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The Broader Connection between Public Transportation, Energy Conservation and Greenhouse Gas Reduction

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Passion. Expertise. Results.

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Executive Summary

Background

This study began with the hypothesis that public transportation interacts with land use patterns, changing travel patterns in neighborhoods served by transit. Importantly, this effect would apply not just to transit riders, who make an exchange of automobile use for transit, but also for people who do not use transit. These people, who live in places shaped by transit, would tend to drive less, reducing their overall petroleum use and their carbon footprint.

In order to test this hypothesis, we began with a survey of the literature on the interaction of land use and travel patterns. The literature focuses on three major categories of influences on travel: land use/urban environment, socio-demographic factors, and cost of travel. For the purposes of this study, land use/urban environment variables were further broken down to include a separate category for transportation infrastructure.

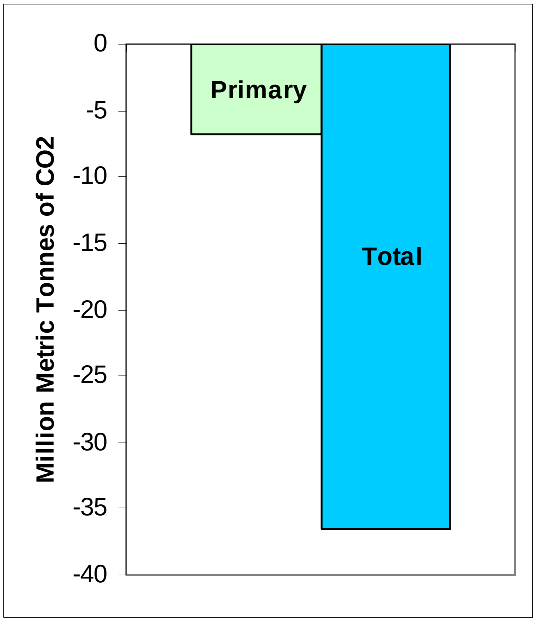
Many past studies have found a significant correlation between land use variables and travel behavior, though results vary depending on how the problem and the variables are defined. Boarnet and Crane (2001) emphasized that without accounting for social characteristics, like age and education, land use-transportation models are incomplete. They also discussed the importance of economic measures, such as household or personal income, as a measure of the cost of travel time. Other studies evaluated the relative importance of these and other variables, informing this model.

After evaluating possible variables for this model, we formed a statistical model that would allow us to tease apart the relationship between land use, transit availability, and travel behavior.

Key Findings

This study found a significant correlation between transit availability and reduced automobile travel, independent of transit use. Transit reduces U.S. travel by an estimated 102.2 billion vehicle miles traveled (VMT) each year. This is equal to 3.4 percent of the annual VMT in the U.S. in 2007.

Figure 1. Reductions in CO_2 Emissions



An earlier study on public transportation fuel savings assessed the total number of automobile VMT required to replace transit trips in the U.S. (ICF 2007). This study calculated the direct petroleum savings attributable to public transportation to be 1.4 billion gallons a year. Under the current study, however, the secondary effects of transit availability on travel were also taken into account. In order to calculate this, we created a statistical model that accounts for the effects of public transportation on land use patterns, and the magnitude of those effects as carried through to travel patterns. The total effect then shows savings from people who simply live near transit (without necessarily using it).

Total effects of public transportation reduce energy use in the U.S. by the equivalent of 4.2 billion gallons of gasoline.

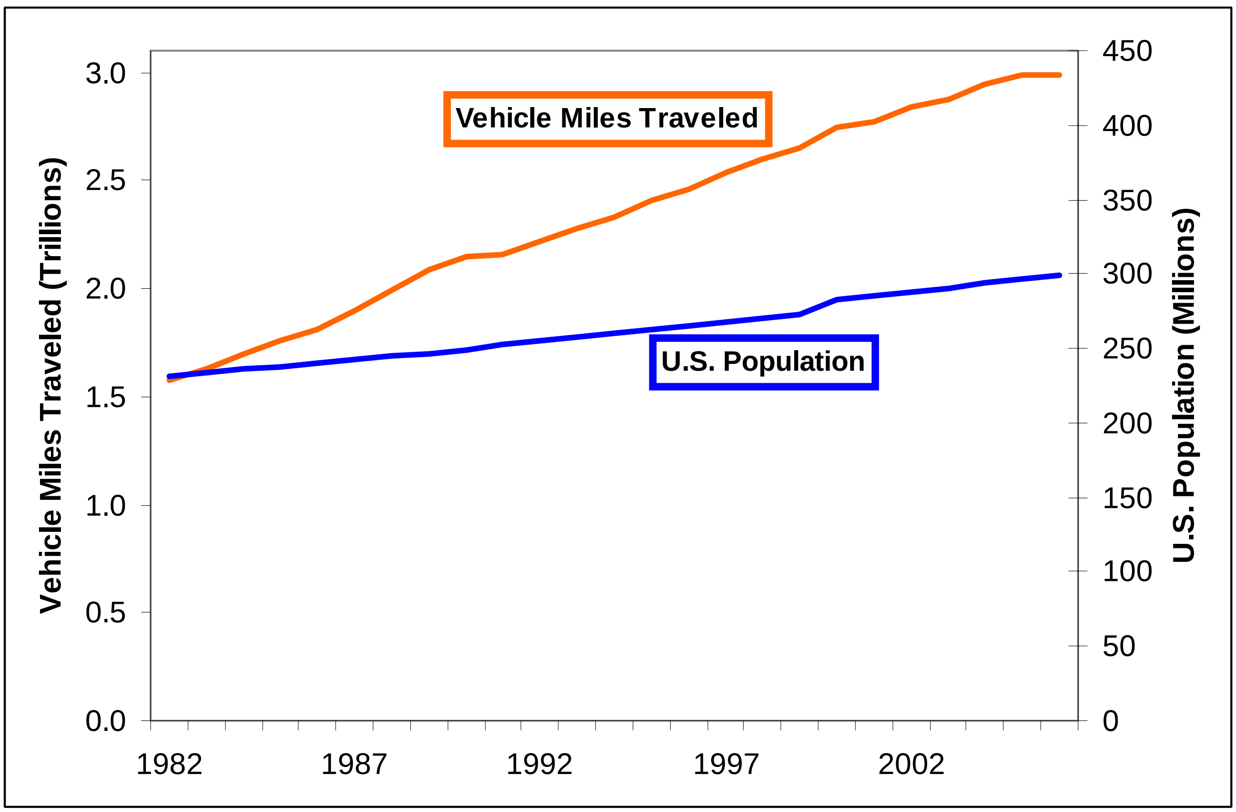
By reducing vehicle miles traveled, public transportation reduces energy use in the transportation sector and emissions. The total energy saved, less the energy used by public transportation and adding fuel savings from reduced congestion, is equivalent to 4.2 billion gallons of gasoline.

