Energy Economics 49 (2015) 93–103

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneco

The rebound effect for automobile travel: Asymmetric response to price changes and novel features of the 2000s

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ARTICLE INFO

Article history:
Received 2 June 2014
Received in revised form 19 December 2014
Accepted 21 December 2014
Available online 13 January 2015

JEL classification:
Q41
R41
L91

Keywords:
Rebound effect
VMT elasticity
Gasoline demand
Asymmetric response

ABSTRACT

Previous research suggests that the elasticity of light-duty motor vehicle travel with respect to fuel cost, known as the "rebound effect," is modest in size and probably declined in magnitude between the 1960s and the late 1990s. However, turmoil in energy markets during the early 2000s has raised new questions about the stability of this elasticity. Using panel data on U.S. states, we revisit the simultaneous-equations methodology of Small and Van Dender (2007) and Hymel et al. (2010) to see whether structural parameters have changed. Using data through 2009, we confirm the earlier finding of a rebound effect that declines in magnitude with income, but we also find an upward shift in its magnitude of about 0.025 during the years 2003–2009. In addition, we find that the rebound effect is much greater in magnitude in years when gasoline prices are rising than when they are falling. It is also greater during times of media attention and price volatility, which explains about half the upward shift just mentioned.

1. Introduction

Many empirical quantities determine the effectiveness of energy policies toward light-duty motor vehicles. Analysts have come increasingly to appreciate the importance of one: the elasticity of vehicle travel with respect to fuel cost, the latter defined as the ratio of fuel price to fuel efficiency. If it is large, this elasticity affects policy evaluation in two notable ways. First, it tends to undermine the effectiveness of direct controls such as the Corporate Average Fuel Efficiency (CAFE) regulations in the United States. This is because the induced travel offsets some of the energy savings that would otherwise occur—the origin of the name "rebound effect". Second, external costs of motor vehicle travel that are not directly related to energy use—mainly congestion, accidents, and local air pollution—can loom large in a cost–benefit analysis of efficiency regulations; they therefore magnify the differences in cost-effectiveness between policy measures that discourage driving versus those that encourage driving.

The rebound effect is often measured as the negative of the elasticity of driving with respect to fuel cost per unit distance—also known as the price-elasticity of vehicle miles of travel (VMT), or simply the "VMT elasticity". This "direct" rebound effect is typically expressed as a percentage: for example, a VMT elasticity of −0.20 corresponds to a rebound effect of 20%. Most demand models assume that fuel efficiency enters the VMT decision only via its role in determining the per-mile price of driving, so that the elasticities of VMT with respect to fuel price and fuel intensity (the reciprocal of fuel efficiency) are identical. We follow this practice, except where we report testing whether VMT indeed responds the same way to fuel price and to fuel intensity.

A substantial body of earlier empirical evidence mostly supported a long-run rebound effect of 15% to 30% over the last few decades of the twentieth century.[1] Differences among the studies demonstrate the importance of model specification: for example, the way dynamics are dealt with, e.g., by whether or not lagged effects and autoregressive errors are accounted for. Small and Van Dender (2007) conclude that omitting dynamics is likely to cause the short-run rebound effect to be overestimated, and to obscure the relationship between short and long run.[2] In addition, results of US studies are sensitive to how they

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[1] For literature reviews, see Greening et al. (2000), Small and Van Dender (2007), and Hymel et al. (2010). For meta-analyses of results from these mostly pre-2000 studies, see Goodwin et al. (2004), Graham and Glaister (2004), and Brons et al. (2008).

[2] We use the term "short run" to designate one year, and "long run" to designate an asymptotic result if a change is continued indefinitely.

http://dx.doi.org/10.1016/j.eneco.2014.12.016
0140-9883/

account for the influence of the US Corporate Average Fuel Efficiency (CAFE) standards, which went into effect in 1978.

More recent literature has extended the earlier literature in several directions. Two directions of special interest are how the rebound effect may change over time, and whether its measurement is sensitive to bias due to omitted variables. We begin with our own previous work, on which the current paper builds.

Small and Van Dender (2007), using data on individual states in the US for years 1966–2001, estimate a three-equation model system in which VMT, vehicle ownership, and fuel efficiency are simultaneously determined. They find that ignoring this endogeneity of fuel efficiency (in particular, that the fuel efficiency chosen jointly by consumers and manufacturers depends on amount of travel) leads to an overestimate of the rebound effect. Furthermore, Small and Van Dender interact fuel cost with other variables to allow the rebound effect to vary with those variables. They find that the rebound effect declines substantially with income and, to a lesser extent, it increases with fuel cost. As a result, although the long-run rebound effect is estimated to be 22.2% averaged over their entire sample, it is only 10.7% averaged over the last five years of their sample. Short-term rebound effects (response in one year) are approximately one-fifth as large, resulting from their finding that the lagged endogenous variable plays a strong role in the VMT equation.

Hymel et al. (2010) extend the model of Small and Van Dender to account for the interrelationship between travel and congestion. They accomplish this by adding a fourth equation predicting the average amount of congestion in a state. At the same time, the equation for VMT is modified to include an influence from congestion, and the data set is extended through 2004. They obtain similar results to Small and Van Dender, although with a somewhat less pronounced decline with respect to income.

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 2007. Greene confirms several results of Small and Van Dender: in particular, he finds a similar value for the price-elasticity of VMT, and finds that it has declined over time and that it declines with income.

Hughes et al. (2008) compare the price-elasticity of gasoline measured over two six-year periods: 1975–80 versus 2001–06. They find a large decline in magnitude, from 0.21 to S0.08 in what appears to be their favored specification. This finding is for the price elasticity of fuel use, of which VMT is but one component; but it suggests that the VMT elasticity declined in magnitude by a similar amount since there is no evidence that the other component of the VMT elasticity, namely the elasticity of fuel efficiency, has changed substantially. In their preferred specification, which deals with possible endogeneity of fuel price, Hughes et al. do not account for dynamics.

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 other direction, and so suggest that the observed decline in the rebound effect over time may be due to suburbanization and declining public transit service, both of which lock travelers more firmly into automobile use. Interestingly, Litman (2013) cites these same factors as *downward* influences on the rebound effect during the earlier period, suggesting that they have waned 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.

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 studies use very large samples of individual vehicles. The first, by Knittel and Sandler (2012), takes advantage of the existence of regions within California 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 for whether the vehicle is a light truck. In some of their specifications they also include 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.[3]

The second study using California smog test data is by Gillingham (2013). Gillingham combines smog test data for years 2005–2009 with micro observations of new-vehicle registrations in 2001–2003 for the same vehicles. In this way he observes VMT over a several-year period, typically six or seven years due to the requirement that vehicles are tested at those ages. 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 US economy entered its most significant recession since the 1930s, accompanied by turmoil in housing markets including foreclosures requiring many people to move. Despite Gillingham's having controlled 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 changing 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 and controls for heterogeneity across individuals. However, both studies assume that VMT responds to contemporaneous gasoline prices; yet the descriptive data shown by Knittel and Sandler, comparing graphs of gasoline prices and VMT over time, suggest a one to two year lag between movement in gasoline price and movement in VMT. As already noted, 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.

