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# The Rebound Effect from Fuel Efficiency Standards: Measurement and Projection to 2035

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This report discusses empirical values of the "rebound effect" for travel in passenger vehicles in the United States. The rebound effect refers to effects on the amount of travel that arises from changes in the fuel efficiency for light-duty motor vehicles (passenger cars and light trucks), caused in turn by regulations or technological developments. We briefly discuss the literature, then summarize previous empirical estimates done at University of California at Irvine in collaboration with Kurt Van Dender and Kent Hymel. Finally we present updated empirical estimates, which take advantage of newer data through the year 2009, and derive the implications of the updated estimates for the rebound effect in the time frame 2010-2035.

The literature review and empirical methodology are described more fully in two published articles (Small and Van Dender 2007a; Hymel, Small, and Van Dender 2010), and even more fully in the working papers from which the published articles ware derived (Small and Van Dender 2007b). The empirical estimates have been updated subsequently, by adding five new years of data, namely 2005-2009. The projections are our own, and use a new methodology developed for this project which improves on that used for earlier reports by K. Small to EPA and an older report to the California Air Resources Board (Small and Van Dender 2005).

## 1. Background and definitions

### 1.1 Determinants of motor-vehicle travel

The rebound effect is simply a statement of the near-universal economic principle of downward-sloping demand: when the price of a good or service decreases, people purchase more of it. In this case the service is passenger transportation, and its price to the user includes the cost of fuel.

If the amount of service is measured as vehicle-miles traveled (VMT), then the component of price accounted for by fuel cost, here called "fuel cost per mile" $P_M$, is equal to the price of fuel $P_f$ (*e.g.* stated in \$/gallon) divided by fuel efficiency $E$ (*e.g.* stated in vehicle-miles/gallon):

$$P_M = P_f / E \,. \tag{1}$$

Thus if fuel efficiency $E$ is increased, fuel cost per mile decreases, and since this is part of the price paid by consumers to drive, they will increase their VMT. See Greening, Greene and Difiglio (2000) for a more extended discussion.

The responsiveness of demand to price is often summarized as a ratio of the percent change in demand, $\Delta M/M$, to the percent change in price causing it, $\Delta P_M/P_M$, where $M$ designates VMT in mathematical equations and $\Delta$ designates a change in a quantity. A ratio such as this is called an *elasticity*, usually defined for the situation when $\Delta P_M$ is very small so that the ratio becomes a derivative. Therefore we define the elasticity of vehicle-miles traveled with respect to cost per mile as follows:

$$\varepsilon_{M,PM} = \frac{P_M}{M} \cdot \frac{dM}{dP_M} \tag{2}$$

where the derivative $dM/dP_M$ is simply the limit of $\Delta M/\Delta P_M$ as $\Delta P_M$ becomes very small. An equivalent way to write this is in terms of the natural logarithms of $M$ and $P_M$, which we denote by lower-case letters *vma* and *pm*, respectively. (The notation *vma* stands for <u>v</u>ehicle-<u>m</u>iles per <u>a</u>dult member of the population, which is how we define $M$ in our empirical work.) Of course the equation for *vma* contains other variables besides *pm*, and these are held constant when considering the effects of *pm*; this makes the derivative in (2) a partial derivative, denoted using the symbol $\partial$. The elasticity written in this form is:

$$\varepsilon_{M,PM} = \frac{\partial(vma)}{\partial(pm)}, \tag{3}$$

which could be a single coefficient in the equation for *vma* or, if *pm* enters in more than one way, a combination of several coefficients.

One of the confusing aspects of the literature is that few studies have accounted for the fact that fuel efficiency $E$ is not simply mandated, but chosen jointly by consumers and motor-vehicle manufacturers, within certain constraints set by regulation. Therefore one might ask the meaning of considering a change in $E$ as though it could simply be set by fiat. In our empirical work, Van

Dender and we meet this challenge by defining a system of three simultaneously determined travel-related quantities, each applying to a state. The first dependent variable is VMT, written mathematically as $M$; it is a function of $P_M$ (as already described), the size of the vehicle fleet, $V$, and various socio-demographic characteristics including income. The second dependent variable is $V$, which is a function of several things reflecting the demand for owning vehicles: a price index $P_V$ of new vehicles, the amount of travel $M$ (since new vehicles are purchased in large part to supply desired travel), the price of travel $P_M$, and other characteristics. Note that we do not distinguish among vehicles of various ages: thus implicitly we ignore possible effects of these variables on the age composition of the fleet. Finally, the third dependent variable, fuel intensity $1/E$ (the inverse of fuel efficiency), is presumed to be chosen based on a combination of motives including the wish to conserve on the cost of traveling $M$ miles, the need to meet various regulations on fuel efficiency and/or emissions, and tradeoffs with vehicle performance; in our empirical work $E$ is assumed to be a function of $M$, price of fuel $P_F$, a variable measuring the stringency during any given year of the US federal Corporate Average Fuel Economy (CAFE) regulations, and other characteristics. This system is summarized in the left panel of Table 1.1.

**Table 1.1. Simultaneous Equation Systems**

| Three-equation system (without congestion) | | | Four-equation system (with congestion) | | |
|---|---|---|---|---|---|
| Equation (dependent variable) | Symbol | | Equation (dependent variable) | Symbol | |
| | Level | Logarithm | | Level | Logarithm |
| VMT per adult | $M$ | *vma* | VMT per adult | $M$ | *vma* |
| Vehicle stock per adult | $V$ | *vehstock* | Vehicle stock per adult | $V$ | *vehstock* |
| Fuel intensity of vehicles | $1/E$ | *fint* | Fuel intensity of vehicles | $1/E$ | *fint* |
| | | | Congestion delay per adult | $C$ | *cong* |

An implicit assumption in the use of aggregate data is that that the response to aggregate changes in fuel efficiency (or other variables) does not depend significantly on how those changes are distributed among segments of the population. This could occur, for example, if drivers are sufficiently homogeneous. In particular, the model assumes that changes in fleet average fuel economy will have the same impact on behavior whether those changes are caused entirely by new vehicles entering the fleet, or partly by new vehicles and partly by the retirement of older ones. This assumption enables us to apply the results of the model to regulations that specifically impact new vehicles only. It should be adequate insofar as the pattern of mileage driven by vehicle age is reasonably stable; if it is not, a more fine-tuned analysis tracking elasticities by vehicle age would reveal additional effects not captured here.

It is worth noting that our system accounts for the effects of a change in regulations through two potential pathways. We illustrate for an increase in fuel-efficiency standards, with no change in vehicle price. First, the regulations increase the average fuel economy of the fleet, and that in turn reduces the cost per mile of travel, $P_M$, through equation (1); this may directly reduce the amount of travel because of downward-sloping demand as just discussed. Second, the size of the vehicle fleet may increase because vehicles are now more useful, in the sense that they can be driven more cheaply; this change in vehicle fleet size may further affect $M$ since, as already noted, $M$ is expected to be a function of $V$ as well as other things. We estimate a simultaneous-equations model of $M$, $V$, and $E$ that fully accounts for these effects. Empirically, we find that the first path is by far the dominant one, so that one could ignore the second path as an approximation; this may simply indicate that vehicle purchases are governed mainly by factors other than the cost of driving.

Our model, through the influence of fuel cost on fuel efficiency, implicitly incorporates some changes in the *relative* prices of vehicles of different sizes and types. (For example, vehicle manufacturers may respond to a fuel efficiency regulation by offering discounts on their fuel-efficient vehicle types.) However, the description just given of the effects of regulations assumes that the *average* price of new vehicles, $P_V$, is held fixed. Of course, the full effect of a regulation would also include any change in this average price on new-vehicle sales. In many cases this would work in the opposite direction to that arising from a change in fuel cost: if fuel cost declines due to regulations that force manufacturers to raise vehicle prices, those higher prices would tend to reduce vehicle sales and thus, ultimately, travel, thereby offsetting some of the rebound effect. Furthermore, changes in new-vehicle sales would also change scrappage rates and the price structure of used vehicles of different ages. These effects are not usually considered part of the "rebound effect", although that is just a matter of definition. Hence they are not discussed here;[1] but they are important to consider as part of the full effects of a regulatory change.

In order to distinguish the ultimate effect of both pathways on VMT, we use the symbol $\hat{M}$ to designate the combined effect, and designate its elasticity with respect to cost per mile as $\varepsilon_{\hat{M},PM}$, reserving the symbol $\varepsilon_{M,PM}$ for the changes operating through the first pathway only. Small and Van Dender (2007a) show that these quantities are related by:

[1] In principle the effect of any specified changes in average new-vehicle price due to regulations could be analyzed using the results of the vehicle-fleet equation in our model, since that equation includes the variable $P_V$, which is an index of nationwide new-car prices. However, the model does not estimate the coefficient of new-vehicle price very precisely, because there is little variation in that variable (none across states); so we would have less confidence in using it for that purpose. Probably a better approach for analyzing effects on vehicle purchases would be to consider the entire range of vehicle sizes and models and how consumers shift between them.

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

where $\varepsilon_{M,V}$ denotes the direct elasticity of travel with respect to vehicle fleet, $\varepsilon_{V,M}$ denotes the direct elasticity of vehicle fleet with respect to amount of travel, and $\varepsilon_{V,PM}$ denotes the elasticity of vehicle fleet with respect to cost per mile of travel. All the quantities on the right-hand side of (4) are measured directly as coefficients, or combinations of coefficients, of the three equations in our model.

In later published work in collaboration with Kent Hymel, the model described above was extended to account for the interrelationship between travel and congestion, denoted by *C* and measured empirically by estimated annual hours of delay due to congestion per adult. To accomplish this, a fourth equation is added to the model predicting the amount of congestion in a state, averaged over both its urban and non-urban areas. At the same time, the equation for vehicle-miles traveled is modified to include an influence from congestion. The expectation is that more VMT causes congestion to rise, but that rise in congestion also inhibits VMT. The result of these simultaneous influences is captured by the simultaneous estimation and application of the VMT and congestion equations.

The result is that in the four-equation model, which includes congestion, equation (4) is modified by adding an additional term in the denominator:

$$\varepsilon_{\tilde{M},PM} = \frac{\varepsilon_{M,PM} + \varepsilon_{M,V}\varepsilon_{V,PM}}{1 - \varepsilon_{M,V}\varepsilon_{V,M} - \varepsilon_{M,C} \cdot \varepsilon_{C,M}} \tag{4a}$$

where $\varepsilon_{M,C}$ is the direct elasticity of VMT with respect to congestion (presumably negative), and conversely $\varepsilon_{C,M}$ is the direct elasticity measuring how congestion is created by VMT (presumably positive). The combined additional term, $-\varepsilon_{M,C}\cdot\varepsilon_{C,M}$, is expected to be positive (because the minus sign cancels the negative sign of $\varepsilon_{M,C}$); therefore its presence reduces the magnitude of the rebound effect. However, Hymel, Small, and Van Dender (2010) find this reduction to be numerically small, and more than offset by the effects of other changes in the specification of the model and of including three additional years (2002-2004) in the data used to estimate it.

### 1.2 Definition of the rebound effect: short-run and long-run

While terminology differs among authors, $\varepsilon_{\hat{M},PM}$ is conceptually what most writers have meant when discussing the rebound effect. To summarize: it measures the ratio of the responsiveness of travelers to the change in fuel efficiency resulting from regulations (with both expressed in percentage terms), while recognizing that the change in fuel efficiency is not directly set by regulations but rather results from a complex interactive process. This responsiveness accounts for both the direct effect of fuel efficiency on the cost of using a given vehicle, and the indirect effect on travel through changes in the number of vehicles purchased, but all the while holding average new-vehicle prices constant.

Our analysis, like nearly all in the literature, assumes that this responsiveness to fuel efficiency arises only through the effect of fuel efficiency on fuel cost per mile. However, this assumption is debatable and is not inherent in the definition of the rebound effect. Thus, one could posit that VMT responds to fuel price $p_F$ and the exogenous components of fuel efficiency $E$ separately and not just as a function of their ratio $p_M \equiv p_F/E$. We explore this question at several points in this report, but basically are unable to resolve it conclusively.

Because the elasticity $\varepsilon_{\hat{M},PM}$ is expected to be negative, it is convenient to express the rebound effect $b^S$ as a number that is normally positive:

$$\hat{b}^S = -\varepsilon_{\hat{M},PM} \tag{5}$$

It is also common to express the rebound effect as a percentage rather than a fraction. Thus, if $\varepsilon_{\hat{M},PM}$=-0.2, we say the rebound effect is 20%.

The empirical equation systems just discussed also account for the slowness with which changes can occur, especially changes in the vehicle fleet size and average efficiency, which require purchases and retirements of vehicles. They are able to do this because we observed a location (a state or District of Columbia) every year – making the data set a *cross-sectional time series*, sometimes also called a *panel data set*. Slow adjustment is accounted for by assuming that each of the three behavioral variables explained by the models ($M$, $V$, and $E$) depends not only on the factors already mentioned, but also on the previous year's value of that same quantity (called a *lagged value* of that variable). This is equivalent to assuming that there is a desired level of $M$, $V$, or $Fint \equiv 1/E$, and that any deviation between this desired level and the level attained in the previous year is diminished in one year by a fraction (1-$\alpha$), where $\alpha$ is the coefficient of the lagged value of the variable. We allow $\alpha$ to differ across the three equations and denote its corresponding values by $\alpha^m$, $\alpha^v$, and $\alpha^f$. Note that congestion formation is an engineering rather than a behavioral relationship, so no lag is postulated for that equation.

This slow adjustment process means that the short-run response (that occurring in the same year) is smaller than the long-run response. Continuing to use the notation $\varepsilon_{\hat{M},PM}$ for the elasticity determined within this system, it is now a short-run elasticity because the long-run response is accounted for elsewhere in the equation (through the lagged variables). We represent the corresponding short-run and long-run rebound effects as $b^S$ and $b^L$, respectively. They are approximately related by:

$$b^L \cong \frac{b^S}{1-\alpha^m} = \frac{-\varepsilon_{\hat{M},PM}}{1-\alpha^m} \tag{6}$$

where $\alpha^m$ is the coefficient of the lagged dependent variable in the equation explaining *vma*. A more precise relationship accounts for the fact that in the full three-equation and four-equation systems, the lagged values in more than one equation can affect the long-run response; specifically, the long-run rebound effect for the three- and four-equation models are:[2]

$$\hat{b}^L = \frac{-\varepsilon_{M,PM} - \alpha^{mv}\beta_2^v/(1-\alpha^v)}{(1-\alpha^m) - \alpha^{mv}\alpha^{vm}/(1-\alpha^v)} \tag{7}$$

$$\tilde{b}^L = \frac{-\varepsilon_{M,PM} - \alpha^{mv}\beta_2^v/(1-\alpha^v)}{(1-\alpha^m - \alpha^{mc}\alpha^{cm}) - \alpha^{mv}\alpha^{vm}/(1-\alpha^v)} \tag{7a}$$

where:

- $\alpha^v$ is the coefficient of the lagged dependent variable in the equation explaining the logarithm of vehicle stock;
- $\alpha^{mv}$ is the coefficient of vehicle stock in the equation explaining *vma*;
- $\alpha^{vm}$ is the coefficient of *vma* in the equation explaining vehicle stock;
- $\alpha_{mc}$ is the coefficient of congestion in the equation explaining *vma*;
- $\alpha_{cm}$ is the coefficient of *vma* in the equation explaining congestion; and
- $\beta_2^v$ is the coefficient of *pm* in the equation explaining vehicle stock.

In addition to accounting for lagged values within the system determining our dependent variables, our empirical system accounts for the possibility that the error terms in each equation are correlated over time. That is, for any given state, the unknown random factors affecting a dependent variable may have some elements that are the same year after year. Most of these common factors are accounted for by a "fixed effects" specification, in which a distinct constant

[2] See Small and Van Dender (2007a), equation (7); and Hymel, Small, and Van Dender (2010), equation (14a).

term is estimated for every state instead of just one for the entire system.[3] Empirically, the effects of lagged dependent variables are difficult to distinguish from those of autocorrelation, a problem plaguing earlier studies investigating changes over time; we are able to distinguish them because of the long time period covered by our panel data set: 36 years in the 2007 published paper, 39 years in the 2010 published paper, and 44 years in this report.

There are many ways besides those considered here that regulations on fuel efficiency or related quantities might affect travel. As already noted, such regulations may raise vehicle prices, which would affect the vehicle fleet size and thus, indirectly, the amount of travel. Regulations may affect fuel prices through the impact of aggregate demand for fuel on petroleum markets. They may influence technological developments, thereby affecting the costs and performance of future vehicles. A broader analysis of the effects of fuel efficiency on travel might account for such factors, but they are outside the realm of the "rebound effect" as we define it here and as most researchers have used the term.[4] An advantage of our more restricted definition is that it is a purely behavioral measure, not depending on supply factors (e.g. the cost to manufacturers of meeting efficiency standards) or macroeconomic conditions (e.g. the responsiveness of world oil prices to a particular policy in the US), and thereby more likely to be a stable number applicable to many situations. However, it is important to be aware that if regulations raise the price of new vehicles, then the response to that price rise would tend to offset somewhat the rebound effect, as defined here, by curtailing the number of vehicles available to travelers. Similarly if regulations curtail U.S. oil demand enough to lower world oil prices and this translates into a lower domestic gasoline price, some additional travel will be stimulated as a result.

### 1.3 Dynamic rebound effect

A vehicle owner responds to a change in fuel efficiency not just in the first year or some hypothetical year in the distant future, but continuously over that lifetime. Thus, the partial adjustment mechanism postulated here, which is the basis for the distinction between short-run and long-run responses, implies a continuing gradual change in VMT each year over the vehicle's life. But at the same time, the driving force itself, i.e. the short-run rebound effect (5), is changing because the interaction variables that help determine it (income, fuel cost per mile, urbanization, and possibly congestion) are changing. Thus, the vehicle owner adjusts

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[3] This is one of two common specifications for panel data, the other being "random effects." A hypothesis test known as a Hausman test soundly rejects random effects in favor of fixed effects for this data set.

[4] Greene (1992) and Gillingham (2011) refer to our definition, combined with any effect due to higher vehicle prices, as the "direct" rebound effect. This constrast with the "indirect" rebound effect caused by income effects (people having more money to spend after fuel purchases on other goods that use energy) and the "macroeconomic" rebound effect (changes in energy use arising from effects of an energy policy on economy-wide prices and growth rates). See Gillingham (2011, pp. 25-26).

dynamically to both sources of change simultaneously. The results of tracking this process can be expressed as the percentage increase in the vehicle's lifetime VMT divided by the percentage decrease in fuel cost per mile that caused it. That ratio is here called the *dynamic rebound effect*.

Calculating the dynamic rebound effect requires disaggregating the vehicle fleet by age, even though that was not done in estimation. Thus, it involves an interpretation of what is happening within the aggregates in the observed data. Specifically, the calculation relies on the assumption mentioned earlier that drivers react the same way to a hypothetical difference in fuel cost per mile whether it occurs at time of purchase or later. It works as follows. Consider the owner of a vehicle purchased in year $t$ deciding how much to drive in year $(t+\tau)$. This owner is postulated to have a target amount of travel based on the average annual mileage for vehicles of age $\tau$, adjusted for the short-run rebound effect as calculated by (5) using values of interacting variables for year $(t+\tau)$. Most of these interacting variables (income, urbanization, and congestion) are simply as projected for that year. The other, fuel cost per mile, is projected based on fuel prices for year $(t+\tau)$ but holding fuel efficiency constant at the value that prevailed when the car was purchased (year $t$).[5]

But this target mileage is not achieved immediately, because of the adjustment lags measured by the coefficient $\alpha_m$ of the lagged dependent variable in the VMT model. The partial adjustment mechanism implies that the actual mileage $M_t$ in year $t+\tau$ will be the weighted average of the previous year's mileage, $M_{\tau-1}$, adjusted for the natural evolution due to the age-mileage profile $\{M_\tau^0\}$, and the target mileage, with weights $\alpha_m$ and $(1-\alpha_m)$, respectively:

$$M_\tau = \alpha^m M_{\tau-1} \frac{M^0{}_\tau}{M^0{}_{\tau-1}} + (1-\alpha^m)(1-\breve{b}^L{}_{t+\tau})M_\tau{}^0$$

where $\breve{b}^L{}_{t+\tau}$ is the long-run rebound effect in year $t+\tau$ for a vehicle purchased in year $t$, and $M_\tau{}^0$ is the normal mileage for a car of this age: thus $(1-\breve{b}^L{}_{t+\tau})M_\tau{}^0$ is the target mileage. The dynamic rebound effect $b_t^D$ is then the fractional increase in mileage over the car's entire life that results from a fractional increase $\delta$ in fuel efficiency:

[5] The underlying hypothesis here is that it is new vehicle owners whose travel changes, and this calculation tracks how it changes over that and subsequent years. Since the model itself does not distinguish new vehicle owners, the change in fuel efficiency they experience is diluted by the fuel efficiency of existing used vehicles (assumed unchanged by the regulations, as discussed earlier). But the resulting change in VMT of new vehicle owners is also diluted by VMT of existing vehicle owners, so that the ratio which defines the rebound effect still applies to the aggregates.

$$b_t^D = \frac{1}{\delta}\sum_{\tau=0}^{T}\frac{M_\tau - M_\tau^0}{M_\tau^0}. \tag{9}$$

The full calculation is described in somewhat greater detail in Appendix C.

Thus, for example, suppose a regulation in year 2020 results in a fractional increase $\delta$ in fuel efficiency of new vehicles purchased that year. Income is rising and fuel price is falling, starting in year 2020 and lasting over those vehicles' lifetimes. (Roughly this is what is projected in the "Low oil price" scenario presented later.) Then the "target" response of VMT to a change in fuel efficiency for a new vehicle purchased in year 2020 is getting smaller in magnitude as the vehicle ages, due to the effects of interacting variables. But at the same time the driver is gradually adjusting to the change that began in that year, meaning the response is shifting gradually from the short-run response to the long-run response. These two forces work in opposite directions so the net result could be to either raise or lower the rebound effect; in practice it usually implies a dynamic rebound effect between the short-run and long-run values.

In effect, this calculation takes account of both the gradual transition from short run to long run behavior over the life of the vehicle, and the changing values of the rebound effects indicating changing responsiveness to fuel cost. Iteration of (8) over additional values of $\tau$ shows that all the terms in the numerator of (9) are proportional to $\delta$, so the value chosen for $\delta$ does not affect the result.

## 2. Prior Literature

The first part of this section of the report is adapted from the review by Hymel, Small, and Van Dender (2010), covering literature mostly before 2000—but with the addition of a recent meta-analysis covering that same literature. The second part updates the review with a discussion of more recent studies.

### 2.1 Earlier Literature

Prior research has measured the rebound effect for passenger transport using a variety of data sources and statistical techniques. Most but not all estimates lie within a range of 10 to 30 percent (expressing the elasticity as an absolute value and as a percentage instead of a fraction). Greening, Greene, and Difiglio (2000) and Small and Van Dender (2007a) contain more complete reviews of the earlier literature. A few key contributions are highlighted here.

The great majority of estimates are based on one of three types of data. The first and probably least satisfactory is a single time series, either of an entire nation or of a single state within the U.S. Examples are Greene (1992) and Jones (1993). These studies have difficulty distinguishing between autocorrelation and lagged effects, and of course suffer from a small number of data points.

Second, some studies have instead used state-level panel data, most often from the US Federal Highway Administration (FHWA). Haughton and Sarkar (1996), using such data from 1970-1991, estimate the rebound effect to be 16% in the short run and 22% in the long run. They account for endogenous regressors, autocorrelation, and lagged effects. Their study is comparable in many ways to that of Small and Van Dender (2007), although the latter uses a longer time period, 1966-2001, and estimates three equations simultaneously explaining VMT, vehicle stock, and fuel efficiency. Small and Van Dender estimate the rebound effect to be 4.5% in the short run and 22.2% in the long-run on average, and also find evidence that it has declined substantially over time due mainly to rising per-capita incomes. Barla et al. (2009), applying the Small and Van Dender methodology to Canadian data, obtain short- and long-run rebound effects of around 8% and 20%, respectively. Due to their shorter time series (1990 to 2004) and more limited cross section (15 provinces), they are not able to investigate changes in these elasticities over time.

A third type of data is from individual households. Mannering (1986), using a US household survey, finds that how one controls for endogenous variables in a vehicle utilization equation strongly influences the estimated rebound effect. He estimates the short- and long-run rebound effects (constrained to be identical) to be 13-26%. Goldberg (1998) estimates a system of equations using data from the Consumer Expenditure Survey for years 1984-1990. In a specification accounting for the simultaneity of the two equations, she cannot reject the hypothesis of a rebound effect of zero. Greene, Kahn and Gibson (1999) estimate the rebound effect to be 23% on average using a simultaneous-equation model of individual household decisions. West (2004), using the Consumer Expenditure Survey for 1997, obtains a somewhat larger VMT elasticity higher than these other studies, although her focus is mainly on how behavior differs across income deciles.[6]

[6] West reports an elasticity of VMT with respect to total operating cost (not just fuel cost) of -0.87 in the most fully controlled specification. Presumably this is a long-run elasticity. If fuel accounted for 50 percent of operating cost, roughly consistent with Small and Verhoef (2007, p. 97), this would imply an elasticity with respect to fuel cost per mile of -0.435. As West notes, there are other reasons why this elasticity is not strictly comparable to others in the literature, one being that it represents a behavior for the entire household with fuel efficiencies (hence fuel cost per mile) averaged across its vehicle holdings.

The studies based on individual households in a single cross-section suffer from a limited range for fuel prices, a key variable for understanding the rebound effect. This disadvantage is partly overcome by Dargay (2007), who observes repeated cross sections of different individuals in the UK. She estimates short- and long-run rebound effects of 10% and 14%, respectively, but suggests that this long-run value may be an underestimate.

Three reviews—Goodwin et al. (2004), Graham and Glaister (2004), and Brons et al. (2008)—provide systematic statistical analyses of various studies. In the first two, estimated short- and long-run rebound effects (based on fuel-price elasticities) average about 12 percent and 30 percent, respectively. In the third, which is a meta-analysis of 43 studies containing 176 distinct elasticity estimates, the implied rebound effects are larger: 17 percent short run and 42 percent long run for the United States, Canada, and Australia.[7] Brons et al. also find that studies using lagged values have a slightly smaller rebound effect (by about 3 percentage points) than these values.[8] Although the study by Brons et al. separately identifies elasticities of driving per car and of car ownership, just as we do, they have only three observations of the former and fifteen of the latter; so in fact their coefficients are mostly identified by variations among studies of total price elasticity of gasoline consumption, and thus are only an indirect measure of the responsiveness of driving.

Most of the studies just reviewed agree on long-run elasticities between -0.15 and -0.30 during the time period of roughly the last third of the twentieth century. In addition, the differences among the studies point out the importance of model specification. How one deals with dynamics — by including lagged effects, autoregressive errors, both, or neither — can have a major impact on results. In particular, omitting such dynamic effects appears to result in over-estimates of the magnitude of the elasticities in question. In addition, results of US studies are sensitive to how they account for the influence of the US Corporate Average Fuel Efficiency (CAFE) standards, which went into effect in 1978.

[7] To calculate these numbers we begin with the sums of estimated "baseline" elasticities for kilometers per car and for car ownership, i.e. columns (3) and (4), as shown in the last two rows of their Table 6, p. 2117. These baseline estimates are defined as the values predicted by their meta-analysis model with all dummy variables taking their most common value. This results in is short- and long-run driving elasticities of -0.331 and -0.581 percent, respectively. The model includes a dummy variable "UCA" for studies in the US, Canada, or Australia, whose most common value is zero; so we add the sum of columns (3) and (4) for the coefficient of UCA, which is +0.165, resulting in elasticities of -0.166 and -0.416, respectively. There is considerable uncertainty around these values, as the standard error of the coefficient of UCA in the equation predicting kilometers per car is very large (0.480).

[8] This statement is based on the sum of coefficients of the dummy variable "Dynamic" in columns (3) and (4) of their Table 6; that sum is 0.027.

## 2.2 Recent Literature

More recent literature has extended this work in several directions, especially paying close attention to the means of identification and controls for bias due to omitted variables. Particularly relevant to this report are studies seeking to determine whether the determinants of the rebound effect or of the price-elasticity of gasoline have changed in the decade starting in 2000. (We refer to such changes as *structural change*, meaning changes in the manner in which underlying factors influence the elasticities, as opposed to simply changes in those factors themselves.) Because that decade is characterized by more closely spaced price fluctuations than has been typical, observers have sometimes noted substantial changes in behavior.

Brand (2009) summarizes some simple calculations of the VMT- and price-elasticities with respect to fuel price, based on observations before and after a sharp increase in fuel prices: specifically, by comparing the first ten months of 2007 and the first ten months of 2008. A calculation based on U.S. national statistics yields a short-run VMT-elasticity of -0.12. This involves no controls, and Brand points out that VMT was trending upward at 2.9% per year over a prior 21-year period of relatively stable prices, which to us suggests a correction to this elasticity of -0.029, bring it to approximately -0.15.[9]

Hughes et al. (2008) undertake a more detailed analysis, using models with some control variables, to compare the price-elasticity of gasoline in the years 1975-80 with that in the years 2001-06. They find a large decline in magnitude, from -0.21 to -0.08 in what appear to be their favored specification. In the case of the later period, that specification treats fuel price as endogenous, estimating it with instrumental variables in a standard manner that accounts for price being determined simultaneously by demand and supply relationships. This finding suggests that the VMT elasticity declined by a similar amount, since it is a component of the fuel-price elasticity and no one has suggested that the other main component (the elasticity of fuel efficiency) has been demonstrated to change significantly.

