relationship between the different components of travel behavior. That is, average VMT per person is a function of how much time people spend traveling, their speeds, the modes used, and so on. In general, the factors that influence one decision, such as mode choice, are not the same as those that influence another component, such as average daily travel time. To really understand differences in VMT it is necessary to understand all these components; the amount of variation shown by each, and the factors that influence them.

3.1 Defining and Measuring Density

This research is concerned with “urbanized areas” (UA). According to the census bureau definition, a UA consists of central cities and parts of surrounding suburbs that are populated at densities in excess of 1,000 people per square mile. Separate cities within the same MSA are sometimes defined as separate UAs; for example, San Jose is a separate UA from San Francisco and Oakland (which are one UA), although all three are in the same MSA.

The point of using UAs rather than MSAs or some other unit is to understand behavior within those parts of cities and their surrounding suburbs that are actually developed. The built-up part of the region is, by definition, where urban land use patterns might be influencing behavior; this relationship is the subject of interest. Rural residents generate more driving mileage than do urban dwellers; including them in the analysis will obscure the true travel patterns of urban residents, in some cities more than in others. The other advantage of using urbanized areas rather than metropolitan statistical areas (MSA) is that the population density of an urbanized area is determined by actual settlement patterns rather than by arbitrary political (county) boundaries.

Unfortunately, restricting analysis to built-up areas still leaves problems in measuring density. The most obvious is that UA density becomes very sensitive to the cutoff density at which a piece of land is no longer considered "urban." If the cutoff is lowered to 500 per square mile, overall densities decline substantially, more in some cities than others with sharper development boundaries. Also, the urbanized areas defined by the census don't seem in every case to match the definition. For example, the "official" density of the Pittsburgh UA is 2,157; when density is calculated manually, including only traffic zones with population density greater than 1,000 (as per the definition), the density rises to 3,032. This is a substantial difference, and again the size of this difference varies across cities.

A deeper problem with using simple UA density is that it gives equal weight to all developed land, regardless of the number of people living on it. For example, if a city has 99,000 people on one square mile, and 1,000 on another, its average would be 50,000, even though 99% of the people live at a density of 99,000. The other square mile carries equal weight in the average, even though only 1% of the population lives there. However, we are interested in human behavior; what we want to know is what people perceive density to be. This would be more closely captured by giving equal weight to each person, rather than to each square mile of land. Thus this research uses a new measure called "perceived density," which is defined as a weighted average of traffic zone densities, where each zone is weighted by the number of residents.

$$\mathrm{PD} = \frac{\sum_z \left(\frac{\mathrm{pop}(z)}{\mathrm{area}(z)} \right) \mathrm{pop}(z)}{\sum_z \mathrm{pop}(z)}$$

Traffic zones are a good basis for this measure because they are defined similarly by all cities. Traffic zones tend to be relatively small areas, ranging from potentially a single square block in a very dense area to perhaps a square mile or more in outlying areas, and typically containing 1,000 – 2,000 residents. The density of a traffic zone is thus a good measure of the immediate few blocks around a person's home, and since adjacent zones tend to be developed in similar ways, it is also a fair approximation of a somewhat larger area.

As a simple example of the perceived density concept, consider two cities, each with two zones of two square miles each. City A has 10,000 people in each zone, so average and perceived density are both 5,000 per square mile. City B has 18,000 people in one zone, and 2,000 in the other. Here the average density is again 5,000, but the perceived density is (9,000*18,000+1,000*2,000)/20,000=8,200. The high-density zone contains most of the people and hence carries most of the weight in determining overall perceived density.

New York and Los Angeles provide a classic real-world example of the difference created when zones are weighted by population rather than by land area. The "official" average population density of New York is 5,407; measuring by the strict census definition raises this number to 5,448. For Los Angeles the corresponding numbers are 5,800 and 6,992. These numbers are obviously at odds with the popular conception of New York as the consummate high-density environment, and Los Angeles as the epitome of sprawl.

There are two reasons why these numbers seem so different from expectations. First is that expectations are not entirely accurate. Los Angeles is, edge-to-edge, one of the most densely populated cities in the United States. The densely populated parts of L.A. are denser and bigger than those of any other city except New York, Chicago, and San Francisco; and the miles of suburbs of L.A. are far denser than those of any other city. Indeed, if "sprawl" (which despite its widespread use remains undefined) is taken to mean excessive low-density suburban land development, L.A. is the least sprawling city in the US. It does, obviously, go on for miles, but the urbanized area also contains in excess of twelve million residents (not even counting San Bernardino-Riverside); as many as the Dallas-Fort Worth, Washington, D.C., Boston, and Atlanta urbanized areas combined. Given this, the amount of land occupied by L.A. seems almost parsimonious.

The other reason why the densities of New York and Los Angeles seem out of order is that they are average densities; each square mile of land is given the same weight regardless of the number of people living on it. New York has a very large, very dense central core; this is what most people see. But New York also has dozens of miles of suburbs, just like every other city, and they are substantially less densely developed than the suburbs of LA. In fact, they go on so far, and are so sparsely developed (although they are dense enough to meet the 1,000 per square mile criteria to be part of the UA), that they pull the overall average below that of L.A.

However, when perceived densities are calculated, the situation comes more in line with prior beliefs. Los Angeles rises to 12,436, still the third highest of any city. But New York shoots up to 34,263, twice as high as any other US city, and nearly three times as high as LA. Most of the land in New York is relatively low density, but a very large fraction of the people live in very high densities. Using this measure makes it possible to describe population density more as it is experienced by the people that live in a UA.

A simple extension to this measure is "concentration," which is defined as UA perceived density defined by average density. If all land were developed at the same density, the two would be equal and concentration would be 1; the greater the extent to which densities are not consistent across the region, the higher perceived density will be relative to average, and the higher concentration will be. New York has an extremely high concentration; other cities vary, but all at a much lower level. These statistics are shown, for the cities in this study, in Table 3.1; the comparison between "official" and perceived density is shown graphically in Figure 3.1.

Table 3.1: 1990 residential density statistics

	Official UA Density	Excluding Low Density Zones	Resident Perceived Density	Residential Concentration
New York	5,407	5,448	34,263	6.29
Los Angeles	5,800	6,992	12,436	1.78
Chicago	4,285	5,218	12,168	2.33
Philadelphia	3,627	3,727	10,755	2.89
Detroit	3,304	3,537	6,079	1.72
San Francisco	4,153	6,109	16,935	2.77
Washington	3,559	4,041	8,732	2.16
Dallas	2,216	3,182	5,477	1.72
Houston	2,466	2,888	5,304	1.84
Boston	3,114	3,243	10,801	3.33
San Diego	3,403	3,761	7,123	1.89
Atlanta	1,897	2,041	2,916	1.43
Minneapolis	1,957	2,951	4,833	1.64
Phoenix	2,707	3,440	4,935	1.43
St. Louis	2,674	2,884	4,992	1.73
Miami	5,425	5,747	10,217	1.78
Baltimore	3,187	3,207	8,577	2.67
Seattle	2,966	3,007	4,928	1.64
Tampa	2,629	3,037	4,341	1.43
Pittsburgh	2,157	3,032	5,358	1.77
Cleveland	2,637	3,176	6,287	1.98
Denver	3,307	3,513	5,397	1.54
Norfolk	1,992	3,124	5,256	1.68
Kansas City	1,673	2,397	3,636	1.52
Milwaukee	2,395	3,366	7,103	2.11
Cincinnati	2,367	2,741	5,073	1.85
Portland	3,021	3,003	4,450	1.48
San Antonio	2,578	3,306	4,888	1.48
Sacramento	3,284	3,684	5,727	1.55
New Orleans	3,852	5,073	8,205	1.62
Buffalo	3,336	3,463	6,737	1.95

Table 3.1 (and the remainder of the report) uses the primary central city of each urbanized area as the UA name. In a few cases clarification is necessary regarding what is and is not included. Los Angeles includes Orange County but not Riverside-San Bernardino. San Francisco includes Oakland but not San Jose. Washington, D.C. does not include Baltimore (which is its own UA elsewhere in the list). Dallas includes Ft. Worth, Minneapolis includes St. Paul. Miami does not include Ft. Lauderdale.

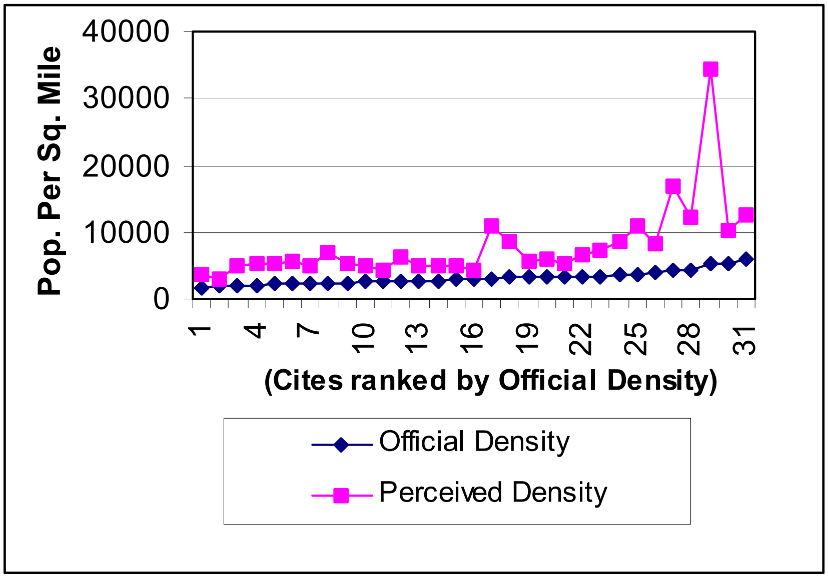

Figure 3.1: Comparison of official and perceived density

The concept of perceived density can be extended to create a number of additional new land use descriptors based on other types of density as perceived from other vantage points. For example, the perceived density of jobs in job locations divided by average job density describes the concentration of employment in the UA. To get this, the density of jobs in each zone is weighted by the number of jobs in that zone. Another object of possible interest is the perceived density of jobs in residential zones; that is, the density of jobs in each zone is weighted by the number of workers in that zone. This is a measure of the density of local opportunity, and possibly a measure of the extent of mixing of jobs and housing. Another measure of mixing is the perceived density of jobs in residential zones divided by the perceived density of workers in residential zones, which adjusts for the amount of local competition for jobs. These statistics describing employment density are shown in Table 3.2.

Table 3.2: 1990 employment density statistics

	Job Perceived Density from Job Location	Job Concentration	Job Perceived Density from Home Location	Mix
New York	128,230	49.9	5,156	0.33
Los Angeles	18,605	5.6	2,354	0.37
Chicago	66,843	26.8	1,736	0.29
Philadelphia	32,374	18.6	1,761	0.40
Detroit	29,083	18.7	807	0.33
San Francisco	53,710	17.3	3,950	0.38
Washington	66,877	29.1	2,337	0.45
Dallas	30,160	18.5	640	0.21
Houston	25,508	18.4	850	0.35
Boston	34,918	21.1	2,222	0.39
San Diego	12,076	6.5	1,347	0.38
Atlanta	23,021	21.2	762	0.48
Minneapolis	27,143	17.2	1,166	0.45
Phoenix	8,811	5.5	758	0.30
St. Louis	22,756	16.8	724	0.32
Miami	22,089	8.4	1,418	0.31
Baltimore	28,297	17.9	1,284	0.37
Seattle	28,842	18.7	1,125	0.42
Tampa	15,759	11.5	583	0.28
Pittsburgh	44,414	34.2	1,042	0.45
Cleveland	31,017	22.0	680	0.27
Denver	21,494	11.8	1,093	0.38
Norfolk	10,371	6.6	900	0.32
Kansas City	11,772	10.0	728	0.40
Milwaukee	17,140	10.8	1,040	0.34
Cincinnati	34,305	26.9	773	0.36
Portland	16,491	11.4	954	0.43
San Antonio	11,537	8.0	673	0.33
Sacramento	16,406	9.7	870	0.32
New Orleans	30,749	14.5	947	0.29
Buffalo	16,979	11.1	911	0.32

For example, suppose city A has two zones of one square mile each, each with 5,000 workers and 5,000 jobs. Here the perceived density of jobs is 5,000, both from job locations and home locations, and the average is also 5,000. The concentration of jobs is 1, and the mixing is 1. In City B there are two zones of one square mile each, but all the 10,000 workers are in one zone and all the 10,000 jobs are in the other. Here the average job density is still 5,000 but the perceived density from job locations is 10,000, so the concentration is 2. The perceived density of jobs from residential location is 0, since there are no jobs in the zone where people live, so mixing is 0. Obviously this is an extreme case, and counting only jobs in the home zone might be too restrictive, but again, in the real world adjacent zones are generally similar, so it is reasonable to think that bias will average out over the hundreds or thousands of zones in a UA.

The point of these measures is to understand the impact of land use as it relates to where people work. A very large fraction of daily travel is between home and work; and while the impacts of residential land use on travel choices have been extensively studied, commercial land use has been relatively ignored. It makes sense intuitively to think that the land use of a person's destination might influence travel choices in much the same way as land use at home does; these measures were developed to provide a way of testing this intuition in a more formal way. The first two measures address the density and concentration of work opportunities; the last two measure the extent to which jobs are mixed into residential areas.

3.2 Components of Vehicle Miles Traveled (VMT)

Both the travel minimization and the time budget theories of travel behavior are consistent with the observation that high-density areas generate less VMT. The difference between the theories lies in how and why VMT is lower in these areas. To identify which theory is right (or the extent to which each is right) requires determining how the components of VMT vary with land use; specifically whether VMT is reduced because of less travel time, lower speeds, different mode choice, or a combination. In general, a detailed understanding of how these different factors affect VMT, and how they are determined, seems a useful input for purposes of effective policy making.

The fundamental relationship is that VMT equals vehicle-minutes per person times speed. A vehicle-minute per person is the total number of minutes that cars are driven, divided by the total number of people. This is independent of the number of people in the car; if four people share a 20-minute ride, that is 20 vehicle-minutes. (It is 80 person-minutes; this shows up under a different variable – total minutes per traveler.)

In Table 3.3 and Figure 3.2, higher VMT seems to arise from a combination of higher speeds and higher vehicle times. Interestingly, the two are somewhat positively correlated (0.39); that is, higher speeds are associated with *more* time traveling in cars, not less. Note that this is total vehicle-minutes, not total travel minutes (which also includes time in transit, walking, auto passenger, etc.); vehicle time is lower in cities with high non-auto mode shares. There is no implication that people in these cities spend less *total* time traveling.

Table 3.3: Components of vehicle miles traveled

	VMT/person	Ave. Speed	VehicleMin. Per Person
New York	11.28	26.70	25.35
Los Angeles	19.67	29.25	40.35
Chicago	15.97	26.38	36.32
Philadelphia	13.03	27.00	28.97
Detroit	19.06	30.20	37.87
San Francisco	19.52	30.97	37.82
Washington	17.40	29.44	35.46
Dallas	22.12	32.99	40.23
Houston	22.07	30.52	43.38
Boston	18.80	30.01	37.58
San Diego	19.30	32.20	35.97
Atlanta	21.45	31.68	40.63
Minneapolis	20.16	31.93	37.90
Phoenix	16.44	27.27	36.19
St. Louis	16.81	29.20	34.53
Miami	16.79	26.71	37.71
Baltimore	18.84	30.75	36.76
Seattle	18.24	28.09	38.97
Tampa	18.89	27.02	41.95
Pittsburgh	14.61	24.92	35.17
Cleveland	14.16	26.62	31.92
Denver	22.96	31.68	43.49
Norfolk	17.53	28.15	37.37
Kansas City	17.41	31.33	33.35
Milwaukee	15.63	28.62	32.77
Cincinnati	15.56	28.76	32.46
Portland	17.98	28.11	38.39
San Antonio	23.18	34.26	40.60
Sacramento	17.60	31.40	33.63
New Orleans	16.70	27.70	36.18
Buffalo	14.58	27.65	31.65

It is important to note that VMT as it is being used here includes only personal travel in private passenger vehicles by residents of the urbanized area. VMT as it is normally measured for forecasting purposes includes all vehicle travel in a region, including commercial and business travel in both cars and trucks, travel by people from outside the region, and any other vehicles. These are all appropriate to include when the objective is to forecast total system usage and capacity constraints. However, the objective here is to understand the personal choices made by residents of a region, thus it is appropriate to exclude these other trips. The point is that VMT as it is used here is a subset of the "total" VMT in a region.

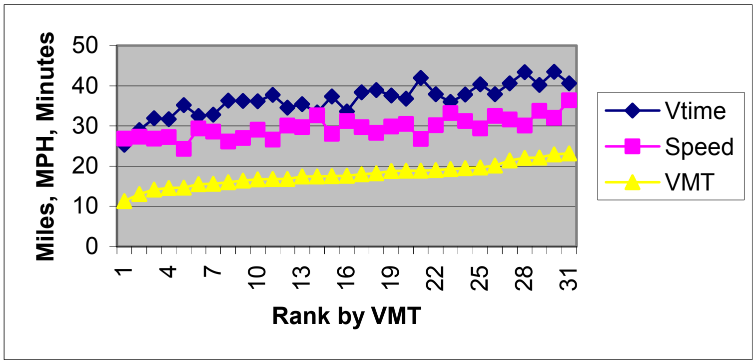

Figure 3.2: Components of vehicle miles traveled

Higher vehicle-minutes could in theory arise from one or both of two sources, more total travel minutes or different mode choice, specifically more driving and less time in alternate modes. Average total travel minutes could be described per person, or per traveler; that is, including only the people who actually make a trip in a given day. Here the second definition is used because it makes the numbers more comparable to other research on travel time budgets. The conversion is done by dividing average minutes per person in each city by the fraction of people in that city who made a trip on the day they were surveyed.

Total minutes per traveler can then be divided into vehicle-minutes per traveler plus minutes in other modes. Other modes include primarily transit, walking, biking, school bus, and passenger in carpool. That is, vehicle time is measuring the amount of time the car, not the person, is on the road. One person driving a car 20 minutes creates 20 vehicle-minutes. But four people sharing a 20-minute ride still create only 20 vehicle-minutes; the fact that there are four people does not increase the number of cars on the road (or the amount of congestion or pollution or other problems associated with this). Thus in the second case each person would be charged with five vehicle-minutes and fifteen other mode minutes. This distinction helps to identify more clearly how decisions and actions by people translate into problems caused by vehicles.

In many cities carpools are the primary alternate mode; this accounts for what may seem like surprisingly high “other mode” times in places like Detroit or Dallas that have very low transit shares. In general though, carpool rates do not vary greatly from one city to the next (the range across cities for carpool as a percent of all work trips is from 10% to about 15%), thus differences between cities largely arise from differences in non-auto modes; this is in fact almost all transit (which varies from 1% to 28%). (See Table 3.4.)

Table 3.4: Other individual travel statistics

	Vehicle min./person	Prob. Of Travel	Vehicle min./traveler	Other mode min./traveler	Total time/ traveler
New York	25.35	0.81	31.26	41.46	72.72
Los Angeles	40.35	0.90	45.03	27.30	72.33
Chicago	36.32	0.86	42.29	30.40	72.69
Philadelphia	28.97	0.85	34.06	33.07	67.13
Detroit	37.87	0.84	45.24	21.28	66.52
San Francisco	37.82	0.89	42.54	32.77	75.31
Washington	35.46	0.85	41.77	32.44	74.21
Dallas	40.23	0.88	45.9	23.33	69.23
Houston	43.38	0.90	47.99	24.83	72.82
Boston	37.58	0.88	42.77	26.44	69.21
San Diego	35.97	0.84	42.73	22.60	65.33
Atlanta	40.63	0.84	48.32	25.53	73.85
Minneapolis	37.90	0.87	43.44	24.12	67.56
Phoenix	36.19	0.86	41.87	27.85	69.72
St. Louis	34.53	0.85	40.58	23.59	64.17
Miami	37.71	0.84	44.67	23.53	68.20
Baltimore	36.76	0.87	42.31	29.19	71.50
Seattle	38.97	0.90	43.42	29.07	72.49
Tampa	41.95	0.88	47.71	25.81	73.52
Pittsburgh	35.17	0.84	42.08	24.82	66.90
Cleveland	31.92	0.86	37.27	24.26	61.53
Denver	43.49	0.85	51.23	28.70	79.93
Norfolk	37.37	0.84	44.44	25.94	70.38
Kansas City	33.35	0.88	38.09	26.31	64.40
Milwaukee	32.77	0.86	38.23	22.88	61.11
Cincinnati	32.46	0.92	35.19	29.43	64.62
Portland	38.39	0.91	42.05	30.07	72.12
San Antonio	40.60	0.93	43.68	29.42	73.10
Sacramento	33.63	0.86	39.13	21.23	60.36
New Orleans	36.18	0.89	40.72	32.05	72.77
Buffalo	31.65	0.86	37	22.05	59.05

Cities with high total travel times seem in general to have both more vehicle time and more other mode time than the cities at the bottom end of the scale. There aretwo cities (New York and Philadelphia) where a high level of time in other modes is associated with a very low level of vehicle time. In general, however, the two don't seem to be strongly correlated. Overall, the correlation is -0.36, however, the relationship is so extreme in New York that it single-handedly changes the outcome; when New York is excluded the correlation is just –0.11.

Figure 3.3 also illustrates the point that the travel time budget is not a single fixed number, but can vary as other influences do. The range from lowest to highest among these cities is 20 minutes, or 33%. This is quite a large range; indeed it could almost be taken to invalidate the whole hypothesis that average travel times are relatively constant for all groups of people. However, the "true" range of average travel times across these cities is almost certainly smaller than is observed here, perhaps significantly so.

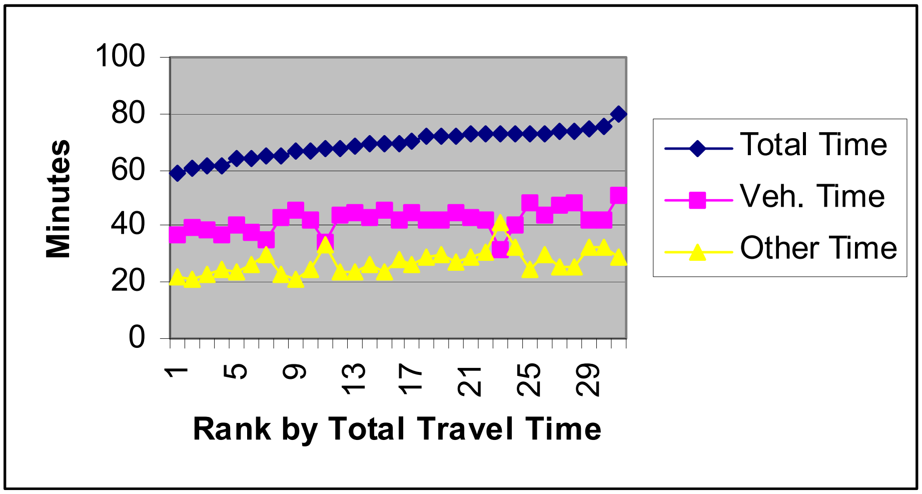

Figure 3.3: Components of total travel time

The reason for this is that most of these averages are based on relatively small sample sizes ranging from about 300 to 700. These may seem like large samples, but there is such dramatic variation in individual daily travel times that for these cities the mean can only be identified within a range of as much as fifteen to twenty minutes (a 95% confidence interval). Without getting deeply into statistical theory, the confidence with which an average can be identified depends both on the sample size and on the variation shown by individual elements in the sample. When individuals show great variation, the sample mean can be changed significantly when more or different people are included, even if the sample is representative of the population. In general, the best that can be done is to identify a range; that is, to say that with 95% probability, the "true" mean is somewhere between some lower and upper bound.

The reason the true range of travel time averages is probably less than is observed here is that the sample mean for some cities will be lower than the true mean and for other it will be higher. Furthermore, the odds of the sample being high or low do not depend on the value of the true mean. So some cities with low true means will have sample means even lower, and likewise for cities with high true means. Thus the range of sample means will almost certainly be larger than the range of true means. To illustrate this point, Figure 3.4 shows the distribution generated by a random drawing of 31 “sample means” from a distribution with mean of 70 minutes and standard deviation of four minutes, which is a typical situation observed in the cities in the sample.

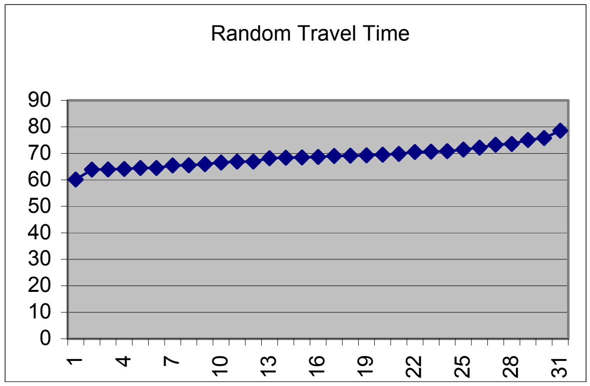

Figure 3.4: Range of average travel times from random generation

Interestingly, almost exactly the same range and distribution of values is observed even when all cities have exactly the same “true” mean (compare this to the “total time” line in Figure 3.3). The point is not that the true mean is in fact the same for all these cities, but just to illustrate that a large range of values can be observed even when the true range of values is small. Thus the large range of average daily travel times in these cities is not automatically inconsistent with the hypothesis that these averages should vary within a fairly small range. To some extent, similar arguments can be applied to many of the other variables in this data set. In particular, the range of “true” average VMT per capita is probably smaller than is seen in the averages presented here.