Why should long-run and short-run responses of VMT differ? Molloy and Shan (2013) provide an intriguing look at one possible reason: induced changes in household location. They analyze how housing construction within small areas responded to fuel prices over the period 1981 to 2008.[4] 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 1% increase in gasoline price reduces construction over the next four years by 1%, which is 0.03% of the total housing stock (their Table 2). Thus residential location provides a 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 mounting evidence 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. We respond here in three ways. First, we re-estimate earlier models with data extending through 2009. Second, within those re-estimated models we test whether there is a structural break in the determinants of VMT during the decade 2000–2009. Third, we consider other explanations for changes in behavior over that decade: specifically, asymmetries between response to rising and falling gasoline prices, and behavioral responses to the intense media attention that was sometimes given to fuel prices.

[3] These numbers are the range of coefficients of log (dollars per mile) in their 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).

[4] The areas are “permit-issuing places, which are usually small municipalities” (Molloy and Shan 2013, p. 1214).

2. Theory and data

2.1. Theory

The model of Small and Van Dender (2007) explains how consumers and manufacturers simultaneously choose how much to travel, the size of their vehicle stock, and the fuel efficiency of their vehicle stock. Conceptually, the structural model is:

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

where M is aggregate VMT per adult; V is size of the vehicle stock per adult; E is average fuel efficiency of the entire vehicle stock; P_V is a price index for new vehicles; P_F is the price of fuel; $P_M \equiv P_F / E$ is the fuel cost per mile; X_M, X_V and X_E are exogenous variables (including constants); and R_E represents regulatory measures that directly or indirectly influence fleet-average fuel efficiency—namely, a variable *cafe* representing how tightly CAFE regulations constrain manufacturers.[5]

The standard definition of the direct rebound effect[6] can be derived from a partially reduced form of Eq. (1), which is obtained by substituting the second equation into the first and solving for M. Thus the solution $\hat{M}$ is implicitly defined by:

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

The VMT elasticity is:

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

where $\varepsilon_{Y,X}$ is the direct structural elasticity of dependent variable Y with respect to independent variable X in equation set Eq. (1).

An important assumption in Eq. (1) is that M responds to E only through the fuel cost per mile, $P_M \equiv P_F / E$. Small and Van Dender (2007) were not able to confirm this assumption, but felt their dataset contained year-to-year variation in fuel efficiency that was inadequate to provide a satisfactory test. We discuss in Section 3 another attempt to test this assumption explicitly, with more promising results.

We generalize Eq. (1) in two ways to handle dynamics. First, we assume that the error terms in the empirical equations exhibit first-order serial correlation, meaning that unobserved factors influencing usage decisions in a given state will be similar from one year to the next. Second, we allow for behavioral inertia by including the one-year lagged value of the dependent variable as a right-hand-side variable. We specify the equations as linear in parameters and with most variables in logarithms, and for reasons explained later we add variables that are interactions between selected exogenous or endogenous variables Z_1^m and fuel cost. Thus we estimate the following system:

$$\begin{aligned} (vma)_t &= \alpha^m \cdot (vma)_{t-1} + \alpha^{mv} \cdot (vehstock)_t + \beta_1^m \cdot (pm)_t + \gamma_1^m \cdot (Z_1^m)_t (pm)_t + \beta_3^m X_t^m + u_t^m \\ (vehstock)_t &= \alpha^v \cdot (vehstock)_{t-1} + \alpha^{vm} \cdot (vma)_t + \beta_1^v \cdot (pv)_t + \beta_2^v \cdot (pm)_t + \beta_3^v X_t^v + u_t^v \\ (fint)_t &= \alpha^f \cdot (fint)_{t-1} + \alpha^{fm} \cdot (vma)_t + \beta_1^f \cdot (pf)_t + \beta_2^f \cdot (cafe)_t + \beta_3^f X_t^f + u_t^f \end{aligned} \tag{4}$$

with autoregressive errors:

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

Note that *fint* measures fuel intensity (gallons per mile), which is the reciprocal of fuel efficiency. Here, lower-case notation indicates that the variable is in logarithms.

In this notation, Eq. (3) and its long-run counterpart derived in Small and Van Dender (2007) imply that the short- and long-run rebound elasticities are:

$$\varepsilon_{\hat{M},PM} = \frac{\varepsilon_{M,PM} + \alpha^{mv}\beta_2^v}{1 - \alpha^{mv}\alpha^{vm}} \tag{5a}$$

$$\varepsilon_{\hat{M},PM}^L = \frac{\varepsilon_{M,PM} \cdot (1 - \alpha^v) + \alpha^{mv}\beta_2^v}{(1 - \alpha^m)(1 - \alpha^v) - \alpha^{mv}\alpha^{vm}}. \tag{5b}$$

These equations make explicit that our system accounts for the effects of a change in regulations through two potential pathways: the direct effect of fuel cost on driving and the indirect effect arising through induced changes in the vehicle stock. 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 decisions on number of vehicle to own are governed mainly by factors other than the fuel cost of driving.

2.2. Data and empirical specification

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 from the US Federal Highway Administration (FHWA), US Census Bureau, and US Energy Information Administration.[7] In addition, we have collected variables on media attention to gasoline prices, as described in Section 3.4.

In Appendix A, we list the primary variables used in the statistical estimation. All the dependent variables, and many others as well, are measured as natural logarithms; variable names starting with lower case letters are logarithms of the variable described. All monetary variables are real (i.e., inflation-adjusted). Each of these variables is updated to 2009 using the same or a 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 used here.[8]

These data on VMT and fuel efficiency, two of our dependent variables, are subject to well-known quality problems, especially the interrelated ways that FHWA calculates VMT and fuel efficiency based on data obtained from individual states. Greene (2012, p. 18) provides an excellent discussion. He concludes that the resulting errors are unlikely to cause large errors in year-to-year changes in these variables. It is those year-to-year changes that drive our results, due to our use of state fixed effects.

[5] Note that operating costs other than fuel are not included explicitly, mainly because they either are fixed in nature (hence belong in the second rather than the first equation) or do not vary enough across our data set to obtain useful coefficients. As a result, we make no attempt to measure a demand elasticity with respect to total operating cost, but only with respect to fuel cost.

[6] The "direct rebound effect" is distinguished from various further responses that may occur in general equilibrium, such as responses to associated vehicle price increases, induced changes in the consumption of other goods, and institutional changes in fuel-tax rates. See Borenstein (2013) for a helpful taxonomy. Our view is that the direct rebound effect is the most useful behavioral quantity that might be considered at least somewhat generalizable across situations, and that other effects should be modeled specifically within any particular regulatory scenario. Specifically, we seek a measure that mainly reflect the demand side of the market, rather than incorporating supply adaptations which will be specific to market organization and manufacturer strategies. The one exception to this is the equation explaining fuel intensity, which necessarily incorporates both demand-side and supply-side features.

[7] See Small and Van Dender (2007) for a full description of data sources and a discussion of possible weaknesses.

