The Effect of Improved Fuel Economy on Vehicle Miles Traveled: Estimates Using U.S. State Panel Data

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Abstract:

We estimate the rebound effect for motor vehicles, by which improved fuel efficiency causes additional travel, using a cross-sectional time series of 50 US states plus the District of Columbia from 1966 to 2001. Our method accounts for endogenous changes of fuel efficiency in response to regulation, prices, and other factors, it incorporates a measure of the stringency of the corporate average fuel economy (CAFE) standards, it distinguishes between autocorrelation and lagged effects, and it allows the rebound effect to depend on levels of income and of urbanization. We find that the endogeneity correction strongly reduces the estimated rebound effect, that the long-run effect is substantially larger than the short-run effect, and that the rebound effect declines with income. Our preferred (3SLS) estimate of the rebound effect at sample averages of income and urbanization is 5.2% for the short run and 24% for the long run. We also find that CAFE regulations have a moderate effect on fuel efficiency of new passenger vehicles, which began immediately upon their implementation and peaked in 1984.

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1. Introduction

It has long been realized that improving energy efficiency releases an economic reaction that is likely to partially offset the original energy saving. As the energy efficiency of some process improves, the process becomes cheaper thereby providing an incentive to increase its use. Increased demand for the energy-using process means that total energy consumption changes less than proportionally with changes in physical energy efficiency. The rebound effect is the extent of the deviation from proportionality. This phenomenon has been studied in many contexts including residential space heating and cooling, appliances, and transportation (Greening, Greene, and Difiglio 2000).

For motor vehicles, the energy input is fuel and the associated service is travel, typically measured as vehicle-miles traveled (VMT). When vehicles are made more fuel-efficient, it costs less to drive a mile, so VMT increases. That in turn causes more fuel to be used than would be the case if VMT were constant; the difference is the rebound effect. These issues are important not only because they help determine the effectiveness of measures intended to increase fuel consumption, but also because they could increase external costs of driving such as congestion and air pollution. For example, the rebound effect was an issue in the evaluation of recently adopted greenhouse-gas regulations for California (CARB 2004, Sect. 12.3-12.4).

This paper presents estimates of the rebound effect for passenger vehicle use that are based on cross-sectional time series data on the U.S. State level. Obtaining reliable measures of the rebound effect is important for designing policies to reduce fuel consumption by motor vehicles (often an important component of broader policies aimed at improving energy security or at decreasing greenhouse gas emissions). If, for example, the rebound effect is very large, then price instruments become relatively more effective than technology standards because higher energy prices counteract the rebound effect.

There is a sizeable literature presenting econometric estimates of the rebound effect. This paper contributes four main improvements. First, we use a longer time series (1966-2001) than was possible in earlier studies. This increases the precision of our estimates, enabling us (among other things) to determine short- and long-run rebound effects and their dependence on income. Second, the econometric specifications rest on an explicit model of simultaneous aggregate demand for VMT, vehicle stock, and fuel efficiency. The model is estimated directly using two- and three-stage least squares (2SLS and 3SLS), so that we can treat consistently the fact that the

rebound effect is defined starting with a given change in fuel efficiency, yet fuel efficiency itself is endogenous. Third, we measure the stringency of the CAFE regulation by the difference between drivers' desired fuel efficiency and the fuel efficiency required by the standard, where desired fuel efficiency is estimated using pre-CAFE data. Fourth, we allow for the dependence of the rebound effect on income and on urbanization, through the use of interaction terms.

Our best estimate of the rebound effect for the US as a whole, over the period 1966-2001, is 5.2% for the short run and 24% for the long run. The 2SLS and 3SLS results are similar except in terms of precision, and differ strongly from ordinary least squares (OLS) results: accounting for the endogeneity of fuel efficiency reduces the estimated long run rebound effect by about 40%. Using values of income and urbanization equal to those measured for California over the most recent five-year period covered in our data set, namely 1997-2001, reduces the short-run rebound effect to 2.0% and the long-run effect to 9.3%. Additional estimation results, like the long-run overall price-elasticity of fuel demand (-0.53) and the proportion of it that is caused by mileage changes (45%) are very much in line with the literature.

The structure of the paper is as follows. Section 2 introduces the standard definition of the rebound effect and reviews some key contributions on estimating it. Section 3 presents the theoretical model and the econometric specification, and Section 4 presents estimation results. Section 5 concludes.

2. Literature

The rebound effect for motor vehicles is typically defined in terms of an exogenous change in fuel efficiency, E, measured in miles per gallon (e.g. USDOE, 1996). Fuel consumption F (in gallons per year) and travel M (vehicle-miles traveled per year) are related through the identity $F \equiv M/E$. The demand for fuel consumption is derived from the demand for vehicle-miles traveled. The latter depends (among other things) on the variable cost per mile of driving, which includes the per-mile fuel cost, $P_M \equiv P_F/E$, where P_F is the price of fuel. The rebound effect arises because VMT depends on P_M, which in turn depends on E; this dependence can be measured by the elasticity of travel with respect to fuel cost per mile, $\varepsilon_{M,PM}$. When E is viewed as exogenous, it is easy to show that fuel usage responds to it according to the equation: $\varepsilon_{F,E} = -1 - \varepsilon_{M,PM}$. Thus the existence of a non-zero values of $\varepsilon_{M,PM}$ is responsible for the lack of

perfect inverse proportionality between F and E: i.e., it causes the absolute value of $\varepsilon_{F,E}$ to be smaller than one. In this sense, $-\varepsilon_{M,PM}$ itself may be taken as a definition of the rebound effect, and most estimates of the rebound effect are based on it.

Before reviewing the empirical work, we note that two of our innovations directly relate to limitations of the standard definition. First, most empirical measurements of the rebound effect have taken advantage of variations in the fuel price P_F more than variations in efficiency E. The connection between corresponding elasticities can be determined by making E a function $E(P_F)$ of fuel price, with elasticity $\varepsilon_{E,PF}$. This leads to $\varepsilon_{F,PF} = \varepsilon_{M,PM} \cdot \left(1 - \varepsilon_{E,PF}\right) - \varepsilon_{E,PF}$, as shown for example in USDOE (1996: 5-11). This equation makes it clear that since empirical estimates of $\varepsilon_{F,PF}$ and $\varepsilon_{M,PM}$ differ greatly,[1] it must be that $\varepsilon_{E,PF}$ is considerably different from zero. Ignoring the dependence of E on P_F, as is done in many studies but not ours, causes the rebound effect to be overestimated if unobserved factors that cause M to be large (such as an unusually long commute) also cause E to be large (as the commuter chooses vehicles to reduce the fuel cost of that long commute).[2]

Second, fuel cost is just one of several components of the cost of using motor vehicles. One of the most important is time costs, which increase as a portion of the cost of using vehicles over time in a growing economy. That increase makes the elasticity of VMT-demand with respect to fuel cost diminish over time or with income (Greene, 1992). Our specification will allow for this dependence. A related extension is to recognize that traffic congestion may be affected by the VMT changes that create the rebound effect. If congestion is substantially increased, the rebound effect would be diminished, yet even a smaller rebound may be of greater concern due to the costly nature of congestion. We use indirect measures of (potential) congestion to account for this.

One set of empirical studies of the rebound effect consists of aggregate studies based on a single time series. Greene (1992) uses a U.S. time series (1957-1989) on fuel prices and fuel efficiency to measure the effect of P_M on VMT, and finds the rebound effect to be between 5 and

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[1] See USDOE (1996, pp. 5-14 and 5-83 to 5-87); Graham and Glaister (2002, p. 17); and the review in Parry and Small (2002, pp. 22-23).

[2] This seems the most likely direction of bias, although it could be the opposite: for example, the person with a long commute may register a *lower* average fuel economy on a given vehicle because a higher proportion of it is used during stop-and-go traffic than someone who mostly uses the car for off-peak or vacation travel.

15% both in the short and long run, with a best estimate of 12.7%. According to Greene, failing to account for autocorrelation – which he estimates at 0.74 – results in spurious measurements of lagged values, and to the erroneous conclusion that long-run effects are larger than short-run effects.[3] Greene also presents evidence that the fuel-cost-per-mile elasticity declines over time, but the evidence has only marginal statistical significance. Jones (1993) re-examines Greene's data, after including observations for 1990, focusing on model selection issues in time series analysis. He finds that Greene's autoregressive model is statistically valid, but that alternative specifications, notably those including lagged dependent variables, are acceptable as well. Such models do produce long-run estimates of the rebound effect of ca. 31%, exceeding the short-run estimates of ca. 11%.[4] Schimek (1996) uses data from a longer time period than Greene (1992) and finds a similarly small or even smaller short-run rebound effect. But he obtains a larger long-run rebound effect, about 30%, similar to Jones (1993). In Schimek's preferred results, the short-run and long-run rebound estimates are 7 and 29%.[5] He accounts for federal Corporate Average Fuel Economy (CAFE) regulations by including a time trend for years since 1978, and he also includes dummy variables for the years 1974 and 1979 when gasoline rationing was in effect. These controls reduce the extent of autocorrelation in the residuals.[6,7]

These aggregate studies highlight the possible importance of lagged dependent variables (inertia) for sorting out short-run and long-run effects, but do not settle the issue as they can not disentangle the presence of a lagged dependent variable from the presence of autocorrelation.