4 DESCRIPTION OF DATA AND VARIABLES

This chapter describes each of the variables used in the subsequent analysis. This description includes how the variable is defined, its abbreviation in the regression analysis, the source of the numbers, and in cases where it is not obvious, the reason for including it in the analysis; that is, what insight it might offer, or what behavior it is expected to possibly influence.

There are two important points about the data used in this research. The first is that urbanized area averages for some of the variables can be calculated only with limited accuracy due to small sample sizes; this was discussed briefly in the previous chapter. Imperfect measurement is almost a given with behavioral data; however, in some cases the imperfections become so large that they constrain the quality of the results that can be obtained. This is particularly an issue with the data that are taken from the NPTS. These problems are discussed in section 4.1.2.

The second point is that data come from both 1990 and 1995. Most comes from 1990 and is drawn directly or indirectly from the census of that year. However, the first seven travel behavior variables listed in section 4.1.1 come from the NPTS of 1995. This was done because the 1995 NPTS benefited from a much improved survey methodology; the results from that year seemed more reliable that those from 1990. With the exception of congestion, aggregate travel behaviors and outcomes do not generally change rapidly; using 1995 data should not introduce much inaccuracy at an aggregate level. The difficulties in measuring these averages in the first place are probably a far larger source of problems than using the wrong year.

4.1 Behaviors to be Explained

This section describes the actual travel choice variables that this research hopes to explain; as opposed to the land use and other factors that might influence those choices. The first subsection describes the variables themselves; the second discusses the statistical issues that arise from their imperfect measurement.

4.1.1 Variables

The first seven variables are the primary behaviors with which this research is concerned. They were all defined in section 3.2. The data for all of them are derived from the Nationwide Personal Transportation Survey (NPTS) of 1995. This data source is discussed at more length in section 4.1.2.

Vehicle Miles Traveled per person per day (VMTpers)

Average Vehicle Speed (Speed95)

Vehicle-minutes Traveled per Person per day (VehTimePers)

Fraction of people who travel each day (TravelProb)

Vehicle-minutes traveled per Traveler per day (VehTimeTr)

Other mode minutes traveled per Traveler per day (OtherTimeTrav)

Total minutes traveled per Traveler per day (TotalTimeTrav)

In addition, there are a few secondary behavioral variables that are examined to see what additional light they can shed.

Trip to work mode shares are studied to see the relationship between them and the larger behavioral outcomes, and to see if the same factors influence both. All come from census journey to work data of 1990, considering just residents of the urbanized area of each metropolitan area, as defined by the census bureau. The shares will not add to 100 because there are other minor modes that are not included in these numbers. For these variables the full name is used in the regression analysis.

Drive Alone

Car Pool (Includes car and van pools up to 10+ passengers)

Transit (Includes bus, light rail/trolley, heavy rail/subway, and commuter rail)

Walk/Bike

Commute times are studied because evidence from the Twin Cities suggests that variations in total travel time arise largely from variations in commute times. As with mode shares, the question is how commute times influence the more basic behavioral variables, and whether the same factors influence both. These are taken from the 1990 census journey to work data, from residents of the urbanized area only.

Median time, all modes (AllCommMed)

Median time, drive alone only (DAcommMed)

Mean time, all modes (AllCommMean)

Mean time, drive alone only (DAcommMean)

Congestion is examined both as an influence on basic behavioral variables and as an outcome in its own right. That is, we are interested both in how congestion influences other decisions such as total travel time and mode choice; and in what factors influence the level of congestion itself, since congestion is a concern that many people find important in its own right. Congestion measurements are taken from the well-known ratings produced each year by the Texas Transportation Institute (tti.tamu.edu) for a large number of cities in the U.S. These ratings are based on estimated congestion both on freeways and on local streets. We use the numbers from both 1990 and 1995 because the travel behavior, land use, and other data to which we are relating congestion are taken from both of these years.

Congestion in 1990 (Congestion90)

Congestion in 1995 (Congestion95)

4.1.2 Issues

Values for the first set of behavior variables described in section 4.1.1 were all derived from the 1995 Nationwide Personal Transportation Survey (NPTS). Residents of the 31 urbanized areas used in this study could be identified because the primary city name was given for residents of large metropolitan areas and each person in the sample was listed as an urban or rural resident. Thus it was possible to restrict the sample, at least within a good approximation, to residents of the actual urbanized area of each city region.

The only adjustment made to the data was that trips that were longer than 100 miles or 120 minutes were excluded from the analysis. The intent of this study is to understand ordinary daily travel within a city; very long trips that leave the region entirely are not within the scope of this analysis. Besides being inappropriate, these trips can also distort the results; a family of four going on a 200-mile vacation trip on the day they were surveyed can significantly change the average VMT for the entire city of which they are residents. Thus we exclude these trips to restrict the analysis to the types of travel we are actually trying to understand.

The original conception of this research was to use the VMT numbers published in the FHWA Highway Statistics; indeed, the extremely large variation observed in these numbers was the single most important observation motivating the project. However, as the research progressed it became clear that these numbers were either inappropriate or incorrect, or both. VMT per person per day in the FHWA data ranges as high as 36 miles a day; no realistic combination of travel times, mode choice, and speed could possibly yield a figure even close to this high. These very high numbers drop by nearly half when diary-based estimates are used. Two plausible explanations have been suggested. First, VMT as defined by FHWA includes all vehicle travel in an urbanized area, not just the subset used in this research, that is, personal travel by residents of the UA. In particular, commercial travel and travel by people from outside the UA are included. This certainly is part of the difference, and probably a variable part depending on how much such traffic goes through different cities.

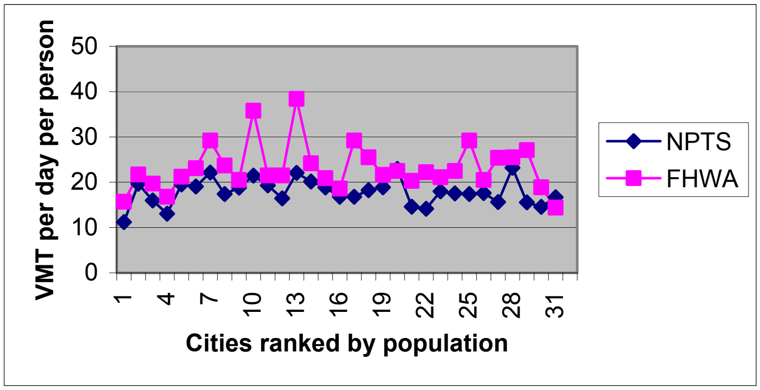

Figure 4.1: Comparison of VMT estimates

Another possibility is simply that the data are not representative of "true" levels of travel. The numbers are calculated by counting traffic on a sample of roads and scaling the resulting estimates up to the entire UA. It could be that the roads sampled were not representative of their type, or that they were sampled on unusual days. Another, perhaps more likely possibility, is that the urbanized area boundaries used to scale up the VMT samples were not the same as were used to calculate population; in which case total VMT would have been measured over a larger area than population, making VMT per person appear unduly high. Some evidence for this is that the miles of roadway per person also vary by what seems like a large amount given the variation in other factors. In any case, the conclusion was to use only the diary-based data from NPTS.

A significant issue that needs to be addressed is that the NPTS sample sizes for some of the 31 cities in this study were relatively small, thus the behavioral variables could be estimated only with a relatively low degree of accuracy. This impacts the quality of the analysis that can be done with the data. Depending on the city, 95% confidence intervals for VMT could be as wide as five or more miles, and for total daily travel time the interval could be as wide as fifteen minutes. These are substantial ranges when the average values for these variables are about 18 miles and 70 minutes.

There is no reason in general why this should bias the results. Indeed, imperfect measurement is more or less taken for granted in the social sciences; unless the measurement itself is systematically biased in some way (which there is no reason to believe to be the case here), the only impact should be on the confidence that can be attached to the estimates. That is, the errors of the estimated regression parameter values will be relatively large and statistical significance will be harder to observe, especially in cases where there is not a very strong relationship to start with.

This need not be a bad thing. The point of policy is to create observable impacts; if the impact of a certain factor on some behavior is so small or so inconsistent that it can only be discerned in very large samples, then this may not be the highest-leverage type of policy to pursue.

Another point to consider is that while the results of this particular study could be written off as an artifact of small sample sizes, it is nonetheless the case that the sample sizes used here are no smaller than those used in other studies. In particular, studies comparing different neighborhoods rely on samples from each neighborhood of at most a few hundred individuals; given the error ranges noted here there is little reason to believe that these studies would turn out the same way if new samples were taken.

The point here is not that this study or studies of this type are pointless or their results without meaning. The point is just that it is hard to draw strong, certain conclusions because most of the time it is very hard to be sure that the averages that are observed are really representative.

Overall, the 1995 NPTS sampled 95,360 people, of which 30,910 were in the urbanized parts of the 31 cities in this study. The appendix contains a sequence of tables showing how this total allocates to the 31 cities, and the 95% confidence intervals around a number of estimated variables of interest such as VMT and total daily travel time.

4.2 Land Use Variables

The first two come from FHWA Highway Statistics 1990, which takes them from the census bureau. Area is measured in square miles, and density in people per square mile. The reason for including area is to test whether the sheer physical size of the built-up region is important. Simple density, as discussed in section 3.1, is probably not the best way of describing how a city is developed, however it is included for completeness.

Total urbanized area land Area in 1990 (Area90)

Official urbanized area Density (Dens90)

The next seven land use descriptors are constructed based on population and employment in traffic analysis zones (TAZs) in the 1990 census data. They are defined in section 3.2.

Alternate urbanized area Density (RevDens) (Including only those tazs with more than 1000 people or 500 jobs per square mile)

Perceived Population Density from Residential locations (ResPD)

Residential Concentration (ResConc)

Perceived Job Density from Work locations (JobPD)

Job Concentration (JobConc)

Perceived Job Density from Home locations (JobPDbyWkr)

Job/Population Mix (Mix)

The final two land use descriptors are alternate simple measures of employment concentration, referring specifically to the central business district (CBD). They too are derived from the census.

Total employment in the CBD (CBDsize)

CBD share of total metropolitan area employment (CBDemplshare)

4.3 Economic and Demographic Variables

All these are derived from the 1990 census.

Median income (MedInc) (This and the next three variables were available only for entire metropolitan areas, including the rural parts of metropolitan counties. This is a different area from that encompassed by the rest of the data. However, as the vast majority of the population of metropolitan areas lives inside the urbanized area, it is likely that the median income of the urbanized area would not be much different.)

Fraction of people in households with incomes less than $15,000/year (Poor15)

Fraction of people in households with incomes less than $30,000/year (Poor30)

Vehicles per capita

Workers per capita (Total number of workers divided by total population, for both groups counting only people living in the urbanized area. This is calculated directly from the census data for each city.)

Population 1990 (For the urbanized area)

4.4 Transportation System Variables

All of these come from FHWA, with the potential measurement problems discussed in section 4.1.2.

Total highway miles per capita (This is simple center line miles, with no adjustment for number of lanes)

Freeway miles as % of total highway miles (fwmilesoftotal) (Again, this is simple centerline miles for both)

Freeway vmt as % of total vmt (fwvmtoftotal) (Total VMT driven on freeways divided by total VMT)

No transit system variables, or measures of walk/bike friendliness, carpool incentives, etc. were easily available. In any case, almost all variation in transit share is explainable without reference to service quality, although other modes are not so clear. A deeper examination of mode choice should include these variables, but that is not the central focus of this research.

4.5 Historical Variables

These are here to test the hypothesis that some cities are different from others simply because they always have been. In the short term, people may not move much between cities based on transportation preferences, but in the longer term this could be a factor. Another possibility is that if a substantial part of a city is organized around a transit system, then it makes sense to keep exploiting that investment, keeping transit share high; while it may be impossible for transit to get a foothold in a city that is not already at least partially organized around it, even if it is otherwise much the same as the first city.

These data came from www.demographia.com, and were originally derived from census data.

Urbanized Area Population in 1950 (population50)

UA Density in 1950 (density50)

UA population growth 1950-1990 (popgrowth5090) (Defined as Pop1990/pop1950)

UA density growth 1950-1990 (densgrowth5090) (Defined as dens1990/dens1950; some cities did get denser, most didn't)

Population in 1900 (pop1900) (This was the big era of transit building; being a big city in 1900 may have had long lasting effects on land use)

Population growth, 1890-1910 (popgrowth1900) (Defined as pop1910/pop1890. Cities that were growing rapidly at this time may have been more likely to invest in substantial transit systems, which again may have had long lasting effects.)

Population growth 1900-1990 (popgrowth20c) (Cities with more stable populations might be more likely to remain relatively more focused around legacy transit systems and land uses.)

5 GENERAL RELATIONSHIPS BETWEEN VARIABLES

This section provides some general background on how the travel behavior variables of interest vary with a few different general factors. The information is all taken from the 1995 NPTS. The data set was divided into categories based on different factors, and the average value of each of the behavioral variables was calculated for each of the categories.

Tables 5.1 through 5.4 include all people, urban and rural, from the entire NPTS. This is the only place in this report where people who do not live in the urbanized parts of cities are counted. It is done here to give a sense of how rural dwellers differ. This is also the only analysis that includes people who live in cities other than the 31 studied in the rest of this report. Again, this is done to show how these cities differ from other, smaller places.

Table 5.1: Individual travel statistics by city size

	No MSA	50-250k	250-500k	500k-1M	1-3M	>3M	NY (18M)
Total Time/Traveler	67.7	65.6	66.0	66.1	66.5	71.5	72.8
Other Time/ Traveler	27.0	24.4	25.4	24.8	24.4	27.0	40.6
Veh. Time/ Traveler	40.7	41.2	40.6	41.3	42.2	44.5	32.1
Prob. of Travel	0.86	0.88	0.86	0.86	0.87	0.87	0.82
Vehicle Time/Person	35.2	36.1	35.0	35.7	36.5	38.8	26.2
Average Speed	34.9	31.9	32.1	31.5	31.6	31.4	27.5
VMT/Person	20.5	19.2	18.8	18.8	19.2	20.3	12.0

Table 5.1 breaks the sample down by the population of the metropolitan area (not urbanized area, in contrast to most of the rest of the report). New York is broken out separately because it has very different behavior from other large cities, and because it is a very large sample, thus it distorts the results when it is included with other cities. There are two striking points. First is that New York is very different even from other large cities. Second is that, excluding New York, there is almost no variation at all in any of these travel behaviors. Particularly noticeable is that the columns containing cities of 50,000 and cities of 2.5 million are essentially identical. The fact that it is possible to drive from one end to the other of a city of 50,000 in less than 10 minutes somehow does not prevent people who reside in these cities from spending 65 minutes a day driving around, just like people in much bigger cities do.

Table 5.2 lends support to a number of findings in the Twin Cities region. First, children travel less than adults. Second, workers spend more time traveling, travel at higher average speeds, and are more likely to travel in a given day, than are nonworkers. This is true for both urban and rural residents. Third, residents of outlying rural areas spend more time traveling and travel at higher average speeds than do residents of the urbanized area. In all these comparisons, the numbers shown here correspond very closely to those observed in the Twin Cities.

Table 5.2: Individual travel statistics by type of person

	Child (<18)	Urban Worker	Urban NonWorker	Rural Worker	Rural NonWorker
Total Time/Traveler	53.2	73.3	65.4	77.6	69.9
Other Time/ Traveler	39.9	23.2	29.3	20.1	26.3
Veh. Time/ Traveler	13.3	50.1	36.1	57.5	43.7
Prob. of Travel	0.87	0.91	0.75	0.91	0.75
Vehicle Time/Person	11.6	45.8	27.2	52.5	32.7
Average Speed	31.2	30.7	25.2	36.4	31.0
VMT/Person	6.0	23.4	11.4	31.9	16.9

Again, in the Twin Cities it was observed that all aspects of travel increase with income; this result is supported in Table 5.3. Higher income people (both workers and non-workers) are more likely to travel in a given day, and they spend more time traveling at higher average speeds. They are also more likely to use cars rather than other modes. All of these facts together lead to a substantial difference in total mileage generated; people in households with income above $45,000 per year drive twice as many miles as those with household income below $15,000 per year. This supports the contention of many critics of travel behavior studies that failure to control for income differences can substantially bias results, especially for an area as small as a neighborhood.

Table 5.3: Individual travel statistics by household income

	<$15,000	$15-25,000	$25-45,000	>$45,000
Total Time/Traveler	63.6	65.9	68.2	71.6
Other Time/ Traveler	32.4	27.7	26.9	27.0
Veh. Time/ Traveler	31.2	38.2	41.3	44.6
Prob. of Travel	0.78	0.84	0.88	0.90
Vehicle Time/Person	24.2	32.1	36.4	40.3
Average Speed	27.7	30.1	32.0	33.0
VMT/Person	11.2	16.1	19.4	22.2

Part of the effect of income probably arises from the fact that higher income households are more likely to have two workers, since workers drive more than non-workers this would tend to increase the average, other things equal. Another important point is that higher-income households are more likely to live in low-density, high-speed, high-VMT suburban settings. This correlation is addressed again in Figure 5.1 later in this chapter.

Table 5.4 breaks people down by the population density of their census block group. This illustrates the effect of density on travel behavior that is typically noted in the literature; that is, given that the sample is self-selected and that higher density areas tend to be more conveniently located relative to major job concentrations. Each column corresponds roughly to a doubling of density from the previous column. Speed declines in a consistent way across all the density levels; this contributes considerably to the observed decline in VMT, especially at lower densities. Vehicle time per traveler, total time per traveler, and VMT decline gradually as density increases to 4,000 to 10,000 per square mile.

Table 5.4: Individual travel statistics by block population density

	0-100	100-500	500-1k	1-2k	2-4k	4-10k	10-25k	>25k
Total Time/Traveler	73.9	70.7	69.6	67.4	65.6	65.6	67.9	74.3
Other Time/ Traveler	28.7	25.8	25.2	24.4	24.0	25.1	33.0	55.5
Veh. Time/ Traveler	45.2	44.8	44.4	43.0	41.7	40.5	34.9	18.8
Prob. of Travel	0.85	0.87	0.88	0.88	0.87	0.87	0.83	0.78
Vehicle Time/Person	38.6	39.0	39.0	37.6	36.4	35.2	29.0	14.6
Average Speed	36.9	34.8	33.1	31.7	30.3	28.7	26.3	23.0
VMT/Person	23.7	22.6	21.5	19.9	18.4	16.8	12.7	5.6

At densities above this level, a noticeable behavior change takes place. The amount of vehicle time per traveler begins to drop precipitously, and time in other modes to increase correspondingly. This leads to a rapid decline in VMT at these higher densities. (Note, however, that residents of these densities do not spend less *total* time traveling – the benefit seems to accrue more to society as less need for road capacity, rather than to the residents themselves.) This large decline in VMT lends strong support to the claims in the literature that higher densities lead to higher use of alternate modes and to less driving.

However, there are three important caveats. First, the last column consists almost entirely of residents of New York. The densities in which these people reside in many cases far exceed 25,000 per square mile; large parts of New York exceed even 100,000 per square mile. Therefore it is important to note that these dramatic effects on behavior are likely not occurring at the relatively low density implied by the column heading. Second, 25,000 per square mile is a very high density, at least in the United States; only a handful of cities besides New York have more than a negligible number of people living at these densities (specifically, Chicago, Los Angeles, San Francisco, and Philadelphia). Thus the more modest effects seen at lower density levels may represent more realistic policy goals for most cities. Third, it is still not clear that lower VMT in high-density parts of cities actually reduces VMT overall; it could be that all that is happening is that people who wouldn't have driven much anyway are choosing to concentrate in certain neighborhoods. Shedding light on this question is a major objective of this study.

A final interesting question is how the last two tables interact. That is, lower income people travel less, and residents of high-density areas travel less. To the extent that the two groups overlap, is it possible to determine the relative influence of each factor?

Figure 5.1 breaks people into groups based both on their income and on the population density of their census block group. The horizontal axis shows the eight density categories from the previous table; the different lines correspond to the four income levels. The vertical axis shows total VMT per person. The lowest income category travels about seven or eight miles per day per person less than the highest income group; this difference persists across all density levels. At the lowest density this amounts to about a 25% reduction compared to high-income people, but at the highest density it is nearly 75%. That is, higher densities reduce VMT for everyone, but they reduce it relatively more for low-income people, who are starting from a lower base.

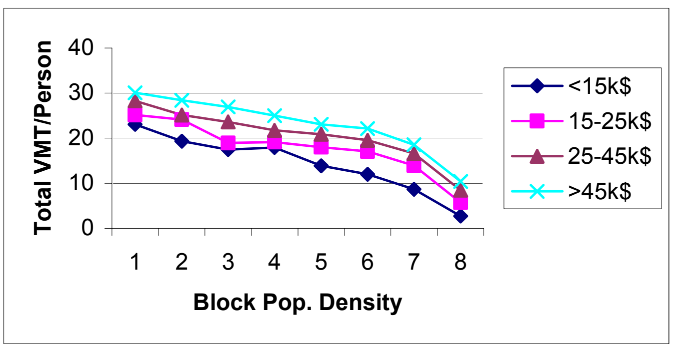

Figure 5.1: VMT, income, and population density

Tables 5.5 through 5.8 include only urban residents of the 31 cities in the rest of the report. The idea of these tables is to divide the cities based on various characteristics and show, for example, how cities with high VMT differ from cities with low VMT in terms of the other behaviors.

New York, as noted earlier, is both very different from other cities and is a much larger sample. Thus it is necessary to exclude it from this analysis, since if it is included it badly skews the averages of whichever column it is in. New York is shown as a separate column in the first table to show its characteristics. (Note that these are only urban residents – this is why New York here has different numbers than it did in an earlier table.)

The first experiment (Table 5.5) was to divide the cities into the half with the highest VMT and the half with the lowest. The difference in VMT between the two halves is substantial, and seems to result about equally from more vehicle time and higher speeds in the high VMT cities.

Table 5.5: Differences between low and high VMT cities

	Low VMT	High VMT	New York
Total Time/Traveler	67.4	70.4	72.7
Other Time/ Traveler	27.7	26.7	41.5
Veh. Time/ Traveler	39.7	43.7	31.3
Prob. of Travel	0.86	0.88	0.81
Vehicle Time/Person	34.0	38.5	25.4
Average Speed	27.6	30.2	26.7
VMT/Person	15.7	19.3	11.3

Table 5.6 shows the results when the cities are broken into groups based first on (official) urbanized area population density, and second, on transit share of work trips. (The two sets of columns are not related to each other; they are just in the same table for display.) These are striking in how little difference they display. High- and low-density cities are nearly identical in all aspects of behavior; cities with high and low transit use differ by only a couple of minutes a day shifted from auto to other modes. Apparently the large differences in VMT observed in the data are not driven by either of these factors.

Table 5.6: Dividing cities by density and by transit use

	Low Density	High Density	Low Transit	High Transit
Total Time/Traveler	69.2	69.5	69.0	69.6
Other Time/ Traveler	26.2	27.3	25.2	27.8
Veh. Time/ Traveler	43.0	42.2	43.7	41.8
Prob. of Travel	0.88	0.87	0.87	0.87
Vehicle Time/Person	37.7	36.7	38.1	36.4
Average Speed	29.4	29.3	29.7	29.2
VMT/Person	18.5	17.9	18.9	17.7

Table 5.7 divides the cities based on average speed and on congestion levels (again, the two sets of columns are not related). The half of cities with the highest speeds generate substantially more VMT, mostly because of the large difference in average speed, but also

because people in these cities spend more *time* traveling. This supports the claim of travel time budget theory that time savings created by higher speeds will just be spent on additional travel rather than shifted to other activities.

Table 5.7: Dividing cities by speed and by congestion

	Low Speed	High Speed	Low Cong	High Cong
Total Time/Traveler	69.2	69.6	66.7	70.4
Other Time/ Traveler	28.0	26.3	26.5	27.2
Veh. Time/ Traveler	41.2	43.3	40.2	43.2
Prob. of Travel	0.87	0.88	0.87	0.87
Vehicle Time/Person	35.7	37.9	34.8	37.7
Average Speed	27.7	30.5	29.1	29.4
VMT/Person	16.5	19.3	16.9	18.5

The congestion columns are interesting in that at first glance they appear to support the belief that high congestion forces people to spend more time in their vehicles. However, it is curious that residents of high congestion cities actually travel at *higher* average speeds than those in low congestion cities. Seemingly congestion does not slow people down that much in general; they are not spending more time because they are going slower. Given this, it seems more likely that high vehicle times are a cause of high congestion rather than an effect of it.

Table 5.8 divides the cities based on median income, and on the fraction of the population that is employed. The results are similar in each case, and support the earlier results where individuals were divided into income levels. Cities with high median incomes, and cities with high workforce participation, generate more total travel time, more vehicle time, higher speeds, and more VMT per person.

