IMPACTS OF TRANSPORTATION ENERGY POLICY ON FUEL CONSUMPTION AND TRANSPORTATION SAFETY

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ABSTRACT

The purpose of this paper is to explore the impacts of transportation energy policies on traffic safety through policy simulations. Considering the changes in vehicle miles traveled (VMT) and in vehicle stock composition as a result of policy changes, we examine the impact on traffic accidents from those changes in terms of the number of traffic accidents, traffic fatalities, and total accident costs. Here we are primarily concerned with the following policy alternatives: *Fuel tax*, mileage based *VMT tax*, Pay-as-you-drive (*PAYD*) and Pay-at-the-pump (*PATP*) insurance premium policy, and Corporate Average Fuel Economy (*CAFE*) standards regulations. By fully integrating three interrelated economic demand decisions – size of vehicle stock, use of the vehicle stock, and energy efficiency – it can predict short-run, long-run, and dynamic effects of a policy change.
The results show that the share of light trucks will keep increasing in the future in all policy alternatives and that fuel consumptions will decrease compared to the baseline scenario in all scenarios except *VMT tax* policy. The results also show that the fatality rates per vehicle miles traveled will decrease but *CAFE* policy result in more fatalities and higher fatality rates compared to the baseline scenario. The results may provide guidance as to which would improve energy dependency while reducing undesirable side effects related to traffic safety.
The outcome of this research provides a set of specific results comparing policy scenarios in a consistent manner. The results will provide guidance concerning whether the policy option would improve energy dependency while reducing undesirable side effects such as environmental problem and safety problem of motor-vehicle travel.

Keywords: Transportation energy, Policy simulation, Two-vehicle crashes, Traffic safety, Pay-as-you-drive (PAYD), Pay-at-the-pump (PATP), Corporate Average Fuel Economy (CAFE), VMT tax, Fuel Tax

1 INTRODUCTION

One of the most distinct trends in the U.S. transportation sector for the past three decades is the shift in vehicle stock composition toward light trucks. Light trucks, which include pickups, vans, and sport utility vehicles (SUVs), increased their share of the new light duty vehicle (LDV) market from 20.9% in 1975 to 54.7% in 2005. The growth in the share of light trucks is partly as a result of lower fuel prices and higher income levels. The continuing increases in demand for and use of light trucks, which have lower fuel economy than cars in average, have offset the improvements in fuel economy due to enhanced motor vehicle engine technology and have resulted in the higher rate of increase in petroleum consumption in the transportation sector than any other sector.

The transportation sector is responsible for a large portion of energy consumption in the U.S. and the highway sector is the largest part of transportation fuel consumption. Light truck energy use has increased at an annual average rate of 4.9% over the period 1970-2005, while overall highway transportation energy use has increased by 1.8%. [1] The actual corporate average fuel economy (*CAFE*) of light trucks was 22.0 miles per gallon (MPG) in 2005, with 20.9% up from 18.2 (MPG) in 1979 (average annual growth rate: 3.4%). Over the same period, corporate average fuel economy of cars increased by 4.1% annually on average.

Motor vehicles contribute to air pollution and global warming, both of which are subject to extensive policy concern in the country. Thus, reducing transportation fuel consumption would not only enhance the country's energy dependency but also help to reduce greenhouse gas emissions, improve air quality, and reduce other driving-related external costs.

The purpose of this paper is to explore the impacts of various transportation energy policies focusing on traffic safety. We narrow our focus regarding transportation energy on highway use of gasoline by light duty vehicles (i.e, cars and light trucks) since gasoline use explains more than 60% of all transportation energy sources and highway gasoline makes up more than 95% of total gasoline consumption in the U.S. In measuring the impacts from a policy change, we pay attention not only to direct impacts on travel demand (i.e., VMT and fuel consumption) but also to indirect (external) impacts on environment (e.g., greenhouse gas (GHG) emissions) and transportation safety, which are often not taken into account. Since the indirect impacts may modify policy outcomes through travelers' behavioral reactions (e.g., changes in consumers' preference of vehicle choice) and other decision making factors, we need a comprehensive review of policy options in measuring the impacts from a policy change.

We consider the changes in vehicle miles traveled (VMT) and in vehicle stock composition as a result of policy changes. Those changes in vehicle fleet composition and the size of vehicles, in turn, may cause changes in the risk of traffic crashes and would have different

[1] Transportation Energy Data Book (26), Table 2.7, Table 4.17, and 4.18

impact on fatality and injury depending on whether the accident is a one-vehicle crash or two-vehicle crash. Considering the current trend of increasing stock of light trucks, which are reportedly safer than smaller cars when involved in traffic crashes, there are concerns about the risk of fatalities in smaller cars involved in traffic crashes, especially in two-vehicle crashes of cars against light trucks.

Considering these changes and factors, we examine the effect on traffic accidents from those changes in terms of the number of traffic accidents, traffic fatalities, and accident costs. The measurement of the impacts of a policy change on traffic safety will be done through an analytical traffic accident model reflecting possible changes in the probabilities of accident of different types of vehicles (i.e., cars and light trucks) and crash type (i.e., single-vehicle crashes and two-vehicle crashes) after implementation of a new policy. In measuring policy impacts on vehicle miles and vehicle stock, this research is based on an analytical framework by Small and Van Dender (2007) to identify the ways that behavioral reactions modify policy outcomes. The model fully integrates three inter-related economic demand decisions: size of vehicle stock, use of the vehicle stock, and energy efficiency.

Here we are primarily concerned with the following economic policy alternatives: (1) raising the existing fuel tax; (2) instituting a tax on vehicle miles traveled (VMT); (3) converting insurance payments to a per-mile basis (pay-as-you-drive, or *PAYD*); (4) converting insurance payments to per-gallon basis (pay-at-the-pump, or *PATP*); and (5) regulating stronger corporate average fuel economy (*CAFE*) standards.

The outcome of this research is a set of specific results comparing policy scenarios in a consistent manner. The changes in vehicle miles and vehicle stock are decomposed by vehicle type and so are other changes regarding traffic safety. The results show that, in all scenarios, the light truck share of new vehicle sales will continue to increase. The changes in per-mile driving cost in response to each policy might affect people's vehicle preference. Higher per-mile driving costs from the *Fuel Tax*, *PATP*, and *PAYD* policies would cause people to choose more fuel efficient vehicles (i.e., cars). Meanwhile, the *VMT Tax* policy does not have any incentive to purchase fuel efficient vehicles so it increases the share of light trucks. *CAFE* regulation policy also slightly increases the share of light trucks compared to the baseline scenario due to the lower per-mile driving cost.

The results may provide guidance concerning which policy option would improve energy dependency while reducing undesirable side effects related to traffic safety. This research also contributes to the literature in the following ways. First, the policy simulation model used in this study enables us to assess the impacts of policies by adding details necessary to account for features of the policies being examined. For example, I construct and add an analytical traffic accident model using the probabilities of accident of different types of vehicles (i.e., cars and light trucks) and different types of accidents (i.e., single-vehicle crashes and two-vehicle crashes). Second, the simulation model can be used and adapted for analysis at the state level or for the entire United States level. Thus, it would provide a tool for potential use in analyzing regional policies, or federal policies. Third, the data set from 1966 to 2004, which is cross-sectional time series data at the U.S. State level, is longer than other studies and it is constructed so that it is easy to use in simulation and to update in the future.

2. LIGHT DUTY VEHICLES AND TRAFFIC SAFETY

2.1 Trends in Light Duty Vehicle Transportation

Cars still dominate the share of light duty vehicle (LDV) stock at 57% in 2005, but not to the same extent as in 1970, when their share was about 83%. In contrast, there was remarkable growth in the share of light trucks thanks to the increasing trends of light truck share in new LDV sales, which is even larger share (54.7%) than the share of new car sales in 2005. The market share of light trucks sales is increasing rapidly with 5.4% of average annual increase rate from 1970 to 2005 while new car sales decreases with -0.3% in average for the same period (Transportation Energy Data Book 26, Table 4.5 and 4.6).

