FHWA Travel Analysis Framework

Development of VMT Forecasting Models for Use by the Federal Highway Administration

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John A. Volpe National Transportation Systems Center

Research and Innovative Technology Administration

Don Pickrell
David Pace
Jacob Wishart

Contents

Introduction

This document details the process that the Volpe National Transportation Systems Center (Volpe) used to develop travel forecasting models for the Federal Highway Administration (FHWA). The purpose of these models is to allow FHWA to forecast future changes in passenger and freight vehicle use (as measured by the number of vehicle-miles traveled, or VMT) that is likely to occur in response to predicted demographic trends and changes in future economic conditions. These models also provide estimates of the volumes of gasoline, diesel, and other fuels consumed by motor vehicles, which are derived from its projections of future vehicle travel and fuel economy.[1] Forecasts of VMT developed using this model will inform and support the development of future Federal transportation planning and policy.

The FHWA VMT forecasting models provide forecasts of VMT for the entire U.S., as well as for individual states. These forecasts are disaggregated into four vehicle type categories, as defined by FHWA: light-duty passenger vehicles, including automobiles and light-duty trucks (FHWA Vehicle Classes 1, 2, and 3); buses (FHWA Vehicle Class 4); single-unit trucks (FHWA Vehicle Classes 5, 6, and 7); and combination trucks (FHWA Vehicle Classes 8 through 13). At the national level, VMT is also decomposed by roadway functional classification (interstate highways versus other highways and roadways) and location (urban and rural). State-level VMT forecasts are provided for three different vehicle classes: light duty vehicles, single-unit trucks, and combination trucks.

In addition to the econometric approaches used to construct the aggregate national- and state-level VMT models, the FHWA models include a methodology for forecasting national VMT from a vehicle fleet perspective. This component of the VMT models disaggregates nationwide total VMT by vehicle class, model year or vintage, and vehicle age. The aggregate national-level VMT models for each vehicle type were estimated and used as control totals for lower-level (functional classification, fleet, and state-level) models; for example, VMT forecasts for the 50 individual states (plus the District of Columbia) are constrained so that their sum equals the forecast of nationwide total VMT produced by the national model.

The FHWA VMT forecasting model was calibrated using widely-used statistical and econometric techniques to estimate the influence of underlying economic and demographic factors on passenger and commercial vehicle use. Forecasts of these underlying demographic trends and economic factors are used in conjunction with the model's individual equations to develop forecasts of future travel demand and VMT growth.

The sections that follow describe the model development process, including the specification and econometric estimation results of the equations that comprise the final set of VMT forecasting models. The first section discusses the economic theory of travel demand, which provided the theoretical basis for identifying and selecting appropriate economic and demographic variables—those likely to influence the demand for vehicle trips—for testing and inclusion in the forecasting models.

The second section details the methodology employed in developing the forecasting equations and selecting the most reliable versions. It describes the statistical tests and criteria used to ensure the final selected equations combine historical explanatory power with accurate forecasting performance.

[1] FHWA's projections of fuel consumption are not intended to replace the more detailed and comprehensive forecasts of transportation energy use produced by the U.S. Energy Information Administration and reported in its Annual Energy Outlook (see http://www.eia.gov/forecasts/aeo/index.cfm).

Subsequent sections of the report provide details of the specific models themselves. These sections offer further insight into the key influences on VMT incorporated in each individual equation, while also providing a more detailed look at the mechanics of the fleet model. The national-level VMT forecasting models are addressed first, followed by the functional class models. Following the functional class models is a discussion of the structure of the state-level VMT forecasting model. Lastly, the structure and mechanics of the fleet model is examined in detail.

Details of the baseline VMT forecasts and the accompanying model tool are available from FHWA by contacting:

Patrick Zhang
FHWA, Room E83-451
U.S. Department of Transportation
1200 New Jersey Avenue, SE.
Washington, DC 20590
202-366-1941

Economic Theory of Travel Demand

Vehicle travel is often described as a derived demand, meaning that a trip taken in either a passenger or commercial vehicle is typically a means to transport passengers or freight from their original location to a desired geographic destination. Generating predictions of how the amount of travel will change in the future thus requires an understanding of the factors that motivate passenger travel and freight shipments, as well as expectations about how these explanatory factors will change going forward.

In the case of passenger VMT, economic theory suggests several factors that exert strong influence on household ownership and use of motor vehicles. The primary determinants of personal motor vehicle travel are household demographics—including the total number of households and their distribution by size, composition, and geographic location—and their economic circumstances, particularly their employment status and income levels. These factors collectively affect household members' participation in activities outside of the home – working, shopping, conducting personal business, recreation, etc. – which is the underlying source of their demand to travel. In turn, household members choose among non-motorized forms of travel (such as walking and cycling), public or school-provided transportation services, and travel in personal motor vehicles to satisfy their demands for travel.

The primary determinant of truck travel is likely to be the overall level of business or economic activity, particularly in manufacturing industries (as distinct from service industries), since goods production and distribution involves extensive movement of both raw materials and finished goods. Because some specific categories of economic activity such as construction and international trade generate particularly large volumes of freight movement, the composition of overall economic activity can also be an important determinant of total truck use.

The price of motor vehicle travel is also a major influence on the demand for travel. In the case of personal vehicles, the price of vehicle use includes the value of the driver's and any other occupants' travel time, mileage-related depreciation of the vehicle itself, the cost of fuel consumed, prices for other operating and maintenance inputs, and any charges levied for roadway use or parking at trip destinations or stop-over points. For freight-carrying trucks, the price of travel includes the driver's wage rate, use-related vehicle depreciation, fuel and other vehicle operating costs, vehicle maintenance, and the inventory value of freight or cargo being carried. In addition, the geographic distribution of households, employment opportunities, production and warehousing facilities, and shopping and recreational destinations are likely to influence the use of both passenger vehicles and freight trucks.

Recent research examining the economic and demographic influences on travel demand indicates that the contributions of these factors to total VMT growth have been changing over time.[2] An example of this is growth in the number of licensed drivers, which has slowed as the fraction of the age-eligible population holding drivers' licenses approaches the saturation point (Figure 1). Growth in licensed drivers was once a key component of increasing passenger VMT: between 1950 and 1960, nearly half of

[2] For example, see David A. Hensher, Nariida C. Smith, Frank W. Milthorpe, "The Demand for Vehicle Use in the Urban Household Sector, Theory and Empirical Evidence," ***Journal of Transport Economics and Policy*** (1990); Don H. Pickrell, "Description of VMT Forecasting Procedure for "Car Talk" Baseline Forecasts," Volpe Center, U.S. Department of Transportation (1995); and Steven E. Polzin, "The Case for Moderate Growth in Vehicle Miles of Travel, A Critical Juncture in U.S. Travel Behavior Trends," Center for Urban Transportation Research, University of South Florida, report to U.S. Department of Transportation (2006).

the growth in passenger vehicle use was associated with an increase in the number of licensed drivers.[3] By the 1980s, however, the contribution of increases in the number of licensed drivers to growth in vehicle travel diminished sharply as the fraction of those already licensed moved toward saturation, and the more recent decline in VMT has accompanied a slight decline in the fraction of the eligible population holding drivers' licenses. Over this same time, factors such as personal income, labor force participation – particularly among women – and the costs of owning and operating personal vehicles also varied in ways that influenced growth in the use of personal vehicles.