The total effects reduce greenhouse gas emissions from automobile travel by 37 million metric tons. This consists of 30.1 million metric tonnes reduced from secondary effects and a net savings of 6.9 million metric tonnes from primary effects and the effects of transit induced congestion reduction. To put the CO_2 reductions in perspective, to achieve parallel savings by planting new forests, one would have to plant a forest larger than the state of Indiana. Total CO_2 emission reductions from public transportation are shown, for primary and total effects, in Figure 1, above.

Introduction

The way that Americans travel on a daily basis is a major determinant of our use of energy, our impacts on the environment, and, more broadly, our quality of life. The quantity of petroleum that we consume in transportation is a significant indicator of our habits—in cities which are built more efficiently, personal energy consumption can be significantly lower than in cities with few travel choices and long distances between destinations. Petroleum is the primary fuel used in transportation, and transportation uses 28% of our national energy budget (EIA, 2006, Table 2.1a). Since 1982, driving vehicle miles traveled (VMT) has increased by 47 percent per person, from an average of 6,800 miles per year for every man, woman and child to almost 10,000 miles per year (FHWA Traffic Volume Trends, August 2007). National consumption of oil for all purposes rose from 3.4 to 5.1 billion barrels per year (EIA 2006, Tables 5.13c and D1). Every additional barrel consumed results in more fuel imports, more money spent by consumers on fuel, and more carbon dioxide and other pollutants emitted into the air.

Figure 2. United States Population and Vehicle Miles Traveled (VMT), 1982-2006



Transportation is the fastest growing sector for greenhouse gas production in the U.S., and how people travel determines this growth rate. Choices about driving, walking, or taking transit to get from A to B are determined partly by individual preference, and partly by the options available (see literature review below). Since the mid-20th century, the automobile has been the mode of choice for developers and their urban designers as they built new neighborhoods in the U.S., creating an environment where trips are typically too far to walk, and difficult to serve with public transportation. In contrast, this analysis and others show that high quality public transportation and walkable, human-scale development often go hand in hand.

In January 2007, APTA released an ICF International analysis that quantified the direct relationship between public transportation use and petroleum conservation in the United States. That study quantified the amount of petroleum that households are saving by taking public transportation in a direct, one-for-one analysis.

Transit systems are likely to achieve a higher return on investment when more potential riders live and work close to their routes. We hypothesize here that the reverse is also true – that transit systems enable more efficient development in general, where in addition to those taking transit, those who drive have shorter distances to go, and walking or bicycling to destinations is made possible through short distance trips and complete streets. This paper describes these “second-order” effects of public transit availability. For example, without public transit, downtown Washington, DC would look very different. According to the 2006 American Community Survey, approximately 39 percent of DC residents commute by public transportation. If each person used a car instead, space constraints would increase the cost of driving due to congestion and constrained parking, which would in turn induce businesses and government offices to reduce the total number of workers in the downtown area. This would reduce the clientele for shops and restaurants, forcing them to spread out to bring in enough customers. This positive feedback loop between public transit availability and more efficient land use patterns is captured by creating a model that can tease out the effects of public transportation availability on driving via the built environment. This model also accounts for the direct effects which had been measured in the 2007 APTA paper.

We use Structural Equations Modeling (SEM) to determine the impact of transit availability on travel behavior in the U.S. Our model accounts for the relationships of three broad categories of variables on household travel behavior: land use characteristics, characteristics of the transportation system, and socioeconomic characteristics. By including a comprehensive range of variables, the model provides a reliable estimate of the total effect (both direct and indirect) of public transit availability on travel behavior. Our thesis is that public transportation enables more efficient land use patterns, thereby shortening overall trip distances. Shorter trip distances allow people to drive less or to walk or bike. Thus even people who do not use public transportation benefit from it. Our results have implications for the importance of transportation and land use policy to reducing our dependence on petroleum both now and in the future.

The remainder of this report is divided into three sections and an appendix. The first two sections explain in more detail the relationship between transportation and land use and review the various factors affecting land use, transportation, and travel behavior. This portion builds on the extensive body of previous research on the relationship between land use and transportation patterns. The third section presents the findings of our research. The appendix provides more detail on the data sources and modeling techniques used.

1. Interdependence of Transportation and Land Use in Practice

As stated above in the introduction, this paper hypothesizes that transportation systems and land use are interdependent. Two surveys of the literature, by Polzin in 2004 and by Ewing and Cervero in 2001, describe numerous studies working on the transportation – land use connection, and the results were generally compelling and consistent. This same body of research has also found that areas with higher population and employment density typically have good public transportation systems (Polzin, 2004). Although this basic relationship is readily observable, the causal link between public transit systems and travel patterns is less clear.

Some recent land use plans (and developments, on a smaller scale) have been predicated on the theory that public transportation is part of a distinct development pattern. The fulfillment of these plans has provided an opportunity to test the theory of interdependence in real time. The county of Arlington, VA, initiated a new land use and transportation development strategy in the 1970s, built on the principle of focusing higher-density development near the new Metro stations that were built in the same time period. The county has also developed bus routes for key corridors and promoted walking and biking. As a result, Arlington has very high rates of public transit usage. Twenty-three percent of residents, ten times the national average, use public transit to get to work. In addition, six percent of residents walk to work (2000 Census), and automobile traffic has grown slower than predicted (Ewing et al, 2007).

Recently, transit-oriented development, or TOD, has become a term used for development projects similar to that in Arlington, though typically on a smaller scale. A 2002 paper defined TOD as "mixed-use, walkable, location-efficient development that balances the need for sufficient density to support convenient transit service with the scale of the adjacent community" (Belzer and Autler, 2002). Developers have built TOD projects in recent years in places as diverse as Oakland, CA; Charlotte, NC; Evanston, IL; and Atlanta, GA. Various studies have examined the travel behavior of TOD residents. One study found that residents in TOD areas are five times more likely to commute to work by rail than residents of other places (Boarnet and Compin, 1999). Cervero also found higher public transit ridership among residents of TODs in California (Cervero, 2007). Some studies have found that many residents of TODs in fact moved to the areas out of a desire to use public transit (Bagley and Mokhtarian, 2002; Lund, 2006; Cervero, 2007).

Comparisons of TOD with other types of developments broadly represent the difference between compact areas with good public transportation and less compact areas that are more dependent on cars. The former tend to be more conducive to walking and biking and provide a wider range of jobs, shops, and services within a given distance of homes. Cervero (2007) compared the commute experiences of people in California before and after moving to a TOD. (Here a TOD is defined as an area within one half mile of a rail station). After moving, residents tend to have access to a greater number of jobs, shorter commute times, and lower commute costs. Residents also drive fewer miles on average to get to work after moving to these areas (Cervero 2007).

2. Factors in Predicting Travel Behavior

A wide body of research addresses the relationships between individual characteristics, land use, transportation systems, and travel behavior. Boarnet and Crane (2001) segmented factors that affect travel behavior into three classes:

- travel cost variables;
- socio-demographic variables; and
- land use/urban design.

For the purposes of this study, we have further subdivided land use variables into land use and transportation system variables.