In terms of the share of vehicle miles traveled (VMT) of light duty vehicles, vehicle miles by cars account for about 61% of the total VMT in 2005, which was decreased by 27% from the share in 1970, while the share of light trucks' VMT increases to 39% from 12% in 1970. Average vehicle miles per vehicle for light truck has increased 31% from 1970 to 2002 while that of automobile has increased 18.8% (FHWA, 2004). The slower rate of increase in VMT share of light trucks may be due to the lower fuel economy (mile per gallon; MPG) in average compared to average car's fuel economy. According to FHWA's *Highway Statistics*, a car can drive up to 22.9 miles consuming one gallon of gasoline while a light truck can drive 16.2 miles in 2005.

The shares of highway transportation energy (i.e., motor fuel gasoline) by cars and by light trucks are about 41.5% and 36.8% respectively in 2005. The share of light trucks rose from 13.1% in 1970 with annual average increase rate of 0.6% while the share of cars decreased from 72.4%.

Regarding vehicle weight, the average weight of a new car and of a new light truck, which were both just over 4,000 lbs, began to decline in the late 1970's and early 1980's. It may be because of the corporate average fuel economy (*CAFE*) standard regulation which was enacted in 1978 and increased at a slow rate extending into the late 1980s. Both cars and light trucks show decreases in their weight till 1987 and then, the weight for both vehicle types has been generally increasing maybe because of the relatively constant level of *CAFE* standards. The weight gap between cars and light trucks becomes larger and, in 2005, light trucks averaged 1,200 lbs. heavier than cars in average (U.S. EPA, 2006).

2.2 Literature on the impact of vehicle attributes on traffic crashes

2.2.1 Vehicle Size and Weight and Traffic Crashes

Collision with another motor vehicle in transport was the most common first harmful event for fatal, injury, and property-damage-only crashes (NHTSA, 2006).[2] In 2005, 31,415 occupants of light duty vehicles (LDV) were killed in traffic crashes (cars 18,440; light trucks 12,975) and an additional 2,446,000 were injured. Occupant fatalities in single-vehicle crashes accounted for 43 percent of all motor vehicle fatalities in 2005. Occupant fatalities in multiple-vehicle crashes accounted for 43 percent of all fatalities, and the remaining 14 percent were non-occupant fatalities such as pedestrians, bicyclists, etc.

Several studies examine the relationship between vehicle weight (or mass)[3] and fatality rate. Here we focus on the effect of vehicle weight and size from two-vehicle crashes since the findings from two-vehicle crashes may give a better understanding of general effects of vehicle crashes.

When two vehicles with different weight crash, it seems likely that the lighter vehicle would have more damage than the heavier one taking into account basic physical principles of vehicle mass and speed. Ross and Wenzel (2001) show that occupants of the lighter car are at greater risk in almost all two vehicle crashes and thus reducing the weight (mass) of light trucks would result in a decrease in car fatalities and in overall fatalities. Evans (2004) also shows that the driver in the light car is 9 times as likely to die as the light truck driver when light cars and light truck (van) crash into each other. NHTSA (2003) analyze the crash data in 1995-2000 and estimate the average increase rate in the fatality rates of (W-100) pounds vehicles compared W pounds weighing vehicles for the same period model year (1991-1999) controlling for the age and gender of drivers, the types of roads they travel, and other factors. 100 pounds weight reduction in light trucks result in a modest net benefit by reducing the risk to the occupants of the other vehicles even though the fatality risk of the occupants in light trucks from rollover or fixed object crash increased. The weight reduction in cars increases the fatality risk to car occupants due to largest fatality increase in collisions with light truck vehicles. The conclusion of the research is that the association between vehicle weight and fatality risk in heavier light trucks was weak and insignificant while it was strong in the lighter cars implying increase in fatality risk from overall weight reduction.

Vehicle size, specifically crush space, does provide safety in case of crashes. In some studies, vehicle weight and size have not been distinguished and the benefits of size have been confused with the benefits of vehicle weight. Evans (1984) examines police reported crashes with different age group and finds that accident involvement rates are lower for small cars than they are for larger cars driven by drivers of similar age.

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[2] For purposes of compiling DOT safety statistics, fatality is defined as any injury that results in death within 30 days of a transportation crash, accident, or incident.
[3] We assume that mass and weight are interchangeable though, conceptually, the two terms are distinct.

Regarding two vehicle crashes, many studies show that the damage is more critical to the occupants in a car than to the occupants in a light truck (See, e.g, White, 2004; Brozović and Ando, 2005). White(2004) measures both the internal effect of large vehicles on their own occupants' safety and their external effect on others and finds that the larger vehicle drivers and passengers are safer in a given two-car crash. She estimates the probabilities of fatalities and serious injuries by vehicle crash type and finds that that the probability of a car driver being killed in a two-vehicle crash is 61 percent higher if the other vehicle is a light truck than if it is another car. She also calculates the impact on the fatalities of replacing 1 million light trucks by cars caused by a policy change and finds the policy change would reduce the number of fatal crashes involving cars, pedestrians, bicyclists, and motorcyclists.

2.2.2 CAFE and Traffic Safety

Many studies have examined the relationship between vehicle safety and fuel economy. While little research has been done on the safety implications of other policy options, e.g., higher gasoline tax, per-mile insurance premium change. Some studies examine the effect of *CAFE* assuming that *CAFE* regulations led to reductions in vehicle weight since fuel is used primarily to overcome inertia and, other factors being equal, making a vehicle lighter reduces its fuel use. Crandall and Graham (1989) investigate the effect of *CAFE* on vehicle weight and on vehicle safety in terms of traffic fatalities using time series data. They find that decreases in vehicle weight caused by *CAFE* regulations increase traffic fatalities holding such variables as income, speed, age of drivers, alcohol consumption, gas price constant, concluding that *CAFE*, which caused decreases in vehicle weight, was associated with an increase in crash fatalities in new cars. But Noland (2004) and Ahmad and Greene (2005) find no supportive evidence of Crandall and Graham's early finding through a statistical analysis of the correlation between fuel economy and traffic fatalities covering the period from 1966 to 2002 using state level data and national level data respectively.

These mixed results may be because there are two different effects from *CAFE* standard changes (Godek, 1997). One is the impact on vehicle stock composition. *CAFE* standards tend to reduce the weight of vehicles as substitute of high fuel efficiency and it seems to have negative impact on safety when a crash occurs. The other is that the increase in light trucks may reduce the fatalities risk of the passengers in light trucks but increase it for passenger of cars. Gordon *et al.* (2006) argue that modern vehicle manufacturing technology can strategically reduce car weight while improving vehicle structure, using advanced materials and designs, and thus can simultaneously increase fuel economy and safety.

3. ANALITICAL MODEL

3.1 Descriptive Impacts of a Policy Change

The primary goal of the policies considered here is to reduce transportation energy consumption and the policy instruments will decrease the fuel consumption by way of travelers' behavioral changes. When a policy is newly implemented, people may reduce unnecessary trips and thus decrease vehicle use and travel distance. They may even change mode to less expensive ones or to a more fuel efficient mode. These behavioral changes would affect not only fuel consumption but also other transportation externalities such as greenhouse gas emissions, traffic safety, and congestion.

The proposed policy options, except *CAFE* standard regulation, may reduce VMT (and fuel consumption) due to an increase of per mile cost of driving. While most policy strategies mainly aim to reduce total vehicle mileage and thus to reduce fuel consumption, those strategies also have other indirect impacts on congestion, safety, vehicle choice, vehicle emissions etc. and some indirect effects are difficult to quantify.