Hughes et al. also test whether the price-elasticity declines in magnitude with income, as found by Small and Van Dender (2007) and Hymel et al. (2010). They find instead an effect in the opposite direction. Thus, they explain the decline in price elasticity as likely due to factors other than those we suggest here. Specifically, they cite suburbanization and declining public transit service, both of which lock travelers more firmly into automobile use, and increased fuel efficiency, which is also consistent with one of the findings of Small and Van Dender (2007) and

[9] Brand asserts without explanation a different number, -0.21, for the VMT elasticity accounting for the trend. Litman (2010, abstract) cites Brand and an unpublished study by Charles Komanoff as supporting an elasticity of -0.15.

Hymel et al. (2010). Interestingly, Litman (2010) cites these same factors in a heuristic argument for an opposite argument: Litman suggests these factors were strong during the 1970-2000 period but likely less important during the 2000's. We have not seen any formal argument, either theoretical or empirical, for why these factors should have a major effect in either direction.

There are some limitations to the Hughes et al. results which make them less than decisive. The limitation to a single five-year period for each estimation reduces the precision of their estimates compared to ones that use longer time series. Also, they do not account for a full range of dynamic effects, as we think is especially necessary to fully capture behavior in the rapidly changing 2000-2006 period.[10]

Greene (2012) carries out a number of analyses similar to those of Small and Van Dender (2007), using national rather than state data but extending the sample to year 2007. Greene confirms several results of Small and Van Dender: in particular, he finds a similar value for the price-elasticity of VMT, finds that it has declined over time, and finds that it declines with income.

Two recent studies make use of odometer readings from California's smog test—arguably the most accurate available measure of VMT—to provide estimates of the elasticity of VMT with respect to either fuel price or fuel cost per mile, both using very large samples of individual vehicles. The first, by Knittel and Sandler (2012), takes advantage of the existence of regions in which older vehicles must take a smog test every two years. They use test data from 1998 through 2010 and a simple log-log specification, with control variables for demographics and whether the vehicle is a light truck, and with fixed effects representing year, vintage, and make. Knittel and Sandler interpret the resulting elasticities as covering a time period of two years, since that is the time interval over which VMT is measured. The estimates of VMT elasticity with respect to fuel cost per mile vary between -0.14 and -0.26, depending on whether or not the make is subdivided further in defining fixed effects.[11]

The second study using California smog test data is by Gillingham (2013). Gillingham combines the test data for years 2005-2009 with micro observations of new-vehicle registrations in 2001-2003, in order to observe VMT over a several-year period, typically six or seven years due to the

[10] To be more precise, they do not include lagged endogenous variables or autocorrelation in any of what we would consider their preferred model results, namely those using instrumental variables to control for simultaneity between supply and demand factors.

[11] These numbers are the range of coefficients of log (dollars per mile) in Table 18.3 for Models 2, 4, and 5. In other models, the authors find heterogeneity with respect to the size of the dollars per mile variable. They explore heterogeneity further in a more recent working paper, in which they find the VMT elasticity to vary between -0.11 and -0.18 across quartiles of fuel efficiency (Knittel and Sandler 2013, Table A.2, next to last column).

requirement that vehicles are tested at those ages. (There are also some observations over four to six years for vehicles that are sold before six years have passed.) He finds an elasticity of VMT with respect to gasoline price of -0.25, a finding quite robust to various specification checks. Gillingham interprets this as roughly a two-year elasticity, because it is identified mainly by a price spike between 2007 and 2009. This means of identification is also a weakness of the study: during this same time interval the economy entered the most significant recession since the 1930s, accompanied by drastic turmoil in housing markets including foreclosures requiring many people to move. Despite controlling for macroeconomic conditions through a measure of unemployment and a consumer confidence index, one must worry that gasoline prices are correlated with unobserved factors related to tumultuous economic conditions that also influence the amount of driving.

The two studies just described have the advantage of very large samples of individuals, permitting greater precision in estimation as well as accounting for heterogeneity across individuals. Both studies also assume that VMT responds to contemporaneous gasoline prices, without explicit lags. Yet the suggestive evidence shown by Knittel and Sandler, comparing graphs of gasoline prices and VMT over time, appears to show a one to two year lag. As already noted, our analysis of earlier studies suggests that omitting such dynamic effects may cause the estimated elasticities to be somewhat larger in magnitude than the true short-run (or even two-year) elasticities, especially when the observations are averaged over periods of more than a year as is the case in both of these studies.

Molloy and Shan (2010) provide an intriguing look at one possible source of VMT response to fuel price: changes in household location. They analyze how housing construction within small areas responded to fuel prices over the period 1981 to 2008.[12] Their model includes lags up to four years, which they found sufficient to account for virtually all the observed responses. Their results imply that a one percent increase in gasoline price reduces construction over the next four years by one percent, which is 0.03 percent of the total housing stock (Table 2). This result suggests one possible explanation for why Small and Van Dender (2007) and Hymel et al. (2010) find substantial lags in the response of VMT to changes in fuel cost.

Our conclusion from the more recent literature is that it raises the strong possibility that the rebound effect has become larger during the 2000s. But not enough time has passed to allow definitive tests, especially because other factors were changing so drastically during that same time period. Our response to this situation in our own study is twofold. First, we investigate explicitly whether there is a structural break in the determinants of VMT during the decade 2000-2009. Second, we consider some other explanations for changes in behavior over this time:

[12] The areas are "permit-issuing places, which are usually small municipalities" (Molloy and Shan 2010, p. 5).

specifically, asymmetries between response to rising and falling gasoline prices, and possible behavioral responses to intense media attention to fuel prices.

### 2.3 Is the rebound effect the same as the responsiveness to price of fuel?

As noted in Section 1.2, one can challenge the assumption that people respond with the same elasticity to fuel price and to the inverse of fuel efficiency. This assumption is prevalent both because it is theoretically attractive, based on full consumer rationality, and because it is difficult to separate the two effects empirically. Nevertheless, only a few studies have tested the assumption and the evidence for it is not very solid.

Small and Van Dender (2007) and Hymel et al. (2010) both report attempts to estimate models where fuel price $p_F$ and efficiency $E$ are entered as separate variables. They find that the measurement of a separate coefficient for $E$ is very small but too imprecise to use with confidence for policy analysis. They interpret their findings as ambiguous, but acknowledge that they are unable to prove that the rebound effect, defined as the elasticity with respect to $E$, is not zero.

Greene (2012, Tables 4-5), using a long time series (1967-2007) of aggregate US data, is similarly unable to estimate the two elasticities separately with much precision, obtaining a small, statistically insignificant, and wrong-signed coefficient for fuel consumption per mile (the inverse of fuel efficiency). Nevertheless, in contrast to the two papers just described, he is able to statistically reject the hypothesis that the coefficients are equal.

Gillingham (2011, table 3.1) similarly tests whether the two coefficients can be separately estimated, using his very large disaggregate data set. When model-specific fixed effects are not included, he is able to separately measure the two elasticities, finding them equal to -0.19 for fuel price and -0.05 for the inverse of fuel efficiency, both statistically significant. This again suggests they are not equal, and that the elasticity with respect to inverse fuel efficiency may actually be considerably smaller in magnitude than the that with respect to fuel price. In some other specifications, the elasticity with respect to fuel efficiency is small and statistically insignificant, as in the studies just discussed.[13]

[13] In other work, Gillingham also measures a rebound effect using a much more elaborate model which includes both vehicle purchase and utilization. He obtains a very small value, equal to 0.06 (i.e. 6 percent) multiplied by the fraction of people who choose a different vehicle when faced with a hypothetical new set of vehicles offered following a feebate policy (Gillingham 2011, Section 4.4.3).

While these studies are too few and statistically imprecise to resolve the question definitively, together they strongly suggest that the effect of fuel efficiency is smaller than that of fuel price, and possibly very small indeed. Therefore, by adopting the conventional assumption that their effects are equal and opposite, this study reports rebound effects that may well be larger in magnitude than those that actually occur when policies are implemented.

## 3. Data and specification for this report

The data set used here is a cross-sectional time series, with each variable measured for 50 US states, plus District of Columbia, annually for years 1966-2009. Variables are constructed from public sources, mainly the US Federal Highway Administration, US Census Bureau, and US Energy Information Administration. Data sources and a fuller description, including some weaknesses of the data, are given in Small and Van Dender (2007a,b) and Hymel, Small, and Van Dender (2010).[14] In addition, we have collected variables on media attention to gasoline prices and on volatility of gasoline prices, as described in Section 3.4.

In the following we list the primary variables used in the statistical estimation. All the dependent variables, and many others as well, are measured as natural logarithms. Variables starting with lower case letters are logarithms of the variable described. All monetary variables are real (i.e. inflation-adjusted).

<u>Dependent Variables</u>

$M$: Vehicle miles traveled (VMT) divided by adult population, by state and year (logarithm: *vma*, for "<u>v</u>ehicle-<u>m</u>iles per <u>a</u>dult").

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

$1/E$: Fuel intensity, $F/M$, where $F$ is highway use of gasoline[15] (logarithm: *fint*).

C: Total hours of congestion delay in the state divided by adult population (logarithm: *cong*). See Section 3.1 for further details

[14] Greene (2012, p. 18) provides an excellent discussion of the VMT data and their weaknesses. He concludes that the errors that may occur in the FHWA data on VMT and fuel efficiency are unlikely to cause large errors in year-to-year changes, which are what are used in both this and Greene's study.

[15] This term is used by FHWA to mean use by vehicles traveling on public roadways of all types. It excludes use by not licensed for roadways, such as construction equipment and farm vehicles.

Independent Variables other than CAFE

$P_M$: Fuel cost per mile, $P_F/E$. Its logarithm is denoted $pm \equiv \ln(P_F) - \ln(E) \equiv pf + fint$. For convenience in interpreting interaction variables based on *pm*, we have normalized it by subtracting its mean over the sample.

$P_V$: Index of real new vehicle prices (1987=100) (logarithm: *pv*). [16]

$P_F$: Price of gasoline, deflated by consumer price index (1987=1.00) (cents per gallon). Variable *pf* is its logarithm normalized by subtracting the sample mean.

*Other*: See Small and Van Dender (2007b), Appendix A; and Small, Hymel, and Van Dender (2010), Appendices A and B. The first three equations include time trends to proxy for unmeasured trends such as residential dispersion, other driving costs, lifestyle changes, and technology. As described below, in equation (8), the set of variables denoted $X_M$ includes the variable $(pm)^2$ and interactions between normalized *pm* and other normalized variables: log real per capita income (*inc*), and fraction urbanized (*Urban* – used only in the three-equation model) and normalized *cong* (used only in the four-equation model).

Each of these variables is updated to 2009 using the same or similar source as before. However, in several cases, the responsible agency has revised the numbers for earlier years. We have taken advantage of these revisions in the updated data series. In order to facilitate comparisons with earlier years, we also use two other data series in this report, making three in all:

- "Original" data: those used for the earlier published reports, along with 2005-2009 values that employ as closely as possible to the same methodology as used earlier. (Only values through 2001 or 2004 are used for estimation; the purpose of the 2005-2009 values in this data series is only for projection.)

- "Revised" data: those incorporating the data revisions just mentioned, including two described in Sections 3.1 and 3.2 below, viz.: (a) smoothing of 2000-2010 population, and (b) substitution of improved congestion data. The term "revised" implies that only values through 2001 or 2004 are used for estimation.

- "Updated" data: like "Revised," but including data through 2009.

Appendix A shows summary statistics for the data used in our main specification. The next three sections explain special features of certain important variables.

[16] We include new-car prices in the second equation as indicators of the capital cost of owning a car. We exclude used-car prices because they are likely to be endogenous; also reliable data by state are unavailable.

### 3.1 Congestion variables (four-equation model)

This description is adapted from Hymel, Small, and Van Dender (2010). The measure of travel delay uses data from the annual report on traffic congestion constructed by the Texas Transportation Institute (TTI) — see e.g. Schrank, Lomax, and Turner (2010). TTI has estimated congestion annually for 85 large urbanized areas, starting in 1982, using data from the Highway Performance Monitoring System database of the US Federal Highway Administration.

The TTI measure of congestion used here is annual travel delay, which is simply the aggregate amount of time lost due to congested driving conditions. TTI has sometimes been criticized for using this measure as an index of the nation's congestion problem because it includes congestion that would remain in an optimized system. Irrespective of the validity of this criticism, for our purposes the TTI measure is appropriate because it describes the experience of the typical driver. The measure is constructed largely from assumed speed-flow relationships, but supplemented with speed observations on specific roads. As with other data in this study, it is probably more reliable in the more recent years.

One criticism of the TTI measures, however, has been addressed in TTI's 2010 edition of its report. The earlier measure, used in the cited papers by Small and Van Dender and by Hymel, Small, and Van Dender, estimated speed from observed traffic volumes using volume-delay relationships. This inevitably introduced some error into the speeds, hence into the estimated total hours of delay. Recently, however, TTI has collaborated with Inrix®, Inc., to make use of speed data collected via a nationwide network of mobile devices in vehicles. These measures are available for a few most recent years, but TTI has back-casted them to 1982 in order to permit comparisons with its earlier measure. They are also available for an additional 26 urban areas. All these changes increase the accuracy of the data on congestion, and so are adopted here except in the "original" data series.

For the collaborative work described earlier and for this report, congestion delays in all covered urbanized areas are aggregated to the level of a state, then divided by the state's adult population to create a per-adult delay measure. This procedure implicitly assumes that congestion outside these 85 urban areas is negligible, a reasonable assumption because congestion in the US is far more costly to drivers in large than in small urban areas. Furthermore, since data are measured at the state level, it is appropriate that the congestion in the larger urbanized areas is, for most states, diluted by the lack of congestion elsewhere in our equations predicting statewide travel response. A further advantages of the use of total delay, rather than some measure of average congestion, is that it is relatively unaffected by possible differences in how boundaries are drawn for urban areas in different states.

### 3.2 State population data

Several variables specification, including all but one of the endogenous variables, make use of data on adult or total state population as a divisor. Such data are published by the U.S. Census Bureau as midyear population estimates; they use demographic information at the state level to update the most recent census count, taken in years ending with zero. However, these estimates do not always match the subsequent census count, and the Census Bureau does not update them to create a consistent series. As a result, the published series contains many instances of implausible jumps in the years of the census count. In both of the published papers discussed above, we applied a correction assuming that the actual census counts taken every ten years are accurate, and that the error in estimating population between them grows linearly over that ten-year time interval. This approach is better than using the published estimates because it makes use of Census year data that were not available at the time the published estimates were constructed (namely, data from the subsequent census count). See Small and Van Dender (2007b) for details.

For this report, the same procedure was applied to the 2000-2009 data because the needed Census counts for 2010 were available in time. This adjustment appears in the "revised" and "updated" data series, but not in the "original" data series.

### 3.3 Variable to measure CAFE regulation ($R_E$)

As in the earlier collaborative work, we define here a variable measuring the tightness of CAFE regulation, starting in 1978, based on the difference between the mandated efficiency of new passenger vehicles and the efficiency that would be chosen in the absence of regulation. The variable becomes zero when CAFE is not binding or when it is not in effect. In our system, this variable helps explain the efficiency of new passenger vehicles, while the lagged dependent variable in the fuel-intensity equation captures the inertia due to slow turnover of the vehicle fleet. Because the CAFE standard is a national one, this variable does not vary by state.

The calculation proceeds in four steps, described more fully in Small and Van Dender (2007a), Appendix B. First, we estimated a reduced-form equation explaining log fuel intensity from 1966-1977, prior to CAFE regulations.[17] Next, this equation is interpreted as a partial adjustment model, so that the coefficient of lagged fuel intensity enables us to form a predicted desired fuel intensity for each state in each year, including years after 1977. Third, for a given year, we averaged desired fuel intensity (in levels, weighted by vehicle-miles traveled) across states to get

[17] This step differs slightly between the three- and four-equation models because they contain slightly different sets of exogenous variables. Thus, the actual values of the variable *cafe* differ slightly between the two models.

a national desired average fuel intensity. Finally, we compared the reciprocal of this desired nationwide fuel intensity to the minimum efficiency mandated under CAFE in a given year (averaged between cars and light trucks using VMT weights, and corrected for the difference between factory tests and real-world driving). The variable *cafe* is defined as the logarithm of the ratio between the mandated and desired fuel efficiency, with that ratio truncated below at one. Thus a value of zero for *cafe* means the constraint is not binding, since desired fuel efficiency is as high as or higher than the mandated level.

The resulting variable suggests that the CAFE standard was strongly binding for the first decade of the CAFE standards; its tightness rose dramatically until 1984 and then gradually diminished until it was stopped being binding at all, either in 1995 (according to the 4-equation model) or 2005 (according to the 3-equation model).[18] This pattern is obviously quite different from a trend starting at 1978 and from the CAFE standard itself, both of which have been used as a variable in VMT equations by other researchers.

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

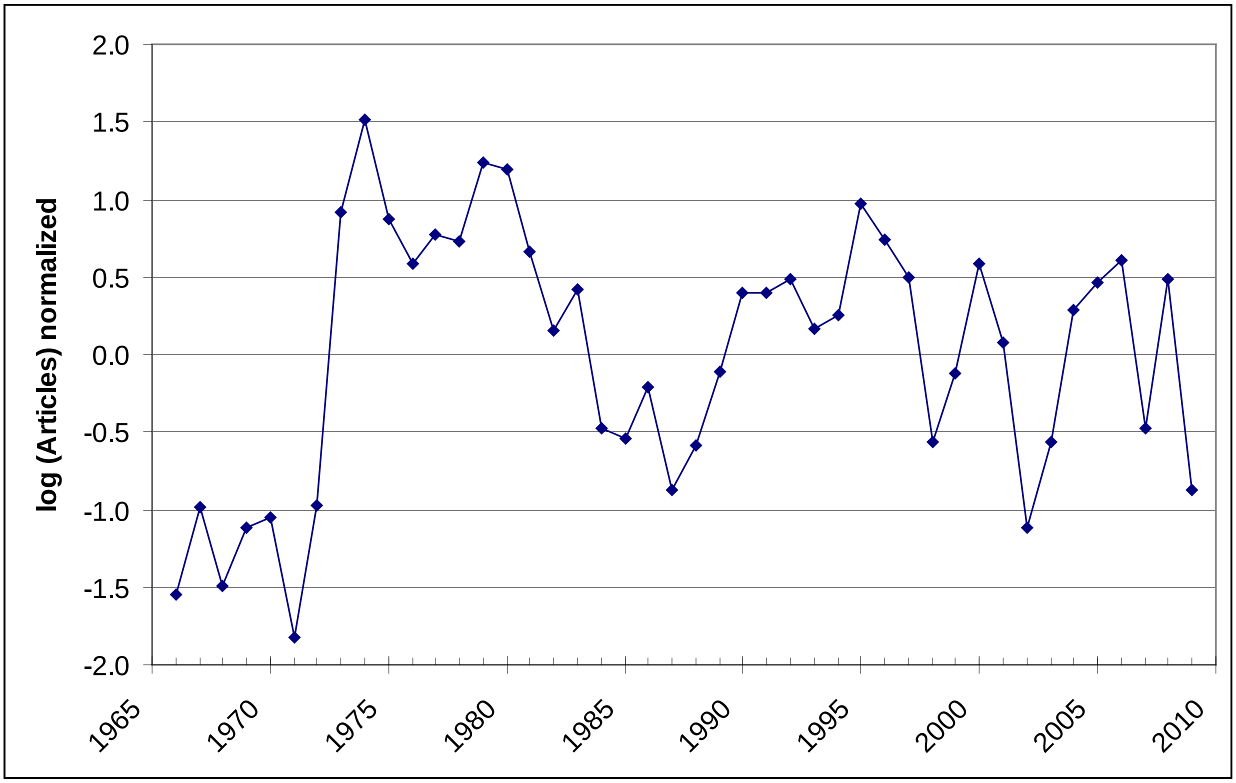
### 3.4 Variables on media coverage and volatility of gasoline prices

Variables measuring media coverage of gasoline price changes are based upon gas-price related articles appearing in the *New York Times* newspaper. We queried the Proquest historical database for years 1960 to 2009, and tallied the annual number of article titles containing the words *gasoline* (or *gas*) and *price* (or *cost*). This count was the basis for the variable used in the econometric analysis: it is formed from the annual number of gas-price-related articles divided by the annual total number of articles, both in the *New York Times*. This ratio ranged from roughly 1 in 4000 during the 1960s to a high of 1 in 500 in 1974. An analogous count of front-page articles yielded a similar pattern of coverage. Its logarithm, after normalization by subtracting its mean, is shown in 3.1. In our specifications, we use either the logarithm of the ratio just defined (called *Media* in the statistical models) or a dummy variable (called *Media_dummy*) defined as one in years where the ratio was greater than the 1996-2009 median

[18] See Small and Van Dender (2007a), Fig. 1, for a graphical depiction.

value and zero otherwise.[19]

**Figure 3.1. Media coverage of gas prices**




A superior measure of media coverage would include broadcast news, other newspapers, radio, and the Internet. But such measures are not readily available for the entire the time series from 1960-2009. So the validity of the two variables as a measure of overall coverage of gasoline prices relies in part on the *New York Times'* influence on other media outlets. Evidence of so-called "inter-media agenda setting" suggests that other media outlets follow the *New York Times* when choosing their news topics. One study by Golon (2006) found that the topics covered by the New York Times in the morning were correlated with evening broadcast news coverage topics, with correlation coefficients between 0.14 and 0.26. In addition, it is reasonable to assume that national topics such gas-price changes would be similar across news outlets even in the absence of direct influence of the New York Times.

[19]This dummy variable was equal to one in years 1973-1981, 1983, 1990-1992, 1994-1997, 2000, 2004-2006, and 2008.

To measure uncertainty in fuel prices, we constructed a variable whose value in year *t* is the logarithm of the variance of fuel prices over the years *t*-4 through *t*. (We chose this five-year interval as the most likely time over which new vehicle purchasers would be aware of volatility.) This measure varies across States.

For both the media and uncertainty variables, we interact the variable in question with either the fuel price or the per-mile cost of driving.

## 4. Results of the Empirical Analysis

A major limitation of the previous literature is its inability to determine whether or not the rebound effect has changed over time. Theoretical arguments, especially by Greene (1992), suggest that it should. Basically, the argument is that the responsiveness to the fuel cost of driving will be larger if that fuel cost is a larger proportion of the total cost of driving. If initial fuel cost is high, that increases the proportion; but if the perceived value of time spent in the vehicle is high, either because of congestion (closely related to urbanization) or because of a high value of time (closely related to income), that decreases the proportion. Thus we expect the rebound effect to increase with increasing initial fuel cost, and decrease with increasing income and urbanization. On the few occasions when such factors are even discussed, most analysts have presumed that income is the dominant one and therefore have hypothesized a decline in the rebound effect over time, due to rising real incomes. Previously used data sets, however, have covered too short a time span to test any of these arguments satisfactorily.[20]

With the longer time span of the data sets compiled for the earlier collaborative papers, and the even longer data set used here (44 years), there is a much better opportunity to see such changes. We explore them in three distinct ways. First (Section 4.1), we see whether the basic model, estimated over different time periods but each with a constant rebound effect, yields different results. We find a substantial diminution in the rebound effect in the period since 1995; it's harder to say whether it has risen again since 2000.

Second (Section 4.2), we explore income, fuel costs, urbanization, and congestion as the causes of these changes. Each of these factors is entered in the model in such a way that the rebound

[20] A recent exception is two studies by Wadud, Graham and Noland (2007a, 2007b) using time-series cross sections of individual households from the US Consumer Expenditure Survey. Cross-sectionally, they find a U-shaped pattern of the absolute value of the price elasticity of fuel consumption, taking values of 0.35 for the lowest income quintile, falling to 0.20 for the middle, and rising again to 0.29 for the highest (2007b, Table 2). But when they hold other variables constant while allowing income to vary both cross-sectionally and over time (1997-2002), they obtain a nearly steady, though small, decline of the absolute value of elasticity with income, from 0.51 in the lowest two income quintiles to 0.40 in the highest.

effect can vary with it rather than varying over time in an unexplained manner, and we do indeed find substantial variation in exactly the manner predicted by theory: the rebound effect (measured as a positive number) declines with increasing income (as well as with either urbanization or congestion), and it increases with increasing fuel cost. By far the most important of these sources of variation is income, which has a profound effect on projections for the rebound effect in future years. In Section 4.3, we consider explicitly how the newer data now available (2002-2009) affect the results from the earlier published studies.

Third (Section 4.4), we consider asymmetry in the response to increases and decreases in fuel prices, finding a much larger response to increases. We also consider the possible role of media coverage and price volatility in explaining this asymmetry.

### 4.1. Variation by Time Period

This section presents the results of estimating a relatively simple version of the three-equation system described earlier. In this version, the variable *pm* (the logarithm of fuel cost per mile) is simply included in the equation explaining *vma* (the logarithm of vehicle-miles traveled per adult). Its coefficient, the "structural elasticity," is the elasticity of VMT with respect to fuel cost per mile, holding vehicle fleet constant. Accounting for how the vehicle fleet also varies with fuel cost, and how lagged adjustment creates differences between short-run and long-run responses, we get the short- and long-run rebound effects from equations (4), (5), and (7).

In order to see whether the rebound effect changes over time, we carry out this estimation on two subsamples: 1966-1995 and 1996-2009. Table 4.1 shows the estimated structural elasticity $\varepsilon_{M,PM}$ . As described earlier, these are nearly identical (except for the minus sign) to the short-run rebound effects, and their values come immediately from the estimated results. The table shows that the short-run rebound effect falls by 46 percent and 72 percent, without and with consideration of congestion respectively, between these two time periods.

**Table 4.1. Short-run structural elasticity of VMT with respect to fuel cost per mile, estimated on subsamples**

| Coefficient of pm (standard error in parentheses) | 1966-1995 | 1996-2009 |
|---|---|---|
| Three-equation model | -0.0458 | -0.0246 |
| | (0.0037) | -0.0071 |
| Four-equation model | -0.0469 | -0.0131 |
| | (0.0058) | (0.0075) |

This result of a falling rebound effect is consistent with results noted earlier by Hughes et al. (2008) and Greene (2012).

## 4.2. Variation of rebound effect with income, fuel cost, and other variables

### 4.2.1 Motivation

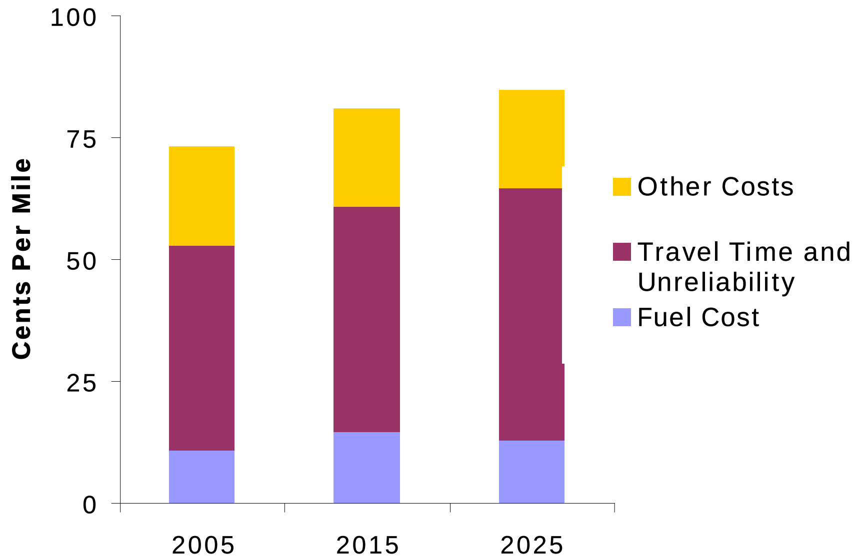
Before proceeding with the formal estimation, we motivate the approach taken here by considering what goes into the costs of automobile travel from the traveler's point of view. Figure 1 shows three categories of the short-run costs of driving and how they are likely to progress over coming decades, based on compilations of Small and Verhoef (2007) for an urban commuting trip by automobile.[21] The values placed by travelers on travel time and unreliability [22]are taken from statistical literature examining how people are willing to trade off those factors against money. We have then projected fuel costs per mile into the future, using the Energy Information Administration's projections for fuel prices and fuel efficiency in their 2011 reference scenario (US EIA 2011). We have projected the values of travel time and unreliability into the future by assuming that the *amounts* of time and unreliability are unchanged (a conservative assumption given trends toward increased congestion) while the *values* of time and unreliability increase with rising per capita real income according to an elasticity of 0.8, a recommendation of Mackie *et al.* (2003) based on many studies of how value of time depends on income (Small and Verhoef 2007, Section 2.6.5).

[21] The initial values are for 2005, taken from Small and Verhoef (2007, Table 3.3) and restated at 2007 prices.

[22] In this context, unreliability refers to day-to-day variability in the travel time faced for a given type of trip. It is typically measured by the standard deviation of travel time across days, although sometimes other measures of dispersion (such as the difference between the 80$^{th}$ and 50$^{th}$ percentiles) are used instead. Its presence means that people cannot accurately predict when they will arrive at their destination. There is a substantial literature, reviewed by Small and Verhoef (2007), showing that travelers are averse to unreliability independently of their aversion to travel time.