Land use characteristics describe the built environment where people live and travel. The characteristics of the transportation system include the availability of transportation networks and the quality of service those networks provide. Some researchers have used income as a proxy for individual's time valuation, and marginal fuel cost of travel. Socioeconomic characteristics include personal and household variables such as age, education level, and car ownership.

This section reviews the current literature on variables that fall within these four classes and have been shown to affect travel behavior. The findings in the literature informed our selection of variables for the statistical model, described below.

2.1. Land use characteristics

The effect of land use characteristics on travel patterns has been studied at both the trip origin and the trip destination. Many studies have focused on the work trip because of its regularity and the wide availability of data on commute mode choice through the U.S. Census. Land use around both residence and place of work have been found to be significant in determining travel patterns.

Density

Population density is measured as the number of residents or employees within a designated geographic area divided by the size of that area. Research has found that higher population and housing density at the trip origin and/or destination is associated with decreased travel distances and trip frequency. Newman and Kenworthy, in their seminal research on the influence of land use on travel outcomes, found an inverse relationship between population density and energy use for transport. They showed that a city with twice the population density of another has 25-30 percent lower gasoline consumption per capita (Dunphy and Fisher, 1996). Other studies have noted that population density is an important factor in predicting travel patterns, while adding socioeconomic and demographic factors to the equation.

Population density has been used to predict both mode choice and vehicle miles traveled (VMT). In a study of modal split, van de Coevering and Schwanen used an ordinary least squares regression model on data collected by Kenworthy and his colleagues from 31 cities in Europe, Canada, and the USA. This study found that higher population density is associated with a smaller share of car mode selections and a larger share of walk/bicycle mode selections (van de Coevering and Schwanen, 2006). Similarly, British National Travel Survey data shows that car ownership between 1989 and 2000 increased significantly in spread-out areas, while remaining stable in the densest areas (Dargay and Hanly, 2004).

Population density is a particularly strong factor when compared to other predictors of mode choice. Davis and Seskin's 1997 study, based on data from the American Housing Survey, found that housing density had an effect ten times greater than land use mix. Likewise, when forty land use and demographic variables were considered, housing and employment density were the most significant in determining public transit demand (Davis and Seskin,1997).

Increased population density has been correlated with reduced VMT by many studies. In a study on travel patterns in the U.S., based on the 1995 Nationwide Personal Transportation Survey (NPTS), Chatman found that an additional 1.5 housing units per gross acre is associated with a 0.2 mile reduction in personal VMT on a given day (Chatman, 2003). A 1996 study also found that residents of denser areas travel fewer miles in automobiles than residents of spread-out areas (Dunphy and Fisher,1996). A 2002 study of the effects of several dimensions of sprawling development found that a group of factors including population density has a significant effect on VMT and transit use (Ewing, Pendall and Chen, 2002).

Employment density, or the number of jobs within a certain area, is also considered a good predictor of travel behavior. Many studies show an even stronger correlation between employment density and VMT than between population density and VMT. Frank and Pivo found a significant positive correlation between employment density at the trip origin and/or destination and public transportation use (Frank and Pivo, 1994). Likewise, Chatman found an average half-mile reduction in personal commercial VMT for each additional 10,000 employees per square mile at the workplace, as well as a 3% decreased probability of using an available car to commute to work for every increase of 1.5 employees per gross acre at the workplace (Chatman, 2003).

Mix of Uses

The ratio of jobs, housing, and services in a certain area measures the diversity of land uses, or "land use mix." Though population and employment density are often used as proxies for land use mix, some studies define a separate variable for mix of uses. Higher diversity of uses results in shorter distances between destinations and facilitates trip chaining. For example, a neighborhood with an equal proportion of homes and jobs can allow some people to both live and work in the area and reduce their commute. When stores and services are closer to people's homes, they can drive shorter distances, or even walk or bike to them. A multinomial logit model by Dargay and Hanly showed that car share increases and walk share declines as distance to services and retail stores increases (Dargay and Hanly, 2004). Land use mix is often measured by a logarithmic land use mix index, which considers the number of different land use types, including single family and multifamily homes, retail and services, offices, places of entertainment, institutional facilities, and industrial and manufacturing facilities, and the proportion of land that is allocated for each use.

Land use mix has a significant effect on mode choice and on VMT. Mix is positively correlated with public transit use and walking and negatively correlated with single-occupancy vehicle use (Frank and Pivo, 1994; de Abreu e Silva et al., 2006). Sun, Wilmot, and Kasturi found that land use mix makes little difference in number of daily trips, but plays a significant role in reducing household VMT. They found that people living in an area with a more balanced mix of land uses drive about 45% fewer miles than those in areas with segregated land uses (Sun et al., 1998).

Urban Design

The built environment of a neighborhood or activity center can vary greatly, depending on the time in history when an urban area was developed, the layout of the city, geographic size of the city or central business district (CBD), and distribution of population density. Traditional urban areas have compact central locations, mixing of land uses, and dense street networks, often in a grid design. Most urban and suburban areas designed in the second half of the 20th century have more dispersed activity centers and segregated land uses. Their road networks have lower connectivity, with branch-and-stem road design and a focus on limited access freeways.

Some evidence suggests that traditional urban settings are associated with shorter trip lengths (Ewing and Cervero, 2001), greater use of public transportation and non-motorized modes, and lower car ownership levels (de Abreu e Silva et al., 2006). However, Ewing and Cervero found that studies that consider the correlation between street network design (i.e., connectivity, directness or routing, block sizes, sidewalk continuity) and travel are relatively inconclusive and often contradict one another.

Some studies have found significant effects of population density distribution on travel patterns. Van de Coevering and Schwanen measured centrality of a city by the percentage of the total number of inhabitants or jobs located in the central business district (CBD). They found that distances traveled by car were significantly shorter in urban areas with a greater centrality (van de Coevering and Schwanen, 2006).

2.2. Transportation System Characteristics

People choose travel mode depending on the availability, speed, convenience and safety of each mode. Research has examined both "carrots" and "sticks" in predicting how much people drive. Convenience factors have been found to promote alternatives to driving (shorter distances, complete streets with sidewalks, and public transit). On the other hand, high parking prices, diminished road supply, and increased congestion have been shown to correlate with decreased driving.

Van de Coevering and Schwanen found that the ratio of public transportation to road supply is positively correlated with average distance traveled by public transportation. The availability of public transportation is also significant. When road supply is removed from the equation, rail density is still positively correlated with distance traveled by public transportation (van de Coevering and Schwanen, 2006).

Accessibility of public transit is extremely important in determining public transportation use. One measure of accessibility is the distance to the nearest transit stop. The 1983 National Personal Transportation Survey found that 70 percent of Americans will walk

500 feet for normal daily trips, 40 percent are willing to walk 1,000 feet, and 10 percent are willing to walk a half mile (U.S. DOT, 1986). In a study of travel behavior for non-work trips, Hedel and Vance found that each additional walking minute to public transportation increases the probability of car use by 0.022 and kilometers driven by 0.15 per day (Hedel and Vance, 2006).