Table 5.8: Dividing cities by average income and by employment rates

	Low Income	High Income	Low Workers	High Workers
Total Time/Traveler	66.0	70.5	68.3	70.0
Other Time/ Traveler	25.1	27.6	26.1	27.6
Veh. Time/ Traveler	40.9	42.8	42.2	42.5
Prob. of Travel	0.87	0.87	0.87	0.87
Vehicle Time/Person	35.6	37.4	36.7	37.1
Average Speed	28.3	29.7	28.2	30.0
VMT/Person	16.8	18.5	17.2	18.6

6 REGRESSION RESULTS FOR 31 LARGE U.S. CITIES

The primary focus of this research was intended to be a regression analysis of travel behavior and its relation to land use and other factors (as described in chapter 4) in a cross-section of large U.S. cities. This turned out both better and worse than expected. On the positive side, it was possible to construct a much larger data set with many more variables than was originally anticipated. On the negative side, the quality of the data, especially of the behavioral outcomes that were the focus of the study, was not generally good enough to isolate influences with much confidence.

Two problems in particular make it difficult to draw conclusions with much confidence. First, for some of the behavioral variables, such as daily time per traveler, the error in measuring the average value for an urbanized area is nearly as large as the total range exhibited by the data. That is, the range from lowest to highest average across cities is about 20; while a 95% confidence interval around some of the averages is as much as 15. The problem is that it becomes very hard to find relationships between variables because it is statistically impossible to be certain that observed variations across cities are not just random sampling error. Indeed, as observed at the end of chapter 3, it is very likely that much of the variation is in fact sampling error. However, this does not negate the possibility that there are real, if subtle relationships that are being obscured by this.

The second problem is that New York has very extreme values of many variables, including some behaviors such as VMT, and several of the land use factors such as concentration and all the measures of perceived density. The reason this becomes a problem is that the regression assigns a lot of weight and statistical significance to these variables for which New York is an outlier, because it is a way of achieving a better fit for New York without worsening the fit for other cities. On the one hand there is merit to the argument that the reason New York has extreme travel behaviors is because it has extreme land uses, so whatever parameter estimates fit New York should be taken seriously. On the other hand, the other 30 cities count for little in this method. When New York is excluded from the regression, the parameter estimates change fairly substantially (and the statistical significance is lost). This analysis reports results both with and without New York for those variables for which there is a noticeable difference.

As discussed in chapter 3, the objective here is to understand not just VMT, but the component factors that make it up. The direct factors are speed and vehicle time, and vehicle time breaks down further into total travel time and mode choice. The method used here is to first regress the behavior of interest on each of the possible explanatory variables, one at a time. Out of this, a few variables will appear significant (or close to it) and the remainder won't. The next step then is to find which combination of these potentially important variables explains the behavior the best. The way this is done is to pick the variable that has the highest explanatory power and regress it in combination with each of the other significant variables, one at a time. Then other pairs that seem promising are regressed together. At this point judgment takes over, and combinations of three or more variables are regressed together depending on their apparent promise shown in simpler regressions.

Perhaps it is best to start with a relatively successful effort – average driving speed.

6.1 Average Speed

In the first, one at a time set of regressions, nine variables were statistically significant or close to it, although only a couple showed more than negligible explanatory power. The most important by far was the fraction of total VMT that was driven on freeways ($R^2 = 0.38$). Perhaps this is obvious; freeways move much faster than surface streets, so what else could matter? But what is surprising is that congestion is not associated with lower speeds. The relevant measure is congestion in 1995, since this is the year speeds are taken from; and the estimated impact of congestion on speed is unquestionably zero.

How could this possibly be right? How could the overall average speed of the city not be reduced by congestion, given that the whole point of congestion is that it makes travel slower? There are a couple of plausible explanations. One is while congestion gets all the press, in most cities only a small minority of travel takes place under congested conditions. So it could be that in many cities congestion consists of relatively minor slowdowns applied to a relatively small portion of total travel, leading to a very small overall impact on average speeds. However, it seems like this logic shouldn't apply to the high congestion cities. How could it be that Los Angeles or Washington, D.C. have average speeds that are right in the middle of the pack?

Another intuitively reasonable possibility is that congestion tends to be worse in cities that have a lot of travel on freeways; so that congestion reduces a speed that would have been much higher than average otherwise. However, regression shows that the prevalence of freeways in the highway network, and the proportion of travel that takes place on freeways, do not explain the level of congestion at all.

Congestion seems to be driven to a large extent by high incomes (the reasons for congestion will be discussed in more detail in section 6.7). High-income people tend to make more and longer trips, and to travel at higher average speeds. So rising incomes would lead people to travel more than they did before. It could be that some of this additional travel is worsening congestion and reducing speeds, while another part of it is in uncongested (off-peak) high speed conditions, pulling the overall average back up. That is, it could be that for every new congested trip there is a new high speed trip that balances it out, leaving *overall average* speeds unchanged, even though the speeds of specific trips might be slower.

Overall, the best set of regressors was the percent of VMT driven on freeways, and job concentration; the latter was associated with lower speeds ($R^2 = 0.48$). The logic here is probably that high job concentration means that a great deal of commuting time is spent driving at low speeds on the surface streets of large, dense employment centers. By contrast, in cities where jobs are more spread out, it may be easier to just get off the freeway and be there, with no local driving to pull the average speed back down.

Other factors that were significant when regressed individually were not when used in combination with these two variables; the reason is probably that they appear significant because they influence the two main variables rather than because they matter in their own right. For example, more workers and more vehicles were associated with higher speeds, more low-income households with lower speeds. Workers tend to travel more on freeways, and low-income people don't, so both of these could simply be explainers of miles driven on freeways rather than independent explainers of speed.

Another interesting example is that transit and walk/bike commute shares were significantly associated with *lower* speeds. This seems illogical, and it probably is; that is, the cause-effect relationship is probably the other way. What is probably happening is that the types of land uses that lead to high use of alternate modes (especially job concentration) also are associated with low speed limits and relatively less use of freeways. Another possibility is that congestion serves as an inducement to use transit; while high congestion is not associated with lower speeds overall, it may be during peak periods when transit trips to work would happen.

The final point then was to take one step back and try to determine what factors influence the fraction of miles driven on freeways. Here the answer is again unsurprising – most of the variation in the fraction of miles driven on freeways is explained by the fraction of total highway miles that are freeways. If you build freeways, people will use them, and the average speed of travel will rise. The other variable that is significant in a regression with this is the fraction of the population with jobs ($R^2 = 0.69$). People will use freeways even more if they have jobs, because work trips tend to be longer than others.

An important point is that the measures of residential density have a relatively small and statistically insignificant effect on speed. This could provide a way of judging between the travel minimization and time budget theories of behavior. Higher densities reduce distances. If speeds are not also substantially reduced (as it appears they are not), then people in high-density cities should be able to access a given set of destinations with less travel time. Thus if high density is associated with low travel times, it would be a mark in favor of the travel minimization hypothesis. If it is not, the evidence would favor the time budget theory.

6.2 Total Travel Time

Total travel time, in conjunction with mode choice, gives total vehicle time, which with speed is the other component of VMT. However, the analysis here indicates that variations in total vehicle time will have to come from mode choice, since variations in total travel time appear to be almost entirely random. The only variables with statistical significance were commute time, congestion and the percent of people with jobs. The last of these makes sense, as people with jobs spend slightly more time traveling than those without. Congestion, to the extent that it disproportionately slows down commute trips, may increase total travel time, since people do not appear to compensate for longer commute times by reducing non-work travel.

Variations in commute time appear to translate almost one-for-one into variations in total travel time. An extra minute of commute is associated with about 0.9 extra minutes of total average time per traveler. This extra commute minute means about two extra minutes per worker (counting the round trip). Workers are about half the total travelers. Thus it appears that longer commutes are not offset by less non-work travel (or only minimally), but instead add to the total daily time budget. This corresponds with observations in the Twin Cities, where longer average commutes in outlying areas led almost one-for-one to increases in average total travel time. Commute time explained about 28% of the variation in total time; adding other variables did not improve this fit.

Finally, it is worth noting, since this is a study of land use and travel, that first, none of the measures of land use produced statistically significant parameter estimates, and second, these (non-significant) estimates were all, without exception, positive. That is, higher density and concentration, whether of people or jobs, always led (weakly) to *more* total travel time, even though origins and destinations are closer together. This appears to be a mark against the travel minimization hypothesis.

6.3 Vehicle Time per Person

We have already seen that high density does not systematically lead to lower speeds. Thus since distances are shorter and speeds are not, there should in theory be less vehicle-travel time per person in high-density cities. Geometrically, a doubling of density should reduce distances by the square root of two, or about 30%. If people want to minimize travel distance while maintaining accessibility, then they should be able to travel 30% fewer miles in a city of density X compared to density X/2. Since auto speeds are not systematically reduced by density, they should be able to reduce their auto time by 30%, plus any auto-time savings due to mode shifts. The average residential perceived density (excluding New York) is about 7,000 per square mile. The average vehicle time for these cities is 42.4 minutes. Thus, roughly speaking, doubling the perceived density to 14,000 per square mile should be associated with a 12-plus minute decrease in vehicle time, if the travel minimization hypothesis is true. If the time budget theory is true, the only vehicle time decrease should be that due to mode shifts.

The evidence comes down pretty strongly on the side of travel time budgets. Vehicle time is another case where the results are different depending on whether New York is included. When it is included, the estimated effect of density is almost twice as high as when it is not. But, even in this "best case" scenario, the impact of density (no matter which measure is used) is only about 15% of what it "should" be if people were trying to minimize travel distance. An increase of 1,000 in residential perceived density is associated with a decrease of about 20 seconds in vehicle time per day, not the two minutes or more that would be expected from shorter distances and mode shifts. Similarly small effects are generated by other measures of density (the effects are sometimes statistically significant, sometimes not). And interestingly, the decrease in auto time is of the same magnitude as the increase in other mode time (30 seconds) associated with the same increase in density.

Thus it appears that while higher densities do lead to small mode shifts, they do not lead to reduced distances or time savings. People appear to take advantage of the greater accessibility to increase their range of choices rather than to reduce their travel time or distance. This is consistent with Twin Cities historical evidence; that when speeds increased after the freeways were built, people used the time savings to expand their ranges of travel. A similar effect seems to occur when time savings arise from shorter distances rather than higher speeds.

Another very interesting point about vehicle time is that the two variables that had by far the most explanatory power were the density (simple density, not perceived) of the urbanized area in 1950 ($R^2 = 0.33$) and population in 1900 ($R^2 = 0.31$). (Compare to residential perceived density

R^2 of 0.18, or 0.0 if New York is not in the regression. By contrast, the two historical variables are still good explainers even without New York.) That is, cities that used to be big and dense generate less auto travel than "new" cities. The obvious first thought is that old cities have different land uses, but none of the measures of land use explained vehicle travel nearly this well.

Another, more subtle possibility is that maybe history really does matter. If a city were originally developed around a big, dense central business district (CBD), an extensive transit network, and high-density residential areas near the CBD, there might be a strong incentive for new development to stay in this pattern. This could happen both because the markets for labor and goods that new workers and firms need are centrally concentrated, and because continuing to use the existing infrastructure of buildings and transit is cheaper than tearing it all down and building a new auto-based system from scratch. By contrast, a city that developed after cars were widespread would more naturally develop around an auto-based infrastructure, because it is cheaper and quicker to get into place if there isn't something extensive already there.

6.4 Other Mode Time per Person

Time spent in "other" modes (transit, walk/bike, and carpool) is best explained by a combination of two variables; central business district (CBD) size and CBD employment share. Residential land use measures are significant when regressed alone, but not when regressed with either of these two; thus it appears that their apparent significance is just due to their correlation with CBD measures. The reason the CBD is so important is because it is the major influence on transit use. Carpooling is significant, but goes on at about the same level everywhere, while walk/bike shows variation but is a very small part of the total. Transit is unique in that it can be a fairly large part (10% or so) of total travel time and it also shows large variations across cities.

Perhaps the reason that total transit time (as opposed to mode share) is so strongly influenced by the CBD is because large and important CBDs are more likely to have extensive subway and commuter rail networks serving them. Thus these CBDs not only attract large transit shares, but the trips into them are longer, affecting the total transit time even more.

6.5 Work Trip Mode Choice

Walk/bike share and transit share are studied here. The first is explained in a straightforward and unsurprising way. The three variables that do the best at explaining the percent of people who walk or bike to work are residential perceived density, residential concentration, and perceived density of jobs in residential areas. The only surprising thing about this outcome is the small size of the effects. To achieve a 1% increase in the walk/bike share would require an increase of 5,000 per square mile in perceived residential density, 0.5 in concentration, or 1,000 per square mile in perceived density of jobs in residential areas. These would be enormous increases relative to the values of these variables in most cities. This does not appear to be a particularly high-leverage way to reduce auto travel, despite the frequent claims in the "new urbanism" literature that more people walking to work will be one of the major benefits of this type of development. This is not to say that it won't happen; indeed it may even be significant at a localized level, but the total number of people involved is likely to be too small to have much regional impact.

The estimation of the percent of people using transit to get to work is the biggest success of this analysis. What makes this estimation work is that there are large variations in transit use, even when New York is excluded, and small measurement errors, since these values are taken from the huge samples in the census. The outcome is simple and logical, and is the same whether New York is included or not.

The two variables that best explain transit share (together they explain 80-90% of the observed variations) are perceived density of jobs from job locations, and residential concentration. At the work end of the trip it is important to have a lot of jobs packed close together, and to have a large fraction of the region's jobs in this type of situation. At the home end concentration, or having a relatively large fraction of the population living in a relatively small fraction of the total land area, is what seems to matter. Residential perceived density was significant, but was not as good in combination with job perceived density as was concentration.

A possible explanation for why concentration could matter more than density is that residential densities are seldom high enough to justify transit service on their own. That is, excepting some parts of New York and a handful of other cities, the only way transit service is viable for most residential areas is because a large fraction of their workers are going to the same place – downtown. In most cities most transit service exists because downtown provides a viable market for it; the question then becomes where the service should originate. And when cities are highly concentrated, the answer to this question is easy – service should originate in the parts of the region that have a lot of people living in them. Thus, even if those areas are not very dense, they still get all the transit service, because they are so much more dense than other areas. By contrast, cities like Los Angeles or San Diego are quite dense overall, but not very concentrated. The limited demand for trips downtown may be spread over a larger residential area, leading to diluted service and low demand; not because these residential neighborhoods aren't dense, but ironically because they all are.

Of course, it helps that most highly concentrated cities are also dense, but when the two factors diverge, concentration seems to win out. Los Angeles and Chicago are equally dense, but Chicago is more concentrated (both in residents and jobs) and thus scores a 16% transit share to LA's 5%. Philadelphia, Boston, and Miami are equally dense, but the first two are also highly concentrated while Miami is not; their transit shares are 13, 14, and 6% respectively. Pittsburgh is ordinary in terms of residential density, but is very concentrated and has high job density, thus scores a 10% transit share, very unusual for a city this size.

6.6 Probability of Traveling

This ranges only from 0.81 (New York) to 0.92 (Cincinnati). The range is small and it is also almost entirely random, thus this variable is not of great interest. The one interesting point is that, as with vehicle time, the two best explainers ($R^2 = 0.14$) are density in 1950 and population in 1900.

6.7 Other Issues: Commute Time and Congestion

These two variables are not directly part of the set that goes into determining VMT, but they are of interest both because they influence the variables that determine VMT, and also because they have significant meaning to people in their own right.

Average commute times are basically driven by congestion and income levels, with higher levels of each of these implying longer commute times. Drive-alone commute times are best explained by just these two; overall (all mode) times are also influenced by job perceived density. This is because job density influences transit share; because transit commutes tend to be longer (in minutes) than auto commutes, higher transit share means longer average commute times.

Congestion is most strongly influenced by density and income levels, with density the more important of the two. Here is an interesting point. The measure of density that strongly impacts congestion is just simple density, population divided by land area. In the other behaviors, perceived density always had a stronger effect. In other words, with everything else, what mattered was how the density was distributed, while with congestion all that matters is simply what the overall density is. Thus it would appear from this that a region with a low overall density but a high level of concentration could achieve both the positive effects of less driving while avoiding the negative effects of congestion.

This is a little hard to believe. While higher concentration is associated with more use of alternate modes, as noted in section 6.3 the effect seems not nearly big enough to compensate for the increased number of people living in close quarters. One possibility is that congestion on local streets (as would be expected in a high-density environment) is not as easily discerned by standard congestion-measurement techniques as is freeway congestion.

6.8 Summary: VMT

The bottom line of all this is: What factors influence the level of VMT in an urbanized area? The two main components, by definition, are speed and vehicle time per person. Speed seems clearly to matter; it explains much of the variation in VMT, and speed itself is well explained by more basic factors. The vehicle time half of the equation seems a little harder to handle. While changes in mode share can be traced to logical factors, these changes in mode choice have only a small impact on total vehicle time. The factor that should logically have a big impact; that is, reduced distances created by higher densities, appears to have almost no effect at all on total travel times. The factors that most strongly affect vehicle time are historical; old cities generate less auto travel than new ones, even when land uses and other factors are the same.

The “standard” travel behavior theory, that people wish to minimize travel and high density will help them to accomplish this, does not fare well in this analysis. A clear implication of this theory is that high densities should reduce distances, and if speeds are not reduced, should thus lead to shorter travel times. To the extent that higher densities also increase the use of alternate modes, the reduction in vehicle times should be even greater. But as discussed in section 6.3, this reduction is not observed in the data. Higher density is associated with a small reduction in vehicle time, but this seems to be driven only by mode shifts, not by reduced distances. High density does not seem to reduce auto travel speeds much; thus the fact that vehicle time does not go down as densities increase indicates that people use the time savings made possible by shorter distances to increase their range of travel. This is consistent with travel time budget theory.

While VMT across the 31 cities ranges from 11 to 23 per day, this range seems to be largely due to speed differentials, measurement error, history, and, to a very small extent, mode choice. Essentially none of the range seems to have to do with distances between origins and destinations implied by any measure of density.

7 EFFECT OF LAND USE: ADDITIONAL ANALYSIS

Because it seemed that the effect of land use was obscured by the relatively large sampling errors when studying individual cities, a last effort to isolate effects was to group cities into larger blocks based on their values of the various land use variables, and a couple of important economic factors.

The strong effect of income observed at the individual level does not seem to extend to entire cities. Except for the very lowest income cities (and New York), cities of all income levels have similar travel characteristics (Table 7.1).

Table 7.1: Cities grouped by median income

	25-30K	30-35K	35-40K	NY (38K)	40K+
Total Time/Traveler	65.4	67.8	70.7	72.7	70.2
Other Time/ Traveler	24.3	25.5	28.1	41.5	27.5
Veh. Time/ Traveler	41.0	42.3	42.6	31.3	42.7
Prob. of Travel	0.86	0.87	0.87	0.81	0.88
Vehicle Time/Person	35.3	37.0	37.0	25.4	37.4
Average Speed	27.5	29.8	28.9	26.7	30.0
VMT/Person	16.2	18.4	17.8	11.3	18.7

The percentage of people with jobs corresponds more closely to expectations in its impact on travel choices. Residents of cities with high workforce participation were more likely to travel, spent more total time and more vehicle time, traveled at higher speeds, and generated considerably more VMT per person (Table 7.2).

Table 7.2: Cities grouped by employment rate

	40-45%	45-50%	NY(47%)	50%+
Total Time/Traveler	63.8	69.6	72.7	70.5
Other Time/ Traveler	23.8	27.8	41.5	27.2
Veh. Time/ Traveler	40.0	41.8	31.3	43.3
Prob. of Travel	0.86	0.87	0.81	0.88
Vehicle Time/Person	34.2	36.4	25.4	37.9
Average Speed	28.2	28.5	26.7	30.2
VMT/Person	16.1	17.3	11.3	19.1

Dividing cities by transit share of work trips again gives results similar to expectations in their direction (Table 7.3). However, the magnitude of the effects is surprisingly small. The cities with the highest transit shares (excluding New York) generated less than two minutes less vehicle time per person than the cities with the lowest share; the lower VMT in the high-transit cities arises as much from lower speeds as from less vehicle time. As Table 5.6, higher transit share is associated with more *total* time spent traveling.

Table 7.3: Cites grouped by transit share

	1-5%	5-10%	10-16%	NY (28%)
Total Time/Traveler	68.5	68.6	70.2	72.7
Other Time/ Traveler	24.8	26.2	28.3	41.5
Veh. Time/ Traveler	43.7	42.4	41.9	31.3
Prob. of Travel	0.87	0.87	0.87	0.81
Vehicle Time/Person	38.0	37.1	36.5	25.4
Average Speed	30.6	28.8	29.2	26.7
VMT/Person	19.3	17.8	17.8	11.3

More people walking or biking to work appears to be associated with a substantial reduction in VMT. However, again the decrease results as much from lower driving speeds as from less time spent driving (Table 7.4).

Table 7.4: Cities grouped by walk/bike share

	1-3%	3-5%	5%+	NY(7%)
Total Time/Traveler	69.1	70.7	68.3	72.7
Other Time/ Traveler	23.8	27.9	27.0	41.5
Veh. Time/ Traveler	45.3	42.8	41.4	31.3
Prob. of Travel	0.86	0.87	0.87	0.81
Vehicle Time/Person	39.1	37.3	36.1	25.4
Average Speed	31.2	28.7	29.5	26.7
VMT/Person	20.3	17.9	17.7	11.3

The population density that residents perceive in the immediate vicinity of their homes does not influence travel in the expected way. There is a considerable decrease in VMT from low to medium densities, but then a sizeable increase as density increases still further (Table 7.5). One possible explanation is that high density cities tend to be large and relatively high income, and that the high incomes are driving up travel times and distances. At the same time, high-density cities also tend to have high transit use, which ought to offset some of this effect. In either case, the point seems clear that whatever the effect of density, it is not sufficiently large or consistent to offset whatever else is going on. This table supports the finding from the regression analysis that increasing population density has no systematic effect on travel behavior.

Table 7.5: Cities grouped by perceived population density

	3-6K	6-10K	10-17K	NY(35K)
Total Time/Traveler	69.7	66.4	70.1	72.7
Other Time/ Traveler	26.1	26.1	27.7	41.5
Veh. Time/ Traveler	43.7	40.3	42.4	31.3
Prob. of Travel	0.87	0.85	0.88	0.81
Vehicle Time/Person	38.2	34.4	37.1	25.4
Average Speed	30.0	28.9	29.2	26.7
VMT/Person	19.1	16.6	18.1	11.3

The extent to which population is concentrated into the dense parts of the region appears to have little effect on travel choices. Only a handful of cities have concentrations higher than 2, and even this high level is associated with only about a minute less vehicle time per day, and less than half a mile less VMT (Table 7.6).

Table 7.6: Cities grouped by residential concentration

	1-2	2-3	NY(6)
Total Time/Traveler	68.5	70.2	72.7
Other Time/ Traveler	25.5	28.3	41.5
Veh. Time/ Traveler	43.0	41.8	31.3
Prob. of Travel	0.87	0.87	0.81
Vehicle Time/Person	37.5	36.5	25.4
Average Speed	29.3	29.4	26.7
VMT/Person	18.3	17.9	11.3

The density of jobs in the vicinity of workplaces also has no systematic effect on travel choices. There seems to be a gradual decline in auto travel at densities higher than 20,000 per square mile, but densities lower than this seem to generate less auto travel than much higher densities (Table 7.7). Another interesting point is that as perceived job densities increase, so does time in other modes (largely transit); however, there is not as much corresponding decrease in auto time (excepting in the extreme case of New York).

Table 7.7: Cities grouped by employment perceived density

	8-20	20-30	30-40	40-70	NY(128)
Total Time/Traveler	67.3	70.6	68.7	73.1	72.7
Other Time/ Traveler	25.4	25.8	27.0	30.9	41.5
Veh. Time/ Traveler	41.9	44.8	41.6	42.2	31.3
Prob. of Travel	0.88	0.87	0.88	0.86	0.81
Vehicle Time/Person	36.6	38.8	36.5	36.3	25.4
Average Speed	29.2	29.7	29.8	27.9	26.7
VMT/Person	17.8	19.2	18.1	16.9	11.3

The extent to which jobs are concentrated in high-density areas likewise appears to have no influence on travel choices (Table 7.8).

Table 7.8: Cities grouped by job concentration

	5-10	10-20	20-35	50
Total Time/Traveler	69.6	68.7	69.8	72.7
Other Time/ Traveler	25.8	27.1	27.4	41.5
Veh. Time/ Traveler	43.9	41.6	42.4	31.3
Prob. of Travel	0.87	0.87	0.87	0.81
Vehicle Time/Person	38.3	36.3	37.0	25.4
Average Speed	29.3	29.5	29.3	26.7
VMT/Person	18.7	17.8	18.0	11.3

Finally, the perceived density of jobs in the vicinity of the home has no systematic effect on travel choices (Table 7.9). The cities with the highest density of jobs around homes (excepting New York) actually have the most vehicle time and the highest VMT. This would appear to contradict the commonly held belief that long travel times and distances can be remedied by better location of housing and jobs (and by association, shopping and other opportunities).