**Figure 4.1.**

**Costs of Driving**




Thus, it appears that despite the general prognosis for rising fuel prices, the actual fuel costs are likely to decline, due mainly to increases in fuel efficiency of automobiles; and the prominence of fuel costs in drivers' decisions is likely to decline even more, due to increases in the value of time (and, to a lesser extent, to amount of time spent in heavy congestion). Our econometric model can capture these possibilities by simply specifying it in a way that allows the rebound effect to vary with income, fuel cost per mile, and other variables that may impinge on travel time: namely, urbanization and congestion.

### 4.2.2 Implementation

To see how this can be done, recall from Section 1.1 that the rebound effect is a combination of elasticities of either three or four distinct equations (known as "structural equations"). Because of the relative sizes of these elasticities, the rebound effect is approximated by just one of them: namely $\varepsilon_{M,PM}$, giving the effect of fuel cost per mile in the structural equation for vehicle-miles traveled per adult. In the notation used here, which uses lower-case names for variables that are expressed in natural logarithms, that elasticity is given by equation (3), *i.e.* $\varepsilon_{M,PM} = \partial(vma)/\partial(pm)$.

In the previous subsection, fuel cost per mile was described as a single variable (*pm* in logarithmic terms) included in the equation for vehicle-miles traveled per adult (*vma* in logarithmic terms). The elasticity was just its coefficient, which we may call $\beta_{pm}$ for convenience.[23] But it is easy to specify the equation for *vma* so that *pm* appears not only as a single variable, but also interacted with other variables including itself. We define four such variables: $pm{\cdot}inc$, $pm{\cdot}pm \equiv pm^2$, $pm{\cdot}Urban$, and $pm{\cdot}cong$, where *inc* is the logarithm of per capita real income, *Urban* is the fraction of state population that is urbanized, and *cong* is congestion as measured by the logarithm of total congestion delay per adult. We denote the coefficients of these four "interacted variables" by $\beta_1$, $\beta_2$, $\beta_3$, and $\beta_4$. In practice, $\beta_4$ is set to zero in the three-equation system (since *cong* is not measured there), and $\beta_3$ is set to zero in the four-equation system (since its estimates were small and statistically insignificant).

Then the derivative in (3) consists of four terms:

$$\varepsilon_{M,PM} = \frac{\partial(vma)}{\partial(pm)} = \beta_{pm} + \beta_1 \cdot inc + 2\beta_2 \cdot pm + \beta_3 \cdot Urban + \beta_4 \cdot cong \quad . \tag{8}$$

The factor 2 in this equation is a consequence of properties of the derivative of the quadratic function $(pm)^2$. Inserting (8) into equations (4) and (7) for the short- and long-run rebound effects, we see that that those rebound effects also depend on *inc*, *pm*, *Urban*, and *cong*.

In order to facilitate interpretation of coefficients, we "normalize" the values of *inc*, *pm*, *Urban*, and *cong* by subtracting from each variable its mean value over our entire data set. This has no effect on the coefficients except to change the constant terms in the equations; but it means that the coefficient $\beta_{pm}$ of the variable *pm* still gives the estimated elasticity $\varepsilon_{M,PM}$ at the point where each of the interacting variables is equal to its mean value in our data set – as can be seen by setting the three normalized variables in (8) to zero. This is especially convenient because the short-run and long-run rebound effects are approximately $-\varepsilon_{M,PM}$ and $-\varepsilon_{M,PM}/(1-\alpha^m)$, respectively, where $\alpha^m$ is coefficient of lagged *vma* in the *vma* equation. Thus, one can see the approximate value of the estimated short- and long-run rebound effects, under average conditions over the sample period, just by looking at $-\beta_{pm}$ and $\alpha^m$.

### 4.2.3 Estimation results: interaction variables

The models are estimated using the maximum-likelihood simultaneous-equations estimator in Eviews 5 (Quantitative Micro Software 2004). Technical details are provided in Small and Van Dender (2007a) and Hymel, Small, and Van Dender (2010).[24] The full results of estimating the

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[23] This coefficient is named $\beta_1^{\,m}$ in Small and Van Dender (2007), eqn. (4) and Hymel et al. (2010), eqn. (9a).

[24] For this report, however, we have replaced the multiple imputations for the missing data by a single imputation; that is, we predict the values of the missing data only once, rather than multiple times using random draws from the

three- and four-equation models on updated data from 1966 through 2009 are presented in Appendix A; some of the most important coefficients are summarized here in Table 4.2.[25]

equation estimating them. For this reason, our estimates of standard errors probably understate the true standard errors.

[25] For reasons that will be explained in the next section, these models are named "Model 3.3" and "Model 4.3" respectively. For simplicity, coefficient estimates and standard errors are shown to three decimal places in these tables. In some later tables, they are shown to four decimal places.

| Table 4.2. Selected results of main model with updated data, 1966-2009 | | | | | |
|---|---|---|---|---|---|
| | | **Three-equation model (Model 3.3)** | | **Four-equation model (Model 4.3)** | |
| Equation and Variable | Coefficient Symbol | Coefficient Estimate | Standard Error | Coefficient Estimate | Standard Error |
| Equation for *vma*: | | | | | |
| *pm* | $\beta_{pm}$ | -0.047 | 0.003 | -0.046 | 0.003 |
| *pm*inc* | $\beta_1$ | 0.053 | 0.011 | 0.056 | 0.011 |
| $pm^2$ | $\beta_2$ | -0.012 | 0.006 | -0.022 | 0.006 |
| *pm*Urban* | $\beta_3$ | 0.012 | 0.009 | | |
| *pm*cong* | $\beta_4$ | | | -0.003 | 0.002 |
| *inc* | | 0.078 | 0.012 | 0.083 | 0.012 |
| lagged *vma* | $\alpha^m$ | 0.835 | 0.010 | 0.825 | 0.010 |
| Equation for *fint*: | | | | | |
| *pf+vma* | | -0.005 | 0.004 | -0.007 | 0.004 |
| *cafe* | | -0.035 | 0.011 | -0.061 | 0.010 |
| lagged *fint* | $\alpha^f$ | 0.904 | 0.010 | 0.889 | 0.010 |

Notes to Table 4.2:

*vma* = logarithm of vehicle-miles traveled per adult
*pm* = logarithm of fuel cost per mile (normalized)
*inc* = logarithm of income per capita
*Urban* = fraction of population living in urban areas
*cong* = logarithm of annual total congestion delay per adult
*fint* = logarithm of fuel intensity, *i.e.* log (1/*E*) where *E* = fuel efficiency
*pf* = logarithm of fuel price
*cafe* = variable reflecting how far the CAFE standard is above the desired fuel efficiency based on other variables (Small and Van Dender 2007a, Section 3.3.3)
*pf+vma* is log (price of fuel * vehicle-miles traveled), representing the natural logarithm of the incremental annual fuel cost of a unit change in fuel intensity; thus it may be interpreted as the logarithm of the "price" the user must pay in annual operating costs, per unit of fuel intensity, for choosing a vehicle with higher fuel intensity.

Most coefficients shown in Table 4.2 easily pass the conventional test of statistical significance, having estimates more than twice the standard deviation of those estimates. Exceptions are $\beta_4$, which indicates how the rebound effect varies with congestion, and the coefficient of annual fuel cost (*pf+vma* in logarithms) in the equation explaining fuel efficiency. The coefficients $\alpha^m$ of lagged *vma* show that the long-run effect of any variable on VMT is about $1/(1-\alpha^m)$ or roughly six times as large as the corresponding short-run effect. Average fleet fuel efficiency responds to changes with an even longer lag, causing the long-run effects of these variables to be $1/(1-\alpha^f)$ or roughly 9-10 times as large as the corresponding short-run effects.

The coefficient of *inc* confirms the conventional expectation that vehicle-miles traveled rises with rising income: the income-elasticity is approximately 0.1 in the short run and 0.5 in the long run. CAFE standards are shown to be important determinants of average fleet fuel efficiency. Another way to interpret this is that each year, fleet turnover and/or changes in driving patterns are able to close $(1-\alpha^f)$, or around ten percent, of the gap between the fuel intensity desired this year (on the basis of variable in the model) and that achieved by the previous year's fleet.

Taking the three-equation model (Model 3.3) for illustration, the short-run rebound effect for average conditions in this sample (1966-2009) is approximately $-\beta_{pm}=0.047$, *i.e.* 4.7%, while the long-run rebound is over six times this value, or about 30%. Furthermore, the coefficients $\beta_1$–$\beta_3$ for the three interacted variables involving *pm* show that the magnitude of the rebound effect, given approximately by the negative of equation (8), declines with increasing income and urbanization and increases with increasing fuel cost of driving.

To get a better idea of the magnitude of this dependence, we show in Table 4.3 the estimated rebound effects, computed more precisely using equations (4), (5), and (7), at two different sets of values for the explanatory variables *inc*, *pm*, and *Urban*. One set consists of the average values over the sample and the other consists of the average values over the last ten years of the sample. Under average conditions over the entire sample period, the measured rebound effect is 4.7% short run and 29.5% long run. However, these values are found to fall by nearly half when we consider conditions in 2000-2009: over those years the rebound effect on average is just 2.8% short run and 17.8% long run. An examination of the detailed components of the calculation (not shown in the table) reveals that it is mainly higher incomes that cause the rebound effect to be lower in the most recent decade than in the entire sample period, although the lower fuel cost per mile also plays a significant role.

**Table 4.3. Estimated Rebound Effects: Model 3.3**

| Average values (real 2009 $) | 1966-2009 | | 2000-2009 | |
|---|---|---|---|---|
| Per capita income ($/year) | $28,452 | | $36,805 | |
| Fuel price ($/gal) | 2.06 | | 2.18 | |
| Fuel cost per mile (cents/mi) | 11.75 | | 9.77 | |
| Calculated rebound effect: | Short run | Long run | Short run | Long run |
| Three-equation model (w/ congestion) | 4.7% | 29.5% | 2.8% | 17.8% |
| Four-equation model (w/o congestion) | 4.6% | 28.4% | 2.5% | 15.0% |

The decline in the rebound effect portrayed in Table 4.3 is consistent with the overall findings of Section 4.1. But now we have an explanation for why the rebound effect is lower today than in the last decades of the previous century. Furthermore, the measured dependence on income, fuel cost, and other variables permits a calculation of both short-run and long-run rebound effects at any level of those variables. In Section 5 we take advantage of this to forecast rebound effects through 2035, based on outside projections of the relevant variables, especially incomes and fuel costs.

To our disappointment, the additional years of data do not change the fact that, as discussed in Small and Van Dender (2007), we cannot definitively isolate the separate effect of fuel efficiency from that of fuel price. In fact, as described there, when we look at fuel efficiency as a separate variable, it exerts no statistically significant influence on VMT. This could be taken as evidence that the rebound effect is in fact zero, but we adopt the more conservative approach of taking it to be the VMT elasticity with respect to fuel price. This is especially conservative (in the sense of perhaps leading us to overstate the rebound effect) in light of Greene's (2012) finding of similar magnitudes as we find, but in his case confirming statistically that the effect of fuel efficiency is in fact smaller than that of fuel price.

### 4.2.4 Combined interaction variables and structural breaks

The fact that the rebound effect varies with income, fuel cost, and other variables explains some of the variation in time observed earlier. But does it explain all of it? To find out, we added to Models 3.3 and 4.3 additional structural breaks at times likely to produce changes in behavior due to other factors. We considered breaks starting at years 1982, 1995, 2003, or 2005.

Generally, we are unable to find consistent and statistically significant structural breaks at years starting in 1982, 1995, or 2005. However, we do find evidence of an increase in the rebound effect, even controlling for the effects of interacting variables, starting in 2003. This is seen by simply adding a dummy variable for years 2003-2009 to Models 3.3 and 4.3 which is done in the models labeled 3.18 and 4.13. These estimation results are shown in Table 4.4, along with the calculation of rebound effect for the most recent five-year period (2005-2009), which falls entirely within the time after the structural break.

**Table 4.4. Models with interacted coefficients and structural break starting in 2003**

| | Model 3.3 | Model 3.18 | Model 4.3 | Model 4.13 |
|---|---|---|---|---|
| Coefficients (standard errors in parentheses) | | | | |
| *pm* | -0.0466<br>(0.0029) | -0.0464<br>(0.0029) | -0.0461<br>(0.0030) | -0.0460<br>(0.0030) |
| *pm*Dummy_2003_09* | | -0.0251<br>(0.0076) | | -0.0237<br>(0.0071) |
| *pm*inc* | 0.0528<br>(0.0108) | 0.0699<br>(0.0121) | 0.0561<br>(0.0111) | 0.0721<br>(0.0121) |
| $pm^2$ | -0.0124<br>(0.0059) | -0.0113<br>(0.0060) | -0.0224<br>(0.0060) | -0.0186<br>(0.0061) |
| *pm*Urban* | 0.0119<br>(0.0094) | 0.0078<br>(0.0096) | | |
| *pm*cong* | | | -0.0031<br>(0.0022) | -0.0032<br>(0.0022) |
| *vma* lagged | 0.8346<br>(0.0102) | 0.8279<br>(0.0105) | 0.8249<br>(0.0105) | 0.8189<br>(0.0107) |
| Calculated rebound effects: | | | | |
| 1966-2009 | | | | |
| Short run | 4.7% | 5.0% | 4.6% | 5.0% |
| Long run | 29.5% | 30.9% | 28.4% | 29.9% |
| 2005-2009 | | | | |
| Short run | 3.1% | 5.1% | 3.1% | 5.0% |
| Long run | 19.4% | 31.1% | 18.6% | 29.8% |

The estimates show that the elasticity increases sharply in magnitude starting in 2003. In the models that take this increase into account, the short-run rebound effect computed at average values of variables over the entire time period is slightly larger, 5.0% instead of 4.6-4.7%. The long-run effect at this sample average also is slightly higher, though not by much because the estimated lag parameter (coefficient of *vma* lagged) is now smaller. Most important, the effect of income (coefficient of *pm*inc*) is measured to be notably larger, and that of fuel cost (coefficient of $pm^2$) becomes slightly smaller in magnitude. These latter changes cause the rebound effect to decline more rapidly over time. This essentially cancels the effect of the dummy variable in calculating the rebound effect over the last five years of the sample, so the rebound effect is virtually the same as in the entire sample. However, , the models containing a break at 2003 will still lead to a sharp decline in the projected rebound effect for years well into the future, as the effect of income is stronger in these models. This is true even if the conditions causing this structural break are assumed to continue to hold; if instead they are reversed, the future rebound effect becomes smaller still.[26]

Probably the best lesson to take from the measured structural break in 2003 is that the evolution of the rebound effect is more irregular than is portrayed in the simpler models such 3.3 and 4.3, but the overall magnitudes those models measure are not affected much by this irregularity. One can speculate that the irregularity occurs because gasoline price started increasing rather sharply in 2003, and this was accompanied by a great deal of publicity. Both events may have caused consumers to become more aware of the significance of fuel prices, and perhaps also to revise their expectations about what future fuel costs would be. These responses may in turn have caused them to begin to adjust their living patterns in ways that involve less driving—a process that can continue gradually as they adapt family structure, household car sharing, and residential and workplace locations. We explore these potential explanations in Sections 4.4 and 4.5.

[26] Projections with Model 4.13, shown in Appendix , show the dynamic rebound effect declining from approximately 20% in 2010 to 15% in 2020 and 10% in 2030, mainly due to trends in income, all on the assumption that whatever factors caused the upward shift in 2003 remain in place indefinitely. If instead those factors disappear, the projected dynamic rebound effect is about 10% in 2010, declining to 5% in 2020 to 1% in 2030.

### 4.3 Effects of newer data

The results in Section 4.2 portray somewhat larger rebound effects than the studies Small and Van Dender (2007) and Hymel, Small, and Van Dender (2010), which used these same two systems of models (the three-equation system without congestion, and the four-equation system with congestion). As described at the beginning of Section 3, there are two main differences between those studies and the present study: the data have now been revised, especially data on congestion, and the data have been extended to 2009. This subsection shows that it is mainly the latter change, the extension to 2009, which accounts for the differences.

In Table 4.5, we present the primary coefficients of interest and the implied rebound effects in 2000-2009 for three closely related estimates, all using the model without congestion. The first (Model 3.1) is the original estimate from the published paper, which uses data through 2001. The second (Model 3.2) is the identical estimate, using identical years, but with the data revised as described. The third (Model 3.3) is the same as the second except now the sample for estimation runs through 2009.

| Table 4.5. Selected results of model estimated on different versions of data: three-equation model | | | | | | |
|---|---|---|---|---|---|---|
| | **Original as published (Model 3.1)** | | **Estimated with revised data (Model 3.2)** | | **Estimated with revised & updated data (Model 3.3)** | |
| Estimation period | 1966-2001 | | 1966-2001 | | 1966-2009 | |
| **Model estimates:** | Coeff. | Std. Err. | Coeff. | Std. Err. | Coeff. | Std. Err. |
| *pm* | -0.045 | 0.005 | -0.046 | 0.005 | -0.047 | 0.003 |
| *pm*inc* | 0.058 | 0.014 | 0.057 | 0.015 | 0.053 | 0.011 |
| $pm^2$ | -0.010 | 0.007 | -0.007 | 0.007 | -0.012 | 0.006 |
| *pm*Urban* | 0.026 | 0.011 | 0.028 | 0.011 | 0.012 | 0.009 |
| *vma* lagged | 0.791 | 0.013 | 0.800 | 0.013 | 0.835 | 0.010 |
| **Calculated rebound effects at values for:** | | | | | | |
| 1966-2009: short run | 4.2% | | 4.2% | | 4.7% | |
| 1969-2009: long run | 20.5% | | 21.5% | | 29.5% | |
| 2000-2009: short run | 2.2% | | 2.4% | | 2.8% | |
| 2000-2009: long run | 10.7% | | 12.3% | | 17.8% | |

Although the coefficients of *pm* look almost identical across the three models, the coefficient in each case has the meaning of the (approximate) short-run elasticity *at the sample average*.[27] In the first two models, the sample average covers a restricted set of years, so when the rebound effect is calculated for the longer period 1969-2009 it is somewhat lower than that coefficient (due mainly to the effect of increasing income). Thus, as shown, Model 3.3 produces a higher short-run rebound effect than the other two. The difference is even greater for the long-run rebound effect because the estimate of the coefficient for the lagged dependent variable ("*vma* lagged") is substantially greater; this means the multiplier $1/(1-\alpha_m)$, which converts from short-run to long-run elasticity, is also greater: 6.1 instead of 4.8 or 5.0.

Table 4.6 carries out the same exercise for the four-equation model. In contrast to the three-equation model, in this case, adding additional years to the estimation sample reduces the short-run rebound effect somewhat, for either time period shown. But as before, the multiplier to convert short-run to long-run elasticities is larger when more recent years are included. In calculating long-run elasticities, the second effect dominates the first and they are larger when the full data set is used for estimation.

[27] This is due to the way the variables *pm*, *inc*, and *Urban* are normalized: namely, they are created from the unnormalized versions by subtracting the sample mean.

| Table 4.6. Selected results of model estimated on different versions of data: four-equation model | | | | | | |
|---|---|---|---|---|---|---|
| | Original as published (Model 4.1) | | Estimated with revised data (Model 4.2) | | Estimated with revised & updated data (Model 4.3) | |
| Estimation period | 1966-2004 | | 1966-2004 | | 1966-2009 | |
| **Model estimates:** | Coeff. | Std. Err. | Coeff. | Std. Err. | Coeff. | Std. Err. |
| *pm* | -0.047 | 0.004 | -0.051 | 0.005 | -0.046 | 0.003 |
| *pm*inc* | 0.064 | 0.016 | 0.067 | 0.015 | 0.056 | 0.011 |
| $pm^2$ | -0.025 | 0.007 | -0.017 | 0.007 | -0.022 | 0.006 |
| *pm*cong* | -0.012 | 0.003 | -0.012 | 0.003 | -0.003 | 0.002 |
| *vma* lagged | 0.795 | 0.013 | 0.789 | 0.013 | 0.825 | 0.010 |
| **Calculated rebound effects at values for:** | | | | | | |
| 1966-2009: short run | -5.0% | | -5.0% | | -4.6% | |
| 1969-2009: long run | -25.2% | | -25.1% | | -28.4% | |
| 2000-2009: short run | -2.8% | | -3.2% | | -2.5% | |
| 2000-2009: long run | -14.1% | | -16.4% | | -15.0% | |

Another feature that appears in this set of models is that the data revision alone makes some difference for estimates for the period 2000-2009, as seen by comparing Models 4.1 and 4.2. Specifically, the influence of fuel cost on the rebound effect, as given by the coefficient of $pm^2$, is smaller; this results in a larger rebound effect in Model 4.2 than in Mode 4.1. The changes due to extending the sample (Model 4.3) mostly compensate for this.

The finding that adding data for years up to 2009 modestly increases the estimated average rebound effect, at least in the three-equation model, is consistent with the finding of Section 4.2 that the rebound effect seems to have taken a sharp jump to a larger value starting in 2003. This observation leads to two further lines of investigation. In Section 4.4, we explore the possibility that rising fuel prices elicit an inherently larger response than falling prices. In Section 4.5, we explore specific mechanisms by which that might occur, namely through media attention and/or changes in how consumer form expectations about future prices.

## 4.4 Asymmetry in response to price changes

Several researchers have found evidence that for various types of energy purchases, demand is more responsive in the short run to price rises than to price decreases. In this section, we investigate whether such asymmetry applies to vehicle-miles traveled as a function of gasoline price.

### 4.4.1 Models based on rises versus falls of fuel *price*

Our preferred approach is to decompose fuel price into components, following the procedure used to decompose demand for gasoline use in Dargay and Gately (1997).[28] Based on experimentation, we have simplified the three-way decomposition used by these authors into a two-way decomposition, measured for each state in our sample.[29] In this subsection, we consider a decomposition of *pf*, the logarithm of fuel price, as follows:

$$pf = pf_{1966} + pf\_rise + pf\_cut$$

where *pf_rise* is the cumulative effects of all annual increases in fuel price since the start of the sample (here 1966); and *pf_cut* is the cumulative effects of all annual falls in fuel price. In other words, the value for state *i* in year *t* is defined as:

$$pf\_rise_{i,t} = \sum_{1967}^{t} \max\left[(pf_{i,t} - pf_{i,t-1}),0\right]$$

$$pf\_cut_{i,t} = \sum_{1967}^{t} \min\left[(pf_{i,t} - pf_{i,t-1}),0\right]$$

Because we include state fixed effects in our specification (i.e., there is a constant term for every state), all coefficient estimates depend on state-specific annual changes in a relevant variable; so in this specification, the coefficients of *pf* and variables constructed from it are replaced by two separate coefficients, one depending on upward annual changes and the other on downward annual changes.

The two decomposed variables, when added together, fully describe annual changes in variable *pf*. Therefore any two of the three variables *pf*, *pf_rise*, and *pf_cut* can be used in the specification, with results that are fully equivalent except for the way a t-statistic is used to test a null hypothesis. The most convenient choice proves to be the two variables, *pf* and *pf_cut*. In that case, the effect of price rises is given by the coefficient of *pf*, while the effect of price falls is given by the sum of the two coefficients.

[28] Nearly identical types of decomposition are also used for other types of energy consumption by Gately and Huntington (2002) and Dargay (2007).

[29] We do this by not distinguishing between increases that occurred before and after the maximum price observed in the data. In addition, we do not place special importance on the year 1973 as do Dargay and Gately (1997), in part because we already have a dummy variable for 1977 in our specification to capture special influences on travel behavior during that year.

These variables are used to replace *pf* in both the equation explaining the logarithm of vehicle-miles traveled (*vma*) and that explaining the logarithm of fuel intensity (*fint*). In both cases, fuel price is also combined with other variables, as in the specifications shown earlier (as well as in the published articles). Specifically, the main variable giving the rebound effect was previously the logarithm of fuel cost per mile: $pm \equiv pf + fint$, to which is now added an additional variable, either *pfcut* or (*pf_cut*+*fint*). The variable giving the effect of fuel price was previously given as the logarithm of annual fuel cost savings per unit change in fuel intensity, (*pf*+*vma*), to which is now added the additional variable (*pf_cut*+*vma*).

The results for these two alternative specifications, labeled 3.20b and 3.21b, respectively, are summarized in Table 4.7, with the base model 3.3 (no asymmetry) shown for comparison. A more complete listing of coefficients is given in the appendix.

**Table 4.7. Selected coefficient estimates: asymmetric specifications**
**(a) Three-equation models**

| | Model 3.3 | | Model 3.20 b | | Model 3.21 b | |
|---|---|---|---|---|---|---|
| Equation and variable: | Coeff. | Std. Error | Coeff. | Std. Error | Coeff. | Std. Error |
| *vma* equation: | | | | | | |
| *pm= pf+ fint* | -0.0466 | 0.0029 | -0.0520 | 0.0046 | -0.0639 | 0.0049 |
| *pf_cut* | | | 0.0124 | 0.0093 | | |
| *pf_cut + fint* | | | | | 0.0340 | 0.0078 |
| *pm*inc* | 0.0528 | 0.0108 | 0.0569 | 0.0110 | 0.0577 | 0.0108 |
| $pm^2$ | -0.0124 | 0.0059 | -0.0159 | 0.0061 | -0.0207 | 0.0061 |
| *pm*Urban* | 0.0119 | 0.0094 | 0.0124 | 0.0094 | 0.0131 | 0.0093 |
| *vma* lagged | 0.8346 | 0.0102 | 0.8256 | 0.0110 | 0.8334 | 0.0105 |
| *fint* equation: | | | | | | |
| *pf + vma* | -0.0050 | 0.0041 | -0.0185 | 0.0057 | -0.0097 | 0.0060 |
| *pf_cut + vma* | | | 0.0316 | 0.0124 | 0.0143 | 0.0123 |

**(b) Four-equation models**

| | Model 4.3 | | Model 4.20b | | Model 4.21b | |
|---|---|---|---|---|---|---|
| Equation and variable: | Coeff. | Std. Error | Coeff. | Std. Error | Coeff. | Std. Error |
| *vma* equation: | | | | | | |
| *pm= pf+ fint* | -0.0461 | 0.0030 | -0.0498 | 0.0046 | -0.0629 | 0.0049 |
| *pf_cut* | | | 0.0100 | 0.0093 | | |
| *pf_cut + fint* | | | | | 0.0340 | 0.0079 |
| *pm*inc* | 0.0561 | 0.0111 | 0.0548 | 0.0111 | 0.0573 | 0.0110 |
| $pm^2$ | -0.0224 | 0.0060 | -0.0225 | 0.0061 | -0.0275 | 0.0061 |
| *pm*cong* | -0.0031 | 0.0022 | -0.0013 | 0.0021 | -0.0016 | 0.0021 |
| *vma* lagged | 0.8249 | 0.0105 | 0.8221 | 0.0107 | 0.8305 | 0.0107 |
| *fint* equation: | | | | | | |
| *pf + vma* | -0.0074 | 0.0041 | -0.0125 | 0.0055 | -0.0041 | 0.0058 |
| *pf_cut + vma* | | | 0.0085 | 0.0112 | -0.0080 | 0.0112 |

These results suggest that the rebound VMT elasticity measured previously becomes modestly stronger (i.e. larger in absolute value) when measured only for price rises. For example, comparing base model 3.3 to asymmetric model 3.21b, that elasticity rises in magnitude, from -0.0466 to -0.0639, when changing from the former to the latter. Note that in these models the rebound effect itself does not depend on whether prices are rising or falling; rather, there is a direct effect of price on VMT which is asymmetric. In all cases, price cuts have a smaller effect on driving than price rises, a difference that is strongly statistically significant (t-statistic 4.3 or 4.4) in two of the four specifications (3.21b, 4.21b). Greene (2012) measures similar differences between the effects of rising and falling prices, although in his case he cannot rule out statistically that they are identical.

The implications of the two asymmetric specifications for rebound effects are different. In Models 3.21b and 4.21b, because variable *fint* (representing the logarithm of inverse of fuel efficiency) is included with both *pf* and *pf_cut*, the rebound effect is assumed equal to the price elasticity for price *cuts*. For example, in Model 3.21b that elasticity is approximately -0.0299 (the sum of coefficients of the two variables containing *fint*): i.e. a short-run rebound effect of approximately 3.0%. This is less than half the rebound effect with respect to fuel price *rises* in the same model, which is 6.4% (short-run structural elasticity of -0.064). As with other responses, the short-run response would be multiplied by approximately six in the long run.

In the alternate specification of Models 3.20b and 4.20b, by contrast, the rebound effect is assumed the same as the price elasticity for price rises. In that case there is no definitive difference between price rises and cuts, because the coefficient of *pf_cut* is small and statistically insignificant.

In these models, a change in fuel efficiency, unlike one in fuel price, is the same regardless of whether fuel efficiency is increased or decreased. In one pair of models (those numbered 20b) this effect is the same as that of a fuel price rise; in the other (numbered 21b) it is the same as that of a fuel price cut. The latter seems more likely theoretically because changes in fuel efficiency are noticed less dramatically than changes in fuel price, and because most of the changes in fuel efficiency we are interested in are improvements, i.e. they lower the fuel cost per mile as does a price cut. Furthermore, the asymmetry in behavior is both more notable and more precisely measured in the second specification, as already noted. For these reasons, we prefer the two models numbered 21b.

