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Explaining the Evolution of Passenger Vehicle Miles Traveled in the United States

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Abstract

After growing steadily for several decades, passenger vehicle miles traveled (VMT) in the United States unexpectedly leveled off in the 2000s. The growth rate of VMT has since rebounded, and determining the factors that explain these developments has implications for future US oil consumption and greenhouse gas emissions. We show that changes in the demographic and economic characteristics of households in the United States, rather than changes in driving habits, explain most of the recent dynamics. These results suggest that over the next decade, VMT in the United States will continue to grow roughly at historical rates, causing substantially higher oil consumption and greenhouse gas emissions than if persistent changes in household driving habits explained the recent changes in VMT.

Key Words: passenger vehicles, miles traveled, demographics, gasoline consumption, greenhouse gas emissions

JEL Classification Numbers: Q4, Q5, L62

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Introduction

How much people drive their vehicles will play a central role in determining future US oil consumption and greenhouse gas emissions. The United States has pledged to reduce its greenhouse gas emissions by about one quarter between 2005 and 2025. Passenger vehicles account for almost half of US oil consumption and about 15 percent of greenhouse gas emissions; given current policies to reduce emissions from other sectors, reducing passenger vehicle emissions will be necessary to meet the pledge. Mechanically, passenger vehicle greenhouse gas emissions depend on (a) the fuel consumption rate (gallons of fuel consumed per mile of travel); (b) the carbon content of the fuel (pounds of carbon dioxide per gallon of fuel); and (c) the total vehicle miles traveled (VMT). The United States, like many other countries, sets standards for new vehicles' fuel economy, which largely determine the average fuel consumption rate across the entire fleet in the long run. Via the Renewable Fuel Standard program, federal policy also determines the carbon content of the fuel. In contrast, existing policies that directly affect VMT are confined to public transportation infrastructure funding and a few other initiatives. Thus, the first two components of total emissions—fuel consumption rate and carbon content—are fixed by policy, whereas the third component, VMT, is largely independent of policy and is chosen by individual drivers.

Recent developments have attracted media and public attention to how much people drive their vehicles. After decades of growing steadily, VMT suddenly leveled off in the mid-2000s and by some estimates decreased. The popular media have offered a range of hypotheses, including household demographics (such as an aging population, since older households tend to drive less) and economic characteristics (such as declining household incomes and rising unemployment attributable to the recession). We refer to such developments as changes in household demographics and economic characteristics. Another set of hypotheses involves

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changes in how much households drive, conditional on demographics and economic characteristics. For example, “the Amazon hypothesis” contends that online shopping reduces driving. Another hypothesis is that current younger households (i.e., the “millennials,” or individuals born after 1980) drive less than younger households in previous generations because of a stronger preference for public transit, virtual connectivity, or other reasons. We refer to these developments as changes in household driving habits, which are defined as the average number of miles driven by groups of households with common demographics and economic characteristics. For example, low-income elderly households typically drive about half as much as high-income young households, reflecting a difference in driving habits between these groups.

These possible explanations have differing long-term implications for VMT, oil consumption, and greenhouse gas emissions. For example, a persistent change in household driving habits would imply that VMT will grow more slowly in the future than it did in the years prior to the 2000s. On the other hand, if the recession was the main factor, expected future economic growth would imply that VMT will rise roughly at historical rates. Whether VMT will be flat or grow at historical rates will have profound effects on US oil consumption and emissions. Comparing these two hypothetical cases, rising VMT would eliminate about half of the savings attributed to US fuel economy standards.

This paper explains the slowdown in VMT growth after 2000 and the subsequent recovery, and draws implications for future VMT growth. Although a vast literature has characterized the effects of income and fuel prices on VMT and gasoline consumption (e.g., Hughes et al. 2008), most of this literature has used aggregate data and assumed linear or log-log relationships among income, fuel prices, demographics, and VMT or gasoline consumption. Such assumptions are necessary given the limited number of observations in most aggregate data sets, but as we explain in Section 2, the assumptions make it challenging to distinguish changes in driving habits over time from a potentially nonlinear relationship among explanatory variables and VMT. A few recent studies (e.g., Blumenberg et al. 2012) have focused on possible changes in driving habits among certain demographic groups, such as millennials, but they have not quantified the overall importance of changes in driving habits, or the implications of any such changes for future VMT growth. In short, the literature offers little insight on whether changes in demographics and economic characteristics or changes in household driving habits explain the recent slowdown and subsequent recovery in VMT growth.

In this paper, we distinguish between the effects of demographics and economic characteristics and the effects of household-level driving habits on national VMT. We begin by estimating the relationships among household VMT, demographics, and economic characteristics in a base year prior to the VMT slowdown. The large sample of households in our data enables us to estimate nonlinear relationships among VMT and variables such as age or income. Subsequently, we decompose changes in total VMT between the base year and any subsequent year into two classes: (a) changes in demographics and economic characteristics, and (b) changes in household driving habits, conditional on demographics and economic characteristics. To conduct this decomposition, we define demographic and economic groups. We compare base-year VMT with the predicted VMT in subsequent years. The predictions use the base-year household driving habits by group, and the changes in group sizes between the base year and following years. As we show below, the change in predicted VMT between the base year and a subsequent year reflects changes in demographics and economic characteristics. The difference between actual and predicted change in VMT in any year following the base year reflects the contribution of changes in household driving habits for particular demographic or economic groups—for example, including the differences in typical miles traveled by millennials compared with other cohorts of young adults.

Our first result is that changes in demographics and economic characteristics, rather than changes in household driving habits, largely explain changes in VMT between 1995 and 2015. Distinguishing nonlinear relationships among variables from changes in habits turns out to be important empirically. Aging of the population made a negative but relatively small contribution to changes in VMT between 1995 and 2015, whereas income and the number of workers per household explain a large share of overall VMT variation. Moreover, the increase in number of workers per household after 2010 explains the increase in VMT per household in the 2010s. However, for reasons discussed in Section 3, we are cautious about making a causal interpretation of the effects of specific demographic or economic variables.

Based on our first result, we predict future VMT assuming that demographics and economic characteristics continue to explain VMT, and that driving habits of each household group remain persistent. Future VMT will therefore reflect the offsetting effects of rising income, which increases VMT, and the aging population, which reduces VMT. Our second result is that we predict average annual VMT growth of about 0.9 percent between 2015 and 2025, which is lower than historical averages although higher than the growth observed during the 2000s; this prediction is smaller than projections from the Energy Information Administration (EIA 2015) but the same as the growth projected by the Federal Highway Administration (FHWA 2015) between 2013 and 2033. Our predicted growth rate implies that future oil consumption and GHG emissions will be about 10 percent higher than if VMT were to remain at 2015 levels. If VMT grows at the predicted rate rather than remaining constant, VMT growth will offset nearly half of the reductions in oil consumption and greenhouse gas emissions caused by fuel economy standards for passenger vehicles over the next decade. Thus, our analysis implies that VMT growth will increase the challenge of meeting the US international pledge to reduce greenhouse gas emissions.

1. Documenting the Recent Decline in VMT Growth and Reviewing the Literature

1.1 The Recent Decline in VMT Growth

Between 1975 and 2000, VMT of US passenger vehicles grew steadily and was strongly correlated with income and employment. Figure 1 shows data on VMT per licensed driver, income per capita, and nonfarm employment from EIA (2014), with all variables normalized to equal one in 1975 for comparability. Between 1975 and 2000, VMT grew at an annual rate of about 1.5 percent, and the graph indicates that periods of rising income and employment are accompanied by rising VMT, and likewise periods of falling income and employment are accompanied by falling VMT. Starting around 2000, the correlations among VMT, income, and employment weakened. Although income continued to rise in the 2000s, VMT leveled off and then declined after 2007. Declining employment growth during the 2000s could at least partly explain this decoupling, although the correlation between employment and VMT is not perfect: between 2010 and 2012, employment rises whereas VMT declines. This graph suggests that the relationship between average income and VMT differed between the 2000s and earlier years.

The United States does not collect comprehensive VMT data annually, so we compare the VMT data in Figure 1 (which originate from FHWA) with VMT from other sources. The FHWA data derive from estimated state-level VMT by road and vehicle type. Figure 2 compares data from FHWA with data from EIA and the National Household Travel Survey (NHTS). The EIA data, reported in the Annual Energy Outlook from various years, reflect a different approach to estimating VMT than that which underlies Figure 1. The NHTS estimates derive from a household travel survey that the Department of Transportation has conducted every five to eight years (prior to 2001, the survey was referred to as the National Personal Transportation Survey). The estimated national VMT in Figure 2 is computed based on each survey respondent's estimated total miles for all vehicles belonging to the household. NHTS provides estimates for 1995, 2001, and 2009, whereas FHWA and EIA report annual estimates for 1995 through 2013.

The patterns are broadly similar across the three estimates of national VMT. National VMT increased between 1995 and 2001 and grew at a slower rate between 2001 and 2009 than between 1995 and 2001. The EIA and FHWA estimates suggest that VMT peaked in the mid-

2000s, decreased until around 2010, and began increasing in the 2010s. There are some differences among the three sources, however. The NHTS indicates that national VMT decreased between 2001 and 2009, whereas FHWA and EIA indicate that VMT increased between these two years. Moreover, FHWA and EIA disagree about the year in which VMT peaked (2006 according to FHWA and 2007 according to EIA) and about the year in which VMT started growing again (2008 according to FHWA and 2012 according to EIA). Overall, however, the different sources consistently show that VMT growth began to slow around 2000, and that VMT reached an inflection point in the mid-2000s. These developments represent a stark contrast to the VMT growth prior to 2000.

1.2 Explanations from the Literature

As discussed in the Introduction, we distinguish between two influences on VMT growth: (a) demographics and economic characteristics, and (b) household driving habits conditional on demographics and economic characteristics. Litman (2013) documents the relationship between economic factors and VMT, showing that low fuel prices, high income, and high employment are associated with high VMT. The slowdown of VMT growth in the 2000s is consistent with recent macroeconomic trends, including a fall in median income for households from 2001 to 2007 and a sharp decline in employment in 2009 that persisted for several years (CEA 2014). However, the literature has not considered specifically whether economic characteristics, particularly income and employment, fully explain the path of VMT after 2000.

Several recent studies have considered the role of aging and urbanization in explaining the recent VMT developments. The elderly typically drive fewer miles than young adults, and individuals in urban areas typically drive fewer miles than individuals in rural areas. The share of elderly in the population has increased as the baby boom generation has aged, and urbanization rates have been increasing, either of which could have reduced average VMT per household (Davis et al. 2012; Baxandall 2013; Blumenberg et al. 2012; the baby boom generation is commonly defined as comprising individuals born between 1945 and 1964). However, aging and urbanization have changed gradually and steadily since 2000, and these variables cannot explain fully the rising and falling periods of VMT.