Table 7.9: Cities grouped by perceived density of jobs in residential areas

	<1	1-2	2-4	NY(5)
Total Time/Traveler	66.9	70.0	70.5	72.7
Other Time/ Traveler	24.9	28.4	27.5	41.5
Veh. Time/ Traveler	42.0	41.7	43.0	31.3
Prob. of Travel	0.87	0.86	0.88	0.81
Vehicle Time/Person	36.5	35.9	37.8	25.4
Average Speed	29.6	28.1	29.9	26.7
VMT/Person	18.0	16.8	18.9	11.3

8 CONCLUSIONS

The conclusions arising from this research fall broadly into two classes: findings about the data and the factors affecting travel behavior (especially land use factors); and conclusions about methodology, that is, how future research in this area should be approached.

Two general methods were employed to try to discern the effect of land use on travel behavior. One was to simply divide all the data up based on whether the city of residence had a "high" or "low" value of the land use variable in question. The other was to use linear regression, with each city as a data point, to isolate land use variables from other possible explainers. The two methods yielded similar results.

Land use measures included simple urbanized area (UA) density, as well as a number of weighted measures of density developed specifically for this study, as described in chapter 3. The following is a concise list of the different travel behaviors that were analyzed, and the effect of the various land use measures on each.

- Average auto travel speed: high-density parts of cities move slower than low-density parts, but high-density UAs do not have lower speeds overall than low-density UAs. In general, no land use factor had a discernable impact on speed at the UA level, with one exception. High job concentration (big, dense central business districts - CBDs) was associated with a slight decline in speed.
- Average total travel time per traveler: This seemed to bottom out at densities of about 5-10 thousand per square mile, measured either as local density or as UA residential perceived density. Densities above and below this generated more total travel time, although the difference was never more than a couple of minutes per day (compared to an average of about 70). Again, big CBDs were associated with a couple of extra minutes of travel time per day for the average traveler.
- Average auto time (SOV equivalent) per traveler: This declines steadily as neighborhood densities increase (as expected), but similar increases in UA density do not have the same impact, indicating that much of the decline may be due to differences in neighborhood accessibility to jobs, and possibly somewhat to income differentials. At the UA level, an increase of 1,000 per square mile in residential perceived density is associated with about a 20 second per day decrease in vehicle time per traveler. As a rough average, this means that a 14% increase in density leads to a 0.5% decrease in auto time per person.

- Average other mode (transit, carpool, walk/bike, etc.) time per traveler: The best explainers are CBD size and CBD share of total UA employment. This is because these two factors strongly influence transit time, which is the source of most of the variation across cities. Carpool is a lot of total time, but is similar everywhere; other modes are significant nowhere.
- Walk/bike share of work trips: Land use factors matter here, but only very slightly. To get a 1% increase in walk/bike share over the entire UA would require on average an increase of 5,000 per square mile in residential perceived density, or 1,000 per square mile in perceived density of jobs in residential areas. Both of these would represent roughly a doubling of values from current levels for most cities.
- Transit share of work trips: Here it was possible to explain 80-90% of the variation across cities with just two variables; job perceived density and residential concentration. The first represents, again, a big dense CBD. Perhaps the moral is that high transit use requires both a lot of jobs at one end of the trip, and a lot of people at the other. Concentration differs from simple density in that it represents roughly the difference between the densest areas and the average. For example, Los Angeles and Chicago have similar overall densities, but Chicago is more concentrated (and has much higher transit share). Again, however, the effect is not huge. Roughly speaking, doubling the density implied by these land use measures would increase transit share by about 5-6%.
- Commute times: no influence of land use.
- Congestion: higher gross density increases congestion, but doesn't have a huge impact.

The overall results of this analysis are mixed. On the one hand, certain relationships emerge which correspond at least roughly to generally held beliefs, for example the connection between transit share and residential concentration. On the other hand, the small size of the effects seems to contradict the common assertion that land use changes are a high-leverage way to address transportation problems such as congestion and air pollution. Much policy seems to be based on the belief that relatively small changes to land use will have a big impact on travel choices. The findings here imply just the opposite; that even very big changes to land use have very little impact on travel behavior, in good ways or in bad. Apparently the larger effects sometimes observed in neighborhood-scale studies are just that: neighborhood-scale effects that do not extend their benefits to the larger urbanized area.

Another important point is that the connections that are often implied between different travel choices do not seem to be supported here. Many studies have noted the impact of density on transit share; that impact is also observed here. But what is not observed is the implication that higher transit share must also lead to less driving, shorter commutes, less congestion, etc. None of these effects are observed; indeed, if anything the higher densities that increase transit share tend to *increase* commute times and congestion levels. This highlights the importance of considering many travel decisions simultaneously, rather than analyzing just one and making assumptions about what must happen to the others.

An interesting observation from this analysis is the apparent importance of history. In a number of cases, historical variables such as density in 1950, or population in 1900, had statistically significant effects on current behaviors; in the case of vehicle travel time, they explained the behavior substantially better than any contemporary variable. The obvious explanation, that these historical terms are proxies for some aspect of present-day land use, is hard to support, since they explain vehicle time much better than any of the actual land use measures. A more intriguing theory is that history really does matter; that the economy of a city develops to some extent around the habits (travel and otherwise) of the people that live there, creating a self-reinforcing system. This would be an interesting subject for future investigation.

A final point from the analysis is the extremely large variation in travel choices across cities, even when the cities seem otherwise very similar. For example, virtually any combination of high or low transit share, VMT, and congestion can be observed in some city.

Table 8.1: Illustration of Variety of Travel Outcomes,
Cities of Overall Density >2,500/sq. mile

	Low VMT (<16.8)	High VMT (>18.8)
High Transit (> 9%)	New York – L*	Baltimore – L
	Chicago – H	San Francisco – H
Low Transit (< 5.5%)	Buffalo – L	San Antonio – L
	Miami – H	Los Angeles – H

* L and H indicate low (<1.05) and high (>1.24) congestion levels

There are two lessons here. First is a reconfirmation of the point made above; that "good" outcomes in one travel behavior, such as transit share, need not imply good outcomes in anything else. Second is a point about the creditability of evidence. If this table says anything, it says that statements based on anecdotal evidence, or evidence from one or two cities, are of questionable value. The high VMT, low transit, high congestion outcome in Los Angeles is often cited as an example of what to avoid; while the fact that Dallas, Kansas City, and many others also have high VMT and low transit (and lower densities), but without the ensuing high congestion is rarely noted. High transit shares, such as in San Francisco and Washington, D.C., are held up as a goal to be strived for, yet many of these high-transit cities still have high VMT and high congestion, a fact that is often overlooked.

This point leads into some broader conclusions about the methodology of urban travel behavior studies. The first is that individual travel behavior is extremely variable, and often not for any apparent reason. Because there is such large variability, a very large sample is needed to calculate averages with any confidence. This was a constraint in this report, where statistically significant relationships were difficult to observe because values for many behavioral variables were so inaccurately measured. However, there are also two other points to consider.

First, the lack of statistical significance is partially due to inaccurate measurement, but is also in large part due to the fact that many of the behavioral variables simply didn't show much variation across cities. For example, while VMT ranged from 11 to 23, a big range, the majority of cities fell between about 15 and 19, a much smaller variation. The 25% difference from low to high is still a relatively big number, but not as big as the potential measurement error for many cities. In other words, the difference might really be zero, if we had a bigger sample.

This leads to the second point, which is that many of the comparative studies showing that some neighborhoods have less auto travel than others are based on similarly small samples. That is, the overall survey on which a study is based may be quite large, but the sample from any individual neighborhood is usually not. Certainly the better studies take this into account in the confidence level of their results; nonetheless it seems like an inherent restriction of that type of study. In a small area, even a 100% sample may not be big enough to know for sure what "average" behavior is, since sampling on a different day could yield different results.

However, there are larger problems with research, and policies, based on the land use in individual neighborhoods. A neighborhood is a subset of a larger system. There are three key issues implied by this. First is that some of the behavioral impact of a neighborhood derives from its place in the larger system rather than from its own characteristics. Barnes and Davis (2001) find that in the Twin Cities commute lengths were shorter in areas of good job access. These areas tended to be densely developed. However, to the extent that high access and high density occurred in different places, it seemed that access, not density, was the main influence on behavior. Regressions on density alone would thus be incorrectly picking up the effect of differences in access. In the Twin Cities, the apparent effect of local density disappeared entirely when differences in access were controlled for.

The second, related point is that the land use in a given neighborhood will in general affect the behavior of non-residents, even of people that neither live nor work there. There are two likely mechanisms. First, if residents of a neighborhood really cut back on driving, then road capacity will be opened up that others will likely take advantage of. In other words, the reduced travel by some people could induce increased travel by others. Second, the physical neighborhood becomes a factor in other people's trip decisions. High density means intersections and traffic signals, which mean slow speeds. Sufficiently slow speeds might induce people to take longer routes or travel to different, more distant destinations, to avoid going through the neighborhood at all.

Third is that residents of a neighborhood are self-selected. People choose where to live based at least in part on their transportation preferences. Those who feel strongly about being able to walk or use transit will try to live in neighborhoods where those activities are possible. Again, the lower travel in these areas will drive up the average elsewhere, because the low-travel people that were pulling down the average in other areas have concentrated in one place.

The first two of these issues point to a direction which could serve as a starting point for a better understanding of urban travel behavior. When people talk about density or some other aspect of land use, and how it affects travel behavior, that is not exactly what they mean. No one thinks that putting houses close together, in itself, will make people want to drive less. The often unspoken point is that density and some other land uses are believed to improve accessibility (and especially non-auto accessibility), making it possible to travel less while maintaining the same range of destinations. A more rigorous theoretical and empirical understanding of the three-way relationship between the transportation system, land use, and accessibility, and especially how land use in one place affects accessibility in others, could dramatically improve our understanding of urban travel choices.

Economists analyze the outcomes of a market from two different directions. First is understanding the choices made by individuals; their preferences and how they respond to prices and the other information they have. Most travel research has focused on this aspect of the problem, although usually without careful specification; for example using density as a proxy for accessibility, which is a more direct measure of the cost of travel. The other side of the problem is the market itself; that is, how prices and information are affected by the decisions that people make. Through the effect on prices, each individual's decisions influence everyone else's. This "market" side of the problem; that is, how the "prices" of transportation are affected by individual decisions, is largely ignored in the literature, the usual, and clearly incorrect, presumption being that changes to one person's behavior will have no impact on anyone else's.

To really integrate land use and transportation planning and use them to make cities better places to live and work seems to be one objective that everyone agrees on. To successfully do this, it will be necessary first to understand the "prices" that influence travel choices; what they are, how they can be measured, and how people respond to them. Then what is needed is an understanding of how these prices are determined; that is, the relative influences of land use both at the local and the "macro" level, the different modes that make up the transportation system, and behavior itself. Such formal, detailed modeling will not only make forecasts more accurate and detailed, but will also help to clarify some of the side effects of various policies, which may or may not be anticipated otherwise. In this way it would be possible to avoid policies that just "tread water;" improving one problem at the expense of making another worse. Finally, such models could help to identify the high-leverage points in the system; in case there are factors, unlike population density, where small changes could have big impacts on travel behavior.

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APPENDIX A

MISCELLANEOUS INFORMATION

Confidence Intervals for Travel Time, VMT Measurements

These two tables show the extent of uncertainty in the average values of total travel time per traveler and VMT per person for individual cities. This uncertainty arises because these averages were calculated from finite and sometimes fairly small samples, and because the extent of individual variation in these variables was quite high.

City	Ave. Time	St. Dev.	Low Time	High Time	Sample Size
New York	72.91	0.65	71.61	74.22	7005
Los Angeles	72.33	1.44	69.44	75.22	1310
Chicago	72.69	1.44	69.81	75.57	1316
Philadelphia	67.13	1.81	63.52	70.75	818
Detroit	66.52	2.28	61.96	71.08	437
San Francisco	75.31	2.21	70.90	79.72	593
Washington	74.21	1.93	70.35	78.07	753
Dallas	69.23	2.14	64.96	73.50	489
Houston	72.82	2.51	67.81	77.83	367
Boston	69.21	0.64	67.94	70.48	6404
San Diego	65.33	2.39	60.55	70.12	335
Atlanta	73.85	2.40	69.05	78.65	375
Minneapolis	67.56	2.71	62.14	72.99	328
Phoenix	69.72	3.11	63.49	75.95	274
St. Louis	64.17	2.80	58.57	69.78	257
Miami	68.20	2.19	63.82	72.59	477
Baltimore	71.50	2.37	66.75	76.24	431
Seattle	72.49	1.80	68.90	76.09	797
Tampa	73.52	3.90	65.71	81.33	189
Pittsburgh	66.90	3.16	60.58	73.22	280
Cleveland	61.53	2.38	56.77	66.29	322
Denver	79.93	3.90	72.14	87.73	191
Norfolk	70.38	4.11	62.17	78.60	185
Kansas City	64.40	3.50	57.39	71.40	169
Milwaukee	61.11	3.11	54.89	67.33	168
Cincinnati	64.62	2.69	59.23	70.00	239
Portland	72.12	3.08	65.97	78.28	294
San Antonio	73.10	4.56	63.98	82.23	158
Sacramento	60.36	2.74	54.88	65.83	226
New Orleans	72.77	4.09	64.59	80.95	167
Buffalo	59.05	1.34	56.38	61.73	916

City	Ave. VMT	St. Dev.	Low VMT	High VMT	Sample Size
New York	11.22	0.23	10.76	11.67	8639
Los Angeles	19.67	0.68	18.30	21.04	1462
Chicago	15.97	0.58	14.80	17.14	1532
Philadelphia	13.03	0.68	11.67	14.39	962
Detroit	19.06	1.04	16.99	21.13	522
San	19.52	1.10	17.31	21.73	667
Washington	17.40	0.85	15.70	19.09	887
Dallas	22.12	1.10	19.92	24.33	558
Houston	22.07	1.28	19.51	24.63	406
Boston	18.80	0.30	18.19	19.41	7287
San Diego	19.30	1.19	16.92	21.68	398
Atlanta	21.45	1.23	18.99	23.92	446
Minneapolis	20.16	1.31	17.55	22.78	376
Phoenix	16.44	1.13	14.19	18.69	317
St. Louis	16.81	1.17	14.46	19.16	302
Miami	16.79	1.08	14.63	18.95	565
Baltimore	18.84	1.13	16.58	21.10	496
Seattle	18.24	0.76	16.73	19.76	888
Tampa	18.89	1.74	15.41	22.37	215
Pittsburgh	14.61	1.10	12.40	16.81	335
Cleveland	14.16	1.01	12.15	16.17	376
Denver	22.96	2.26	18.45	27.47	225
Norfolk	17.53	1.73	14.07	21.00	220
Kansas City	17.41	1.49	14.44	20.39	193
Milwaukee	15.63	1.26	13.12	18.14	196
Cincinnati	15.56	1.23	13.09	18.03	259
Portland	17.98	1.10	15.79	20.18	322
San Antonio	23.18	2.24	18.71	27.66	170
Sacramento	17.60	1.32	14.96	20.23	263
New Orleans	16.70	1.60	13.50	19.91	188
Buffalo	14.58	0.62	13.35	15.81	1071

Full Data Set and Correlations

The following three multi-page tables show first the full data set used in the regressions, second the simple correlations between each pair of variables, and third the correlations when New York is excluded. When variables are highly correlated, it is difficult to distinguish the relative importance of each in a regression. These tables should help the reader to judge the extent to which this might be an issue. Positive correlations mean the variables generally move in the same direction, negative means they move in opposite directions. The range is –1 to 1.

Raw Data

City	TotTime	OtherTime	VTimeTrav	ProbOfTravel	VtimePers	Speed95	AvgOfPvmt
New York	72.7	41.5	31.3	0.81	25.4	26.7	11.3
Los Angeles	72.3	27.3	45.0	0.90	40.3	29.3	19.7
Chicago	72.7	30.4	42.3	0.86	36.3	26.4	16.0
Philadelphia	67.1	33.1	34.1	0.85	29.0	27.0	13.0
Detroit	66.5	21.3	45.2	0.84	37.9	30.2	19.1
San Francisco	75.3	32.8	42.5	0.89	37.8	31.0	19.5
Washington	74.2	32.4	41.8	0.85	35.5	29.4	17.4
Dallas	69.2	23.3	45.9	0.88	40.2	33.0	22.1
Houston	72.8	24.8	48.0	0.90	43.4	30.5	22.1
Boston	69.2	26.4	42.8	0.88	37.6	30.0	18.8
San Diego	65.3	22.6	42.7	0.84	36.0	32.2	19.3
Atlanta	73.9	25.5	48.3	0.84	40.6	31.7	21.5
Minneapolis	67.6	24.1	43.4	0.87	37.9	31.9	20.2
Phoenix	69.7	27.9	41.9	0.86	36.2	27.3	16.4
St. Louis	64.2	23.6	40.6	0.85	34.5	29.2	16.8
Miami	68.2	23.5	44.7	0.84	37.7	26.7	16.8
Baltimore	71.5	29.2	42.3	0.87	36.8	30.7	18.8
Seattle	72.5	29.1	43.4	0.90	39.0	28.1	18.2
Tampa	73.5	25.8	47.7	0.88	41.9	27.0	18.9
Pittsburgh	66.9	24.8	42.1	0.84	35.2	24.9	14.6
Cleveland	61.5	24.3	37.3	0.86	31.9	26.6	14.2
Denver	79.9	28.7	51.2	0.85	43.5	31.7	23.0
Norfolk	70.4	25.9	44.4	0.84	37.4	28.1	17.5
Kansas City	64.4	26.3	38.1	0.88	33.3	31.3	17.4
Milwaukee	61.1	22.9	38.2	0.86	32.8	28.6	15.6
Cincinnati	64.6	29.4	35.2	0.92	32.5	28.8	15.6
Portland	72.1	30.1	42.0	0.91	38.4	28.1	18.0
San Antonio	73.1	29.4	43.7	0.93	40.6	34.3	23.2
Sacramento	60.4	21.2	39.1	0.86	33.6	31.4	17.6
New Orleans	72.8	32.0	40.7	0.89	36.2	27.7	16.7
Buffalo	59.1	22.1	37.0	0.86	31.6	27.6	14.6

City	dacar	carpool	transit	wb	AllMed	Damed	allMean
New York	50.5	10.2	28.4	7.0	29.9	22.7	31.3
Los Angeles	71.8	15.0	5.4	3.7	23.9	23.5	26.2
Chicago	64.0	12.0	16.3	4.7	28	24.3	28.9
Philadelphia	66.0	12.0	13.2	6.0	23.2	22.1	24.9
Detroit	83.2	10.0	2.7	2.0	22.3	22.3	23.1
San Francisco	62.7	12.9	13.7	5.3	24	22	26.5
Washington	61.4	15.4	15.2	4.3	29.9	25.7	29
Dallas	78.7	13.6	2.7	2.0	22.5	22.3	23.5
Houston	75.6	14.4	4.4	2.6	24.3	23.8	25.9
Boston	65.1	9.9	14.3	7.3	22.6	21.5	24.1
San Diego	71.4	13.8	3.4	4.9	21.1	21	21.9
Atlanta	77.6	11.8	5.8	1.7	24.6	24.1	25.6
Minneapolis	76.1	10.6	6.0	3.7	20.5	20.2	20.4
Phoenix	75.3	14.2	2.1	4.0	22	22	22.9
St. Louis	80.1	11.4	3.4	2.2	22.3	21.9	22.5
Miami	72.4	15.6	5.8	3.0	23.9	23.6	24.8
Baltimore	69.2	14.5	9.1	4.1	24	23.4	25.4
Seattle	72.2	11.4	8.0	4.1	22.8	22	23.9
Tampa	79.1	12.9	1.5	3.1	20.5	20.5	21.4
Pittsburgh	68.9	12.9	10.0	5.6	21.6	20.8	22.6
Cleveland	77.1	10.5	6.9	3.1	22	21.5	22.3
Denver	75.4	12.5	4.5	3.5	21.8	21.5	22.2
Norfolk	72.7	13.9	2.1	4.2	20.9	20.9	21.4
Kansas City	80.3	12.0	2.4	2.0	20.7	20.5	20.7
Milwaukee	75.8	11.0	6.1	4.5	19.6	19.3	19.7
Cincinnati	78.1	11.4	4.8	3.1	21.4	21.2	21.6
Portland	73.3	12.1	6.5	4.0	20.3	19.7	20.9
San Antonio	74.1	14.7	4.1	4.0	21.1	21	21.5
Sacramento	76.1	13.9	2.7	3.5	20.9	20.6	21.6
New Orleans	70.0	14.8	8.1	3.9	21.9	21.1	23.4
Buffalo	75.7	11.4	5.4	5.0	19.1	18.9	18.9

City	Damean	cong90	cong95	Area90k	Official	new dens	resperden
New York	25.1	1.05	1.04	2.967	5.407	5.448	34.263
Los Angeles	25.4	1.56	1.5	1.966	5.8	6.992	12.436
Chicago	25.9	1.15	1.24	1.585	4.285	5.218	12.168
Philadelphia	23.2	0.99	1	1.164	3.627	3.727	10.755
Detroit	22.7	1.08	1.15	1.119	3.304	3.537	6.079
San Francisco	23.9	1.36	1.34	0.874	4.153	6.109	16.935
Washington	26.4	1.21	1.32	0.945	3.559	4.041	8.732
Dallas	23	0.99	0.98	1.443	2.216	3.182	5.477
Houston	24.9	1	0.98	1.177	2.466	2.888	5.304
Boston	22.5	1.08	1.19	0.891	3.114	3.243	10.801
San Diego	21.3	1.15	1.13	0.69	3.403	3.761	7.123
Atlanta	24.6	0.95	1.12	1.137	1.897	2.041	2.916
Minneapolis	19.7	0.89	1.06	1.063	1.957	2.951	4.833
Phoenix	22.5	1.04	1.06	0.741	2.707	3.440	4.935
St. Louis	21.8	0.93	1	0.728	2.674	2.884	4.992
Miami	24	1.23	1.28	0.353	5.425	5.747	10.217
Baltimore	24.1	0.94	1.03	0.593	3.187	3.207	8.577
Seattle	22.6	1.21	1.2	0.588	2.966	3.007	4.928
Tampa	21.3	1.02	1.11	0.65	2.629	3.037	4.341
Pittsburgh	21.5	0.75	0.76	0.778	2.157	3.032	5.358
Cleveland	21.3	0.89	0.98	0.636	2.637	3.176	6.287
Denver	21.3	0.91	1.03	0.459	3.307	3.513	5.397
Norfolk	21	0.92	0.93	0.664	1.992	3.124	5.256
Kansas City	20.1	0.66	0.72	0.762	1.673	2.397	3.636
Milwaukee	18.9	0.93	1.02	0.512	2.395	3.366	7.103
Cincinnati	21	0.89	1	0.512	2.367	2.741	5.073
Portland	19.7	1.02	1.15	0.388	3.021	3.003	4.450
San Antonio	20.8	0.75	0.88	0.438	2.578	3.306	4.888
Sacramento	20.9	1.06	1.12	0.334	3.284	3.684	5.727
New Orleans	22	1.01	1.02	0.27	3.852	5.073	8.205
Buffalo	18.3	0.64	0.72	0.286	3.336	3.463	6.737

City	rescon	jobpd	jobcon	jpbw	mix	CBDsizeK	CBDshare
New York	6.29	128.230	49.91	5.156	0.33	1851.004	19.78
Los Angeles	1.78	18.605	5.59	2.354	0.37	322.762	4.74
Chicago	2.33	66.843	26.77	1.736	0.29	336.313	8.69
Philadelphia	2.89	32.374	18.64	1.761	0.40	247.945	10.19
Detroit	1.72	29.083	18.69	0.807	0.33	74.339	3.59
San Francisco	2.77	53.710	17.27	3.950	0.38	246.154	7.81
Washington	2.16	66.877	29.12	2.337	0.45	324.056	13.72
Dallas	1.72	30.160	18.50	0.640	0.21	141.493	7.04
Houston	1.84	25.508	18.41	0.850	0.35	127.759	7.18
Boston	3.33	34.918	21.12	2.222	0.39	148.4	6.80
San Diego	1.89	12.076	6.50	1.347	0.38	48.166	3.96
Atlanta	1.43	23.021	21.19	0.762	0.48	112.654	7.67
Minneapolis	1.64	27.143	17.17	1.166	0.45	168.673	12.90
Phoenix	1.43	8.811	5.46	0.758	0.30	83.746	8.39
St. Louis	1.73	22.756	16.82	0.724	0.32	101.749	8.79
Miami	1.78	22.089	8.38	1.418	0.31	41.214	2.80
Baltimore	2.67	28.297	17.90	1.284	0.37	127.682	11.35
Seattle	1.64	28.842	18.67	1.125	0.42	130.374	9.25
Tampa	1.43	15.759	11.47	0.583	0.28	59.853	6.80
Pittsburgh	1.77	44.414	34.25	1.042	0.45	114.814	11.89
Cleveland	1.98	31.017	21.99	0.680	0.27	106.899	8.41
Denver	1.54	21.494	11.78	1.093	0.38	107.773	10.97
Norfolk	1.68	10.371	6.63	0.900	0.32	36.277	5.12
Kansas City	1.52	11.772	9.98	0.728	0.40	56.901	7.22
Milwaukee	2.11	17.140	10.83	1.040	0.34	86.457	10.43
Cincinnati	1.85	34.305	26.93	0.773	0.36	77.198	9.32
Portland	1.48	16.491	11.44	0.954	0.43	95.734	11.29
San Antonio	1.48	11.537	8.04	0.673	0.33	47.651	8.18
Sacramento	1.55	16.406	9.72	0.870	0.32	68.368	9.42
New Orleans	1.62	30.749	14.53	0.947	0.29	93.292	18.11
Buffalo	1.95	16.979	11.13	0.911	0.32	54.828	10.25