### 4.4.2. Models based on rises versus falls of fuel *cost*

We also estimated models that base the asymmetry on the variable measuring fuel cost per mile (*pm*), instead of on fuel price (*pf*). These models assume that people respond differently depending on whether their fuel cost per mile is rising or falling, regardless of whether this is due to a change in fuel price or in fuel efficiency.

The variables are formed analogously to the previous subsection. The fuel cost per mile, *pm* (the price of mileage), is decomposed into *pm_rise* and *pm_cut*. This raises a new problem because *pm_rise* and *pm_cut* are, like *pm*, endogenous; but not in a simple way because their values in a given year depend on values of *pm* in previous years. In the case of *pm*, endogeneity is accounted for as part of the three- or four-equation model.[30] A full endogenous treatment would be impossible, so we have used an approximation instead: the variables are replaced by predicted values, *pm_rise_hat* and *pm_cut_hat*, each of which is the value predicted by a regression of the corresponding variable (*pm_rise* or *pm_cut*) on all the exogenous variables in the system – that is, on the same set of variables as those used as instruments in the 3SLS estimation routine. This is basically what instrumental variables does in the case of a simpler endogenous variable, so the result of this approximation should be reasonably accurate although the standard errors of these variables may be inaccurately measured.

[30] Formally, this is accomplished by entering the variable *pm* as the sum of two variables, *pf* + *fint*, where *fint* is the logarithm of fuel intensity (see Section 3, "Dependent variables", definition of $1/E$). Since *fint* is the dependent variable of the third equation of our model system, the simultaneous estimation performed by the three-stage least squares procedure treats it as endogenous where it enters the first equation as part of *pm*.

Table 4.8 shows selected results of a specification, named Model 3.23, analogous to that of Model 3.21b. The latter is shown for comparison. Each model contains three interaction variables, whose coefficients are shown just below the second dashed line.

**Table 4.8. Selected coefficient estimates: asymmetry in response to fuel cost per mile**
**(a) Three-equation models**

| | Model 3.21b | | Model 3.23 | | Model 3.29 | |
|---|---|---|---|---|---|---|
| Equation and variable: | Coeff. | Std. Error | Coeff. | Std. Error | Coeff. | Std. Error |
| *vma* equation: | | | | | | |
| *pm= pf+ fint* | -0.0639 | 0.0049 | -0.0623 | 0.0055 | | |
| *pm_rise_hat* | | | | | -0.1134 | 0.0153 |
| *pm_rise_hat(-1)* | | | | | 0.0490 | 0.0216 |
| *pm_rise_hat(-2)* | | | | | 0.0210 | 0.0129 |
| *pf_cut + fint* | 0.0340 | 0.0078 | | | | |
| *pm_cut_hat* | | | 0.0284 | 0.0093 | -0.0037 | 0.0105 |
| *pm_cut_hat(-1)* | | | | | -0.0486 | 0.0141 |
| *pm_cut_hat(-2)* | | | | | 0.0171 | 0.0150 |
| *pm_cut_hat(-3)* | | | | | 0.0239 | 0.0108 |
| *pm*inc* | 0.0577 | 0.0107 | 0.0535 | 0.0112 | 0.0281 | 0.0120 |
| $pm^2$ | -0.0207 | 0.0061 | -0.0180 | 0.0062 | -0.0276 | 0.0068 |
| *pm*Urban* | 0.0131 | 0.0093 | 0.0187 | 0.0099 | 0.0273 | 0.0103 |
| *vma* lagged | 0.8334 | 0.0104 | 0.8084 | 0.0122 | 0.8802 | 0.0119 |
| *fint* equation: | | | | | | |
| *pf + vma* | -0.0097 | 0.0060 | | | | |
| *pfrise* | | | -0.0133 | 0.0062 | -0.0108 | 0.0064 |
| *pf_cut + vma* | 0.0143 | 0.0123 | | | | |
| *pf_cut* | | | 0.0042 | 0.0096 | -0.0154 | 0.0097 |
| *vma* | | | 0.0107 | 0.0166 | -0.0533 | 0.0179 |

**(b) Four-equation models**

| | Model 4.21b | | Model 4.23 | | Model 4.29 | |
|---|---|---|---|---|---|---|
| Equation and variable: | Coeff. | Std. Error | Coeff. | Std. Error | Coeff. | Std. Error |
| *vma* equation: | | | | | | |
| *pm= pf+ fint* | -0.0629 | 0.0049 | -0.0615 | 0.0054 | -0.0629 | 0.0049 |
| *pm_rise_hat* | | | | | -0.1068 | 0.0159 |
| *pm_rise_hat(-1)* | | | | | 0.0426 | 0.0229 |
| *pm_rise_hat(-2)* | | | | | 0.0343 | 0.0137 |
| *pf_cut + fint* | 0.0340 | 0.0079 | | | | |
| *pm_cut_hat* | | | 0.0325 | 0.0091 | -0.0051 | 0.0108 |
| *pm_cut_hat(-1)* | | | | | -0.0540 | 0.0149 |
| *pm_cut_hat(-2)* | | | | | 0.0161 | 0.0163 |
| *pm_cut_hat(-3)* | | | | | 0.0233 | 0.0117 |
| *pm*inc* | 0.0573 | 0.0110 | 0.0534 | 0.0115 | 0.0394 | 0.0129 |
| $pm^2$ | -0.0275 | 0.0061 | -0.0245 | 0.0063 | -0.0005 | 0.0002 |
| *pm*cong* | -0.0016 | 0.0021 | -0.0042 | 0.0022 | -0.0046 | 0.0029 |
| *vma* lagged | 0.8305 | 0.0107 | 0.8229 | 0.0112 | 0.8656 | 0.0125 |
| *fint* equation: | | | | | | |
| *pf + vma* | -0.0041 | 0.0058 | | | | |
| *pfrise* | | | -0.0122 | 0.0063 | -0.0144 | 0.0063 |
| *pf_cut + vma* | -0.0080 | 0.0112 | | | | |
| *pf_cut* | | | 0.0024 | 0.0086 | 0.0267 | 0.0118 |
| *vma* | | | 0.0210 | 0.0152 | -0.0081 | 0.0153 |

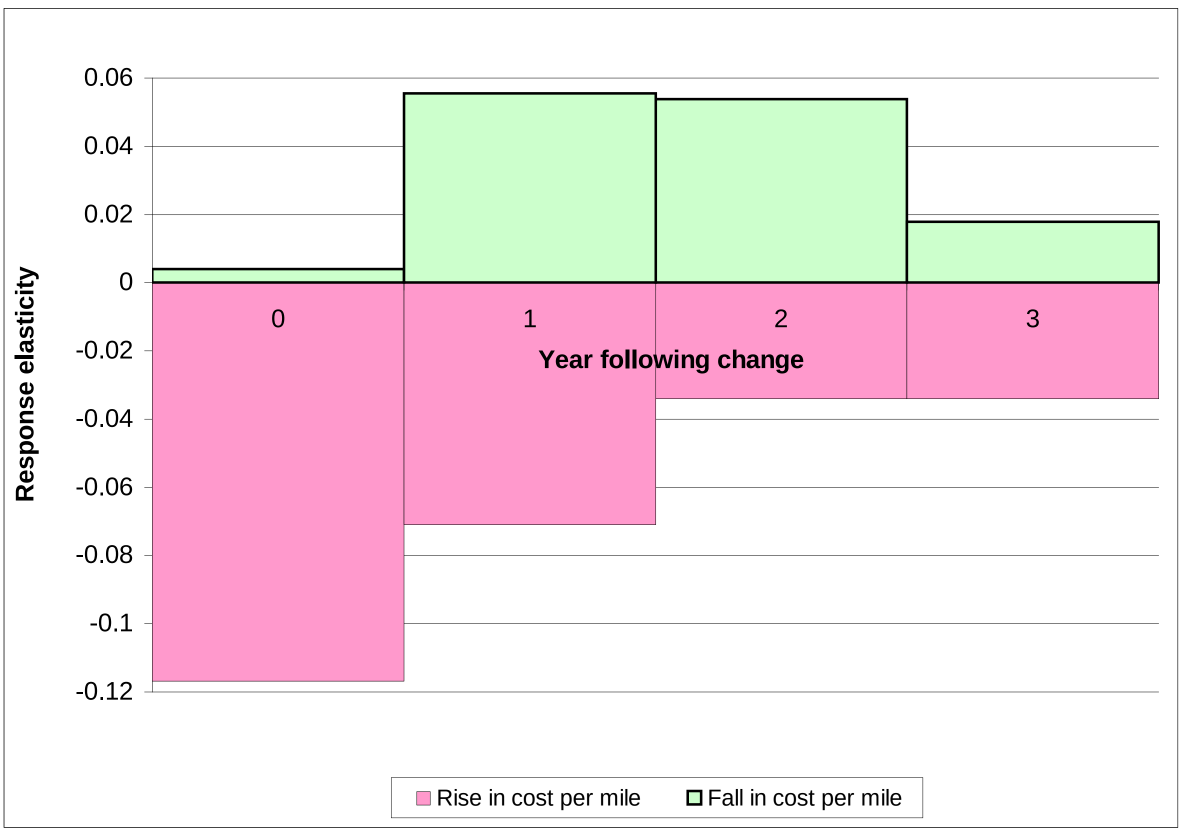
The variable *pm_cut_hat*, just like the previous variable *pf_cut*, is an increasing function of cost per mile.[31] Given its construction, we expect a negative sign on *pm* (which is the direct short-run rebound elasticity if fuel costs are rising) and also on the *sum* of coefficients of *pm* and *pm_cut_hat* (which gives the direct short-run rebound elasticity if fuel costs are falling). The coefficient on *pm_cut_hat* itself tells us the degree of asymmetry: it is positive if the magnitude of the elasticity is smaller for price cuts than for price rises. Equation (3.23) shows exactly this, very similarly to (3.21b). The short-run rebound effect is given by elasticity -0.0623 when prices are rising, and -0.0339 (=-0.0623+0.0284) when prices are falling. The rebound effect is influenced by *pm*, *income*, and *Urban* much as before. The fact that the coefficient on *pm_cut_hat* is statistically significant (more than twice its standard error) indicates that we can confidently reject the hypothesis that the magnitude of response to cost rises and cuts are the same.

[31] The actual values of *pm-cut* are negative by construction, but become less so as *pm* increases.

Model 3.29 deals with an alternative view of how asymmetry might work. Perhaps the difference in response between cost rises or cuts is not so much in the magnitude, but in the speed with which the response occurs. All the models considered in this report already have an "inertia" built into them, in the form of a lagged dependent variable which governs the speed of response to all variable changes. But in Model 3.29, we allow also for the possibility that the speed of the response differs between rises and cuts in cost per mile.

Model 3.29 shows a very plausible and revealing pattern. Adjustment to price rises takes place quickly; in fact it overshoots and then retreats to a small value after two years. But the adjustment to price cuts occurs more slowly: it is essentially zero in the year of the price change (0.0037); takes a modest value after one year (0.0523, from the sum of the first two coefficients below the first dashed line); remains approximately the same for a second year (sum of three coefficients); and then retreats to a value of 0.0112 (sum of all four coefficients). These response patterns are shown in Figure 4.2.

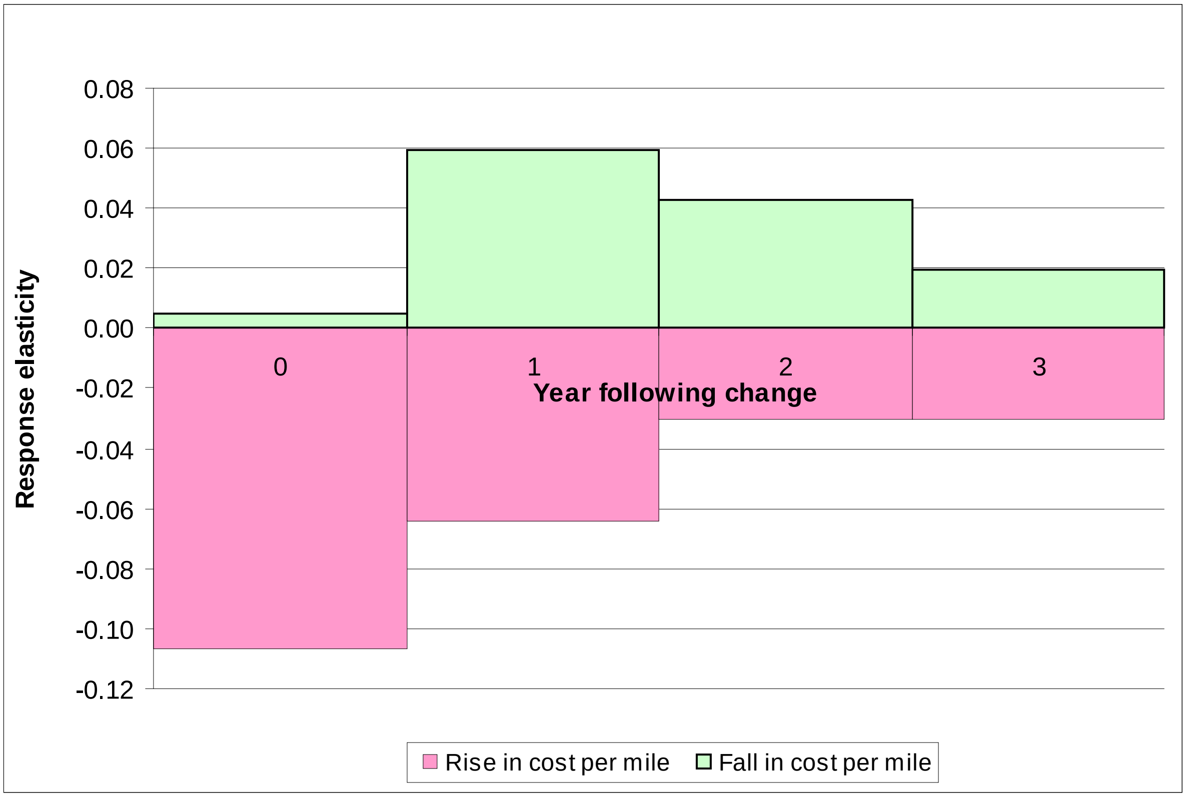
**Figure 4.2. Short-run elasticity of VMT with respect to a sustained change in fuel cost per mile (Model 3.29)**




In these models, unlike those in the previous subsection, the response to a change in fuel efficiency depends on what's happening to overall fuel costs. If fuel price is rising more rapidly than fuel efficiency, then the variable remains constant; therefore, these models predict that people would still respond to a small change in fuel efficiency according to the combination of coefficients of variable *pm*. In other words, they respond to any change in fuel efficiency, including an improvement, as they would to a *rise* in fuel price. Thus, the effect of a CAFE tightening could differ depending on whether overall fuel prices are generally rising or not, and if they are on how fast. The behavioral rationale is as follows: if fuel costs are rising due to increasing fuel prices and this has heightened people's awareness, then an improvement in fuel efficiency would have a large effect on their driving decisions because it would help offset that fuel price rise at a time when they are highly sensitive to it. This is a debatable assumption, as it implies a degree of rationality in calculating fuel costs that people may not have in reality. Indeed, as noted elsewhere, our results cannot definitively show that the rebound effect differs from zero if the responses to fuel price and fuel efficiency are estimated separately. Thus it is possible that all the rebound results are overstated, and actually are measuring the response to changes in price rather than in fuel efficiency. For this reason, we prefer the models of Section 4.4.1.

*Four-equation results.* The same kind of model development was done for four-equation models, with similar results as shown in Table 4.8(b) and Figure 4.3.

**Figure 4.3. Short-run elasticity of VMT with respect to a sustained change in fuel cost per mile (Model 4.29)**



## 4.5 Effects of media attention and expectations

Two important findings of previous sections are that the responsiveness of vehicle travel to costs sharply increased starting around 2003, and that this responsiveness is much larger when fuel prices or costs are rising than when they are falling. These findings naturally invite the question: why? In this section, we consider two factors that may help explain the variations in responsiveness.

The first is variations in media attention to fuel prices and costs. Motor vehicle fuel is a moderately important part of many people's budgets, and the price of crude oil which tends to underlie fuel price has even more pervasive effects on consumers. As a result, there is a tendency for turmoil in gasoline or oil markets to gain much attention in public media. Could it be that this attention is the underlying cause of some of the variations found in this report?

The second is the uncertainty in future fuel costs. There is evidence that at most times, consumers' best guess at future prices, i.e. their expectation, is the current price.[32] However, we hypothesize that if prices are viewed as highly uncertain, a recent change in price is more likely to be viewed as temporary. Therefore, the responsiveness to price changes may be muted during times when recent history suggests that prices are volatile.

Results for three promising models are presented in Table 4.9. For comparison, we also show the most comparable base model incorporating asymmetry but not media or uncertainty: namely, Models 3.21b and 4.21b. Variables *Media*, *Media_dummy*, and log (*fuel price variance*) are as explained in Section 3, all normalized by subtracting their mean values on the entire sample. (As with other interacting variables, this normalization is done for convenience: as a result the coefficients of *pm* remains equal to the estimated short-run structural elasticity of VMT with respect to fuel cost when interacting variables take their mean values in the sample.)

[32] Supporting evidence comes from two separate surveys, reported by Anderson et al. (2011) and Allcott (2011), both of which asked people directly about their price expectations. Technically, the stated result can arise from consumers assuming a "random walk" in fuel prices: starting at the current level, they are equally likely to go up or down at each new time period. Anderson et al. (2011) find that this assumption accurately explains their answers except in late 2008, when they expected (correctly, as it turned out) that the recent fall in prices would prove to be temporary.

### Table 4.9. Selected coefficient estimates: asymmetry with media coverage or fuel-price uncertainty
### (a) Three-equation models

| | Model 3.21b | | Model 3.35 | | Model 3.37 | | Model 3.42 | | Model 3.45 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Equation and variable: | Coeff. | Std. Error | Coeff. | Std. Error | Coeff. | Std. Error | Coeff. | Std. Error | Coeff. | Std. Error |
| *vma* equation: | | | | | | | | | | |
| *pm= pf+ fint* | -0.0639 | 0.0049 | -0.0587 | 0.0052 | -0.0641 | 0.0057 | -0.0699 | 0.0069 | -0.0666 | 0.0053 |
| *pf_cut + fint* | 0.0340 | 0.0078 | 0.0286 | 0.0081 | 0.0332 | 0.0083 | 0.0529 | 0.0091 | 0.0210 | 0.0083 |
| *pm*dummy*_0309 | | | | | -0.0216 | 0.0079 | -0.0265 | 0.0078 | -0.0347 | 0.0084 |
| *pf**(*Media_dummy*) | | | -0.0301 | 0.0101 | -0.0319 | 0.0101 | -0.0316 | 0.0101 | | |
| *pf_rise*Media* | | | | | | | | | -0.2680 | 0.0544 |
| *pm** log(*fuel price variance*) | | | | | | | 0.0028 | 0.0007 | 0.0081 | 0.0024 |
| *pm*inc* | 0.0577 | 0.0107 | 0.0583 | 0.0109 | 0.0711 | 0.0126 | 0.0779 | 0.0124 | 0.0807 | 0.0136 |
| $pm^2$ | -0.0207 | 0.0061 | -0.0053 | 0.0075 | -0.0064 | 0.0075 | -0.0126 | 0.0070 | -0.0302 | 0.0081 |
| *pm*Urban* | 0.0131 | 0.0093 | 0.0118 | 0.0094 | 0.0100 | 0.0097 | 0.0091 | 0.0095 | 0.0118 | 0.0106 |
| *vma* lagged | 0.8334 | 0.0104 | 0.8325 | 0.0106 | 0.8276 | 0.0109 | 0.8321 | 0.0108 | 0.8247 | 0.0117 |
| *fint* equation: | | | | | | | | | | |
| *pf + vma* | -0.0097 | 0.0060 | -0.0124 | 0.0059 | -0.0104 | 0.0058 | -0.0079 | 0.0058 | -0.0033 | 0.0058 |
| *pf_cut + vma* | 0.0143 | 0.0123 | 0.0220 | 0.0120 | 0.0129 | 0.0118 | 0.0031 | 0.0115 | -0.0225 | 0.0114 |

### (b) Four-equation models

| | Model 4.21b | | Model 4.35 | | Model 4.37 | | Model 4.42 | | Model 4.45 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Equation and variable: | Coeff. | Std. Error | Coeff. | Std. Error | Coeff. | Std. Error | Coeff. | Std. Error | Coeff. | Std. Error |
| *vma* equation: | | | | | | | | | | |
| *pm= pf+ fint* | -0.0629 | 0.0049 | -0.0638 | 0.0050 | -0.0729 | 0.0054 | -0.0706 | 0.0054 | -0.0719 | 0.0053 |
| *pf_cut + fint* | 0.0340 | 0.0079 | 0.0352 | 0.0080 | 0.0420 | 0.0081 | 0.0506 | 0.0083 | 0.0626 | 0.0085 |
| *pm*dummy*_0309 | | | | | -0.0359 | 0.0071 | -0.0308 | 0.0072 | -0.0321 | 0.0072 |
| *pf**(*Media_dummy*) | | | 0.0061 | 0.0058 | 0.0071 | 0.0058 | -0.0080 | 0.0063 | | |
| *pf_rise*Media* | | | | | | | | | -0.3117 | 0.0490 |
| *pm** log(*fuel price variance*) | | | | | | | -0.0100 | 0.0019 | -0.0044 | 0.0019 |
| *pm*inc* | 0.0573 | 0.0110 | 0.0575 | 0.0110 | 0.0825 | 0.0122 | 0.0944 | 0.0124 | 0.0905 | 0.0124 |
| $pm^2$ | -0.0275 | 0.0061 | -0.0296 | 0.0065 | -0.0263 | 0.0066 | 0.0037 | 0.0085 | -0.0114 | 0.0074 |
| *pm*Urban* | -0.0016 | 0.0021 | -0.0025 | 0.0021 | -0.0028 | 0.0021 | -0.0044 | 0.0021 | -0.0057 | 0.0021 |
| *vma* lagged | 0.8305 | 0.0107 | 0.8314 | 0.0106 | 0.8314 | 0.0106 | 0.8275 | 0.0109 | 0.8423 | 0.0112 |
| *fint* equation: | | | | | | | | | | |
| *pf + vma* | -0.0041 | 0.0058 | -0.0060 | 0.0057 | -0.0059 | 0.0057 | -0.0049 | 0.0057 | -0.0035 | 0.0057 |
| *pf_cut + vma* | -0.0080 | 0.0112 | -0.0031 | 0.0110 | -0.0022 | 0.0110 | -0.0018 | 0.0110 | -0.0129 | 0.0111 |

The media variable is specified to influence the response to fuel price but not to fuel efficiency, because the variable involves news about fuel price. Therefore, including this variable does not affect the rebound effect except insofar as it changes coefficients of *pm* and its interactions. The uncertainty variable, by contrast, represents a consumer's own experience with variation in fuel costs, and therefore is specified so as to influence both responses (i.e., it is interacted with *pm* rather than *pf*).

Consider first the four-equation models. The last of these models (4.45) suggests that both media coverage and fuel-price volatility, taken together, have significant effects in increasing the magnitude of the elasticity of VMT with respect to fuel price, just as we hypothesized. The effect of *Media* is strongest when it is entered as a continuous rather than a dummy variable and when it is interacted with price rises (*pf_rise*). The effect of these additional variables on coefficients involving *pm* is minimal except for one: the coefficient of $pm^2$ becomes smaller when fuel price volatility is included. This could mean that the previously observed tendency of the price elasticity (and rebound effect) to increase with fuel price is explained in part by correlation between high prices and media coverage. But the results are not consistent enough to draw a firm conclusion on this point.

In the three-equation models, the media variables alone seem powerful (Models 3.35 and 3.37), but when fuel price variability is included (Model 3.45), its coefficient has an unexpected sign. We do not have a good explanation for this. Generally, the sensitivity shown in these models to the precise form in which variables are entered into the equation is an undesirable property, and probably indicates that we have reached the limits of our ability to discern these fine-grained effects using this data set.

Comparing Model 3.35 or 4.35 with the higher-numbered models, which all contain the variable "*dummy* 0309", we see there continues to be a structural break toward a larger rebound effect in years 2003-2009, even with these other variables are accounted for. The amount of this break (an increase in the short-run rebound effect of roughly 2.0 to 3.5 percentage points) is about the same size as found previously, in Table 4.4 (Models 3.18 and 4.13). Therefore, it seems these new variables have not captured whatever factors changed the responsiveness to price and fuel efficiency starting in 2003. Thus, further research is needed if one wishes to understand the reason for this change, and in particular the likelihood that it will persist into the future.

Taking into account explanatory power, consistency across three- and four-equation models, and consistency with theory, our preferred models remain those that omit media and volatility variables: namely, Models 3.21b and 4.21b. While the exploration of media and volatility elicit considerable evidence that one or both of these factors helps explain.

## 5. Implications of the Empirical Analysis: Projections to 2035

By distinguishing the causes of the observed decline in the rebound effect, we are in a position to consider how the rebound effect is likely to change in the future. By inserting projected values for real per capita income, real fuel costs of driving, urbanization, and congestion into our model, we obtain a projection for the rebound effect. Of course, like any projection, the farther into the future we project, the uncertain are the values of these variables. In addition, in both cases projections show one or both variables moving outside the range in which they were observed in our sample; as a result, statistical uncertainty in the estimated model can magnify the uncertainty in the projected values.

The models estimated here imply the rebound effect is a linear function of the logarithms of per capita income and fuel cost per mile. This is probably a good approximation within limited ranges of those variables, but for extreme values the linear function becomes less satisfactory. In particular, since rising income lowers the rebound effect, linearity implies that the rebound effect could become negative at high enough incomes. This is unrealistic and so to avoid it, we truncate the rebound effect for any given state and year at zero. As a result, the aggregate rebound approaches zero only gradually as incomes rise, because an increasing number of states hit this limit. In the base projections here, the number of states with zero rebound effects rises from one in 2008 to either five or seven in 2035, depending on whether the three- or four-equation model is used.

The first two of the variables needed for projections — per capita income and fuel cost per mile — are projected in the 2011 *Annual Energy Outlook* published by the U.S. Energy Information Administration (US EIA 2011). WWe refer to these input projections as AEO2011. The AEO's projections are national, whereas the rebound effects calculated here vary by state. Thus for each state, we use the average of 2008 and 2009 as a starting value, and then change the two variables (per capita income and fuel cost per mile) by the same proportion that the national projection changes from those same two starting years.

It is worth noting that these projected values do not take into account any change that might occur from the regulation itself. Thus, for example, the rebound effect in 2025 is based on fuel efficiency projections from AEO that do not incorporate the impact of tightened efficiency regulations in years 2017-2024. Because the effect of fuel costs is to raise the rebound effect, this means the projections here slightly overestimate the rebound effect compared to one that tracks the cumulative effects of the regulations on average fuel economy in each year.

For urbanization, we extrapolate from the changes observed in national averages within the data set from 1999 to 2009. Specifically, the proportion of non-urban population and the number of hours of delay are each assumed to change at the same annual rate as observed over that decade. That annual rate is -0.4%, resulting in average urbanization (fraction of population in urban areas) rising from 74.3% in 2010 to 76.7% in 2035.

For congestion, we use a projection by the U.S. Federal Highway Administration that under current funding for infrastructure, congestion will increase at an average annual rate of 1.26 percent (US FHWA 2011) between 2006 and 2026.[33] Applying this same rate to the entire projection period implies that annual hours of delay per person, averaged over states, rises over from 8.6 to 11.9. (Congestion affects the projections only for the four-equation model.)

The projection methodology computes the short-run and long-run rebound effects, based on the formulas already given using values of the "interaction variables" (per capita income, fleet-average fuel efficiency, urbanization, and congestion) as just described for every state and every year from 2010-2035. The same methodology is used to "back-cast" the values of rebound effect that our model implies occurred during years 2000-2009, using the actual values of interacting variables.

For a given year, the short-run and long-run rebound effects refer to projected changes in VMT that would occur from a permanent change in the cost per mile beginning in that year, relative to its baseline projected value, if all the relevant interaction variables (income, fuel price, urbanization, and congestion) were to remain constant in time following this change. The short-run rebound describes the change in VMT during the year in question, whereas the long-run rebound describes the change in VMT in the distant future caused by this same permanent change. The long-run rebound is larger in magnitude than the short-run rebound because people adjust slowly to a change, as demonstrated by the coefficients on the lagged dependent variables in the equations. (Especially, the coefficient of approximately 0.8 on lagged vehicle-miles per adult indicates that about 80% of the choice about travel in a given year is determined by "inertia," i.e. by travel the previous year, whereas only 20% is given by the new "target" travel resulting from new conditions.) These projections provide the best comparison with other values for the "rebound effect" estimated in the literature, which are based on the same hypothetical experiment.

For purposes of regulatory analysis, however, a more relevant measure is how much the path of VMT is shifted by a permanent change in cost per mile in a given year. This measure takes the interacting variables to be changing over time, as in fact they are projected to be, rather than being held constant. It tracks how the VMT changes in the years following a regulatory change

[33] US FHWA (2008), Exhibit 7-9, column headed "Percent Change in Delay on Roads Modeled in HERS Congestion Delay per VMT, Funding Mechanism: Fixed Rate User Charges."

from two sources simultaneously: (a) the transition from short to long run, as already described; and (b) the changes in variables that influence the rebound effect. This is what was defined earlier as the *dynamic rebound effect*. (See Section 1 and Appendix C for details of its calculation.)