[8] In Small and Hymel (2013) we have compared estimates with and without these data revisions, ascertaining that they did not have important effects on the results.

The variable *cafe* measuring the stringency of CAFE standards is, as before, constructed by using a reduced-form version of the model system to predict the desired fuel intensity under a counter-factual scenario where CAFE standards are absent, then taking the logarithm of the ratio of that desired efficiency to the actual CAFE standard.[9] This variable is judged unsatisfactory by Greene (2012), who offers an alternative based on the hypothetical fleet average fuel efficiency if manufacturers were to meet CAFE standards exactly in each year. While it would be interesting and valuable to analyze these (and possibly other) approaches in terms of their efficacy in explaining fuel intensity, doing so would have little effect on the VMT elasticities on which we focus here because the variable *cafe* enters only the equation for fuel intensity, not that for vehicle-miles traveled.[10]

As in Small and Van Dender (2007), the estimation uses three-stage least squares, accounting for first-order autocorrelation by transforming the equations into a nonlinear system and defining instrumental variables as described there. It includes state fixed effects, but not time fixed effects (year dummies) because early experimentation revealed that this removed too much of the needed variation in variables, leading to very imprecise estimates.[11]

3. Empirical results

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 to 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. Most previously used data sets, however, have covered too short a time span to test any of these arguments satisfactorily.[12]

With the longer time span used here (44 years), there is a much better opportunity to see such changes. We explore them in three distinct ways. First (Section 3.1), 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. As for the decade beginning in 2000, the data series is too short to apply this methodology.

Second (Section 3.2), we explore income, fuel costs, and urbanization as the causes of these changes. Each of these factors is entered in the model in such a way that the rebound effect can vary with it rather than varying over time in an unexplained manner. We find results consistent with those of Small and Van Dender: the rebound effect declines with increasing income and urbanization, and it increases with increasing fuel cost. By far the most important of these sources of variation is income, whose effect is large enough to greatly reduce the projected rebound effect for time periods of interest to current policy decisions. Despite these controls, we find a consistent negative coefficient (indicating a strengthening of the rebound effect) for a dummy variable for years 2003–2009 when it is added to the *vma* equation, suggesting some additional unaccounted-for factors that have strengthened the rebound effect.

Third (Section 3.3), 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, finding that they explain about half of the previously mentioned upward shift in the rebound effect during 2003–2009.

We focus on the three-equation model of Small and Van Dender (2007) because it is simpler and somewhat less sensitive to specification than the four-equation model of Hymel et al. (2010). While the latter is theoretically more complete, it is more complex and estimating it requires imputation of pre-1980 congestion values, thereby introducing more places for data uncertainties to affect the results. However, we have estimated most specifications described here using the four-equation model, and occasionally comment on the results.

3.1. Variation by time period

This section presents the results of including variable *pm* (log fuel cost per mile), without any interactions but with all other controls, in the equation explaining *vma* (log vehicle-miles traveled per adult). That is, we estimate system (4) setting $\gamma_1^m = 0$. The coefficient of *pm* is the "structural" VMT elasticity, i.e., $\varepsilon_{M,PM}$, which as noted earlier differs little from the partial-reduced-form elasticity given by Eq. (2).

In order to see whether the rebound effect changes over time, we carry out this estimation on the full sample and on two subsamples: 1966–1995 and 1996–2009. Table 1 shows that the estimated structural elasticity falls in magnitude by 46% between these two time periods. For completeness, the table also shows the results of applying the same procedure to the four-equation model of Hymel et al. (2010); in that case the decline in the later time period is even more pronounced. In both cases, the estimated long-run rebound effect is approximately five times as large as the short-run version, based mainly on the estimated coefficient of the lagged dependent variable.[13]

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

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

This section explores how the main specification of Small and Van Dender is affected by the addition of new data covering years 2002–2009.

Table 2 shows selected results from our main specification (Model 1), in which three variables—income, fuel cost, and urbanization—are

[9] We have not adjusted the estimated standard errors of our coefficient for the fact that we use predicted values to construct an independent variable means. Thus our reported standard errors are probably slightly understated.

[10] See Small and Van Dender (2007, Section 3.3.3) and Greene (2012, Section 4.1) for discussions of strengths and weaknesses of our *cafe* variable and two alternatives.

[11] In addition, doing so would make the identification of the VMT elasticity more dependent on state-specific price fluctuations, which might be due to short-term turmoil in gasoline markets leading drivers to expect such price changes to be erratic and temporary. (We are indebted to James Sallee for this point.) We do control for time through the dummy variable for years 1973 and 1979, and a single time trend in the *vma* equation and three time trends in the *fint* equation; experimentation did not reveal more complex time trends that could be reliably estimated.

[12] Two recent exceptions are the studies by Wadud et al. (2007a, 2007b) using time-series cross sections of individual households from the US Consumer Expenditure Survey. Cross-sectionally, they find that the absolute value of the price elasticity of fuel consumption has a U-shaped pattern with respect to income, 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 (Wadud et al. 2007b, Table 2). But when they hold other variables constant while allowing income to vary both cross-sectionally and over time (1997–2002), they find that the elasticity declines in magnitude with income, from 0.51 in the lowest two income quintiles to 0.40 in the highest.

[13] In the three-equation models, that coefficient, denoted by α^m in Eq. (4), varies between 0.82 and 0.84 for the "full" and "early" samples. Applying Eqs. (5a) and (5b) when α^{mv} and/or α^{vm} are small, the ratio of long-run to short-run rebound effect is approximately $1 / (1 - \alpha^m)$, or 5.6 to 6.3. The coefficient is not well estimated in the "late" sample. The elasticity formulas for the four-equation model are more complex (see Hymel et al. 2010, Eq. (14)) and not as easily approximated. As noted in Hymel et al. (2010, p. 1227), persistent measurement error in some of the variables could be interfering with an accurate measurement of α^{vm}, causing us to overestimate the ratio between long- and short-run elasticities.

Table 1
Short-run structural elasticity of VMT with respect to fuel cost, estimated over different time periods (no interacting variables).

Sample:	Full	Early	Late
	1966–2009	1966–1995	1996–2009
Coefficient of pm (standard errors in parentheses)			
Three-equation model	−0.0447	−0.0458	−0.0246
	(0.0029)	(0.0037)	−0.0071
Four-equation model	−0.0440	−0.0469	−0.0131
	(0.0030)	(0.0058)	(0.0075)

Note: This table shows the coefficient of log real fuel cost per mile (*pm*), which is an endogenous explanatory variable in the equation explaining log vehicle-miles traveled per adult (*vma*) in a state in the U.S. That equation is part of a three- or four-equation model system also explaining number of vehicles, average fuel efficiency, and (in the 4-equation version) congestion. The control variables are described in Appendix A. The set of control variables for this table is similar to the set used in Model 1 in Table 2, differing only by not including any interacting variables.

interacted with fuel cost, thereby allowing the estimated structural VMT elasticity to vary with those three variables.[14] All three are entered in normalized form, meaning their mean values have been subtracted off, so that the coefficient of *pm* itself gives the structural VMT elasticity computed at mean values of these three interacting variables. Note that one of the interacting variables is *pm* itself, meaning that the interacted variable is pm^2. In each case, the incremental effect of variable Z on the rebound effect is given by $\partial(\partial vma/\partial pm)/\partial Z$.[15] Since $\partial vma/\partial pm < 0$ at most variable values, a negative coefficient on γ_1^m indicates that higher values of Z imply larger absolute elasticities, i.e., larger rebound effects.