City	MedIncK	Poor15	Poor30	vehpers	Workers	Pop90M	hwpc	fwmile%
New York	37.869	20.3	39.7	0.45	46.92	16.044	2.3	17.57
Los Angeles	36.711	18.5	40.2	0.60	47.86	11.402	2.1	19.63
Chicago	35.916	19.1	41	0.55	47.77	6.792	2.9	11.20
Philadelphia	35.735	19.5	41.4	0.56	46.41	4.222	2.9	12.95
Detroit	34.729	22	43.2	0.62	43.63	3.697	3.4	13.87
San Francisco	41.459	15.1	34.4	0.66	51.24	3.63	2.3	25.03
Washington	46.856	10.4	27.6	0.64	56.87	3.363	3	18.95
Dallas	32.825	19.3	44.9	0.66	51.37	3.198	4.8	18.07
Houston	31.488	22.3	47.3	0.60	48.30	2.902	6.5	15.67
Boston	40.647	17.5	35.9	0.59	51.98	2.775	3.5	12.91
San Diego	35.022	17.9	42.2	0.65	49.44	2.348	2.2	29.72
Atlanta	36.051	17.2	40.3	0.68	53.26	2.157	4.6	17.60
Minneapolis	36.564	16.6	39.4	0.67	53.71	2.08	4.6	14.41
Phoenix	30.797	21.1	48.4	0.64	47.33	2.006	3.9	9.38
St. Louis	31.706	21.9	46.6	0.64	47.22	1.947	4	21.97
Miami	28.503	26	52.1	0.58	45.88	1.915	2.7	13.45
Baltimore	36.55	18.2	40	0.59	49.09	1.89	3.1	22.37
Seattle	35.047	17.4	41.6	0.73	53.18	1.744	3.5	18.68
Tampa	26.036	26.3	57.1	0.66	45.66	1.709	4	8.75
Pittsburgh	26.501	28.2	55.6	0.59	43.81	1.678	4.7	14.19
Cleveland	30.332	24	49.4	0.63	44.65	1.677	3.2	22.56
Denver	33.126	19.5	44.5	0.72	52.00	1.518	3.7	14.88
Norfolk	30.841	20.1	48.3	0.62	50.08	1.323	3.8	14.78
Kansas City	31.948	20.9	46.8	0.67	49.94	1.275	5.5	22.74
Milwaukee	32.359	21.3	45.8	0.61	47.49	1.226	4	12.12
Cincinnati	30.979	23.1	48.3	0.65	47.04	1.212	4.4	18.07
Portland	31.07	20.8	47.9	0.69	49.71	1.172	3.8	12.61
San Antonio	26.092	27.8	56.6	0.58	43.64	1.129	4.2	20.81
Sacramento	32.734	20.2	45.1	0.68	46.28	1.097	3.1	16.15
New Orleans	24.442	32.7	58.8	0.53	41.65	1.04	3.1	12.51
Buffalo	28.084	26.8	52.9	0.59	44.34	0.954	3.7	15.95

City	fwvmt%	Pop50M	Dens50k	popgr	densgr	pop00k	popgr00	popgr20c
New York	37.7	12.296	9.813	1.30	0.55	3437	1.90	4.67
Los Angeles	44.5	3.997	4.589	2.85	1.26	102	6.38	111.78
Chicago	30.4	4.921	6.951	1.38	0.62	1698	1.99	4.00
Philadelphia	30.8	2.922	9.365	1.44	0.39	1293	1.48	3.27
Detroit	34.8	2.752	6.506	1.34	0.51	286	2.26	12.93
San Francisco	53.1	2.022	7.045	1.80	0.59	343	1.39	10.58
Washington	41.6	1.287	7.23	2.61	0.49	279	1.44	12.05
Dallas	43.1	0.855	3.263	3.74	0.68	43	2.42	74.37
Houston	43	0.701	2.596	4.14	0.95	45	3.04	64.49
Boston	37.4	2.233	6.472	1.24	0.48	560	1.50	4.96
San Diego	51.8	0.433	3.256	5.42	1.05	18	2.50	130.44
Atlanta	40.4	0.507	4.783	4.25	0.40	90	2.35	23.97
Minneapolis	45.3	0.987	4.273	2.11	0.46	203	1.82	10.25
Phoenix	29.8	0.216	3.927	9.29	0.69	6	3.67	334.33
St. Louis	42.7	1.401	6.145	1.39	0.44	575	1.52	3.39
Miami	32.7	0.459	3.923	4.17	1.38	2	5.00	957.50
Baltimore	48.2	1.162	7.645	1.63	0.42	509	1.29	3.71
Seattle	46.1	0.622	5.057	2.80	0.59	81	5.51	21.53
Tampa	20.3	0.408	2.267	4.19	1.16	1	1.00	1709.00
Pittsburgh	30.4	1.533	6.035	1.09	0.36	452	1.55	3.71
Cleveland	44.1	1.384	4.613	1.21	0.57	382	2.15	4.39
Denver	39.4	0.499	4.752	3.04	0.70	133	2.00	11.41
Norfolk	32.8	0.385	6.21	3.44	0.32	1	1.00	1323.00
Kansas City	45.4	0.698	4.685	1.83	0.36	164	1.86	7.77
Milwaukee	28	0.829	8.127	1.48	0.29	285	1.83	4.30
Cincinnati	46.6	0.813	5.568	1.49	0.43	326	1.23	3.72
Portland	38.7	0.513	4.5	2.28	0.67	90	4.50	13.02
San Antonio	46.4	0.45	5	2.51	0.52	53	2.55	21.30
Sacramento	40.2	0.212	5.048	5.17	0.65	29	1.73	37.83
New Orleans	37.4	0.66	2.973	1.58	1.30	287	1.36	3.62
Buffalo	28.6	0.895	7.276	1.07	0.46	353	1.66	2.70

Correlations

	TotTime	OtherTime	VTimeTrav	ProbOfTravel	VtimePers	Speed	AvgOfPvmt
TotTime	1.00						
OtherTime	0.57	1.00					
VTimeTrav	0.56	-0.36	1.00				
ProbOfTravel	0.18	0.06	0.14	1.00			
VtimePers	0.58	-0.30	0.96	0.41	1.00		
Speed	0.14	-0.23	0.39	0.30	0.44	1.00	
AvgOfPvmt	0.48	-0.30	0.84	0.42	0.89	0.79	1.00
DrAlone	-0.39	-0.79	0.35	0.29	0.39	0.25	0.37
noncar	0.28	0.77	-0.45	-0.35	-0.50	-0.30	-0.47
Auto Pass	0.42	0.12	0.36	0.22	0.40	0.20	0.36
Tran %	0.28	0.78	-0.47	-0.33	-0.51	-0.33	-0.49
WB	0.02	0.46	-0.45	-0.26	-0.48	-0.29	-0.46
cong90	0.39	0.22	0.22	0.05	0.22	-0.06	0.11
cong95	0.42	0.19	0.28	0.08	0.28	0.01	0.19
Area90k	0.26	0.46	-0.17	-0.30	-0.22	-0.08	-0.17
Official	0.24	0.42	-0.15	-0.16	-0.18	-0.29	-0.26
new dens	0.26	0.39	-0.09	-0.07	-0.10	-0.23	-0.18
resperden	0.21	0.69	-0.45	-0.32	-0.49	-0.26	-0.44
rescon	0.10	0.65	-0.54	-0.36	-0.58	-0.23	-0.49
jobpd	0.27	0.70	-0.41	-0.35	-0.46	-0.30	-0.44
jobcon	0.13	0.53	-0.39	-0.31	-0.44	-0.33	-0.44
jpbw	0.32	0.70	-0.34	-0.25	-0.37	-0.14	-0.31
mix	0.20	0.16	0.06	-0.01	0.05	0.12	0.09
CBDsizeK	0.22	0.70	-0.45	-0.36	-0.49	-0.23	-0.43
CBDshare	0.15	0.63	-0.46	-0.09	-0.44	-0.23	-0.40
MedIncK	0.25	0.33	-0.04	-0.20	-0.09	0.23	0.05
Poor15	-0.24	-0.17	-0.10	0.14	-0.06	-0.34	-0.20
Poor30	-0.23	-0.28	0.02	0.20	0.08	-0.26	-0.08
vehpers	0.02	-0.43	0.46	0.25	0.48	0.42	0.51
Workers	0.32	0.14	0.22	-0.10	0.17	0.41	0.32
Pop90M	0.26	0.56	-0.26	-0.27	-0.30	-0.20	-0.28
hwpc	-0.08	-0.35	0.26	0.29	0.32	0.23	0.33
fwmile%	-0.11	0.00	-0.12	0.05	-0.10	0.48	0.17
fwvmt%	0.12	0.11	0.03	0.35	0.13	0.63	0.40
Pop50M	0.16	0.62	-0.45	-0.37	-0.50	-0.30	-0.47
Dens50k	-0.14	0.44	-0.60	-0.40	-0.66	-0.25	-0.56
popgr	0.13	-0.22	0.38	-0.01	0.34	0.17	0.31
densgr	0.27	-0.04	0.35	0.18	0.38	-0.10	0.20
pop00k	0.08	0.67	-0.58	-0.41	-0.64	-0.38	-0.60
popgr00	0.17	-0.05	0.25	0.28	0.32	-0.06	0.18
popgr20c	0.14	-0.15	0.31	-0.10	0.26	-0.27	0.03

	DrAlone	*noncar*	*Auto Pass*	*Tran %*	*WB*	*cong90*	*cong95*	*Area90k*
TotTime								
OtherTime								
VTimeTrav								
ProbOfTravel								
VtimePers								
Speed								
AvgOfPvmt								
DrAlone	1.00							
noncar	-0.96	1.00						
Auto Pass	-0.15	-0.11	1.00					
Tran %	-0.92	0.96	-0.15	1.00				
WB	-0.75	0.79	-0.15	0.64	1.00			
cong90	-0.32	0.24	0.34	0.21	0.14	1.00		
cong95	-0.26	0.20	0.26	0.19	0.07	0.95	1.00	
Area90k	-0.56	0.59	-0.09	0.66	0.22	0.35	0.27	1.00
Official	-0.56	0.52	0.19	0.52	0.39	0.69	0.62	0.42
new dens	-0.51	0.44	0.30	0.43	0.33	0.72	0.62	0.40
resperden	-0.82	0.86	-0.12	0.87	0.60	0.38	0.29	0.72
rescon	-0.79	0.88	-0.29	0.89	0.65	0.15	0.09	0.68
jobpd	-0.81	0.86	-0.17	0.94	0.46	0.22	0.19	0.71
jobcon	-0.59	0.68	-0.33	0.79	0.31	-0.04	-0.04	0.58
jpbw	-0.84	0.86	-0.04	0.84	0.62	0.49	0.43	0.66
mix	-0.21	0.21	-0.02	0.17	0.17	0.01	0.11	0.00
CBDsizeK	-0.78	0.84	-0.17	0.87	0.49	0.19	0.12	0.81
CBDshare	-0.58	0.59	-0.06	0.64	0.39	-0.23	-0.21	0.19
MedIncK	-0.49	0.51	-0.02	0.49	0.29	0.51	0.57	0.46
Poor15	0.30	-0.30	-0.03	-0.25	-0.14	-0.45	-0.51	-0.34
Poor30	0.44	-0.46	0.04	-0.44	-0.25	-0.50	-0.56	-0.44
vehpers	0.58	-0.57	-0.03	-0.63	-0.43	-0.01	0.09	-0.47
Workers	-0.24	0.23	0.07	0.16	0.08	0.24	0.34	0.13
Pop90M	-0.66	0.68	-0.03	0.72	0.38	0.47	0.38	0.93
hwpc	0.51	-0.50	-0.06	-0.42	-0.55	-0.62	-0.59	-0.18
fwmile%	-0.05	0.02	0.13	-0.02	-0.03	0.07	0.01	0.04
fwvmt%	-0.03	0.00	0.17	-0.03	-0.11	0.19	0.18	0.04
Pop50M	-0.72	0.80	-0.28	0.85	0.49	0.24	0.18	0.86
Dens50k	-0.54	0.64	-0.37	0.65	0.57	-0.04	-0.03	0.33
popgr	0.18	-0.29	0.45	-0.38	-0.15	0.22	0.18	-0.11
densgr	0.01	-0.14	0.49	-0.14	-0.13	0.53	0.45	-0.01
pop00k	-0.74	0.84	-0.35	0.89	0.54	0.03	-0.01	0.72
popgr00	0.08	-0.14	0.22	-0.14	-0.15	0.52	0.47	0.12
popgr20c	0.15	-0.21	0.23	-0.27	-0.13	0.09	0.07	-0.15

	Official	new dens	resperden	rescon	jobpd	jobcon	jpbw	mix
TotTime								
OtherTime								
VTimeTrav								
ProbOfTravel								
VtimePers								
Speed								
AvgOfPvmt								
DrAlone								
noncar								
Auto Pass								
Tran %								
WB								
cong90								
cong95								
Area90k								
Official	1.00							
new dens	0.91	1.00						
resperden	0.71	0.67	1.00					
rescon	0.48	0.37	0.93	1.00				
jobpd	0.46	0.41	0.84	0.84	1.00			
jobcon	0.14	0.05	0.58	0.69	0.89	1.00		
jpbw	0.67	0.66	0.94	0.85	0.81	0.54	1.00	
mix	-0.15	-0.21	-0.09	-0.01	0.06	0.18	0.15	1.00
CBDsizeK	0.50	0.41	0.91	0.90	0.87	0.71	0.81	-0.01
CBDshare	0.09	0.05	0.41	0.47	0.58	0.57	0.36	0.16
MedIncK	0.26	0.23	0.40	0.44	0.47	0.34	0.61	0.44
Poor15	-0.05	-0.03	-0.16	-0.21	-0.23	-0.13	-0.39	-0.45
Poor30	-0.23	-0.19	-0.36	-0.39	-0.42	-0.30	-0.56	-0.44
vehpers	-0.51	-0.48	-0.66	-0.65	-0.55	-0.43	-0.46	0.28
Workers	-0.12	-0.13	0.02	0.10	0.12	0.06	0.26	0.49
Pop90M	0.68	0.63	0.85	0.74	0.73	0.51	0.78	-0.05
hwpc	-0.78	-0.72	-0.57	-0.40	-0.34	-0.04	-0.57	0.09
fwmile%	0.02	0.04	0.09	0.08	0.03	0.00	0.18	0.15
fwvmt%	-0.02	0.03	0.03	0.01	0.02	0.01	0.17	0.26
Pop50M	0.58	0.50	0.91	0.88	0.85	0.69	0.79	-0.06
Dens50k	0.25	0.17	0.56	0.67	0.56	0.49	0.56	0.20
popgr	-0.08	-0.06	-0.26	-0.34	-0.38	-0.46	-0.24	-0.15
densgr	0.55	0.54	0.08	-0.17	-0.14	-0.33	0.02	-0.33
pop00k	0.45	0.33	0.85	0.89	0.86	0.75	0.70	-0.06
popgr00	0.40	0.33	-0.02	-0.20	-0.20	-0.30	0.00	0.08
popgr20c	-0.01	0.02	-0.12	-0.18	-0.25	-0.32	-0.16	-0.32

	CBDsizeK	CBDshare	MedIncK	Poor15	Poor30	vehpers	Workers	Pop90M
TotTime								
OtherTime								
VTimeTrav								
ProbOfTravel								
VtimePers								
Speed								
AvgOfPvmt								
DrAlone								
noncar								
Auto Pass								
Tran %								
WB								
cong90								
cong95								
Area90k								
Official								
new dens								
resperden								
rescon								
jobpd								
jobcon								
jpbw								
mix								
CBDsizeK	1.00							
CBDshare	0.55	1.00						
MedIncK	0.35	0.06	1.00					
Poor15	-0.18	0.09	-0.92	1.00				
Poor30	-0.31	-0.03	-0.99	0.95	1.00			
vehpers	-0.57	-0.35	0.08	-0.37	-0.14	1.00		
Workers	0.05	-0.02	0.78	-0.90	-0.81	0.44	1.00	
Pop90M	0.87	0.25	0.41	-0.24	-0.38	-0.57	0.01	1.00
hwpc	-0.34	-0.07	-0.35	0.20	0.32	0.29	-0.04	-0.44
fwmile%	0.04	-0.15	0.29	-0.30	-0.30	0.18	0.26	0.05
fwvmt%	0.00	-0.04	0.38	-0.40	-0.40	0.30	0.39	0.02
Pop50M	0.94	0.41	0.35	-0.14	-0.32	-0.66	-0.06	0.93
Dens50k	0.50	0.35	0.46	-0.29	-0.44	-0.44	0.16	0.40
popgr	-0.20	-0.33	-0.11	-0.11	0.08	0.32	0.08	-0.15
densgr	-0.05	-0.19	-0.27	0.31	0.29	-0.13	-0.31	0.15
pop00k	0.89	0.54	0.28	-0.07	-0.25	-0.69	-0.07	0.76
popgr00	-0.03	-0.31	-0.02	-0.06	-0.01	0.16	-0.03	0.23
popgr20c	-0.15	-0.37	-0.34	0.22	0.36	0.03	-0.11	-0.12

	hwpc	fwmile%	fwvmt%	Pop50M	Dens50k	popgr	densgr	pop00k	popgr00
TotTime									
OtherTime									
VTimeTrav									
ProbOfTravel									
VtimePers									
Speed									
AvgOfPvmt									
DrAlone									
noncar									
Auto Pass									
Tran %									
WB									
cong90									
cong95									
Area90k									
Official									
new dens									
resperden									
rescon									
jobpd									
jobcon									
jpbw									
mix									
CBDsizeK									
CBDshare									
MedIncK									
Poor15									
Poor30									
vehpers									
Workers									
Pop90M									
hwpc	1.00								
fwmile%	-0.18	1.00							
fwvmt%	-0.05	0.83	1.00						
Pop50M	-0.41	0.00	-0.07	1.00					
Dens50k	-0.37	0.03	-0.13	0.57	1.00				
popgr	0.07	-0.12	-0.07	-0.34	-0.54	1.00			
densgr	-0.28	-0.09	-0.04	-0.06	-0.63	0.37	1.00		
pop00k	-0.34	-0.06	-0.14	0.93	0.67	-0.39	-0.21	1.00	
popgr00	-0.15	0.00	0.14	-0.01	-0.32	0.32	0.48	-0.21	1.00
popgr20c	-0.01	-0.34	-0.49	-0.19	-0.32	0.36	0.37	-0.22	-0.03

Correlations excluding New York

	TotTime	OtherTime	VTimeTrav	ProbOfTravel	VtimePers	Speed	AvgOfPvmt
TotTime	1.00						
OtherTime	0.62	1.00					
VTimeTrav	0.71	-0.11	1.00				
ProbOfTravel	0.25	0.40	-0.04	1.00			
VtimePers	0.76	0.02	0.95	0.27	1.00		
Speed	0.17	-0.13	0.33	0.24	0.39	1.00	
AvgOfPvmt	0.60	-0.05	0.80	0.31	0.87	0.80	1.00
DrAlone	-0.41	-0.65	0.07	0.04	0.07	0.15	0.13
noncar	0.28	0.59	-0.18	-0.10	-0.20	-0.22	-0.25
Auto Pass	0.47	0.33	0.29	0.15	0.34	0.15	0.30
Tran %	0.29	0.62	-0.19	-0.07	-0.20	-0.26	-0.27
WB	-0.05	0.27	-0.30	-0.11	-0.32	-0.22	-0.33
cong90	0.39	0.25	0.27	0.07	0.28	-0.05	0.15
cong95	0.42	0.26	0.30	0.07	0.31	0.00	0.19
Area90k	0.24	0.06	0.25	-0.05	0.23	0.09	0.21
Official	0.21	0.24	0.04	-0.01	0.04	-0.23	-0.10
new dens	0.24	0.29	0.04	0.04	0.06	-0.18	-0.06
resperden	0.19	0.41	-0.13	-0.01	-0.13	-0.15	-0.16
rescon	-0.02	0.32	-0.32	-0.07	-0.32	-0.10	-0.26
jobpd	0.26	0.46	-0.09	-0.09	-0.11	-0.23	-0.19
jobcon	0.05	0.23	-0.14	-0.10	-0.17	-0.25	-0.24
jpbw	0.33	0.48	-0.02	0.03	-0.01	0.01	0.00
mix	0.21	0.26	0.03	-0.04	0.01	0.11	0.07
CBDsizeK	0.37	0.53	-0.01	0.03	0.00	-0.10	-0.05
CBDshare	0.10	0.45	-0.28	0.14	-0.23	-0.14	-0.22
MedIncK	0.24	0.28	0.05	-0.14	0.00	0.28	0.15
Poor15	-0.24	-0.19	-0.13	0.14	-0.08	-0.35	-0.23
Poor30	-0.21	-0.24	-0.05	0.16	0.00	-0.30	-0.16
vehpers	0.12	-0.14	0.27	0.05	0.27	0.37	0.36
Workers	0.33	0.21	0.23	-0.12	0.18	0.41	0.33
Pop90M	0.25	0.19	0.15	0.04	0.17	-0.06	0.08
hwpc	-0.05	-0.25	0.16	0.22	0.22	0.19	0.25
fwmile%	-0.11	-0.03	-0.12	0.06	-0.09	0.50	0.20
fwvmt%	0.12	0.16	0.02	0.37	0.13	0.64	0.43
Pop50M	0.08	0.24	-0.12	-0.08	-0.13	-0.25	-0.21
Dens50k	-0.22	0.24	-0.50	-0.29	-0.57	-0.18	-0.46
popgr	0.16	-0.17	0.35	-0.07	0.32	0.14	0.27
densgr	0.28	-0.01	0.37	0.17	0.41	-0.11	0.20
pop00k	-0.06	0.36	-0.40	-0.19	-0.44	-0.37	-0.48
popgr00	0.18	-0.02	0.25	0.27	0.33	-0.07	0.18
popgr20c	0.15	-0.14	0.32	-0.14	0.26	-0.29	0.00

	DrAlone	*noncar*	*Auto Pass*	*Tran %*	*WB*	*cong90*	*cong95*	*Area90k*
TotTime								
OtherTime								
VTimeTrav								
ProbOfTravel								
VtimePers								
Speed								
AvgOfPvmt								
DrAlone	1.00							
noncar	-0.94	1.00						
Auto Pass	-0.43	0.09	1.00					
Tran %	-0.85	0.92	0.05	1.00				
WB	-0.67	0.76	-0.05	0.51	1.00			
cong90	-0.40	0.32	0.36	0.28	0.14	1.00		
cong95	-0.38	0.34	0.26	0.34	0.09	0.95	1.00	
Area90k	-0.15	0.14	0.11	0.25	-0.15	0.45	0.40	1.00
Official	-0.42	0.35	0.32	0.35	0.26	0.74	0.69	0.20
new dens	-0.45	0.35	0.40	0.34	0.24	0.74	0.65	0.29
resperden	-0.62	0.64	0.16	0.63	0.47	0.64	0.59	0.33
rescon	-0.56	0.69	-0.19	0.70	0.58	0.23	0.23	0.21
jobpd	-0.61	0.67	0.01	0.84	0.20	0.30	0.34	0.35
jobcon	-0.28	0.39	-0.24	0.60	0.03	-0.09	-0.03	0.24
jpbw	-0.69	0.71	0.18	0.66	0.48	0.66	0.63	0.33
mix	-0.35	0.40	-0.03	0.36	0.23	0.02	0.11	0.07
CBDsizeK	-0.65	0.65	0.21	0.75	0.23	0.57	0.58	0.71
CBDshare	-0.35	0.34	0.08	0.42	0.20	-0.29	-0.23	-0.30
MedIncK	-0.51	0.57	0.03	0.57	0.24	0.52	0.59	0.47
Poor15	0.37	-0.42	-0.03	-0.36	-0.14	-0.45	-0.52	-0.44
Poor30	0.46	-0.53	0.00	-0.52	-0.21	-0.50	-0.57	-0.48
vehpers	0.33	-0.28	-0.19	-0.38	-0.25	0.02	0.08	-0.13
Workers	-0.37	0.40	0.06	0.32	0.11	0.24	0.34	0.22
Pop90M	-0.31	0.26	0.23	0.32	0.06	0.68	0.62	0.85
hwpc	0.47	-0.49	-0.13	-0.36	-0.50	-0.63	-0.62	0.00
fwmile%	-0.03	-0.01	0.14	-0.07	-0.05	0.07	0.01	0.02
fwvmt%	-0.08	0.03	0.17	0.00	-0.11	0.19	0.17	0.09
Pop50M	-0.35	0.45	-0.15	0.57	0.21	0.43	0.41	0.72
Dens50k	-0.38	0.53	-0.30	0.55	0.46	-0.07	-0.03	0.05
popgr	0.11	-0.28	0.44	-0.43	-0.10	0.23	0.17	-0.02
densgr	-0.03	-0.15	0.49	-0.16	-0.12	0.53	0.45	0.04
pop00k	-0.42	0.57	-0.30	0.69	0.33	0.00	0.03	0.33
popgr00	0.06	-0.14	0.21	-0.15	-0.14	0.52	0.47	0.22
popgr20c	0.14	-0.24	0.22	-0.35	-0.12	0.09	0.07	-0.14