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[3] Another study that found autocorrelation is that by Blair, Kaserman, and Tepel (1984). They obtain a rebound effect of 30%, based on monthly data from Florida from 1967 through 1976. They did not estimate models with lagged variables.

[4] Estimate from the linear lagged dependent variable model (model III in Table 1). Estimates for the loglinear model are nearly identical.

[5] Schimek (1996), p. 87, Table 3, model (3).

[6] The CAFE variable makes even more difference in another equation, explaining fuel consumption, where without the CAFE variable income has the wrong sign and the lagged dependent variable takes an unreasonably large coefficient. See his Table 1, models (1) and (4).

[7] Schimek (1996, Table 2) also estimates three equations, which decompose fuel consumption into vehicle stock, fleet-average fuel efficiency, and driving per vehicle. The third of these equations permits fuel price and fuel efficiency to have distinct effects, but the estimated coefficients are opposite in sign and nearly identical in magnitude, as would be expected if they enter as a ratio as assumed in the specification used by most authors. Greene *et al.* (1999) also test whether consumers care separately about fuel price P_F and fuel economy E in their usage decision, and find that they do not (cf. fn. 6).

None of the three studies demonstrates definitively which is the right specification, and the answer appears sensitive to the time period considered and treatment of the CAFE standards.

Haughton and Sarkar (1996) construct a cross-sectional time series set for the 50 U.S. States and the District of Columbia from 1970 to 1991. Fuel prices vary by state, primarily due to different rates of fuel tax, providing an additional opportunity to observe its effects on amount of motor-vehicle travel. The authors estimate equations both for VMT per driver and for fuel intensity (the inverse of fuel efficiency). Haughton and Sarkar's estimate of the rebound effect is about 16% in the short run and 22 to 23% in the long run.[8] Here, autocorrelation and the effects of a lagged dependent variable are measured with sufficient precision to distinguish them. The measure of the correlation between residuals in adjacent years is 0.38 to 0.48. Like Greene (1992), they find that accounting for autocorrelation strongly reduces the effect of lagged dependent variable; unlike Greene (1992) they still obtain a statistically significant effect, implying a long-run effect 32 to 45% larger than the short-run effect.

Haughton and Sarkar find that fuel efficiency is unaffected by the current price of gasoline unless that price exceeds its historical peak (pure hysteresis). CAFE effects are taken into account in the fuel-intensity equation through a variable measuring the difference between the legal minimum and actual fuel efficiency in 1975; however, that variable is so strongly correlated with the historical maximum real price of gasoline that they omit it in most specifications, casting doubt on whether the resulting estimates really control adequately for CAFE regulation.

It appears that the confounding of the rebound effect with effects of CAFE regulation is a limiting factor in many studies. Different authors have defined and included a variety of variables, and results seem sensitive to just how it is done (Schimek, 1996). Partly this is because the standards were imposed about the same time as a major increase in fuel prices occurred, and they became more stringent as incomes rose during the 1980s; therefore the effects of CAFE standards are hard to separate from those of fuel prices and incomes. But partly it is because no one has constructed such a variable from an explicit theory of CAFE. We attempt to remedy this in our empirical work.

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[8] This paragraph is based on models E and F in their Table 1, p. 115. Their variable, "real price of gasoline per mile," is evidently the same as fuel cost per mile.

Studies that have used micro data to measure the rebound effect show a wider disparity of results than those based on aggregate data, covering a range from zero to about 50%. Goldberg (1998) uses a variety of sources, including the Consumer Expenditure Survey, to estimate (amongst others) consumers' vehicle purchase and usage decisions. When instrumental variables are used to account for simultaneity between both decisions, the estimated rebound effect is reduced from about 20% to essentially zero.[9] Pickrell and Schimek (1999) estimate a vehicle-use model with 1995 cross-sectional data from the National Personal Transportation Survey (NTPS). The elasticity of VMT with respect to gasoline price, controlling for ownership levels, is –0.04 (model 3 with odometer readings as dependent variable). This low figure emerges when residential density is included as an explanatory variable; residential density is collinear with the fuel price, so that it is hard to separate their effects. This suggests that the value of a cross-sectional micro data set for a single year is diminished by the fact that fuel prices vary only across states, and those variations may be correlated with unobserved factors that also influence VMT. Greene, Kahn, and Gibson (1999) use a micro data sets covering six different years, between 1979 and 1994, to estimate separate equations explaining paid fuel price and fuel efficiency, for each owned vehicle and for households with each of four exogenous ownership levels of passenger vehicles. In order to account for CAFE regulations, the usage equations include as an explanatory variable the average fuel economy of all passenger vehicles produced in the same model year as the vehicle whose use is being explained. The long-run rebound effect is estimated at 23% overall, with a range from 17% for three-vehicle households to 28% for one-vehicle households.

Some studies using micro data have explicitly addressed the issue of endogeneity of vehicle characteristics that influence fuel efficiency. Train (1986), Hensher *et al.* (1992), and West (2004) estimate model systems in which vehicle choice and usage are both endogenous. Mannering (1986) explicitly addresses the endogeneity bias we referred to above; he finds a large bias although it is in the direction opposite to what we expect, i.e. he finds that the usage

[9] In the usage equation with instrumental variables, the variables representing vehicle type attain astronomical yet statistically insignificant coefficients (Goldberg's Table I), casting doubt in our minds on the ability of the data set to measure this simultaneity and hence on the reliability of the zero-rebound result. Furthermore, the utilization equation is estimated using data only on households who purchased a new car the previous year, so is not necessarily representative of all vehicle users.

elasticity with respect to cost per mile becomes considerably *greater* in absolute value when endogeneity is taken in to account.

In summary, the literature review shows that aggregate estimates of the short-run rebound effect are fairly robust. Estimates of the long-run rebound effect, by contrast, are sensitive to the particular specification, especially the treatment of time patterns and CAFE standards. Disaggregate cross-sectional analyses tend to produce a greater range of estimates. One disaggregate study that exploits both cross-sectional and temporal variation (Greene et al., 1999) finds a long-run rebound effect of 23%, similar to several other studies.

3. Theoretical Foundations and Empirical Specification

3.1 System of Simultaneous Equations

Most of the reviewed studies measure the rebound effect relative to a stated change in energy efficiency, while almost any model of manufacturers' and consumers' decisions will derive energy efficiency as an output of the model, not as the result of an exogenous policy change. Our empirical specification is based on a simple aggregate model of simultaneous demand for VMT, vehicles and fuel efficiency, in which the rebound effect is embedded.[10]

More specifically, we assume that consumers, representative of states, choose how much to travel on the basis of their vehicle ownership, the per-mile cost of driving, and exogenous characteristics. They choose how many vehicles to own on the basis of the price of new vehicles, the cost of driving, and other characteristics. Fuel efficiency is determined jointly by consumers and manufacturers taking into account the price of fuel, the regulatory environment, the (expected) amount of driving, and other characteristics. This process may include manufacturers' adjustments to the relative prices of various models, consumers' adjustments on relative purchases of various models (including light trucks), consumers' decisions about vehicle scrappage, and driving habits. The assumptions lead to the following structural model:

$$\begin{aligned} M &= M\left(V, P_M, X_M\right) \\ V &= V\left(P_V, P_M, X_V\right) \\ E &= E\left(P_F, M, R_E, X_E\right) \end{aligned} \tag{1}$$

[10] It is certainly possible to model the relevant chain of decisions in more detail than is done here, see for example in Hensher (1986) and Bunch et al. (1996); doing so greatly increases data requirements and introduces additional assumptions, each potentially reducing confidence in the results.

where M is aggregate VMT; V is the size of the vehicle stock; E is fuel efficiency; P_V is a price index for the ownership cost of new vehicles; P_F is a price index for fuel; $P_M \equiv P_F/E$ is the fuel cost per mile; X_M, X_V and X_E are exogenous variables affecting M, V and E, respectively; and R_E represents any of a wide variety of measures that directly or indirectly influence fleet-average fuel efficiency.