Turning to the second class of explanations for the declining VMT growth rate, recent studies have focused on the possibility that young adults in the 2000s drove fewer miles than did previous generations of young adults. According to the 2009 NTHS, commuting accounts for about 19 percent of miles traveled (not including work-related business trips) and shopping accounts for about 14 percent of miles traveled. A change in household driving habits among younger age groups could be explained by cultural shifts in commuting patterns, including a stronger preference for public transit and for virtual connectivity for working and socializing (McDonald 2015; Brown et al. 2016). In addition, the media have suggested that the growth of internet shopping may have reduced shopping trips (Tuttle 2012; Yglesias 2012), although Zhou and Wang (2014) and Zhai et al. (forthcoming) do not find strong evidence supporting this hypothesis.

Overall, the literature has not explained the factors underlying the dynamics of VMT shown in Figures 1 and 2. For example, the relationship between VMT and average income may have changed because of changes in driving habits by income group or because of changes in the income distribution. That is, individuals belonging to certain income groups may have started driving less in the 2000s than did individuals belonging to the same income groups in prior years, representing a habitual change. Alternatively, income may have a nonlinear effect on VMT. If average VMT is a concave function of income, a mean preserving spread of the income distribution (i.e., an increase in variance, holding the mean fixed) could reduce average VMT. In that case, an increase in the share of low-income households after 2000 may have caused the decrease in VMT relative to average income, representing a situation in which changes in economic characteristics, rather than driving habits, caused VMT to decrease in the 2000s. Thus, aggregate data cannot be used to distinguish between changes in driving habits and nonlinear relationships among variables.

In short, the literature has identified several possible explanations for the patterns depicted in Figures 1 and 2. A few studies have provided evidence of changes in demographics, economic characteristics, and driving habits. However, the literature has not evaluated the relative importance of these changes, nor has it distinguished between the possibilities of nonlinear relationships among variables and changes in habits. In the next two sections of the paper, we quantify the contributions of demographics and economic characteristics to VMT, allowing for nonlinear relationships among the variables.

2. Data and Methodology

2.1 Data

Our analysis combines the Current Population Survey (CPS) and NHTS. The CPS provides accurate annual estimates of demographics over a long period of time. The NHTS links household driving to demographics during specific survey years. As we explain in this subsection and the next, we combine the data sets to take advantage of their relative strengths.

From the CPS we compute counts of households by year, household income category, and demographic category from 1995 through 2015. We begin by assigning each household in the March CPS to a unique income and demographic category. For consistency with the 1995 NHTS, we convert nominal income reported in the CPS to 1995 dollars using the consumer price index from the Bureau of Labor Statistics, and we define household income categories by $5,000 intervals (0 to $5,000, $5,000 to $10,000, etc.), top-coded at $80,000. Demographics include age category of the household head, census division, urbanization status, number of workers in the household, household size, education category, and race. We use five-year age categories, and we define education and race categories identically to the 1995 NHTS categories (education categories are less than high school degree, high school degree, some college, college, and postcollege; race categories are white, black, and other). The household counts are computed using the CPS household sampling weights.

Figure 3 provides summary information from the CPS data, focusing on variation over time in age, income, and number of workers per household. Panel A shows that between 1995 and 2009 the share of households with a household head aged 31 through 45 declined, and the share of households with a household head of age 45 through 60 increased. The share of households with a household head aged 61 or above decreased until the early 2000s, and then increased. These patterns are consistent with the overall aging of the baby boom generation.

Panel B shows the dynamics of the income distribution between 1995 and 2009, particularly the fact that income has not risen uniformly across income categories. The share of low-income households (defined as having an income below $35,000 in 1995 dollars) decreased in the late 1990s and then remained flat. The share of middle-income households (between $35,000 and $70,000) decreased gradually over the period, and the share of high-income households (above $70,000) increased, particularly in the late 1990s and early 2000s. Thus, the data indicate an overall decrease in the shares of low- and middle-income households, and an increase in the share of high-income households.

Panel C shows changes in the shares of households with zero, one, or more than one worker. The share of households with more than one worker was steady in the 1990s and declined in the 2000s, and it was offset by an increase in the share of one-worker households through most of the 1990s and 2000s.

The NHTS data set contains households from the 1995, 2001, and 2009 survey waves. For each household we compute the total VMT across its vehicles and construct the same income and demographic categories as those in the CPS data set. The NHTS includes a few variables that may be correlated with household VMT but are not in the CPS—particularly, the number of licensed drivers, the size of the metropolitan statistical area (MSA), and the number of vehicles belonging to the household. The coding of the MSA size and race variables varies across NHTS waves, and we harmonize the coding across waves.

About 10 percent of NHTS households do not report an income category, so we impute income for these households based on the income of households with similar demographics. To perform this imputation, for each household with a reported income category we construct a numerical income variable equal to the midpoint of the corresponding income category (for example, numerical income is $2,500 for households in the $0 to $5,000 income category). We assign these households to demographic cells based on the number of workers, household size, MSA size, race category, and education category. For each demographic cell we compute the average income, and we assign households with missing income to the corresponding income category based on the average income of the corresponding demographic cell.[1]

The income categories in the available NHTS data refer to nominal income. The main challenge to using multiple NHTS survey waves is the need to convert the income categories based on nominal income to income categories based on income in 1995 dollars. To accomplish this, we take advantage of the fact that the CPS includes income in dollars rather than as a categorical variable. We assign NHTS households to demographic cells based on nominal income category, number of workers, urbanization status, and census division.[2] We randomly select a CPS household from each corresponding NHTS survey year and cell, and we use that household's income (in 1995 dollars) as the imputed value of income for NHTS households belonging to the corresponding cell.[3] The imputed income in 1995 dollars is then used to assign

[1] The definition of the demographic cells used for the income imputation reflects a balance of concerns about measurement error. On the one hand, more narrowly defined cells reduce measurement error because households with missing income are assigned income categories based on more similar households. On the other hand, more narrowly defined cells can increase measurement error because fewer households with reported income are used to impute income for households with missing income. In practice, we impute income for only about 10 percent of households in the sample and the specific definition of the cells does not appear to affect the main results.

[2] The cell definition used for this imputation is different from that used for imputing income for NHTS households with missing income. The definition used for this imputation balances concerns about measurement error noted above, as well as the need to define the cells broadly enough to be able to match all NHTS households to CPS cells.

[3] For example, consider a 2009 household with two workers located in an urban area in the West South Central United States. According to the NHTS this household has an income between $75,000 and $80,000 (current dollars). A randomly selected CPS household with the same characteristics and nominal income has an income of $53,421 in 1995 dollars. We assign the NHTS household to the income category of $50,000 to $55,000 in 1995 dollars.

NHTS households to an income category, using the same $5,000 intervals for the real income categories as for the nominal income categories.[4]

Figure 4 reports age and income information from the three NHTS waves for comparison with the CPS data from Figure 3. Panel A shows that the share of households by broad age category follows similar patterns in the two data sets, although there is a difference for the youngest age category. This difference could reflect sampling variation or the fact that we use the survey respondent to define the age category for NHTS households, whereas we use the household head for CPS households.

Panel B shows shares of NHTS households by income category, and we observe differences between the NHTS data and the CPS data reported in Figure 3. According to the NHTS data, the share of low-income households increased from 1995 through 2009, whereas according to the CPS data, the share of low-income households decreased between 1995 and 2001, and then increased. This difference could arise from sampling variation, as with the age data, but it may also reflect the measurement error in the NHTS introduced by the income imputations discussed above. Because of the NHTS's measurement error and its focus on travel, versus the CPS's focus on labor market outcomes and income and its extensive use for estimating income distributions, we consider the CPS income data to be the more reliable.

Table 1 shows changes in demographics across the NHTS survey waves. The data indicate large shifts in some of the demographics, such as a doubling of the percentage of households in the Mountain census division, and an 18 percent increase in the urbanization rate. We also observe a shift from two-worker to one-worker households, which reflects macroeconomic conditions and the retiring of the baby boom generation from the workforce.

2.2 Methodology

Much prior research has used aggregate data to link VMT with demographics and economic characteristics (e.g., Small and Van Dender 2007). Typically, these studies estimate an equation of the form

$$V_t = \delta_1 Y_t + \delta_2 P_t + \varepsilon_t \tag{1}$$

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[4] Alternatively we could match randomly selected CPS household to NHTS households belonging to the same cell. This approach would yield the same expected value of income as the approach described in the text.

where V_t is national VMT in year t, Y_t is income, P_t is the gasoline price, ε_t is an error term, and the δ s are coefficients to be estimated (the equation could include other controls, such as a time trend, which we omit for exposition). The equation may be estimated at the national or subnational level (e.g., by state, as in Baxandall 2013), in which case variables vary by year and geographic region. The equation could be estimated in levels, as written above, or after taking logs of the variables, in which case the coefficients would be interpreted as elasticities. Some studies use the average fuel costs per mile of driving instead of the fuel price to account for the effect of fuel economy on driving costs.

Equation (1) assumes a linear relationship between independent variables and VMT (or log-log if the variables enter the equation in logs). In that case, if the relationship between VMT and average income changes over time, as it might have since 2000, it is not possible to distinguish between possibilities that (a) that the coefficients in equation (1) have changed, and (b) equation (1) is misspecified and there is in fact a nonlinear relationship between at least one independent variable and VMT. For example, the income coefficient in equation (1) may have changed after 2000; or a mean preserving spread of income, combined with a nonlinear relationship between a household's income and its VMT, could change the relationship between average income and national VMT. In principle, one could add to equation (1) higher-order moments of the independent variables, such as the standard deviation of income, but doing so with aggregated data would introduce the challenges of limited degrees of freedom and multicolinearity.

Instead of continuing in the tradition of using aggregated data, we adapt an Oaxaca-Blinder decomposition using household-level data from the NHTS and CPS. We decompose temporal changes in VMT into two classes: (a) the contributions of explanatory variables, and (b) the contribution of changes in the coefficients on those explanatory variables. This method, which was first applied by Blinder (1973) and Oaxaca (1973) to quantify wage discrimination in labor markets, is an intuitive tool for decomposing the sources of changes in a variable, such as VMT, over time. To the best of our knowledge, our analysis is the first to adopt the Oaxaca-Blinder methodology for examining the relationships between VMT and demographics, economic characteristics, and driving habits at the household level (CEA 2015 reports our results using an earlier version of this methodology). This approach has been used in other environmental and energy contexts, such as for household energy efficiency (Levinson 2014) and energy efficiency in service establishments (Morikawa 2012).