The results for Model 1, our base specification, have only one important difference from the results of using the shorter sample, 1966–2001, of Small and Van Dender (2007). On that shorter sample, the coefficient on pm^2 was estimated to be smaller and statistically insignificant.[16] We think the additional variation in fuel prices during the 2000s enables us to measure this coefficient more precisely.

Table 2 also shows a model, named Model 2, that allows for an additional unexplained shift in the structural VMT elasticity starting in 2003. This starting year, chosen mostly by trial and error, marks roughly the time when it became apparent that a major rise in fuel price was underway.

The lower panel of the table shows elasticities calculated at two different sets of average values of interacting variables: the average over the full sample and that over the last ten years of the sample. As in the earlier paper, there is a substantial drop in their absolute values, although it is much less in Model 2 due to the boost given by the dummy variable for 2003–2009. Model 2 shows a strong upward shift of 0.025 in the absolute value of the short-run structural VMT elasticity starting in 2003. Nevertheless, the effect of income remains strong, in fact slightly stronger. As a result, it fully counteracts the upward structural shift, so the rebound effect is again smaller in magnitude during the last ten years of the sample than over the entire sample. Furthermore, one can anticipate that the downward influence of income on the rebound effect will continue as incomes grow, whereas we have no reason at this point to expect a further structural shift or even the continuation of the one exhibited by the variable *Dummy_2003_09*. And even if fuel prices continue to rise, the resulting upward pressure will not likely overcome the downward pressure because the coefficient of pm^2 is too small, and projected increases in fuel efficiency are likely to offset some or all of the increases in fuel price.[17]

Model 2 does not fully account for the large differences by time period illustrated by Table 1. This is not surprising, since the use of this dummy variable is an admission of ignorance about what might be changing. Thus, in subsequent sections of the paper we pursue a more complete explanation of what changed starting in the early 2000s.[18]

We also estimated Model 2 omitting years 2008 and 2009, in order to evaluate the effect of the financial crisis on the rebound effect. This change decreases the rebound effect through changes in *pm*, pm^2, and $pm * inc$. The short run rebound effect falls by about 1 percentage point and the long run rebound effect falls by about 8 percentage points, relative to the version of Model 2 that includes years 2008 and 2009. One would expect that drivers would be more sensitive to driving costs following the financial crisis, and our estimation bears that out.[19]

As detailed in Small and Hymel (2013), we obtain comparable results with the four-equation model of Hymel et al. (2010).[20]

We hoped our longer data set would enable us to better test the assumption implicit in Eq. (1) that consumers respond equally, in elasticity terms, to fuel price and fuel intensity (the inverse of fuel efficiency). This assumption is tested by simply replacing the variable *pm* by two variables equal to its two constituents, namely *pf* and *fint*. When we do this, we find the variable *fint* to have a very small but imprecisely measured coefficient, just as in our earlier papers. However, in the four-equation model, we obtain statistically significant and quite different coefficients on the two variables.[21] Like Gillingham (2011, Table 3.4 and Section 3.1.3) and Greene (2012), we find that fuel intensity has a smaller impact on driving than does fuel price. Nevertheless we remain agnostic about whether the difference in coefficients of fuel price and fuel intensity reflects a real difference in behavior or a measurement problem.[22] By maintaining the hypothesis of equality, we are conservative both in the sense of adhering to standard theory and of ensuring that we do not underestimate the rebound effect on this account, so that our overall finding of rather low rebound effects is not undermined.

[14] Income per capita (*inc*) and fuel cost per mile (*pm*) are in logarithms; urbanization (*Urban*) is a simple ratio (fraction of population living in urban areas). Our naming convention uses all lower case for variables in logarithms, but a capitalized name otherwise.

[15] Hence if $\gamma_1^m = (\gamma_{1k}^m, k = 1, 2, 3)$ is the coefficient vector of these three interacted variables, as in Eq. (4), this incremental effect is equal to γ_{1k}^m for the appropriate value of k in the case of variables *inc* and *Urban*, and is equal to $2\gamma_{1k}^m$ in the case of variable *pm*.

[16] Coefficient estimate −0.0074, standard error 0.0069. The 1966–2001 results described here do not precisely match the published results from the earlier paper because we have taken advantage of some data revisions to improve the accuracy of our variables.

[17] Even without the new CAFE standards recently promulgated for new cars of model years 2017–2025, EIA (2012) projects new-vehicle fuel cost per mile to be roughly flat over the period 2015–2035.

[18] One possibility we do not explore is that the shape of the income distribution had changed, specifically that much of the increased average income in recent years measured occurred only at the top of the income distribution, whereas most of the driving is accounted for by people in the lower parts of the distribution.

[19] The estimates from a version of Model 1 without years 2008 and 2009 also yielded smaller rebound effect estimates compared to the 1966–2009 version.

[20] We also estimated a version of Model 1 adding the national unemployment rate as a variable in each of the three equations (see Appendix B, Table B2, Model 1a). We thank Robert Mendelsohn for suggesting this improvement in the model. The variable is expressed as a percentage. The result suggests that unemployment increases fuel intensity, probably because it causes drivers to keep older cars. Including this variable makes the price variable in the fuel intensity equation stronger and statistically significant. It makes very little difference otherwise, so we omit this variable in our subsequent discussion in order to use the previously published version of the model as our starting point for further changes.

[21] Specifically, when this decomposition of *pm* is applied to the four-equation counterpart of Model 1, the coefficient of *pf* is −0.0544 (0.0035) and that of *fint* is −0.0232 (0.0107), with standard errors in parentheses.

[22] Greene (2012) offers two possible explanations for why the theoretically expected equal and opposite elasticities with respect to fuel price and fuel efficiency seems not to be found empirically in most studies. First, historically the changes in fuel efficiency are closely tied to CAFE regulations which also raise vehicle purchase costs; we try to control for this through the vehicle price variable in our *vehstock* equation, but that variable's estimated coefficient is very small and it may inadequately measure this effect. Second, historical changes in fuel efficiency have been very gradual and so may be empirically difficult to distinguish from other factors—in contrast to changes in fuel price, which have occurred suddenly and frequently. We would add a third explanation, which is perceptual: drivers may simply pay more attention to changes in fuel price, which is visible and prominently publicized, than to fuel efficiency.

Table 2
Equations explaining vehicle-miles traveled (selected coefficients and elasticities: three-equation models).