	Official	new dens	resperden	rescon	jobpd	jobcon	jpbw	mix
TotTime								
OtherTime								
VTimeTrav								
ProbOfTravel								
VtimePers								
Speed								
AvgOfPvmt								
DrAlone								
noncar								
Auto Pass								
Tran %								
WB								
cong90								
cong95								
Area90k								
Official	1.00							
new dens	0.91	1.00						
resperden	0.76	0.83	1.00					
rescon	0.28	0.25	0.73	1.00				
jobpd	0.25	0.31	0.55	0.52	1.00			
jobcon	-0.18	-0.19	0.09	0.35	0.81	1.00		
jpbw	0.59	0.68	0.89	0.67	0.57	0.15	1.00	
mix	-0.13	-0.20	-0.05	0.11	0.18	0.30	0.29	1.00
CBDsizeK	0.47	0.53	0.66	0.48	0.74	0.42	0.70	0.24
CBDshare	-0.17	-0.12	-0.08	0.02	0.31	0.35	-0.03	0.24
MedIncK	0.21	0.19	0.48	0.56	0.54	0.30	0.70	0.46
Poor15	-0.04	-0.03	-0.26	-0.36	-0.34	-0.15	-0.52	-0.45
Poor30	-0.18	-0.16	-0.44	-0.53	-0.49	-0.27	-0.65	-0.46
vehpers	-0.37	-0.40	-0.44	-0.40	-0.23	-0.11	-0.12	0.29
Workers	-0.12	-0.12	0.11	0.28	0.25	0.11	0.41	0.49
Pop90M	0.63	0.66	0.59	0.26	0.32	0.04	0.52	0.01
hwpc	-0.76	-0.70	-0.68	-0.37	-0.22	0.17	-0.57	0.08
fwmile%	0.00	0.04	0.12	0.10	0.00	-0.03	0.23	0.15
fwvmt%	0.00	0.04	0.11	0.08	0.08	0.04	0.27	0.26
Pop50M	0.51	0.53	0.65	0.52	0.57	0.34	0.51	0.00
Dens50k	0.10	0.06	0.41	0.65	0.39	0.32	0.40	0.26
popgr	-0.02	-0.02	-0.25	-0.42	-0.43	-0.49	-0.19	-0.16
densgr	0.62	0.58	0.23	-0.24	-0.15	-0.39	0.08	-0.33
pop00k	0.21	0.18	0.47	0.61	0.61	0.50	0.29	0.00
popgr00	0.47	0.36	0.06	-0.29	-0.24	-0.34	0.06	0.07
popgr20c	0.02	0.04	-0.11	-0.24	-0.31	-0.36	-0.16	-0.33

	CBDsizeK	*CBDshare*	*MedIncK*	*Poor15*	*Poor30*	*vehpers*	*Workers*	*Pop90M*
TotTime								
OtherTime								
VTimeTrav								
ProbOfTravel								
VtimePers								
Speed								
AvgOfPvmt								
DrAlone								
noncar								
Auto Pass								
Tran %								
WB								
cong90								
cong95								
Area90k								
Official								
new dens								
resperden								
rescon								
jobpd								
jobcon								
jpbw								
mix								
CBDsizeK	1.00							
CBDshare	0.18	1.00						
MedIncK	0.68	-0.04	1.00					
Poor15	-0.56	0.12	-0.93	1.00				
Poor30	-0.66	0.06	-0.99	0.95	1.00			
vehpers	-0.19	-0.08	0.22	-0.46	-0.27	1.00		
Workers	0.36	0.00	0.81	-0.90	-0.82	0.50	1.00	
Pop90M	0.77	-0.29	0.43	-0.34	-0.42	-0.26	0.07	1.00
hwpc	-0.35	0.08	-0.32	0.20	0.30	0.18	-0.05	-0.39
fwmile%	0.02	-0.20	0.29	-0.30	-0.30	0.24	0.26	0.04
fwvmt%	0.13	-0.02	0.39	-0.40	-0.41	0.34	0.38	0.07
Pop50M	0.76	-0.13	0.40	-0.22	-0.39	-0.45	-0.05	0.82
Dens50k	0.36	0.16	0.43	-0.31	-0.42	-0.26	0.20	0.12
popgr	-0.23	-0.30	-0.08	-0.11	0.06	0.28	0.08	-0.06
densgr	0.00	-0.19	-0.26	0.31	0.29	-0.19	-0.31	0.29
pop00k	0.56	0.21	0.24	-0.09	-0.23	-0.50	-0.05	0.34
popgr00	0.12	-0.33	-0.01	-0.06	-0.02	0.15	-0.04	0.42
popgr20c	-0.31	-0.39	-0.33	0.21	0.36	-0.01	-0.11	-0.11

	hwpc	*fwmile%*	*fwvmt%*	*Pop50M*	*Dens50k*	*popgr*	*densgr*	*pop00k*	*popgr00*
TotTime									
OtherTime									
VTimeTrav									
ProbOfTravel									
VtimePers									
Speed									
AvgOfPvmt									
DrAlone									
noncar									
Auto Pass									
Tran %									
WB									
cong90									
cong95									
Area90k									
Official									
new dens									
resperden									
rescon									
jobpd									
jobcon									
jpbw									
mix									
CBDsizeK									
CBDshare									
MedIncK									
Poor15									
Poor30									
vehpers									
Workers									
Pop90M									
hwpc	1.00								
fwmile%	-0.18	1.00							
fwvmt%	-0.06	0.84	1.00						
Pop50M	-0.39	-0.07	-0.08	1.00					
Dens50k	-0.30	0.01	-0.12	0.45	1.00				
popgr	0.04	-0.11	-0.07	-0.44	-0.53	1.00			
densgr	-0.30	-0.09	-0.05	-0.03	-0.67	0.37	1.00		
pop00k	-0.24	-0.16	-0.21	0.75	0.62	-0.50	-0.30	1.00	
popgr00	-0.17	0.00	0.14	0.08	-0.33	0.32	0.48	-0.30	1.00
popgr20c	-0.03	-0.34	-0.50	-0.26	-0.32	0.35	0.36	-0.30	-0.03

APPENDIX B

FULL REGRESSION RESULTS

Summary

Regressions use cities as the unit of analysis. Thus there are 31 data points for each regression. Each independent variable such as VMT is covered in a single section. The first part of the section shows the results when each explanatory variable is regressed individually. Subsequent parts show combinations of different variables. The results are given in a bracketed list of the form {R^2, intercept, {v1, b1, t1},…{vn, bn, tn}}, where v1 is the first regressor, b1 is its parameter estimate, and t1 is the t-statistic. A t-statistic above or close to two is generally taken as a rough cutoff for judging statistical significance.

In a couple of cases a part of a section is devoted to running regressions on a “deeper” variable that is an important explainer of the primary variable in question. For example, when examining speed, the percent of miles driven on freeways is the main explainer. It might then reasonably be asked what factors affect the percent of miles driven on freeways. This variable then is taken as the regressor in a separate part of the speed section.

VMT (All Cities)

{0.617236,-11.2691,{{Speed95,0.995188,7.0269}}}
{0.126627,5.8345,{{DriveAlone,0.165749,2.31291}}}
{0.0701788,11.0825,{{Carpool,0.535322,1.80673}}}
{0.207885,19.6106,{{Transit,-0.240756,-2.97881}}}
{0.185458,21.5599,{{WalkBike,-0.938278,-2.7983}}}
{-0.00499721,22.0445,{{AllCommMed,-0.184216,-0.922404}}}
{-0.0140059,12.2179,{{DAcommMed,0.258928,0.765263}}}
{-0.0163678,20.9769,{{AllCommMean,-0.132398,-0.71894}}}
{-0.0310333,16.09,{{DAcommMean,0.0794761,0.311485}}}
{-0.0211002,16.1488,{{congestion90,1.70029,0.616501}}}
{0.00116726,14.599,{{congestion95,3.06102,1.01738}}}
{-0.00557263,18.5998,{{area90,-0.85456,-0.913098}}}
{0.0333103,20.0775,{{density90,-0.70488,-1.42609}}}
{-0.0027928,19.4719,{{RevDens,-0.436117,-0.957314}}}
{0.168201,19.5753,{{ResPD,-0.217561,-2.65827}}}
{0.213068,20.9456,{{ResConc,-1.51682,-3.02039}}}
{0.169624,19.5018,{{JobPD,-0.0541621,-2.66987}}}
{0.166506,20.1006,{{JobConc,-0.132145,-2.64444}}}
{0.062517,19.0326,{{JobPDbyWkr,-0.871528,-1.73222}}}
{-0.0260459,16.3814,{{Mix,4.15974,0.488322}}}
{0.152886,18.5496,{{CBDsize,-0.0037713,-2.53266}}}
{0.127286,20.6116,{{CBDemplshare,-0.302059,-2.31851}}}
{-0.031517,16.8217,{{MedianIncome,0.0313805,0.288753}}}
{0.00639196,20.5637,{{IncomeLT15,-0.128389,-1.09224}}}
{-0.0282764,19.2993,{{IncomeLT30,-0.0317204,-0.418371}}}
{0.23642,2.33256,{{vehiclepercapita,24.9022,3.20759}}}
{0.115455,2.97247,{{workerpercapita,0.30821,2.21715}}}

{0.0481278,18.6058,{{population90,-0.25259,-1.58645}}}
{0.0800863,14.3351,{{hwmilespercapita,0.963666,1.90046}}}
{-0.00416509,16.1485,{{fwlanemilesoftotal,0.102325,0.935717}}}
{0.130643,12.1062,{{fwvmtoftotal,0.147291,2.34697}}}
{0.193528,18.7909,{{population50,-0.586189,-2.8634}}}
{0.291013,22.5225,{{density50,-0.850142,-3.64882}}}
{0.0630119,16.5345,{{popgrowth5090,0.494529,1.73709}}}
{0.00782585,16.6485,{{densgrowth5090,1.91153,1.11204}}}
{0.333771,18.8463,{{pop1900,-0.00251288,-4.00369}}}
{0.00084757,16.9539,{{popgrowth1900,0.392253,1.01264}}}
{-0.0336475,17.8317,{{popgrowth20c,0.000198775,0.153078}}}

VMT excluding New York

{0.331779,-3.53346,{{TotalTimeTr,0.312964,3.92413}}}
{0.630093,-4.60573,{{VehTimeTr,0.535207,7.09917}}}
{0.742865,-5.59037,{{VehTimePers,0.64238,9.20767}}}
{0.62159,-9.00766,{{Speed95,0.922725,6.97398}}}
{0.000468202,11.5467,{{DriveAlone,0.0891558,1.00677}}}
{0.0205156,13.3956,{{Carpool,0.367661,1.26784}}}
{0.0502722,19.249,{{Transit,-0.178002,-1.59219}}}
{0.0886972,20.7601,{{WalkBike,-0.697755,-1.95514}}}
{-0.0311496,16.3713,{{AllCommMed,0.0762085,0.352067}}}
{0.00919111,10.5035,{{DAcommMed,0.348098,1.12651}}}
{-0.0230662,15.3863,{{AllCommMean,0.115941,0.588355}}}
{0.00128705,12.6909,{{DAcommMean,0.242658,1.01851}}}
{-0.013827,16.1048,{{congestion90,1.96417,0.777487}}}
{0.00250669,15.0283,{{congestion95,2.86176,1.0358}}}
{0.00959883,17.009,{{area90,1.35652,1.13184}}}
{-0.0256947,18.9036,{{density90,-0.267782,-0.522993}}}
{-0.0319539,18.5964,{{RevDens,-0.141506,-0.31942}}}
{-0.00770199,19.0415,{{ResPD,-0.137178,-0.882241}}}
{0.0342774,20.7922,{{ResConc,-1.43352,-1.42454}}}
{0.00300819,19.0003,{{JobPD,-0.0340047,-1.04283}}}
{0.0225865,19.4137,{{JobConc,-0.0840742,-1.29234}}}
{-0.0357046,18.0962,{{JobPDbyWkr,-0.0111164,-0.0161507}}}
{-0.0312572,17.1058,{{Mix,2.73605,0.347875}}}
{-0.0334438,18.2638,{{CBDsize,-0.00143375,-0.248027}}}
{0.0135628,19.6369,{{CBDemplshare,-0.177776,-1.18268}}}
{-0.0134294,15.4757,{{MedianIncome,0.0789089,0.784671}}}
{0.0214339,20.9692,{{IncomeLT15,-0.137082,-1.27875}}}
{-0.00976172,20.7737,{{IncomeLT30,-0.0592031,-0.84832}}}
{0.101801,5.9813,{{vehiclepercapita,19.2245,2.07047}}}
{0.119928,4.33935,{{workerpercapita,0.284185,2.22527}}}
{-0.02933,17.8367,{{population90,0.0983051,0.416732}}}
{0.0314957,15.5275,{{hwmilespercapita,0.689365,1.39394}}}
{0.00770948,16.2324,{{fwlanemilesoftotal,0.110583,1.10694}}}
{0.152922,12.5193,{{fwvmtoftotal,0.142166,2.49706}}}
{0.0120216,18.6909,{{population50,-0.496382,-1.16313}}}
{0.185257,21.8164,{{density50,-0.699712,-2.75573}}}
{0.0418938,16.9826,{{popgrowth5090,0.402495,1.506}}}

{0.0054651,16.9947,{{densgrowth5090,1.70439,1.07674}}}
{0.20297,19.0497,{{pop1900,-0.00333875,-2.8957}}}
{-0.00309942,17.288,{{popgrowth1900,0.34072,0.954146}}}
{-0.0357098,18.0849,{{popgrowth20c,-0.0000131983,-0.0110271}}}

Speed (All Cities)

One Regressor

{0.0568051,22.0518,{{DriveAlone,0.0995088,1.67535}}}
{-0.0137871,26.8685,{{Carpool,0.189856,0.769423}}}
{0.0859116,30.2555,{{Transit,-0.135334,-1.95438}}}
{0.0872716,31.4669,{{WalkBike,-0.556781,-1.96685}}}
{-0.00780133,32.4455,{{AllCommMed,-0.139763,-0.876226}}}
{-0.0344356,29.0574,{{DAcommMed,0.00990764,0.0363502}}}
{-0.00608689,32.3824,{{AllCommMean,-0.132206,-0.904709}}}
{-0.0277479,31.2496,{{DAcommMean,-0.0885707,-0.435934}}}
{-0.0310241,29.9686,{{congestion90,-0.689398,-0.311901}}}
{-0.0343846,29.1368,{{congestion95,0.128072,0.0524459}}}
{-0.0274812,29.5624,{{area90,-0.335412,-0.444539}}}
{0.0507639,31.2536,{{density90,-0.630412,-1.6138}}}
{0.0187074,30.9355,{{RevDens,-0.450631,-1.25376}}}
{0.0341699,30.068,{{ResPD,-0.100987,-1.43574}}}
{0.0200664,30.4273,{{ResConc,-0.567884,-1.27056}}}
{0.0614969,30.1695,{{JobPD,-0.0296224,-1.72215}}}
{0.0752258,30.5917,{{JobConc,-0.0778661,-1.85482}}}
{-0.0132589,29.7096,{{JobPDbyWkr,-0.325141,-0.779383}}}
{-0.0193712,27.6916,{{Mix,4.4401,0.655672}}}
{0.0198828,29.5682,{{CBDsize,-0.0016202,-1.2683}}}
{0.0199303,30.5446,{{CBDemplshare,-0.139721,-1.26889}}}
{0.0223254,25.6374,{{MedianIncome,0.109537,1.2981}}}
{0.0826733,32.9195,{{IncomeLT15,-0.173359,-1.92451}}}
{0.0372174,33.1659,{{IncomeLT30,-0.0859893,-1.46959}}}
{0.143815,19.2244,{{vehiclepercapita,16.1127,2.45747}}}
{0.122474,17.1222,{{workerpercapita,0.251503,2.2775}}}
{0.00586856,29.6872,{{population90,-0.140796,-1.08494}}}
{0.0209942,27.3152,{{hwmilespercapita,0.534826,1.28193}}}
{0.203993,25.4373,{{fwlanemilesoftotal,0.228886,2.94756}}}
{0.381566,21.9849,{{fwvmtoftotal,0.186469,4.41697}}}
{0.0598198,29.7491,{{population50,-0.300666,-1.70551}}}
{0.0307645,30.9371,{{density50,-0.303573,-1.39722}}}
{-0.00586747,28.6992,{{popgrowth5090,0.21368,0.908297}}}
{-0.0248262,29.7363,{{densgrowth5090,-0.728353,-0.52274}}}
{0.111635,29.7672,{{pop1900,-0.00126245,-2.18401}}}
{-0.0308838,29.5049,{{popgrowth1900,-0.0998488,-0.318186}}}
{0.0414008,29.5139,{{popgrowth20c,-0.00151112,-1.51515}}}

Two or More Regressors

{0.48255,22.9743,{{Transit,-0.134451,-2.58061},{fwvmtoftotal,0.186118,4.81967}}}
{0.424538,24.0312,{{WalkBike,-0.404957,1.77918},{fwvmtoftotal,0.174932,4.2422}}}
{0.476285,23.2945,{{JobConc,-0.0789496,-2.49898},{fwvmtoftotal,0.18716,4.81747}}}

{0.36831,23.512,{{IncomeLT15,0.05103,0.625905},{fwvmtoftotal,0.17483,3.75682}}}
{0.41776,16.914,{{vehiclepercapita,9.5031,1.67427},{fwvmtoftotal,0.16456,3.82691}}}
{0.3864,17.378,{{workerpercapita,0.11099,1.11047},{fwvmtoftotal,0.16711,3.67156}}}
{0.4477,22.849,{{pop1900,-0.000974188,-2.11487},{fwvmtoftotal,0.174111,4.31813}}}
{0.47561,23.2575,{{Transit,-0.0824349,-0.981834},{JobConc,-0.0401501,0.79338},
{fwvmtoftotal,0.186605,4.7996}}}
{0.463474,22.9655,{{Transit,-0.140422,1.3502},
{pop1900,0.000059409,0.0667502},{fwvmtoftotal,0.186856,4.57457}}}
{0.460409,23.2949,{{JobConc,-0.0633137,-1.28816},{pop1900,-0.000292942,0.41978},
{fwvmtoftotal,0.183307,4.52736}}}

Regressions on FW VMT

{-0.03447,39.1215,{{Transit,-0.0047452,-0.0189403}}}
{-0.0344303,38.9891,{{JobConc,0.00578914,0.038338}}}
{0.0612993,14.0377,{{vehiclepercapita,40.1644,1.72019}}}
{0.117176,-1.53549,{{workerpercapita,0.8408,2.23201}}}
{0.685987,16.4107,{{fwlanemilesoftotal,1.35304,8.15704}}}
{0.72358,5.50597,{{workerpercapita,0.479241,2.22352},{fwlanemilesoftotal,1.2792,8.03864}}}

Probability of Travel (All Cities)

One Variable

{0.0261024,0.795952,{{DriveAlone,0.000986396,1.34315}}}
{0.00547839,0.826876,{{Carpool,0.00321009,1.07947}}}
{0.0514536,0.877634,{{Transit,-0.00139125,-1.62091}}}
{0.000932229,0.881933,{{WalkBike,-0.00365384,-1.0139}}}
{0.0559718,0.938607,{{AllCommMed,-0.00313124,-1.66695}}}
{-0.00788809,0.929975,{{DAcommMed,-0.00286366,-0.874762}}}
{0.0228096,0.921272,{{AllCommMean,-0.002285,-1.30394}}}
{-0.00907266,0.914247,{{DAcommMean,-0.00209335,-0.854557}}}
{-0.0319884,0.860354,{{congestion90,0.00712375,0.264752}}}
{-0.0280809,0.854113,{{congestion95,0.0125883,0.424952}}}
{0.0564258,0.88021,{{area90,-0.0147061,-1.67153}}}
{-0.00668749,0.881296,{{density90,-0.00438011,-0.894823}}}
{-0.028961,0.874054,{{RevDens,-0.00176667,-0.394491}}}
{0.0738905,0.879686,{{ResPD,-0.00154387,-1.84217}}}
{0.100512,0.889626,{{ResConc,-0.0108702,-2.08622}}}
{0.0901154,0.879961,{{JobPD,-0.000410676,-1.99279}}}
{0.0673626,0.882993,{{JobConc,-0.000912877,-1.77956}}}
{0.0294478,0.876749,{{JobPDbyWkr,-0.00686636,-1.38211}}}
{-0.0343631,0.869251,{{Mix,-0.00480771,-0.0579227}}}
{0.0985641,0.873149,{{CBDsize,-0.0000308405,-2.06887}}}
{-0.025261,0.873906,{{CBDemplshare,-0.000699888,-0.510726}}}
{0.00549601,0.904653,{{MedianIncome,-0.00111811,-1.07972}}}
{-0.0139698,0.848974,{{IncomeLT15,0.000882658,0.765951}}}
{0.00697232,0.831524,{{IncomeLT30,0.000795585,1.10029}}}
{0.0306318,0.793645,{{vehiclepercapita,0.118481,1.3957}}}
{-0.0344811,0.868024,{{workerpercapita,-0.0000100594,-0.00689512}}}
{0.0397832,0.87437,{{population90,-0.00232418,-1.49765}}}
{0.0541156,0.837427,{{hwmilespercapita,0.00822399,1.64814}}}

{-0.0322338,0.863005,{{fwlanemilesoftotal,0.00027046,0.251364}}}
{0.0958019,0.81791,{{fwvmtoftotal,0.00126968,2.04416}}}
{0.106679,0.87462,{{population50,-0.00447605,-2.14069}}}
{0.133737,0.900043,{{density50,-0.00593109,-2.37308}}}
{-0.0343043,0.86809,{{popgrowth5090,-0.000205318,-0.0707332}}}
{-0.00203096,0.857212,{{densgrowth5090,0.0162466,0.969121}}}
{0.140767,0.874118,{{pop1900,-0.000016823,-2.43205}}}
{0.0439519,0.854387,{{popgrowth1900,0.00567183,1.54246}}}

Two or More Variables

{0.119391,0.901294,{{ResConc,-0.00501684,-0.726344},{density50,-0.00429925,-1.27347}}}
{0.126103,0.898429,{{JobPD,-0.000210108,-0.864102},{density50,-0.00447684,-1.4813}}}
{0.138079,0.894887,{{CBDsize,-0.000018013,-1.07056},{density50,-0.00439224,-1.52627}}}
{0.11021,0.872965,{{ResConc,0.000740056,0.0650905},{pop1900,-0.0000177178,-1.14727}}}
{0.110288,0.873516,{{JobPD,0.0000323297,0.080842},{pop1900,-0.0000177839,-1.28745}}}
{0.142172,0.890351,{{density50,-0.00341291,-1.02347},{pop1900,-0.0000105053,-1.13364}}}

Vehicle Time (All Cities)

One Variable

{0.0987305,51.6919,{{OtherTimeTr,-0.355712,-2.07036}}}
{0.100911,25.2191,{{DriveAlone,0.231681,2.08976}}}
{0.0880908,30.8437,{{Carpool,0.883323,1.97434}}}
{0.185416,44.5703,{{Transit,-0.349665,-2.79797}}}
{0.163379,47.3786,{{WalkBike,-1.35694,-2.61888}}}
{-0.0264074,45.3691,{{AllCommMed,-0.146995,-0.47766}}}
{0.030356,26.7154,{{DAcommMed,0.702529,1.39255}}}
{-0.0320902,43.7581,{{AllCommMean,-0.0733662,-0.259283}}}
{-0.00191349,33.7243,{{DAcommMean,0.372362,0.97093}}}
{0.0156987,36.9704,{{congestion90,5.02026,1.21592}}}
{0.0462363,34.5431,{{congestion95,7.02302,1.56663}}}
{-0.00591584,43.1489,{{area90,-1.29524,-0.907507}}}
{-0.0101062,44.0572,{{density90,-0.644478,-0.836568}}}
{-0.025376,43.3476,{{RevDens,-0.356471,-0.507505}}}
{0.178887,44.711,{{ResPD,-0.34036,-2.74514}}}
{0.268549,47.2324,{{ResConc,-2.55886,-3.46617}}}
{0.138617,44.3334,{{JobPD,-0.0760527,-2.41406}}}
{0.124586,45.0675,{{JobConc,-0.179249,-2.29554}}}
{0.0846476,44.0084,{{JobPDbyWkr,-1.47268,-1.94275}}}
{-0.0304428,40.4692,{{Mix,4.38897,0.33719}}}
{0.173423,43.1349,{{CBDsize,-0.00605725,-2.70079}}}
{0.18152,46.8748,{{CBDemplshare,-0.5322,-2.76646}}}
{-0.0327155,43.2588,{{MedianIncome,-0.0369352,-0.222769}}}
{-0.0235654,44.1606,{{IncomeLT15,-0.101172,-0.556161}}}
{-0.0339252,41.3766,{{IncomeLT30,0.0144964,0.125053}}}
{0.182911,20.8193,{{vehiclepercapita,34.0138,2.77772}}}
{0.0651165,23.5276,{{workerpercapita,0.383018,1.75771}}}
{0.0381397,43.0942,{{population90,-0.361105,-1.47972}}}
{0.033737,37.8815,{{hwmilespercapita,1.13383,1.43089}}}
{-0.0200122,43.8393,{{fwlanemilesoftotal,-0.107789,-0.641414}}}