The decomposition differs from a standard Oaxaca-Blinder decomposition in that we use one data set, the NHTS, to estimate the relationships among VMT, demographics, and economic characteristics, and a second data set, the CPS, to measure changes in demographics and economic characteristics over time. Alternatively, we could use only the NHTS data, but using both data sets takes advantage of their relative strengths. The strength of the NHTS data is that they include household-level VMT as well as economic and demographic factors that are highly correlated with VMT. The strength of the CPS is the ability to estimate counts of households for each year between 1995 and 2015, which enables a comparison of annual VMT estimates with the level of VMT predicted by changes in demographics and economic characteristics (recall that the NHTS data are available only for 1995, 2001, and 2009). A further strength of the CPS is the lower measurement error of income, relative to the NHTS.

More specifically, we generalize equation (1) to include a broader set of explanatory variables:

$$V_t = \boldsymbol{\gamma}_t \mathbf{C}_t + \eta_t .$$

We model VMT in a semiparametric manner by assigning an average VMT for each household group. The bolded terms $\boldsymbol{\gamma}_t$ and $\mathbf{C}_t$ denote vectors, and each element of the vector represents a household group. In the main analysis, groups are defined based on income, number of workers, and age group. For example, one group includes households with income between \$50,000 and \$55,000, with one worker and with a household head aged 35 to 39. The coefficients $\boldsymbol{\gamma}_t$ represent the average driving of households in each group in year t, and $\mathbf{C}_t$ contains the number of households in year t belonging to each group. The final term, η_t, represents idiosyncratic differences in driving that are not explained by household group driving habits. Taking the expectation of this equation, we have

$$E[V_t] = \boldsymbol{\gamma}_t \mathbf{C}_t .$$

Using this equation, we can express the change in expected national VMT between years 0 and t as

$$E[V_t - V_0] = \boldsymbol{\gamma}_0 (\mathbf{C}_t - \mathbf{C}_0) + (\boldsymbol{\gamma}_t - \boldsymbol{\gamma}_0)\mathbf{C}_t .$$

We compute the decomposition with

$$\hat{V}_t - \hat{V}_0 = \hat{\boldsymbol{\gamma}}_0 (\mathbf{C}_t - \mathbf{C}_0) + (\hat{\boldsymbol{\gamma}}_t - \hat{\boldsymbol{\gamma}}_0)\mathbf{C}_t , \tag{2}$$

where the coefficients with hats represent empirical estimates. The two terms in this equation conform precisely to the two classes of potential explanations for the changes in VMT that we defined in the Introduction: changes in demographics and economic characteristics as represented by changes in the number of households in each group (i.e., $\mathbf{C}_t - \mathbf{C}_0$), and changes in driving habits, conditional on demographics and economic characteristics (i.e., $\hat{\boldsymbol{\gamma}}_t - \hat{\boldsymbol{\gamma}}_0$).

We implement the decomposition in two steps, the first of which is to use a single cross section of NHTS data from 1995 and estimate the household-level equation

$$V_{h0} = \boldsymbol{\gamma}_0 \mathbf{I}_{h0} + \varepsilon_{h0}, \tag{3}$$

where $\mathbf{I}_{h0}$ is a vector indicator function where the corresponding group element is equal to one if household h in year 0 belongs to the group and ε_{h0} is a household-specific error term. The groups and coefficients $\boldsymbol{\gamma}_0$ have the definitions from above. We estimate equation (3) by weighted least squares using NHTS sample weights, yielding coefficient estimates $\hat{\boldsymbol{\gamma}}_0$. Thus, the coefficients represent the weighted average VMT across households belonging to the corresponding groups, and we refer to $\hat{\boldsymbol{\gamma}}_0$ as the vector of expected group VMT per household in the base year (i.e., 1995).[5]

In the second step, we predict national VMT based on the changes in demographics and economic characteristics, combined with the estimated group g VMT per household. For each year between 1995 and 2015, we multiply the estimated group VMT by the count of households in the corresponding group from the CPS, to obtain the predicted group g VMT. Summing the predicted group g VMT across groups yields the predicted national VMT in year t:

$$\hat{V}_t^0 = \hat{\boldsymbol{\gamma}}_0 \mathbf{C}_t. \tag{4}$$

The superscript 0 on the left-hand term in equation (4) denotes that the prediction is performed using the coefficients estimated from equation (3) and household data from year 0. The difference between predicted VMT in year t, $\hat{V}_t^0$, and VMT in year 0, $\hat{V}_0$, represents the first class of potential explanations for the change in VMT between year 0 and year t—that is, changes in demographics and economic characteristics:

$$\hat{V}_t^0 - \hat{V}_0 = \hat{\boldsymbol{\gamma}}_0 (\mathbf{C}_t - \mathbf{C}_0). \tag{5}$$

An advantage of using this decomposition is that the second class of potential explanations, which is changes in driving habits conditional on demographics and economic characteristics, is equal to the difference between actual national VMT in year t and $\hat{V}_t^0$. This

[5] Because we weight the household observations by household weights, estimation of equation (3) yields the same coefficient estimates as those estimated if we aggregate VMT by group and estimate the model at the group level.

result follows from the fact that $\hat{V}_t^0 - \hat{V}_0$ is equal to the first term in equation (2). Therefore, subtracting equation (5) from equation (2) and substituting $V_t = \hat{V}_t$ yields

$$\hat{V}_t^0 - \hat{V}_0 = (\hat{\boldsymbol{\gamma}}_t - \hat{\boldsymbol{\gamma}}_0)\mathbf{C}_t . \tag{6}$$

Thus, equation (5) represents the first term of the decomposition and equation (6) represents the second term of the decomposition.

Figure 5 presents a graphical interpretation of the decomposition. To simplify the presentation, the horizontal axis is a scalar that summarizes the demographics and economic characteristics in $\mathbf{C}_t$. The two sloped lines represent VMT growth between year 0 and year t. The bottom line is the predicted VMT using habits estimated in year 0, and the top line is the predicted VMT using habits estimated in year t (i.e., 2009 in the figure). The bottom bracketed term on the vertical axis is the change in VMT over time that is explained by changes in household demographics and economic characteristics. The top bracketed term is the change in VMT over time that is explained by changes in habits.

We make several remarks about this decomposition. First, we do not assign a causal interpretation to the decomposition. Equation (3) likely omits variables that affect VMT and that are correlated with the variables included in equation (3). If the relationships among the omitted variables and the variables that we include in equation (3) change over time, we will erroneously attribute changes in variables included in equation (3) as causing changes in VMT. This issue is present in the literature on wage discrimination for which the Oaxaca-Blinder method was first applied, where race or gender may be correlated with variables that are omitted from typical wage equations. In our context, as well as in that one, the decomposition is nonetheless useful because we can interpret the two terms in equation (2) as characterizing the share of the variance in VMT that is explained by changes in demographics and economic characteristics rather than changes in driving habits of groups of households with common demographics and economic characteristics.

Second, equation (3) does not include gasoline prices. We omit prices from this equation because much of past research using cross sections of household data (e.g., Goldberg 1998; Li et al. 2013) has failed to identify the effect of gasoline prices on VMT, largely because of limited cross-sectional price variation (we reach a similar conclusion using a cross section of NHTS data). In implementing the decomposition, we adjust equation (4) by the change in national average gasoline prices between 1995 and year t, and assuming an elasticity of VMT to gasoline prices of –0.1. This elasticity is comparable to Small and Van Dender (2007) and is midway between estimates of West et al. (2015) and Gillingham (2014).[6] The main results are generally robust to alternative values of the elasticity taken from the literature, including allowing the coefficient to vary over time or with income.

Third, equation (3) uses only income category, number of household workers, and age category in defining the household groups. This parsimony reflects the need to define demographic groups such that each group appears in the 1995 NHTS cross section as well as each year from 1995 through 2015 in the CPS data. The typical annual CPS sample size of about 70,000 households prevents us from defining groups that are much more disaggregated or that have additional variables, such as education category, compared with the group definition we use. However, the variables that are included capture much of the cross-household VMT variation. Adding other variables to equation (3) increases the R-squared only somewhat and yields predicted VMT per household that is highly correlated with the predicted VMT per household using the baseline group definition. This similarity reduces concerns about using a subset of the available NHTS variables (see Sections 4.1 and 4.2 for robustness results using alternative group definitions).

Above we noted our preference for combining the NHTS and CPS data to perform the decomposition. On the other hand, a potential drawback of the CPS is that it does not include certain variables, such as the number of licensed drivers in the household, that are likely correlated with VMT.[7] Given these trade-offs, below we report a complementary set of results that use the NHTS data for equations (3) and (4) and include these additional variables.

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[6] An important difference between West et al. and Gillingham is that the latter controls for vehicle attributes whereas the former does not. It is not clear which assumption is preferable in our context, where changes in gasoline prices across years could affect household vehicle holdings, in which case vehicle attributes would also change. However, the changes in holdings during our period of interest are likely less than the full long-run changes.

[7] These variables are examples of variables omitted from equation (3), and which prevent us from interpreting the coefficients in equation (3) as the causal effects of the independent variables on VMT. However, even if we were to include these variables in equation (3) we would still be concerned about other factors that are omitted from equation (3) and are not included in the NHTS survey.

3. Explaining the Recent Changes in VMT Growth

3.1 CPS Results

Figure 6 compares the estimated national VMT from EIA and the NHTS (repeated from Figure 2) with the predicted national VMT based on equations (3) and (4). To predict national VMT, we estimate equation (3) using 1995 NHTS data, yielding estimated VMT per household for each income–worker count–age group. For reference, Appendix Figure 1 reports means of estimated VMT per household by income, age, and worker count group. For each year from 1995 through 2015, the estimated VMT for each group is equal to the estimated VMT per household multiplied by the number of households in the corresponding group computed from the CPS. Predicted national VMT in each year is the sum across groups of estimated VMT by group (equation 4); the figure plots predicted national VMT for each year from 1995 through 2015. All national estimates are normalized to one in 1995 for comparability.

The predicted VMT closely follows the dynamics of the EIA and NHTS data, both of which suggest a slowdown in VMT growth during the 2000s even though they disagree about its magnitude. The predicted VMT lies between the EIA and NHTS estimates in both 2001 and 2009. Moreover, the predicted VMT increases in the 2010s by about the same percentage as the EIA estimate increases. The similarity of the predicted VMT and the estimated VMT suggests that demographics and economic characteristics explain the slowdown of VMT growth in the 2000s and the recovery of VMT growth in the 2010s. Although there were changes over time in driving habits for particular groups—for example, among millennials, as we show in Section 4.3—these changes make relatively small contributions to the overall changes in VMT. To a large extent, changes in driving habits among certain groups cancel out changes among other groups; on balance, demographics and economic characteristics explain most of the VMT dynamics during this period.