### 5.1 Results: Projections using models without media or uncertainty

Tables 5.1 through 5.3 summarize the results of projecting Models 3.3 and 3.21b, our preferred symmetric and asymmetric models and for the corresponding four-equation models. Year by year details of these projections are given in the appendix. Table 5.1 compares the two models, both using the AEO 2011 "Reference Case," while Tables 5.2 and 5.3 give results for each model if input variables are instead taken from the AEO 2011 "High Oil Price" and Low Oil Price" cases. Figures 5.1 through 5.3 present some of the same information—specifically, for the dynamic rebound effect—graphically. Figure 5.1 also shows, for comparison, the results of Models 3.23 and 4.23 with asymmetry based on fuel cost; this graph illustrates one of the problems with using such a model to project rebound effects, which is that the effect can fluctuate wildly from year to year due to the fact that projected cost per mile is relatively flat but with small variations up or down in various years.

**Table 5.1**
**Projection Results: Rebound Effect (expressed as positive percentage), comparing symmetric and asymmetric models**

### (a) Three-equation models: Model 3.3 (symmetric) and 3.21b (asymmetric)

| | Historical | ----------------------Projected---------------------------------- | | | | | Regulated average |
|---|---|---|---|---|---|---|---|
| | 2000-2009 | 2010 | 2017 | 2025 | 2030 | 2035 | 2017-2025 |
| **Model 3.3 (symmetric)** | | | | | | | |
| Short Run Rebound | 2.8% | 2.8% | 2.4% | 1.6% | 1.2% | 0.8% | 2.0% |
| Dynamic Rebound | NA | 11.4% | **8.8%** | **5.3%** | 3.8% | 3.2% | **6.9%** |
| Long Run Rebound | 17.8% | 17.6% | 15.4% | 10.2% | 7.2% | 4.8% | 12.9% |
| **Model 3.21b (with asymmetry based on fuel price)** | | | | | | | |
| Short Run Rebound | 0.7% | 1.0% | 0.8% | 0.2% | 0.0% | 0.0% | 0.4% |
| Dynamic Rebound | NA | 4.2% | **2.3%** | **0.2%** | 0.0% | 0.0% | **1.0%** |
| Long Run Rebound | 4.2% | 5.8% | 4.5% | 1.0% | 0.2% | 0.0% | 2.7% |

### (b) Four-equation models: Model 4.3 (symmetric) and 4.21b (asymmetric)

| | Historical | ----------------------Projected---------------------------------- | | | | | Regulated average |
|---|---|---|---|---|---|---|---|
| | 2000-2009 | 2010 | 2017 | 2025 | 2030 | 2035 | 2017-2025 |
| **Model 4.3 (symmetric)** | | | | | | | |
| Short Run Rebound | 2.5% | 3.0% | 2.9% | 2.0% | 1.5% | 1.0% | 2.4% |
| Dynamic Rebound | NA | 13.2% | **10.7%** | **6.6%** | 4.7% | 3.9% | **8.6%** |
| Long Run Rebound | 15.0% | 18.2% | 17.2% | 11.6% | 8.3% | 5.6% | 14.5% |
| **Model 4.21b (with asymmetry based on fuel price)** | | | | | | | |
| Short Run Rebound | 0.5% | 1.1% | 1.0% | 0.3% | 0.1% | 0.0% | 0.6% |
| Dynamic Rebound | NA | 5.4% | **3.3%** | **0.3%** | 0.0% | 0.0% | **1.5%** |
| Long Run Rebound | 2.4% | 6.4% | 5.9% | 1.4% | 0.2% | 0.0% | 3.5% |

**Table 5.2**
**Projection Results: Rebound Effect (expressed as positive percentage) with symmetric models, comparing different oil price cases**
**(a) Three-equation symmetric model (Model 3.3)**

| | Historical | ----------Projected | | | | ----------- | Regulated average |
|---|---|---|---|---|---|---|---|
| | 2000-2009 | 2010 | 2017 | 2025 | 2030 | 2035 | 2017-2025 |
| **Reference Case** | | | | | | | |
| Short Run Rebound | 2.8% | 2.8% | 2.9% | 2.8% | 2.8% | 2.8% | 2.0% |
| Dynamic Rebound | NA | 11.4% | **11.1%** | **10.8%** | 10.5% | 10.1% | **6.9%** |
| Long Run Rebound | 17.8% | 17.6% | 18.1% | 17.7% | 17.9% | 17.4% | 12.9% |
| **High Oil Price Case** | | | | | | | |
| Short Run Rebound | 2.8% | 2.8% | 3.3% | 3.5% | 3.6% | 3.5% | 2.9% |
| Dynamic Rebound | NA | 14.4% | 14.5% | 14.4% | 14.1% | 13.7% | **10.6%** |
| Long Run Rebound | 17.8% | 17.6% | 20.8% | 22.1% | 22.6% | 22.2% | 18.3% |
| **Low Oil Price Case** | | | | | | | |
| Short Run Rebound | 2.8% | 2.8% | 2.4% | 2.2% | 2.1% | 1.9% | 0.9% |
| Dynamic Rebound | NA | 7.8% | 7.1% | 6.5% | 6.0% | 5.5% | **2.3%** |
| Long Run Rebound | 17.8% | 17.6% | 14.8% | 13.8% | 12.9% | 11.8% | 5.8% |

**(b) Four-equation symmetric model (Model 4.3)**

**Selected Projection Results: Rebound Effect (expressed as positive percentage)**
**Four-equation model estimated on 1966-2009 revised & updated data (Model 4.3)**

| | Historical | ----------Projected | | | | ----------- | Regulated average |
|---|---|---|---|---|---|---|---|
| | 2000-2009 | 2010 | 2017 | 2025 | 2030 | 2035 | 2017-2025 |
| **Reference Case** | | | | | | | |
| Short Run Rebound | 2.5% | 3.0% | 2.9% | 2.0% | 1.5% | 1.0% | 2.4% |
| Dynamic Rebound | NA | 13.2% | **10.7%** | **6.6%** | 4.7% | 3.9% | **8.6%** |
| Long Run Rebound | 15.0% | 18.2% | 17.2% | 11.6% | 8.3% | 5.6% | 14.5% |
| **High Oil Price Case** | | | | | | | |
| Short Run Rebound | 2.5% | 3.0% | 4.4% | 3.5% | 2.9% | 2.5% | 4.0% |
| Dynamic Rebound | NA | 18.6% | 17.4% | 13.0% | 11.0% | 9.9% | **15.1%** |
| Long Run Rebound | 15.0% | 18.1% | 26.5% | 21.1% | 17.5% | 14.5% | 24.0% |
| **Low Oil Price Case** | | | | | | | |
| Short Run Rebound | 2.5% | 3.0% | 1.0% | 0.1% | 0.0% | 0.0% | 0.5% |
| Dynamic Rebound | NA | 6.9% | 2.4% | 0.1% | 0.0% | 0.0% | **0.8%** |
| Long Run Rebound | 15.0% | 18.1% | 5.8% | 0.4% | 0.1% | 0.0% | 2.8% |

## Table 5.3
## Projection Results: Rebound Effect (expressed as positive percentage) with asymmetric models, comparing different oil price cases

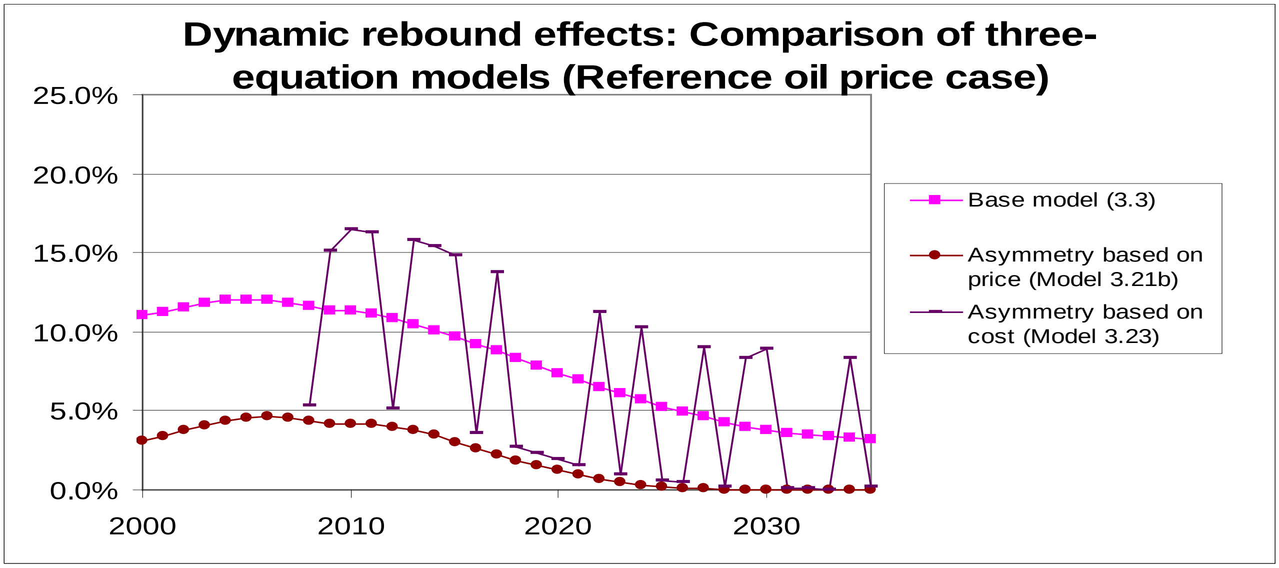
### (a) Three-equation asymmetric model (Model 3.21b)

| | Historical | ---Projected--- | | | | | Regulated average |
|---|---|---|---|---|---|---|---|
| | 2000-2009 | 2010 | 2017 | 2025 | 2030 | 2035 | 2017-2025 |
| **Reference Case** | | | | | | | |
| Short Run Rebound | 0.7% | 1.0% | 0.8% | 0.2% | 0.0% | 0.0% | 0.4% |
| Dynamic Rebound | NA | 4.2% | **2.3%** | **0.2%** | 0.0% | 0.0% | **1.0%** |
| Long Run Rebound | 4.2% | 5.8% | 4.5% | 1.0% | 0.2% | 0.0% | 2.7% |
| **High Oil Price Case** | | | | | | | |
| Short Run Rebound | 0.7% | 0.9% | 2.1% | 1.2% | 0.7% | 0.3% | 1.6% |
| Dynamic Rebound | NA | 8.5% | 7.5% | 3.4% | 1.7% | 1.3% | **5.3%** |
| Long Run Rebound | 4.2% | 5.7% | 12.7% | 7.2% | 3.9% | 1.9% | 10.0% |
| **Low Oil Price Case** | | | | | | | |
| Short Run Rebound | 0.7% | 1.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| Dynamic Rebound | NA | 2.0% | 0.0% | 0.0% | 0.0% | 0.0% | **0.0%** |
| Long Run Rebound | 4.2% | 5.7% | 0.1% | 0.0% | 0.0% | 0.0% | 0.0% |

### (b) Four-equation asymmetric model (Model 4.21b)

| | Historical | ---Projected--- | | | | | Regulated average |
|---|---|---|---|---|---|---|---|
| | 2000-2009 | 2010 | 2017 | 2025 | 2030 | 2035 | 2017-2025 |
| **Reference Case** | | | | | | | |
| Short Run Rebound | 0.5% | 1.1% | 1.0% | 0.3% | 0.1% | 0.0% | 0.6% |
| Dynamic Rebound | NA | 5.4% | **3.3%** | **0.3%** | 0.0% | 0.0% | **1.5%** |
| Long Run Rebound | 2.4% | 6.4% | 5.9% | 1.4% | 0.2% | 0.0% | 3.5% |
| **High Oil Price Case** | | | | | | | |
| Short Run Rebound | 0.5% | 1.1% | 2.8% | 1.9% | 1.3% | 0.8% | 2.4% |
| Dynamic Rebound | NA | 11.8% | 11.3% | 6.5% | 4.3% | 3.1% | **8.8%** |
| Long Run Rebound | 2.4% | 6.3% | 17.4% | 11.6% | 7.7% | 4.5% | 14.7% |
| **Low Oil Price Case** | | | | | | | |
| Short Run Rebound | 0.5% | 1.1% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| Dynamic Rebound | NA | 2.5% | 0.0% | 0.0% | 0.0% | 0.0% | **0.0%** |
| Long Run Rebound | 2.4% | 6.3% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |

**Figure 5.1**
**Selected projection results: Symmetric and two asymmetric models**
**(a) Three-equation models**




**(b) Four-equation models**

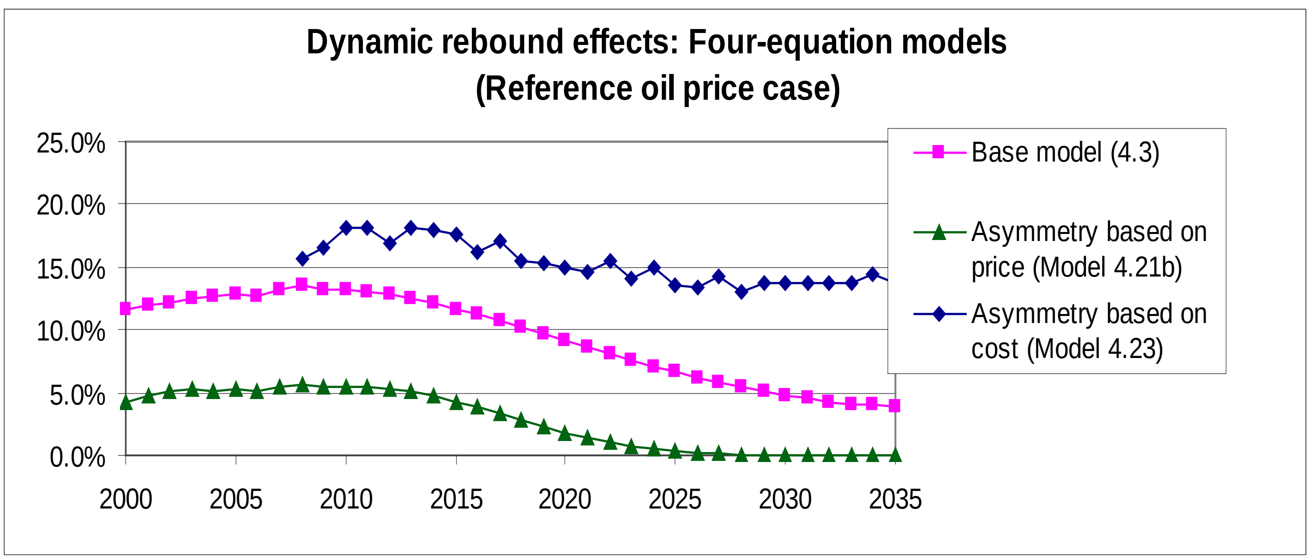
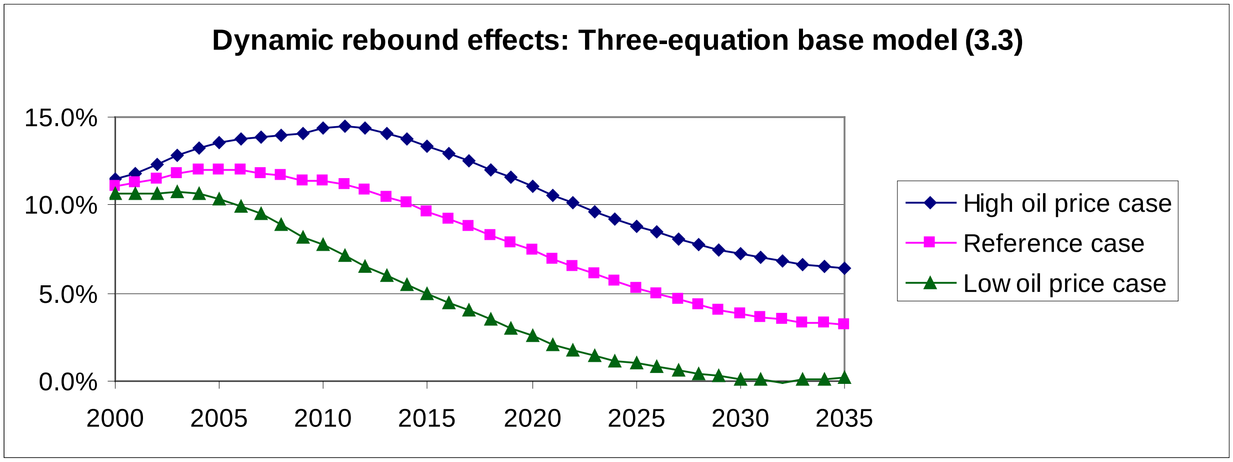


**Figure 5.2**
**Selected Projection Results: Symmetric Models**
**(a) Three-equation model**




**(b) Four-equation models**

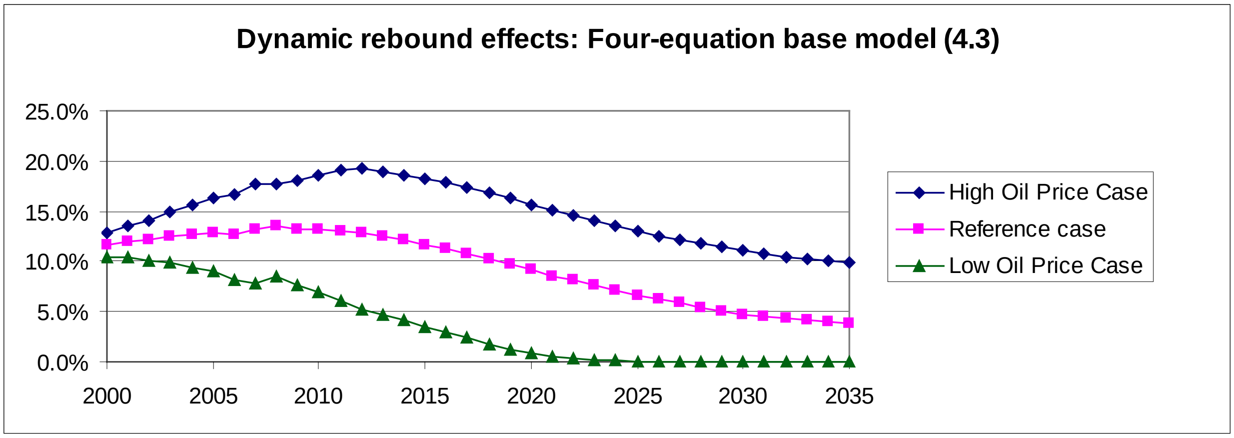
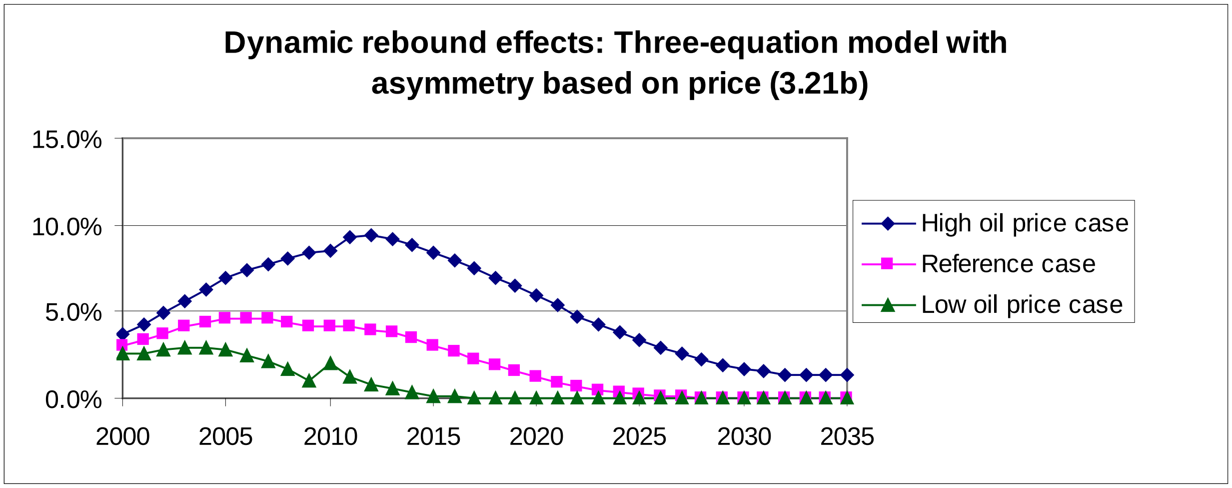
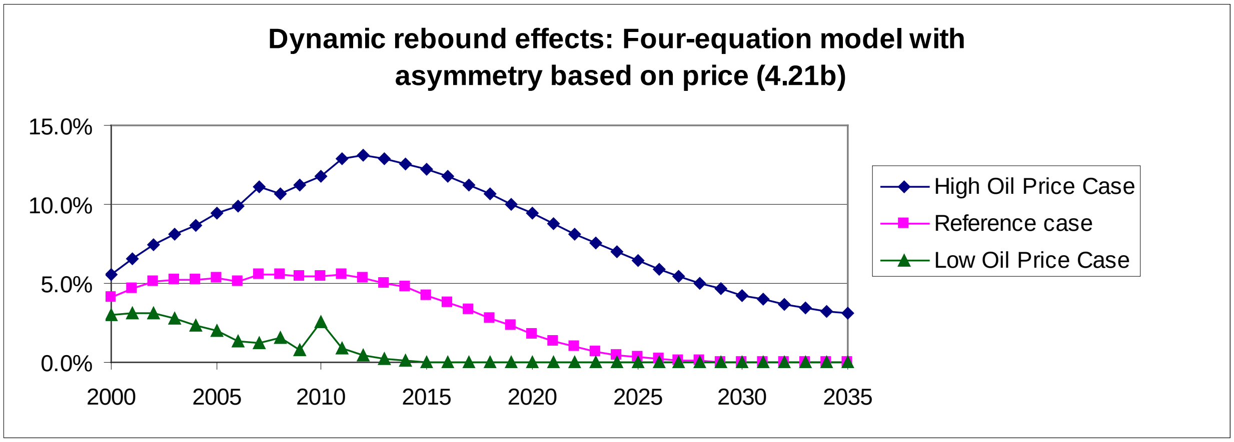


**Figure 5.3**
**Selected projection results: Preferred asymmetric models**
**(a) Three-equation model**

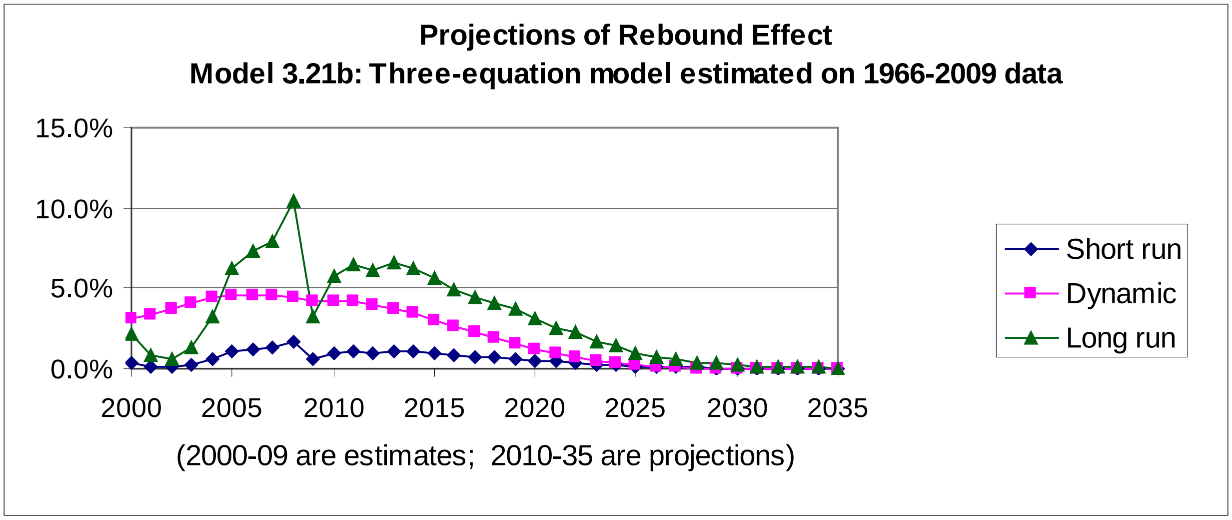



**(b) Four-equation models**

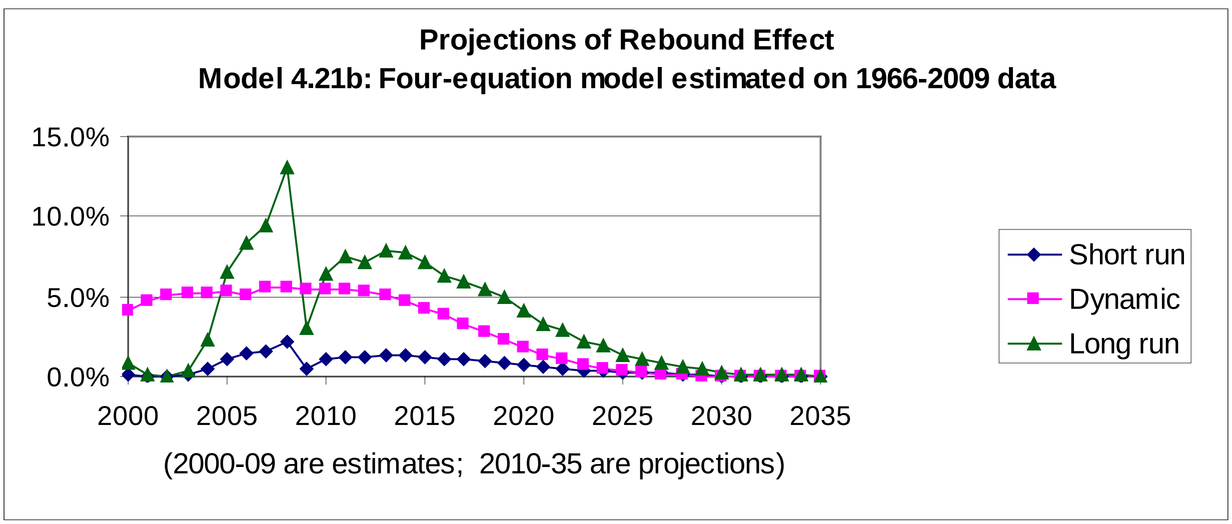



The projections from asymmetric models show more fluctuations than those from symmetric models, because the sharp break between years of rising and falling fuel costs causes jumps in the short-run and long-run rebound effects. This occurs each year when the change in fuel price switches sign, as happened in 2009 (becoming negative) and 2010 (becoming positive again). In the "low oil price" projections, it happens again in 2011 as the price spike in 2010 is projected to be reversed, and then again in 2017 when the 2011-2016 downward trend changes to a steady though very gradual increase. These fluctuations are mainly seen in the short-run and long-run rebound effects, as illustrated in Figure 5.4.

**Figure 5.4**
**Projection results for preferred models with asymmetry**
**(a) Three-equation model**




**(b) Four-equation model**




The dynamic rebound effect does not have such large jumps, because it effectively averages the responses over the lifetime of a vehicle purchased during the year in question. Thus, if over the next 15 years the impact on VMT is sometimes large and sometimes small, this is diluted first by the "inertia" in consumer response, which is tracked in the dynamic rebound calculation, and also by the summation over years in mileage driven. For this reason, it can be larger than the long-run rebound effect in years when fuel costs have just fallen, because the long-run rebound effect assumes that all variables, including the indicator for falling prices, will remain unchanged over the life of the vehicle.

The projection results thus far are summarized in Table 5.4, focusing on the regulated average value of the rebound effect (i.e., average over years 2017-2025). The first two panels present dynamic rebound effects, the third presents long-run rebound effects.

**Table 5.4**
**Selected summary measures**

**(a) Dynamic rebound effect: symmetric models**
**(Average over years 2017-2025)**

| | Three-equation model (3.3) | Four-equation model (4.3) | **Average** |
|---|---|---|---|
| High Oil Price Case | 10.6% | 15.1% | 12.8% |
| **Reference Case** | 6.9% | 8.6% | **7.8%** |
| Low Oil Price Case | 2.3% | 0.8% | 1.5% |

Note: Rebound effect is defined as minus the elasticity of VMT with respect to fuel cost per mile, expressed as positive percentage). Dynamic rebound effect refers to total miles driven by a vehicle over its life. "Regulated average" over 2017-2015 is weighted by projected sales of all light duty vehicles.