The standard definition of the rebound effect treats E as exogenous. It can be derived from a partially reduced form of (1), which is obtained by substituting the second equation in the first. This produces (2), where P_M is endogenous.

$$M = M\left[V\left(P_V, M, P_M, X_V\right), P_M, X_M\right] \equiv \hat{M}\left(P_V, P_M, X_V, X_M\right). \tag{2}$$

With P_V, X_V, and X_M constant, equation (2) leads to the standard definition of the rebound effect. But the rebound effect can also be written in terms of the structural equations (1), which enables one to see explicitly how much of it comes from changes in usage per vehicle and how much in changes in number of vehicles and their subsequent effect on usage, as in the expression on the far right (cf. Appendix A)

$$\varepsilon_{\hat{M},PM} \equiv \frac{P_M}{M} \cdot \frac{\partial \hat{M}}{\partial P_M} = \frac{\varepsilon_{M,PM} + \varepsilon_{M,V}\varepsilon_{V,PM}}{1 - \varepsilon_{M,V}\varepsilon_{V,M}}. \tag{3}$$

While most studies reviewed in the previous section are implicitly based on (2), we estimate the full structural model based on system (1), consisting of three simultaneous equations explaining logarithms of VMT per adult, vehicle stock per adult, and fuel efficiency. The system is generalized in two ways to handle the dynamic dimensions of observed statewide averages of these three dependent variables. First, we assume that the error terms in the empirical equations exhibit first-degree serial correlation, meaning that unobserved factors influencing usage decisions in a given state will be similar from one year to the next: for example, laws governing driving by minors. Second, we handle assumed inertia by including the one-year lagged value of the dependent variable. Formally, then, the system is the following.

$$\begin{aligned}
(vma)_t &= \alpha^m (vma)_{t-1} + \alpha^{mv} (vehstock)_t + \beta_1^m (pm)_t + \beta_3^m X_t^m + u_t^m \\
(vehstock)_t &= \alpha^v (vehstock)_{t-1} + \alpha^{vm} (vma)_t + \beta_1^v (pv)_t + \beta_2^v (pm)_t + \beta_3^v X_t^v + u_t^v \\
(fint)_t &= \alpha^f (fint)_{t-1} + \alpha^{fm} (vma)_t + \beta_1^f (pf)_t + \beta_2^f (cafe)_t + \beta_3^f X_t^f + u_t^f
\end{aligned} \tag{4}$$

with error terms following the rule

$$u_t^k = \rho^k u_{t-1}^k + \varepsilon_t^k, \; k=m,v,f. \tag{5}$$

Here, lower-case notation indicates that the variable is in logarithms. Thus *vma* is the natural logarithm of VMT per adult; *vehstock* is the log of number of vehicles per adult; and *fint* is the log of *fuel intensity*, defined as the reciprocal of fuel efficiency, or equivalently *fint* is the negative of the log of fuel efficiency. Variable *pf* is the log of fuel price; hence log fuel cost per mile, *pm*, is equal to *pf*+*fint*. The parameter β_1 is the coefficient of the log of a price and β_2 is the coefficient of a single additional variable (in log form), whereas β_3 is a vector of coefficients of the set of variables (including a constant) in the corresponding list *X*, which may be either in levels or logarithms. Subscript *t* designates a year, and *u* and ε are error terms assumed to have zero expected value, where ε is assumed to be "white noise".[11]

The coefficient of variable *pm* in the usage equation, β_1^m, is the same as $\varepsilon_{M,PM}$, which is by far the most important part of the equation (3) defining the rebound effect. In addition to the other small terms in equation (3), there are two further features of our specification that modify the rebound effect. The first is that we include some variables in X^m that are interactions of *pm* with income or urbanization, so that the rebound effect varies with these measures. We do so in such a way that β_1^m remains the same as $\varepsilon_{M,PM}$ at the mean values of income and urbanization. In our tables of results, we show the result of calculating equation (3) exactly, both at the sample mean values of income and urbanization and at the mean values for California in years 1997-2001. Using the notation of (4), (3) takes the value:

$$-b^S = \varepsilon_{\tilde{M},PM} = \frac{\beta_1^m + \alpha^{mv}\beta_2^v}{1-\alpha^{mv}\alpha^{vm}} \qquad (6)$$

where the symbol b^S designates the short-run rebound effect.

The second feature modifying the rebound effect is the inclusion of lagged values. The coefficient on lagged *vma* (α^m) in the usage equation indicates how much a change in one year will continue to cause changes in subsequent years, due to people's inability to make fast adjustments in lifestyle. Ignoring the small indirect effects via the equation for vehicle stock, we can identify β_1^m as the short-run rebound effect and $\beta_1^m/(1-\alpha^m)$ as the long-run rebound effect, in both cases at the mean values of income and urbanization in the data set. The precise equation

[11] We use the autocorrelation feature in the computer package Eviews 5, which estimates a model with first-order autocorrelation by transforming it to a nonlinear model with no autocorrelation but additional lags, and applying nonlinear least squares. The two-step Cochrane-Orcutt procedure is known to be statistically biased when the model contains a lagged dependent variable, as ours does (Davidson and MacKinnon, p. 336).

for the long-run rebound effect is given by (6) with β_1^m replaced by $\beta_1^m/(1-\alpha^m)$ and β_2^v replaced by $\beta_2^v/(1-\alpha^v)$:

$$-b^L = \varepsilon^L_{\tilde{M},PM} = \frac{\beta_1^m/(1-\alpha^m) + \alpha^{mv}\beta_2^v/(1-\alpha^v)}{1-\alpha^{mv}\alpha^{vm}} \tag{7}$$

The same considerations apply to other elasticities. It can be shown that the short- and long-run elasticities of vehicle usage with respect to new-car price are:[12]

$$\varepsilon^S_{\tilde{M},PV} = \frac{\alpha^{mv}\beta_1^v}{1-\alpha^{mv}\alpha^{vm}}; \qquad \varepsilon^L_{\tilde{M},PV} = \frac{\alpha^{mv}\beta_1^v/(1-\alpha^v)}{1-\alpha^{mv}\alpha^{vm}} \tag{8}$$

and the short- and long-run elasticities of fuel intensity with respect to fuel price are:

$$-\varepsilon^S_{\tilde{E},PF} = \frac{\beta_1^f + \alpha^{fm}\beta_1^m}{1-\alpha^{fm}\beta_1^m}; \qquad -\varepsilon^L_{\tilde{E},PF} = \frac{\beta_1^f/(1-\alpha^f) + \alpha^{fm}\beta_1^m/(1-\alpha^v)}{1-\alpha^{fm}\beta_1^m/(1-\alpha^v)}. \tag{9}$$

3.2 Specification of the Equations

This section describes the variables used in (4) and their rationale, paying special attention to a variable describing CAFE regulation. In each case we give first the notation used in (1), and end with the variable name used in our base regressions (variants are described along with results). Variables starting with lower case letters are logarithms of the variable described. Data sources are given in Appendix B.

3.2.1 Dependent Variables

M: Vehicle miles traveled (VMT) divided by adult population, by state and year (logarithm: *vma*, for "vehicle-miles per adult").

V: Vehicle stock divided by adult population (logarithm: *vehstock*).

1/*E:* Fuel intensity, calculated as highway use of gasoline divided by VMT (logarithm: *fint*).

3.2.2 Independent Variables other than R_E

P_M: Ratio of the real price of fuel to *E.* Its logarithm is denoted $pm \equiv \ln(P_F) - \ln(E) \equiv pf + fint$.

[12] Equations (8) are approximations in which just the two-way causation between *fint* and *vma* is accounted for, rather than also including the even more indirect effect of *pf* on *fint* via the effect of vehicle stock on vehicle usage combined with the effect of vehicle usage on fuel intensity (this effect which will be especially small because it involves the triple product $\beta_2^v\alpha^{mv}\alpha^{fm}$).

For convenience in interpreting interaction variables based on *pm*, we have normalized it by subtracting its mean for the sample.

X_M: This set of variables includes the following: Real personal income per capita at 1987 prices, in log form and normalized by subtracting the sample mean (*inc*); number of adults divided by public road mileage (logarithm: *adrm*) as a rough measure of urbanization or potential congestion; ratio of total population to adults (logarithm: *popratio*) as a measure of family size; fraction of state's population living in metropolitan statistical areas (*Urban*), normalized by subtracting its mean in the sample; fraction of the state's population living in metropolitan statistical areas with a heavy-rail transit system (*Railpop*); a dummy variable to represent gasoline supply disruptions in 1974 and 1979 (D7479); and a time trend measured in years since 1966 (*Trend*). We hope the time trend captures some of the changes in technology and consumer preferences that we are unable to specify quantitatively.[13]

We interact *pm* with *inc* and with *Urban* in order to test the hypothesis that the cost elasticity declines as time costs become a more prominent part of the cost of driving, which could happen either because those costs are valued more (as incomes rise) or because they are larger (because of urban congestion). As alternative measures of income, we considered disposable income (personal income after taxes) and gross state product (which unlike personal income includes the business sector). They are approximated for earliest years in the sample and, like personal income, are put in log form and then normalized by subtracting the corresponding sample mean. They are named *dispinc* and *gsp*; like *inc*, each is entered in the equation both by itself and interacted with *pm*.

P_V: Index of real new vehicle prices (1987=100) (logarithm: *pv*).

X_V: We include *inc*, *adrm*, and *Trend*, already defined in X_M. In addition there are two other variables: the national interest rate for auto loans (logarithm: *interest*); and the ratio of licensed drivers to adults (logarithm: *licad*).

P_F: Price of gasoline, real at 1987 prices (cents per gallon). Its logarithm (*pf*) is normalized by subtracting the mean in the sample.

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[13] Instead of the Trend, we have experimented with three technology variables: vehicle volume (*Vol*), engine horsepower (*Hp*), and top speed (*Speed*), each in the form a fractional change in that measure since 1975, the earliest year for which we have the measure, and zero prior to 1975. For years 1966-1974, we include a trend variable *Techtrend* equal to min{(year-1975), 0} in order to capture the effects of any earlier changes (assumed linear) in these variables. This experiment has not yet proven fruitful.

R_E: This variable is described in the next subsection.

X_E: These variables include six variables in X_M, namely *inc*, *adrm*, *popratio*, *Urban*, *Railpop*, and *D7479*. Instead of using a single linear time trend, we allow for the possibility of three distinct trends in fuel efficiency: one before the OPEC embargo (1966-1973), another between the embargo and the Iranian revolution (1974-1979), and a third after the Iranian revolution in 1979. The rationale is that these events changed people's perception of long-term prospects for oil supplies and therefore affected research and development efforts related to fuel efficiency. On the assumption that changes in technology cannot happen immediately, these variables are specified in such a way that there is a break in the slope of the trend line but not a sudden "jump" from one regime to another.