We briefly discuss the robustness of this conclusion to alternative versions of equation (3), referring to Figure 6 as the baseline. Figure 7 displays the results of several additional decompositions that differ from the baseline projection in Figure 6, as indicated in the figure notes. First, we show that the results are insensitive to using VMT based on odometer readings rather than self-reported VMT. The VMT data used for the baseline are based on the household's reported annual mileage for each vehicle (in cases of missing data, the Department of Transportation imputes the VMT). By comparing self-reported and odometer-based VMT, Li et al. (2013) suggest that the self-reported data include measurement error. Households appear to accurately estimate their VMT on average, but there is evidence of compression; low-VMT households overestimate their VMT and high-VMT households underestimate theirs. If it is correlated with demographics or income, this measurement error could yield misleading inferences about the importance of demographics and income in explaining VMT growth. To address potential concerns about measurement error in the self-reported VMT, we replace the self-reported VMT with a measure of household VMT based on odometer readings in equation (3). Figure 7 shows that projected national VMT is similar to the baseline if we use odometer-based rather than self-reported VMT. We prefer to use self-reported VMT rather than odometer-based VMT as the baseline because the odometer-based VMT data are missing for a large share of households (in fact, missing values caused the Department of Transportation to discontinue collecting odometer readings after the 2001 survey).

Second, the variables included in equation (3) as the basis for the decomposition reflect a balancing between the desire to include as many variables as possible—which increases the fit of the equation and reduces the influence of omitted variables—with the need to combine the CPS and NHTS data. The main conclusions are robust to alternative ways of estimating equation (3) that represent different balances of these considerations. As noted in Section 3.2, we define groups based on income, age, and number of workers to ensure a balanced panel of groups in the CPS data. Basing groups on additional information, such as education, creates an unbalanced panel, such that an individual age–income–worker count–education group may appear in the CPS data but not in the NHTS cross section. For such groups we cannot estimate γ_0 in equation (3). However, as an alternative to the baseline, we can construct groups based on other combinations of demographics and economic variables. For example, Figure 7 shows the results if we define groups based on income category, number of workers, age category, urbanization status, and household size. In equation (4) we sum over the groups that appear in every year in the CPS data. Therefore, the national estimate is based on a subset of US households, whereas the baseline national estimate is based on all US households. Despite the difference in variable construction and estimation, the results are similar to the baseline.

Third, an alternative approach to adding variables besides income, age, and number of workers to equation (3) is to include the demographic and economic variables independently of one another rather than as interactions. We include as independent variables in equation (3) the fixed effects for income category, age category, and number of workers, as well as fixed effects for other categorical variables: census division, education category, race category, and urbanization status (the largest set of variables that are defined consistently in the NHTS and CPS). Compared with the baseline, this approach allows us to include additional variables in predicting VMT and does not require a balanced panel of CPS household counts to predict VMT in each year. Although we prefer the baseline because it allows for interactions among demographic and economic variables and because it facilitates the projections in Section 5, Figure 7 shows that the results are nearly identical if we use these variables as fixed effects in equation (3).

As a final robustness analysis, which is not reported but available upon request, we can perform the decomposition using 2001 or 2009 as the base year, rather than 1995. The conclusions regarding the roles of demographic and economic variables are similar using the alternative base years.

We next consider which demographic and economic variables made the largest contribution to changes in VMT. Changes in national VMT depend on changes in the number of households and changes in the VMT per household. To simplify the analysis, we focus on the contributions of economic and demographic variables to VMT per household rather than national VMT (on average, the number of US households increased 1 percent per year between 1995 and 2015).

To address this question, we first estimate equation (3) using fixed effects for the variables indicated in the row headings of Table 3. The bottom of Table 3 shows the change in average VMT per household predicted using the changes in CPS household counts during the five-year intervals indicated in the column headings. Each of the other rows reports a separate counterfactual. For example, in column 1 the first row reports the difference in predicted VMT per household using the 2000 income distribution rather than the 1995 income distribution. The first row shows that between 1995 and 2000 the change in the income distribution increased average VMT per household by 557 miles, which is about 3 percent of the 1995 mean. Between 2000 and 2005 the change in the income distribution reduced VMT by about 246 miles. The fact that income had a negative effect on VMT during this period underscores the importance of allowing for nonlinear effects of income on VMT. Appendix Figure 1 shows that VMT per household increases steeply with income at low income levels, but is largely independent of income at higher income levels. This nonlinear relationship between income and VMT per household explains why income had a negative effect on VMT per household in the early 2000s even though average income increased during this period (see Figure 1).

Table 3 also shows that age had a persistent and negative effect on VMT per household, which is consistent with explanations offered in the literature. This effect is typically small compared with the overall changes in average VMT per household, however. Finally, changes in the number of workers per household reduced average VMT per household during the 2000s and increased VMT per household in the 2010s; although not shown in the table, the increasing number of households further contributed to the national VMT growth in the 2010s. Thus, the income and number of worker variables appear to be more strongly correlated with changes in VMT per household than is age, but again we caution against making causal interpretations of these results.

3.2 NHTS Results

As discussed in Section 3.2, we use the CPS household data from 1995 to 2015 for predicting national VMT according to equation (4) partly because of the lower measurement error for income, relative to the NHTS. For comparison with the baseline results, we use NHTS data for equation (4) and show the results in Figure 8. To fully take advantage of the NHTS data, we first estimate equation (3) including fixed effects for a larger set of variables than we use in the baseline: income category, age category, census division, MSA size category interacted with urbanization status, number of workers, number of drivers, number of vehicles, and population density category. Including these variables improves the fit of equation (3), increasing the R-squared from about 0.2 to 0.3, compared with the baseline in which we include interactions of income category, age category, and number of workers. Despite the differences in the variables used in equation (3) and the differences between NHTS and CPS household counts (see Figures 3 and 4), the overall conclusion is the same as the baseline regarding the contribution of demographics and economic characteristics to VMT dynamics. The figure indicates an increase in predicted national VMT between 1995 and 2001, followed by a decrease in predicted national VMT between 2001 and 2009. The increase in the first time period is less than that using CPS household data in Figure 6, but nonetheless the pattern of predicted VMT over the two periods mirrors the evolution of actual national VMT estimated from the NHTS survey responses.

Figure 9 shows that the conclusions using NHTS household data for equation (4) are similar if we take alternative approaches to constructing the variables and estimating equation (3). Section 3.1 discusses the procedure for imputing household income categories based on income in 1995 dollars. For the analysis plotted in Figure 8, we match NHTS and CPS households based on demographics and income category, and we impute the income of the NHTS household using a randomly selected CPS household belonging to the same cell. As an alternative, we use the mean income of CPS households in the same cell rather than the income of a randomly selected household. In expectation the two imputation methods should yield the same imputed income, and Figure 9 shows that the results are qualitatively similar using the alternative imputation method.

The results using NHTS household counts for equation (4) (i.e., Figure 8) are qualitatively similar although not identical to the results using CPS counts for equation (4) (i.e., Figure 6). In principle, this difference could be explained by our use of different variables in equation (3) for the two cases, or by our inclusion of fixed effects for categorical variables in Figure 8, versus interactions of categorical variables in Figure 6. However, two additional results shown in Figure 9 suggest that these explanations are not the cause of the differences between Figures 6 and 8. Specifically, the results are similar to Figure 8 if we use the NHTS household counts but use only the CPS variables for equations (3) and (4), or if we include interactions of variables rather than fixed effects. Thus, the differences between the CPS and NHTS results appear to be due to differences in sampling methodology and possibly the greater measurement error for the NHTS income data.

3.3 Revisiting the Millennials and Amazon Hypotheses

As discussed in Section 2.2, several recent studies and popular media accounts have suggested that changes in driving habits, particularly related to millennials and internet shopping, explain a substantial portion of the slowdown in VMT growth in the 2000s. Our results, however, suggest that changes in demographics and economic characteristics, rather than household driving habits, explain this slowdown, as well as the subsequent increase. In this section we reconcile our findings with those of other studies and popular media. In Table 4, we compare the average VMT per household of households headed by adults aged 21 to 30 (Panel A) with average VMT per household of households headed by adults aged 31 to 40 (Panel B). The first row of each panel shows the mean VMT per household as reported in the 1995 and 2009 waves of the NHTS. Panel A includes household heads born between 1965 and 1974 in the first column and household heads born between 1979 and 1988 in the second column; the latter group corresponds roughly to millennials. The first row of Panel A shows that younger (i.e., aged 21 to 30) households drove about 3.5 percent less in 2009 than did younger households in 1995. The next two rows show that after controlling for income and other demographics, younger households in 2009 drove about 11.5 percent less than did younger households in 1995; this estimate is similar to that in Blumenberg et al. (2012). By comparison, Panel B shows that after controlling for income and demographics, older households (i.e., aged 31 to 40) drove 4.1 percent less in 2009 than did older households in 1995. Thus, we observe a downward trend in demographic and income-adjusted VMT between 1995 and 2009 for both age categories, but a larger decrease for the younger group than for the older group.

This differential downward trend is consistent with claims that millennials drive less than did earlier cohorts. However, the results of the decomposition in Figure 6 suggest that the apparent change in driving habits of young adults is not large enough to be the major factor explaining changes in VMT growth since 2000. That is, millennials represent too small a share of the population to explain the national trends, but it remains possible that changes in driving habits of different age-based groups of households could grow in importance if future cohorts of young adults drive less than earlier cohorts, and if aging millennials continue to drive less than have earlier cohorts.

Turning to the Amazon hypothesis, in Table 5, we compare daily VMT for shopping trips (columns 1–3) and share of shopping trips in daily VMT (columns 4–6), computed using the NHTS trip diaries. The different columns represent the 1995, 2001, and 2009 waves of the NHTS. Panel A reports results by age group and Panel B by income group. Panel A shows that daily VMT for shopping trips has decreased between 2001 and 2009 for all age groups, especially the middle-aged groups. The share of shopping trips in daily VMT displays a similar but less pronounced trend, except for the increase in the share for the youngest age group. Panel B shows that daily VMT for shopping trips has decreased between 2001 and 2009 for all income groups, especially the upper two income groups, and that the share of shopping trips in daily VMT displays a similar but less pronounced trend.

These results are consistent with the hypothesis that shopping trips have decreased and suggest that online shopping could have played a role in this decrease, although the available data do not permit a direct link between shopping trips and online shopping. The magnitude of this decrease is not sufficiently large to explain the overall trends in VMT. Consistent with this finding, DOT (2015) reports that although online shopping has increased rapidly, it did not significantly substitute for traditional shopping trips in 2009. As with millennials, however, the change in shopping habits could grow in importance over time.