**(b) Dynamic rebound effect: asymmetric models**
**(Average over years 2017-2025)**

| | Three-equation model (3.21b) | Four-equation model (4.21b) | **Average** |
|---|---|---|---|
| High Oil Price Case | 5.3% | 8.8% | 7.0% |
| **Reference Case** | 1.0% | 1.5% | **1.3%** |
| Low Oil Price Case | 0.0% | 0.0% | 0.0% |

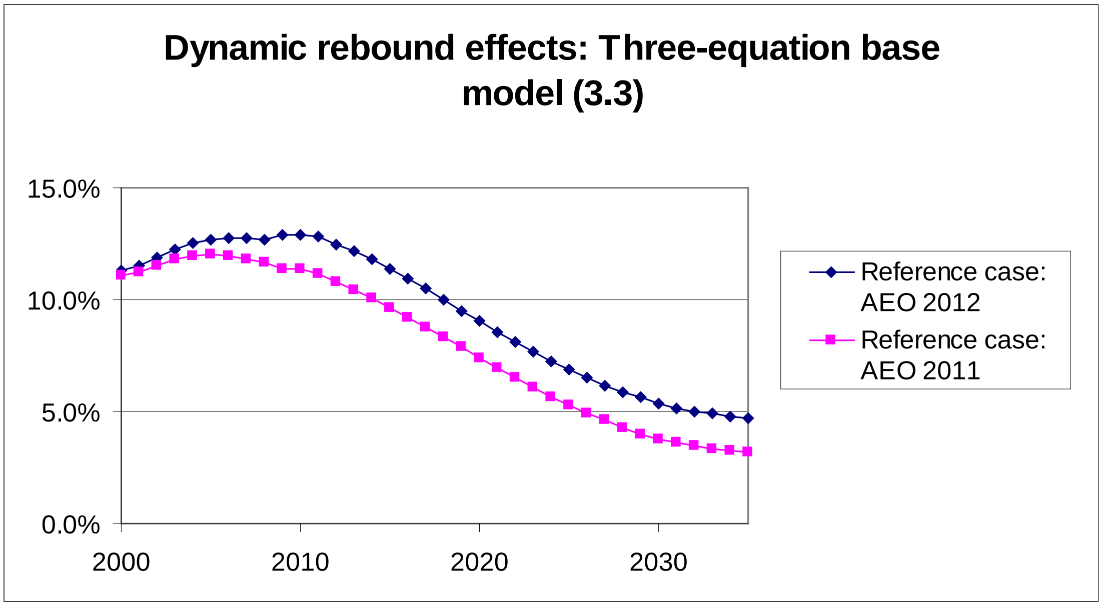
**(c) Long run rebound effect: asymmetric models**
**(Average over years 2017-2025)**

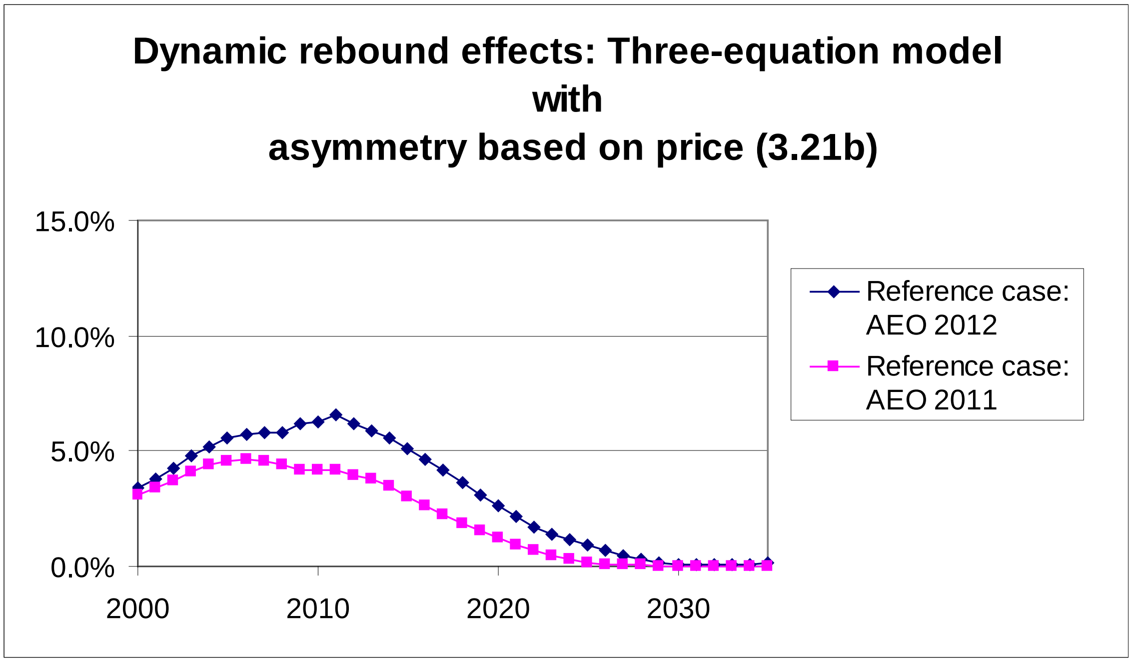
| | Three-equation model (3.21b) | Four-equation model (4.21b) | **Average** |
|---|---|---|---|
| High Oil Price Case | 10.0% | 14.7% | 12.4% |
| Reference Case | 2.7% | 3.5% | 3.1% |
| Low Oil Price Case | 0.0% | 0.0% | 0.0% |

Note: Unlike the dynamic rebound effect, which accounts for changes in fuel prices after a car is purchased, the long-run rebound effect forecasts the result if fuel prices remained the same throughout the life of the vehicle. This is why it can sometimes be smaller than the dynamic rebound effect.

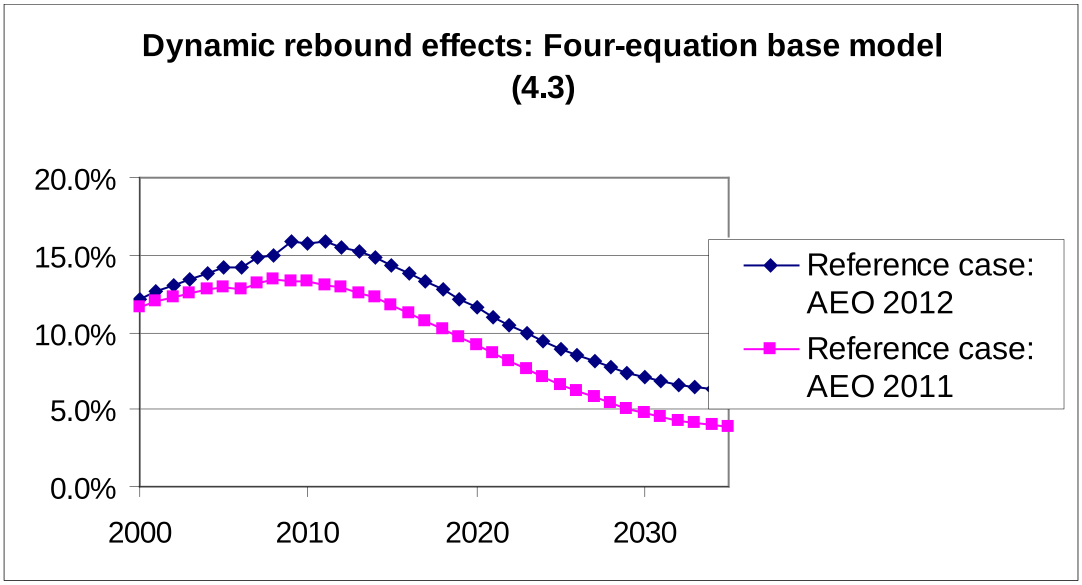
Recently, a Reference Case projection has become available using the 2012 version of the Annual Energy Outlook (AEO2012). In order to see whether this substantially affects the projections of the rebound effects, a comparison is presented in Figure 5.5. Using our base models (Models 3.3 and 4.3), the projected dynamic rebound effects are about two percentage points larger using AEO2012, because of its higher energy prices. In the case of the asymmetric models, however, this differential disappears by the end of the projection period because the rebound effect falls essentially to zero due to the strong effect of variable *pm_cut* in reducing the rebound effect.

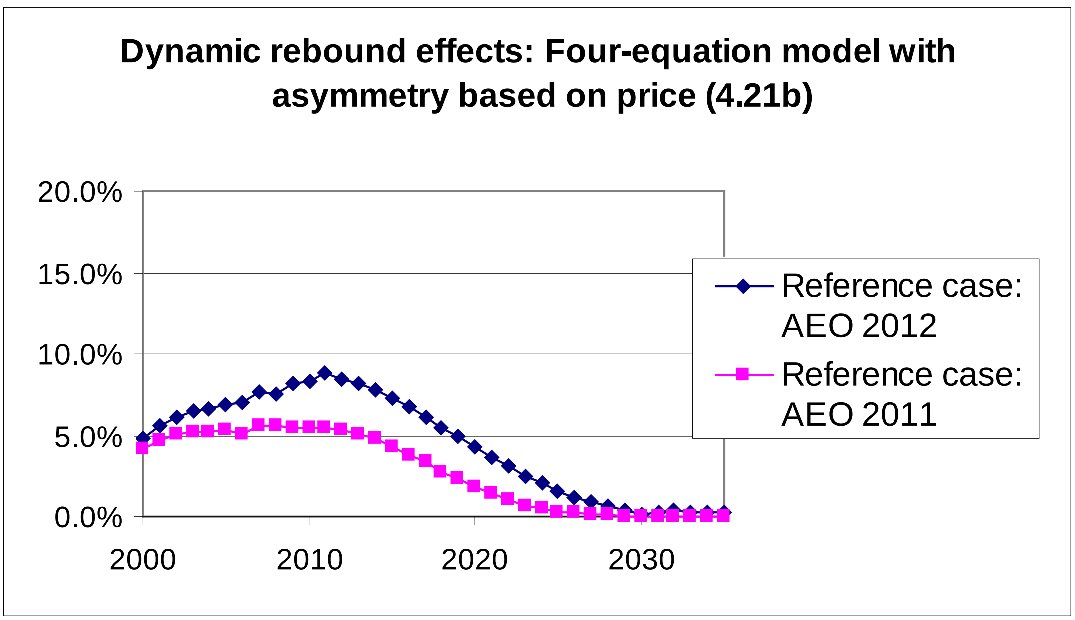
**Figure 5.5**
**Comparisons of projections using AEO2011 and AEO2012**
**(a) Three-equation models**



**(b) Four-equation models**



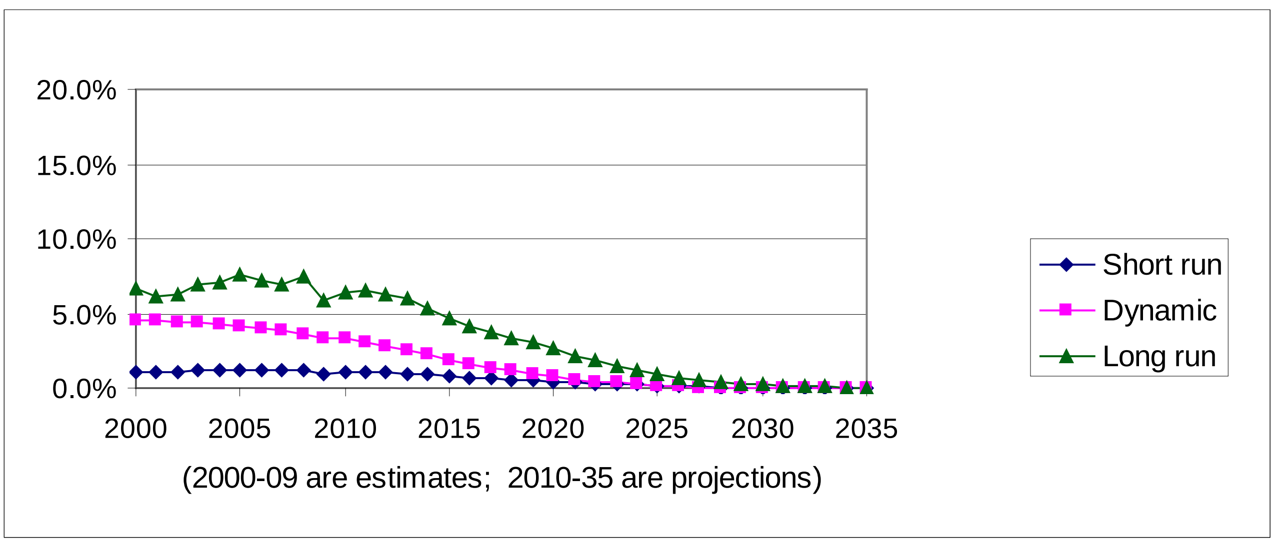

## 5.2 Results: Projections using models with media variable

Table 5.5 and Figure 5.6 show the results of projecting Model 3.35. Because the media variable is specified so that it affects the response of VMT to price but not to fuel efficiency, its only impact on the projections is the way it changes other coefficients. As it happens, the only notable effect it has is to lessen the impact of future changes in fuel cost per mile, whose effect on projections is not very large anyhow except in the "high oil price" case. Thus, the projections for the AEO reference case are little different from those with the corresponding model without media variable (Model 3.21b): they are slightly lower during the early part of the regulatory period, leading to a "regulated average" dynamic rebound effect of 0.7%.

**Table 5.5**
**Projection results for model with media coverage variable:**
**Three-equation model**

| | Historical | ---Projected--- | | | | | Regulated average |
|---|---|---|---|---|---|---|---|
| | 2000-2009 | 2010 | 2017 | 2025 | 2030 | 2035 | 2017-2025 |
| **Model 3.21b** | | | | | | | |
| Short Run Rebound | 0.7% | 1.0% | 0.8% | 0.2% | 0.0% | 0.0% | 0.4% |
| Dynamic Rebound | NA | 4.2% | **2.3%** | **0.2%** | 0.0% | 0.0% | **1.0%** |
| Long Run Rebound | 4.2% | 5.8% | 4.5% | 1.0% | 0.2% | 0.0% | 2.7% |
| **Model 3.35** | | | | | | | |
| Short Run Rebound | 0.7% | 1.1% | 0.6% | 0.2% | 0.0% | 0.0% | 0.4% |
| Dynamic Rebound | NA | 3.3% | 1.4% | 0.2% | 0.0% | 0.0% | **0.7%** |
| Long Run Rebound | 4.2% | 6.4% | 3.7% | 0.9% | 0.2% | 0.0% | 2.2% |

**Figure 5.6**
**Projection results for model with media coverage variable:**
**Three-equation model**



In the four-equation model, the media variable has virtually no effect on results, so the projections would be essentially the same as in Model 4.21b.

We do not project the rebound effect using the models containing price volatility, because we do not have an obvious way to forecast volatility. Nor is any significant volatility included in the AEO forecasts. Nevertheless, one can expect the future to contain some periods of stability and some of volatility, causing the rebound effect to fluctuate in some unknown manner around the trends we have projected.

## 6. Conclusions

The research reported here confirms the findings of previous studies that the long-run rebound effect, measured over a period of several decades extending back to 1966, is 28–30% (Table 4.3). We also find a short-run (one-year) rebound effect of 4.6–4.7%, which is harder to compare to previous studies because previous work contains so much variation depending on the treatment of dynamics and of CAFE regulations.

This research also provides strong evidence that the rebound effect became substantially lower in more recent years, and that probably this was due to a combination of higher real incomes, lower real fuel costs, and higher urbanization. Because time spent in travel rises with urbanization and its attendant congestion, and the value of that time rises with incomes, all three of these differences tend to make fuel costs a smaller portion of the total cost of traveling. Thus it is not surprising that people would become less sensitive, on a percentage basis, to changes in those fuel costs. Our base model implies that the long-run rebound effect was 15-18% on average over the years 2000-2009 (Table 4.3). Projections suggest that the effect of income is very strong, reducing the long-run rebound effect from about 11-14% in 2010 to 3-5% in 2035, according to the base model (Figure 5.1)

There is strong evidence of asymmetry in responsiveness to price increases and decreases. This makes interpretation of the rebound effect somewhat more difficult, because it accentuates the unresolved question as to whether travelers respond to a change in fuel efficiency in the same way as to a change in fuel price. Different assumptions lead to quite different implications for detailed projections. Still, the overall tendency of the results is to show that the rebound effect is likely to be moderate, and to decline with income. Furthermore, accounting for asymmetry greatly reduces the rebound effect when it is identified, as seems plausible, with the observed response to fuel price declines. For example, using the AEO 2011 reference case, the projected dynamic rebound effect averaged over the years 2017-2025 and averaged between the three-equation and four-equation models is 7.8% using a symmetric model, but only 1.3 percent using the preferred asymmetric model (Table 5.4).

There is weaker evidence that media coverage, and perhaps recent fuel-price volatility, also affect travelers' responsiveness to changes in fuel cost. This evidence tends to confirm expectations that such variables are important, but it is not conclusive at this point. Furthermore, it does not undermine the most important finding of this and earlier work, which is that the rebound effect will decline over time as incomes rise.

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## Appendix A. Calculation of Dynamic Rebound Effect

The dynamic rebound takes into account that interacting variables, especially income and fuel price, are changing over the course of the life of a vehicle—even its life beyond the projection period which ends in 2035. It is calculated by projecting the dynamic adjustment process that is implied by the estimated equations but allowing the "target" amount of travel to change each year according to actual or projected conditions (income, fuel price, and urbanization and/or congestion) for that year—using actual data from my data sources for 2000-2009 and data from the AEO projections for 2010-2035. (The projection data are adjusted to match the estimation data for years 2008-2009, so that projections are consistent with the estimated equations.)

This "target" is based on an adjustment to the typical mileage for a vehicle of a given age, as derived from the National Personal Travel Survey (NPTS) and reported by the Transportation Energy Data Book, ed. 29, Table 8.9. The adjustment occurs from two sources: changes in the interaction variables that determine the long-run rebound effect, and the assumed unit change in fuel cost per mile resulting from a policy. The adjustment is derived from the equations for the structural elasticity of mileage with respect to fuel cost per mile ($\varepsilon_{M.\,PM}$ in the source papers), which is influenced directly by the interaction variables according to their estimated coefficients, and from the equation that converts $\varepsilon_{M.\,PM}$ into a long-run rebound effect.[34] The actual mileage of a vehicle purchased in year $t$ in a subsequent year $t+\tau$, where $\tau$ is the age of the vehicle, is projected as the weighted average of the previous year's mileage, adjusted for the natural evolution due to the age-mileage profile, and the target mileage, which is based on the age-mileage profile and the long-term rebound elasticity; the weights in taking this average are $\alpha_m$ and $(1-\alpha_m)$, respectively, where $\alpha_m$ is the coefficient of the lagged dependent variable in the estimated equation for vehicle-miles per adult. (This notation conforms with the two papers just cited in the footnote.)

The actual procedure used to compute the dynamic rebound effect has three steps:

• First, the short-run rebound effect is recomputed for each year assuming that all variables *except fuel efficiency* change as in the projection being considered.[35] This projects the desired short-run response that would occur for the owner of a vehicle whose fuel efficiency remains fixed as it ages, but who faces other changes (income, fuel price, urbanization, congestion) that

[34] Those equations are equation (7) in Small and Van Dender (2007) and equations (14a) and (15) in Hymel, Small, and Van Dender (2010).

[35] Our projections are through year 2035. Vehicles sold in the later years of the projection will last beyond 2035, and for those years we use 2035 values of interacting variables to compute the short-run rebound effect applying to these vehicles as they age.

affect the owner's response. [36] The resulting change over the vehicle's lifetime is denoted by $\Delta\breve{b}^{S}{}_{t,\tau} = \breve{b}^{S}{}_{t+\tau} - \breve{b}^{S}{}_{t}$, where $t$ is the year of purchase and $\tau$ is the vehicle's age.

• Simultaneously, these changes in short-run rebound as the vehicle ages are converted to the corresponding change in structural elasticity using equation (11a) of Hymel et al. (2010), and that in turn is converted to a change in long-run target response using equation (14a) of the same paper:

$$\hat{b}^{L}{}_{t+\tau} = b^{L}{}_{t} + \left(\hat{b}^{S}{}_{t+\tau} - b^{S}{}_{t}\right)\cdot\frac{D}{D^{L}}$$

where $b^{L}{}_{t}$ is the long-run rebound for year $t$ as already calculated, and $D$ and $D^L$ are quantities defined in Hymel et al.'s equation which account for effects of the equations for vehicle fleet size and vehicle fuel efficiency when computing the short- and long-run rebound effects, respectively. As an approximation, we assume the conversion factors $D$ and $D^L$ are constant, although they actually change very slightly over time. The ratio $D/D^L$ is actually very close to the simple multiplier, $1/(1-\alpha^m)$, which converts a short-run to a long-run response.[37]

• Finally, the baseline age-mileage profile mentioned earlier, denoted by $M_{\tau}{}^{0}$ for ages $\tau$=0,1, …, 15, is used as the starting point for changes in mileage over each year of the vehicle's age.[38] The computation assumes a unit increase in fuel cost per mile. (The size and sign of the change in fuel cost per mile is immaterial because the equations are linear so they lead to the same answer once one divides by that change.) The projected mileage after response to the change in fuel cost per mile, for a new car purchased in year $t$, is the weighted average described earlier:

$$M_{\tau} = \alpha^{m} M_{\tau-1}\frac{M^{0}{}_{\tau}}{M^{0}{}_{\tau-1}} + (1-\alpha^{m})(1-\breve{b}^{L}{}_{t+\tau})M_{\tau}{}^{0}$$

[36] Because of the form of the estimating equations, which are linear in logarithms even accounting for interaction variables, this calculation depends only very slightly on which year's fuel efficiency is chosen to hold constant: namely, it depends on it through the truncation that occurs for those few state-year combinations that would otherwise lead to a positive projected elasticity of VMT with respect to fuel cost (those values are truncated at zero). Thus for the projections starting in 2010, the computation is simplified by assuming fuel efficiency is held constant at its projected value for 2020; for the historical computations for 2000-2009, it is held constant at its actual value for 2005.

[37] The equations for $D$ and $D^L$ in Hymel et al. (2010) are for the four-equation version of the model; they are also valid for the 3-equation version, simply by setting the coefficient $\alpha^{cm}$, which is absent in the latter, equal to zero.

[38] The age-mileage profile is derived from the National Personal Travel Survey (NPTS) and reported in the Transportation Energy Data Book, ed. 29, Table 8.9.

This is computed iteratively; for year 0 (the year the vehicle is purchased), the simple short-run response as already projected is used:

$$M_0 = (1 - b^S{}_t)M^0{}_t$$

In these equations, *b* is a "rebound effect" defined as the negative of the relevant elasticity, so is normally positive (or zero, if truncated); this is why it appears with a minus sign in the equation.

## Appendix B. Coefficient estimates

### Table B1. Coefficient estimates: Symmetric and asymmetric models

### (a) Three-equation models

| | | Model 3.3 | | Model 3.18 | | Model 3.20b | | Model 3.21b | | | Model 3.23 | | | Model 3.29 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Equation | Variable | Coeff. | Std. Error | Coeff. | Std. Error | Coeff. | Std. Error | | Coeff. | Std. Error | | Coeff. | Std. Error | | Coeff. | Std. Error |
| vma | intercept | 1.6261 | 0.1022 | 1.6771 | 0.1035 | 2.2568 | 0.4424 | | 3.1468 | 0.3541 | | 3.3926 | 0.5490 | | 2.8829 | 0.5547 |
| vma | income | 0.0781 | 0.0117 | 0.0782 | 0.0117 | 0.0814 | 0.0117 | | 0.0770 | 0.0118 | | 0.0792 | 0.0120 | | 0.0783 | 0.0128 |
| vma | adults per road mile | -0.0149 | 0.0038 | -0.0147 | 0.0038 | -0.0147 | 0.0037 | | -0.0151 | 0.0037 | | -0.0200 | 0.0041 | | -0.0080 | 0.0043 |
| vma | popratio | 0.0726 | 0.0322 | 0.0836 | 0.0325 | 0.0804 | 0.0329 | | 0.0630 | 0.0323 | | 0.0732 | 0.0334 | | 0.1077 | 0.0416 |
| vma | Urban | -0.0205 | 0.0391 | -0.0372 | 0.0395 | -0.0211 | 0.0388 | | -0.0061 | 0.0395 | | 0.0021 | 0.0407 | | 0.0492 | 0.0455 |
| vma | Railpop | -0.0067 | 0.0043 | -0.0053 | 0.0043 | -0.0080 | 0.0043 | | -0.0082 | 0.0042 | | -0.0061 | 0.0045 | | -0.0095 | 0.0048 |
| vma | D7479 | -0.0439 | 0.0034 | -0.0436 | 0.0034 | -0.0432 | 0.0034 | | -0.0445 | 0.0035 | | -0.0425 | 0.0034 | | -0.0374 | 0.0043 |
| vma | Trend | -0.0004 | 0.0002 | -0.0003 | 0.0002 | 0.0002 | 0.0004 | | 0.0013 | 0.0004 | | 0.0013 | 0.0006 | | 0.0010 | 0.0005 |
| vma | vma(-1) | 0.8346 | 0.0102 | 0.8279 | 0.0105 | 0.8256 | 0.0105 | | 0.8334 | 0.0104 | | 0.8084 | 0.0122 | | 0.8802 | 0.0119 |
| vma | vehstock | 0.0209 | 0.0067 | 0.0238 | 0.0068 | 0.0202 | 0.0067 | | 0.0161 | 0.0067 | | 0.0203 | 0.0070 | | 0.0195 | 0.0074 |
| vma | pf+fint | **-0.0466** | 0.0029 | **-0.0464** | 0.0029 | **-0.0520** | 0.0046 | pf+fint | **-0.0639** | 0.0049 | pf+fint | -0.0623 | 0.0055 | pmrise_hat | **-0.1134** | 0.0153 |
| vma | pm^2 | **-0.0124** | 0.0059 | **-0.0113** | 0.0060 | **-0.0159** | 0.0061 | | **-0.0207** | 0.0061 | | -0.0180 | 0.0062 | pm^2 | **-0.0276** | 0.0068 |
| vma | pm*inc | **0.0528** | 0.0108 | **0.0699** | 0.0121 | **0.0569** | 0.0108 | | **0.0577** | 0.0107 | | 0.0535 | 0.0112 | pm*Income | **0.0281** | 0.0120 |
| vma | pm*Urban | 0.0119 | 0.0094 | 0.0078 | 0.0096 | 0.0124 | 0.0093 | | 0.0131 | 0.0093 | | 0.0187 | 0.0099 | pm*Urban | **0.0273** | 0.0103 |
| vma | pm*(dummy 2003-09) | | | **-0.0251** | 0.0076 | | | | | | | | | | | |
| vma | pfcut | | | | | **0.0124** | 0.0093 | pfcut + fint | **0.0340** | 0.0078 | pmcut_hat | 0.0284 | 0.0093 | pmcut_hat | **-0.0037** | 0.0105 |
| vma | | | | | | | | | | | | | | pmrise_hat(-1) | **0.0490** | 0.0216 |
| vma | | | | | | | | | | | | | | pmrise_hat(-2) | **0.0210** | 0.0129 |
| vma | | | | | | | | | | | | | | pmcut_hat(-1) | **-0.0486** | 0.0141 |
| vma | | | | | | | | | | | | | | pmcut_hat(-2) | **0.0171** | 0.0150 |
| vma | | | | | | | | | | | | | | pmcut_hat(-3) | **0.0239** | 0.0108 |
| vma | AR(1) | -0.1018 | 0.0204 | | | -0.1038 | 0.0205 | | -0.1021 | 0.0204 | | -0.0978 | 0.0215 | | -0.1203 | 0.0215 |
| veh | intercept | -0.2253 | 0.1452 | -0.2188 | 0.1451 | -0.2174 | 0.1450 | | -0.2188 | 0.1449 | | -0.2232 | 0.1451 | | -0.2016 | 0.1662 |
| veh | pnewcar | 0.0400 | 0.0317 | 0.0376 | 0.0317 | 0.0432 | 0.0317 | | 0.0460 | 0.0317 | | 0.0444 | 0.0317 | | 0.0716 | 0.0352 |
| veh | interest | -0.0008 | 0.0042 | -0.0011 | 0.0042 | -0.0006 | 0.0042 | | -0.0004 | 0.0042 | | -0.0003 | 0.0042 | | -0.0066 | 0.0053 |
| veh | income | 0.0032 | 0.0146 | 0.0033 | 0.0146 | 0.0037 | 0.0146 | | 0.0038 | 0.0146 | | 0.0036 | 0.0146 | | -0.0057 | 0.0163 |
| veh | Adults per road mile | -0.0136 | 0.0060 | -0.0135 | 0.0060 | -0.0137 | 0.0060 | | -0.0137 | 0.0060 | | -0.0138 | 0.0060 | | -0.0149 | 0.0070 |
| veh | licenses/adult | 0.0345 | 0.0184 | 0.0344 | 0.0183 | 0.0345 | 0.0183 | | 0.0349 | 0.0183 | | 0.0339 | 0.0184 | | 0.0345 | 0.0220 |
| veh | trend | 0.0002 | 0.0007 | 0.0002 | 0.0007 | 0.0003 | 0.0007 | | 0.0004 | 0.0007 | | 0.0004 | 0.0007 | | 0.0008 | 0.0008 |
| veh | vehstock(-1) | 0.9318 | 0.0104 | 0.9323 | 0.0104 | 0.9319 | 0.0104 | | 0.9316 | 0.0104 | | 0.9316 | 0.0104 | | 0.9233 | 0.0114 |
| veh | vma | 0.0291 | 0.0147 | 0.0285 | 0.0147 | 0.0281 | 0.0147 | | 0.0281 | 0.0146 | | 0.0286 | 0.0147 | | 0.0279 | 0.0167 |
| veh | pm | 0.0013 | 0.0058 | 0.0009 | 0.0058 | 0.0015 | 0.0058 | | 0.0019 | 0.0058 | | 0.0017 | 0.0058 | | 0.0045 | 0.0062 |
| veh | AR(1) | -0.1461 | 0.0230 | 0.0376 | 0.0317 | -0.1464 | 0.0230 | | -0.1469 | 0.0230 | | -0.1461 | 0.0230 | | -0.1473 | 0.0244 |
| fint | intercept | -0.2447 | 0.0631 | -0.2577 | 0.0631 | 2.4538 | 1.0475 | | 0.9282 | 1.0517 | | 1.1934 | 1.2081 | | -0.3690 | 1.2382 |
| fint | pf + vma | -0.0050 | 0.0041 | -0.0052 | 0.0041 | -0.0185 | 0.0057 | pf + vma | -0.0097 | 0.0060 | pfrise | -0.0133 | 0.0062 | pfrise | -0.0108 | 0.0064 |
| fint | income | -0.0016 | 0.0144 | -0.0009 | 0.0144 | -0.0048 | 0.0145 | | 0.0000 | 0.0146 | | -0.0041 | 0.0151 | | 0.0069 | 0.0158 |
| fint | fint(-1) | 0.9040 | 0.0100 | 0.9036 | 0.0100 | 0.9140 | 0.0109 | | 0.8977 | 0.0115 | | 0.9106 | 0.0128 | | 0.8577 | 0.0135 |
| fint | Population Ratio | -0.0168 | 0.0603 | 0.0154 | 0.0602 | -0.0160 | 0.0592 | | -0.0005 | 0.0586 | | -0.0073 | 0.0594 | | 0.0645 | 0.0664 |
| fint | Trend66-73 | 0.0005 | 0.0011 | 0.0006 | 0.0011 | 0.0005 | 0.0011 | | -0.0005 | 0.0011 | | 0.0001 | 0.0012 | | 0.0011 | 0.0065 |
| fint | Trend74-79 | -0.0068 | 0.0010 | -0.0060 | 0.0010 | -0.0058 | 0.0011 | | -0.0061 | 0.0011 | | -0.0057 | 0.0011 | | -0.0046 | 0.0012 |
| fint | Trend80+ | -0.0007 | 0.0003 | -0.0007 | 0.0003 | 0.0008 | 0.0007 | | -0.0002 | 0.0007 | | 0.0001 | 0.0007 | | -0.0013 | 0.0007 |
| fint | D7479 | -0.0070 | 0.0048 | -0.0082 | 0.0048 | -0.0041 | 0.0048 | | -0.0032 | 0.0048 | | -0.0046 | 0.0048 | | -0.0077 | 0.0048 |
| fint | Urban | -0.0905 | 0.0467 | -0.0869 | 0.0467 | -0.0778 | 0.0470 | | -0.0890 | 0.0471 | | -0.0828 | 0.0463 | | -0.1213 | 0.0532 |
| fint | cafe | -0.0345 | 0.0108 | -0.0402 | 0.0108 | -0.0202 | 0.0186 | | -0.0256 | 0.0183 | | -0.0312 | 0.0185 | | -0.0875 | 0.0188 |
| fint | pfcut | | | | | 0.0316 | 0.0124 | pfcut + vma | 0.0143 | 0.0123 | pfcut | 0.0042 | 0.0096 | pfcut | -0.0154 | 0.0097 |
| fint | | | | | | | | | | | vma | 0.0107 | 0.0166 | vma | -0.0533 | 0.0179 |
| fint | AR(1) | -0.1773 | 0.0201 | -0.1756 | 0.0201 | -0.1822 | 0.0201 | | -0.1804 | 0.0202 | | -0.1807 | 0.0202 | | -0.1837 | 0.0216 |