To fully explain the impacts of policy options, we need to consider a variety of impacts besides energy conservation and emission reductions, including impacts on consumer costs and transportation choice, congestion, traffic safety. Policy strategies that increase per-mile vehicle operating costs tend to reduce total vehicle travel, and so can further reduce congestion and traffic crashes while strategies aiming to reduce per-mile vehicle operating costs tend to induce additional vehicle travel, and so tend to increase traffic congestion and crash risk. Assuming the per-mile crash risk, either one-car crash or two-car crashes, are constant, the number of traffic accidents will be reduced proportionately to the decrease in VMT. Therefore, the policy option which leads to larger VMT with the given same % of reduction in gasoline consumption may have larger (negative) impact on crash risk.

Three interrelated economic demand decisions (size of vehicle stock, use of the vehicle stock in terms of VMT or fuel consumption, and energy efficiency) are integrated into systems of equations to predict policy impacts as in Small and Van Dender (2007).

Figure 1 shows the framework and the relations among results from a change in policy instruments.

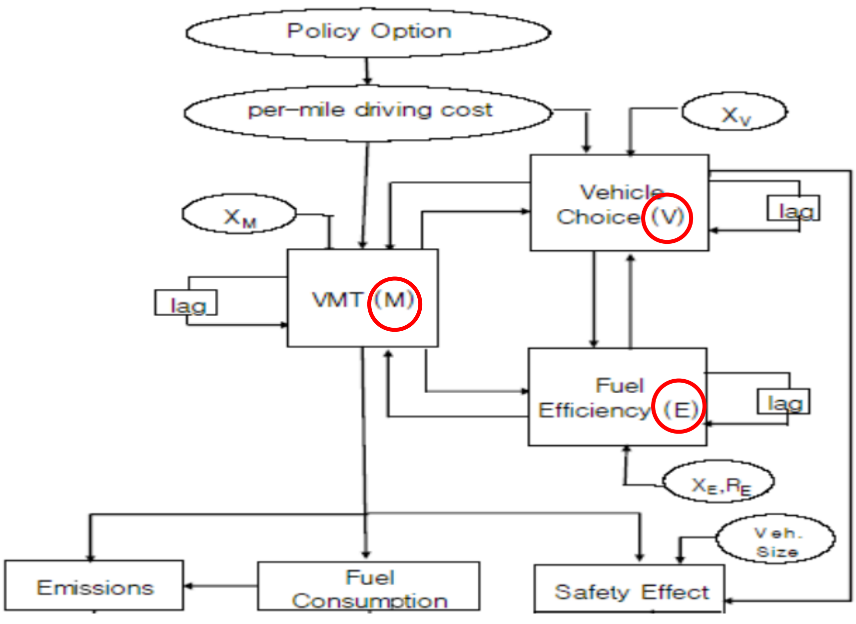

Figure 1 – Framework of Analysis and Policy Simulation

3.2 Vehicle miles, vehicle stock, and fuel efficiency

We define VMT as a function of the per-mile cost of driving, vehicle ownership, and other exogenous characteristics. Likewise, consumers choose how many vehicles to own based on vehicle purchase and operating price, how much they intend to drive, and other characteristics. The fuel efficiency choice is determined jointly by consumers and manufacturers taking into account the price of fuel, how much they intend to drive, the regulatory environment, and other characteristics. So we consider simultaneity in vehicle usage (i.e. vehicle miles, *M*) and vehicle stock (*V*) and fuel intensity (*E*) as specified in Small and Van Dender (2007).

These definitions can be shown as following equations:

$$\begin{aligned} M &= M(P_m, V, X_M), \\ V &= V(P_v, M, P_m, X_V), \\ E &= E(P_f, M, R_E, X_E). \end{aligned} \tag{1}$$

where *M* is aggregate VMT; *V* is the size of the vehicle stock; *Pv* is a price index for the ownership cost of new vehicles; X_M, X_V and X_E are exogenous variables affecting *M*, *V* and *E*, respectively; and R_E represents one or more regulatory variables. Total fuel consumption (in gallons per year), *F*, is defined by the identity $F = M / E$.

A policy change (e.g., gas tax increase) would decrease VMT directly because of the increased fuel price (ΔM_0) through the first equation in (1). But there are also indirect change in VMT through the impact of gas price on fuel efficiency (ΔM_E) and vehicle stock (ΔM_V) in the other two equations. Consumers are in favor of fuel efficient vehicles and thus fuel efficiency technology would affect vehicle price. Vehicle prices (and other vehicle characteristics) would affect vehicle ownership cost and high ownership cost would cause decrease in vehicle stock (probably with some changes in vehicle composition) and in vehicle miles (*M*). Total change in *M* including indirect effect from a change in vehicle stock and in fuel efficiency can be determined by solving the equations (1) with respect to the change of a policy variable change.

The change in fuel efficiency *E* can take place through different policy instruments: a change in fuel price per gallon, a change in vehicle prices, and a change in the regulatory parameter. Because these three exogenous variables all have different impacts on *E* via the other equations, the effects of these on other variables like VMT will not be the same.

In estimating the system equations (1) econometrically, we include a one-year lagged value of dependent variable of each equation and we also include some variables in X_M that are interactions of per-mile cost of driving, P_m, with income, urbanization, and P_m itself. We normalize the interaction variables by subtracting their mean value over the sample period (1966-2004). We assume that the error terms in the equations show first-degree serial correlation.

3.3 Impacts on Transportation Safety

3.3.1 Traffic Crashes and Damage

In our analysis, we assume that two types of vehicle, cars (*C*) and light trucks (*LT*), are available to consumers. We also assume that light trucks are larger and cars are smaller in average. We defined the total vehicle stock ($V \equiv V_C + V_{LT}$) as a function of vehicle purchase price, per-mile driving cost, vehicle miles in the system of equations (1).

A traffic crash can be categorized into either single-vehicle crash or multi-vehicle crash. We only consider single vehicle or two-vehicle crashes. That is, there are five types of vehicle crashes: single car crash (A_C), single light truck crash (A_{LT}), car-car crash ($A_{C,C}$), car-truck crash ($A_{C,T}$), truck-truck crash ($A_{LT,LT}$)).

Crash rate can be defined as the crash frequency divided by some measure of exposure, such as the traffic volume, time, or distance. It is usually measured in crashes per million vehicle miles. Annual crash risk can be considered the product of two factors: per-mile crash risk times annual mileage. Therefore, traffic crash risk seems to increase with respect to an increase in vehicle miles. We assume the probabilities of a driver of each vehicle type getting involved in an accident, either one-vehicle accident or two-vehicle accident, may be different.

We define the accident involvement rate of a vehicle (a_{ij}) as the number of vehicles of vehicle type *i* (*i*= *C, LT*) involved in crash type *j* (j=1, 2: 1= single vehicle crash, 2=two-vehicle crash), V_{ij}, divided by the total vehicle miles of vehicles type *i*, VMT_i. The probability of crashes can also be defined as the number of crashes per year by vehicle type divided by the total stock of vehicles of that type (See, e.g., White (2004), Table 4). Taking into account of the relations between the number of crashes and the number of vehicles involved in crashes and between the vehicle stock and the vehicle miles ($VMT_i = V_i \cdot m_i$), the one concept of probability of crashes can be converted into the other.[4]

$$a_{ij} = \frac{V_{ij}}{VMT_i} \qquad (2).$$

Therefore a_{C1}, for example, is the rate of a car to be involved in a single car accident and a_{C2} is the rate of a car to be involved in a two-vehicle crash. Likewise, the accident involvement rates for a light truck are denoted as a_{LT1} and a_{LT2} for single truck crash and for two-vehicle crash respectively.