4. Implications for Future VMT Growth

Having shown that demographics and economic characteristics, rather than driving habits, explain the changes in VMT growth since 1995, in this section we quantify the implications of this finding for future VMT growth. Specifically, we predict VMT growth between 2015 and 2025 under the assumption that the driving habits of individual groups do not change.

Because this prediction requires counts of households by group in equation (4), and we are not aware of projections of household counts by group, we take three steps that incorporate a reduced-form model of the dynamics of demographics and economic characteristics. First, we assume that the past trend in number of household members per household continues through 2025. Using CPS estimates of the total US population and number of households from 1980 through 2015, we fit a linear time trend to the average number of households per person (i.e., the reciprocal of the number of people per household). We extrapolate this trend through 2025 and multiply the predicted number of households per person by annual Census Bureau estimates of the US population. This calculation yields the predicted number of US households for each year between 2015 and 2025.

In the second step, we predict the number of US households in each income–age–worker count group from equation (4). We calculate the share of households by group and year in the CPS from 1980 through 2015. We fit a linear trend for each group and extrapolate the group-specific trends through 2025, renormalizing the predicted shares to sum to one in each year. Multiplying these predicted group shares by the predicted number of US households from the first step yields the predicted number of households by group and year from 2015 through 2025.

Third, we predict national VMT through 2025 using equation (4), the household counts from the second step, and the baseline estimates of group VMT (i.e., the estimates used for the baseline decomposition in Figure 6). Figure 10 plots the results, along with the EIA projection of national VMT from the 2015 Annual Energy Outlook. Our projections imply annual growth of about 0.9 percent per year between 2015 and 2025, versus 1.4 percent growth projected by EIA.

The results are similar if we use the 2009 NHTS rather than the 1995 NHTS to estimate equation (3), which accounts for possible changes in driving habits between 1995 and 2009, such as the changes for young adults discussed in Section 4.3. The similarity of the results using 1995 or 2009 NHTS data confirms the conclusion from Section 4 about the importance of demographics and economic characteristics in explaining recent VMT growth, relative to driving habits.

The prediction of VMT between 2015 and 2025 depends on changes in the share of households by income category, age category, and number of workers. The final series plotted in Figure 10 shows that income plays a dominant role in the estimated VMT growth during this 10-year period. If we assume that the income distribution does not change between 2015 and 2025 and that there is no income growth, predicted VMT would be roughly flat during this period.

5. Conclusions

The US commitment to reduce greenhouse gas emissions, combined with recent developments in VMT, has generated interest in understanding the dynamics of VMT. The United States has pledged to reduce its economy-wide emissions by about one quarter between 2005 and 2025, and the transportation sector will likely play a major role in meeting that pledge. Because current fuel economy and renewable fuel standards effectively fix the long-run rate of fuel consumption of the vehicle fleet and carbon content of the fuel, future oil consumption and greenhouse gas emissions will depend crucially on VMT growth. After growing steadily for several decades, in the 2000s VMT growth slowed and perhaps leveled off, before apparently growing in the 2010s. The importance of VMT in meeting the climate pledge and the recent dynamics have raised questions about what factors explain those dynamics and what they imply for future VMT.

Recent studies and public discussion of these dynamics have introduced a range of demographic, economic, and behavioral explanations. In particular, the aging of the population, the economic downturn, and changes in the income distribution, as well as changes in driving habits, could explain the slowdown of VMT growth in the 2000s. However, this research, as well as the extensive literature on gasoline demand and VMT, has not tested these hypotheses in a single framework that distinguishes changes in driving habits from nonlinear relationships among the variables.

We use an Oaxaca-Blinder decomposition and allow for nonlinear relationships among variables. We distinguish between changes in (a) demographics and economic characteristics, and (b) driving habits conditional on demographics and economic characteristics. Demographics and economic characteristics, particularly income and number of workers per household, explain both the slowdown of VMT growth in the 2000s and the apparent growth recovery in the 2010s. Aging of the population made a negative but relatively small contribution to the overall change in VMT. We caution, however, about making a causal interpretation of such a decomposition.

The results imply that if the overall stability of aggregate driving habits persists through 2025, VMT will grow at nearly historical rates between 2015 and 2025. In that case, VMT growth will erode a substantial portion of the fuel savings and greenhouse gas emissions reductions expected under the current US fuel economy standards. However, we also document evidence of changes in driving habits for certain segments of the population, such as for millennials. In the data that are currently available, these segments account for a small share of the population and total VMT. Consequently, habit changes do not substantially affect national

VMT. If, however, the habit changes persist over time and spread to other groups, the effects of driving habits on future national VMT would be correspondingly greater.

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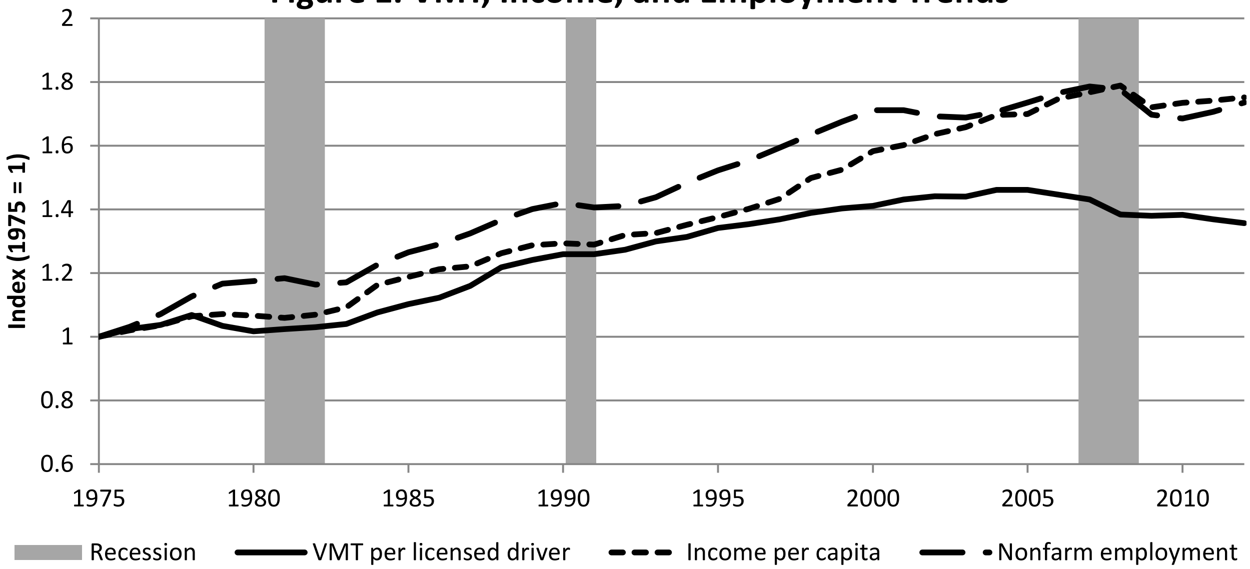
Figures and Tables

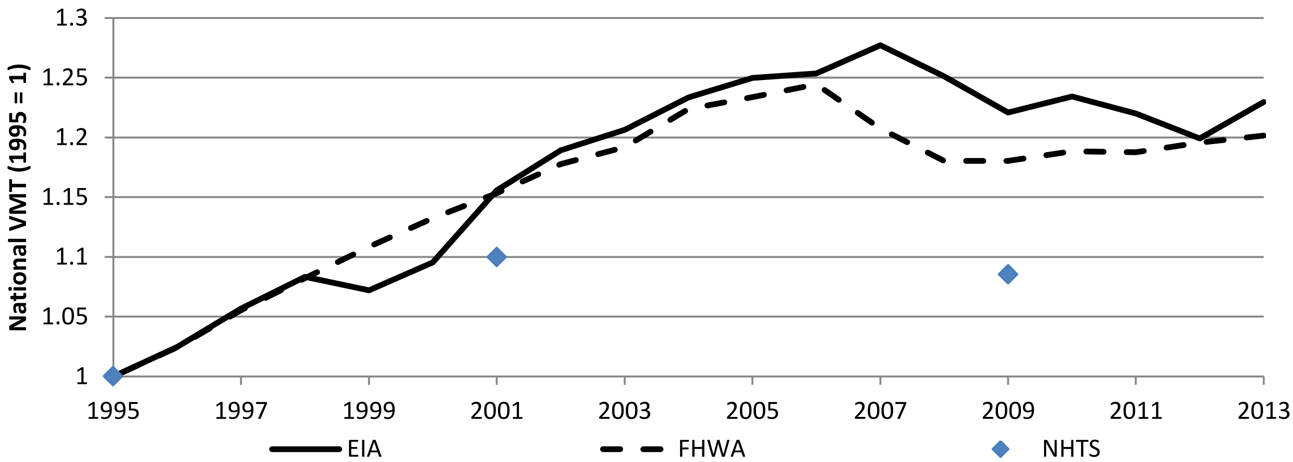
See following pages.