Research has also shown a positive correlation between frequency of public transportation service and use levels. When bus service alone is considered, the frequency of service is more important than distance to the nearest stop in determining public transportation use; modal share for automobiles significantly decreases as bus service frequency at the nearest stop increases (Dargay and Hanly, 2004).

Davis and Seskin (1997) showed that people are more likely to walk or bicycle for shorter trips, and both walking and bicycling are more viable when streets are built for those on foot as well as drivers, or "complete streets." This 1997 analysis of California Air Resources Board data showed a significant correlation between improved pedestrian access to shopping centers and reduced vehicle trip rates (Davis and Seskin, 1997).

2.3. Socio-economic Characteristics

Research has shown that socioeconomic factors, such as family status, working status, income, and race, are significant determinants of household travel patterns. While some studies have focused on estimating the effects of socioeconomic factors, research that examines the effects discussed above also control for these factors by including them in their models. Including socioeconomic variables in analyses prevents overestimating the effects of environmental variables on travel behavior. The discussion below is tailored to the variables considered in this study; for a more complete discussion of the research on this topic, see the overview articles by Polzin (2004), and Ewing and Cervero (2001).

Household Composition

The presence and number of children in a household particularly influences travel behavior. Several studies have shown that the presence of children in the household is positively correlated with personal VMT (Chatman, 2003; van de Coevering and Schwanen, 2006). Likewise, in a study of mode choice, Hedel and Vance found that the number of persons under the age of 18 is positively correlated with non-work automobile use (Hedel and Vance, 2006). These results hold in Portland, OR and Boston, MA where the presence of children under the age of 5 is positively correlated with automobile use (Zhang, 2005).

Income and Employment Status

Income and employment status determine the affordability of travel by different modes. Higher income households are more likely to drive automobiles (van de Coevering and Schwanen, 2006). Automobile ownership is a significant part of this effect, and is correlated with income, presumably as an indicator of overall household assets (data correlating wealth, rather than income, with travel patterns is relatively rare). Higher income travelers are more likely to own a car, and automobile ownership is positively correlated with VMT (Zhang, 2005). In general, higher income is correlated with higher VMT. In a logit model, Dargay and Hanly found that the share of travel by automobile increases with individual and household income (Dargay and Hanly, 2004). Employed people are more likely to own automobiles and more likely to drive (Dargay and Hanly, 2004).

Gender

Current research is inconclusive on the effect of gender on total travel. While Chatman found that women drive more than men for errands, Hedel and Vance found that their female "dummy" variable had negative effects on the probability of non-work automobile use (Chatman, 2003; Hedel and Vance, 2006). Zhang found that women are less likely to use an automobile than men for all types of trips (Zhang, 2005). Other research has found significant differences in the types of trips women make, especially in low-income families with children (Blumenberg, 2004).

Age

Age is associated with retirement, ability to drive, and life cycle. Research has found that people between the age of 16 and 65 drive more on average than those in other age groups. Younger people in school are more likely to walk, bike, or take public transportation. Travelers over the age of 65 are also less likely to use a personal vehicle for non-work uses (Hedel and Vance, 2006).

2.4. Self-selection

The possibility of self-selection complicates any study of land use, transportation, and travel behavior. Self-selection occurs when people move to areas specifically because of the travel options that they offer. For example, people who are predisposed to public transit use are more likely to move to a dense, mixed-use area with public transit than people who prefer to drive, while people who prefer to travel by automobile may continue to do so regardless of land use patterns and availability of public transit (Lund, 2006; Bagley and Mokhtarian, 2002).

Some studies have controlled for self-selection by including survey data on individuals' lifestyle and travel preferences (Bagley and Mokhtarian, 2002). However, some experts have pointed out that there is currently limited choice in the housing market, and surveys in many U.S. cities have shown a latent demand for denser developments with multiple transportation options. Individuals who would like to walk, bike, or take public transportation may be prevented from doing so because of their location in contemporary car-dependent developments. If that is the case, then densification and expansion of public transportation in urban areas would affect travel behavior, but only until this latent demand is satisfied (Ewing et al, 2007).

3. Key Findings

This study sought to estimate the effect of public transportation availability on household travel through the medium of land use, specifically on total vehicle miles traveled (VMT). We generally refer to this effect as a "secondary" effect, compared to the primary effect of substituting a mile traveled by automobile with a mile in a bus or train. For the secondary effects described here, lower household VMT is associated with public transportation availability via built environment characteristics in cities and suburbs across the U.S. The statistical model is relatively complex because it must account for the fact that built environment and public transit availability are intertwined historically. We discuss the findings briefly here, with a more thorough discussion of the methodology in the appendix.

3.1. Methodology Overview

The data used in this study are from a national survey of travel patterns conducted in 2001, the most recent year available. The National Household Travel Survey 2001 (NHTS 2001) is a representative sample of the entire U.S., including cities, suburbs, and rural areas. Participants were asked to answer some survey questions about their household, then to record their travel in a diary for one day. The variables used were based on household travel patterns and household characteristics. This created a better model for effects based on residential location, although it restricted the ability of the model to show effects of certain personal characteristics, such as gender and age. See the appendix for a more detailed discussion of the variables.

In order to capture the effect of public transportation availability on VMT as mediated through the built environment, we used Structural Equations Modeling (SEM). This methodology allows us to tease apart these historically intertwined variables and estimate the effect of each component on VMT, as well as their interrelationship. The model has two types of variables, "endogenous," which are the product of other variables in the model, and "exogenous," which exert an effect on the endogenous variables. Among the exogenous variables is a set of instrumental variables which are related to population density, but not public transportation availability. This type of variable is a modeling requirement for correctly identifying the SEM equations.

3.2. Household Fuel Use and Public Transit Availability

In a 2007 report, ICF estimated the savings from public transportation for U.S. households at 1.4 billion gallons of gasoline per year, after adjusting for gasoline use by public transit and congestion effects (ICF 2007). This figure represents the direct substitution of public transit passenger miles with private automobile travel, considering average rates of vehicle occupancy. If transit systems across the country were to shut down, households would have to drive 35 billion more miles per year to meet their transportation needs. With average fuel economy of personal vehicles at 19.7 miles per gallon (Highway Statistics 2005), households would use an extra 1.8 billion gallons of gasoline. This figure assumes that population behaviors are constant, residential patterns are constant, and also that land use patterns are fixed. That is, it does not take into account the interaction of public transit and urban form.

The model in the current paper confirms the hypothesis that public transportation availability has a significant secondary effect on VMT beyond the primary effect of using transit. The secondary effect is mainly generated through land use patterns. The magnitude of the secondary effect is approximately twice as large as the primary effect of actual public transit trips. This result suggests that public transit is a significant enabler of an efficient built environment. These effects are seen both through the relationship between availability of public transit and VMT and the same relationship mediated by land use patterns.