These involvement rates can be obtained by averaging over the period of available historical data and, regarding future accident involvement rates, we assume these rates remain the

[4] By further defining a_{ij}^{κ} as the accident involvement rate of crash severity (κ= F (fatality), H (injury), P (property damage only)) we can also compute the number of vehicles involved by crash severity.

same after a policy change. By applying the accident involvement rate, a_{ij}, to the changed vehicle miles by vehicle type, we can compute the number of vehicles by vehicle type and by accident type.

A policy change would also cause changes in VMT and in vehicle stock and its composition through the system equations (1). Changes in vehicle fleet composition, in turn, would affect the severities (i.e., fatalities or injuries) of an accident differently by vehicle type and by crash type, especially in a two-vehicle crash, because of the differences in weight and size of the vehicle. Therefore it is important to analyze how the changes in vehicle fleet mix and in vehicle miles would impact the severity of two-vehicle crash.

We first analyze the changes in vehicle fleet composition as a result of a policy change. Consumers would also take account of the expected personal safety of occupants of each vehicle type, and their heterogeneous preferences for each vehicle type as specified in Brozović and Ando (2005).

Vehicle miles by vehicle type can be obtained by decomposing the total vehicle miles (*VMT*) into:

$$\begin{aligned} VMT &= m \cdot V = m_C \cdot (1-\theta)V + m_{LT} \cdot \theta V \\ &= m_C \cdot V_C + m_{LT} \cdot V_{LT} = VMT_C + VMT_{LT} \end{aligned} \tag{4}$$

where, m_C and m_{LT} are average annual mileage of cars and trucks respectively. Likewise, V_C and V_{LT} denotes the number of cars and light trucks respectively and θ is the share of light trucks in the vehicle fleet.

3.3.2 Fatalities and Accident Costs

In general, the probability of a driver or passenger, either in a car or a light truck, being killed in a two-vehicle crash is higher if the other vehicle is a light truck than if it is a car. Increased VMT would by itself have a negative impact on safety. But the safety implications of *CAFE* standards have been controversial and seem to be a mixture of two effects of increased safety in light truck occupants and increased fatality risk in cars involved in car-truck crash.

Changes in vehicle fleet mix would result in different probabilities of accident by vehicle type, especially the probabilities of two-vehicle crashes by vehicle type, and thus the number of vehicle crashes. In other words, the vehicle type with higher share of total vehicle stock would have higher probabilities of getting involved in an accident, and any given vehicle has a higher probability of crashes into this type of vehicle.

Let's define V_2 as the number of vehicles involved in two-vehicle crashes, which is the sum of cars (V_{C2}) and light trucks (V_{LT2}) involved in two-vehicle crashes ($V_2 = V_{C2} + V_{LT2}$). Then we can compute the probability of a car (light truck) being in an accident with another vehicle conditional on being in a two vehicle crash by each crash type : car-car crash (*p(C,C)*), car-truck crash (*p(C,LT)*), and truck-truck crash (*p(LT,LT)*).[5]

Once we can compute the number of vehicle of two-vehicle crashes (V_2), we can compute the number of vehicles involved in two-vehicle crashes by crash type. It is calculated by multiplying the number of vehicles computed using Eq. (2).

$$\begin{aligned} V_{C,C} &= p(C,C)\times V_2, \\ V_{C,LT} &= p(C,LT)\times V_2, \\ V_{LT,LT} &= p(LT,LT)\times V_2. \end{aligned} \tag{3}$$

We can compute the number of people involved in traffic accidents by multiplying the number of vehicles of type *i* involved in accidents of crash type *j* by the average occupancy rate of that vehicle type (o_i).

The number of fatalities after policy implementation would be affected by the change in vehicles (and thus occupants) involved in crashes due to changes in vehicle fleet composition and vehicle miles and can be computed by applying the (assumed) fatality rates obtained from historical data.

In summary, we may project the number of vehicles involved in traffic crashes by crash type from the projected vehicles miles from the model. Then we can compute the probabilities of two-vehicle crashes by crash type and we can decompose the number of vehicles involved two-vehicle crashes by vehicle type. Next, we can compute the number of people involved and the fatalities in traffic crashes by crash type and by vehicle type using the assumed average occupancy rate and relative fatality risk of striking and struck vehicle. Finally, we can compute the changes in fatality rate (or injury rate) using the simulated fatalities and injuries.

3.3.3 Traffic Accident Costs

A policy change would impact VMT, the vehicle stock, and the fleet mix and these changes would affect the number of accidents (A_{ij}), the probabilities of two-vehicle crashes, and the number of fatalities (F_{ij}) and thereby the fatality rate. The changes in accident costs should be obtained by reflecting all these changes. Conditional on an accident occurring, the costs of fatalities and injuries from two-vehicle crashes in a year can be defined as the sum of the cost of fatalities and of injuries. We apply the value of statistical life (*VSL*) to calculate the

[5] The probability of car-car crash, for example, can be calculated from the equation $p(C,C)=\binom{V_{C2}}{2}/\binom{V_2}{2}$, where $\binom{V_{C2}}{2}$ denotes the combination function of choosing two vehicles out of the number of V_{C2} and, by definition, $\binom{V_{C2}}{1}=V_{C2}$.

costs of fatalities and the willingness-to-pay (*WTP*) to avoid the accident to calculate the costs of injuries.

Conditional on an accident occurring, the costs of fatalities and injuries from two-vehicle crashes of vehicle *l* against *m* in a year ($C(A)_{l,m}$)can be defined as:

$$\mathrm{C(A)}_{\mathrm{l,m}} = (F^{1}_{l,m} + F^{2}_{l,m})VSL + (H^{1}_{l,m} + H^{2}_{l,m})WTP \qquad (5)$$

where *F* and *H* is the number of fatalities and injured people respectively and the superscript numbers 1 and 2 denote striking vehicle and struck vehicle respectively. *VSL* is the value of statistical life and *WTP* is willingness to pay to avoid the accident. Then the total accident costs in a society are just sum of $C(A)_{l,m}$ over vehicle type *i* and crash type *j*.

4. SIMULATION RESULTS

4.1 Simulation model structure

We estimate the system equations by three-stage least squares (3SLS) as explained in Small and Van Dender (2007). In the first stage, we estimate an ordinary least squares (OLS) regression of each variable in the model on the set of instruments. In the second stage, we estimate the original equation while replacing the endogenous variables on its right-hand side by their predicted values from the first stage. In the third stage, we estimate correlations in the error terms in the two equations. The entire system is re-estimated taking these correlations into account. The estimates of this procedure will be used as parameter values in policy simulation model.

Regarding policy scenarios, we consider following changes in pricing policy variables as following: (1) *Fuel Tax:* one time permanent change in state fuel tax level (100% increase in 2008); (2) *VMT Tax:* conversion of fuel tax level in scenario (1) to equivalent mileage based tax; (3) *PATP*: surcharging liability insurance premium to the fuel purchased with fuel tax level in scenario (1) at the gas station; (4) *PAYD*: converting scenario (3) to mileage based surcharging liability insurance premium system; (5) *CAFE*: a gradual change in fuel economy standard over 2008-2012 (up to 50% increase from current fuel economy standard level).

Any policy change would impact many interrelated factors either directly or indirectly and may cause changes in consumer's behavior. That is, a policy change may simultaneously change two or even all endogenous variables in the system of equations (1). First, P_m is affected by any changes in policy instruments: fuel price per gallon; fuel tax either per gallon or per-mile; insurance premium (either per gallon or per mile); and fuel efficiency. Increasing gas tax, for example, would affect fuel price per gallon (P_f) directly and the change in P_f will be reflected in P_m. The three equations in (1) can be solved for *M*, *V*, and *E*. We can use system equations (1) and the definition of P_m to find the changes in all three endogenous variables (*V*, *M*, and *E*) by applying chain rule differentiation.