Figure 1: Licensed Drivers as a Percent of Driving Age-Population

(Source: FHWA Highway Statistics, U.S. Census Bureau)

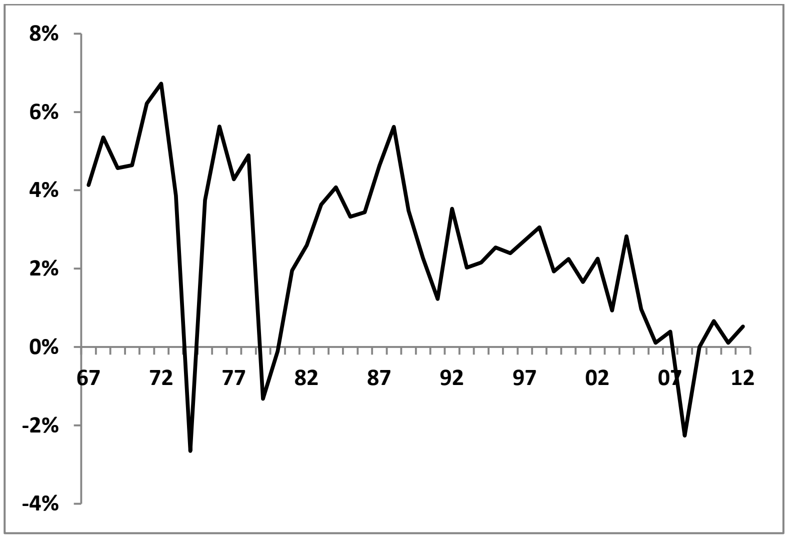
Changes in the price of gasoline have historically had a pronounced effect on the demand for vehicle travel: for example, the sharp oil price spikes of the mid-1970s and early 1980s, together with the accompanying economic recessions, exerted strong downward pressure on VMT growth. However, a subsequent sharp drop in petroleum prices during the mid-1980s was partly responsible for the resumption of growth in vehicle use. Other factors whose effect on VMT growth has varied widely over time include changes in the distribution and density of the U.S. population, including major shifts in population between regions of the country, between urban and rural locations, and within many major metropolitan areas.

Since the mid-1970s there has been a gradual downward trend in the rate of VMT growth, and year-to-year variation in travel growth rates has become less pronounced over time (Figure 2). Within this long-term trend, however, there have been shorter periods during which VMT growth advanced strongly; this was particularly evident during the mid-1980s, when the U.S. economy's emergence from recession combined with the sharp decline in petroleum prices from their early-decade highs to produce a surge in VMT growth. The 1990s, a period of sustained economic growth and low oil prices, also showed short periods of strong VMT growth.

[3] More specifically, if the annual VMT per licensed driver had remained at its 1950 level, growth in the number of licensed drivers would have resulted in half of the growth in total annual VMT that actually occurred between 1950 and 1960.

More recently, the sharp increase in gasoline prices beginning in 2008 combined with the subsequent deep recession and other developments to produce a prolonged period of declining vehicle use. Unlike the pattern observed after previous post-war recessions, vehicle use still remains below its mid-2000s peak, prompting extensive speculation about the causes of its prolonged decline and prospects for a resumption of growth in travel.

Figure 2: Light Duty Vehicle Miles Traveled (Annual Percent Change 1967 – 2012)



(Source: FHWA Highway Statistics)

Although this discussion has focused primarily on passenger vehicle travel, developing approaches to modeling truck VMT is also important. While truck use represented only about 10% of total VMT in 2012 (Figure 3), freight traffic is a central component of the nation's transportation activity. Truck use is also an important consideration for infrastructure investment policy, since trucks are responsible for a large portion of highway wear and tear, and may contribute disproportionately to congestion and road safety conditions. Trucks also play an important role in the national economy; in 2002 trucks moved 58% and 64% of all commercial freight, as measured by weight and value, respectively. More recently, rapid growth in the international trade in goods has relied largely upon trucks to move imports and exports between U.S. coastal ports and inland distribution centers.

Figure 3: Truck VMT as a Percent of Total VMT

(Source: FHWA Highway Statistics)

Because of the importance of freight transportation, careful consideration was given to distinguishing the factors likely to influence truck travel from those more likely to affect the use of passenger vehicles. In particular, since the demand for truck use is largely derived from raw materials shipments to supply manufacturing and distribution of finished goods, particular attention was paid to including various measures of manufacturing activity and goods production and delivery. These include the fraction of total economic activity accounted for by goods production, the volume of international trade, and the value of mail-order and internet sales, which substitute increased truck use for home delivery for shoppers' travel to and from retail stores.

Model Development Methodology

A major challenge in developing VMT forecasting models arises in when comparing and selecting the best specification from among multiple alternative possibilities (ranging into the hundreds). To meet this challenge, this effort employed a comprehensive and systematic approach to model development, evaluation, and selection.

The first step in the model development process was identifying the factors likely to influence vehicle use. Guided by the economic theory of travel demand, these factors were selected separately for each vehicle category: light-duty vehicles, single-unit trucks, combination trucks, and buses. Within each broad category of underlying influences on vehicle use, alternative measures were identified for potential inclusion in varying model formulations; for example, household income levels could alternatively be measured by total or per capita GDP, total or per capita disposable personal income, median household income, and other measures. Table 1 summarizes the broad categories of explanatory variables and the alternative measures that were used to represent each category.

Historical data are drawn from a range of sources, most of which are publicly available. These include FHWA (notably, its annual *Highway Statistics* publication), the Energy Information Administration, R.L. Polk, the U.S. Bureau of the Census, and the U.S. Department of Labor. The historical range over which the national-level models are estimated spans 47 continuous years for light-duty vehicles, and 43 years for trucks and buses; these data series begin in 1966 and 1970, respectively. Data used in the state-level models were collected from 1993 onward.

An important category of variables that was explored comprises data representing land use; that is, measures capturing the geographic distribution of the population—particularly, its density within and dispersion around central cities, and its distribution between urban and suburban regions of metropolitan areas. At the nationwide level, however, no suitable measure of the influence of land use on motor vehicle travel could be identified. Candidate measures either did not display sufficient variation over time to identify their influence on vehicle use, or were inadequately or inconsistently defined at the national level throughout the historical period used to develop the models. At the state level, however, one land-use measure was included in the final model specification: the percent of each state's population living within the boundaries of its metropolitan statistical areas (MSAs).

The economic and demographic variables selected as candidates for testing were then entered into a model specification matrix. Within this matrix, alternative model specifications were carefully designed to test and compare how effectively each variable captured the underlying influences it was intended to measure, both individually and in conjunction with other important determinants of VMT. This allowed for examination of the stability and robustness of each individual variable in its relationship to vehicle use, particularly when combined with other explanatory influences, and also enabled easy tracking of the many specifications that were tested. At the national level, approximately 300 different model specifications were examined for each vehicle class as part of this process.

Table 1: Alternative Variables Tested in Modeling Procedures

Variable Type	Light-Duty	Single-Unit Trucks	Combination Trucks
Dependent Variable	Total Annual VMT*†	Total Annual VMT	Total Annual VMT
Demographic Characteristics	Total Population Percent of Population Aged 20-65 Yrs. Number of Households Average Persons per Household Percent of Households that are Families Percent of Families with Children < 18 Yrs. Percent of Population in Urban Areas Regional Population Variables	[no variables]	[no variables]
Economic Activity/Income Measures	Total GDP*† Disposable Personal Income*† Median Household Income Consumer Confidence Index	Total GDP Real Value of Durable Nondurable Goods Real Retail Sales Real Retail Sales (% of GDP) Electronic and Mail-Order Sales (as % of Retail Sales) Real Value of Service Sector (% of GDP) Real Consumer Spending Real Private Fixed Residential Investment	Total GDP* Value of Durable plus Nondurable Goods Value of Durable plus Nondurable Goods (% of GDP) Imports plus Exports of Goods (% of GDP) US Industrial Production Diesel Price per gallon
Cost of Driving	Gasoline Price per Gallon Fuel Economy (MPG) Fuel Cost per Mile Driven	Diesel Price per Gallon Single Unit Truck MPG Fuel Cost per Mile Driver Wages	Diesel Price per Gallon Fuel Cost per Mile Driver Wages Combination Truck MPG
Vehicle Price	New Vehicle Price Index Used Vehicle Price Index Vehicle Parts and Price Index New Vehicle Price Index/Consumer Price Index New Vehicle Real Sales Price	Producer Price Index (Transportation Equipment) New Vehicle Price Index	Producer Price Index (Transportation Equipment) New Vehicle Price Index
Road Supply	Total Road-Miles*† Road-Miles per Vehicle	Total Highway-Miles Total Highway-Miles per All Vehicles Highway-Miles in Urban Areas Percent of Population in Urban Areas	Total Highway Miles per All Vehicles Total Highway-Miles Total Public Road-Miles
Employment	Total Employment Labor Force Participation Rate (%) Employed Persons per Household	[no variables]	[no variables]
Transit Service	Vehicle-Miles of Bus and Rail Transit Service* Vehicle-Miles of Rail Transit Service* Number of Cities with Rail Transit Service	[no variables]	[no variables]

Entries marked with "*" were examined in per capita terms
Entries marked with "†" were examined in per household terms

The strength of each model specification was judged based upon several statistical criteria, including:

- Plausibility of the arithmetic signs and magnitudes of the estimated coefficients on each explanatory variable included in the specification

- Precision and statistical significance of estimated coefficients
- Tests for serial correlation in model residuals or error terms
- Adjusted R-squared value and other measures of goodness of fit of the overall model
- Mean absolute percent error and other indicators of accuracy for within-sample and out-of-sample forecasts generated using each specification

The primary aim of this model-building procedure was to develop a model that forecasts accurately—in other words, to minimize *total* forecasting error. The error in the forecasts produced using a given model can be separated into two components. First, future values of the model's explanatory (or input) variables are unknown and must themselves be forecast; "input error" refers to the component of error in the model's forecast that can be attributed to imperfect predictions of its input variables. Minimizing such input error will tend to favor the development of parsimonious models: the smaller the number of input variables a model includes, the lower the combined uncertainty of the predictions of these variables.