Figure 1. VMT, Income, and Employment Trends



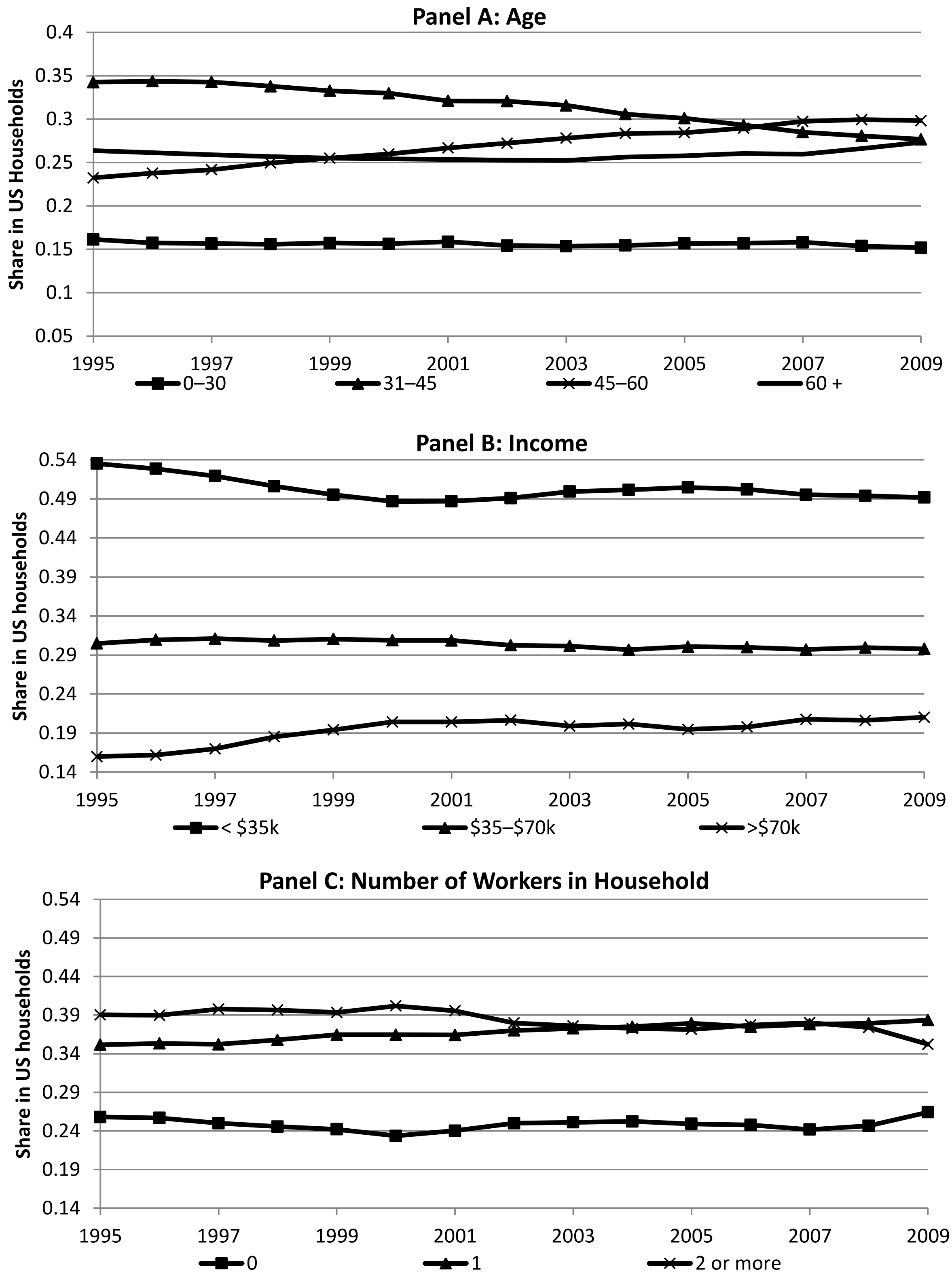
Notes: Data are from EIA (2014). Vehicle miles traveled (VMT) includes light-duty vehicles. All data series are normalized to one in 1975. Shaded areas indicate National Bureau of Economic Research recession periods.

Figure 2. Comparison of National VMT Growth, 1995–2013



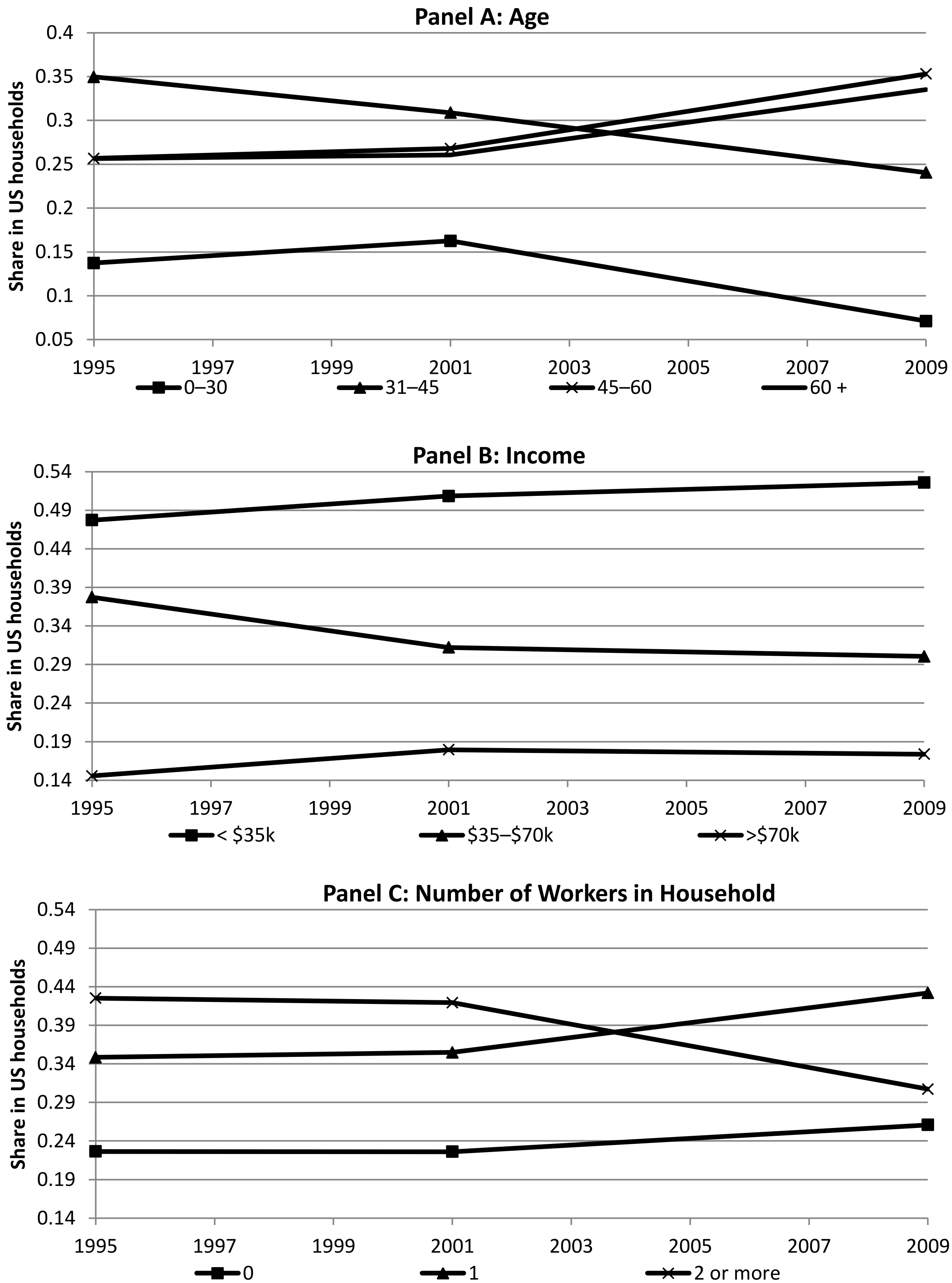
Notes: The figure reports the total VMT by passenger vehicles, with VMT normalized to one in 1995. The Energy Information Administration (EIA) series is from Appendix Table A7 for the reference case, various years. The Federal Highway Administration (FHWA) series is from the VM-1 publication. The National Household Travel Survey (NHTS) series is from Summary of Travel Trends (NHTS 2011).

Figure 3. Age, Income, and Worker Count Shares, CPS



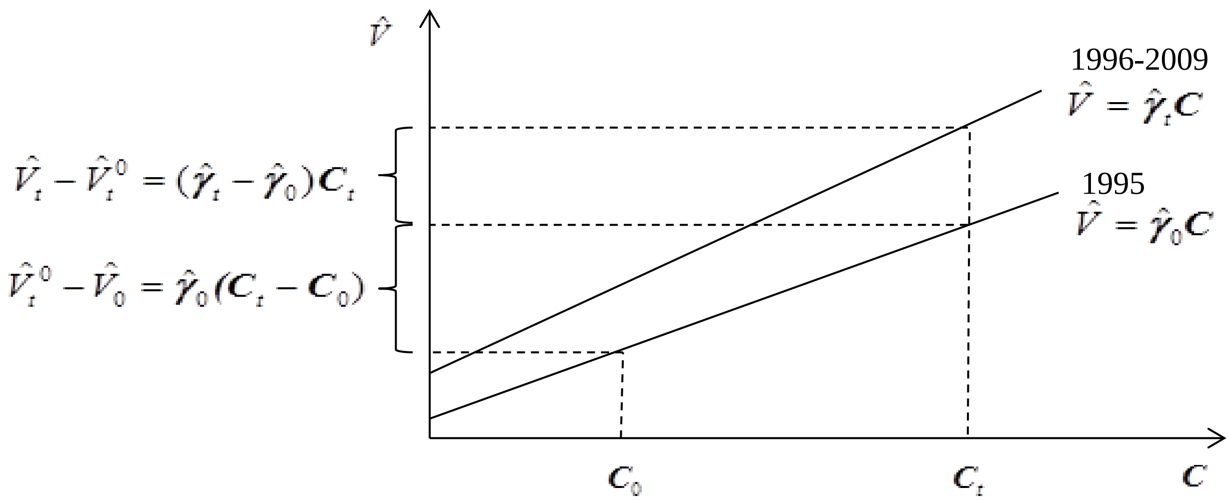
Notes: Panel A reports shares of the indicated age categories in the total number of US households, Panel B reports income shares based on income in 1995 dollars, and Panel C reports shares of households with the indicated numbers of workers. All data are from the Current Population Survey (CPS).

Figure 4. Age, Income, and Worker Count Shares, NHTS



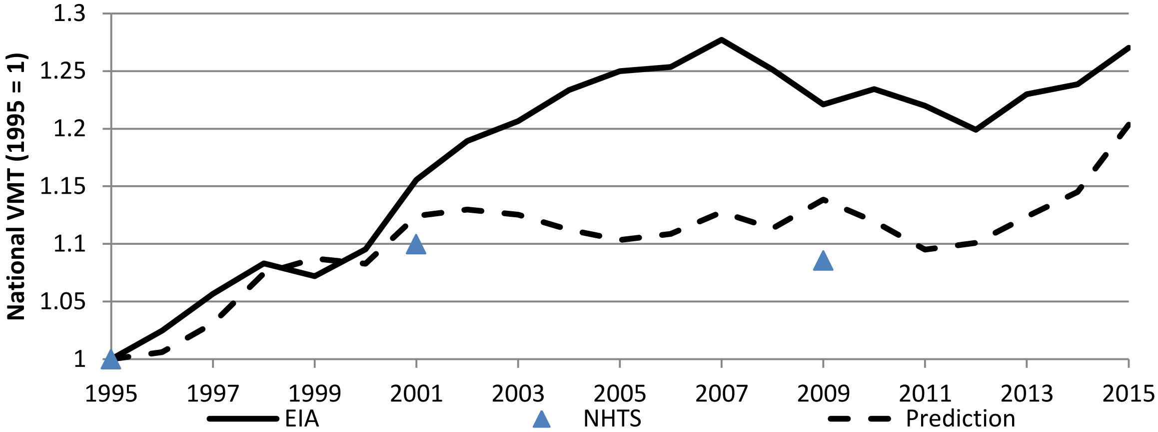
Notes: Panel A reports shares of the indicated age categories in the total number of US households, Panel B reports income shares based on income in 1995 dollars, and Panel C reports shares of households by number of workers. Data are from the NHTS.