4.1.1 Data set

State level aggregate cross-sectional times series data set over the period from 1966 to 2004 are used in the simulation. Transportation data such as vehicle miles traveled (VMT), vehicle stock, highway use of gasoline, state and federal gasoline taxes, number of drivers and public road mileage are from *Highway Statistics* by U.S. FHWA. Data regarding traffic accidents are from Fatality Analysis Reporting System (FARS) of National Highway Traffic Safety Administration (NHTSA). Demographic data such as population and urbanization are from U.S. Census Bureau. Other economic data such as consumer price index (CPI), new car price index, personal income, interest rate, and price of gasoline are from Bureau of Labor Statistics or Bureau of Economic Analysis. Detailed definition and the source of each data are explained in Appendix B.

In system equations (1), M and V are divided by adult population in log form by state and year. Income and price data, stated in 2004 prices, are also in log form and normalized by subtracting the sample mean.

To examine simulation results using the model under different scenarios, we need to decide on values for the exogenous variables during the forecast period. Future exogenous variables are determined outside the model and some of the required parameters are taken from existing literature.

As a baseline scenario for the annual growth rate for future years of exogenous variables such as population, income, price indexes, we assume that the exogenous variables increase with previous 10 years' (1995-2004) average growth rate in 2005 and then keep the same increase rate after 2006. Regarding interest rate, we assume that it is fixed at 2004 rate considering cyclical fluctuations. Regarding gasoline price, we apply high price case from *Annual Energy Outlook* by U.S. Department of Energy.

4.1.2 Parameters

The analysis of the safety effects considering the changes in vehicle weights and sizes together is very complex since there are many different specifications of cars and light trucks available in terms of weight and size. Some large 4-door cars are heavier than compact pick-up trucks or small 4-door SUVs (NHTSA (2003), Table 3). With advanced technology it would be also possible to make a vehicle lighter without reducing the size of the vehicle (Ross and Wenzel, 2001, p.33). So we assume, for simplicity, a policy change would cause changes in vehicle weights only while keeping current vehicle sizes. *CAFE* standards regulation, for example, would tend to reduce vehicle weights to meet the standards with less changes in other vehicle characteristics (e.g., horsepower).

We measure the impacts of a policy change on traffic safety by estimating the changes in the number of accidents by vehicle type, by crash type, and by crash severity and the simulations are based on the (fixed) factors such as crash involvement rate, fatality and injury rate. These rates can be obtained from historical data or from other study results (e.g., White (2004)). Table 1 shows the accident involvement rate (a_{ij}) and fatality rate (f_{ij}) from actual historical data.

Table 1 - Vehicle Crash Involvement and Fatality Rate

	Accident Involvement Rate (a_{ij}) (Accident Veh.'s/VMT (in mil.))		Fataity Rate (f_{ij}) (Fatalities/Occupants)	
	Single Crash	2-veh. Crash	Single Crash	2-veh. Crash
Car	0.6687	2.8243	0.00441	(C-C) 0.00068
				(C-LT) 0.00168
LT	0.6707	2.6853	0.00418	(LT-C) 0.00040
				(LT-LT) 0.00100

Traffic accident costs can be estimated by reflecting the changes in VMT and the changes in vehicle fleet composition with incorporating the changes of fatalities or injuries. To estimate the accident costs per crash or the total social costs of accident, we need the values of WTP and VSL. We apply average social cost per injury type as in Parry (2004) and, for fatalities, we apply the Value of Statistical Life (VSL) of $5 million in Small and Verhoef (2007).

4.1.3 Decomposing Vehicle miles and Vehicle stock by vehicle type

As explained earlier, each policy option would cause changes in vehicle use and vehicle preference and therefore it would be better if we could decompose the vehicle miles and vehicle stock into cars and light trucks to measure the safety effects from different policy scenarios.

But we are not be able to decompose the projected vehicle miles and vehicle stock by vehicle type exactly due to data limitation. We will only have combined light duty vehicle stock (V) and total vehicle miles (M), which is the sum of all vehicle types including heavy trucks and buses. We don't have information on average vehicle miles by different vehicle type but we are more interested in the effect on light duty vehicles (LDV). Using the available data and some plausible assumptions on how to decompose vehicle stock, we can approximate projected vehicle miles by vehicle type.

Total vehicle stock of a current year is the sum of one previous year's vehicle stock minus scrapped vehicles plus newly purchased (and registered) vehicles in that current year. Vehicles are scrapped due to physical wear and tear of aging vehicles or as a result of severe crashes. The owner of a scrapped vehicle would then make an economic decision whether to purchase a new (or used) vehicle or to switch to an alternative means of transportation such as public transportation. Once he decided to buy a new vehicle then he determines which type of vehicle to buy. Therefore, newly purchased vehicles of a current year, cars and light trucks altogether, are:

$$V_t^{New} = (V_t - V_{t-1}) + V_t^{Scrp} \tag{6}$$

where V_t^{Scrp} is the number of vehicles scrapped (i.e., not used and not registered) vehicles in a state in year *t*. We use national level scrappage rates by cars (σ_C) and by light trucks (σ_{LT}) projected using previous 5 years' average.

In our analytical model, the only change among policy options happens in fuel price. All other variables but per mile driving costs are the same among policy options we consider and therefore the changes in the share of LT in new vehicle purchases, θ_{new}, would be mainly affected by the difference of new vehicle price compared to the baseline scenario (in case of *CAFE* policy) and by the difference of per mile driving costs. Therefore, figuring out θ_{new} can be done using the elasticity of the demand for light trucks with respect to fuel price (P_f) change. We apply their estimated elasticity (-0.045) of the demand for light trucks with respect to fuel price change from the baseline ($\theta_{new} = -0.045 \cdot P_m$).[6]

4. SIMULATION RESULTS

4. 1 Impacts on vehicle usage and fuel consumption

4.1.1 Per-mile driving cost

The simulation results in Figure 2 show that the per-mile cost of driving increases in all scenarios except *CAFE* scenario as we expected. *PAYD* scenario has the highest per-mile driving cost, with 83.6% increase in average from the baseline scenario over the period of 2008-2030, followed by *PATP* scenario, 71.9%, *VMT Tax* scenario, 24.8%, and *Fuel Tax* scenario, 15.2%. The reason of high per-mile cost in *PAYD* or *PATP* scenario is because the insurance costs which were regarded as fixed costs are now variable costs along with fuel prices. The per-mile cost of *CAFE* standards regulation is slightly lower, with 7.6% decrease in average over the same period, than the baseline scenario. The results also show a decreasing trend of per-mile driving cost after an increase in 2008.

[6] Busse et al. (2008) investigate the effect of fuel prices on car prices and market shares. They estimate the effect of fuel prices on new light duty vehicle shares with more segments of LDV types (i.e., Compact, Midsize, Luxury, Sports, SUV, Pickup, and Minivan) using a linear probability model.