Variable	Model 1		Model 2		Model 2	
	1966–2009		1966–2009		1966–2007	
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
pm	−0.0466	0.0029	−0.0464	0.0029	−0.0413	0.0031
pm ∗ *Dummy_2003_09*			−0.0251	0.0076		
pm ∗ *Dummy_2003_07*					−0.0176	0.0080
pm ∗ *inc*	0.0528	0.0108	0.0699	0.0121	0.0791	0.0123
pm^2	−0.0124	0.0059	−0.0113	0.0060	−0.0111	0.0060
pm ∗ *Urban*	0.0119	0.0094	0.0078	0.0096	0.0124	0.0096
vma lagged	0.8346	0.0102	0.8279	0.0105	0.8151	0.0110
Calculated rebound elasticities:						
	1966–2009		1966–2009		1966–2007	
Short run	−0.047		−0.050		−0.041	
Long run	−0.295		−0.309		−0.231	
	2000–2009		2000–2009		2000–2007	
Short run	−0.028		−0.042		−0.026	
Long run	−0.178		−0.255		−0.148	

Note: See note to Table 1. Variables *inc* and *Urban* are log real per capita income and the (unlogged) fraction of the state that is urbanized, respectively. The full list of other control variables, and their estimated coefficients for Model 1, can be found in Table B2 in Appendix B.

3.3. Asymmetry in response to price changes

We now consider factors that may have contributed to the apparent structural break in 2003. In this section we consider asymmetric response to price changes; in Section 3.4 we consider media coverage and price volatility.

Evidence suggests that for various types of energy purchases, demand is more responsive in the short run to increases than to decreases in operating cost.[23] In this section, we investigate whether such asymmetry applies to vehicle-miles traveled.

3.3.1. Models based on rises versus falls of fuel price

We decompose our fuel price variable into separate components, similarly to Dargay and Gately (1997). We have simplified their three-way decomposition into a two-way decomposition, and do so for each state in our sample.[24] In this subsection, we decompose *pf*, the logarithm of fuel price; in the next subsection we decompose *pm*, the logarithm of fuel cost per mile.

The decomposition of fuel price for state *i* in year *t* is as follows:

$$pf_{i,t} = pf_{i,1966} + pf\_rise_{i,t} + pf\_cut_{i,t},$$

where $pf\_rise_{i,t}$ and $pf\_cut_{i,t}$ are the cumulative effects of all annual increases and decreases, respectively, since the start of the sample (here 1966):

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

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

Thus the coefficients of *pf* and variables constructed from it are replaced, in our asymmetric specifications, by two separate coefficients, one depending on upward annual changes and the other on downward annual changes. Because we account for state fixed effects in our specification (i.e., there is a constant term for every state), $pf_{i,1966}$ is absorbed into the fixed effects and we need only any two of the three variables *pf*, *pf_rise*, and *pf_cut*. The most convenient choice proves to be the two variables, *pf* and *pf_cut*; the effect of price increases is then given by the coefficient of *pf*, while the effect of price decreases is given by the sum of the coefficients of *pf* and *pf_cut*. These variables replace *pf* in both the equation explaining the logarithm of vehicle-miles traveled (*vma*) and that explaining the logarithm of fuel intensity (*fint*). We also include interactions of one or both of these variables with income, fuel cost per mile, and urbanization.

The results for our preferred specification, labeled Model 3, are summarized in Table 3. The symmetric Model 1 is shown for comparison. These results suggest that the fuel-cost elasticity of *vma* becomes modestly larger in absolute value when it applies only for price increases, and smaller for price cuts. Specifically, the direct short-run effect on driving of a price increase is more than twice as large as that of a price cut (−0.0639 compared to −0.0639 + 0.0340); and it is one-third larger than the effect measured in the model assuming symmetry. Greene (2012) measures similar differences between the effects of rising and falling prices, although he cannot rule out statistically that they are identical.

In the asymmetric model just described (Model 3), a change in fuel efficiency, unlike a change in fuel price, has the same impact on *vma* regardless of whether fuel efficiency is increased or decreased. Furthermore, the model posits that an increase in fuel efficiency has the same impact (in percentage terms) as that of a fuel price cut. This

Table 3
Selected coefficient estimates: base model and asymmetric model (three-equation models).

Equation and variable:	Model 1		Model 3	
	Coeff.	Std. error	Coeff.	Std. error
vma equation:				
pm = *pf* + *fint*	−0.0466	0.0029	−0.0639	0.0049
pf_cut + *fint*			0.0340	0.0078
pm ∗ *inc*	0.0528	0.0108	0.0577	0.0107
pm^2	−0.0124	0.0059	−0.0207	0.0061
pm ∗ *Urban*	0.0119	0.0094	0.0131	0.0093
vma lagged	0.8346	0.0102	0.8334	0.0104
fint equation:				
pf + *vma*	−0.0050	0.0041	−0.0097	0.0060
pf_cut + *vma*			0.0143	0.0123

Note: See note to Table 2. The *fint* equation explains fuel intensity (the inverse of fuel efficiency). The variable *pf* is log real fuel price. See text for *pf_cut*.

[23] For example, energy and oil demand (Gately and Huntington 2002, Dargay and Gately 2010); transportation fuels (Dargay and Gately 1997); and motor vehicle ownership (Dargay et al. 2007).

[24] 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 in our specification to capture special influences on travel behavior during that year.

makes sense from a theoretical standpoint because most of the changes in fuel efficiency we are interested in are improvements, i.e., they lower the fuel cost per mile just like price cuts. Furthermore, the pathways by which consumers consider fuel efficiency are quite different from those by which they consider fuel prices, so whatever is causing asymmetry need not affect both parts of fuel cost in the same way.[25]

The estimated coefficients of the interaction terms from Model 3 are similar to those from Model 1; the rebound effect increases with fuel price and decreases with income. But in the asymmetric model, the coefficient on pm^2 is larger in magnitude than in the model without asymmetry.[26 27]

We also estimated Model 3 using the generalized method of moments (GMM) estimator instead of three stage least squares (3SLS). One drawback of the 3SLS estimator is the difficulty involved in calculating clustered standard errors for a model as complex as Model 3. If there is indeed correlation in the standard errors within an individual state across years, the usual standard errors are not consistent. We can, however, calculate standard errors clustered at the state level for our primary model (3) by using the GMM estimator if we omit the time trend variables. Doing so also enables us to compare results across these two types of estimators.

Table 4 shows select results for three versions of Model 3: the left column uses 3SLS as before, the middle column uses 3SLS but drops the time trend variable, and the right column uses GMM without the time trend variable. The GMM point estimates and standard errors related to the rebound effect have a pattern broadly similar to those obtained from the 3SLS estimator, although they are all smaller in magnitude. Some of the difference is a result of excluding the time trend variable, while some is attributable to the change in estimator. Nevertheless, the implications of the GMM results are mainly consistent with those from 3SLS, and this remains true for alternate model specifications presented below. Finally, using the GMM estimator, we find that clustering the standard errors either by state or by year changes the standard errors of coefficients very little (not shown in the table).[28]

An alternative view of how asymmetry might work is that the difference in response between fuel price 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 paper 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 4 in Table 5, we allow also for the possibility that the speed of the response differs

Table 4
Alternate estimators: selected coefficients from the *vma* equation (three-equation model).