Figure 5. Schematic Representation of the Oaxaca-Blinder Decomposition



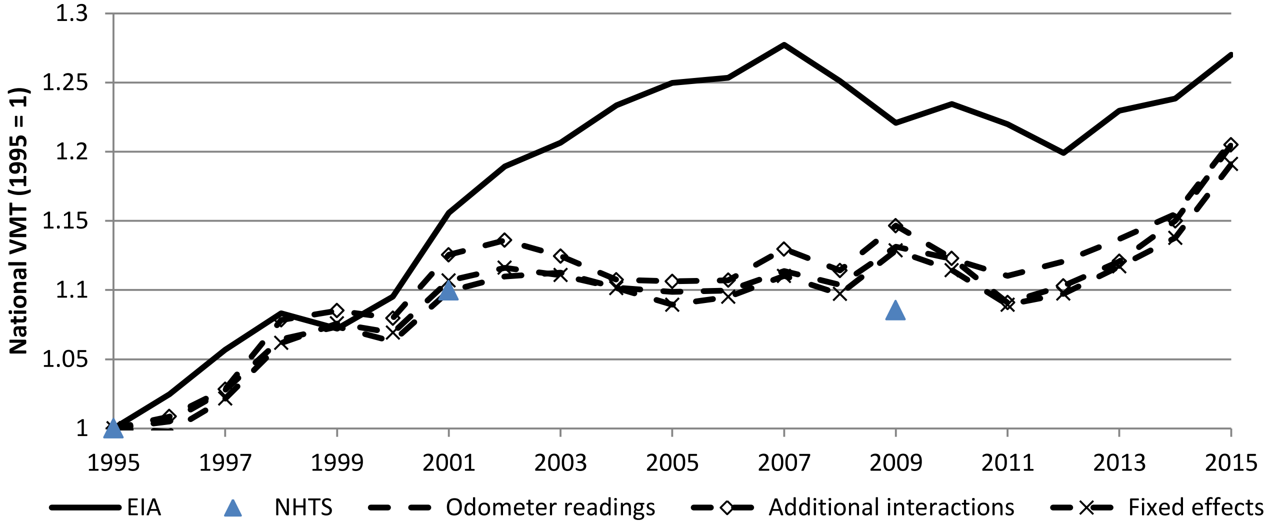
Notes: The vertical axis plots national VMT and the horizontal axis plots a scalar representing demographics and economic conditions. The two sloped lines are the predicted national VMT using habits from 1995 (the bottom line) and from 2009 (the top line). The bottom bracketed term is equation (5) and the top bracketed term is equation (6); see text for details.

Figure 6. Comparing Estimated and Predicted VMT Growth, CPS



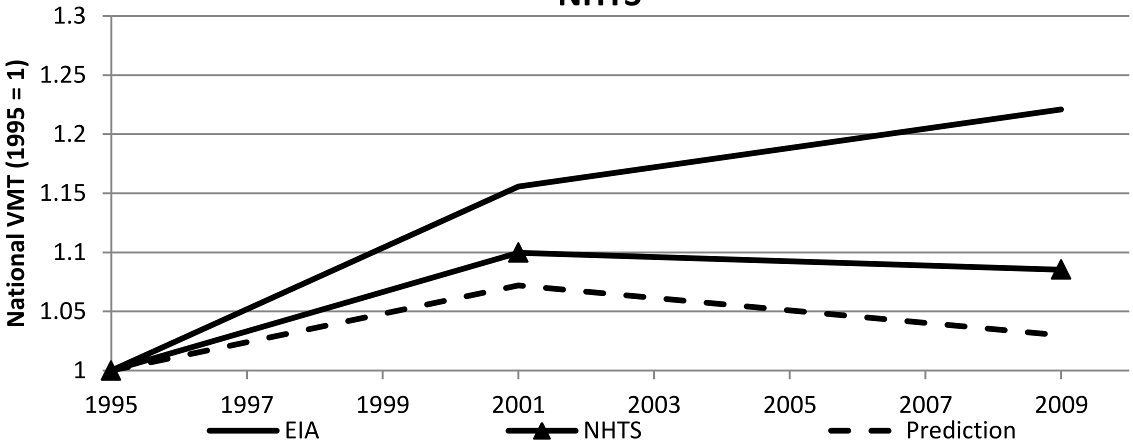
Notes: The EIA and NHTS data series are the same as in Figure 2. The prediction data series is the predicted national VMT using the 1995 NHTS to predict VMT per household, and using CPS household counts for 1995 through 2015. The VMT per household is predicted using interactions of household income category, number of workers, and age category of the household head.

Figure 7. Alternative Models, CPS



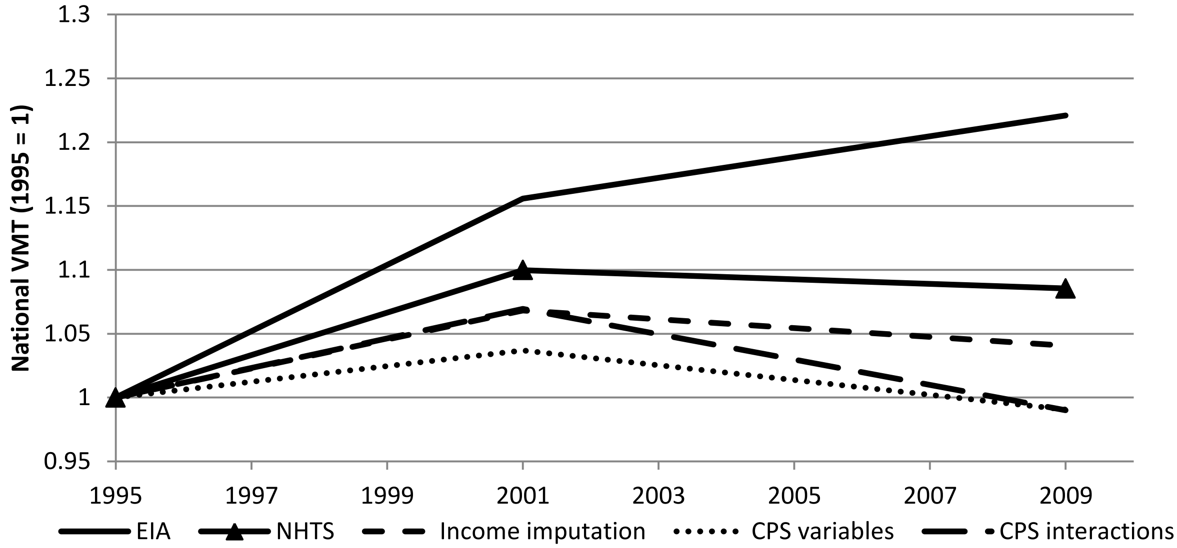
Notes: The EIA and NHTS data series are the same as in Figure 1. The prediction data series is the predicted national VMT using the 1995 NHTS to predict VMT per household, and using CPS household counts for 1995 through 2015. The VMT per household is predicted as in Figure 6. The series odometer readings uses the NHTS VMT estimated by odometer readings. The series additional interactions uses predicted VMT based on interactions of income category, number of workers, age category, urbanization status, and household size. The series fixed effects uses predicted VMT based on fixed effects for income category, 5-year age category, census division, number of workers, education category, household size, race category, and urbanization status instead of the interactions of income category, number of workers, and age category.

Figure 8. Comparing Estimated and Predicted VMT Growth, NHTS



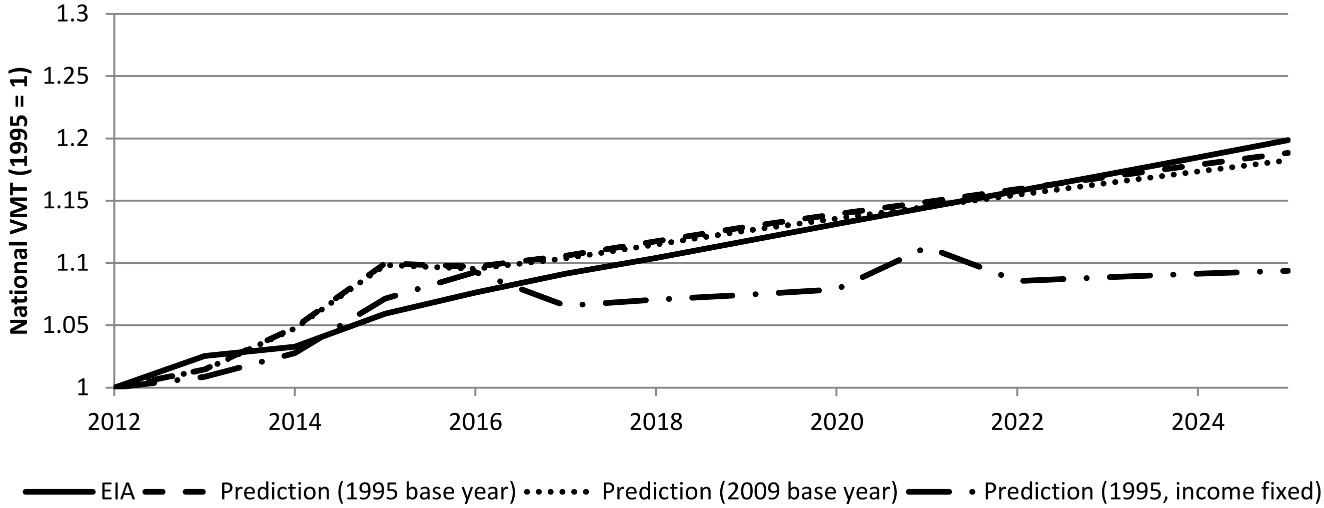
Notes: The EIA and NHTS data series are the same as in Figure 2. The prediction series is the predicted national VMT using the 1995 NHTS to predict VMT per household, and using NHTS household counts for 1995, 2001, and 2009. The VMT per household is predicted using fixed effects for income category, age category, census division, MSA size by urbanization status, number of workers, number of drivers, number of vehicles, and population density. The fixed effect for income is drawn randomly from demographic groups (categorized by combinations of income, worker count, urbanization status, and census division) constructed using the CPS.