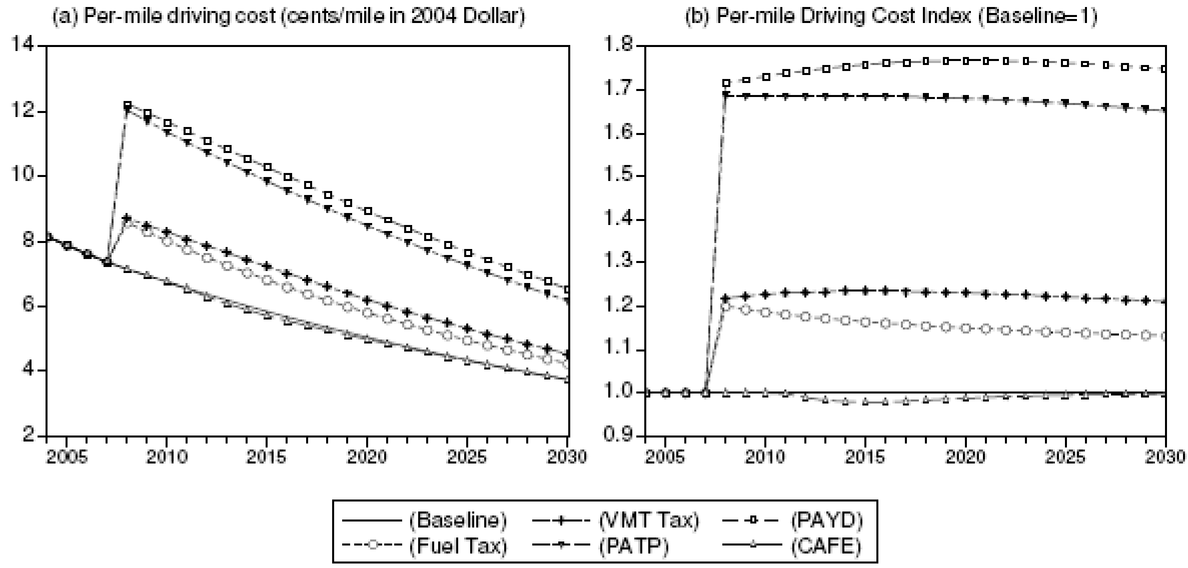

Figure 2. Comparison of Per-mile Driving Cost

4.1.2 Vehicle miles and fuel consumption

Figure 3 presents the results on vehicle miles and fuel consumption. Predicted vehicle miles from simulations in panel (a) keep increasing in the future in all policy scenarios but the differences from the baseline scenario results are less than 1%. Due to the changes in per-mile cost, *PATP* and *PAYD* policy scenario show larger decrease in vehicle miles (per adult) from the baseline scenario. The gaps between an alternative policy and the baseline are also decreasing in later years and it seems to be from increasing income. On the contrary, *CAFE* policy scenario results in slight increase in vehicle miles because of the relatively cheaper per-mile cost.

The increase in per-mile driving cost might cause people to choose more fuel efficient vehicles in policies of *Fuel Tax*, *PATP*, and *PAYD*. Meanwhile, *VMT Tax* policy does not have any incentive to purchase fuel efficient vehicles so it increases the share of light trucks. *CAFE* policy also slightly increases the share of light trucks compared to the baseline scenario since some people can afford to operate light trucks thanks to the lowered per-mile driving cost. That is, a light truck in *CAFE* policy can travel more miles with the same or less amount of gasoline use. It can be said as part of "rebound effect."

Total fuel consumption shows increasing trend as vehicle miles do. The increase in the share of light trucks and the lower fuel economy of light trucks than cars would contribute to the increase in fuel consumption. All policy scenarios except *VMT Tax* scenario show less fuel consumption than the baseline scenario. The largest decrease in fuel consumption is achieved by *PATP* policy scenario, about 12.8% decrease in average from the baseline scenrio result, followed by *CAFE* (7.2%), *PAYD* (5.6%), and *Fuel Tax* (4.6%) while *VMT Tax* shows increase in 3.5% in average over 2008-2030. The decrease in overall fuel consumption in spite of the increased vehicle miles was possible by the higher decrease in fuel intensity which allows less fuel use per mile of travel.

VMT Tax policy shows more fuel consumption than the baseline scenario even with the decrease in vehicle miles. It is because there is no incentive to use fuel efficient vehicle in *VMT Tax* scenario and there is overall increase in vehicle stock as we see in panel (b) of Figure 3. Less fuel efficiency and more vehicle stock lead to a more fuel consumption. Therefore, *VMT Tax* policy does not achieve the assumed policy goal of reducing fuel consumption.

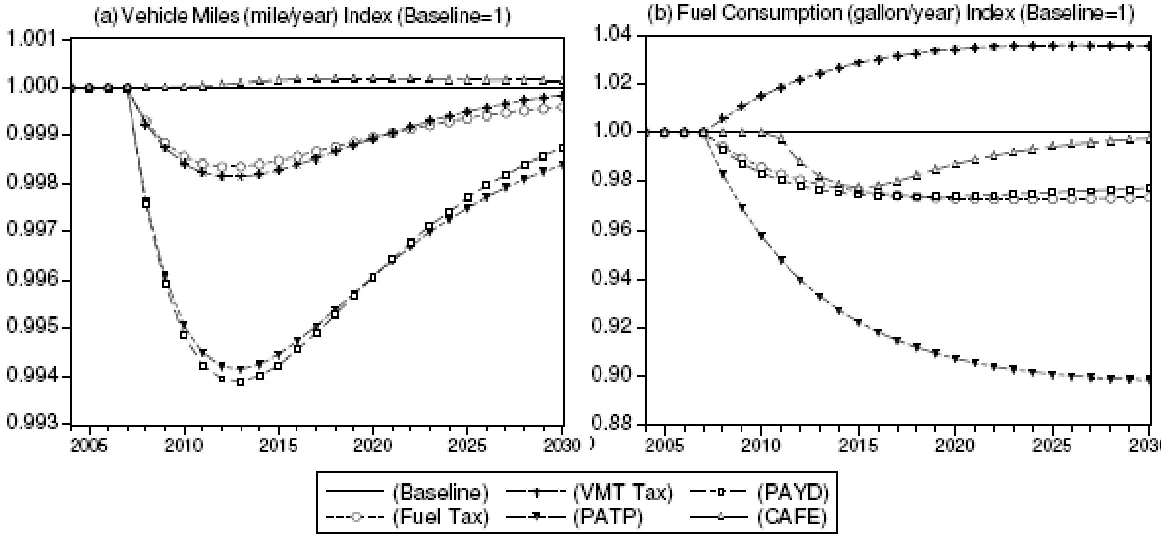

Figure 3 Comparison of Vehicle Miles and Fuel Consumption

4.2 Impacts on transportation safety

4.2.1 Number of Vehicles Involved in Accidents

We can easily expect that the number of vehicles involved in accidents would increase as vehicle miles increase with the same increase rate of vehicle miles from the equation (2). We can also expect that the number of cars involved in accidents would keep decreasing along with the reduced share of cars in total vehicle stock and less vehicle miles of cars than the baseline scenario. But the number of light trucks involved in accidents would increase as the share of light trucks increase. VMT tax policy would result in the highest decrease in the number of cars involved in both single and two-vehicle crashes due to biggest decrease in vehicle miles by cars. The number of light trucks involved in any type of crash decreases the most in *PATP* policy compared to the baseline scenario. It is mainly due to the decrease in vehicle miles since the number of crashes is proportional to vehicle miles.

4.2.2 Fatalities and Fatality Rates

Figure 4 presents the total fatalities in index terms and we can see that all policy options except *CAFE* policy slightly decrease the number of people killed from traffic accidents than the baseline scenario by less than 1%. It shows the similar trend as the vehicle miles difference since the accident involvement rates and the fatality risks are assumed constant and therefore the fatalities are proportionate to vehicle miles.

Panel (b) in Figure 4 also shows that fatality rates, which are defined as the fatalities divided by vehicle miles, are decreased by most policies, implying that a policy goal of reducing traffic fatalities may also be achieved from transportation energy policy changes. *PATP* and *PAYD* policy result in the largest decrease in fatalities.

Inverted U-shaped curves of these fatality rates can be explained from the changes in θ and vehicle miles by vehicle type. As θ increases the fatalities from single car crash and two-car crashes would decrease while there would be increase in fatalities from single light truck crashes and two light truck crashes.

Considering fatality risk parameters in Table 1, the sum of these changes would have little difference from the baseline. Therefore the difference of the fatality rates come from the changes in fatalities from Car-LT crashes. Simulation results show that both vehicle miles by cars (M_C) and by light trucks (M_{LT}) increase while the share of MLT shows decreasing trend with slight increases in the first 5 years.