"Specification error," on the other hand, is the component of error inherent in the design and calibration of a particular model. This error reflects how well the variables it includes (and the relationships expressed by their estimated coefficients) capture the "true" determinants of the dependent variable. If a model is poorly designed— for example, if it excludes important variables, includes variables that do not belong, or its functional form causes it to understate or exaggerate the contributions of certain explanatory variables— the forecasts it produces will exhibit high specification error, even when they are generated with perfect foresight about the model's input variables. Minimizing specification error would generally lead the model developer to include more, rather than fewer, explanatory variables, so as not to omit any important influences from the model. Thus, attempts to reduce each type of error will frequently entail conflicting recommendations for the model-building procedure.

The emphasis during the testing process was placed on models exhibiting the lowest level of specification error. In isolating the magnitude of specification error from that of input error, the mean average percentage error (MAPE) statistic is a particularly useful tool. The relative extent of the two error components for a given model can be examined by comparing the MAPEs calculated from out-of-sample and in-sample forecasting tests. Specifically, the accuracy of a model's in-sample "forecasts," which are constructed using the actual historical values of its explanatory variables, provides a measure of its specification error. This form of error was also examined by using the models to generate out-of-sample forecasts, which are constructed using the known values of the explanatory variables to forecast VMT for part of the historical period over which the model was calibrated. The model's accuracy can then be examined by comparing its forecasts of vehicle use against their actual values for this part of the period.[4] The final model selection process aimed to ensure high forecasting accuracy, while also insuring the structural integrity of the model by including all theoretically influential and significant factors.

[4] As an illustration, the most promising alternative model specifications were re-estimated over a period ending in 2005, and then used in conjunction with the actual values of their explanatory variables to produce VMT "forecasts" for 2007-12. The forecasting accuracy of the models in this test – particularly their ability to predict the downturn in total VMT beginning in 2007 and its sustained sluggishness – is a particularly useful test of their likely future forecasting performance.

Data Considerations

During the model development process, particular attention was paid to issues that commonly arise due to the time series nature of economic data. One particular concern is the presence of autocorrelation in the residuals of an econometric equation, which occurs when the unexplained residual or error terms in successive time periods tend to be correlated. Another concern is the potential existence of strong underlying time trends or unit roots in the individual variables used to estimate model parameters, and the potential for accompanying cointegration between the model's dependent variable and its explanatory variables. In the presence of such cointegration, relying on standard statistical estimation and diagnostic methods may lead to the development of models that appear reliable, but embody spurious associations rather than stable behavioral relationships.

Autocorrelation

If autocorrelation is present, regression coefficients will be inefficiently estimated (although their estimates remain unbiased), normal significance tests are not valid, and the performance of the forecast from the equation is not as good as it could be. Autocorrelation can occur if the model's specification does not accurately reproduce fluctuations in the growth of its dependent variable over time, or conversely, if the model predicts more variation in the growth of its dependent variable than has actually occurred over time. This problem can also arise if the explanatory variables in an equation are themselves autocorrelated, which is often the case with economic time series data (i.e., the current value is correlated with the previous value). Indeed, the fact that many economic time series increase over time (i.e., the mean of the series does not remain constant) often leads to problems with autocorrelation, as well as to the related problems of unit roots and cointegration.

Remedies for autocorrelation, which were examined and used during the model building process, include introducing a lagged dependent variable into the equation, adding an auto regressive term or estimating the equation in differences to make the time series data stationary.

Unit Roots

The presence or absence of a unit root is one way to characterize the underlying temporal structure of a data series. The absence of a unit root essentially means that the data series lacks a trend, and instead varies around a stable mean; such a variable is referred to as stationary. Its average may be positive, negative, or zero–as long as it remains approximately constant. Conversely, the presence of a unit root implies that the variable is non-stationary–its mean is either rising or declining consistently over time, in which case the change in its value between two successive time periods tends to be approximately constant. The existence of unit roots is often discussed in terms of whether the series is "integrated;" a series is integrated of order one when the first difference of the variable is stationary, or the difference between successive values is roughly constant.

Many of the economic variables included in the models have unit roots (or are integrated of order one); in practical terms, these series typically show a steady upward trend over time.[5] A similar pattern can be seen in the dependent variable (vehicle use, as measured by VMT) as well. In the presence of unit roots, the standard errors estimated via the models may be inaccurate, leading to improper inference about the significance of the model coefficients. More important, estimated relationships that fit the data well and appear to reflect causal association may in fact be spurious if their variables have unit roots.

[5] Similarly, a variable is integrated of higher orders when the variable must be differenced more than once to produce a stationary series. However, series that are integrated of more than order one are uncommon in econometric analysis.

Cointegration

Cointegration is a concern related to the unit root issue; while the presence of a unit root is a characteristic of an individual variable, cointegration is a property of multiple variables. In practical terms, two variables that have unit roots and share a common underlying trend are cointegrated, in the sense that they tend to increase (or decline) over time in a consistent pattern.[6] Thus growth in one of two cointegrated variables can appear to cause the other to grow, when in fact they simply happen to share similar underlying trends and their apparent relationship is spurious.[7]

Nevertheless, cointegration can provide useful information regarding the long-run equilibrium relationship between two variables. The fact that they share underlying trends means that the value of one variable may be useful in producing a more reliable prediction of the value of the other, although the resulting prediction is of course still prone to random variation. Estimating and utilizing cointegrating relationships offers an alternative to differencing time series as a means of resolving the problems that unit roots introduce. That is, if cointegrating relationships are detected among the variables included in a proposed model specification, they can sometimes be exploited to estimate its coefficients more reliably, and thus to improve its forecasting performance.[8]

During the model development process, every variable was first tested for the presence of a unit root. Extensive testing was then conducted to identify the existence of cointegration between pairs of variables displaying unit roots, focusing particularly on cointegration between the VMT measures to be used as dependent variables in the models and the candidate explanatory variables listed previously in Table 1.[9] These tests indicated the presence of unit roots in some variables, as well as some degree of cointegration among the variables included in many of the proposed model specifications.

Accordingly, alternative econometric estimation procedures were tested for their effectiveness in using cointegrating relationships to improve these specifications and develop models that produced more reliable forecasts. These alternative approaches included estimating single-equation error correction models in cases where tests showed only limited cointegration between a model's dependent variable and its candidate explanatory variables. Where potential simultaneity among a model's variables was suspected and tests detected more pervasive cointegration among them, multi-equation vector autoregression (VAR) models that included error correction terms (often referred to as vector error

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[6] Technically, two non-stationary variables are cointegrated if there exists a linear combination of the variables that is stationary. For example, if two series x and y are integrated of order one, but a third variable z can be created as some linear combination of x and y (say, the difference between x and y) and has no unit root itself, then x and y are cointegrated.

[7] Engle, Robert F., Granger, Clive W. J. (1987) "Co-integration and error correction: Representation, estimation and testing", ***Econometrica***, 55(2), 251-276.

[8] The usual procedure for doing this is to use the residual terms from estimated cointegrating relationships, which provide a measure of the extent to which the values of two cointegrated variables during a specific time period diverge from their common underlying trends, as additional explanatory variables in a model relating changes in the same two variables to each other. Because cointegrating relationships in theory capture useful information about long-term equilibrium relationships between variables, exploiting these relationships in constructing models is often preferable to simply differencing the individual series and using their differenced values to estimate the relationship between their period-to-period changes.