3.2.3 Variable to Measure CAFE Regulation

We define a variable measuring the tightness of CAFE regulation starting in 1978 as the difference between the mandated efficiency of new passenger vehicles and the efficiency that would be chosen in the absence of regulation. This difference is truncated at zero, that is, the variable is zero when CAFE is not binding or when it is not in effect. This variable influences the efficiency of new passenger vehicles, as the inclusion of a lagged dependent variable in the fuel-intensity equation already captures the inertia due to slow turnover of the vehicle fleet.

The calculation proceeds in four steps (See Appendix C for formal and empirical detail). First, we estimate a reduced-form equation explaining fuel intensity from 1966-1977. Next, this equation is interpreted as a partial adjustment model, so that the coefficient γ of lagged fuel intensity enables us to form a predicted desired fuel intensity for each state in each year (from which actual fuel intensity is obtained by moving a fraction γ of the way from last year's value to the desired value, plus the random error term). This prediction is done for all years in the sample by applying the values of the independent variables for those years. Third, for a given year, we average desired fuel intensity (weighted by vehicle-miles traveled) across states to get a national desired average fuel intensity. Finally, we measure the strength of CAFE regulation by whether and how far the minimum mandated efficiency (corrected for the difference between testing equipment and real-world driving) exceeds the reciprocal of the national desired average fuel intensity. Specifically, after taking logarithms of both the mandated and desired fuel efficiency, the variable *cafe* is set equal to their difference if it is positive, or to zero if it is not.

Implicit in this definition is a view of the CAFE regulations as exerting a force on every state toward greater fuel efficiency of its fleet, even if that particular state has a desired fuel efficiency that meets the CAFE standard. The reason is that the standard applies to the nationwide fleet average for each manufacturer, and the manufacturer therefore has an incentive to use pricing or other means to improve fuel efficiency everywhere, not just where it is low.

4. Results

4.1 Structural Equations

Our data set is a cross-sectional time series, with each state observed 36 times. We follow conventional practice by allowing for the possibility that the error terms u_{it} are not independent, and use a fixed effects specification (which a standard Hausman test easily favors over a random effects model). The results of estimating the structural system are presented in Tables 1-3. Each table shows three different estimation methods: three-stage least squares (3SLS), two-stage least squares (2SLS), and ordinary least squares (OLS). It is encouraging that there is little difference between 3SLS and two-stage least squares 2SLS;[14] the former provides slightly better precision of estimates, as it theoretically should, and there are no signs of problems that might arise from mis-specification. We therefore accept the 3SLS results as our best estimates.

The OLS results are shown for comparison. As expected, OLS overestimates the rebound effect because it attributes all the relationship between VMT and cost per mile as causal, whereas some of it is due to reverse causality. In this particular model, OLS overestimates the structural coefficient of cost per mile by 65%.

The usage equation (Table 1) explains how much driving is done by the average adult, holding the vehicle stock constant. Many of its coefficients are identified with good precision and demonstrate a strong and plausible effect. Each adult tends to travel more if there is a larger road stock available (as indicated by the negative coefficient on *adrm*), and if the average adult is responsible for more total people (*popratio*). While *adrm* may capture the effects of congestion, our measure of urbanization does not seem to have much effect, although it is in the expected direction. The proportion of population with rail transit available has no discernable effect,

[14] In the first-stage estimation, each equation contains as variables only the exogenous contemporary variables, but for technical reasons it must also contain one lagged value of all the exogenous variables and two lagged values of all three endogenous variables. See Fair (1984, ch. 6) or Davidson and MacKinnon (1993, ch. 10) for an explanation.

probably because it is too crude a measure of what transit options are really available. The two years 1974 and 1979 exhibited a lower usage, by about 4.4%, other things equal.

The vehicle stock equation (Table 2) is less satisfactory for purposes of tracking price effects as the price of a new car nor the cost of driving a mile have a significant effect on the vehicle stock. Income does have a significant effect (5% significance in a one-tail test), and so does road provision (*adrm*) and a high proportion of adults having drivers' licenses (*licad*). It seems that the vehicle stock is better explained by basic characteristics of the population of potential car-owners and of the road infrastructure than by price variation. Of course, stronger variation in car prices than what is observed in our data may still significantly affect car ownership decisions. As expected, there is strong inertia in expanding or contracting the vehicle stock, as indicated by the coefficient of about 0.85 on the lagged value of vehicle stock. This means that any short-run effect, for example from an increase in income, will be magnified by a factor of 1/(1-0.85) = 6.7 in the long run.

The equation for fuel intensity (Table 3) plausibly shows a substantial effect of fuel price, in the expected direction. It also suggests that CAFE regulation had a substantial effect of enhancing the fuel efficiency of vehicles. Urbanization appears to reduce fuel intensity, perhaps due to a preference for small cars in areas with tight street and parking space. The time trends show a break following 1979 toward more fuel-efficient cars. Surprisingly, the period between 1974 and 1979 showed the opposite trend. But since all trends are less than 1% per year, probably not too much consequence should be attributed to them.

Table 1. Usage Equation

	Estimated Using Three-Stage Least Squares		Estimated Using Two-Stage Least Squares		Estimated Using Ordinary Least Squares	
Variable	Coefficient	Stndrd. Error	Coefficient	Stndrd. Error	Coefficient	Stndrd. Error
vma(t-1)	**0.7786**	**0.0133**	**0.7785**	**0.0149**	**0.7434**	**0.0153**
vehstock	**0.0538**	**0.0114**	**0.0332**	**0.0152**	**0.0556**	**0.0127**
pm	**-0.0521**	**0.0046**	**-0.0528**	**0.0048**	**-0.0860**	**0.0048**
pm*(inc)	**0.0837**	**0.0166**	**0.0920**	**0.0218**	**0.0682**	**0.0180**
pm*(Urban)	0.0050	0.0119	0.0103	0.0159	0.0135	0.0140
inc	**0.0933**	**0.0146**	**0.0964**	**0.0157**	**0.0955**	**0.0157**
adrm	**-0.0162**	**0.0063**	**-0.0194**	**0.0068**	**-0.0166**	**0.0068**
popratio	**0.1476**	**0.0363**	**0.1381**	**0.0405**	0.0460	0.0385
Urban	**-0.0447**	**0.0207**	**-0.0529**	**0.0223**	-0.0353	0.0224
Railpop	0.0021	0.0082	0.0030	0.0087	0.0009	0.0088
D7479	**-0.0437**	**0.0035**	**-0.0436**	**0.0036**	**-0.0360**	**0.0036**
Trend	0.0003	0.0003	0.0005	0.0004	-0.0006	0.0004
constant	**2.1014**	**0.1274**	**2.1142**	**0.1408**	**2.4991**	**0.1466**
rho	**-0.0954**	**0.0235**	**-0.0643**	**0.0288**	-0.0239	0.0294
No. observations	1,785		1,785		1,785	
Adjusted R-squared	0.9805		0.9806		0.9812	
S.E. of regression	0.0318		0.0317		0.0313	
Durbin-Watson stat	1.9196		1.9860		1.9870	
Sum squared resid	1.6861		1.6817		1.6333	

Notes: Bold or italic type indicates the coefficient is statistically significant at the 5% or 10% level, respectively.
Estimates of fixed effects coefficients (one for each state except Wyoming) are not shown.
Variables *inc*, *Urban*, and the constituent variables in *pm* are normalized by subtracting their mean value in the sample, both in the variable itself and in any interactions it takes. As a result, the coefficient of any variable in its uninteracted form gives the effect of that variable on *vma* at the mean values of the other variables.

OLS is a particularly bad estimator of the fuel intensity equation (Table 3). It greatly underestimates the lag coefficient and instead attributes observed serial correlation in fuel intensity to a very strong autocorrelation pattern—so strong that if it were true, it would indicate serious omissions from the explanatory variables. Fortunately the 3SLS and 2SLS estimators show that in fact autocorrelation is modest, and the inertia in fuel intensity (lag coefficient 0.79) is nearly as large as that in the vehicle stock.

4.2 Rebound Effects and Other Elasticities

Table 4 shows the rebound effects (stated as the negative of the cost-per-mile elasticity of driving), as well as other elasticities implied by the structural models. The interactions through the simultaneous equations modify only slightly the numbers that can be read directly from the coefficients. In particular, the average cost-per-mile elasticity in the sample is -0.0526, which is nearly identical to the coefficient of *pm* in Table 1. Our best estimate of the long-run elasticity in

the average state over the time period of our sample is -0.2387. Thus the average rebound effect in this sample is estimated to be approximately 5.3% in the short run and 24% in the long run.