Figure 9. Alternative Models, NHTS



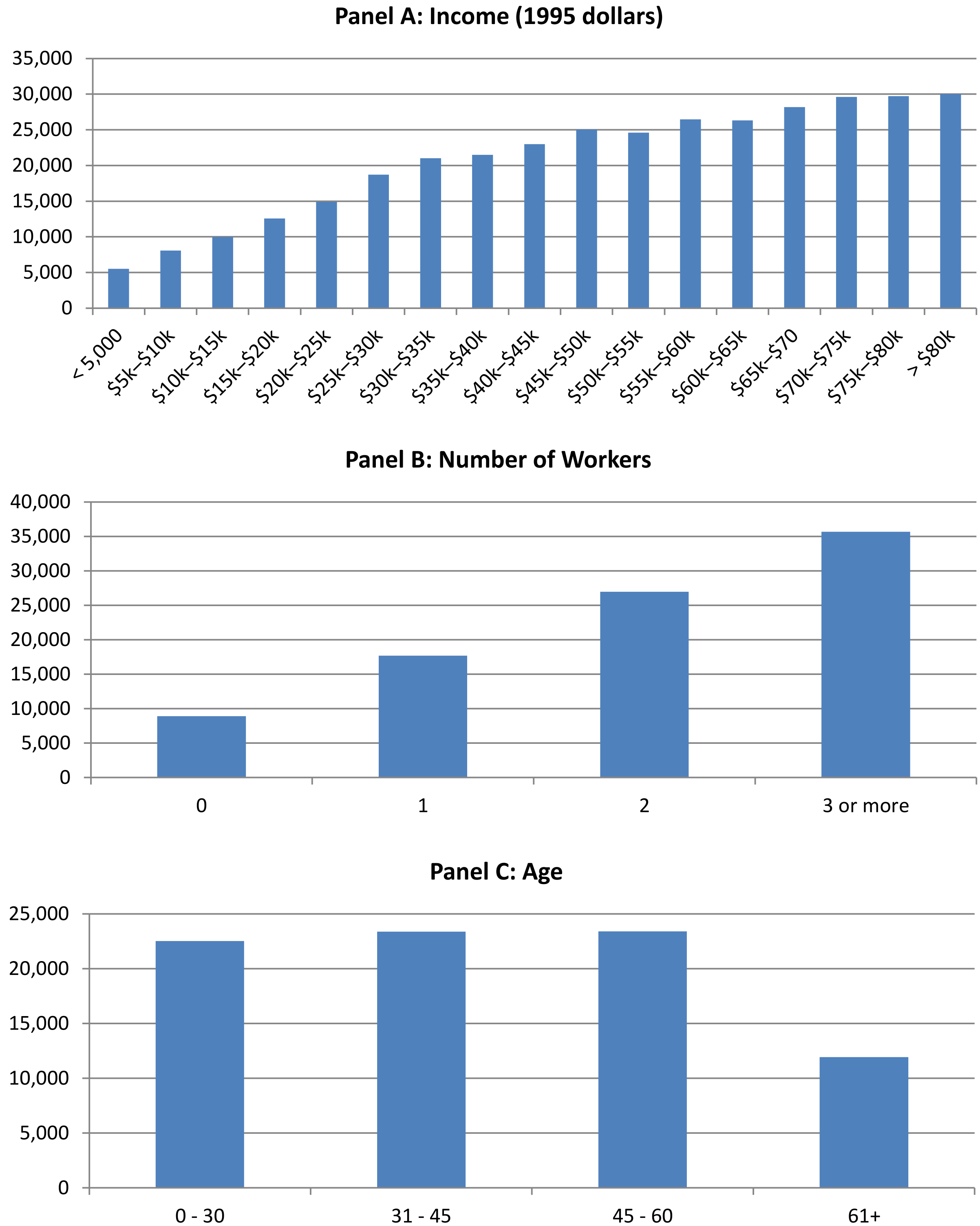
Notes: The EIA and NHTS data series are the same as in Figure 2. The series income imputation, CPS variables, and CPS interactions are constructed similarly to the prediction series in Figure 8. Income imputation uses the mean income of CPS households in the same income–worker count–urbanization–census division cell to impute income, rather than the income of a randomly selected CPS household in the same cell. The series CPS variables uses income, age, census division, number of workers, education category, household size, race category, and urbanization status to predict household VMT. The series CPS interactions uses the interaction of income category, age category, and number of workers to predict household VMT.

Figure 10. Comparison of EIA and CPS-based Projections



Notes: The EIA series is the projected national VMT from the 2015 Annual Energy Outlook. The prediction (1995 base year) series is the predicted VMT using the same prediction model as in Figure 5 and the 1995 NHTS data, combined with projected counts of households by income–worker count–age category group. The household counts are the product of the projected number of US households and the projected share of each group in the total. The projected total number of US households through 2025 is the ratio of the US population predicted by the Census Bureau, and the projected average number of people per household. The number of people per household is a linear projection based on CPS data from 1980 through 2015. The share of each group in total households is projected through 2025 using a linear extrapolation of a 1980–2015 trend specific to each group. The series prediction (2009 base year) is the same as the 1995 prediction but uses the 2009 NHTS instead of the 1995 NHTS. The series prediction (1995, income fixed) is the same as the 1995 prediction but holds income fixed at 2012 levels.

Appendix Figure 1. Mean Estimated VMT per Household by Income, Number of Workers, or Age Group



Notes: The figure plots the mean estimated VMT per household by income, number of workers, or age group. The estimates are from equation (3) and are weighted using NHTS survey weights.

Table 1. Percentage of Households, by Demographic Category and NHTS Year				
	1995	2001	2009	Change (2009–1995)
Number of households	34,314	59,145	144,417	
Census division				
New England	3.8	3.8	5.0	1.2
Middle Atlantic	16.0	14.7	13.5	-2.5
East North Central	18.1	17.6	15.9	-2.3
West North Central	7.3	6.7	7.3	0.0
South Atlantic	19.0	20.2	19.8	0.8
East South Central	5.6	6.2	6.3	0.7
West South Central	11.1	10.5	11.1	0.0
Mountain	3.0	4.1	7.0	4.0
Pacific	16.0	16.2	14.2	-1.8
MSA size (population)				
< 250k	7.4	6.8	7.1	-0.3
250–500k	7.1	8.3	8.6	1.6
500k–1 million	8.1	7.8	7.7	-0.4
1–3 million	18.6	22.3	22.0	3.4
> 3 million	40.4	37.0	34.9	-5.5
Not in MSA	18.3	17.8	19.6	1.3
In urban area	65.4	80.0	77.2	11.8
Number of drivers				
0	6.0	5.4	4.7	-1.3
1	30.4	32.6	34.0	3.7
2	50.6	48.7	47.9	-2.6
3	10.2	10.2	10.2	0.0
4 or more	2.9	3.2	3.3	0.3
Number of vehicles				
0	9.1	8.4	8.7	-0.4
1	29.9	31.4	31.9	2.0
2	41.4	37.1	36.6	-4.8
3	14.4	14.9	14.5	0.1
4 or more	5.2	8.2	8.4	3.2

Notes: The table reports percentages of households in the indicated demographic category using data from the 1995, 2001, and 2009 NHTS waves. The rightmost column reports the percentage point change between the 2009 and 1995 waves.

Table 2. Average VMT, by Demographic and Income Category and NHTS Year				
	1995	2001	2009	Change (2009–1995)
Age group				
0–30	22,527	24,086	22,831	304
31–45	23,379	25,543	24,964	1,585
46–60	23,405	24,471	24,059	654
61 +	11,925	12,403	14,230	2,304
Income group				
< $35k	14,162	15,149	14,545	383
$35k–$70k	24,370	26,559	26,844	2,474
> $70k	30,097	31,218	29,817	-280
Number of workers				
0	8,924	9,515	10,325	1,401
1	17,695	17,801	19,249	1,555
2 or more	28,565	31,315	32,180	3,615

Notes: The table reports the weighted mean VMT of households in the indicated demographic category using data from the 1995, 2001, and 2009 NHTS waves, using household survey weights. The rightmost column reports the percentage point change between the 2009 and 1995 waves.

Table 3. Contributions of Income, Age, and Worker Count to Changes in Household VMT, 1995–2015

	(1) 1995–2000	(2) 2000–2005	(3) 2005–2010	(4) 2010–2015
Income	557	-246	30	-12
Age	-22	-19	-52	-61
Number of workers	211	-349	-293	83
Total	747	-614	-315	10

Notes: The table reports changes in VMT per household over the 5-year intervals indicated in the column headings. Equation (3) is estimated including fixed effects for the variables indicated in the row headings. Each row in the table reports a single counterfactual. For example, the first row of column 1 reports the difference between the predicted VMT using 2000 household income rather than 1995 household income, and holding all other demographic variables fixed at 1995 levels. The other columns report results for the indicated 5-year intervals.

Table 4. Changes in Household VMT by Age Group, 1995–2009

	Panel A: Household head is 21–30 years old		
	1995	2009	Percentage difference between 2009 and 1995
Mean VMT per household	22,717	21,950	-3.50
Control for income and number of workers	22,329	21,817	-2.35
Add other demographics	22,606	20,284	-11.45
	Panel B: Household head is 31–40 years old		
	1995	2009	Percent difference between 2009 and 1995
Mean VMT per household	22,841	23,950	4.63
Control for income and number of workers	20,483	21,026	2.58
Add other demographics	19,980	19,188	-4.12

Notes: Panel A reports VMT per household for households with respondents aged 21–30, and Panel B includes households with respondents aged 31–40. The first column includes households in the 1995 NHTS wave, and the second column includes households in the 2009 NHTS wave. The first row in both panels reports the weighted mean of VMT per household using NHTS survey weights. The second row reports the predicted mean household VMT after controlling for income category and the number of workers. The third row also includes household size, urbanization status, census division, education category, and race category.

Table 5. Daily Shopping Trips by Age and Income Groups

	(1)	(2)	(3)	(4)	(5)	(6)
	Daily VMT for shopping trips			Share of shopping trips in daily VMT		
	1995	2001	2009	1995	2001	2009
				Panel A: Age		
0–30	9.5	12.7	11.6	0.142	0.168	0.178
31–45	11.8	13.2	10.4	0.156	0.168	0.165
46–60	12.8	14.6	12.1	0.165	0.195	0.189
61 +	11.3	11.6	11.3	0.243	0.286	0.253
				Panel B: Income		
< $35k	10.0	12.0	11.0	0.190	0.218	0.231
$35k–$70k	11.7	14.7	11.3	0.163	0.191	0.177
> $70k	14.8	14.5	11.8	0.159	0.172	0.162

Notes: The table reports daily VMT for shopping trips in columns 1– 3 and the share of shopping VMT in total daily VMT in columns 4–6. For each household, total daily VMT is computed from the household's trip diaries. Shopping VMT is computed using trips for which the reported purpose is shopping. Each column reports the mean shopping VMT and share of shopping VMT in total daily VMT for the NHTS wave indicated in the column heading and for the age group (Panel A) or income group (Panel B) indicated in the row heading. All cells report weighted averages using NHTS trip weights.