## (b) Four-equation models

| Equation | Variable | Model 4.3 | | Model 4.13 | | Model 4.20b | | | Model 4.21b | | | Model 4.23 | | | Model 4.29 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Equation | Variable | Coeff. | Std. Err. | Coeff. | Std. Err. | Coefficient | Std. Error | | Coefficient | Std. Error | | Coefficien | Std. Error | | Coefficient | Std. Error |
| vma | intercept | 1.6801 | 0.1066 | 1.7249 | 0.1078 | 2.1693 | 0.4400 | | 3.1388 | 0.3529 | | 3.4021 | 0.4991 | | 1.8244 | 0.5610 |
| vma | inc | 0.0835 | 0.0117 | 0.0839 | 0.0117 | 0.0847 | 0.0117 | | 0.0807 | 0.0119 | | 0.0781 | 0.0120 | | 0.0827 | 0.0127 |
| vma | congestion | 0.0014 | 0.0027 | 0.0014 | 0.0027 | 0.0032 | 0.0026 | | 0.0016 | 0.0026 | | -0.0001 | 0.0028 | | 0.0076 | 0.0031 |
| vma | cong*inc | -0.0156 | 0.0032 | -0.0146 | 0.0032 | -0.0134 | 0.0031 | | -0.0131 | 0.0031 | | -0.0166 | 0.0033 | | -0.0234 | 0.0042 |
| vma | cong*pm | -0.0031 | 0.0022 | -0.0032 | 0.0022 | -0.0013 | 0.0021 | | -0.0016 | 0.0021 | | -0.0042 | 0.0022 | pmrise_hat*cong | -0.0046 | 0.0029 |
| vma | D7479 | -0.0430 | 0.0034 | -0.0429 | 0.0034 | -0.0430 | 0.0034 | | -0.0441 | 0.0035 | | -0.0441 | 0.0035 | | -0.0401 | 0.0044 |
| vma | Trend | -0.0003 | 0.0002 | -0.0002 | 0.0002 | 0.0000 | 0.0005 | | 0.0013 | 0.0005 | | 0.0014 | 0.0005 | | 0.0003 | 0.0006 |
| vma | vma(-1) | 0.8249 | 0.0105 | 0.8189 | 0.0107 | 0.8221 | 0.0107 | | 0.8305 | 0.0107 | | 0.8229 | 0.0112 | | 0.8656 | 0.0125 |
| vma | vehstock | 0.0276 | 0.0065 | 0.0308 | 0.0066 | 0.0282 | 0.0066 | | 0.0242 | 0.0066 | | 0.0274 | 0.0067 | | 0.0146 | 0.0079 |
| vma | pm | -0.0461 | 0.0030 | **-0.0460** | 0.0030 | -0.0498 | 0.0046 | | -0.0629 | 0.0049 | | -0.0615 | 0.0054 | pmrise_hat | -0.1068 | 0.0159 |
| vma | pm^2 | -0.0224 | 0.0060 | **-0.0186** | 0.0061 | -0.0225 | 0.0061 | | -0.0275 | 0.0061 | | -0.0245 | 0.0063 | pmrise_hat*pm | -0.0005 | 0.0002 |
| vma | pm*inc | 0.0561 | 0.0111 | **0.0721** | 0.0121 | 0.0548 | 0.0111 | | 0.0573 | 0.0110 | | 0.0534 | 0.0115 | pmrise+hat*inc | 0.0394 | 0.0129 |
| vma | popratio | 0.1201 | 0.0384 | 0.1289 | 0.0386 | 0.1006 | 0.0419 | | 0.1010 | 0.0410 | | 0.1437 | 0.0394 | | 0.1763 | 0.0487 |
| vma | urban | -0.0842 | 0.0413 | -0.0980 | 0.0416 | -0.0694 | 0.0409 | | -0.0589 | 0.0415 | | -0.0763 | 0.0419 | | -0.0499 | 0.0500 |
| vma | road miles/land area | 0.0180 | 0.0065 | 0.0173 | 0.0066 | 0.0181 | 0.0065 | | 0.0155 | 0.0066 | | 0.0181 | 0.0067 | | 0.0234 | 0.0086 |
| vma | pm*(dummy for 2003-09) | | | **-0.0237** | 0.0071 | | | | | | | | | | | |
| vma | pfcut | | | | | 0.0100 | 0.0093 | pfcut+fint | 0.0340 | 0.0079 | pmcut_hat | 0.0325 | 0.0091 | pmcut_hat | -0.0051 | 0.0108 |
| vma | | | | | | | | | | | | | | pmrise_hat(-1) | 0.0426 | 0.0229 |
| vma | | | | | | | | | | | | | | pmrise_hat(-2) | 0.0343 | 0.0137 |
| vma | | | | | | | | | | | | | | pmcut_hat(-1) | -0.0540 | 0.0149 |
| vma | | | | | | | | | | | | | | pmcut_hat(-2) | 0.0161 | 0.0163 |
| vma | | | | | | | | | | | | | | pmcut_hat(-3) | 0.0233 | 0.0117 |
| vma | AR(1) | -0.0900 | 0.0207 | -0.0856 | 0.0208 | -0.0901 | 0.0207 | | -0.0888 | 0.0206 | | -0.0932 | 0.0212 | | -0.1106 | 0.0227 |
| vehstock | intercept | -0.3535 | 0.1422 | -0.3516 | 0.1422 | -0.3569 | 0.1421 | | -0.3554 | 0.1421 | | -0.3653 | 0.1422 | | -0.3608 | 0.1419 |
| vehstock | pnewcar | 0.0418 | 0.0317 | 0.0392 | 0.0317 | 0.0430 | 0.0317 | | 0.0445 | 0.0317 | | 0.0412 | 0.0318 | | 0.0416 | 0.0317 |
| vehstock | interest | -0.0033 | 0.0040 | -0.0036 | 0.0040 | -0.0032 | 0.0040 | | -0.0030 | 0.0040 | | -0.0030 | 0.0040 | | -0.0031 | 0.0040 |
| vehstock | income | 0.0044 | 0.0146 | 0.0043 | 0.0146 | 0.0043 | 0.0146 | | 0.0044 | 0.0146 | | 0.0041 | 0.0146 | | 0.0043 | 0.0146 |
| vehstock | urban | -0.0420 | 0.0465 | -0.0424 | 0.0465 | -0.0418 | 0.0465 | | -0.0416 | 0.0465 | | -0.0424 | 0.0466 | | -0.0423 | 0.0465 |
| vehstock | licenses/adult | 0.0441 | 0.0178 | 0.0440 | 0.0178 | 0.0442 | 0.0178 | | 0.0445 | 0.0178 | | 0.0438 | 0.0178 | | 0.0441 | 0.0178 |
| vehstock | trend | 0.0000 | 0.0007 | -0.0001 | 0.0007 | 0.0000 | 0.0007 | | 0.0000 | 0.0007 | | -0.0001 | 0.0007 | | 0.0000 | 0.0007 |
| vehstock | vehstock(-1) | 0.9354 | 0.0102 | 0.9357 | 0.0102 | 0.9353 | 0.0102 | | 0.9351 | 0.0102 | | 0.9348 | 0.0102 | | 0.9347 | 0.0102 |
| vehstock | vma | 0.0384 | 0.0143 | 0.0384 | 0.0143 | 0.0387 | 0.0143 | | 0.0384 | 0.0143 | | 0.0396 | 0.0143 | | 0.0391 | 0.0143 |
| vehstock | pm | 0.0028 | 0.0057 | 0.0025 | 0.0057 | 0.0030 | 0.0057 | | 0.0032 | 0.0057 | | 0.0028 | 0.0058 | | 0.0030 | 0.0057 |
| vehstock | rho | -0.1468 | 0.0230 | -0.1471 | 0.0230 | -0.1468 | 0.0230 | | -0.1471 | 0.0230 | | -0.1458 | 0.0230 | | -0.1464 | 0.0230 |
| fint | intercept | -0.3202 | 0.0618 | -0.3191 | 0.0619 | 0.4210 | 0.9482 | | -1.0263 | 0.9488 | | 0.7587 | 1.0646 | | 2.0808 | 1.0989 |
| fint | pf + vma | -0.0074 | 0.0041 | -0.0075 | 0.0041 | -0.0125 | 0.0055 | | -0.0041 | 0.0058 | prfise | -0.0122 | 0.0063 | prfise | -0.0144 | 0.0063 |
| fint | inc | -0.0002 | 0.0143 | -0.0002 | 0.0143 | 0.0021 | 0.0144 | | 0.0064 | 0.0144 | | 0.0005 | 0.0149 | | 0.0087 | 0.0149 |
| fint | fint(-1) | 0.8894 | 0.0102 | 0.8900 | 0.0102 | 0.8950 | 0.0106 | | 0.8805 | 0.0111 | | 0.9108 | 0.0117 | | 0.8904 | 0.0123 |
| fint | Trend66-73 | 0.0013 | 0.0009 | 0.0013 | 0.0010 | 0.0011 | 0.0010 | | 0.0001 | 0.0010 | | 0.0010 | 0.0010 | | 0.0016 | 0.0012 |
| fint | Trend74-79 | -0.0038 | 0.0008 | -0.0037 | 0.0008 | -0.0028 | 0.0009 | | -0.0034 | 0.0009 | | -0.0048 | 0.0010 | | -0.0045 | 0.0010 |
| fint | Trend80+ | -0.0010 | 0.0003 | -0.0010 | 0.0003 | -0.0005 | 0.0006 | | -0.0014 | 0.0006 | | 0.0004 | 0.0006 | | 0.0007 | 0.0006 |
| fint | 7479 dummy | -0.0118 | 0.0047 | -0.0119 | 0.0047 | -0.0088 | 0.0047 | | -0.0078 | 0.0047 | | -0.0033 | 0.0046 | | -0.0027 | 0.0046 |
| fint | Urban | -0.0847 | 0.0468 | -0.0839 | 0.0468 | -0.0801 | 0.0470 | | -0.0919 | 0.0471 | | -0.0724 | 0.0462 | | -0.0775 | 0.0459 |
| fint | cafe | -0.0607 | 0.0103 | -0.0601 | 0.0103 | -0.0678 | 0.0158 | | -0.0714 | 0.0155 | | 0.0064 | 0.0158 | | -0.0171 | 0.0172 |
| fint | popratio | 0.1096 | 0.0556 | 0.1130 | 0.0557 | 0.1293 | 0.0562 | | 0.1302 | 0.0556 | | 0.1744 | 0.0542 | | 0.1555 | 0.0575 |
| fint | pfcut+vma | | | | | 0.0085 | 0.0112 | pfcut+vma | -0.0080 | 0.0112 | pfcut | 0.0024 | 0.0086 | pfcut | 0.0267 | 0.0118 |
| fint | | | | | | | | | | | vma | 0.0210 | 0.0152 | vma | -0.0081 | 0.0153 |
| fint | rho | -0.1694 | 0.0201 | -0.1691 | 0.0201 | -0.1702 | 0.0201 | | -0.1691 | 0.0202 | | -0.1753 | 0.0198 | | -0.1795 | 0.0209 |
| cong | intercept | -3.8401 | 0.9940 | -3.8457 | 0.9940 | -4.1046 | 0.9274 | | -4.0860 | 0.9273 | | -4.6094 | 0.9904 | | -4.3021 | 0.9677 |
| cong | urban-lane-miles/adult | -0.6926 | 0.1316 | -0.6931 | 0.1316 | -0.6057 | 0.1102 | | -0.6058 | 0.1102 | | -0.7682 | 0.1296 | | -0.7034 | 0.1233 |
| cong | (vehicle miles/adult)+log(u | 0.2258 | 0.0885 | 0.2263 | 0.0885 | 0.2825 | 0.0860 | | 0.2799 | 0.0860 | | 0.2914 | 0.0900 | | 0.2886 | 0.0896 |
| cong | population / state land are | 0.6121 | 0.0520 | 0.6119 | 0.0520 | 0.5900 | 0.0490 | | 0.5908 | 0.0490 | | 0.6424 | 0.0521 | | 0.6517 | 0.0516 |
| cong | percent trucks | 0.4597 | 0.2062 | 0.4594 | 0.2062 | 0.4622 | 0.1983 | | 0.4634 | 0.1983 | | 0.4061 | 0.2093 | | 0.3840 | 0.2081 |
| cong | urban | -4.3113 | 0.3550 | -4.3124 | 0.3550 | -4.0385 | 0.3434 | | -4.0331 | 0.3434 | | -4.6372 | 0.3616 | | -4.6468 | 0.3604 |

## Table B2. Coefficient estimates: models with media and uncertainty variables

## (a) Three-equation models

| Equation | Variable | Model 3.21b Coeff. | Model 3.21b Std. Error | | Model 3.35 Coeff. | Model 3.35 Std. Error | | Model 3.37 Coeff. | Model 3.37 Std. Error | | Model 3.42 Coeff. | Model 3.42 Std. Error | | Model 3.45 Coeff. | Model 3.45 Std. Error |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| vma | intercept | 3.1468 | 0.3541 | | 2.9103 | 0.3668 | | 3.1487 | 0.3810 | | 3.9416 | 0.4020 | | 2.6376 | 0.3750 |
| vma | inc | 0.0770 | 0.0118 | | 0.0830 | 0.0121 | | 0.0828 | 0.0123 | | 0.0746 | 0.0121 | | 0.0912 | 0.0127 |
| vma | Adults / road mile | -0.0151 | 0.0037 | | -0.0142 | 0.0038 | | -0.0145 | 0.0039 | | -0.0140 | 0.0038 | | -0.0155 | 0.0042 |
| vma | popratio | 0.0630 | 0.0323 | | 0.0725 | 0.0328 | | 0.0786 | 0.0334 | | 0.1462 | 0.0376 | | 0.1205 | 0.0368 |
| vma | Urban | -0.0061 | 0.0395 | | -0.0114 | 0.0400 | | -0.0231 | 0.0407 | | -0.0132 | 0.0401 | | -0.0333 | 0.0407 |
| vma | Railpop | -0.0082 | 0.0042 | | -0.0084 | 0.0043 | | -0.0076 | 0.0044 | | -0.0065 | 0.0043 | | -0.0052 | 0.0048 |
| vma | D7479 | -0.0445 | 0.0035 | | -0.0440 | 0.0035 | | -0.0436 | 0.0035 | | -0.0429 | 0.0035 | | -0.0278 | 0.0043 |
| vma | Trend | 0.0013 | 0.0004 | | 0.0011 | 0.0005 | | 0.0014 | 0.0005 | | 0.0024 | 0.0005 | | 0.0006 | 0.0005 |
| vma | vma(-1) | 0.8334 | 0.0104 | | 0.8325 | 0.0106 | | 0.8276 | 0.0109 | | 0.8321 | 0.0108 | | 0.8247 | 0.0117 |
| vma | vehstock | 0.0161 | 0.0067 | | 0.0162 | 0.0068 | | 0.0181 | 0.0070 | | 0.0185 | 0.0069 | | 0.0253 | 0.0075 |
| vma | pf+fint | -0.0639 | 0.0049 | pf +fint | -0.0587 | 0.0052 | pf +fint | -0.0641 | 0.0057 | pf +fint | 3.9959 | 0.0069 | pf +fint | -0.0666 | 0.0053 |
| vma | pm^2 | -0.0207 | 0.0061 | | -0.0053 | 0.0075 | | -0.0064 | 0.0075 | | -0.0126 | 0.0070 | | -0.0302 | 0.0081 |
| vma | pm*inc | 0.0577 | 0.0107 | | 0.0583 | 0.0109 | | 0.0711 | 0.0126 | | 0.0779 | 0.0124 | | 0.0807 | 0.0136 |
| vma | pm*Urban | 0.0131 | 0.0093 | | 0.0118 | 0.0094 | | 0.0100 | 0.0097 | | 0.0091 | 0.0095 | | 0.0118 | 0.0106 |
| vma | pfcut + fint | 0.0340 | 0.0078 | pfcut + fint | 0.0286 | 0.0081 | pfcut + fint | **0.0332** | 0.0083 | pfcut + fint | **0.0529** | 0.0091 | pfcut + fint | **0.0210** | 0.0083 |
| vma | Media variable | | | pf * Media_dummy | -0.0301 | 0.0101 | pf * Media_dummy | **-0.0319** | 0.0101 | pf*Media_dummy | **-0.0316** | 0.0101 | pf_rise * Articles | **-0.2680** | 0.0544 |
| vma | pm*(dummy 2003-09)[a] | | | | | | | -0.0216 | 0.0079 | | -0.0265 | 0.0078 | | -0.0347 | 0.0084 |
| vma | Fuel price variance | | | | | | | | | pm*log(pf_var) | **0.0028** | 0.0007 | pm*log(pf_var) | **0.0081** | 0.0024 |
| vma | AR(1) | -0.1021 | 0.0204 | | -0.0969 | 0.0206 | | -0.0894 | 0.0209 | | -0.0960 | 0.0207 | | -0.0780 | 0.0221 |
| | | | | | | | | | | | | | | | |
| veh | intercept | -0.2188 | 0.1449 | | -0.2117 | 0.1449 | | -0.1996 | 0.1445 | | -0.2249 | 0.1443 | | -0.1865 | 0.1380 |
| veh | pnewcar | 0.0460 | 0.0317 | | 0.0449 | 0.0317 | | 0.0434 | 0.0317 | | 0.0423 | 0.0317 | | 0.0400 | 0.0316 |
| veh | interest | -0.0004 | 0.0042 | | -0.0002 | 0.0042 | | -0.0004 | 0.0042 | | -0.0004 | 0.0042 | | -0.0006 | 0.0042 |
| veh | income | 0.0038 | 0.0146 | | 0.0039 | 0.0146 | | 0.0043 | 0.0146 | | 0.0033 | 0.0146 | | 0.0045 | 0.0145 |
| veh | adults / road mile | -0.0137 | 0.0060 | | -0.0139 | 0.0060 | | -0.0139 | 0.0060 | | -0.0136 | 0.0060 | | -0.0137 | 0.0060 |
| veh | licenses/adult | 0.0349 | 0.0183 | | 0.0348 | 0.0183 | | 0.0346 | 0.0183 | | 0.0355 | 0.0183 | | 0.0350 | 0.0183 |
| veh | trend | 0.0004 | 0.0007 | | 0.0004 | 0.0007 | | 0.0003 | 0.0007 | | 0.0003 | 0.0007 | | 0.0003 | 0.0007 |
| veh | vehstock(-1) | 0.9316 | 0.0104 | | 0.9316 | 0.0104 | | 0.9319 | 0.0104 | | 0.9314 | 0.0104 | | 0.9324 | 0.0104 |
| veh | vma | 0.0281 | 0.0146 | | 0.0274 | 0.0146 | | 0.0262 | 0.0146 | | 0.0289 | 0.0146 | | 0.0250 | 0.0139 |
| veh | pm | 0.0019 | 0.0058 | | 0.0016 | 0.0058 | | 0.0012 | 0.0058 | | 0.0014 | 0.0058 | | 0.0000 | 0.0058 |
| veh | AR(1) | -0.1469 | 0.0230 | | -0.1469 | 0.0230 | | -0.1475 | 0.0230 | | -0.1466 | 0.0230 | | -0.1469 | 0.0230 |
| | | | | | | | | | | | | | | | |
| fint | intercept | 0.9282 | 1.0517 | | 1.6171 | 1.0241 | | 0.8319 | 1.0025 | | 0.0017 | 0.9813 | | -2.1591 | 0.9725 |
| fint | pf + vma | -0.0097 | 0.0060 | pf + vma | -0.0124 | 0.0059 | pf + vma | -0.0104 | 0.0058 | pf + vma | -0.0079 | 0.0058 | pf + vma | -0.0033 | 0.0058 |
| fint | inc | 0.0000 | 0.0146 | | -0.0031 | 0.0145 | | -0.0003 | 0.0145 | | 0.0050 | 0.0144 | | 0.0038 | 0.0144 |
| fint | fint(-1) | 0.8977 | 0.0115 | | 0.9070 | 0.0115 | | 0.9009 | 0.0115 | | 0.8930 | 0.0112 | | 0.8881 | 0.0116 |
| fint | popratio | -0.0005 | 0.0586 | | -0.0391 | 0.0590 | | 0.0020 | 0.0585 | | 0.0070 | 0.0583 | | 0.0813 | 0.0615 |
| fint | Trend66-73 | -0.0005 | 0.0011 | | 0.0000 | 0.0011 | | -0.0002 | 0.0011 | | -0.0017 | 0.0011 | | 0.0010 | 0.0012 |
| fint | Trend74-79 | -0.0061 | 0.0011 | | -0.0075 | 0.0011 | | -0.0063 | 0.0011 | | -0.0045 | 0.0010 | | -0.0037 | 0.0011 |
| fint | Trend80+ | -0.0002 | 0.0007 | | 0.0005 | 0.0007 | | -0.0001 | 0.0007 | | -0.0009 | 0.0006 | | -0.0019 | 0.0006 |
| fint | D7479 | -0.0032 | 0.0048 | | -0.0015 | 0.0048 | | -0.0031 | 0.0048 | | -0.0049 | 0.0047 | | -0.0097 | 0.0047 |
| fint | Urban | -0.0890 | 0.0471 | | -0.0872 | 0.0470 | | -0.0876 | 0.0468 | | -0.0920 | 0.0467 | | -0.0921 | 0.0466 |
| fint | cafe | -0.0256 | 0.0183 | | -0.0023 | 0.0172 | | -0.0210 | 0.0169 | | -0.0592 | 0.0166 | | -0.0879 | 0.0165 |
| fint | pfcut | 0.0143 | 0.0123 | pfCut + vma | 0.0220 | 0.0120 | pfCut + vma | 0.0129 | 0.0118 | PFCut + VMA | 0.0031 | 0.0115 | PFCut + VMA | -0.0225 | 0.0114 |
| fint | AR(1) | -0.1804 | 0.0202 | | -0.1851 | 0.0202 | | -0.1810 | 0.0202 | | -0.1786 | 0.0202 | | -0.167898 | 0.021329 |