[9] The augmented Dickey-Fuller test was used to check for the presence of unit roots in individual variables. The Engle-Granger test was relied on to detect cointegration between individual pairs of variables, while the more complex Johansen test was used to analyze the presence of multiple cointegrating relationships

correction models) were tested for their ability to improve econometric results and produce more reliable forecasting models.

Despite extensive experimentation with both approaches, neither single equation nor vector error correction approaches proved successful in using information from estimated relationships between cointegrated variables to improve the econometric performance or predictive reliability of the VMT forecasting models. That is, neither approach yielded econometric results that appeared to improve the models. Using single-equation error correction specifications produced models that were very similar to the analogous versions of the same equations estimated using ordinary least squares (OLS) regression, while vector error correction models consistently showed little statistical significance or explanatory power. These result suggested that standard ordinary least squares (OLS) regression produced acceptably accurate representations of the relationships being modeled, and the OLS-estimated versions of the VMT models would provide reasonably reliable forecasts.

Forecast Data

Forecasts of the input variables come from three sources: IHS Incorporated (IHS), the Energy Information Administration (EIA), and the Volpe Center. IHS provides the majority of the variables used in forecasting for the national, state, and fleet models. Forecasts of the changing distribution of total fuel consumption by specific type of fuel are drawn from the U.S. Energy Information Administration's ***Annual Energy Outlook***. The Volpe Center developed independent forecasts of road supply and truck fuel efficiency; Volpe's forecasts employed growth rates of light-duty fuel efficiency that were previously developed for NHTSA as part of its analysis of future Corporate Average Fuel Economy (CAFE) standards. Both IHS and EIA provide scenario-based forecasts (i.e., a baseline and high and low growth outlooks). The Volpe-produced forecasts are not constructed around the same scenarios, but can be modified to produce alternative future outlooks.

IHS Forecasts

IHS provides forecasts for three potential macroeconomic outlooks, referred to as the baseline, optimistic, and pessimistic scenarios. The optimistic and pessimistic scenarios are to be considered relative to the baseline. The optimistic scenario has relatively high U.S. economic growth and low world oil prices, while the pessimistic scenario combines relatively low domestic economic growth with high world oil prices. Table 2 shows the forecast growth rates of several important aggregate economic indicators for each scenario, to illustrate the differences among the alternatives.[10]

Table 2: 30-Year Annual Growth Rates for Selected Economic Indicators

	Baseline Scenario	Optimistic Scenario	Pessimistic Scenario
GDP	2.5%	2.9%	1.9%
Employment	0.8%	1.0%	0.6%
Goods Production	3.1%	3.6%	2.1%
U.S. Population	0.7%	0.8%	0.6%
Gasoline Prices	-0.4%	-0.6%	-0.4%

EIA Forecasts

Forecasts of the fractions of total energy use by light-duty vehicles and trucks represented by different fuel types were obtained from the most recent edition of the U.S. Energy Information Administration's

[10] These data are from the IHS April 2014 U.S. Macro long-term forecast

Annual Energy Outlook.[11] These were aggregated to produce estimated shares of total fuel energy consumption represented by gasoline, diesel, other liquid fuels (including ethanol and liquid petroleum gas), gaseous fuels (natural gas and hydrogen), and electricity.

Volpe Forecasts

The data series forecast by Volpe were those that were not available from external sources, and thus they are not tied to specific future scenarios. Future fuel economy of the light-duty vehicle fleet will be heavily dependent upon the corporate average fuel economy (CAFE) standards. The baseline forecast of average fleet-wide fuel economy was based on Volpe's analysis of fuel economy trends for NHTSA, which accounts for expected future increases in CAFE standards and fuel efficiency standards for medium- and heavy-duty trucks.[12]

Road-supply variables appear in both the national- and state-level models. In most cases the Volpe forecasts simply extrapolate historical trends in total road mileage, while also considering whether historical growths rates might reasonably be expected to moderate over the future. For example, construction of the U.S. Interstate Highway System is now largely complete, meaning that future growth in Interstate Highway mileage is likely to be close to zero. Volpe's forecasts of road supply growth in urbanized and rural areas account for differences in their historical rates of road construction activity, as well as for the effect of gradual reclassification of rural territory at the boundaries of growing metropolitan areas to urbanized status.

A similar approach was applied to produce the state-level road-supply forecasts. Specifically, each state's historical growth rate in total roadway mileage over the last 16 years was applied annually each year in the forecast period. In some specific instances, however (such as where data were unavailable or were determined to be inaccurate, or where historical growth rates were judged to be unsustainable), a state's future growth rate was further constrained to prevent unrealistic forecasts.

National Aggregate Travel Forecasting Models

The FHWA travel forecasting system includes separate models to forecast nationwide total vehicle-miles traveled by four separate vehicle classes: light-duty vehicles (automobiles plus light trucks used primarily as passenger vehicles), single-unit trucks, combination trucks, and buses. The four national-level models are similar in structure and in the types of explanatory variables they include. This is particularly the case with regards to the light-duty, single-unit, and combination truck models; although the bus travel forecasting model has a similar economic structure, due to the difficult nature of forecasting bus VMT, it includes slightly different categories of variables.[13]

In general, each model includes one or more measures of the level and composition of the specific components of economic activity that affect demand for personal travel or freight shipping. For example, truck usage is influenced by the level of real GDP, as well as the fraction of GDP accounted for by specific economic sectors such as manufacturing, construction, and international trade. Similarly,

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[11] U.S. Department of Energy, Energy Information Administration, ***Annual Energy Outlook 2014***, http://www.eia.gov/forecasts/aeo/index.cfm.

[12] See NHTSA, *Environmental Impact Statement for the Joint Rulemaking to Establish CAFE and GHG Emissions Standards, MY 2012-2016* (2010). Available from http://www.nhtsa.gov/fuel-economy.

[13] The difficulty of forecasting nationwide bus VMT arises from the fact that buses serve several distinct markets, each with different influences on demand: urban public transit, intercity coach travel, charter and commuter service, and school travel.

light-duty vehicle use is partly a product of real personal disposable income, since this variable influences household members' opportunities to participate in activities that require travel away from home. Household characteristics such as average size, number of children, age distribution of members, metropolitan location, and distribution by geographic region were also expected to affect the volume of light-duty vehicle travel, but their effects generally proved difficult to identify.

Each model also includes a measure of fuel cost per mile driven, which is equal to fuel price per gallon divided by average fuel economy in miles per gallon for the relevant vehicle class. This variable is intended to capture the fuel-related cost of driving, which is typically the largest component of the total cost of operating each type of vehicle. Although there are several alternative measures of fuel-related costs, fuel price divided by fuel efficiency was preferred because it accurately reflects the independent influences of both variables on vehicle operating costs.[14] The effects of vehicle purchase prices and ownership costs on aggregate vehicle use were also tested in the VMT forecasting models for each vehicle class, but the influence of these variables on vehicle use was difficult to detect.

Measures of aggregate highway mileage or average highway miles per registered vehicle were also included in the national-level VMT forecasting models for single-unit and combination trucks. These variables were intended to capture the effect of road capacity and the intensity with which it is utilized on travel speeds, which in turn are expected to influence demands for personal travel and freight shipping. Measures of the supply and prices of competing travel modes – public transit service levels and fares, as well as rail shipping rates – were also tested for their influence on aggregate light-duty vehicle and truck use, but no such effects could be detected.

Light-Duty Vehicles

As Table 3 shows, the national light-duty vehicle forecasting model includes personal disposable income per capita, average fuel cost per mile, and a measure of consumer confidence in the economic outlook. Personal disposable income per capita enters the equation in both linear form, and with a squared term; the estimated coefficient on the linear term is positive, while that on the quadratic term is negative. This implies that personal disposable income per capita has a positive impact on VMT (that is, as household income levels rise, vehicle use per person increases), but that the magnitude of this effect declines as income rises.

Table 3: Explanatory Variables Included in Light-Duty VMT Forecasting Model*

Variable	Coefficient	Functional Form
Lagged dependent variable	**0.6274**	**Log**
Personal disposable income per capita	**1.7217**	**Log**

[14] This specification implies that the effects of variation in fuel prices and average fuel economy on the demand for vehicle use that are equal in magnitude but opposite in direction. While some research suggests that fuel prices and fuel efficiency may have different effects on vehicle use, when these variables were entered separately the estimated magnitudes of their effects did not differ significantly from each other for any of the four vehicle classes.