Variable	Model 3		Model 3		Model 3	
	3SLS		3SLS no trend variable		GMM no trend variable	
	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Trend	0.0013	0.0004				
vma lagged	0.8334	0.0104	0.8347	0.0101	0.8462	0.0141
$pm = pf + fint$	−0.0639	0.0049	−0.0545	0.0035	−0.0480	0.0034
pm^2	−0.0207	0.0061	−0.0291	0.0056	−0.0146	0.0060
$pm * inc$	0.0577	0.0107	0.0498	0.0105	0.0354	0.0117
$pm * Urban$	0.0131	0.0093	0.0186	0.0092	0.0218	0.0100
$pf\_cut + fint$	0.0340	0.0078	0.0142	0.0038	0.0096	0.0039

Note: See note to Table 2; this table refers to the first equation (vehicle-miles traveled) of the 3-equation system.

between rises and cuts in fuel price. This is done by adding various lags of *pf_rise* and *pf_cut*.

The results suggest that adjustment to price *rises* takes place quickly; the response elasticity is large in the year of and the first year following a price rise, then diminishes to a smaller yet substantial value. But the adjustment to price *cuts* occurs more slowly: in absolute value it is the smallest in the year of the change (0.0140); takes its largest value after one year (0.0626, from the sum of $pf\_cut + fint$ and $pf\_cut(-1) + fint$ in Table 5); then retreats to a value of 0.0215 (sum of all four coefficients) after three years. These response patterns are shown in Fig. 1.

3.3.2. 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 used are formed analogously to the previous subsection: fuel cost per mile, *pm* (the price of mileage), is decomposed into *pm_rise* and *pm_cut*.

This decomposition raises a new problem because *pm_rise* and *pm_cut* are, like *pm*, endogenous. In the symmetric model, endogeneity

Table 5
Selected coefficient estimates: asymmetry in response to fuel price (three-equation models).

Equation and variable:	Model 3		Model 4	
	Coeff.	Std. error	Coeff.	Std. error
vma equation:				
$pm = pf + fint$	−0.0639	0.0049		
pf_rise			−0.0792	0.0144
$pf\_rise(-1)$			−0.0023	0.0197
$pf\_rise(-2)$			0.0381	0.0130
$pf\_cut + fint$			−0.0140	0.0095
$pf\_cut(-1) + fint$			−0.0486	0.0141
$pf\_cut(-2) + fint$			0.0171	0.0150
$pf\_cut(-3) + fint$			0.0239	0.0108
$pm * inc$	0.0535	0.0112	0.0340	0.0121
pm^2	−0.0180	0.0062	−0.0322	0.0069
$pm * Urban$	0.0187	0099	0.0328	0.0103
$pf\_rise * media$				
$pm * sqrt(fuel\ price\ var)$				
vma lagged	0.8334	4	0.8571	0.0125
fint equation:				
$pf + vma$	−0.0097	0.0060		
$pfrise$			0.0020	0.0063
$pf\_cut + vma$				
pf_cut			−0.0215	0.0099
vma			−0.0147	0.0172

Note: See note to Table 3. See text for definitions of *pf_rise*, *pf_cut*, and their lagged values (given in years).

[25] Nevertheless, from a purely empirical point of view, the specification is arbitrary in that we could equally easily have used the variable *pf_cut* instead of $pf\_cut + fint$—that is, we could have assumed that a change in fuel efficiency is viewed like a *rise* in price, not like a *fall* in price. Ideally we would include both variables, but this would effectively amount to measuring separate elasticities on *pm* and *fint* which, as explained in Section 3.2, our data seem mostly incapable of distinguishing. Also, for Model 3 the regression predicting desired fuel efficiency (which is an input to the cafe strictness variable) did not perform as expected. Its estimated coefficient for $pf\_cut + fint$ has the incorrect sign and is insignificant. We performed a sensitivity test by using the *cafe* variable from Model 1 in the Model 3 regression; we found that this had a negligible impact on the estimates shown here.

[26] We find very similar behavior if the unemployment rate is included in both the *vma* and *fint* equations, just as in Model 1a (as described at the end of Section 3.2). This model is reported in Appendix B as Model 3a. Just as with Model 1a, this model is superior in that it exhibits the expected effect of fuel price on desired fuel efficiency, in the form of a statistically significant coefficient for $pf + vma$ in the *fint* equation. Nevertheless, this improvement makes essentially no difference to the results discussed in this paper.

[27] We also estimated a version of Model 3 in which the fuel-price variables were measured in nominal rather than real dollars; (We thank Stuart Rosenthal for this suggestion.). The motivation for this model was the possibility that nominal price changes are more noticeable to drivers than real changes. The results, however, showed only a small and non-significant difference between drivers' responses to fuel price rises and cuts. This finding lends support to our primary asymmetric models and suggests that drivers are most responsive when fuel prices rise faster than inflation.

[28] Clustering does not change the statistical significance of any of the variables in the model, except that the coefficient of $pm * Urban$ becomes statistically significant when the GMM estimator is used to cluster by year (mainly because the coefficient becomes larger).

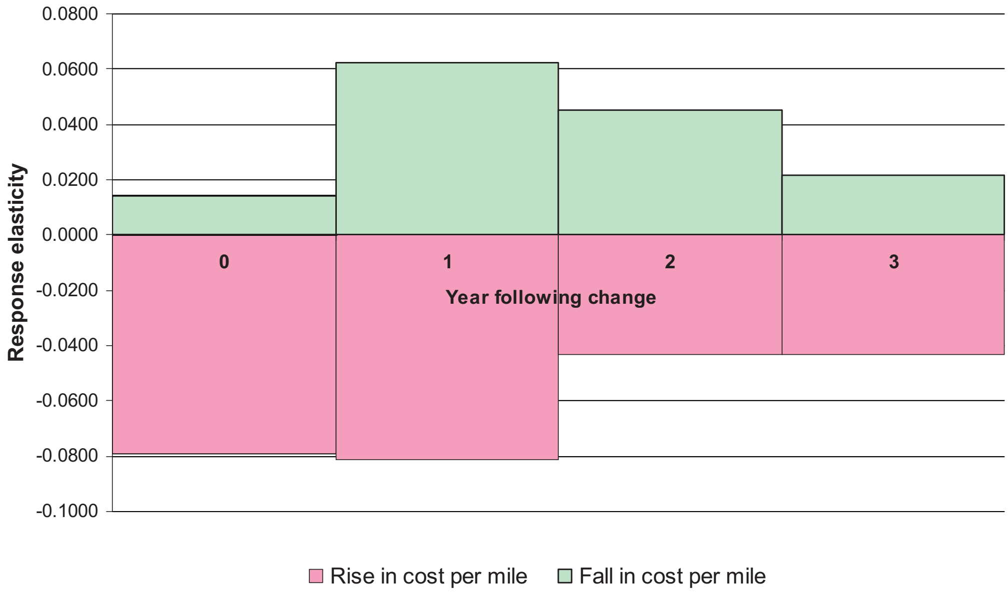

Fig. 1. Short-run elasticity of VMT with respect to a sustained change in fuel price (Model 4).

of *pm* is accounted for as part of the three-equation model.[29] But here the problem is worse: the values of these new variables in any given year depend on values taken by an endogenous variable (fuel intensity) in previous years. A fully endogenous treatment of *pm_rise* and *pm_cut* is thus not feasible, so we have used an approximation: 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 on all the exogenous variables in the system — that is, on the instruments in the 3SLS estimation routine. This procedure basically replicates what instrumental variables do 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.