If public transit systems had never existed in American cities and their effects on our urban landscapes were completely erased, American households would drive 102.2 billion more miles per year. The VMT reduction in this model can also be expressed as total estimated reduction in petroleum use. Assuming average mileage for each vehicle, we estimate the total effect of public transit on household fuel consumption to be a reduction of 5.2 billion gallons of gasoline per year.

Table 1 below shows the total effects of public transportation, including primary (replacement) and secondary (via land use) effects.

Table 1. Total Effects of Public Transportation Availability on Households

	Total Effects
VMT Reduced per Year as a Result of Public Transportation (billions)	102.2 billion VMT
Gallons Reduced per Year as a Result of Public Transportation (billions)	5.2 billion gallons

Subtracting the primary effect (1.8 billion gallons) from the total effect estimated in this model, we show a total secondary reduction in gasoline use of 3.4 billion gallons annually from transit availability.

Table 2. Secondary Effects of Public Transportation Availability on Petroleum Consumption

	Gallons Reduced per Year (billions)
Total Effect of Transit on Reducing Equivalent Gallons of Gasoline	5.2
Less Primary Effect Gallons of Gasoline	(1.8)
Equals Secondary Effects of Transit Availability on Equivalent Gallons of Gasoline	3.4

See ICF 2007 for a full description of transit petroleum use and primary effect of ridership on transit.

As shown above in Table 3, below, we can then calculate the net savings in energy use by subtracting energy used by public transportation, while accounting for the benefits of public transportation in reducing congestion. Here, we remove energy used by transit, which would be equivalent to 1.4 billion gallons of gasoline, including all energy sources. To the result, we add the energy benefits of public transit in reducing congestion, which has been estimated by the Texas Transportation Institute at 340 million gallons per year (TTI, 2007). The net total effect of public transportation on energy savings is then estimated at 4.16 billion equivalent gallons of gasoline per year.

Table 3. Total Energy Savings Due to Public Transportation

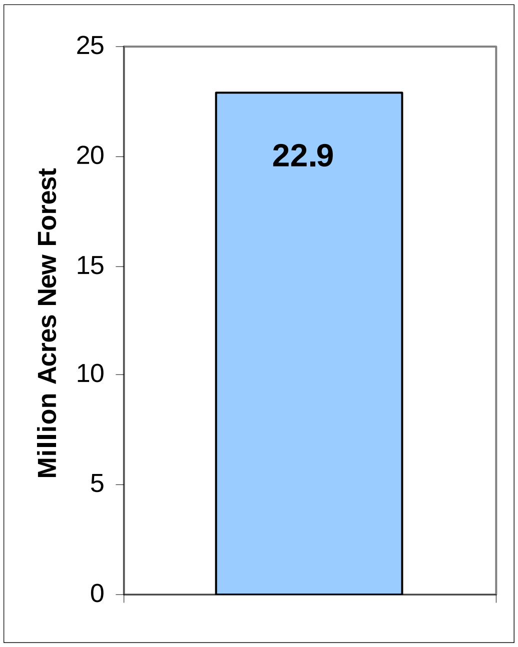
	Equivalent Gallons Gasoline per Year (billions)
Total Effect (Primary and Secondary) of Transit on Reducing Energy Used	5.19
Less Energy Used by Transit	(1.38)
Plus Savings Resulting from Transit Effect on Congestion Reduction	0.34
Total Energy Savings Due to Transit Availability	**4.16**

3.3. Greenhouse Gas Implications

The estimated savings in petroleum use from public transportation can also be expressed in terms of greenhouse gas emissions. Carbon dioxide (CO_2) is by far the most prevalent greenhouse gas emitted from motor vehicles. Each gallon of gasoline burned releases 8.9 kg of CO_2. The total effects of public transit availability reduce CO_2 emissions by 37 million metric tonnes annually.

We can consider these savings in terms of equivalent acres of forest. Planting new forest is one way to remove CO_2 from the atmosphere. Trees sequester carbon as they grow; other effects such as cooling from reduced reflectivity and carbon emissions upon decay are omitted for the purpose of this comparison. Figure 3 below shows how much new forest plantings would be required to absorb the same amount of CO_2 that bus and rail transit currently keep out of the atmosphere annually. To match the total effect of public transportation, the U.S. would have to plant 23.2 million acres of new forest. In other words, if the United States had no public transportation systems, it would need a new forest the size of Indiana to absorb the additional CO_2 emissions from the transportation system.

Figure 3. Public Transportation's Impact in New Forest Equivalent for CO_2 Emissions



Appendix A: Methodology

Structural Equations Models (SEM)

To account for the complex relationships between public transportation availability, land use, and travel behavior, this study uses Structural Equations Modeling (SEM). SEM allows for the simultaneous prediction of multiple variables in one model. With multiple equations, a variable can be dependent in one equation and explanatory in another equation. As a result, SEM can account for feedback loops between explanatory variables and can predict both the direct and indirect effects of one variable on another. This capability allows for a more realistic picture of the factors that affect travel behavior than does single-equation modeling, in which only one variable is impacted by other variables.

In SEM, variables can affect one another in two ways: direct and indirect effects. Using one of the key relationships in this study as an example, the direct effect of rail availability on household VMT is the effect of putting rail availability in the equation for VMT. The indirect effects are the sum of all of the other paths linking rail availability to household VMT, most notably the path via population density. The direct effects in SEM terms are closely related to the first order effect of replacing driving miles with transit use, but not exactly the same: Since there are other potential indirect paths between availability and VMT not specified in our model, such as through increasing mixed use or reduced congestion, the direct effects likely incorporates some second order effects as well. This also implies that the indirect effects in our model capture the second-order effects of public transit via population density, but not necessarily all of the second-order effects.

SEM can also help disentangle feedback loops between explanatory variables. For example, if public transit availability causes an increase in urban density, which in turn causes an increase in public transit availability, a positive feedback loop exists. SEM can estimate the magnitude of the influence of each variable on the other. This step is necessary in order to determine the total effect of any one variable on another.

SEM analyzes the circular relationship between endogenous explanatory variables by allowing each variable to act as a predictor in the equation of the other along with other, purely exogenous, variables. In order to be able to separate out the effects in each direction, however, we needed some exogenous variables that would directly affect only one of the two endogenous variables but not the other. To provide this distinct “entry point” to the loop, we selected two natural population growth factors, birth and death rates. These variables (known as instrumental variables) directly affect only the population density variable of the feedback loop.

Data source Description and Limitations

The core dataset for this study is the National Household Travel Survey (NHTS) 2001. This survey represents the most recent data available on daily travel patterns across the U.S. The NHTS provides data on a probability sample of households, including both survey questions and information on trip-making. The NHTS surveyed over 69,000 households nationwide. Households reported on their characteristics, answered questions about their transportation behaviors and preferences, and filled out a travel diary for one specific day. The days selected were representative of all days of the week and times of the year.