Personal disposable income per capita squared	**-0.2304**	**Log**
Fuel cost per mile	**-0.0292**	**Log**
Consumer confidence index	**0.0565**	**Log**

* Dependent variable is log of annual light-duty VMT per Capita.

The negative sign on the squared disposable income variable presumably captures the increasing opportunity cost of driving: at high levels of income, household members' time becomes so valuable that they choose to spend less of it travelling. Throughout the forecast period, the linear term dominates, and the effect of an increase in personal disposable income continues to produce an increase in VMT. However, by about the year 2025, the model predicts that the opportunity cost of driving will have increased to the point where it causes the growth rate in VMT to slow noticeably.

Fuel cost per mile appears with a negative coefficient, indicating that as the cost of driving increases, households choose to travel less. As expected, higher consumer confidence in the future of the economy is associated with an increase in the number of vehicle-miles driven per person.

As Table 3 also indicates, the light-duty VMT forecasting equation also includes the previous period's value of the dependent variable. The significance of this variable implies that aggregate light-duty vehicle use adjusts gradually to changes in disposable income, fuel costs, and prices for new vehicles. Specifically, the magnitude of its estimated coefficient suggests that the effects of changes in these factors on VMT are only partly felt in the year when they occur, and require almost three years to be felt completely. This presumably reflects the existence of structural inertia in households' decisions affecting travel demand and vehicle use, such as where their residences or workplaces are located and the number of vehicles they own. As a consequence, the longer-term effects of changes in income levels, fuel costs, and vehicle prices are nearly three times as large as their immediate effects, but require approximately three years to be realized fully.

Single-Unit Trucks

The national single-unit truck VMT forecast is a function of consumer spending, residential construction activity, and fuel cost per mile. Table 4 shows that the estimated coefficients on each of these three variables are positive, which is the expected result for consumer spending and residential construction, but opposite of that anticipated for fuel cost per mile.[15] The "jackknife" specification of this equation allows the effects of each of these variables to increase after 1994, with the effects of residential

[15] The coefficients on fuel cost per mile variables are statistically insignificant and indistinguishable from 0. Nevertheless, despite the suggestion from this result that fuel cost per mile is not a significant determinant of VMT at an aggregate national level, which possibly could be the case if fuel is not a completely transparent component of final invoice cost in this market, these variables were left in the equation to maintain theoretical completeness of model specification. While its' forecasting performance is satisfactory, the specification of the single unit truck equation remains under investigation and with the inclusion of more data will likely be updated prior to the next forecast release in May 2015.

investment increasing after that date, while that of consumer spending becomes significantly less pronounced.

Table 4: Explanatory Variables Included in Single-Unit Truck VMT Forecasting Model*

Variable	Coefficient	Functional Form
Lagged dependent variable	0.6286	Log
Consumer spending	0.2507	Log
Private residential investment	0.0694	Log
Fuel cost per mile	0.0023	Log
Consumer spending X Jackknife	-0.1875	Log
Private residential investment X Jackknife	0.0642	Log
Fuel cost per mile X Jackknife	0.0697	Log
Jackknife	1.4443	Level

*Dependent variable is log of annual single-unit truck VMT.

As with the light-duty VMT forecasting equation, the past period's level of single-unit truck VMT is an important predictor of VMT in the current period, as indicated by the inclusion of the lagged value of the equation's dependent variable. Again, the magnitude of its effect indicates that the response of single-unit truck use to changes in consumer spending and residential construction activity require nearly three years to be felt completely. The time lag required for use of single-unit trucks to adjust to changes in economic activity of may reflect factors such as the prevalence of long-term contracts for transportation services, difficulties in adjusting service frequency or routing decisions for goods delivery and distribution services, and rigidities in the market for drivers' services.

Combination Trucks

As Table 5 shows, the national aggregate forecasting model for combination truck VMT includes real GDP, fuel cost per mile, and the extent of the U.S. Interstate Highway system (measured as center-line miles rather than lane-miles). As expected, the coefficient on real GDP is positive, implying that growth in overall economic activity increases demand for the longer-distance shipping services typically provided using combination trucks. Fuel cost per mile appears with a negative sign, again as expected, which suggests that declining retail fuel prices or improvements in combination-truck fuel economy will also increase shipping activity using combination trucks. Not surprisingly, combination truck use is closely related to the extent of the U.S. Interstate Highway System, since its nationwide geographic coverage, connectivity, and generally higher travel speeds are ideally suited to combination truck operations.

Table 5: Explanatory Variables Included in Combination Truck VMT Forecasting Model*

Variable	Coefficient	Functional Form
AR(1)	**0.6962**	**Log**
AR(2)	**0.2251**	**Log**
Real GDP	**0.5580**	**Log**
Fuel cost per mile	**-0.0750**	**Log**
Interstate center-line miles	**0.6174**	**Log**
Real GDP X Jackknife	**1.1496**	**Log**
Fuel cost per mile X Jackknife	**0.0662**	**Log**
Jackknife	**-10.0536**	**Level**

*Dependent variable is log of annual combination truck VMT.

Like the forecasting equation for single-unit trucks, the specification of the VMT forecasting model for combination trucks allows the effects of its explanatory variables to change during the estimation period. In the case of the combination truck model, the effect of GDP becomes significantly less pronounced after 1980, while that of fuel costs becomes much more important after that year. This probably reflects the effect of deregulation of interstate trucking services beginning about that year, which allowed carriers to exercise much more flexibility in pricing truck services to reflect variation in their costs by shipment distance, origin and destination, and time.

Unlike the light-duty and single-unit truck equations, however, the combination truck model does not include a lagged dependent variable, although it does employ terms intended to correct for the effects of autocorrelation in the model's error terms. This specification suggests that freight shipping activity using combination trucks adjusts relatively rapidly to changes in aggregate economic activity, fuel costs, and historical expansion of Interstate Highway mileage. This may be due to the highly competitive nature of shipping services that operate combination trucks and the high ratio of variable to total costs characterizing long-distance trucking. In such an environment, truck operators must be capable of adjusting supply and shipping rates dynamically in response to changing levels of freight-generating economic activity, or fluctuating prices for fuel and other operating inputs.

Buses

The national-level bus VMT measure includes activity in four distinct sub-markets: school transportation, urban transit service, intercity bus service, and charter and tour operations. Although it was not possible to separate VMT for these categories, it is likely that school bus VMT accounts for the largest portion, probably followed by urban transit service. Due to the heterogeneous nature of the factors influencing these four distinct sources of travel demand and the inability to examine them separately, forecasting aggregate bus VMT presents a difficult challenge. In an attempt to capture the varying influences on these distinct markets in a single equation, the bus VMT forecasting model includes the size of the school-age population, real personal disposable income per capita, and consumer spending on fuel as a fraction of total consumer spending (a measure of the burden fuel prices impose on household budgets).

Table 6: Variables Included in Bus VMT Forecasting Model*

Variable	Coefficient	Functional Form
AR(1)	**0.9693**	**Log**
AR(2)	**-0.4574**	**Log**
Population between ages 5-21	**1.0091**	**Log**
Personal disposable income per capita	**0.3243**	**Log**
Consumer spending on fuel as a percent of total consumer spending	**0.0559**	**Log**
Jackknife	**-0.0359**	**Level**

*Dependent variable is log of annual bus-miles.

As Table 6 shows, the population measure appears with a strong positive sign, indicating that bus VMT is highly sensitive to the number of school-age children: as this subset of the population has grown historically, school bus service has increased as well. While the model implies that a change in school-age population produces a proportional change in bus VMT, this probably captures related developments such as the effect of urban decentralization on school bus route lengths, and more frequent busing of school children to extracurricular activities such as sports or vocational training. Growth in disposable income and the fuel price burden on household budgets both appear to be associated with increased bus VMT, although their effects are far smaller than that of the school-age population. The bus VMT equation also includes terms intended to remove the effect of serial correlation in its error terms.

Functional Class VMT Models

The functional class models break down the forecasts of nationwide aggregate VMT for each vehicle type into separate forecasts for each roadway type. To ensure robust forecasts for low-volume roadway types, certain components of FHWA's nine roadway functional classifications were aggregated to produce larger categories. Five roadway classes were ultimately used: urban interstate highways, urban other roadways (including all other roadway functional classes in urbanized areas), rural interstate highways, rural arterials, and rural other roadways (including all other functional classes outside urbanized areas). In combination with the three vehicle types (light-duty vehicles, single-unit trucks, and combination trucks), these five roadway classes required the development of fifteen separate forecasting models. For each vehicle type, forecasts of VMT for the five separate functional classes are constrained to sum to the forecast of national aggregate VMT for that vehicle type.