Table 6 shows selected results of a specification, named Model 5, analogous to that of Model 3 (which is also shown for comparison). Note that each model contains three *pm* interaction variables. The coefficient on *pm_cut_hat* tells us the degree of asymmetry: it is positive, showing that the magnitude of the elasticity is smaller for cost cuts than for cost rises. The short-run rebound effect is given by elasticity −0.0623 when per-mile fuel costs are rising, and −0.0339 (=− 0.0623 + 0.0284) when costs are falling. The rebound effect is influenced by *pm*, *income*, and *Urban* much as before.

In Model 5, 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 these models predict that people would still respond to a small change in fuel efficiency according to the combination of coefficients multiplying variable *pm*—that is, they respond as they would to a *rise* in fuel price, even if they are actually responding to a fall in fuel efficiency. 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.[30] For this reason, we prefer the models of Section 3.3.1.

Table 6
Selected coefficient estimates: asymmetry in response to fuel price or fuel cost per mile.

Equation and variable:	Model 3		Model 5	
	Coeff.	Std. error	Coeff.	Std. error
vma equation:				
pm = *pf* + *fint*	−0.0639	0.0049	−0.0623	0.0055
pf_cut + *fint*	0.0340	0.0078		
pm_cut_hat			0.0284	0.0093
pm ∗ *inc*	0.0577	0.0107	0.0535	0.0112
pm^2	−0.0207	0.0061	−0.0180	0.0062
pm ∗ *Urban*	0.0131	0.0093	0.0187	0.0099
vma lagged	0.8334	0.0104	0.8084	0.0122
fint equation:				
pf + *vma*	−0.0097	0.0060		
pfrise			−0.0133	0.0062
pf_cut + *vma*	0.0143	0.0123		
pf_cut			0.0042	0.0096
vma			0.0107	0.0166

Note: See note to Table 3.

3.4. 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. But why? In this section, we consider two factors that may help explain these variations in responsiveness.

The first factor is variations in media attention to fuel prices and costs. Consumers tend to be mindful of gasoline prices, but not necessarily at all times. So an increase in news media coverage of gasoline and oil markets may heighten consumers' attentiveness to price changes. As we

[29] 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*.

[30] For example, Larrick and Soll (2008) find that consumers have difficulty calculating the impact of fuel economy changes on fuel consumption when fuel economy is measured in miles per gallon. The authors refer to this phenomenon as the “MPG Illusion”.

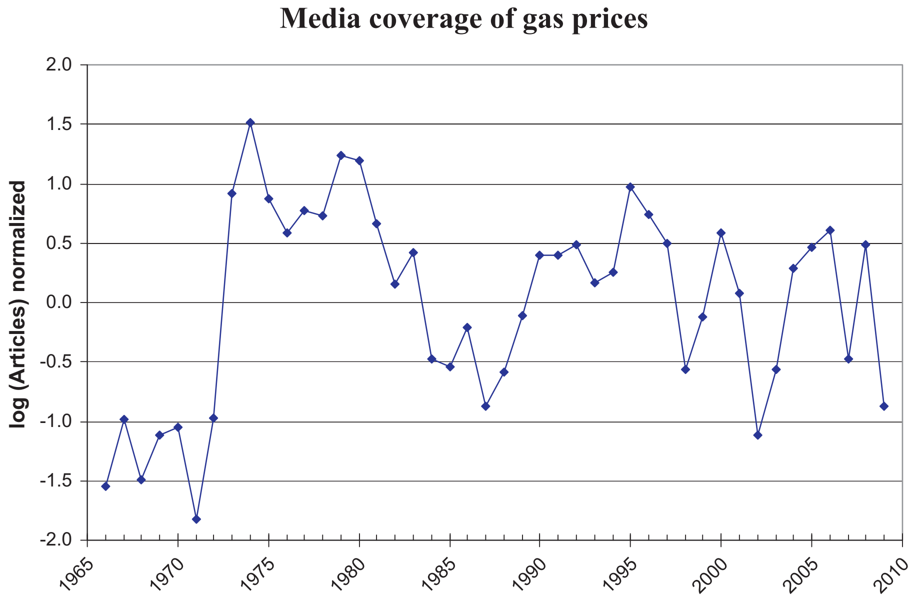

Fig. 2. Media coverage of gas prices.

show in what follows, such coverage is not especially highly correlated either with prices themselves or with their fluctuation. This could be for several reasons. News media often report milestones regarding nominal gasoline prices, such as when prices exceed their historical peak or cross integer thresholds (e.g., going from \$3.99 to \$4.00 per gallon). Also, news media may pay more attention when elections are near, when there is political turmoil in oil-producing nations, or when domestic oil-related issues such as a controversial pipeline or expanded production from shale oil are contentious.

The second factor is volatility in fuel costs. Volatility could cause consumers to adopt contingency plans and thus pay more attention to fuel prices, even without help from the media. On the other hand, consumers could ignore what they think are temporary price fluctuations; for example, although consumers' most common expectation of future prices is the current price, under some circumstances they apparently expect some reversion to previous price levels.[31] Volatility may also activate risk aversion, but again it is not clear in which direction this would work: would purchasers of motor vehicles regard fuel efficiency as a risky investment, or as a hedge against the risk of higher future operating costs? Thus it is unclear theoretically in which direction volatility should affect consumers' responsiveness to price changes.

3.4.1. Data description

We construct measures of media coverage based upon gas-price-related articles appearing in the *New York Times* newspaper. Using the Proquest historical database, we tally the annual number of article titles containing the words *gasoline* (or *gas*) and *price* (or *cost*). We then form a variable equal to the annual fraction of all *New York Times* articles that are gas-price-related. This fraction ranged from roughly 1/4000 during the 1960s to a high of 1/500 in 1974. Its logarithm, normalized by subtracting its mean, is shown in Fig. 2. In the specifications shown here, we use a dummy variable *Media_dummy* equal to one when the ratio exceeds its 1996–2009 median value.[32]

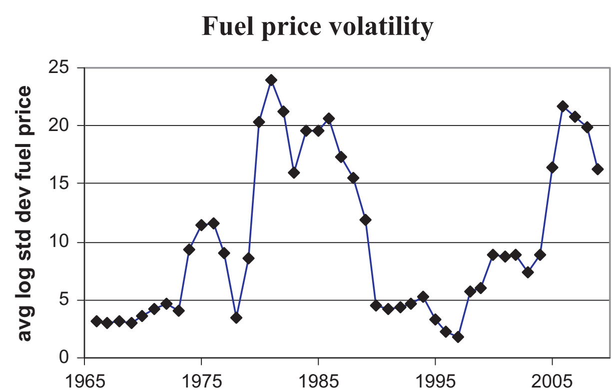

Fig. 3. Fuel price volatility.