Therefore, there will be decreases in fatalities from Car-LT crashes taking into account the trends of vehicle miles by vehicle type along with the increase in θ and higher fatality risk of car passengers.

Focusing on the fatalities from two-vehicle crashes, fatalities from car-car crash are higher than baseline scenarios in *PATP* and Fuel Tax policy and lower in *VMT Tax*, *CAFE* scenario. The share of fatalities of car occupants in two vehicle crashes keep decreasing while the share of fatalities of light truck occupants keep increasing mainly due to the increase in the share of light trucks (θ) in all scenarios. The fatality share of car occupants decreases down to about 70.3% in 2030 from 73.6% in 2005 while the share of light truck occupants increase to about 29.7%over the same period.

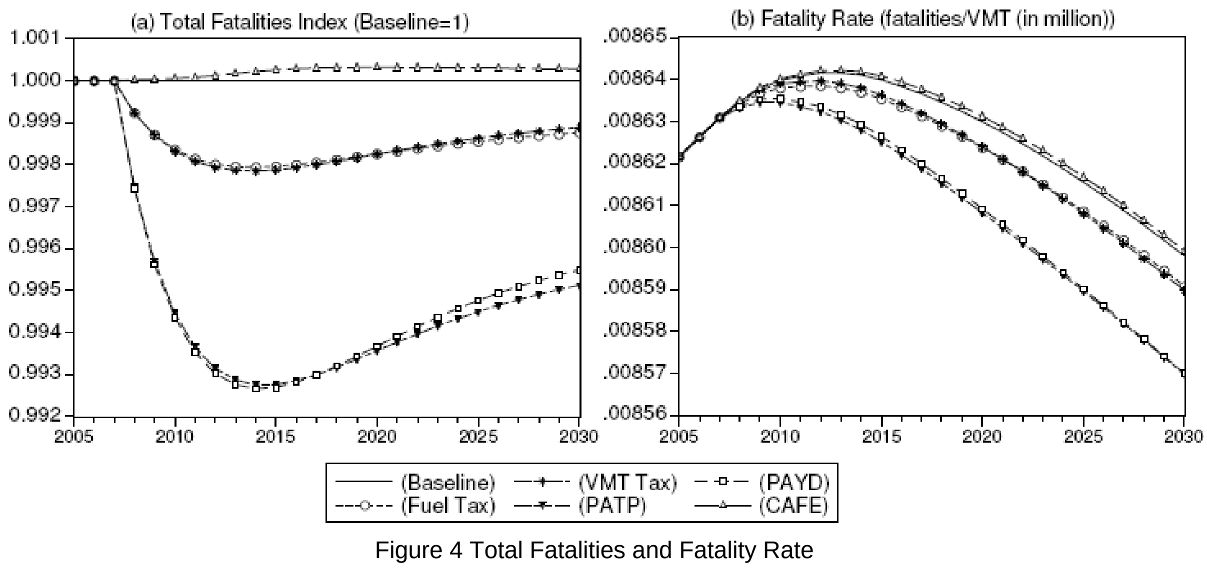

Figure 4 Total Fatalities and Fatality Rate

4.2.3 Accident Costs

Assuming *VSL* or Value of Statistical Life as $5.5 million and *WTP* or Willingness To Pay as $29,792, we compute about $208 billion of accident costs from fatalities and injuries in 2008 in baseline scenario. The costs increases up to $363.1 billion in case of *CAFE* policy scenario in 2030, which is almost the same costs as the baseline scenario. When we look at the cost changes in index term it looks similar to the changes of fatalities since *VSL* and *WTP* are assumed fixed. The total accident costs are smaller than the baseline scenario in all scenarios except *CAFE* policy scenario. The costs of the lives lost from traffic crashes increase from 66.1% up to 66.5% of total accident costs, showing the same pattern as fatality rates in Figure 3.

4.3 Results Summary

Table 1 compares the simulation results in average over 2005-2030. *CAFE* scenario shows almost the same in the share of light trucks and in the number of total fatalities. The problem of *CAFE* scenario is that the improved fuel efficiency in light trucks leads to an increase in the share of light trucks and it may cause an increase in fatalities of two-vehicle crashes. *PATP* and *PAYD* policy decrease the share of light trucks and total number of fatalities and thus decrease in accident costs as well. *Fuel Tax* and *VMT Tax* policy shows almost no difference in impacts on traffic safety.

Table 1- Summary of simulation results (Average over 2005-2030)

Policy	Per-mile cost (cent/mile)	Veh. Miles (bill. Miles)	Fuel Consumption (bill. gallons)	Fatalities (person)	Total Accident Costs ($ in billion)
Baseline	5.55	3,743.3	129.2	32,386	268.0
Fuel Tax	6.30	3,740.0	126.5	32,238	267.8
VMT Tax	6.61	3,740.0	132.6	32,239	267.8
PATP	8.72	3,730.9	119.8	32,112	267.0
PAYD	9.06	3,731.1	126.6	32,116	267.0
CAFE	5.51	3,743.8	128.1	32,293	268.1

5. CONCLUSION

The trend of increasing demand for light trucks has resulted in the higher rate of increase in motor fuel consumption by offsetting the fuel economy improvements in motor vehicle engine technology. The higher demand and consumption of motor fuel raised a concern regarding energy security along with the unstable international oil prices. Thus many policy options are being considered to reduce transportation fuel consumption not only to enhance the country's energy dependency but also to help to reduce greenhouse gas emissions, to improve air quality, and to reduce other driving-related external costs.

Another concern raised from the shift toward light trucks is safety issue because of higher fatality risk of occupants in smaller and lighter cars compared to the risk of larger and heavier light truck occupants. Many policy options considered here would cause changes in per-mile vehicle costs of driving and the cost changes, in turn, would affect vehicle usage and vehicle stock (and its composition) through changes in consumers' preference of vehicle choice. This research examined the impacts of transportation energy policies on traffic safety through an analytical traffic accident model reflecting possible changes in the probabilities of accident of different type of vehicles (i.e., cars and light trucks) and different crash type (i.e., single-vehicle crashes and two-vehicle crashes). The simulations of policy options are done through a model which fully integrates three inter-related economic demand decisions: size of vehicle stock, use of the vehicle stock, and energy efficiency. The changes in vehicle miles and vehicle stock from each policy scenario are decomposed by vehicle type along with the changes regarding traffic safety.

The results show ongoing trend of increase in the light truck share of new vehicle sales in all scenarios. Higher per-mile driving costs from *Fuel Tax*, *PATP*, and *PAYD* policies would cause people to choose more fuel efficient vehicles (i.e., cars) and thus those policy options would lead to slow growth rate of the share of light trucks. Meanwhile, *VMT Tax* policy does not have any incentive to purchase fuel efficient vehicles so the policy would cause an increase in the share of light trucks. *CAFE* regulation policy also slightly increases the share of light trucks compared to the baseline scenario due to the lower per-mile driving cost.

Fuel consumption will decrease compared to the baseline scenario in all scenarios except *VMT Tax* policy. The higher share of light trucks and relatively lower fuel economy of light trucks would result in more fuel consumption in *VMT Tax* policy even though the policy contributes to reductions in vehicle miles.

The highest decrease in fuel consumption is achieved by *PATP* policy scenario, about 7.2% decrease in average from the baseline scenrio result, followed by *PAYD* (2.1%), *Fuel Tax* (2.1%), and *CAFE* (0.9%), while *VMT Tax* shows increase in 2.6% in average over 2008-2030.