Table 2. Vehicle Stock Equation

	Estimated Using Three-Stage Least Squares		Estimated Using Two-Stage Least Squares		Estimated Using Ordinary Least Squares	
Variable	Coefficient	Stndrd. Error	Coefficient	Stndrd. Error	Coefficient	Stndrd. Error
vehstock(t-1)	**0.8477**	**0.0149**	**0.8466**	**0.0153**	**0.8425**	**0.0153**
vma	0.0155	0.0161	0.0175	0.0164	0.0341	0.0147
pv	-0.0437	0.0384	-0.0505	0.0393	-0.0430	0.0391
pm	-0.0084	0.0064	-0.0076	0.0066	-0.0016	0.0065
inc	*0.0277*	*0.0154*	*0.0264*	*0.0157*	0.0220	0.0155
adrm	**-0.0239**	**0.0069**	**-0.0234**	**0.0070**	**-0.0224**	**0.0070**
Trend	-0.0006	0.0008	-0.0008	0.0008	-0.0006	0.0008
interest	-0.0017	0.0070	-0.0038	0.0072	-0.0049	0.0072
licad	**0.0375**	**0.0153**	**0.0417**	**0.0157**	**0.0412**	**0.0157**
constant	-0.0268	0.1579	-0.0394	0.1613	-0.2014	0.1452
rho	**-0.1538**	**0.0281**	**-0.1504**	**0.0288**	**-0.1472**	**0.0289**
No. observations	1,785		1,785		1,785	
Adjusted R-squared	0.9638		0.9638		0.9638	
S.E. of regression	0.0365		0.0364		0.0364	
Durbin-Watson stat	1.9508		1.9546		1.9537	
Sum squared resid	2.2234		2.2227		2.2207	

Notes: Bold or italic type indicates the coefficient is statistically significant at the 5% or 10% level, respectively. Estimates of fixed effects coefficients (one for each state except Wyoming) are not shown.

It is not surprising, then, that OLS overestimate the short-run rebound effect by about the same amount as the coefficient of *pm*, namely 64%. As for the long-run rebound effect, OLS overestimates it by 41% in our results. Our estimate of the short-run rebound effect without correcting for endogeneity is quite close to the consensus of the literature, whereas with the correction it is somewhat lower than this consensus. This comparison leads us tentatively to suggest that many of the estimates of the rebound effect in the literature are overestimates, and might be reduced by around one-third if they accounted for endogeneity of cost per mile. We also note that Greene *et al.* (1999), one of the very few previous studies that takes endogeneity of fuel efficiency into account, obtains a long-run rebound effect of 23%, very close to ours. (They do not estimate a short-run rebound effect.)

Table 3. Fuel Intensity Equation

	Estimated Using Three-Stage Least Squares		Estimated Using Two-Stage Least Squares		Estimated Using Ordinary Least Squares	
Variable	Coefficient	Stndrd. Error	Coefficient	Stndrd. Error	Coefficient	Stndrd. Error
fint(t-1)	**0.7901**	**0.0187**	**0.8046**	**0.0230**	**-0.0758**	**0.0197**
vma	**-0.0635**	**0.0239**	**-0.0624**	**0.0270**	**-0.8426**	**0.0207**
pf	**-0.0549**	**0.0068**	**-0.0423**	**0.0072**	**-0.0747**	**0.0078**
cafe	**-0.1021**	**0.0118**	**-0.0766**	**0.0146**	**-0.2860**	**0.0210**
inc	0.0089	0.0183	0.0223	0.0190	**0.4005**	**0.0281**
adrm	-0.0093	0.0077	-0.0092	0.0079	**-0.0481**	**0.0183**
popratio	**0.1289**	**0.0498**	**0.1163**	**0.0554**	**0.7457**	**0.0857**
Urban	**-0.1521**	**0.0533**	*-0.1200*	*0.0653*	-0.2105	0.2268
Railpop	-0.0134	0.0099	-0.0129	0.0100	**-0.0452**	**0.0206**
D7479	**-0.0090**	**0.0045**	-0.0070	0.0047	**-0.0164**	**0.0025**
Trend1	0.0006	0.0011	0.0004	0.0014	0.0066	0.0050
Trend2	**0.0032**	**0.0013**	-0.0003	0.0014	-0.0010	0.0025
Trend3	**-0.0039**	**0.0004**	**-0.0034**	**0.0004**	**-0.0137**	**0.0008**
constant	-0.0583	0.2058	-0.0064	0.2279	**4.9574**	**0.2425**
rho	**-0.1218**	**0.0240**	**-0.1339**	**0.0289**	**0.7886**	**0.0168**
No. observations	1,785		1,785		1,785	
Adjusted R-squared	0.9610		0.9613		0.9793	
S.E. of regression	0.0394		0.0393		0.0288	
Durbin-Watson stat	1.9390		1.9609		2.2598	
Sum squared resid	2.5965		2.5768		1.3825	

Notes: Bold or italic type indicates the coefficient is statistically significant at the 5% or 10% level, respectively.
Estimates of fixed effects coefficients (one for each state except Wyoming) are not shown.

Table 4. Rebound Effect and Other Price Elasticities

	Estimated Using Three-Stage Least Squares		Estimated Using Two-Stage Least Squares		Estimated Using Ordinary Least Squares	
	Short Run	Long Run	Short Run	Long Run	Short Run	Long Run
Elasticity of VMT with respect to fuel cost per mile: (a)						
At sample average	-0.0526	-0.2387	-0.0531	-0.2401	-0.0862	-0.3361
Calif. 1997-2001	-0.0220	-0.1002	-0.0181	-0.0824	-0.0587	-0.2290
Elasticity of VMT with respect to new veh price:	-0.0024	-0.0155	-0.0017	-0.0109	-0.0024	-0.0152
Elasticity of fuel intensity with respect to fuel price:						
At sample average	-0.0518	-0.2504	-0.0059	-0.0327	-0.0025	0.2964
Calif. 1997-2001	-0.0536	-0.2570	-0.0081	-0.0422	-0.0267	0.1519
Elasticity of fuel consumption with respect to fuel price:						
At sample average	-0.1044	-0.4890	-0.0590	-0.2728	-0.0887	-0.0397
Calif. 1997-2001	-0.0756	-0.3572	-0.0262	-0.1246	-0.0855	-0.0772

Note: (a) The rebound effect is just the negative of this number (multiplied by 100 if expressed as a percent)

The model for vehicle usage discerns an additional influence of real income on the rebound effect. The coefficient on *pm* interacted with logarithm of income (both normalized by subtracting the mean value over the entire sample) shows that each increase in the logarithm of income by 0.1 (roughly a ten% increase in income) reduces the magnitude of the short-run rebound effect by 0.1 x 0.0837 = 0.008, or just under one%age point. This appears to confirm the theoretical expectation that higher incomes make people less sensitive to fuel costs.

To get an idea of the implications of income for the rebound effect, we compute the elasticity of usage with respect to cost per mile for values of income and urbanization equal to those measured for California over the most recent five-year period covered in our data set, namely 1997-2001. These results are also shown in Table 4. Again using the 3SLS results, the short-run rebound effect is reduced to 2.2% and the long-run effect to 10.0%. About half of the difference between these results and those at the sample average is due to the difference between California and other states, and about half to the higher incomes prevailing in 1997-2001 than over the entire period 1966-2001. [15]

The third and fourth panels in Table 4 provide information about how fuel prices affect fuel intensity and overall fuel consumption. The former effect is estimated with great precision, as seen in the small standard error on the coefficient of *pf* in Table 3. It implies that a 10% increase in fuel price causes consumers to choose cars with 0.55% greater fuel efficiency in the same year, and 0.55/(1-0.79) = 2.6% greater over a long period of time if the rise in fuel price were to persist. Adding the elasticity due to vehicle-miles traveled gives the total elasticity of fuel consumption, shown in the last panel of Table 4. This estimate of long-run price-elasticity of fuel consumption is -0.49, very close to the middle of recent studies. In fact, our estimates of both this long-run overall price-elasticity of fuel demand and the proportion of it due to changes in usage (0.2387/0.4890 = 49%) are very much in line with the literature; see the review by Parry and Small (2002), who choose as the best consensus an elasticity equal to -0.55, with 40% of it caused by mileage changes.

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[15] We also allowed the rebound effect to differ by degree of urbanization, but that estimated effect is essentially zero. In other estimates not shown, we included a variable allowing the rebound effect to differ in California from other states even aside from the influence of income and urbanization, but this variable was very small and statistically insignificant. We conclude that, apart from the fixed effect, income is the primary source of any difference between California and other states in the size of the rebound effect. California is not an outlier in per capita income: in 1997-2001 it ranked 11th among the 51 states (including Washington, DC), with the highest-ranking state, Connecticut, exceeding California's per capita income by nearly 30%.

We investigated two other measures of income to see if they changed the strong influence that we find for income on the rebound effect. The first is to substitute disposable income, which excludes taxes, for personal income. These results are barely distinguishable from those using personal income, so we do not present them here. The second is to use gross state product instead (GSP) of income, which might better capture the role of business travel. On theoretical grounds, we think GSP is less justified than personal income because most travel is personal, not business-related, and furthermore the fraction that is personal is increasing over time. In addition, figures on GSP are not available for the first 11 years of our sample, requiring some extrapolation. Nevertheless, the results using GSP fit about as well as those using personal income, and they are presented as a comparison in Tables 5 and 6, which show the usage equation and the rebound effect. These results show the rebound to be declining in GSP, but less so than with personal income. (Some of this difference is compensated by the fact that urbanization plays a stronger, though still small, role in this version of the model.)