The national aggregate VMT forecasting models previously developed for each vehicle models were used as the starting point to guide development of forecasting models at the roadway functional class level. In most cases, the road supply measures included as explanatory variables in the national aggregate models were redefined to correspond to the VMT measure used as the dependent variable in each functional class VMT model. For example, the road supply measure included in the light-duty VMT forecasting models for each roadway class included only mileage for that particular category of facilities (Interstate Highways, Arterials, or Other Roadways) and location (urban or rural). Limitations on the availability of geographically-specific measures of economic activity prevented similar "tailoring" of the economic activity and fuel cost variables used in the models for individual roadway classes, so identical values were generally used in the VMT forecasting models for different roadway classes. As an illustration, both real U.S. GDP and nationwide average fuel cost per mile for single-unit trucks appear in the models for single-unit truck VMT on each of the five roadway classes.

Light-Duty Vehicles

Table 7 summarizes the explanatory variables included in the light-duty VMT forecasting models for individual roadway classes. As it shows, disposable personal income per Capita appears in each of the models, although the squared value of this variable is used only in those for the two categories of urban roadways. The arithmetic signs on both variables match those on the same variables in the nationwide aggregate forecasting equation for light-duty VMT (positive for the linear income term, and negative for its squared term), indicating the expected positive influence of income on personal vehicle travel, although the strength of this influence declines at higher income levels for travel on both categories of urban roadways. The nationwide average value of fuel cost per mile for light-duty vehicles also appears in each model with the expected negative sign, and has similar effects on light-duty vehicle travel using each of the five roadway classes.

Table 7: Explanatory Variables Included in Light-Duty VMT Forecasting Models for Individual Roadway Classes

Variable Category	Roadway Functional Class				
	Urban Interstate	**Urban Other**	**Rural Interstate**	**Rural Arterial**	**Rural Other**
Economic Activity Measure	Real Personal Disposable Income per capita*	Real Personal Disposable Income per capita*	Real Personal Disposable Income per capita	Real Personal Disposable Income per capita	Real Personal Disposable Income per capita
Operating Cost Measure	Fuel cost per mile	Fuel cost per mile	Fuel cost per mile	Fuel cost per mile	Fuel cost per mile
Demographic Variable	Average persons per household	Average persons per household	None	None	None
Road Supply Measure	Fraction of centerline miles that are urban	Fraction of centerline miles that are urban	Fraction of centerline miles that are rural	Fraction of centerline miles that are rural	Fraction of centerline miles that are rural
Additional Variables	Lagged Dependent Variable	Lagged Dependent Variable	Lagged Dependent Variable	Lagged Dependent Variable	Lagged Dependent Variable

* Indicates that variable was also included in both linear and squared forms.

The two models for light-duty VMT on urban roadway classes include a measure of average household size; because smaller households tend to generate more commuting and shopping trips per household member, the historical decline in this measure has been associated with rising light-duty VMT per person. Each model also incorporates the fraction of nationwide road mileage that is located in urban or rural areas, depending on whether its dependent variable represents VMT for an urban or rural roadway category.

Not surprisingly, the rising fraction of roadway mileage located in urban areas over time has been associated with a shift of light-duty VMT from rural roadway categories to urban roadways; part of this effect may simply reflect the reclassification of some rural areas as urban over the time period analyzed. Finally, each model also includes the previous period's value of its dependent variable, reflecting the previous finding that more than a single year is required for light-duty VMT to respond fully to changes in any of the influences on vehicle use that are captured by the model's other explanatory variables.

Single-Unit Trucks

Table 8 summarizes the structure of the forecasting equations for single-unit truck VMT occurring on the different roadway classes. As it shows, real GDP is uses as a measure of economic activity in the VMT models for individual roadway types, and has the expected positive influence on single-unit truck travel on each category of roadways. Fuel cost per mile for single-unit trucks is also included in each model; higher fuel costs reduce VMT on each roadway class, and this effect tends to be similar in magnitude to across roadway classes.

Table 8: Explanatory Variables Included in VMT Forecasting Models for Single-Unit Trucks by functional class

Variable Category	Roadway Functional Class				
	Urban Interstate	**Urban Other**	**Rural Interstate**	**Rural Arterial**	**Rural Other**
Economic Activity Measure	Real GDP	Real GDP	Real GDP	Real GDP	Real GDP
Operating Cost Measure	Fuel cost per mile	Fuel cost per mile	Fuel cost per mile	Fuel cost per mile	Fuel cost per mile
Road Supply Measure	Fraction of centerline miles that are urban interstate	Fraction of centerline miles that are urban other	Fraction of centerline miles that are rural interstate	None	None
Additional Variables	Lagged Dependent Variable	Lagged Dependent Variable	Lagged Dependent Variable	AR(1) term (autocorrelation correction)	Lagged Dependent Variable

As Table 8 also shows, the equations for single-unit truck VMT on urban interstate, urban other, and rural interstate roadways include the fraction of nationwide total road mileage in that functional class, and increases in this fraction have the expected effect of increasing VMT in each functional class. With one exception, these models also incorporate the previous period's value of single-unit truck VMT on the relevant functional class. The significance of this variable indicates that as at the national aggregate level, demand for the services provided by single-unit trucks requires 2-3 years to adjust completely to variation in overall economic activity, changes in fuel prices or fuel economy, and expansion of road supply.

Combination Trucks

Table 9 shows details of VMT forecasting equations for combination truck use of the five roadway functional classes. Most of these utilize real GDP, the same measure of economic activity found to influence nationwide combination truck VMT, although the equation for urban interstate VMT uses the real value of goods production instead. As expected, increasing economic activity has a positive influence on combination truck travel using each category of roadways. Fuel cost per mile for combination trucks is also employed in each equation, and the estimated coefficients on this measure show that higher fuel costs reduce combination trucks' use of all roadway classes. The magnitude of this effect varies slightly among roadway classes, but is generally similar to that observed at the national aggregate level.

Table 9: Explanatory Variables Included in Forecasting Models for Combination Truck VMT by Roadway Functional Class

Variable Category	Roadway Functional Class				
	Urban Interstate	**Urban Other**	**Rural Interstate**	**Rural Arterial**	**Rural Other**
Economic Activity measure	Real Goods Production	Real GDP	Real GDP	Real GDP	Real GDP
Operating Cost Measure	Fuel cost per mile	Fuel cost per mile	Fuel cost per mile	Fuel cost per mile	Fuel cost per mile
Road Supply Measure	None	Fraction of centerline miles that are urban	None	None	None
Additional Variables	Lagged Dependent Variable	Lagged Dependent Variable	AR(1) term (autocorrelation correction)	Lagged Dependent Variable	Lagged Dependent Variable

For combination trucks, only the equation for combination truck VMT on urban other roadways includes a road supply measure. Not surprisingly, historical growth in the fraction of total road mileage in urban areas, which has resulted from both new investments and incorporation of some rural area into urbanized areas, has been associated with increasing use of combination trucks on roads in that functional class.

Again with a single exception, the models for combination truck VMT on different roadway functional classes also incorporate the previous period's value of VMT, reflecting the result that (unlike at the national aggregate level) the use of combination trucks on most classes of roadways appears to require more than one year to respond fully to changes in economic activity or fuel costs. This result may suggest that the origin-destination pattern of the long-distance freight shipments usually carried by combination trucks shifts more slowly than aggregate shipping activity, or that combination truck routings over different types of roadway classes require some time to adjust to changes in shipping patterns.

State-Level VMT Forecasting Models

The national-level and functional class VMT forecasting models utilize aggregate time-series data for the nation as a whole, so that only a single measure of each variable is available during each time period (year). In contrast, the state-level VMT models have an additional data dimension, since both their dependent variable (VMT) and most explanatory variables have 51 separate observations available for each time period (one for each of the 50 states as well as Washington, DC). In this context, the states represent a "cross-section," and a continuous annual sequence of these cross-sections is available.

Data with this structure (i.e., containing both time-series and cross-sectional information) is often referred to as a panel, and using it to estimate a model offers two advantages over relying on time-series data alone. First, the finer granularity of this information means that VMT can be forecast for each individual state simultaneously; the same model is equipped to make 51 separate predictions, rather than a single one, for a given future year. This may lead to more stable and reliable forecasts, as errors in forecasting VMT for individual states partially offset one another.