{-0.0336136,41.3959,{{fwvmtoftotal,0.0162939,0.156162}}}
{0.177507,43.3965,{{population50,-0.86182,-2.73395}}}
{0.334286,49.5943,{{density50,-1.37974,-4.00804}}}
{0.111487,39.5535,{{popgrowth5090,0.922639,2.18272}}}
{0.0914269,38.8371,{{densgrowth5090,5.02801,2.0047}}}
{0.316185,43.4953,{{pop1900,-0.00373892,-3.85636}}}
{0.0307059,40.1491,{{popgrowth1900,0.812417,1.39655}}}
{0.066934,41.5012,{{popgrowth20c,0.00333978,1.77541}}}

Two or More Variables

{0.25927,48.2321,{{ResPD,0.24951,0.797965},{ResConc,-4.01701,-2.03643}}}
{0.249097,47.5782,{{JobPD,0.0267246,0.498778},{ResConc,-3.12688,-2.29495}}}
{0.243129,47.2716,{{JobConc,-0.0161904,-0.161346},{ResConc,-2.44327,-2.35416}}}
{0.249479,48.3502,{{CBDsize,0.00245923,0.512991},{ResConc,-3.32914,-1.98464}}}
{0.299513,48.8271,{{CBDemplshare,-0.304067,-1.5106},{ResConc,-1.98219,-2.42588}}}
{0.264033,37.4574,{{vehiclepercapita,13.8177,0.906675},{ResConc,-1.98929,-2.04854}}}
{0.350334,49.8988,{{density50,-0.982527,-2.15657},{ResConc,-1.22116,-1.31011}}}
{0.294493,44.3116,{{pop1900,-0.0031059,-1.43752},{ResConc,-0.523591,-0.329165}}}

Vehicle Time excluding New York

{-0.0227696,45.6932,{{OtherTimeTr,-0.123746,-0.5953}}}
{-0.021692,36.2965,{{DriveAlone,0.0831463,0.61991}}}
{0.0330973,34.6244,{{Carpool,0.609295,1.41162}}}
{0.0161801,43.7493,{{Transit,-0.207158,-1.21529}}}
{0.0621613,45.9495,{{WalkBike,-0.927134,-1.70943}}}
{0.00351585,34.876,{{AllCommMed,0.334687,1.04991}}}
{0.0841041,23.8451,{{DAcommMed,0.851817,1.91389}}}
{0.0258694,33.4787,{{AllCommMean,0.383258,1.33046}}}
{0.0846979,27.8206,{{DAcommMean,0.655775,1.91925}}}
{0.0395392,36.8977,{{congestion90,5.45607,1.48116}}}
{0.057591,35.2426,{{congestion95,6.69836,1.66499}}}
{0.0289105,40.471,{{area90,2.42686,1.36505}}}
{-0.0338594,41.8628,{{density90,0.172603,0.224134}}}
{-0.033629,41.819,{{RevDens,0.157861,0.237671}}}
{-0.0168881,43.5694,{{ResPD,-0.168471,-0.719984}}}
{0.069925,47.3787,{{ResConc,-2.63831,-1.78333}}}
{-0.027512,43.0246,{{JobPD,-0.0234453,-0.472772}}}
{-0.0155644,43.5642,{{JobConc,-0.0740448,-0.745353}}}
{-0.0352964,42.5251,{{JobPDbyWkr,-0.109595,-0.106309}}}
{-0.034605,41.6619,{{Mix,2.04476,0.173262}}}
{-0.0355285,42.4696,{{CBDsize,-0.000614392,-0.0708761}}}
{0.0462883,45.3953,{{CBDemplshare,-0.343555,-1.55162}}}
{-0.0334142,41.1373,{{MedianIncome,0.0379772,0.249638}}}
{-0.0176984,44.8199,{{IncomeLT15,-0.115303,-0.704039}}}
{-0.032939,43.7102,{{IncomeLT30,-0.029003,-0.274282}}}
{0.0425816,28.7127,{{vehiclepercapita,21.7311,1.5132}}}
{0.0653239,25.8035,{{workerpercapita,0.343016,1.73977}}}
{-0.0114092,41.6729,{{population90,0.287344,0.820284}}}
{-0.00882852,39.9709,{{hwmilespercapita,0.65317,0.863836}}}
{-0.0215706,43.9739,{{fwlanemilesoftotal,-0.0945446,-0.622624}}}

{-0.0354709,42.0926,{{fwvmtoftotal,0.00764981,0.0811231}}}
{-0.0218723,42.8826,{{population50,-0.40043,-0.615858}}}
{0.22136,48.4249,{{density50,-1.13061,-3.04046}}}
{0.0922862,40.2755,{{popgrowth5090,0.774364,1.98706}}}
{0.10346,39.3953,{{densgrowth5090,4.69399,2.08485}}}
{0.133398,43.6114,{{pop1900,-0.0042101,-2.33753}}}
{0.0307413,40.6925,{{popgrowth1900,0.728599,1.38556}}}
{0.0683688,41.8978,{{popgrowth20c,0.00300773,1.76867}}}

Other Mode Time (All Cities)

One Variable

{0.591979,63.6402,{{DriveAlone,-0.50275,-6.67275}}}
{-0.0339781,26.43,{{Carpool,0.0571787,0.118972}}}
{0.571553,22.9046,{{Transit,0.585602,6.40471}}}
{0.224103,20.989,{{WalkBike,1.56493,3.10885}}}
{0.367904,3.39556,{{AllCommMed,1.04679,4.29665}}}
{0.0674605,7.77846,{{DAcommMed,0.888668,1.78051}}}
{0.400083,3.69752,{{AllCommMean,0.997476,4.58333}}}
{0.173134,5.99202,{{DAcommMean,0.948432,2.69844}}}
{0.0159893,22.0325,{{congestion90,5.07918,1.21962}}}
{0.00405353,21.9336,{{congestion95,4.89535,1.05929}}}
{0.185762,24.0279,{{area90,3.62813,2.80076}}}
{0.151713,21.51,{{density90,1.79689,2.52297}}}
{0.123556,21.6288,{{RevDens,1.49808,2.28675}}}
{0.456288,23.0567,{{ResPD,0.520745,5.11628}}}
{0.406222,20.8285,{{ResConc,3.11308,4.63939}}}
{0.478881,23.1573,{{JobPD,0.132127,5.34494}}}
{0.256642,23.0126,{{JobConc,0.244635,3.37008}}}
{0.4736,23.0383,{{JobPDbyWkr,3.06815,5.29064}}}
{-0.00751702,23.079,{{Mix,11.4392,0.881006}}}
{0.467338,25.4269,{{CBDsize,0.00949358,5.22694}}}
{0.37311,20.4442,{{CBDemplshare,0.737517,4.34227}}}
{0.0763031,17.3614,{{MedianIncome,0.295019,1.86499}}}
{-0.00485321,30.6907,{{IncomeLT15,-0.168142,-0.92472}}}
{0.0454307,35.0799,{{IncomeLT30,-0.175083,-1.55814}}}
{0.155775,47.1746,{{vehiclepercapita,-32.1008,-2.55647}}}
{-0.019187,19.8385,{{workerpercapita,0.151422,0.659716}}}
{0.289776,24.8916,{{population90,0.769763,3.63871}}}
{0.0907081,32.8275,{{hwmilespercapita,-1.5495,-1.99818}}}
{-0.0344729,27.2018,{{fwlanemilesoftotal,-0.00283485,-0.0166044}}}
{-0.0229312,24.812,{{fwvmtoftotal,0.0599245,0.572265}}}
{0.367768,25.2593,{{population50,1.19763,4.29545}}}
{0.161332,21.5957,{{density50,1.01427,2.60211}}}
{0.0162162,28.6283,{{popgrowth5090,-0.548547,-1.2225}}}
{-0.0330937,27.4929,{{densgrowth5090,-0.532767,-0.197463}}}
{0.423495,25.4682,{{pop1900,0.00431057,4.79976}}}
{-0.0314689,27.5629,{{popgrowth1900,-0.176224,-0.291092}}}
{-0.0100235,27.4176,{{popgrowth20c,-0.00165462,-0.83802}}}

Two or More Variables

{0.493962,22.7721,{{ResPD,0.248454,1.36538},{JobPD,0.0802346,1.77736}}}
{0.474782,22.1081,{{ResConc,1.01115,0.879597},{JobPD,0.098892,2.18759}}}
{0.514287,22.6645,{{JobPDbyWkr,1.66191,1.76464},{JobPD,0.0747179,1.85183}}}
{0.490224,24.0046,{{CBDsize,0.00467094,1.28268},{JobPD,0.0760246,1.5172}}}
{0.537917,20.7123,{{CBDemplshare,0.388164,2.16911},{JobPD,0.0962102,3.36796}}}
{0.462978,26.1533,{{vehiclepercapita,-4.50325,-0.375798},{JobPD,0.125931,4.19398}}}
{0.462197,23.3045,{{population50,0.156507,0.316803},{JobPD,0.119077,2.46818}}}
{0.474748,23.6929,{{pop1900,0.00147792,0.878532},{JobPD,0.0953116,1.95697}}}

Other Mode Time excluding New York

One Variable

{0.400457,57.3903,{{DriveAlone,-0.418946,-4.51333}}}
{0.0249417,20.0888,{{Carpool,0.516808,1.31978}}}
{0.341304,23.3721,{{Transit,0.504451,4.00329}}}
{0.0893198,23.0446,{{WalkBike,0.946707,1.9607}}}
{0.181325,10.706,{{AllCommMed,0.711204,2.72454}}}
{0.0667928,11.1791,{{DAcommMed,0.711799,1.75375}}}
{0.21929,10.2912,{{AllCommMean,0.704577,3.02419}}}
{0.117617,11.8222,{{DAcommMean,0.668546,2.2058}}}
{0.0275587,22.1258,{{congestion90,4.51983,1.34976}}}
{0.0368859,20.9798,{{congestion95,5.33802,1.45281}}}
{-0.0317518,26.2476,{{area90,0.542906,0.327925}}}
{0.0259169,23.9218,{{density90,0.898847,1.33101}}}
{0.0485219,23.3872,{{RevDens,0.906442,1.57445}}}
{0.141157,23.4168,{{ResPD,0.466519,2.40133}}}
{0.0712348,22.1443,{{ResConc,2.39827,1.79562}}}
{0.187667,23.6945,{{JobPD,0.110537,2.77482}}}
{0.0184045,24.9417,{{JobConc,0.10963,1.24247}}}
{0.205579,23.788,{{JobPDbyWkr,2.37922,2.91626}}}
{0.0339912,21.4485,{{Mix,14.644,1.42142}}}
{0.25726,23.893,{{CBDsize,0.0220422,3.32335}}}
{0.176397,22.3134,{{CBDemplshare,0.499184,2.68536}}}
{0.0453287,19.9487,{{MedianIncome,0.203661,1.54174}}}
{0.001476,29.8288,{{IncomeLT15,-0.149666,-1.02121}}}
{0.0233191,32.1701,{{IncomeLT30,-0.120846,-1.30092}}}
{-0.0153096,32.9862,{{vehiclepercapita,-10.0224,-0.750144}}}
{0.00986183,16.612,{{workerpercapita,0.208131,1.13527}}}
{0.00046128,25.8847,{{population90,0.316707,1.00667}}}
{0.0288299,30.0663,{{hwmilespercapita,-0.914302,-1.36414}}}
{-0.034894,27.0215,{{fwlanemilesoftotal,-0.0205706,-0.148979}}}
{-0.00966934,23.8795,{{fwvmtoftotal,0.0714946,0.849867}}}
{0.0246141,25.752,{{population50,0.755238,1.31599}}}
{0.0257443,24.0124,{{density50,0.499426,1.32903}}}
{-0.00600454,27.5985,{{popgrowth5090,-0.337043,-0.909345}}}
{-0.0356737,26.7235,{{densgrowth5090,-0.0724293,-0.0331302}}}
{0.0995865,25.6919,{{pop1900,0.00340213,2.0512}}}
{-0.0351267,26.8217,{{popgrowth1900,-0.0618922,-0.126066}}}
{-0.0154232,26.8744,{{popgrowth20c,-0.00119977,-0.748011}}}

Two or More Variables

{0.237615,23.3879,{{ResPD,0.127905,0.527719},{CBDsize,0.0189643,2.13133}}}
{0.242366,23.4814,{{JobPD,0.0380437,0.670503},{CBDsize,0.0171732,1.73826}}}
{0.255619,23.388,{{JobPDbyWkr,1.06942,0.968641},{CBDsize,0.015759,1.69772}}}
{0.370465,20.6937,{{CBDemplshare,0.40601,2.45663},{CBDsize,0.0192711,3.10348}}}

Total Time (All Cities)

One Variable

{0.108785,88.8593,{{DriveAlone,-0.271069,-2.15914}}}
{0.0729278,57.2737,{{Carpool,0.940502,1.83301}}}
{0.042907,67.4749,{{Transit,0.235938,1.53131}}}
{-0.0308894,68.3677,{{WalkBike,0.207991,0.317939}}}
{0.199406,48.7647,{{AllCommMed,0.899794,2.9107}}}
{0.222631,34.4938,{{DAcommMed,1.5912,3.09705}}}
{0.258941,47.4556,{{AllCommMean,0.92411,3.3886}}}
{0.282268,39.7163,{{DAcommMean,1.32079,3.57748}}}
{0.122501,59.0029,{{congestion90,10.0994,2.27774}}}
{0.145211,56.4767,{{congestion95,11.9184,2.46908}}}
{0.0371524,67.1768,{{area90,2.3329,1.46887}}}
{0.0257645,65.5672,{{density90,1.15241,1.33917}}}
{0.0377152,64.9764,{{RevDens,1.14161,1.47506}}}
{0.0118431,67.7677,{{ResPD,0.180384,1.166}}}
{-0.0234946,68.0609,{{ResConc,0.554218,0.557981}}}
{0.0382567,67.4908,{{JobPD,0.0560747,1.481}}}
{-0.0181219,68.0801,{{JobConc,0.0653856,0.682656}}}
{0.0736002,67.0467,{{JobPDbyWkr,1.59547,1.83941}}}
{0.00613165,63.5482,{{Mix,15.8281,1.08862}}}
{0.0172393,68.5618,{{CBDsize,0.00343633,1.23542}}}
{-0.00963252,67.3191,{{CBDemplshare,0.205317,0.844856}}}
{0.0322137,60.6202,{{MedianIncome,0.258083,1.41371}}}
{0.0253153,74.8514,{{IncomeLT15,-0.269314,-1.33386}}}
{0.0184041,76.4565,{{IncomeLT30,-0.160587,-1.24999}}}
{-0.0339512,67.994,{{vehiclepercapita,1.91301,0.122101}}}
{0.115412,43.366,{{workerpercapita,0.53444,2.21678}}}
{0.0374115,67.9859,{{population90,0.408658,1.47172}}}
{-0.0273953,70.709,{{hwmilespercapita,-0.415673,-0.447274}}}
{-0.0227012,71.0411,{{fwlanemilesoftotal,-0.110624,-0.577998}}}
{-0.0197816,66.2079,{{fwvmtoftotal,0.0762184,0.646577}}}
{-0.00960398,68.6557,{{population50,0.335806,0.845353}}}
{-0.0144833,71.19,{{density50,-0.365463,-0.756112}}}
{-0.0159335,68.1818,{{popgrowth5090,0.374092,0.727661}}}
{0.0433108,66.33,{{densgrowth5090,4.49525,1.53563}}}
{-0.0281466,68.9635,{{pop1900,0.000571644,0.422749}}}
{-0.00358251,67.712,{{popgrowth1900,0.636192,0.944938}}}
{-0.0145243,68.9189,{{popgrowth20c,0.00168516,0.755321}}}

Two or More Variables

{0.259756,45.7744,{{AllCommMean,0.751903,2.34253},{congestion95,5.37372,1.01584}}}

{0.305905,31.784,{{AllCommMean,0.813191,2.99316},{workerpercapita,0.378356,1.72111}}}
{0.289256,32.3594,{{AllCommMean,0.722826,2.29367},{congestion95,3.16564,0.586599},{workerpercapita,0.340553,1.47044}}}

Transit Share (All Cities)

One Variable

{0.54718,-30.0784,{{AllCommMed,1.64497,6.10339}}}
{0.10183,-22.0272,{{DAcommMed,1.34311,2.09791}}}
{0.553931,-28.4182,{{AllCommMean,1.51705,6.18499}}}
{0.233347,-24.1585,{{DAcommMean,1.40795,3.18294}}}
{0.0279585,-0.188831,{{congestion90,7.38395,1.36487}}}
{0.0223361,-1.0285,{{congestion95,7.76926,1.29823}}}
{0.346002,1.88617,{{area90,6.23281,4.10752}}}
{0.242053,-1.73341,{{density90,2.86217,3.25278}}}
{0.168587,-0.929467,{{RevDens,2.21954,2.66142}}}
{0.709084,0.664778,{{ResPD,0.83778,8.60945}}}
{0.751263,-3.78294,{{ResConc,5.43302,9.57127}}}
{0.83406,0.461932,{{JobPD,0.224626,12.3203}}}
{0.596231,-0.71079,{{JobConc,0.470629,6.73052}}}
{0.711423,0.738684,{{JobPDbyWkr,4.85888,8.65785}}}
{0.00674538,0.670853,{{Mix,18.4872,1.09715}}}
{0.630642,4.65779,{{CBDsize,0.0142854,7.22647}}}
{0.319195,-0.91256,{{CBDemplshare,0.89794,3.88143}}}
{0.254915,-13.4301,{{MedianIncome,0.623218,3.35617}}}
{0.0427292,14.7186,{{IncomeLT15,-0.354765,-1.52941}}}
{0.201272,25.0496,{{IncomeLT30,-0.393051,-2.9257}}}
{0.336473,43.7952,{{vehiclepercapita,-58.5856,-4.02653}}}
{-0.0160178,-3.24896,{{workerpercapita,0.217452,0.725976}}}
{0.431884,3.71037,{{population90,1.20659,4.87915}}}
{0.168003,16.6873,{{hwmilespercapita,-2.57565,-2.65665}}}
{-0.0344514,7.36784,{{fwlanemilesoftotal,-0.00661099,-0.0296264}}}
{-0.03447,7.35894,{{fwvmtoftotal,-0.00260684,-0.0189403}}}
{0.637143,4.05656,{{population50,2.02265,7.32647}}}
{0.42822,-3.91113,{{density50,2.03783,4.84435}}}
{0.158706,11.0178,{{popgrowth5090,-1.39956,-2.58058}}}
{-0.00575458,9.26979,{{densgrowth5090,-3.16679,-0.910138}}}
{0.715625,4.43662,{{pop1900,0.00721039,8.74612}}}
{-0.0122623,8.70713,{{popgrowth1900,-0.625413,-0.797863}}}
{0.0603446,7.93479,{{popgrowth20c,-0.00425821,-1.71073}}}

Two or More Variables

{0.849597,0.0600749,{{ResPD,0.259182,1.9989},{JobPD,0.170493,5.30027}}}
{0.867819,-1.8059,{{ResConc,2.18542,2.89938},{JobPD,0.152794,5.15479}}}
{0.87286,5.53958,{{ResConc,2.09,2.8161},{JobPD,0.143533,4.8228},
{MedianIncome,0.126762,1.4528}}}
{0.878515,-3.11932,{{ResConc,1.52875,1.90115},{JobPD,0.152713,5.37408},
{density50,0.483583,1.86155}}}
{0.862993,-1.67292,{{ResConc,2.11564,2.18262},{JobPD,0.150924,4.42647},
{pop1900,0.000167138,0.117832}}}

{0.888495,-4.7893,{{ResConc,2.82069,2.71167},{JobPD,0.184387,5.7319},
{CBDsize,-0.0055587,-1.84839},{density50,0.318993,1.20682}}}
{0.851719,-13.37,{{MedianIncome,0.37381,4.26621},{CBDemplshare,0.386484,2.93325},
{density90,0.913532,2.03277},{pop1900,0.00468577,5.69256}}}

Transit Share excluding New York

One Variable

{0.384766,-20.0359,{{AllCommMed,1.18397,4.37454}}}
{0.129887,-17.0082,{{DAcommMed,1.08207,2.30847}}}
{0.398087,-19.0096,{{AllCommMean,1.09911,4.49219}}}
{0.201584,-15.5508,{{DAcommMean,0.994729,2.88477}}}
{0.0573776,-0.0508916,{{congestion90,6.55708,1.6629}}}
{0.0906783,-2.43904,{{congestion95,8.42392,1.97279}}}
{0.0240097,4.5567,{{area90,2.52092,1.30897}}}
{0.0967392,1.72067,{{density90,1.57601,2.0263}}}
{0.0940612,1.66777,{{RevDens,1.34564,2.00275}}}
{0.455861,0.0509664,{{ResPD,0.930203,5.02943}}}
{0.560354,-6.24722,{{ResConc,6.77171,6.16134}}}
{0.689653,0.123351,{{JobPD,0.238236,8.08973}}}
{0.347452,1.02879,{{JobConc,0.348891,4.05478}}}
{0.481878,1.49083,{{JobPDbyWkr,4.16772,5.2888}}}
{0.0869268,-1.74321,{{Mix,23.232,1.9393}}}
{0.519951,1.9659,{{CBDsize,0.0363069,5.69303}}}
{0.0955496,2.4462,{{CBDemplshare,0.469671,2.01585}}}
{0.29813,-9.7815,{{MedianIncome,0.494383,3.64941}}}
{0.0888183,13.4494,{{IncomeLT15,-0.32756,-1.95622}}}
{0.246348,20.9124,{{IncomeLT30,-0.315935,-3.23717}}}
{0.0996413,25.9864,{{vehiclepercapita,-30.8737,-2.05168}}}
{0.0310231,-8.01543,{{workerpercapita,0.301227,1.3887}}}
{0.06562,4.96551,{{population90,0.633972,1.74259}}}
{0.112507,12.6945,{{hwmilespercapita,-1.65713,-2.16247}}}
{-0.034254,7.10134,{{fwlanemilesoftotal,-0.0328252,-0.198828}}}
{-0.0349766,5.98892,{{fwvmtoftotal,0.014391,0.141271}}}
{0.315214,3.88289,{{population50,2.17858,3.78801}}}
{0.301004,-0.908473,{{density50,1.39816,3.67261}}}
{0.185379,9.55771,{{popgrowth5090,-1.09968,-2.7567}}}
{-0.00209213,8.14358,{{densgrowth5090,-2.49295,-0.969255}}}
{0.466039,4.28256,{{pop1900,0.00783588,5.12943}}}
{-0.0132563,7.61959,{{popgrowth1900,-0.457664,-0.787781}}}
{0.0916469,7.1428,{{popgrowth20c,-0.00359506,-1.98139}}}

Two or More Variables

{0.760739,-1.61223,{{ResPD,0.446719,3.0527},{JobPD,0.186855,6.05631}}}
{0.834354,-5.62323,{{ResConc,3.97455,5.04573},{JobPD,0.1728,6.87863}}}
{0.828139,-5.3238,{{ResConc,4.02788,4.60765},{JobPD,0.174256,6.38621},
{MedianIncome,-0.0133034,-0.153688}}}
{0.831662,-5.79498,{{ResConc,3.56767,3.71577},{JobPD,0.171032,6.72484},
{density50,0.185253,0.753861}}}
{0.835087,-4.88966,{{ResConc,3.57484,4.09963},{JobPD,0.160156,5.76791},

{pop1900,0.00125368,1.05836}}}
{0.838361,-5.60223,{{ResConc,3.39296,3.57673},{JobPD,0.140623,4.30664},
{CBDsize,0.00798862,1.44137},{density50,0.175687,0.729324}}}
{0.727351,-13.6418,{{MedianIncome,0.365604,4.13975},{CBDemplshare,0.409214,3.04473},
{density90,0.963669,2.12298},{pop1900,0.00546653,4.62811}}}

Walk/Bike Share (All Cities)