Tables 5 and 6 also show a model in which the effect of income on the rebound effect is replaced by letting a time trend, instead of income, affect the relationship between cost per mile (*pm*) and usage. In this model, *inc* is still used as a variable by itself, its coefficient being the income elasticity. This version of the model shows a very small and statistically insignificant coefficient for the interaction between time trend and *pm*. Some other coefficients of the usage equation are affected, including those of adults per road mile (*adrm*) and population per adult (*popratio*). The interaction between cost per mile and urbanization shows the biggest change: it is now statistically significant at a 10% significance level, and it is large enough to have a moderate effect on the rebound effect. We regard this model as less satisfactory because the time trend is just a mask for unknown effects. However it fits nearly as well as the preferred model and demonstrates that the effect of income on the rebound effect is somewhat tenuously estimated, making it difficult to discriminate between income and other factors in explaining why the rebound effect declined over the period of our sample.

Table 5. Comparison of Usage Equations

	Estimated Using Personal Income		Estimated Using Gross State Product		Estimated Using Time Trend	
Variable	Coefficient	Stndrd. Error	Coefficient	Stndrd. Error	Coefficient	Stndrd. Error
vma(t-1)	**0.7786**	**0.0133**	**0.7876**	**0.0153**	**0.7898**	**0.0137**
vehstock	**0.0538**	**0.0114**	**0.0496**	**0.0127**	**0.0464**	**0.0115**
pm	**-0.0521**	**0.0046**	**-0.0544**	**0.0048**	**-0.0598**	**0.0108**
pm*(inc, gsp, or trend)	**0.0837**	**0.0166**	**0.0548**	**0.0179**	0.0004	0.0006
pm*(Urban)	0.0050	0.0119	*0.0251*	*0.0140*	**0.0341**	**0.0108**
inc or gsp	**0.0933**	**0.0146**	**0.0545**	**0.0157**	**0.0985**	**0.0146**
adrm	**-0.0162**	**0.0063**	**-0.0198**	**0.0068**	**-0.0128**	**0.0063**
popratio	**0.1476**	**0.0363**	**0.0930**	**0.0385**	**0.0869**	**0.0439**
Urban	**-0.0447**	**0.0207**	-0.0304	0.0224	*-0.0371*	*0.0207*
Railpop	0.0021	0.0082	0.0064	0.0089	-0.0017	0.0082
D7479	**-0.0437**	**0.0035**	**-0.0435**	**0.0036**	**-0.0438**	**0.0036**
Trend	0.0003	0.0003	0.0006	0.0004	-0.0002	0.0003
constant	**2.1014**	**0.1274**	**2.0263**	**0.1466**	**2.0220**	**0.1357**
rho	**-0.0954**	**0.0235**	**-0.1057**	**0.0295**	**-0.0982**	**0.0237**
No. observations	1,785		1,785		1,785	
Adjusted R-squared	0.9805		0.9807		0.9804	
S.E. of regression	0.0318		0.0316		0.0319	
Durbin-Watson stat	1.9196		1.9189		1.9213	
Sum squared resid	1.6861		1.6729		1.7001	

Notes: Bold or italic type indicates the coefficient is statistically significant at the 5% or 10% level, respectively.
In the third equation, the variable *inc*, not *gsp*, is used by itself.
Estimates of fixed effects coefficients (one for each state except Wyoming) are not shown.

Table 6. Rebound Effect with Alternative Specification of Income

	Estimated Using Personal Income		Estimated Using Gross State Product		Estimated Using Time Trend	
	Short Run	Long Run	Short Run	Long Run	Short Run	Long Run
Elasticity of VMT with respect to fuel cost per mile: (a)						
At sample average	-0.0526	-0.2387	-0.0549	-0.2593	-0.0603	-0.2875
Calif. 1997-2001	-0.0220	-0.1002	-0.0292	-0.1385	-0.0456	-0.2179

4.3 Caveats

Despite the generally good performance of our equation system, there are many caveats that need to be considered. First, there are known problems with the VMT data collected by the US Federal Highway Administration. We have no reason to think that these problems bias the results one way or the other, but better data would add considerably to our confidence in results of this methodology.

Second, our estimates, like those of most previous studies, rely on theory that requires people to react to any change in cost per mile the same way, whether it is caused by variations in fuel prices or in fuel efficiency. There is more variation over time in fuel prices than there is in fuel efficiency, so this theoretical reliance is critical. Our methodology allows us to test for whether fuel intensity (*fint*) exhibits an independent influence on vehicle usage by simply decomposing the composite variable for price per mile as $pm = pf + fint$ (in log form). The test therefore consists of entering *pf* and *fint* separately in the equation instead of combined into *pm*, and seeing whether they attain the same coefficient. In contrast to some earlier studies using different data, such as Greene *et al.* (1999) and Schimek (1996), we found they do not.[16] The coefficient of *pf* is very similar to that on *pm*, but that on *fint* is small and statistically insignificant. In other words, we cannot prove that there is *any* rebound effect resulting from stricter fuel efficiency regulations; in the absence of theory, we would have to conclude that fuel price but not fuel intensity has the expected effect. However, we think that this is an unwarranted conclusions because in fact the model with *pf* and *fint* entered separately does not perform very well. The coefficients of interaction terms change greatly and implausibly, while the usage equation ends up with a higher sum of squared residuals, and a lower R-squared, than it did with the coefficients constrained. Thus we conclude that the best estimate of the rebound effect is attained by using the theoretically justified equating of the effects of fuel price and fuel intensity.

Third, we found that the role of fuel price in determining fuel efficiency (the model in Table 3) is quite sensitive to how the *cafe* variable is defined. We tried equations with additional variables, including lagged values, in the prediction equation shown in Appendix C for the short time period 1966-78. The time pattern exhibited by the *cafe* variable was quite different, and the influence of both *cafe* and fuel price on *fint* in the structural model (Table 3) diminished to statistical insignificance. However, we believe that the richer specification was unreliable because it was over-fitting the data: coefficients on a variable and its lag were in several instances large and opposite in sign, and the predicted desired fuel intensity showed implausible oscillations over time. Therefore, we believe the current specification is the most suitable one given the short time period over which we can observe pre-CAFE behavior.

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[16] A Wald test easily rejects the hypothesis of equality of the coefficients for *pf* and *fint*, *pf*inc* and *fint*inc*, and *pf*Urban* and *fint*Urban*. The test's χ^2 value, with three degrees of freedom, is 28.7; in the model with *inc* replaced by *gsp* it increases to 32.2.

An extension not studied here would be to consider that the price of fuel might be affected by policies affecting fuel demand, especially in as large and geographically isolated state such as California. Suppliers of California-specific fuel mixes often appear to be operating at or near capacity (USDOE, 2003). Thus a reduction in fuel demand following an improvement in the fuel efficiency of cars may reduce the price of fuel, which would make the rebound effect stronger.

5. Conclusion

Using a cross-sectional time series of the 50 US states plus District of Columbia over a 36-year period, we estimate equations for motor-vehicle travel demand, fleet size and fleet efficiency. The estimated system produces estimates of the rebound effect and other elasticities.

We find that accounting for the endogeneity of fuel efficiency when calculating the per-mile fuel cost elasticity of VMT demand substantially reduces the estimated rebound effect. It seems likely that many previous estimates, on the order of 10-20% for short run and higher for long run, would be reduced by around 40% if this endogeneity were controlled for. In addition, a better measure of the effects of the CAFE standards seems to help stabilize results, which have shown considerable variation in the literature. Our longer time series also enables us to distinguish the effect of a lagged dependent variable (and therefore the difference between short- and long-run effects) from other sources of autocorrelation. Our best estimate of the rebound effect for the US as a whole, over the period 1966-2001, is 5.2% for the short run and 24% for the long run. For California in the recent five-year period 1997-2001, it is 2.0% in the short run and 9.3%in the long run.

We are unable to confirm the maintained assumption that people react to a change in cost of driving a mile the same way whether it is caused by variations in fuel prices or in fuel efficiency. However, we think this inability is due to limited variation of fuel efficiency in our data. We therefore impose the equality as a theoretical assumption, as do virtually all studies on the topic.