The publicly available NHTS data includes information for each household on workers, age of household members, vehicles, income, population density, and proximity to public transit. For the selected travel day, the dataset provides information on driver vehicle miles traveled, rail miles traveled, and bus miles traveled. NHTS staff provided additional data on the urban environment, transportation system, and land use mix based on a geographic analysis with Census data.

Although the NHTS provides detailed information on the travel behavior and socioeconomic characteristics of households, there were some limitations in the dataset. We supplemented the NHTS data with variables that address mix of land uses, mix of job types, public transit service intensity and quality, and road supply. Some of these are based on analyses provided by NHTS staff, as noted above. In addition, the research team collected data on birth rates, death rates, housing stock, and business patterns by county from the US Census.

Variables Used and Model Characteristics

To construct our SEM equations, we tested variables across all of the categories described in the literature review for their relationships to household travel by rail, bus, and car. We experimented with transformations of many variables in order to find the best possible fit. Table 4 below provides a list of variables used along with mean values and standard deviations.

Table 4. Variables Included

Variable	Source	Unit	Mean	Std. Dev.
Household Travel Behavior				
Miles Traveled on Rail	Based on travel diary	Miles	0.46	4.94
Miles Traveled on Bus	Based on travel diary	Miles	0.50	4.38
Miles Driven	Based on travel diary (driver's miles, not including passenger mileage)	Miles	43.75	51.79
Urban Form (Land Use)				
Natural Log of Population Density	Block Group density (US Census)	Natural Log of People per Square Mile	7.32	2.04
Measure of Land Use Mix	Mix of residents and jobs by Census tract (US Census, NHTS staff analysis)	Ranges from zero (low mix) to one (high mix)	0.59	0.26
In an MSA of 1-3 Million (Dummy)	Survey question	1 = yes, 0=no	0.21	0.41
In an MSA over 3 million (Dummy)	Survey question	1 = yes, 0=no	0.36	0.48
Total Household Distance to Work	Survey question	Miles	12.48	22.27
Transportation System Variables				
Rail Availability Measure	Calculated shortest distance to nearest rail transit station, with a logistic transformation centered around ¾ of a mile limit (Bridgewater College data on transit service, NHTS staff analysis)	Ranges from zero (arbitrarily far away) to one (right next to rail station)	0.09	0.23
Bus Availability Measure	Calculated shortest distance to nearest bus line, with a logistic transformation centered around ¼ of a mile (Bridgewater College data on transit service, NHTS staff analysis)	Ranges from zero (arbitrarily far away) to one (right next to bus line)	0.37	0.42
Travel Day is a Weekday	Survey question	1 = yes, 0=no	0.71	0.45
Travel Cost Variables				
Middle Family Income (Dummy)	Survey question, category is defined as households with annual incomes between $15,000 and $49,999	1 = yes, 0=no	0.36	0.48
High Family Income (Dummy)	Survey question, category is defined as households with annual incomes of $50,000 or more.	1 = yes, 0=no	0.41	0.49
Household Socioeconomic Attributes				
Vehicle Ownership (Dummy)	Survey question	1 = yes, 0=no	0.92	0.27
Ratio of household members age 16+ to vehicles	Survey question	Persons per Car	1.02	0.60
Number of School-age Children (Age 6 to 15)	Survey question	Count	0.33	0.72
Number of Adult Working Non-Drivers	Survey question	Count	0.06	0.27
Number of Adult Working Drivers	Survey question	Count	1.58	0.81
Other Demographic Variables				
County Level Birth Rate per 10,000 people, 1990-1999	U.S. Census	Births per 10,000 people	148.0	28.8
County Level Death Rate per 10,000 people, 1990-1999	U.S. Census	Deaths per 10,000 people	83.9	20.1

All variables directly assessed through the NHTS 2001 survey unless otherwise stated. Trips over 100 miles are not included.

Travel behavior is indicated by miles traveled by rail, bus, and car at the household level. These are the primary variables explained by the model.

Five different variables serve as indicators of urban form. Population density is the most basic determinant. Our population density variable represents density of residents in each household's block group. We use the natural log of population density because that transformation has a more normal distribution.

Our land use mix variable, based on the Smart Growth Index Job-population balance, ranges from zero (when the household's area is entirely residential or entirely commercial) to one (where the ratio of employees to population in the household's area is equal to the ratio at the county level). It is defined as:

$$\text{Jobpopmix} = 1 - \frac{|\,\text{worker density}_{\text{tract}} - c * \text{population density}_{\text{block group}}\,|}{\text{worker density}_{\text{tract}} + c * \text{population density}_{\text{block group}}}$$

$$\text{Where } c = \frac{\text{employees}_{\text{county}}}{\text{population}_{\text{county}}}.$$

Two dummy variables (where the variable shows a 'yes' or 'no' for a specific characteristic) account for the size of the metropolitan area in which a household is located. Initial modeling results found the threshold MSA sizes in relation to travel behavior to be 1 million people and 3 million people. Finally, total household distance to work proxies for the geographical location of each household in relation to other regional destinations.

Our model characterizes the transportation system available to each household with two primary variables: rail availability and bus availability. Each of these variables is a transformation of distance to the nearest transit stop. Research shows that the average person is willing to walk around ¾ mile to access rail transit. We calculate our rail availability measure with a logistic transformation such that its value drops most sharply around a ¾-mile distance. The formula used is:

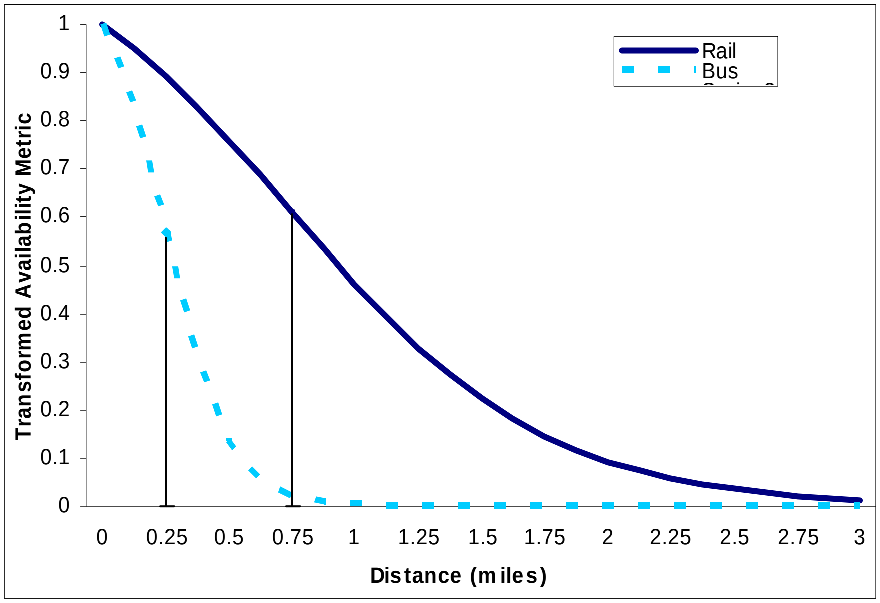
$$\text{Rail Availability} = 1.223 / (1+e^{2*(\text{distance} - 0.75)}).$$

For bus availability, ¼ mile is the distance that most people will walk to a bus stop. We calculate bus availability such that its value drops steeply around ¼ mile, using the following formula:

$$\text{Bus Availability} = 1.135 / (1+e^{8*(\text{distance} - 0.25)}).$$

Figure 4 shows the values of the transformations for a distance of up to three miles.