One Variable

{-0.0347761,3.45176,{{AllCommMed,0.0171616,0.159334}}}
{-0.00368353,7.01672,{{DAcommMed,-0.14603,-0.945288}}}
{-0.0261153,2.67036,{{AllCommMean,0.0501702,0.511793}}}
{-0.0338834,4.43291,{{DAcommMean,-0.0268117,-0.222676}}}
{-0.0202046,3.01012,{{congestion90,0.821281,0.652434}}}
{-0.0268945,3.10833,{{congestion95,0.682841,0.490395}}}
{-0.0295197,4.03435,{{area90,-0.249129,-0.410456}}}
{0.0272547,2.81493,{{density90,0.333447,1.3463}}}
{0.0300536,2.77019,{{RevDens,0.293952,1.37788}}}
{0.271386,2.26038,{{ResPD,0.22561,3.43534}}}
{0.459841,0.256013,{{ResConc,1.89467,5.06832}}}
{0.0568143,3.13259,{{JobPD,0.0261097,1.65737}}}
{-0.0167315,3.45991,{{JobConc,0.0238294,0.723029}}}
{0.280657,2.62293,{{JobPDbyWkr,0.99986,3.50921}}}
{0.0232134,2.0727,{{Mix,4.94156,1.29969}}}
{0.0577923,3.25985,{{CBDsize,0.00457024,1.66697}}}
{0.0129444,3.07005,{{CBDemplshare,0.087748,1.17487}}}
{0.0303927,1.60682,{{MedianIncome,0.0675075,1.38167}}}
{-0.0227987,4.51876,{{IncomeLT15,-0.0323701,-0.594623}}}
{0.00868252,5.5854,{{IncomeLT30,-0.0384625,-1.11982}}}
{0.102474,9.8628,{{vehiclepercapita,-9.57243,-2.0763}}}
{-0.0351391,3.42217,{{workerpercapita,0.00858106,0.124731}}}
{-0.0271484,3.6956,{{population90,0.0565606,0.483224}}}
{0.152627,5.96185,{{hwmilespercapita,-0.573209,-2.49468}}}
{-0.0222787,4.34839,{{fwlanemilesoftotal,-0.0305534,-0.606629}}}
{-0.0100496,4.85646,{{fwvmtoftotal,-0.0260471,-0.843482}}}
{0.0529981,3.42534,{{population50,0.336119,1.61955}}}
{0.217481,1.85196,{{density50,0.372037,3.00995}}}
{0.0134267,4.27197,{{popgrowth5090,-0.159087,-1.18096}}}
{-0.0130534,4.23808,{{densgrowth5090,-0.628023,-0.79141}}}
{0.142802,3.42175,{{pop1900,0.00143423,2.41478}}}
{-0.00914689,4.19343,{{popgrowth1900,-0.152747,-0.858571}}}
{-0.0237564,3.89269,{{popgrowth20c,-0.000338027,-0.571884}}}

Two or More Variables

{0.414272,1.77111,{{ResPD,-0.0215644,-0.240634},{ResConc,1.15069,2.03539}}}
{0.433999,2.05851,{{JobPDbyWkr,0.371564,1.01774},{ResConc,0.68045,1.71077}}}
{0.448263,1.36667,{{density50,0.180865,1.33657},{ResConc,0.778424,2.81171}}}

Drive Alone Median Commute Time (All Cities)

One Variable

{0.222631,10.9963,{{TotalTimeTr,0.156199,3.09705}}}
{0.0674605,18.7921,{{OtherTimeTr,0.110891,1.78051}}}
{0.030356,18.0532,{{VehTimeTr,0.0892169,1.39255}}}
{-0.00788809,29.5915,{{TravelProb,-8.97739,-0.874762}}}
{0.00301027,19.1434,{{VehTimePers,0.0729082,1.04431}}}
{-0.0344356,21.6686,{{Speed95,0.00459861,0.0363502}}}
{-0.0140059,20.4376,{{VMTpers,0.0764472,0.765263}}}
{0.101236,27.8022,{{DriveAlone,-0.0826615,-2.09265}}}
{0.0939913,17.721,{{Carpool,0.32227,2.02787}}}
{0.10183,21.0913,{{Transit,0.0981069,2.09791}}}
{-0.0206582,22.3068,{{WalkBike,-0.127819,-0.626735}}}
{0.719038,10.3183,{{AllCommMed,0.506014,8.81906}}}
{0.707783,10.974,{{AllCommMean,0.460503,8.58274}}}
{0.908745,5.8695,{{DAcommMean,0.714104,17.3133}}}
{0.26367,17.4059,{{congestion90,4.36079,3.42675}}}
{0.271688,16.6051,{{congestion95,4.87427,3.49158}}}
{0.191003,20.6858,{{area90,1.29678,2.84305}}}
{0.128541,19.9376,{{density90,0.593935,2.32917}}}
{0.0826473,20.1229,{{RevDens,0.455583,1.92427}}}
{0.0423857,21.2304,{{ResPD,0.072801,1.52573}}}
{0.00671827,21.12,{{ResConc,0.336239,1.09677}}}
{0.148119,20.9612,{{JobPD,0.0278362,2.49323}}}
{0.0884202,20.8526,{{JobConc,0.0561484,1.97735}}}
{0.0719549,21.1377,{{JobPDbyWkr,0.496061,1.82374}}}
{-0.0233851,20.8797,{{Mix,2.59229,0.560784}}}
{0.034951,21.5763,{{CBDsize,0.00124744,1.44447}}}
{-0.0291946,22.0732,{{CBDemplshare,-0.0296748,-0.386012}}}
{0.258383,16.1788,{{MedianIncome,0.169441,3.3841}}}
{0.163525,25.0326,{{IncomeLT15,-0.153544,-2.62007}}}
{0.244472,27.034,{{IncomeLT30,-0.115552,-3.2722}}}
{0.00557053,25.0481,{{vehiclepercapita,-5.20286,-1.08076}}}
{0.079077,14.7617,{{workerpercapita,0.145745,1.89104}}}
{0.145592,21.2076,{{population90,0.202635,2.47225}}}
{0.000537168,22.8632,{{hwmilespercapita,-0.289495,-1.00803}}}
{-0.0213515,21.19,{{fwlanemilesoftotal,0.0365914,0.610612}}}
{0.00275399,20.3177,{{fwvmtoftotal,0.0380056,1.0406}}}
{0.0483919,21.4994,{{population50,0.192027,1.58921}}}
{-0.0268765,21.4162,{{density50,0.0706147,0.463473}}}
{-0.0180988,21.5072,{{popgrowth5090,0.110154,0.683146}}}
{0.00129213,21.1962,{{densgrowth5090,0.955097,1.01922}}}
{0.0121237,21.6132,{{pop1900,0.00048575,1.16969}}}
{0.011244,21.241,{{popgrowth1900,0.242476,1.15808}}}
{-0.0287794,21.8481,{{popgrowth20c,-0.000282242,-0.400964}}}

Two or More Variables

{0.271653,16.8258,{{JobPD,0.0144599,1.23627},{MedianIncome,0.13677,2.43283}}}
{0.332575,17.5549,{{congestion90,3.45791,2.67421},{area90,0.883656,1.99849}}}

{0.339739,17.3446,{{congestion90,3.79164,3.0686},{JobPD,0.0209989,2.08353}}}
{0.332703,15.195,{{congestion90,2.90611,2.05666},{MedianIncome,0.110796,2.00002}}}
{0.274474,17.9195,{{congestion90,3.55268,2.48024},{population90,0.102484,1.1966}}}
{0.330718,17.4478,{{congestion90,3.50552,2.70528},{area90,0.481098,0.78905},
{JobPD,0.0134192,0.960365}}}
{0.356106,15.8715,{{congestion90,2.60695,1.85692},{area90,0.657084,1.42045},
{MedianIncome,0.0824457,1.42241}}}
{0.369563,16.1307,{{congestion90,4.41313,3.18109},{area90,2.58292,2.28544},
{population90,-0.341328,-1.62567}}}
{0.325011,15.751,{{congestion90,2.49069,1.652},{MedianIncome,0.100478,1.75965},
{population90,0.0698626,0.825176}}}
{0.370791,15.1414,{{congestion90,3.60651,2.26341},{area90,2.10373,1.72177},
{MedianIncome,0.061213,1.026},{population90,-0.278865,-1.27677}}}

Total Median Commute Time (All Cities)

One Variable

{0.199406,5.31206,{{TotalTimeTr,0.251271,2.9107}}}
{0.367904,12.6066,{{OtherTimeTr,0.371588,4.29665}}}
{-0.0264074,24.9289,{{VehTimeTr,-0.0531047,-0.47766}}}
{0.0559718,46.9227,{{TravelProb,-27.9249,-1.66695}}}
{-0.0104241,26.2904,{{VehTimePers,-0.0985053,-0.830964}}}
{-0.00780133,28.0989,{{Speed95,-0.184542,-0.876226}}}
{-0.00499721,25.4607,{{VMTpers,-0.154724,-0.922404}}}
{0.488292,42.5548,{{DriveAlone,-0.27363,-5.44309}}}
{-0.0176844,20.2071,{{Carpool,0.196548,0.691872}}}
{0.54718,20.2162,{{Transit,0.341815,6.10339}}}
{0.0217139,20.9844,{{WalkBike,0.434659,1.29069}}}
{0.719038,-8.68879,{{DAcommMed,1.43949,8.81906}}}
{0.935333,1.81889,{{AllCommMean,0.887811,20.8546}}}
{0.792741,-2.47094,{{DAcommMean,1.12794,10.7585}}}
{0.194386,16.1986,{{congestion90,6.4441,2.87031}}}
{0.190446,15.182,{{congestion95,7.04648,2.83856}}}
{0.436693,19.9723,{{area90,3.16172,4.92513}}}
{0.254396,18.5081,{{density90,1.33351,3.35199}}}
{0.17842,18.8757,{{RevDens,1.03597,2.74135}}}
{0.400446,20.3985,{{ResPD,0.292076,4.58663}}}
{0.327786,19.2797,{{ResConc,1.68164,3.95331}}}
{0.635853,19.9756,{{JobPD,0.0899555,7.30646}}}
{0.407918,19.6548,{{JobConc,0.179675,4.65496}}}
{0.424474,20.366,{{JobPDbyWkr,1.73739,4.80897}}}
{-0.0212581,20.9964,{{Mix,4.7729,0.612807}}}
{0.420526,21.7168,{{CBDsize,0.00538601,4.77191}}}
{0.0560011,20.8131,{{CBDemplshare,0.207036,1.66724}}}
{0.362491,11.6522,{{MedianIncome,0.332728,4.24949}}}
{0.169488,28.225,{{IncomeLT15,-0.262845,-2.66876}}}
{0.317052,32.6007,{{IncomeLT30,-0.218786,-3.86357}}}
{0.155935,34.6299,{{vehiclepercapita,-19.1337,-2.55779}}}
{0.0590322,11.9192,{{workerpercapita,0.223072,1.69767}}}
{0.437263,21.0707,{{population90,0.55318,4.93061}}}

{0.0818038,25.9544,{{hwmilespercapita,-0.889759,-1.91644}}}
{-0.0278336,21.9607,{{fwlanemilesoftotal,0.0439169,0.433133}}}
{-0.0224227,21.2709,{{fwvmtoftotal,0.0364804,0.584868}}}
{0.406457,21.5147,{{population50,0.747075,4.64154}}}
{0.113834,19.8144,{{density50,0.525932,2.20312}}}
{-0.0270819,23.0323,{{popgrowth5090,-0.124869,-0.457127}}}
{-0.0321963,22.4379,{{densgrowth5090,0.407255,0.253456}}}
{0.361409,21.7628,{{pop1900,0.00238782,4.2401}}}
{-0.0323373,22.4914,{{popgrowth1900,0.088587,0.2455}}}
{-0.00664483,22.8642,{{popgrowth20c,-0.00105171,-0.895528}}}

Two or More Variables

{0.636465,25.7172,{{DriveAlone,-0.0721411,-1.02412},{JobPD,0.0732242,3.58052}}}
{0.623851,19.9595,{{Transit,0.0348194,0.273212},{JobPD,0.0821341,2.6289}}}
{0.702772,14.9502,{{JobPD,0.0737002,5.84813},{MedianIncome,0.166207,2.74392}}}
{0.483722,16.658,{{congestion90,3.66044,1.90832},{area90,2.72439,4.1536}}}
{0.719159,15.9582,{{congestion90,4.2118,3.09874},{JobPD,0.0823605,7.42891}}}
{0.373178,10.6962,{{congestion90,2.82373,1.22247},{MedianIncome,0.275745,3.04497}}}
{0.448986,18.5929,{{congestion90,2.67728,1.27161},{population90,0.477707,3.79469}}}
{0.714181,16.0614,{{congestion90,3.92571,2.74862},{area90,0.48104,0.715793},
{JobPD,0.0747817,4.85559}}}
{0.544981,12.9934,{{congestion90,1.80793,0.908265},{area90,2.23116,3.40178},
{MedianIncome,0.17948,2.18396}}}
{0.465419,16.9346,{{congestion90,3.47491,1.61274},{area90,2.39435,1.36407},
{population90,0.0662957,0.203299}}}
{0.553779,13.9413,{{congestion90,0.399268,0.193111},{MedianIncome,0.21553,2.75239},
{population90,0.407732,3.51178}}}
{0.540524,13.7014,{{congestion90,0.838515,0.365115},{area90,0.828138,0.470251},
{MedianIncome,0.200073,2.32668},{population90,0.270455,0.859129}}}

Congestion 1990 (All Cities)

One Variable

{0.122501,-0.0311978,{{TotalTimeTr,0.0150257,2.27774}}}
{0.0159893,0.747548,{{OtherTimeTr,0.00960581,1.21962}}}
{0.0156987,0.602241,{{VehTimeTr,0.00966259,1.21592}}}
{-0.0319884,0.71475,{{TravelProb,0.338472,0.264752}}}
{0.0170752,0.624405,{{VehTimePers,0.0105255,1.23335}}}
{-0.0310241,1.15035,{{Speed95,-0.00484965,-0.311901}}}
{-0.0211002,0.872476,{{VMTpers,0.00760836,0.616501}}}
{0.103057,1.75185,{{DriveAlone,-0.0102444,-2.10877}}}
{0.0523115,0.595317,{{Carpool,0.03261,1.62971}}}
{0.0279585,0.949065,{{Transit,0.00817448,1.36487}}}
{-0.0174836,0.939643,{{WalkBike,0.0174493,0.696065}}}
{0.194386,0.229159,{{AllCommMed,0.0343321,2.87031}}}
{0.26367,-0.432636,{{DAcommMed,0.0660922,3.42675}}}
{0.303512,0.108753,{{AllCommMean,0.038256,3.75143}}}
{0.393074,-0.312295,{{DAcommMean,0.0591892,4.5199}}}
{0.896951,-0.107799,{{congestion95,1.04664,16.1902}}}
{0.091799,0.905436,{{area90,0.119473,2.00807}}}

{0.457018,0.609588,{{density90,0.12696,5.12352}}}
{0.495234,0.568457,{{RevDens,0.119274,5.51666}}}
{0.111636,0.911154,{{ResPD,0.0123569,2.18402}}}
{-0.0102465,0.943874,{{ResConc,0.0317482,0.8341}}}
{0.016078,0.953837,{{JobPD,0.00180326,1.22075}}}
{-0.0326408,1.02271,{{JobConc,-0.000846237,-0.227441}}}
{0.215742,0.882771,{{JobPDbyWkr,0.0936363,3.04183}}}
{-0.0342615,0.992334,{{Mix,0.04506,0.0787618}}}
{0.00223384,0.988067,{{CBDsize,0.000111675,1.03304}}}
{0.0180387,1.11314,{{CBDemplshare,-0.0115132,-1.24543}}}
{0.239607,0.338525,{{MedianIncome,0.0201801,3.23315}}}
{0.174462,1.41679,{{IncomeLT15,-0.0194178,-2.70923}}}
{0.227364,1.63229,{{IncomeLT30,-0.0137825,-3.13498}}}
{-0.0344199,1.02422,{{vehiclepercapita,-0.025383,-0.0419931}}}
{0.0354779,0.327968,{{workerpercapita,0.0140832,1.45034}}}
{0.195468,0.925524,{{population90,0.0281903,2.87902}}}
{0.359775,1.44621,{{hwmilespercapita,-0.119582,-4.22593}}}
{-0.0289956,0.959583,{{fwlanemilesoftotal,0.002912,0.393248}}}
{0.00227786,0.826677,{{fwvmtoftotal,0.00464885,1.03368}}}
{0.0264374,0.976316,{{population50,0.0202686,1.34709}}}
{-0.0325742,1.03225,{{density50,-0.00435464,-0.231519}}}
{0.0155479,0.944709,{{popgrowth5090,0.0236975,1.214}}}
{0.257258,0.794976,{{densgrowth5090,0.335775,3.37504}}}
{0.244155,0.837534,{{popgrowth1900,0.073688,3.26966}}}
{-0.0265803,1.00188,{{popgrowth20c,0.0000409005,0.472481}}}

Two or More Variables

{0.585597,0.30424,{{DAcommMean,0.0464358,4.09915},
{hwmilespercapita,-0.0906704,-3.8043}}}
{0.499687,0.810271,{{RevDens,0.0940189,3.01825},
{hwmilespercapita,-0.0406037,-1.12164}}}
{0.367853,1.30962,{{JobPDbyWkr,0.0393985,1.17073},
{hwmilespercapita,-0.0967102,-2.82457}}}
{0.445069,0.919687,{{MedianIncome,0.0133085,2.3361},
{hwmilespercapita,-0.0964311,-3.42596}}}
{0.455408,1.70647,{{IncomeLT15,-0.0146657,-2.46831},
{hwmilespercapita,-0.106419,-3.99508}}}
{0.447788,1.79004,{{IncomeLT30,-0.0093069,-2.3711},
{hwmilespercapita,-0.0984226,-3.54624}}}
{0.390177,1.32528,{{population90,0.0148401,1.56389},
{hwmilespercapita,-0.0984652,-3.20301}}}
{0.485758,1.21283,{{densgrowth5090,0.245544,2.84686},
{hwmilespercapita,-0.0984636,-3.72638}}}
{0.596254,-0.102516,{{DAcommMean,0.0352779,2.87332},{RevDens,0.0877759,3.9489}}}
{0.477813,0.573276,{{JobPDbyWkr,0.00604283,0.180225},{RevDens,0.11577,3.94389}}}
{0.616025,0.139395,{{MedianIncome,0.0144997,3.18164},{RevDens,0.10511,5.42488}}}
{0.671174,0.964169,{{IncomeLT15,-0.018394,-4.06405},{RevDens,0.116876,6.69374}}}
{0.626336,1.08453,{{IncomeLT30,-0.0104127,-3.34286},{RevDens,0.107152,5.65368}}}
{0.478145,0.576411,{{population90,0.00227028,0.224353},{RevDens,0.115309,4.08762}}}
{0.507755,0.554906,{{densgrowth5090,0.127253,1.3182},{RevDens,0.10102,3.9696}}}
{0.635261,0.143957,{{DAcommMean,0.0213788,1.57376},{MedianIncome,0.010334,1.99863},

{RevDens,0.090091,4.25789}}}
{0.687012,0.531753,{{DAcommMean,0.0188207,1.55465},{IncomeLT15,-0.0149332,3.01982},
{RevDens,0.100523,5.02093}}}

Congestion 1995 (All Cities)

One Variable

{0.145211,0.0580869,{{TotalTimeTr,0.0145745,2.46908}}}
{0.00405353,0.859818,{{OtherTimeTr,0.00760961,1.05929}}}
{0.0462363,0.599451,{{VehTimeTr,0.0111104,1.56663}}}
{-0.0280809,0.639964,{{TravelProb,0.491607,0.424952}}}
{0.047774,0.62674,{{VehTimePers,0.0120531,1.58276}}}
{-0.0343846,1.04477,{{Speed95,0.000740511,0.0524459}}}
{0.00116726,0.865341,{{VMTpers,0.0112582,1.01738}}}
{0.0633699,1.63498,{{DriveAlone,-0.00783394,-1.74061}}}
{0.0085944,0.802624,{{Carpool,0.020828,1.12253}}}
{0.0223361,1.01515,{{Transit,0.00706951,1.29823}}}
{-0.0290341,1.03117,{{WalkBike,0.00895628,0.391859}}}
{0.190446,0.366106,{{AllCommMed,0.0308566,2.83856}}}
{0.271688,-0.257441,{{DAcommMed,0.06072,3.49158}}}
{0.25407,0.31285,{{AllCommMean,0.0320462,3.34936}}}
{0.339354,-0.0531444,{{DAcommMean,0.0501771,4.05094}}}
{0.896951,0.198969,{{congestion90,0.860267,16.1902}}}
{0.0390028,0.995251,{{area90,0.0826268,1.48915}}}
{0.363651,0.741046,{{density90,0.103595,4.25957}}}
{0.358882,0.722752,{{RevDens,0.0931842,4.21821}}}
{0.0508028,0.999105,{{ResPD,0.00855879,1.6142}}}
{-0.0258215,1.03149,{{ResConc,0.0172066,0.494828}}}
{0.00419722,1.0232,{{JobPD,0.00142992,1.06134}}}
{-0.032733,1.07911,{{JobConc,-0.000747757,-0.221666}}}
{0.152936,0.96789,{{JobPDbyWkr,0.0734692,2.53307}}}
{-0.0225942,0.959766,{{Mix,0.299463,0.580647}}}
{-0.0185935,1.05433,{{CBDsize,0.0000666033,0.672589}}}
{0.0102407,1.15409,{{CBDemplshare,-0.00963199,-1.14473}}}
{0.304461,0.391112,{{MedianIncome,0.0203451,3.75926}}}
{0.238946,1.49001,{{IncomeLT15,-0.0201384,-3.22785}}}
{0.291125,1.69721,{{IncomeLT30,-0.0139339,-3.64974}}}
{-0.0269194,0.909072,{{vehiclepercapita,0.252343,0.462156}}}
{0.095757,0.224785,{{workerpercapita,0.0174207,2.04375}}}
{0.11401,1.00608,{{population90,0.0205378,2.20464}}}
{0.330781,1.44851,{{hwmilespercapita,-0.104351,-3.97849}}}
{-0.0344171,1.06161,{{fwlanemilesoftotal,0.000288771,0.0429012}}}
{-0.00261694,0.913072,{{fwvmtoftotal,0.00392406,0.96005}}}
{-0.00275898,1.04547,{{population50,0.0132603,0.957841}}}
{-0.0332256,1.08401,{{density50,-0.00320415,-0.187842}}}
{-0.00209703,1.02,{{popgrowth5090,0.0172854,0.968102}}}
{0.177131,0.901669,{{densgrowth5090,0.259264,2.7309}}}
{0.19034,0.927315,{{popgrowth1900,0.0600088,2.83771}}}
{-0.0295214,1.06178,{{popgrowth20c,0.000029381,0.373838}}}

Two or More Variables

{0.519281,0.491702,{{DAcommMean,0.0389066,3.51732},
{hwmilespercapita,-0.0801275,-3.44301}}}
{0.38545,1.04795,{{RevDens,0.0592195,1.89203},
{hwmilespercapita,-0.0546055,-1.50123}}}
{0.318791,1.37168,{{JobPDbyWkr,0.0221611,0.699709},
{hwmilespercapita,-0.0914863,-2.83913}}}
{0.468209,0.86552,{{MedianIncome,0.0147357,2.91451},
{hwmilespercapita,-0.0787176,-3.15113}}}
{0.481167,1.73467,{{IncomeLT15,-0.0161249,-3.06688},
{hwmilespercapita,-0.0898789,-3.81299}}}
{0.470445,1.82712,{{IncomeLT30,-0.0102481,-2.94082},
{hwmilespercapita,-0.081052,-3.28938}}}
{0.325324,1.384,{{population90,0.00791691,0.874907},
{hwmilespercapita,-0.093086,-3.17538}}}
{0.40166,1.27967,{{densgrowth5090,0.177637,2.10602},
{hwmilespercapita,-0.0890734,-3.44707}}}
{0.460892,0.0996519,{{DAcommMean,0.0327609,2.54703},{RevDens,0.0639329,2.74551}}}
{0.336548,0.726965,{{JobPDbyWkr,0.0052824,0.154168},{RevDens,0.0901208,3.0043}}}
{0.545834,0.244487,{{MedianIncome,0.0161625,3.59687},{RevDens,0.0773957,4.05123}}}
{0.596984,1.13891,{{IncomeLT15,-0.0193442,-4.25832},{RevDens,0.0906623,5.17335}}}
{0.554279,1.28883,{{IncomeLT30,-0.0114215,-3.70312},{RevDens,0.0798868,4.25694}}}
{0.336085,0.720393,{{population90,0.000673306,0.0650676},{RevDens,0.0943604,3.27113}}}
{0.356727,0.712629,{{densgrowth5090,0.0950652,0.950186},{RevDens,0.0795473,3.01604}}}
{0.548885,0.046509,{{DAcommMean,0.0149374,1.09057},{MedianIncome,0.0132519,2.5416},
{RevDens,0.0669017,3.13602}}}
{0.601876,0.809193,{{DAcommMean,0.0143507,1.15932},{IncomeLT15,-0.0167054,3.30385},
{RevDens,0.078193,3.81963}}}