Second, certain variables that have theoretically important influences on travel behavior but display insufficient historical variation at the national level to identify their contributions to VMT growth (such as the concentration of population in metropolitan areas or the average number of persons in a household) may vary widely across states, even within a single year. While aggregating state-level data to national totals can mask the underlying cross-sectional variation in such measures, using a combination of cross-sectional and time-series variation in their values can allow their effects to be more successfully incorporated into state-level forecasting models.

Annual data on VMT by vehicle type and many of the variables hypothesized to influence light-duty vehicle travel and truck shipping activity were collected for each individual state over the period from 1993 through 2008. As with development of the functional class VMT forecasting models described previously, the initial specifications of the state-level models was guided by the final variable selection in the national aggregate VMT models developed for each vehicle class. One important distinction, of course, was that most of the variables included in the initial specifications of the state VMT models were the state-specific analogs of those utilized at the national level. For example, state-level estimates of GDP were included as explanatory variables, rather than national aggregate GDP.

Light-Duty Vehicles

Table 10 summarizes the structure of the state-level light-duty VMT forecasting model. As it indicates, light-duty vehicle travel per capita in each state was found to be a function of the average number of persons per household in that state, its level of disposable personal income per capita, the percent of the state's population living in metropolitan statistical areas (MSAs), the fraction of each state's population under 19 years of age, fuel cost per mile for that state[16], and state-level highway lane-miles per capita. The equation also contains a lagged dependent variable, as well as "fixed effect" coefficients for each state, which are intended to capture differences among states' VMT that are not fully attributable to other explanatory variables included in the model.

The household size measure appears with a negative coefficient, reflecting the fact that as the size of the average household has declined over time, light-duty vehicle travel per person has increased. This result is consistent with the hypothesis that at least some decisions involving travel-generating activities are made at the household rather than the individual level, and that if a given total population is organized into fewer households, the total number of vehicle trips made for some purposes (such as shopping, recreation, and perhaps commuting) can be reduced. Personal disposable income per capita shows the same positive impact on driving as was evident in the forecasting model for aggregate nationwide light-duty VMT.

[16] Recall that fuel cost per mile is equal to retail fuel price per gallon divided by average miles per gallon achieved by each type of vehicle. Retail fuel prices vary among states for two reasons: delivered wholesale (or pre-tax) prices for gasoline and diesel vary geographically, primarily due to refinery locations and transportation costs, and state-level fuel taxes vary widely. Although average fuel economy probably does differ among states, no measures of its variation are readily available, so its annual value for each state was assumed to be identical to its nationwide average during that year. Thus the measure of fuel cost per mile used in the models varies over time as well as among states during any single year, but the latter source of variation reflects only interstate differences in retail fuel prices.

The fraction of a state's population living in MSAs also appears with a negative sign, which appears to reflect the effect of higher population density in urban areas on trip distances, as well as perhaps on the fraction of trips using private vehicles. Thus as more of a state's population resides in urbanized areas, which can occur as population density in rural areas at the periphery of its metropolitan regions increases, personal vehicle trips will tend to be shorter and fewer. As the magnitude of the coefficient estimate indicates, however, this effect appears to be quite small.

Table 10: Explanatory Variables Included in State-Level Forecasting Model for Light-Duty VMT

Variable	Coefficient	Functional Form
Lagged dependent variable	0.7416	Log
Average persons per household	-0.4951	Log
Disposable personal income per capita	0.0690	Log
Percent of population in MSAs	-0.0002	Level
Percent of population under 19	0.6650	Level
Fuel cost per mile	-0.0387	Log
Lane Miles per capita	0.0349	Log

The final demographic variable, the fraction of a state's population under 19, enters with a positive sign and its influence is quite strong, indicating that when children represent a larger fraction of its total population, light-duty vehicle use increases. This presumably reflects "chauffeuring" of children to and from destinations such as school and recreation activities, which increases per capita VMT by household vehicles. Fuel cost per mile appears with the expected negative sign, but appears to have a larger effect on VMT at the state level than was evident at the national level, particularly after the adjustment to higher fuel prices is complete. Finally, the number of roadway lane-miles per capita shows a positive influence on light-duty VMT, again presumably reflecting the effect of additional highway capacity on travel speeds and thus on the time component of the inclusive cost of personal travel.

Single-Unit Trucks

As Table 11 shows, the state-level forecasting equation for single-unit truck travel is a function of state GDP, fuel cost per mile for that state, and lane-miles of urban roadways in that state. The equation also includes the one-period lagged value of its dependent variable and cross-sectional fixed effects, which again are used to capture interstate differences in single-unit truck use that are not accounted for by the economic and road supply variables included in the model. State GDP appears with a positive sign, illustrating the positive effect of overall economic activity on demand for transportation services provided using single-unit trucks. Fuel cost per mile again has the expected negative impact on single-unit truck VMT, while an increase in the extent of a state's urban roadway network has a positive impact on single-unit truck activity. The magnitude of the coefficient on the lagged value of VMT reveals that changes in these variables require about three years for their impacts on single-unit truck travel to be felt completely, but their effects are considerably larger when that adjustment is complete.

Table 11: Explanatory Variables Included in State-Level Forecasting Model for VMT by Single-Unit Trucks

Variable	Coefficient	Functional Form
Lagged dependent variable	**0.6628**	**Log**
State GDP per capita	**0.2571**	**Log**
Fuel cost per mile	**-0.0561**	**Log**
Urban lane miles	**0.1829**	**Log**

Combination Trucks

The state-level forecasts of combination truck VMT are produced using a model that includes state GDP, the value of U.S. exports and imports expressed as a fraction of GDP, fuel cost per mile for each state, and the density of rural roadways per square mile of each state's land area. However, the variable measuring the importance of the U.S. trading sector, U.S. imports plus exports as a fraction of total U.S. GDP, can only be measured at the national aggregate level. Thus it varies over time, but takes the same value for all states during any specific year, while each of the other variables the model uses varies both year-by-year and among individual states. Fixed effect terms for each state are also included in the equation, again to control for the influence of factors other than the variables included in the equation.

As Table 12 reports, state GDP exercises the usual positive influence on VMT, meaning that higher economic activity within a state is associated with more of the large-volume and long-haul freight shipments that are typically carried by combination trucks. The variable measuring the contribution of international trade to U.S. GDP, imports plus exports as a fraction of GDP, also has a positive impact on combination truck use. This measure appears to capture the effect of national trends in the use of combination trucks for transporting goods over long distances to and from U.S. coastal ports, which often causes truck shipments to be routed through multiple states. Other measures of international trading activity, such as container movements at U.S. coastal ports, were also examined, but did not perform as well in the combination truck VMT model.

Table 12: Explanatory Variables Included in State-Level Forecasting Model for VMT by Combination Trucks

Variable	Coefficient	Functional Form
State GDP	0.3793	Log
Imports and exports as a percent of GDP (national)	1.4759	Log
Fuel cost per mile	-0.1036	Log
Rural lane miles per square mile	0.3576	Log

Fuel cost per mile shows the expected negative impact on VMT, indicating that increases in retail diesel prices – which raise costs for shipping via combination truck – reduce the demand for freight movements by truck (or increase utilization of combination trucks' carrying capacity), while increases in combination truck fuel economy have the opposite effect. The variable measuring rural roadway lane-miles per square mile is intended to capture the coverage or "connectivity" that each state's highway network provides among its metropolitan areas, as well as to those in neighboring states. As expected, higher values of this measure have a positive effect on combination truck use, since highway networks providing more complete coverage of a state's land area or greater connectivity among freight origins and destinations have the effect of reducing costs for shipping by combination truck. In turn, this would be expected to raise the volume of freight that is shipped to and from (or even within) a state using combination trucks.

Fleet Model

The vehicle fleet models represent a different approach to forecasting VMT than do the econometric equations discussed above. The previous models directly estimate and predict total light-duty and truck VMT for a specific geographic region (the U.S. as a whole or individual states) or a particular category of roadways (urban interstate highways, rural arterials, etc.). In contrast, the fleet models build up estimates of light-duty or truck VMT by first decomposing the relevant vehicle fleet by model year or vintage during each calendar year, and then using well-defined relationships between vehicle age and average utilization – measured by average annual miles driven per vehicle during a year – to develop annual estimates of total travel by each vehicle class for the current and future years.