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Appendix A: The partially reduced form

Starting from the structural form model in (1), we clarify that the rebound effect due to a regulatory change may indeed be viewed as the negative of a particular elasticity, as is done in studies like Greene (1992) and USDOE (1996), but that this elasticity applies to a 'partially reduced form' model. The theory helps select the appropriate variables for such a reduced form approach. The reduced form corresponding to (1), denoted ~, is:

$$y = \tilde{y}(P_V, P_F, R_E, X_M, X_E, X_V), \quad y = M, V, E \tag{A.1}$$

Many of the available estimates of the rebound effect are implicitly based on a *partially reduced form* for the usage equation, denoted here by ^, as they estimate VMT as a function of P_M but not of other endogenous variables. In this form the second of equations (A.1) is substituted into the first, while leaving both still as functions of the endogenous variable P_M:

$$M = M\left[V\left(P_V, M, P_M, X_V\right), P_M, X_M\right] \equiv \hat{M}\left(P_V, P_M, X_V, X_M\right). \tag{A.2}$$

This equation corresponds to an empirical equation for usage in which vehicle stock is not included and in which efficiency is included only indirectly via the per-mile fuel-cost variable. Equation (A.2) shows that such an equation should include the exogenous variables that influence the vehicle stock, P_V and X_V; their influence on M arises through their influence on V, as seen explicitly in (A.2). If P_V, X_V, and X_M are all held constant, equation (A.2) leads to the standard definition of the rebound effect. In particular, the elasticity identified as the rebound effect can be written more generally as the elasticity of this function:

$$\varepsilon_{M,PM} \equiv \frac{P_M}{M} \cdot \frac{\partial \hat{M}}{\partial P_M}. \tag{A.3}$$

But the rebound effect can also be written in terms of the structural equations (1), which enables one to see explicitly how much of it comes from changes in usage per vehicle and how much in changes in number of vehicles and their subsequent effect on usage. This is done by differentiating (A.2) at its solution given by the last term of (A.2), multiplying by (P_M/M) to convert to elasticities, and solving for $\varepsilon_{\hat{M},PM}$. The result is:[17]

[17] The partially reduced form can be written as follows, omitting for clarity the variables P_V and X_V, which are fixed in this calculation:

$$\hat{M}(P_M) = M\left[P_M, V\left(P_M, \hat{M}(P_M)\right)\right].$$

$$\varepsilon_{\hat{M},PM} = \frac{\varepsilon_{M,PM} + \varepsilon_{M,V}\varepsilon_{V,PM}}{1 - \varepsilon_{M,V}\varepsilon_{V,M}} \tag{A.4}$$

where $\varepsilon_{M,PM}$ and $\varepsilon_{M,V}$ and elasticities of the first of equations (1) (with respect to P_M and V, respectively) and $\varepsilon_{V,M}$ is the elasticity of the second (with respect to M).

To summarize we have discovered two features of a valid empirical specification for measuring a function relating travel M to the per-mile fuel cost P_M. First, the empirical specification should include as independent variables all the exogenous factors determining both vehicle stock and usage but need not include vehicle stock itself, which has been substituted out in deriving (A.2). Second, the equation needs to be estimated taking account of the endogeneity of E in forming variable P_M. A comparison of the variables in the last of equations (AA.2) with those in (A.2) tells us immediately what variables to use as instruments: P_F, R_E, and X_E. Third, the variable(s) describing energy regulation belong in the list of instruments for P_M, but not directly in the equation for M, unless there is a direct effect on demand for vehicle mileage (such as an unmeasured reduction in vehicle performance). This is different from the approach taken in most of the empirical literature, which has placed regulatory descriptors directly in the usage equation and, except in a few cases, has not used instrumental variables to account for endogeneity of P_M.

Appendix B: Data Sources

This appendix lists the variables used in the estimation and their sources.

Adult population (18 and over)

Definition: midyear population
1966-2001: U.S. Census Bureau (http://www.census.gov)
(http://eire.census.gov/popest/archives/1990.php and
http://eire.census.gov/popest/data/states/ST-EST2002-ASRO-02.php)

Differentiating,

$$\frac{\partial \hat{M}}{\partial P_M} = \frac{\partial M}{\partial P_M} + \frac{\partial M}{\partial V}\left(\frac{\partial V}{\partial P_M} + \frac{\partial V}{\partial M}\frac{\partial \hat{M}}{\partial P_M}\right)$$

or, in elasticity terms:

$$\varepsilon_{\hat{M},PM} = \varepsilon_{M,PM} + \varepsilon_{M,V}\left(\varepsilon_{V,PM} + \varepsilon_{V,M}\varepsilon_{\hat{M},PM}\right).$$

Solving this equation for $\varepsilon_{\hat{M},PM}$ gives (A.4).

(*accessed 12/03/2004*)

Corporate Average Fuel Economy (CAFE: Mile Per Gallon (MPG))

1978-2001: National Highway Traffic Safety Administration (NHTSA), *CAFE Automotive Fuel Economy Program, Annual update 2001*, Table II-6 (http://www.nhtsa.dot.gov/cars/rules/cafe/FuelEconUpdates/2001/Index.html)

* Note: The CAFE standards are different from vehicle types. The CAFE standard data used in this study is for passenger cars from "summary of fuel economy performance". (http://www.nhtsa.dot.gov/cars/rules/cafe/CAFEData.htm#)

Consumer price index – all urban consumers (1982-84=100)

1966-2001: Bureau of Labor Statistics (BLS), CPI (http://www.bls.gov/cpi/)

* Note: all monetary variables (gas tax, new passenger vehicle price index, price of gasoline, personal income) are put in real 1987 dollars by first deflating by this CPI and then multiplying by the CPI in year 1987 (divided by 100). The purpose of using 1987 is for ease in replicating Haughton and Sarkar (1996).

Cumulative Population Growth Rate (%)

Definition:*%age of population in year t that has been added since 1950.*

1950: *Statistical Abstract of the United Sates* (SAUS)

1960-2001: Bureau of Economic Analysis (BEA) (http://www.bea.doc.gov)

* Note: Original source for both is from midyear population estimates by U.S. Census Bureau

Family size

Definition: average number of people per household

1966-2001: Bureau of Labor Statistics, Current Population Survey (CPS) (http://www.bls.gov/cps/)

* Note: Data was extracted from a CPS Data CD

Federal Gas Tax (cents per gallon)

1966-2001: Federal Highway Administration (FHWA), Highway Statistics, Annual Report, Table FE-101A 1A

Highway use of gasoline (including public use) (thousands of gallons)

1966-1995: FHWA, Highway Statistics Summary to 1995, Table MF-226

1996-2001: FHWA, Highway Statistics Annual Report, Table MF-21

* Note: The FHWA estimates highway use of gasoline by subtracting estimated non-highway use from the total use reported by States.

Income per capita ($/year, 1987 dollars)

Definition: Personal income deflated to 1987, divided by midyear population

1966-2001: Bureau of Economic Analysis (BEA) (http://www.bea.doc.gov/)

* Note: Per capita personal income is total personal income divided by total midyear population.

Alternative measure: Disposable income (similarly deflated and divided by population);

available from same web site as above, but only starting 1969; for 1966-68 we interpolated by assuming it bore the same ratio to per capita personal income as existed in the same state for 1969-78.

Second alternative measure: Gross state product (similarly deflated and divided by population), available only starting 1977; for 1966-1976 we interpolated by assuming it bore the same ratio to per capita personal income as existed in the same state for 1977-87.

Interest rate (%)

Definition: national average interest rate for auto loans

1966-1971: Interpolated using Moody's AAA corporate bond interest rate

1972-2001: Federal Reserve Systems, Economic Research and Data, Federal Reserve Statistical Release G.19 Consumer Credit (http://www.federalreserve.gov/releases/g19/hist/cc_hist_tc.html)

*Note: We average two different interest rates: that for new-car loans at auto finance companies, and that for commercial banks for 48-month lanes for new car. These two rates are averaged over a year from monthly and quarterly data, respectively.

New Car Price Index

Definition: price index for U.S. passenger vehicles, city average, not seasonally adjusted, 1982-84=100)

1966-2001: Bureau of Labor Statistics (BLS), CPI

* Note: Original index has 1982-84=100; converted to 1987=100 using the Consumer Price Index.

Number of vehicles

Definition: Number of automobiles and light trucks registered

1966-1995: FHWA, Highway Statistics Summary to 1995, Table MV-201

1996-2001: FHWA, Highway Statistics Annual Report, Table MV-1

*Note: Trucks include pickups, panels and delivery vans; beginning 1985, personal passenger vans, passenger minivans, and utility-type vehicles are no longer included in automobiles but are included in trucks.

Price of gasoline (cents per gallon)

1960-1977: U.S. Department of Energy (USDOE 1977), Table B-1, pp. 93-94

1970-2000: Energy Information Administration, *State Energy Data 2000: Price and Expenditure Data*, Table 5

2001: Energy Information Administration, *Petroleum Marketing Annual*, Table A1.

* Note: Data for 1966-1970 were spliced by averaging the two overlapping sets of data.

Public road mileage (miles)

1966-1979: FHWA, *Highway Statistics*, annual editions, Table M-1 (Total rural and municipal mileage)

1980-1995: FHWA, *Highway Statistics Summary to 1995*, Table HM-220

1996-2001: FHWA, *Highway Statistics*, annual editions, Table HM-20

Rail Transit Availability Index (Railpop)

Definition: The fraction of the state's population living in metropolitan statistical areas with a subway or heavy rail transit system)

Heavy rail transit system Initial Segment opening year: American Public Transportation Association (APTA) (http://www.apta.com)

(Rail transit dummy for years: 1= rail transit available, 0=otherwise)

Population data for the Metropolitan Statistical Areas (MSA) (1966-2001): SAUS, "Metropolitan Statistics" section (table number changes)

* Note Data for missing years (1969, 1971, 1974, 1979, 1981, 1982, 1989) were interpolated using its state population in which the MSA is included.