[a]dummy is normalized

## (b) Four-equation models

| Equation | Variable | Model 4.21b Coeff. | Model 4.21b Std. Error | Model 4.35 | Model 4.35 Coeff. | Model 4.35 Std. Error | Model 4.37 | Model 4.37 Coeff. | Model 4.37 Std. Error | Model 4.42 | Model 4.42 Coeff. | Model 4.42 Std. Error | Model 4.45 | Model 4.45 Coeff. | Model 4.45 Std. Error |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| vma | intercept | 3.1388 | 0.3529 | | 3.1737 | 0.3555 | | 3.5432 | 0.3653 | | 3.8758 | 0.3711 | | 4.2917 | 0.3752 |
| vma | inc | 0.0807 | 0.0119 | | 0.0791 | 0.0119 | | 0.0794 | 0.0119 | | 0.0652 | 0.0122 | | 0.0683 | 0.0123 |
| vma | cong | 0.0016 | 0.0026 | | 0.0011 | 0.0027 | | 0.0006 | 0.0027 | | -0.0004 | 0.0027 | | 0.0019 | 0.0027 |
| vma | cong*income | -0.0131 | 0.0031 | | -0.0144 | 0.0032 | | -0.0128 | 0.0032 | | -0.0117 | 0.0032 | | -0.0137 | 0.0032 |
| vma | cong*pm | -0.0016 | 0.0021 | | -0.0025 | 0.0021 | | -0.0028 | 0.0021 | | -0.0044 | 0.0021 | | -0.0057 | 0.0021 |
| vma | 7479 dummy | -0.0441 | 0.0035 | | -0.0445 | 0.0035 | | -0.0444 | 0.0035 | | -0.0467 | 0.0035 | | -0.0320 | 0.0042 |
| vma | trend | 0.0013 | 0.0005 | | 0.0014 | 0.0005 | | 0.0019 | 0.0005 | | 0.0024 | 0.0005 | | 0.0027 | 0.0005 |
| vma | vma(-1) | 0.8305 | 0.0107 | | 0.8314 | 0.0106 | | 0.8221 | 0.0109 | | 0.8275 | 0.0109 | | 0.8423 | 0.0112 |
| vma | vehstock | 0.0242 | 0.0066 | | 0.0236 | 0.0065 | | 0.0277 | 0.0066 | | 0.0268 | 0.0066 | | 0.0299 | 0.0066 |
| vma | pm | -0.0629 | 0.0049 | PM | -0.0638 | 0.0050 | PM | -0.0729 | 0.0054 | PM | -0.0706 | 0.0054 | PM | -0.0719 | 0.0053 |
| vma | pm^2 | -0.0275 | 0.0061 | | -0.0296 | 0.0065 | | -0.0263 | 0.0066 | | 0.0037 | 0.0085 | | -0.0114 | 0.0074 |
| vma | pm*inc | 0.0573 | 0.0110 | | 0.0575 | 0.0110 | | 0.0825 | 0.0122 | | 0.0944 | 0.0124 | | 0.0905 | 0.0124 |
| vma | popratio | 0.1010 | 0.0410 | | 0.1093 | 0.0397 | | 0.1248 | 0.0399 | | 0.0669 | 0.0414 | | 0.0581 | 0.0410 |
| vma | urban | -0.0589 | 0.0415 | | -0.0639 | 0.0415 | | -0.0828 | 0.0419 | | -0.0967 | 0.0420 | | -0.0801 | 0.0422 |
| vma | road miles/state land area | 0.0155 | 0.0066 | | 0.0148 | 0.0065 | | 0.0133 | 0.0066 | | 0.0111 | 0.0066 | | 0.0103 | 0.0066 |
| vma | pfcut + fint | 0.0340 | 0.0079 | pfcut+fint | 0.0352 | 0.0080 | pfcut+fint | 0.0420 | 0.0081 | pfcut+fint | 0.0506 | 0.0083 | pfcut+fint | 0.0626 | 0.0085 |
| vma | Media variable | | | pf * Media_dummy | 0.0061 | 0.0058 | pf * Media_dummy | 0.0071 | 0.0058 | pf*Media_dummy | **-0.0080** | 0.0063 | PF_rise * Articles | **-0.3117** | 0.0490 |
| vma | pm*(dummy 2003-09)[a] | | | | | | | -0.0359 | 0.0071 | | -0.0308 | 0.0072 | | -0.0321 | 0.0072 |
| vma | Fuel price variance | | | | | | | | | pm*log(pf_var) | **-0.0100** | 0.0019 | PM * log(pf_var) | **-0.0044** | 0.0019 |
| vma | AR(1) | -0.0888 | 0.0206 | | -0.0913 | 0.0206 | | -0.0840 | 0.0207 | | -0.0849 | 0.0206 | | -0.0838 | 0.0205 |
| vehstock | intercept | -0.3554 | 0.1421 | | -0.3577 | 0.1421 | | -0.3557 | 0.1420 | | -0.3592 | 0.1420 | | -0.3689 | 0.1420 |
| vehstock | pnewcar | 0.0445 | 0.0317 | | 0.0443 | 0.0317 | | 0.0412 | 0.0317 | | 0.0403 | 0.0318 | | 0.0400 | 0.0318 |
| vehstock | interest | -0.0030 | 0.0040 | | -0.0030 | 0.0040 | | -0.0035 | 0.0040 | | -0.0038 | 0.0040 | | -0.0039 | 0.0040 |
| vehstock | income | 0.0044 | 0.0146 | | 0.0043 | 0.0146 | | 0.0042 | 0.0146 | | 0.0041 | 0.0146 | | 0.0037 | 0.0146 |
| vehstock | urban | -0.0416 | 0.0465 | | -0.0417 | 0.0465 | | -0.0421 | 0.0465 | | -0.0425 | 0.0465 | | -0.0427 | 0.0465 |
| vehstock | licenses/adult | 0.0445 | 0.0178 | | 0.0446 | 0.0178 | | 0.0445 | 0.0178 | | 0.0444 | 0.0178 | | 0.0443 | 0.0178 |
| vehstock | trend | 0.0000 | 0.0007 | | 0.0000 | 0.0007 | | -0.0001 | 0.0007 | | -0.0001 | 0.0007 | | -0.0001 | 0.0007 |
| vehstock | vehstock(-1) | 0.9351 | 0.0102 | | 0.9350 | 0.0102 | | 0.9354 | 0.0102 | | 0.9354 | 0.0102 | | 0.9355 | 0.0102 |
| vehstock | vma | 0.0384 | 0.0143 | | 0.0387 | 0.0143 | | 0.0387 | 0.0143 | | 0.0391 | 0.0143 | | 0.0402 | 0.0143 |
| vehstock | pm | 0.0032 | 0.0057 | | 0.0031 | 0.0057 | | 0.0028 | 0.0057 | | 0.0028 | 0.0057 | | 0.0029 | 0.0057 |
| vehstock | rho | -0.1471 | 0.0230 | | -0.1469 | 0.0230 | | -0.1474 | 0.0230 | | -0.1467 | 0.0230 | | -0.1468 | 0.0230 |
| fint | intercept | -1.0263 | 0.9488 | | -0.6026 | 0.9380 | | -0.5382 | 0.9373 | | -0.5531 | 0.9355 | | -1.4809 | 0.9456 |
| fint | pf + vma | -0.0041 | 0.0058 | pf + vma | -0.0060 | 0.0057 | pf + vma | -0.0059 | 0.0057 | pf + vma | -0.0049 | 0.0057 | pf + vma | -0.0035 | 0.0057 |
| fint | inc | 0.0064 | 0.0144 | | 0.0064 | 0.0144 | | 0.0066 | 0.0144 | | 0.0046 | 0.0144 | | 0.0029 | 0.0144 |
| fint | fint(-1) | 0.8805 | 0.0111 | | 0.8833 | 0.0110 | | 0.8823 | 0.0110 | | 0.8749 | 0.0112 | | 0.8686 | 0.0112 |
| fint | Trend66-73 | 0.0001 | 0.0010 | | 0.0002 | 0.0010 | | 0.0000 | 0.0010 | | 0.0009 | 0.0010 | | 0.0016 | 0.0010 |
| fint | Trend74-79 | -0.0034 | 0.0009 | | -0.0037 | 0.0009 | | -0.0035 | 0.0009 | | -0.0036 | 0.0009 | | -0.0035 | 0.0009 |
| fint | Trend80+ | -0.0014 | 0.0006 | | -0.0010 | 0.0006 | | -0.0010 | 0.0006 | | -0.0010 | 0.0006 | | -0.0015 | 0.0006 |
| fint | 7479 dummy | -0.0078 | 0.0047 | | -0.0069 | 0.0047 | | -0.0068 | 0.0047 | | -0.0071 | 0.0046 | | -0.0087 | 0.0046 |
| fint | urban | -0.0919 | 0.0471 | | -0.0896 | 0.0470 | | -0.0894 | 0.0470 | | -0.0898 | 0.0470 | | -0.0952 | 0.0471 |
| fint | cafep | -0.0714 | 0.0155 | | -0.0585 | 0.0148 | | -0.0583 | 0.0148 | | -0.0554 | 0.0148 | | -0.0747 | 0.0145 |
| fint | popratio | 0.1302 | 0.0556 | | 0.1330 | 0.0553 | | 0.1360 | 0.0553 | | 0.1700 | 0.0556 | | 0.1640 | 0.0554 |
| fint | pfcut+vma | -0.0080 | 0.0112 | pfcut+vma | -0.0031 | 0.0110 | pfcut+vma | -0.0022 | 0.0110 | pfcut+vma | -0.0018 | 0.0110 | pfcut+vma | -0.0129 | 0.0111 |
| fint | rho | -0.1691 | 0.0202 | | -0.1706 | 0.0202 | | -0.1704 | 0.0202 | | -0.1697 | 0.0203 | | -0.1681 | 0.0204 |
| cong | intercept | -4.0860 | 0.9273 | | -3.9180 | 0.9530 | | -3.8896 | 0.9664 | | -3.8874 | 0.9650 | | -4.3568 | 0.9984 |
| cong | urban-lane-miles/adult | -0.6058 | 0.1102 | | -0.6394 | 0.1176 | | -0.6352 | 0.1217 | | -0.6311 | 0.1209 | | -0.7236 | 0.1269 |
| cong | (vehicle miles/adult)+log(ur | 0.2799 | 0.0860 | | 0.2546 | 0.0872 | | 0.2533 | 0.0872 | | 0.2552 | 0.0871 | | 0.2682 | 0.0882 |
| cong | population / state land area | 0.5908 | 0.0490 | | 0.6062 | 0.0502 | | 0.6088 | 0.0504 | | 0.6103 | 0.0503 | | 0.6056 | 0.0509 |
| cong | percent trucks | 0.4634 | 0.1983 | | 0.4554 | 0.2016 | | 0.4506 | 0.2020 | | 0.4493 | 0.2018 | | 0.4685 | 0.2037 |
| cong | urban | -4.0331 | 0.3434 | | -4.2241 | 0.3484 | | -4.2191 | 0.3485 | | -4.2251 | 0.3483 | | -4.3221 | 0.3514 |

[a]dummy is normalized

# Appendix C. Detailed yearly projections

## Model 3.3:

| | ---Calculated using values of variables from historical data--- | | | | | | | | ---Calculated using values of variables from AEO--- | | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 | 2025 | 2026 | 2027 | 2028 | 2029 | 2030 | 2031 | 2032 | 2033 | 2034 | 2035 |
| **Reference Case** | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| Short Run Rebound | 2.3% | 2.1% | 2.1% | 2.4% | 2.6% | 2.9% | 3.0% | 3.0% | 3.3% | 2.5% | 2.8% | 2.9% | 2.8% | 2.8% | 2.8% | 2.7% | 2.5% | 2.4% | 2.4% | 2.3% | 2.2% | 2.0% | 2.0% | 1.8% | 1.8% | 1.6% | 1.5% | 1.5% | 1.4% | 1.3% | 1.2% | 1.1% | 1.0% | 0.9% | 0.9% | 0.8% |
| Dynamic Rebound | 11.1% | 11.3% | 11.5% | 11.8% | 12.0% | 12.0% | 12.0% | 11.8% | 11.7% | 11.4% | 11.4% | 11.1% | 10.8% | 10.5% | 10.1% | 9.6% | 9.2% | **8.8%** | **8.3%** | **7.9%** | **7.4%** | **6.9%** | **6.5%** | **6.1%** | **5.7%** | **5.3%** | 4.9% | 4.6% | 4.3% | 4.0% | 3.8% | 3.6% | 3.5% | 3.4% | 3.3% | 3.2% |
| Long Run Rebound | 14.7% | 13.1% | 13.0% | 14.9% | 16.4% | 18.4% | 18.8% | 19.0% | 20.7% | 15.9% | 17.6% | 18.1% | 17.7% | 17.9% | 17.4% | 16.7% | 15.9% | 15.4% | 14.9% | 14.4% | 13.7% | 12.9% | 12.3% | 11.5% | 11.0% | 10.2% | 9.6% | 9.1% | 8.5% | 8.0% | 7.2% | 6.7% | 6.2% | 5.7% | 5.3% | 4.8% |
| **High Oil Price Case** | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| Short Run Rebound | 2.3% | 2.1% | 2.1% | 2.4% | 2.6% | 2.9% | 3.0% | 3.0% | 3.3% | 2.5% | 2.8% | 3.3% | 3.5% | 3.6% | 3.5% | 3.4% | 3.3% | 3.3% | 3.2% | 3.2% | 3.1% | 2.9% | 2.8% | 2.7% | 2.6% | 2.5% | 2.4% | 2.3% | 2.2% | 2.1% | 2.0% | 1.9% | 1.8% | 1.7% | 1.6% | 1.5% |
| Dynamic Rebound | 11.5% | 11.8% | 12.3% | 12.8% | 13.2% | 13.5% | 13.7% | 13.9% | 14.0% | 14.1% | 14.4% | 14.5% | 14.4% | 14.1% | 13.7% | 13.3% | 12.9% | 12.5% | 12.0% | 11.6% | 11.1% | 10.6% | 10.1% | 9.6% | 9.3% | 8.8% | 8.4% | 8.1% | 7.8% | 7.5% | 7.2% | 7.0% | 6.8% | 6.6% | 6.5% | 6.4% |
| Long Run Rebound | 14.7% | 13.1% | 13.0% | 14.9% | 16.4% | 18.4% | 18.8% | 19.0% | 20.7% | 15.9% | 17.6% | 20.8% | 22.1% | 22.6% | 22.2% | 21.7% | 21.0% | 20.8% | 20.4% | 19.9% | 19.3% | 18.6% | 17.6% | 17.0% | 16.3% | 15.7% | 14.9% | 14.2% | 13.6% | 13.1% | 12.4% | 11.9% | 11.3% | 10.8% | 10.2% | 9.6% |
| **Low Oil Price Case** | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| Short Run Rebound | 2.3% | 2.1% | 2.1% | 2.4% | 2.6% | 2.9% | 3.0% | 3.0% | 3.3% | 2.5% | 2.8% | 2.4% | 2.2% | 2.1% | 1.9% | 1.7% | 1.5% | 1.4% | 1.3% | 1.2% | 1.2% | 0.9% | 0.8% | 0.7% | 0.6% | 0.5% | 0.4% | 0.4% | 0.4% | 0.3% | 0.3% | 0.2% | 0.2% | 0.1% | 0.1% | 0.0% |
| Dynamic Rebound | 10.6% | 10.6% | 10.7% | 10.7% | 10.6% | 10.4% | 10.0% | 9.5% | 8.9% | 8.2% | 7.8% | 7.1% | 6.5% | 6.0% | 5.5% | 4.9% | 4.5% | **4.0%** | **3.5%** | **3.0%** | **2.6%** | **2.1%** | **1.8%** | **1.4%** | **1.2%** | **1.0%** | 0.8% | 0.6% | 0.5% | 0.3% | 0.1% | 0.1% | -0.1% | 0.1% | 0.1% | 0.2% |
| Long Run Rebound | 14.7% | 13.1% | 13.0% | 14.9% | 16.4% | 18.4% | 18.8% | 19.0% | 20.7% | 15.9% | 17.6% | 14.8% | 13.8% | 12.9% | 11.8% | 10.6% | 9.6% | 8.7% | 8.1% | 7.4% | 7.4% | 5.5% | 4.7% | 4.0% | 3.7% | 3.1% | 2.7% | 2.4% | 2.2% | 1.8% | 1.6% | 0.9% | 1.0% | 0.4% | 0.3% | 0.3% |

## Model 3.21b:

| | ---Calculated using values of variables from historical data--- | | | | | | | | ---Calculated using values of variables from AEO--- | | | | | | | | | | | | | | ---Calculated using values of variables from AEO--- | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 | 2025 | 2026 | 2027 | 2028 | 2029 | 2030 | 2031 | 2032 | 2033 | 2034 | 2035 |
| **Reference Case** | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| Short Run Rebound | 0.4% | 0.1% | 0.1% | 0.2% | 0.5% | 1.0% | 1.2% | 1.3% | 1.7% | 0.6% | 1.0% | 1.1% | 1.0% | 1.1% | 1.0% | 0.9% | 0.8% | 0.8% | 0.7% | 0.6% | 0.5% | 0.4% | 0.4% | 0.3% | 0.2% | 0.2% | 0.1% | 0.1% | 0.1% | 0.1% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| Dynamic Rebound | 3.1% | 3.4% | 3.7% | 4.1% | 4.4% | 4.6% | 4.6% | 4.6% | 4.4% | 4.2% | 4.2% | 4.2% | 4.0% | 3.8% | 3.5% | 3.0% | 2.7% | 2.3% | 1.9% | 1.6% | 1.2% | 0.9% | 0.7% | 0.5% | 0.3% | 0.2% | 0.1% | 0.1% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| Long Run Rebound | 2.2% | 0.8% | 0.6% | 1.4% | 3.2% | 6.2% | 7.3% | 8.0% | 10.5% | 3.3% | 5.8% | 6.5% | 6.1% | 6.6% | 6.2% | 5.6% | 4.9% | 4.5% | 4.0% | 3.7% | 3.2% | 2.6% | 2.2% | 1.7% | 1.4% | 1.0% | 0.7% | 0.6% | 0.4% | 0.3% | 0.2% | 0.1% | 0.1% | 0.1% | 0.1% | 0.0% |
| **High Oil Price Case** | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| Short Run Rebound | 0.4% | 0.1% | 0.1% | 0.2% | 0.5% | 1.0% | 1.2% | 1.3% | 1.7% | 0.6% | 0.9% | 1.7% | 2.1% | 2.3% | 2.2% | 2.2% | 2.1% | 2.1% | 2.0% | 1.9% | 1.8% | 1.7% | 1.5% | 1.4% | 1.3% | 1.2% | 1.1% | 0.9% | 0.8% | 0.8% | 0.7% | 0.6% | 0.5% | 0.5% | 0.4% | 0.3% |
| Dynamic Rebound | 3.7% | 4.3% | 4.9% | 5.6% | 6.3% | 6.9% | 7.4% | 7.8% | 8.1% | 8.4% | 8.5% | 9.3% | 9.4% | 9.2% | 8.8% | 8.4% | 8.0% | 7.5% | 7.0% | 6.4% | 5.9% | 5.3% | 4.7% | 4.2% | 3.8% | 3.4% | 2.9% | 2.5% | 2.2% | 1.9% | 1.7% | 1.5% | 1.4% | 1.3% | 1.3% | 1.3% |
| Long Run Rebound | 2.2% | 0.8% | 0.6% | 1.4% | 3.2% | 6.2% | 7.3% | 8.0% | 10.5% | 3.3% | 5.7% | 10.6% | 12.9% | 14.0% | 13.7% | 13.4% | 12.6% | 12.7% | 12.2% | 11.8% | 11.1% | 10.4% | 9.2% | 8.6% | 7.8% | 7.2% | 6.3% | 5.7% | 5.0% | 4.5% | 3.9% | 3.5% | 3.1% | 2.8% | 2.3% | 1.9% |
| **Low Oil Price Case** | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| Short Run Rebound | 0.4% | 0.1% | 0.1% | 0.2% | 0.5% | 1.0% | 1.2% | 1.3% | 1.7% | 0.6% | 1.0% | 0.4% | 0.3% | 0.2% | 0.1% | 0.1% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| Dynamic Rebound | 2.5% | 2.6% | 2.8% | 2.9% | 2.9% | 2.8% | 2.5% | 2.1% | 1.6% | 1.0% | 2.0% | 1.2% | 0.8% | 0.5% | 0.3% | 0.1% | 0.1% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| Long Run Rebound | 2.2% | 0.8% | 0.6% | 1.4% | 3.2% | 6.2% | 7.3% | 8.0% | 10.5% | 3.3% | 5.7% | 2.5% | 1.6% | 1.1% | 0.6% | 0.3% | 0.2% | 0.1% | 0.1% | 0.0% | 0.1% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |

## Model 3.35 (Reference case):

| | ---Calculated using values of variables from historical data--- | | | | | | | | | | | | | | | | | | | ---Calculated using values of variables from AEO--- | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 | 2025 | 2026 | 2027 | 2028 | 2029 | 2030 | 2031 | 2032 | 2033 | 2034 | 2035 |
| Short Run Rebound | 1.1% | 1.0% | 1.0% | 1.1% | 1.2% | 1.3% | 1.2% | 1.2% | 1.2% | 1.0% | 1.1% | 1.1% | 1.0% | 1.0% | 0.9% | 0.8% | 0.7% | 0.6% | 0.6% | 0.5% | 0.4% | 0.4% | 0.3% | 0.3% | 0.2% | 0.2% | 0.1% | 0.1% | 0.1% | 0.1% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| Dynamic Rebound | 4.5% | 4.5% | 4.4% | 4.4% | 4.3% | 4.2% | 4.0% | 3.8% | 3.6% | 3.4% | 3.3% | 3.0% | 2.8% | 2.5% | 2.2% | 1.9% | 1.6% | 1.4% | 1.2% | 1.0% | 0.8% | 0.6% | 0.5% | 0.3% | 0.2% | 0.2% | 0.1% | 0.1% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| Long Run Rebound | 6.6% | 6.1% | 6.3% | 6.9% | 7.0% | 7.6% | 7.3% | 7.0% | 7.5% | 5.9% | 6.4% | 6.5% | 6.3% | 6.0% | 5.4% | 4.7% | 4.1% | 3.7% | 3.3% | 3.0% | 2.6% | 2.2% | 1.8% | 1.5% | 1.2% | 0.9% | 0.7% | 0.5% | 0.4% | 0.3% | 0.2% | 0.2% | 0.1% | 0.1% | 0.0% | 0.0% |

# Model 4.3:

| | ---Calculated using values of variables from historical data--- | | | | | | | | ---Calculated using values of variables from AEO--- | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 |
| **Reference Case** | | | | | | | | | | | | | | | | | | |
| Short Run Rebound | 2.0% | 1.6% | 1.4% | 1.9% | 2.5% | 3.1% | 3.3% | 3.4% | 3.9% | 2.5% | 3.0% | 3.2% | 3.1% | 3.2% | 3.2% | 3.1% | 2.9% | 2.9% |
| Dynamic Rebound | 11.7% | 12.0% | 12.2% | 12.5% | 12.7% | 12.9% | 12.8% | 13.1% | 13.5% | 13.2% | 13.2% | 13.1% | 12.9% | 12.5% | 12.2% | 11.7% | 11.2% | 10.7% |
| Long Run Rebound | 12.1% | 9.2% | 8.0% | 11.4% | 14.7% | 18.6% | 20.0% | 20.8% | 23.5% | 14.9% | 18.2% | 19.0% | 18.7% | 19.3% | 19.0% | 18.4% | 17.6% | 17.2% |
| **High Oil Price Case** | | | | | | | | | | | | | | | | | | |
| Short Run Rebound | 2.0% | 1.6% | 1.4% | 1.9% | 2.5% | 3.1% | 3.3% | 3.4% | 3.9% | 2.5% | 3.0% | 3.9% | 4.3% | 4.5% | 4.5% | 4.5% | 4.3% | 4.4% |
| Dynamic Rebound | 12.8% | 13.5% | 14.1% | 14.9% | 15.6% | 16.3% | 16.7% | 17.7% | 17.7% | 18.1% | 18.6% | 19.1% | 19.2% | 19.0% | 18.6% | 18.3% | 17.8% | 17.4% |
| Long Run Rebound | 12.1% | 9.2% | 8.0% | 11.4% | 14.7% | 18.6% | 20.0% | 20.8% | 23.5% | 14.9% | 18.1% | 23.8% | 26.2% | 27.5% | 27.3% | 27.1% | 26.3% | 26.5% |
| **Low Oil Price Case** | | | | | | | | | | | | | | | | | | |
| Short Run Rebound | 2.0% | 1.6% | 1.4% | 1.9% | 2.5% | 3.1% | 3.3% | 3.4% | 3.9% | 2.5% | 3.0% | 2.2% | 2.0% | 1.8% | 1.6% | 1.4% | 1.2% | 1.0% |
| Dynamic Rebound | 10.4% | 10.3% | 10.1% | 9.8% | 9.5% | 9.1% | 8.2% | 7.9% | 8.6% | 7.6% | 6.9% | 6.0% | 5.3% | 4.7% | 4.1% | 3.4% | 2.9% | 2.4% |
| Long Run Rebound | 12.1% | 9.2% | 8.0% | 11.4% | 14.7% | 18.6% | 20.0% | 20.8% | 23.5% | 14.9% | 18.1% | 13.3% | 11.7% | 10.6% | 9.4% | 7.9% | 6.8% | 5.8% |

| | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 | 2025 | 2026 | 2027 | 2028 | 2029 | 2030 | 2031 | 2032 | 2033 | 2034 | 2035 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Reference Case** | | | | | | | | | | | | | | | | | | |
| Short Run Rebound | 2.8% | 2.7% | 2.6% | 2.4% | 2.3% | 2.2% | 2.1% | 2.0% | 1.9% | 1.8% | 1.7% | 1.6% | 1.5% | 1.3% | 1.3% | 1.2% | 1.1% | 1.0% |
| Dynamic Rebound | 10.2% | 9.7% | 9.1% | 8.6% | 8.1% | 7.6% | 7.1% | 6.6% | 6.2% | 5.8% | 5.4% | 5.0% | 4.7% | 4.5% | 4.3% | 4.1% | 4.0% | 3.9% |
| Long Run Rebound | 16.6% | 16.2% | 15.4% | 14.4% | 13.9% | 13.0% | 12.5% | 11.6% | 11.0% | 10.6% | 9.8% | 9.4% | 8.3% | 7.7% | 7.1% | 6.5% | 6.2% | 5.6% |
| **High Oil Price Case** | | | | | | | | | | | | | | | | | | |
| Short Run Rebound | 4.3% | 4.2% | 4.1% | 4.0% | 3.8% | 3.7% | 3.6% | 3.5% | 3.4% | 3.3% | 3.1% | 3.1% | 2.9% | 2.9% | 2.8% | 2.7% | 2.6% | 2.5% |
| Dynamic Rebound | 16.8% | 16.3% | 15.7% | 15.1% | 14.5% | 14.0% | 13.5% | 13.0% | 12.5% | 12.1% | 11.7% | 11.4% | 11.0% | 10.8% | 10.5% | 10.3% | 10.1% | 9.9% |
| Long Run Rebound | 26.1% | 25.7% | 25.1% | 24.3% | 23.1% | 22.5% | 21.7% | 21.1% | 20.2% | 19.5% | 18.8% | 18.3% | 17.5% | 17.0% | 16.3% | 15.8% | 15.1% | 14.5% |
| **Low Oil Price Case** | | | | | | | | | | | | | | | | | | |
| Short Run Rebound | 0.9% | 0.8% | 0.9% | 0.4% | 0.3% | 0.2% | 0.2% | 0.1% | 0.1% | 0.1% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| Dynamic Rebound | 1.8% | 1.3% | 0.8% | 0.4% | 0.3% | 0.2% | 0.1% | 0.1% | 0.1% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| Long Run Rebound | 5.1% | 4.2% | 4.7% | 2.0% | 1.4% | 1.0% | 0.9% | 0.4% | 0.3% | 0.2% | 0.2% | 0.1% | 0.1% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |

# Model 4.21b:

| | ---Calculated using values of variables from historical data--- | | | | | | | | ------------Calculated using values of variables from AEO--------------- | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 |
| **Reference Case** | | | | | | | | | | | | | | | | | | |
| Short Run Rebound | 0.2% | 0.0% | 0.0% | 0.1% | 0.4% | 1.1% | 1.4% | 1.6% | 2.1% | 0.5% | 1.1% | 1.3% | 1.2% | 1.3% | 1.3% | 1.2% | 1.1% | 1.0% |
| Dynamic Rebound | 4.1% | 4.7% | 5.1% | 5.2% | 5.2% | 5.3% | 5.1% | 5.5% | 5.6% | 5.4% | 5.4% | 5.5% | 5.3% | 5.1% | 4.8% | 4.3% | 3.8% | 3.3% |
| Long Run Rebound | 0.9% | 0.1% | 0.0% | 0.4% | 2.2% | 6.5% | 8.4% | 9.5% | 13.0% | 3.0% | 6.4% | 7.4% | 7.1% | 7.9% | 7.7% | 7.1% | 6.3% | 5.9% |
| **High Oil Price Case** | | | | | | | | | | | | | | | | | | |
| Short Run Rebound | 0.2% | 0.0% | 0.0% | 0.1% | 0.4% | 1.1% | 1.4% | 1.6% | 2.1% | 0.5% | 1.1% | 2.2% | 2.7% | 2.9% | 2.9% | 2.9% | 2.8% | 2.8% |
| Dynamic Rebound | 5.5% | 6.5% | 7.4% | 8.1% | 8.7% | 9.4% | 9.9% | 11.1% | 10.7% | 11.3% | 11.8% | 12.9% | 13.1% | 12.9% | 12.5% | 12.2% | 11.7% | 11.3% |
| Long Run Rebound | 0.9% | 0.1% | 0.0% | 0.4% | 2.2% | 6.5% | 8.4% | 9.5% | 13.0% | 3.0% | 6.3% | 13.3% | 16.4% | 18.1% | 18.0% | 17.8% | 17.0% | 17.4% |
| **Low Oil Price Case** | | | | | | | | | | | | | | | | | | |
| Short Run Rebound | 0.2% | 0.0% | 0.0% | 0.1% | 0.4% | 1.1% | 1.4% | 1.6% | 2.1% | 0.5% | 1.1% | 0.3% | 0.2% | 0.1% | 0.0% | 0.0% | 0.0% | 0.0% |
| Dynamic Rebound | 2.9% | 3.1% | 3.1% | 2.8% | 2.3% | 2.0% | 1.3% | 1.2% | 1.6% | 0.8% | 2.5% | 0.9% | 0.4% | 0.2% | 0.1% | 0.0% | 0.0% | 0.0% |
| Long Run Rebound | 0.9% | 0.1% | 0.0% | 0.4% | 2.2% | 6.5% | 8.4% | 9.5% | 13.0% | 3.0% | 6.3% | 1.6% | 0.7% | 0.4% | 0.2% | 0.1% | 0.0% | 0.0% |

| | | | | | ---------------Calculated using values of variables from AEO--------------- | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 | 2025 | 2026 | 2027 | 2028 | 2029 | 2030 | 2031 | 2032 | 2033 | 2034 | 2035 |
| **Reference Case** | | | | | | | | | | | | | | | | | | |
| Short Run Rebound | 0.9% | 0.9% | 0.7% | 0.6% | 0.5% | 0.4% | 0.4% | 0.3% | 0.2% | 0.2% | 0.1% | 0.1% | 0.1% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| Dynamic Rebound | 2.8% | 2.3% | 1.8% | 1.4% | 1.0% | 0.7% | 0.5% | 0.3% | 0.2% | 0.1% | 0.1% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| Long Run Rebound | 5.4% | 4.9% | 4.2% | 3.3% | 2.9% | 2.2% | 1.9% | 1.4% | 1.0% | 0.9% | 0.6% | 0.5% | 0.2% | 0.1% | 0.1% | 0.1% | 0.1% | 0.0% |
| **High Oil Price Case** | | | | | | | | | | | | | | | | | | |
| Short Run Rebound | 2.8% | 2.7% | 2.6% | 2.5% | 2.3% | 2.2% | 2.0% | 1.9% | 1.8% | 1.6% | 1.5% | 1.4% | 1.3% | 1.2% | 1.1% | 1.0% | 0.9% | 0.8% |
| Dynamic Rebound | 10.6% | 10.0% | 9.4% | 8.8% | 8.1% | 7.5% | 7.0% | 6.5% | 5.9% | 5.4% | 5.0% | 4.6% | 4.3% | 4.0% | 3.7% | 3.4% | 3.3% | 3.1% |
| Long Run Rebound | 16.9% | 16.5% | 15.9% | 15.1% | 13.8% | 13.1% | 12.2% | 11.6% | 10.6% | 9.8% | 9.0% | 8.5% | 7.7% | 7.1% | 6.5% | 5.9% | 5.2% | 4.5% |
| **Low Oil Price Case** | | | | | | | | | | | | | | | | | | |
| Short Run Rebound | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| Dynamic Rebound | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| Long Run Rebound | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |

Appendix D. Projections from model with structural break in 2003