Three distinct steps are involved in developing each fleet VMT models: (1) estimating the number of vehicles of each age that will be in service during a given calendar year, (2) estimating average annual VMT per vehicle for vehicles of each age, and (3) multiplying the number of vehicles of each age that are in use during a calendar year by average annual VMT for vehicles of that age. The results of these calculations can then be summed to yield an estimate of national-level VMT for each calendar year.

The resulting estimates of total VMT for each future year are unlikely to agree exactly with the forecasts produced by the national aggregate VMT forecasting models for each vehicle class described previously. In order to insure that they do, the results of step 3 are used to predict the *fraction* of total annual VMT that will be produced by the vehicles of each age during each future calendar year. These shares are subsequently applied to the forecasts of total VMT during each calendar year produced by the national-level econometric forecasting equations to estimate the number of VMT accounted for by vehicles of each age.

The fleet profile for each calendar year, which consists of the number of vehicles produced during each model year that are expected to be in service during each future calendar year, was constructed using vehicle registration data obtained from R. L. Polk and forecasts of future new vehicle sales developed by IHS. The process outlined below is similar for each of the four vehicle types used in the fleet model (automobiles, light-duty trucks, single-unit trucks, and combination trucks), although the discussion highlights some minor differences among the vehicle classes.

Constructing the fleet profile begins by obtaining counts of the number of vehicles produced during each model year that were registered for use during a sequence of calendar years ending with the most recent year for which these data are available. A vehicle's age during any calendar year is defined as the difference between that calendar year and the model year when it was produced; for example, vehicles produced in model year 2000 are defined as 10 years old in calendar year 2010 (2010 – 2000 = 10).[17]

These data are then used to calculate the survival rates for vehicles of each age in each calendar year prior to the most recent. As an illustration, dividing the number of model-year 2000 vehicles registered during calendar year 2006 (when they are defined to be 6 years of age) by the number registered during 2005, when those same vehicles were 5 years of age, yields the (conditional) survival rate for 5-year old vehicles in calendar year 2005. Where no strong trend in the survival rates for vehicles of a specific age is evident over time, their values for recent calendar years can be averaged to develop an estimate of survival rates for future model years as they reach each age. Where survival rates for vehicles of the same age have exhibited a clear trend during recent calendar years, these trends can be extrapolated to develop estimated survival rates for vehicles that will reach that age during future calendar years.

These projected survival rates are then applied to the registration data for the most recent calendar year available (say, 2012) to estimate the number of vehicles of each model year and age that will remain in service during the following calendar year (2013). Forecast sales of new vehicles during that year (2013) are then added to the fleet, virtually all of which are predicted to survive and remain in service as age 1 vehicles during the following calendar year (2014 in this example).[18] This process is

[17] This convention ignores the fact that vehicle model years do not correspond exactly to calendar years. Because vehicles produced during a model year may be sold as early as the preceding calendar year (for example, most model year 2010 cars and light trucks were first offered for sale during calendar year 2009) or as late as the following calendar year, not all vehicles of the same model year will have been in use equally long during any future calendar year. Nevertheless, they are assumed to be of the same age for purposes of this analysis. This problem is most acute for light-duty vehicles (cars and light trucks), and much less serious for heavy trucks.

[18] Again, distinctions between model year and calendar year are ignored; for example, all new vehicles projected to be sold during calendar year 2011 are assumed to be produced during model year 2011. For light trucks and automobiles, the assumption may create some distortion, since, for example, a significant number of model year 2012 vehicles will be sold during 2011, for instance. However, in the long term, any resulting distortions to estimates of VMT and the aggregate number of vehicles in service are likely to be minor.

repeated to produce estimates of the number of vehicles of each model year (and thus age) that will be in use during each subsequent calendar year through the forecast horizon.

Average yearly VMT by vehicle age was estimated separately for four vehicle classes: combination trucks, single-unit trucks, automobiles, and light trucks; the latter two classes were then combined to produce estimates of average annual VMT by age for all light-duty vehicles. For each of these vehicle classes, regression analysis was used to develop a function relating average annual VMT to vehicle age. After extensive experimentation, a quadratic structure was chosen for each vehicle type, in which average annual VMT per vehicle depends on both vehicle age and its squared value. Data on vehicle age and annual use for single-unit and combination trucks were obtained from the 2002 Vehicle Inventory and Use Survey (VIUS), while information on age and estimated annual use for automobiles and light trucks was drawn from the 2009 National Household Transportation Survey (NHTS). Average annual VMT by vehicles of each type and age was projected to grow over the future at rates derived from analyses of differences in historical growth rates of total VMT and the number of vehicles in use.

Finally, the number of vehicles of each model year and age projected to be in use during each future calendar year was multiplied by the estimate of average annual miles driven for vehicles of that age to calculate the contribution by vehicles of that age to total VMT during each future year. These contributions can then be summed to develop forecasts of fleet-wide aggregate VMT during future calendar years, and this entire process is repeated for each class of vehicles.

As indicated previously, however, the resulting estimates of total VMT for future calendar years differ slightly from the annual forecasts produced by the aggregate VMT models for the three vehicle classes. Thus to ensure that they correspond, the estimated contributions by vehicles of each model year and age to total VMT for that vehicle class are expressed as proportions, and these proportions are then applied to the forecast of total annual VMT for that class. This produces revised estimates of VMT by vehicles of each model year and age during future calendar years that are consistent with the forecast of total VMT for that vehicle class and year.

Description of Forecasting Tool

The forecasting tool is separated into two distinct parts, both of which are Microsoft Excel 2007 files. A first spreadsheet file contains the national-level models (nationwide aggregate, roadway functional classification, and fleet forecasts), while a second contains the state-level forecasts. Although the forecasts are separated for ease of use, the general capabilities of each of the spreadsheet tools are the same.

Each of the spreadsheet tools allows the user to modify and customize various forecasting parameters, reflecting assumptions about economic and demographic conditions, as well as policy decisions that affect projected future growth in vehicle use. Macroeconomic and demographic conditions such as growth in population, gross domestic product, personal income, imports and exports, and fuel prices tend to be closely linked to one another. In the case of these factors, the user may select one of three possible scenarios—baseline, optimistic, or pessimistic, which correspond to the alternative IHS outlooks for economic growth. In each scenario, all of these related variables are forecast as a single “package,” in order to preserve their expected relationships.

Two other factors that were found to have important effects of VMT in many of the models, fleet-wide fuel efficiency and the cost of driving, are partially exogenously determined; that is, future changes in these two variables may be independent of domestic economic and demographic conditions. The primary exogenous effects on these two factors would come directly from federal regulation. Changes in fleet-wide fuel efficiency come about as a result of both technological advancement and consumers' purchase decisions regarding new vehicles. Both of which may be directly affected by government mandates, such as the CAFE standards.

Further, the federal government may directly alter current tax rates on fuel, which constitute a significant component of retail fuel prices, and thus affect the cost of driving. Although not a policy that has been previously adopted, the federal government could also influence the cost of driving through non-fuel-related policy regulations, such as by imposing VMT fees. Such a policy has been discussed extensively in recent months, and advocated by one Congressional Commission created to study alternatives for financing future investments in transportation infrastructure.

Expectations regarding both of these exogenous parameters may be controlled by the spreadsheet user. In the case of fleet fuel efficiency, changes are made relative to a baseline forecast for each vehicle type by applying a multiplicative factor to the baseline forecast growth. The user may input expected changes in the fuel-related cost of driving in several manners. Changes in federal fuel taxes may be made subject to several possible future scenarios (for example, by modifying the federal fuel tax in one or many isolated future years, or by linking the growth of the gas and/or diesel taxes to the expected rate of inflation). Future changes in the cost of driving may also be simulated by introducing per-mile VMT fees.

Detailed tables and graphs illustrate the effect of the predictions made for the explanatory variables, by way of comparison to historical growth and baseline forecasts. The resulting VMT forecasts are displayed by vehicle type, as well as by roadway functional class or state, in both graphical and numerical form, and growth rates in VMT over various time horizons are computed and displayed. The composition of the vehicle stock may also be examined in detail for any selected future year using the output from the fleet models. Energy consumption estimates are also generated for five fuel types, based on projected vehicle use, fuel shares, and future trends in fuel efficiency.