Regarding traffic accident fatalities, the results show that total average fatalities of each policy option will decrease from the baseline scenario except *CAFE* policy. In *CAFE* policy scenario, the lower per-mile driving cost would increase vehicle usage, which means more exposure of drivers (and occupants) to traffic crash risk and would cause more fatalities. In terms of total fatality rates per vehicle miles traveled, *CAFE* policy shows almost the same fatality rate as the baseline scenario. *PATP* and *PAYD* policy result in the lowest fatality rate compared to the baseline scenario. But the change in accident costs is very small, which is less than 1% from the baseline scenario, since the total fatalities change very little as we see in Figure 4.3 (a). Also the gap between a new policy option and the baseline scenario decreases leading to just 0.4% decrease in total accident costs over 2005–2030 in case of *PATP* policy.

The share of fatalities of car occupants, either in single crashes or in two vehicle crashes involving at least a car, will keep decreasing while the share of fatalities of light truck occupants will keep increasing. Fatalities from car-car crash are higher than baseline scenarios in *PATP* and *Fuel Tax* policy and lower in *VMT Tax*, *CAFE* scenario. *PAYD* policy has lower fatalities than the baseline scenario over the simulation period. On the contrary, VMT Tax and *CAFE* policy result in higher fatalities in LT-LT crashes while other policies have lower fatalities than the baseline scenario. Fatalities from Car-LT crash take up about 54% of the total fatalities from all types of two-vehicle crashes with about 4 times larger fatalities of occupants in cars than of occupants in light trucks.

The results may provide guidance as to which would improve energy dependency while reducing undesirable side effects related to traffic safety since the results of this study may contain an element to predict aggregate vehicle stock and how that in turn affects vehicle use. It may be used and adapted for other uses in analyzing regional policies, such as the greenhouse-gas regulations in a state or federal policies.

Since the simulations are based on the projections of exogenous variables to future years, the results may be inherently uncertain. In addition, the simulation model does not incorporate the congestion factor. The projected increase in vehicle miles may lead to increase in congestion and this would raise the travel time. As a future extension of this study, it needs to consider new per-mile costs of driving including time costs.

For the simulation model in this research can be used and adapted for the analysis of each state level policy impacts by vehicle type, it is crucial to collect the decomposed vehicle miles and vehicle stock by vehicle type. Along with the data by vehicle type it would provide a tool for potential use in analyzing regional policies. It also can be extended by empirically estimating the social welfare impacts from policy changes.

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APPENDIX 1: ESTIMATION OF SYSTEM EQUATIONS

We estimate the full structural model based on system equations (1) and Table A.1 shows the estimation results. Formally, then, the system is the following:

$$\begin{aligned}
(vma)_t &= \alpha^m (vma)_{t-1} + \alpha^{mv}(vehstock)_t + \beta_1^m (pm)_t + \beta_3^m X_t^m + u_t^m, \\
(vehstock)_t &= \alpha^v (vehstock)_{t-1} + \alpha^{vm}(vma)_t + \beta_1^v (pv)_t + \beta_2^v (pm)_t + \beta_3^v X_t^v + u_t^v, \\
(f\ \mathrm{int})_t &= \alpha^f (f\ \mathrm{int})_{t-1} + \alpha^{fm}(vma)_t + \beta_1^f (pf)_t + \beta_2^f (cafe)_t + \beta_3^f X_t^f + u_t^f,
\end{aligned} \tag{A.1}$$

with error terms following the rule

$$u_t^k = \rho_t^k u_{t-1}^k + \varepsilon_t^k, \qquad k = m, v, f. \tag{A.2}$$

See Small and Van Dender (2007) for data sources and detailed description of how the variables were generated and estimated.

Table A.1 Estimation Results of System Equations (1) Using 3SLS

Vehicle Usage Equation			Vehicle Stock Equation			Fuel Intensity Equation		
Variable	Coefficient	Std. Error	Variable	Coefficient	Std. Error	Variable	Coefficient	Std. Error
vma(t-1)	**0.7971**	0.0119	vehstock(t-1)	**0.8623**	0.0148	fint(t-1)	**0.8517**	0.0127
vehstock	**0.0254**	0.0093	vma	**0.0332**	0.0169	vma+pf	**-0.0170**	0.0055
pm	**-0.0378**	0.0037	pv	0.0306	0.0343	cafe	**-0.0898**	0.0123
pm*pm	**-0.0223**	0.0063	pm	0.0007	0.0062	inc	-0.0017	0.0161
pm*inc	**0.0782**	0.0120	inc	0.0146	0.0167	pop/adult	-0.0263	0.0667
pm*Urban	**0.0243**	0.0101	adults/road-mile	**-0.0273**	0.0070	Urban	*-0.1094*	0.0581
inc	**0.1037**	0.0134	Trend	0.0007	0.0007	D7479	**-0.0107**	0.0047
adults/road-mile	**-0.0218**	0.0044	interest	0.0072	0.0047	Trend66-73	-0.0007	0.0011
pop/adult	**0.1854**	0.0369	licenses/adult	**0.0411**	0.0166	Trend74-79	**-0.0040**	0.0012
Urban	**-0.1073**	0.0498				Trend80+	**-0.0022**	0.0004
Railpop	-0.0039	0.0061						
D7479	**-0.0436**	0.0035						
Trend	**0.0008**	0.0003						
constant	**1.9046**	0.1172	constant	-0.2500	0.1709	constant	-0.2663	0.0726
rho	**-0.0866**	0.0219	rho	**-0.1136**	0.0263	rho	**-0.1490**	0.0221
No. obs.	1,887		No. obs.	1,887		No. obs.	1,887	
Adj. R-squared	0.9821		Adj. R-squared	0.9572		Adj. R-squared	0.9599	
S.E. of regression	0.9814		S.E. of regression	0.0401		S.E. of regression	0.0415	
D-W stat.	1.9687		D-W stat.	2.0204		D-W stat.	2.0037	

Notes:

1. Bold or italic type indicates the statistical significance at the 5% or 10% level, respectively.
2. Estimates of fixed effects coefficients (one for each state except Wyoming) are not shown.
3. Variables starting with lower case are in logarithm and those with upper case are its level value.

APPENDIX 2: DATA SOURCES

Variable	Definition	Source
Adult population	midyear population estimate, 18 years and over	U.S. Census Bureau (http://www.census.gov)
Corporate Average Fuel Economy Standard	Miles Per Gallon	National Highway Traffic Safety Administration (NHTSA)
Consumer price index (CPI)	all urban consumers (1982-84=100)	Bureau of Labor Statistics (BLS), http://www.bls.gov/cpi/
Fatalities & Injuries	People killed or hurt from vehicle crashes	National Highway Traffic Safety Administration (NHTSA), FARS-Web
Fuel Efficiency	Computed as VMT divided by Highway Use of Gasoline	
Highway Use of Gasoline	millions of gallons per year	FHWA, Highway Statistics
Income per capita ($/year)	Personal income divided by midyear population	Bureau of Economic Analysis (BEA)
Interest rate (%)	national average interest rate for auto loans	Federal Reserve Systems
New Car Price Index	price index for U.S. passenger vehicles, city average, not seasonally adjusted (1987=100)	Bureau of Labor Statistics (BLS),
Price of gasoline	cents per gallon, 1987 dollars	Energy Information Administration
Public road mileage	Total length of roads in state (miles)	FHWA, Highway Statistics
Number of Licensed Drivers		FHWA, Highway Statistics
Traffic Accident	Number of Vehicles involed in accident per million VMT	National Highway Traffic Safety Administration (NHTSA), FARS-Web
Urbanization	Share of total state population living in Metropolitan Statistical Areas (MSAs), with MSAs based on December 2003 definitions	Bureau of Economic Analysis
Vehicle Stock	Number of automobiles and light trucks registered	FHWA, Highway Statistics
VMT	Vehicle Miles Traveled, , million miles	FHWA, Highway Statistics