Number of Licensed Drivers

1966-1995: FHWA, *Highway Statistics Summary to 1995*, Table DL-201

1996-2001: FHWA, *Highway Statistics*, annual editions, Table DL-1C

Urban Road Mileage (miles)

1966-1979: FHWA, *Highway Statistics*, annual editions, Table M-1 (Total municipal mileage)

1980-1995: FHWA, *Highway Statistics Summary to 1995*, Table HM-220

1996-2001: FHWA, *Highway Statistics*, annual editions, Table HM-20

Urbanization

Definition: Share of total state population living in Metropolitan Statistical Areas (MSAs), with MSAs based on December 2003 definitions

1966-1968: Extrapolated exponentially (i.e. assuming constant annual%age growth rate) from 1969-79 values

1969-2001: Bureau of Economic Analysis, Regional Economic Accounts (http://www.bea.doc.gov/bea/regional/reis/)

VMT (Vehicle Miles Traveled, , million miles)

1966-1979: FHWA, *Highway Statistics*, annual editions, Table VM-2

1980-1995: FHWA, *Highway* Statistics Summary to 1885, Table VM-202

1996-2001: FHWA, *Highway Statistics*, annual editions, Table VM-2

Appendix C: Variable Measuring Strength of CAFE Regulation

Steps in creating the variable

1. We first estimate the reduced-form equation explaining fuel intensity—i.e., the empirical counterpart of the third of equation set (1)—on data only from 1966-1977, with no regulatory variable included (since there was no regulation then). This equation should in principle include all exogenous variables from all three models (including P_V for the V equation); we simplified it by dropping the variable *Railpop*, which seemed to have little effect in this short time series. Like our other equations, it also includes one lag of the dependent variable, and allows for fixed effects and autocorrelated errors. It does not include other endogenous variables, either current or lagged; the reason is that, unlike in an instrumental variables regression, our objective is to estimate a predictive model for what fuel intensity would have been in the absence of CAFE regulation and therefore we cannot use information about what actually happened to the endogenous variables. In theory, this equation could include any number of lagged values of independent variables, because they would be present in a complete solution of system (1) for the time path of *fint*; however on this very short time series it is impractical to estimate so many parameters, especially of variables that are highly correlated as current and lagged values are likely to be. For the same reason of parsimony, we included only a single time trend in this predictive equation. Let us denote this estimating equation by the following reduced-form and simplified variant of the third of equations (1):

$$(fint)_{i,t} = \alpha^{fR}(fint)_{i,t-1} + \beta^{fR} X_{it}^{fR} + u_{it} \qquad \text{(C.1)}$$

where i designates a state, superscript R indicates the reduced form, and X^{fR} denotes the set of all exogenous variables used, including prices, as described above. The results of this estimation are shown below. The statistically significant coefficients are that of $(fint)_{t-1}$ with value 0.638, *D7479* with value -0.021, and *pv* with value -0.221. The price of fuel is not statistically significant (t-statistic -1.02) but has the reasonable value of -0.021.

2. The coefficient α^{fR} of the lagged dependent variable is interpreted as arising from the following partial adjustment model:

$$(fint)_{i,t} = (fint)_{i,t-1} + \gamma \cdot \left\{(fint)_{i,t}^{*} - (fint)_{i,t-1}\right\} + u_{it} \qquad \text{(C.2)}$$

where $(fint)^*_{i,t}$ denotes a long-run desired value for the logarithm of fuel intensity. That is, users basing decisions in year *t* desire to shift the vehicle stock toward one with fuel efficiency $(fint)^*_{i,t}$ but they can do so only part way by changing a portion γ of the stock in that year. Thus it is natural to interpret $(fint)^*_{i,t}$ as the target fuel efficiency for new car purchases and γ as the fraction of the fleet that turns over each year. It is easy to see that (C.2) is the same as (C.1) if we choose γ=1-α^f and

$$(fint)^*_{i,t} = \frac{\beta^{fR} X^{fR}_{it}}{1-\alpha^f}. \tag{C.3}$$

This value is computed for each state and each year *t*, not just the years from which the coefficients were estimated.

3. We then form from this the US average desired fuel intensity, averaged the same way as vehicles are averaged under CAFE regulations: namely,

$$(FintUS)^*_t \frac{\sum_i M_{it} \exp\left((fint)^*_{it}\right)}{\sum_i M_{it}} \tag{C.4}$$

where M_{it} is aggregate VMT for state *i*.

4. Finally, we assume CAFE is binding whenever the desired efficiency $E^*_t \equiv \left(1/FintUS^*_t\right)$ is less than the minimum mandated efficiency, $\overline{E}_t$. The latter is computed as a weighted average of the CAFE standards for light trucks and cars, the weights being current nationwide light truck and car VMT, reduced by 16% which is an estimate of the difference between fuel efficiency achieved in real driving and that achieved on the tests used to enforce the CAFE standard.[18] A measure of the strength of CAFE regulation is then

$$R_E \equiv \max\left\{\frac{\overline{E}_t}{E^*_t}, 1\right\} \text{ or its logarithm,}$$

[18] The factor 16% is taken from Harrington (2003).

$$cafe \equiv \max\left\{\left(\bar{e}_t - e_t^*\right), 0\right\}, \text{ where } \bar{e}_t = \ln(\bar{E}_t) \text{ and } e_t^* = \ln(E_t^*). \quad \text{(C.5)}$$

Estimated Equation for Projecting Desired Fuel Intensity

Table C1. Fuel Intensity Equation: Reduced Form Estimated on 1966-1977 Data

Variable	Coefficient	Std. Error
fint(t-1)	0.6386	0.0443
pf	-0.0209	0.0204
Inc	0.0169	0.0288
adrm	0.0363	0.0273
popratio	0.0852	0.0910
Urban	-0.1974	0.2328
D7479	-0.0213	0.0060
Trend	-0.0097	0.0024
pv	-0.2209	0.0798
Interest	0.0213	0.0298
licad	0.02605	0.0262
constant	-0.9822	0.3584
Rho	-0.1241	0.0625

No. of observations	510
Adjusted R-squared	0.8967
S.E. of regression	0.0253
Sum squared resid	0.2858
Durbin-Watson stat	1.9975

Note: 50 constants for individual states are not shown.

Results.

Figure 2 shows the results of this procedure. It compares our estimate of desired nationwide fuel efficiency (E^*) with the *de facto* standard ($\bar{E}$). We see that the desired efficiency of new passenger vehicles was mildly increasing over much of our time period, especially 1975-1978 and 1984-1997, with one-year upticks in 1974 and 1979 due to queues at gasoline stations and small downturns in 1986 and 1998-99 due to decreases in fuel prices.[19] The CAFE standard

[19] The uptick in 1979 results from our assumption that the gasoline queues in 1979 would have the same effect on desired efficiency as those in 1974, which are captured by the 1974 dummy variable in the equation for fuel intensity fit on 1966-1977 data.

exhibited a very different pattern, rising rapidly from 1978-1984 and then flattening out. The variable *cafe* is zero until 1978, after which it is the logarithm of the ratio of these two values. We can see that by this definition, the CAFE standard has been binding throughout its time of application, but that its tightness rose dramatically during its first six years and then gradually diminished until it is just barely binding in 2001. This pattern is obviously quite different from either a trend starting at 1978, or the CAFE standard itself, both of which have been used as a variable in VMT equations by other researchers.

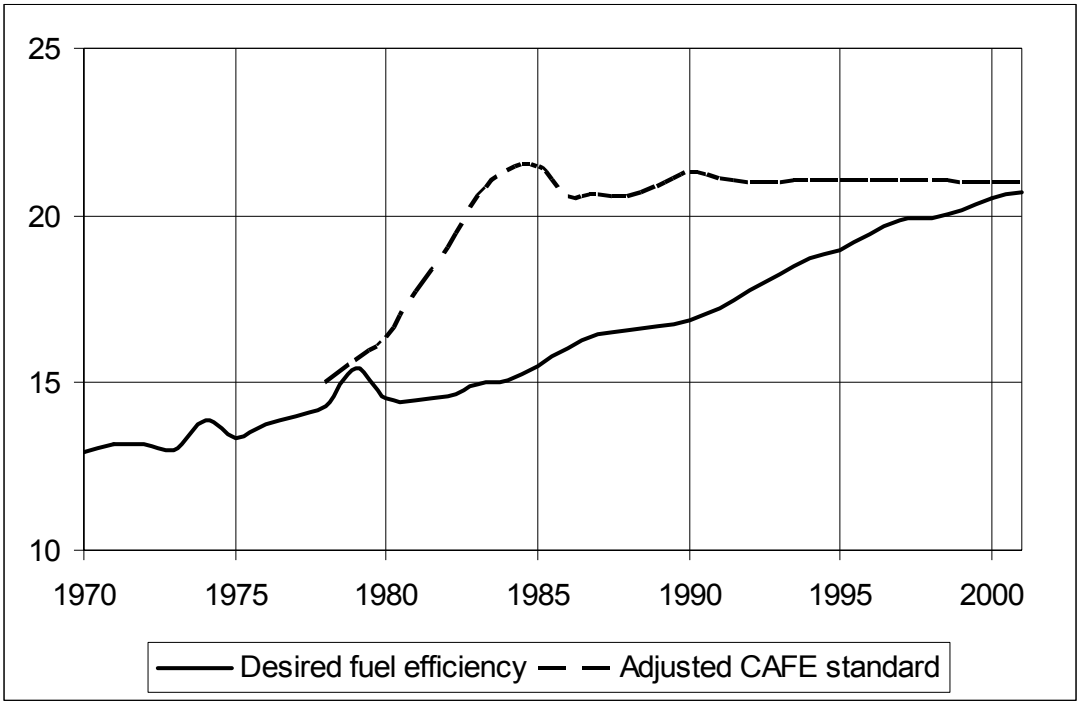

Figure 2. Desired and Mandated Fuel Efficiencies