Figure 4. Transformations of Rail and Bus Availability



The transformed variables vary from 1 (highest availability, when distance is 0) to 0 (lowest availability). Both the rail and the bus availability measures produced significant results in the linear model. A final variable related to the transportation system captures whether the travel day surveyed (by the NHTS) was a weekday or a weekend. This variable accounts for different travel patterns on different days of the week.

Socioeconomic variables account for economic characteristics and household composition. Four dummy variables relate to income and wealth of the household: vehicle ownership status and two dummy variables that account for income level. Other variables account for the age, employment status, and driving status of household members, as well as the relative availability of vehicles.

Two additional variables serve as instruments in the model. These are birth rates and death rates at the county level. As discussed above under SEM, these instrumental variables are related most strongly to population density in the transportation/land use feedback loop.

A number of variables were not included in the model because of inadequate data. Others were excluded because they did not contribute meaningfully to the model. A summary of excluded data is below:

- Road supply: The number of lane miles from the Highway Performance Monitoring System was used as a proxy for road supply, but was insignificant in the model.
- Urban compactness: Compactness, roughly determined by the distribution of population density within an urban area, is another potential indicator of urban form. Cities that are more compact have dense central areas. Less compact

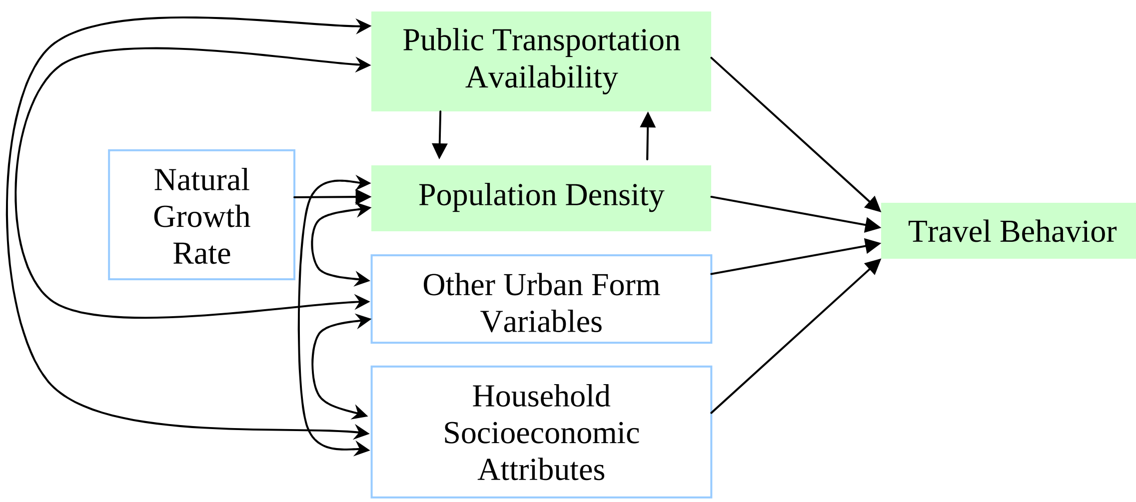
areas have no distinct center. Available data on compactness did not cover our full sample and did not improve the model enough to offset the loss of data.

- Public transit intensity: More regular transit service attracts more riders because of reduced waiting times. However, the data available at the national scale was not detailed enough to allow us to estimate the service frequency by household, and the larger scale data was not significant.
- Land use at the workplace: Population density, mix of uses, and urban design at the workplace are important factors in work-related travel behavior. Because the NHTS does not include detailed data on places of employment, we were unable to include workplace-based variables.
- Pedestrian friendliness: While an index of pedestrian environment would be a beneficial addition to this model, there are no national datasets on this factor.

Detailed Model Results

Figure 5 summarizes the relationships in the final model. Endogenous variables are represented with shaded boxes, and exogenous variables are represented with unshaded boxes. A straight, one-headed arrow from variable category A to variable category B indicates that one or more variables in A are predictors in the equation for a variable in B. Curved, double-headed arrows indicate variables that are allowed to covary without a specified direction.

Figure 5. Schematic Diagram of the SEM



The final model shown has equations predicting population density, public transportation availability (rail and bus), and travel behavior (driving VMT, rail miles traveled, bus miles traveled). Household socioeconomic attributes (e.g., number of adult drivers, family income) and other urban form variables (e.g., distance to work, land use mix) are used as explanatory variables for travel behavior. These variables are also allowed to covary with the public transportation availability measures and population density, which allows the model to account for their relationship without explicitly modeling it (which could introduce problems with model identification or create problems with the key feedback loop). The components of the natural growth rate appear in the equation for population density but not for public transportation availability, allowing the feedback loop to be solved. Due to high levels of multivariate non-normality among the variables used, the model was estimated using the asymptotic distribution-free method.

Tables 5-7 show the unstandardized direct, indirect and total effects of all of the variables in the model on the six endogenous variables. For example, the model predicts that a change of one unit in rail availability (i.e., going from no availability to having a rail stop next door) would have a direct effect of reducing household VMT by -5.8 miles, an indirect effect of -5.2 miles, and a total effect of -10.9 miles.

Table 5. Direct Effects

Explanatory Variable	Endogenous Variable					
	Natural Log of Population Density	Rail Availability Measure	Bus Availability Measure	Miles Driven	Miles Traveled on Rail	Miles Traveled on Bus
Household Travel Behavior						
Miles Traveled on Rail	-0.002	-0.001	-0.003	0.074	-0.003	-0.002
Miles Traveled on Bus						
Miles Driven	-0.002	-0.001	-0.003	0.074	-0.003	-0.002
Urban Form (Land Use)						
Natural Log of Population Density		0.029	0.111	-2.700	0.031	
Measure of Land Use Mix				-1.679		-0.459
In an MSA of 1-3 Million (Dummy)				2.816	-0.103	0.262
In an MSA over 3 million (Dummy)				4.215	0.235	0.457
Total Household Distance to Work						
Transportation System Variables						
Rail Availability Measure	1.530			-5.760	3.429	
Bus Availability Measure	0.225			-2.562	-0.064	0.588
Travel Day is a Weekday				9.155	0.391	0.289
Travel Cost Variables						
Middle Family Income (Dummy)				5.638		
High Family Income (Dummy)				11.148	0.358	-0.099
Household Socioeconomic Attributes						
Vehicle Ownership (Dummy)				11.950	-0.720	-2.293
Ratio of household members age 16+ to vehicles				-6.930	0.133	0.428
Number of School-age Children (Age 6 to 15)				3.346		0.171
Number of Adult Working Non-Drivers				5.781	0.470	1.425
Number of Adult Working Drivers				19.710	0.192	0.141
Other Demographic Variables						
County Level Birth Rate per 10,000 people, 1990-1999	0.015					
County Level Death Rate per 10,000 people, 1990-1999	-0.013					

Table 6. Indirect Effects

Explanatory Variable	Endogenous Variable: Natural Log of Population Density	Rail Availability Measure	Bus Availability Measure	Miles Driven	Miles Traveled on Rail	Miles Traveled on Bus
Household Travel Behavior						
Miles Traveled on Rail						
Miles Traveled on Bus						
Miles Driven						
Urban Form (Land Use)						
Natural Log of Population Density	0.075	0.002	0.008	-0.689	0.102	0.070
Measure of Land Use Mix						
In an MSA of 1-3 Million (Dummy)						
In an MSA over 3 million (Dummy)						
Total Household Distance to Work						
Transportation System Variables						
Rail Availability Measure	0.115	0.048	0.183	-5.185	0.204	0.108
Bus Availability Measure	0.017	0.007	0.027	-0.764	0.030	0.016
Travel Day is a Weekday						
Travel Cost Variables						
Middle Family Income (Dummy)						
High Family Income (Dummy)						
Household Socioeconomic Attributes						
Vehicle Ownership (Dummy)						
Ratio of household members age 16+ to vehicles						
Number of School-age Children (Age 6 to 15)						
Number of Adult Working Non-Drivers						
Number of Adult Working Drivers						
Other Demographic Variables						
County Level Birth Rate per 10,000 people, 1990-1999	0.001	0.000	0.002	-0.051	0.002	0.001
County Level Death Rate per 10,000 people, 1990-1999	-0.001	0.000	-0.002	0.043	-0.002	-0.001

Table 7. Total Effects

Explanatory Variable	Endogenous Variable					
	Natural Log of Population Density	Rail Availability Measure	Bus Availability Measure	Miles Driven	Miles Traveled on Rail	Miles Traveled on Bus
Household Travel Behavior						
Miles Traveled on Rail						
Miles Traveled on Bus						
Miles Driven						
Urban Form (Land Use)						
Natural Log of Population Density	0.075	0.031	0.120	-3.389	0.133	0.070
Measure of Land Use Mix				-1.679		-0.459
In an MSA of 1-3 Million (Dummy)				2.816	-0.103	0.262
In an MSA over 3 million (Dummy)				4.215	0.235	0.457
Total Household Distance to Work						
Transportation System Variables						
Rail Availability Measure	1.644	0.048	0.183	-10.945	3.633	0.108
Bus Availability Measure	0.242	0.007	0.027	-3.326	-0.034	0.604
Travel Day is a Weekday				9.155	0.391	0.289
Travel Cost Variables						
Middle Family Income (Dummy)				5.638		
High Family Income (Dummy)				11.148	0.358	-0.099
Household Socioeconomic Attributes						
Vehicle Ownership (Dummy)				11.950	-0.720	-2.293
Ratio of household members age 16+ to vehicles				-6.930	0.133	0.428
Number of School-age Children (Age 6 to 15)				3.346		0.171
Number of Adult Working Non-Drivers				5.781	0.470	1.425
Number of Adult Working Drivers				19.710	0.192	0.141
Other Demographic Variables						
County Level Birth Rate per 10,000 people, 1990-1999	0.016	0.000	0.002	-0.051	0.002	0.001
County Level Death Rate per 10,000 people, 1990-1999	-0.014	0.000	-0.002	0.043	-0.002	-0.001

After completing the model, we used the results to calculate the total effect of public transportation availability on VMT. Those calculations are shown in Table 8, below.

Table 8. Calculation of National Effect Based on Model Results

Step 1.	Predicted Reduction of VMT Per "Unit" of Rail Availability (from total effects table)	-10.9 VMT (daily)
Step 2.	Average Rail Availability for Households in Sample (from variable summary table)	0.09 on availability scale
Step 3.	Predicted Reduction of VMT Per "Unit" of Bus Availability (from total effects table)	-3.3 VMT (daily)
Step 4.	Average Bus Availability for Households in Sample (from variable summary table)	0.37 on availability scale
Step 5.	Predicted Average Reduction of VMT per Household per Day (Row 1 * Row 2 + Row 3 * Row 4)	-2.2 VMT per household (daily)
Step 6.	Total Number of Households in U.S, 2006	126,316,181 households
Step 7.	VMT Reduced per Day as a Result of Availability (Row 5 * Row 6)	-279,981,596 VMT (daily)
Step 8.	VMT Reduced per Year as a Result of Availability (Row 7 * 365)	-102,193,282,584 VMT (annual)
Step 9.	Average miles per gallon in US vehicles	19.7 miles per gallon
Step 10.	Gallons Reduced per Year as a Result of Availability (Row 8 / Row 9)	-5.2 billion gallons

Notes: Total number of households from http://www.census.gov/popest/housing/HU-EST2006.html

Goodness of Fit Measures

The model performs very well by most measures of model fit. The goodness of fit index, normed fit index, and comparative fit index are all above 0.999, with 1.0 indicating the best fit. The largest absolute residual correlation is 0.0015 (between the bus miles and rail miles), well below a generally used cutoff of 0.10. A measure less sensitive to sample size, the root mean square error of approximation, is 0.011, well below the generally accepted upper bound of 0.050 for a "good" model. Table 9 summarizes goodness of fit measures for the final model.

Table 9. Selected Goodness-of-Fit Measures

Measure	Statistic	Standard for Acceptable Values
Goodness of Fit Index (GFI)	0.99999	Numbers close to 1 indicate a good fit.
Bentler & Bonett's (1980) NFI	0.99970	
Root Mean Square Residual	0.002	<0.0500
Chi-Square	161.5	Some suggested thresholds for the ratio between chi-sq to degrees of freedom include 2:1, 3:1, and 5:1; however, these generally refer to models with much smaller sample sizes. Given the large sample size here, these values are acceptable.
Chi-Square Degrees of Freedom	21	
RMSEA Estimate	0.0099	<0.0500
RMSEA 90% Lower Confidence Limit	0.0085	Close to Zero
RMSEA 90% Upper Confidence Limit	0.0114	<0.0800

The R-squared values from the individual equations are not very high, but typical for household-level data. The household VMT model has an R-Squared of 0.296, in the same range as the values from the initial testing with single equation models. The equations with the poorest R-squared values, rail and bus miles traveled, have the least direct impact on the key relationships of this study. Table 10 shows the R-squared values for the six equations in the final model.

Table 10. R-Squared Values for Individual Equations

Equation	R-Squared
Rail Availability	0.151
Bus Availability	0.348
Natural Log of Population Density	0.252
Household VMT	0.296
Rail Miles Traveled	0.043
Bus Miles Traveled	0.044

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