The validity of this variable 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 follow the *New York Times* when choosing their news topics. One study by Golan (2006) finds 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 as gas-price changes would be similar across news outlets even in the absence of direct influence of the New York Times.

To measure volatility in fuel prices, we construct a variable whose value in year t is the standard deviation of annual fuel prices over the years $t-4$ through t.[33] (We choose this five-year interval as the most likely time over which new vehicle purchasers would be aware of volatility.) This measure, named *Price_volatility*, varies across states; the average of its logarithm, by year, is plotted in Fig. 3.

Our measures of media attention and price volatility are only very slightly correlated with each other ($\rho = 0.02$), and only mildly correlated with fuel cost per mile pm ($\rho = 0.28$ and 0.27). Furthermore, when fuel cost per mile is regressed on these other two variables, the R^2 is only 0.19, and a residual plot (see Appendix A) shows substantial

[31] Supporting evidence comes from two separate surveys, reported by Anderson et al. (2013) and Allcott (2011), both of which asked people directly about their price expectations. Anderson et al. (2013) find that a random walk assumption accurately explains their answers except in late 2008, when people expected (correctly, as it turned out) that the recent fall in prices would prove to be temporary.

[32] *Media_dummy* is equal to one in years 1973–1981, 1983, 1990–1992, 1994–1997, 2000, 2004–2006, and 2008. It is not normalized.

[33] Although use of monthly or quarterly fuel price data would have been preferable, such data do not exist at the state level prior to 1976.

Table 7
Selected coefficient estimates: asymmetry with media coverage and/or fuel-price uncertainty.

Equation and variable	Model 3		Model 6		Model 7		Model 8		Model 9	
	Coeff.	Std. error	Coeff.	Std. error	Coeff.	Std. error	Coeff.	Std. error	Coeff.	Std. error
vma equation:										
$pm = pf + fint$	−0.0639	0.0049	−0.0710	0.0052	−0.0587	0.0052	−0.0325	0.0088	−0.0351	0.0097
$pf\_cut + fint$	0.0340	0.0078	0.0394	0.0080	0.0286	0.0081	0.0242	0.0089	0.0246	0.0092
$pm * Dummy\_0309$			−0.0277	0.0076					−0.0144	0.0086
$pf * Media\_dummy$					−0.0301	0.0101	−0.0412	0.0102	−0.0443	0.0105
$pm * Price\_volatility$							−0.0018	0.0005	−0.0011	0.0005
$pm * inc$	0.0577	0.0107	0.0759	0.0122	0.0583	0.0109	0.0620	0.0113	0.0671	0.0131
pm^2	−0.0207	0.0061	−0.0216	0.0061	−0.0053	0.0075	0.0204	0.0100	0.0107	0.0105
$pm * Urban$	0.0131	0.0093	0.0099	0.0094	0.0118	0.0094	0.0025	0.0099	0.0056	0.0102
vma lagged	0.8334	0.0104	0.8265	0.0106	0.8325	0.0106	0.8439	0.0108	0.8397	0.0115
fint equation:										
$pf + vma$	−0.0097	0.0060	−0.0078	0.0059	−0.0124	0.0059	−0.0109	0.0058	−0.0093	0.0058
$pf\_cut + vma$	0.0143	0.0123	0.0069	0.0120	0.0220	0.0120	0.0210	0.0119	0.0120	0.0117

Note: See note to Table 3. *Dummy_0309* is a dummy variable for years 2003 and higher. See text for definitions of *Media_dummy* and *Price_volatility*.

remaining unexplained variation. (These tests were performed on national average time series, since we observe media coverage only at the national level, and they were performed before converting *media* to a dummy variable.) Furthermore, our main specification includes a quadratic of *pm* and interactions of it with two other variables. Thus, we do not believe that these new variables will merely pick up nonlinearities or other specification errors in the price variable.

3.4.2. Specification and results

Table 7 shows several models which include the one or both of the variables for media coverage and price volatility, each interacted with either fuel price or fuel cost.[34] The media variable is specified to influence the response to fuel price but not to fuel efficiency, because the variable involves news about fuel prices; this is accomplished by interacting it with *pf* and not *pm*. This implies that media coverage impacts the rebound elasticity only indirectly, via changes in estimated coefficients. The volatility variable, by contrast, reflects a consumer's own experience with variation in fuel costs, and therefore we specify it so as to influence the response to both price and fuel efficiency (i.e., it is interacted with *pm* rather than *pf*). For comparison, the table also shows two models incorporating asymmetry but not media or uncertainty (Models 3 and 6).

Models 7 and 8 show that both media coverage and price volatility exert strong influences on the price-elasticity of motor vehicle travel, increasing the response to fuel price changes and, in the case of volatility, to fuel efficiency changes as well.[35] In fact, the effect of price volatility is so strong as to eliminate the previously observed positive effect of fuel cost itself on the magnitude of the rebound elasticity: the coefficient of pm^2 is now reversed in sign and just barely statistically significant. This suggests that the rise in the magnitude of the elasticity of VMT during the 2000s was due more to volatility than to the higher level of fuel price.[36]

Because we specified the media variable to interact with fuel price but volatility to interact with fuel cost, the "rebound effect", defined as the response to changes in fuel efficiency, is increased in magnitude by fuel-price volatility but not by media coverage. To put it differently, given the assumptions of the specification, we find that media coverage tends to intensify the effect of fuel prices, while fuel price volatility intensifies the effect of per mile fuel costs whatever their source. Furthermore, media coverage undoubtedly responds to consumer interest and therefore could be correlated with other variables affecting VMT, thus making it endogenous and limiting its usefulness for drawing policy implications.

We noted earlier the appearance of a shift in the structural elasticity toward higher values during the period 2003–09. Model 6 confirms that this shift exists even in models with asymmetric responses.[37] Model 9 reveals, however, that our media and volatility variables can explain about half this shift. (Other models, not shown, demonstrate that those two variables share approximately equally in this task of explaining the shift.) The remainder of the shift (1.44 percentage points of elasticity) is still unexplained, leaving room for future research to uncover the missing factors.

3.4.3. Caveats and summary of quantitative results

The two new variables presented in this section explain approximately half of the observed increase in the rebound effect starting in 2003. But the extent to which these variables are useful in forecasting future values of the rebound effect is somewhat limited, because they are themselves difficult to forecast. Nevertheless, these findings could guide future research aimed at predicting fuel consumption. Such research may involve gaining a better understanding of the underlying factors that govern media attention and fuel price volatility.

For completeness, Table 8 shows the long-run price elasticities and fuel-cost elasticities of VMT, fuel efficiency, and fuel consumption using our most preferred models. The elasticities are calculated using Eqs. (5a) and (5b) and their counterparts as described by Small and Van Dender (2007). The full estimation results for these three models are listed in Appendix B.2.

4. Conclusion

The research reported here, extending Small and Van Dender (2007) with data through 2009, confirms the findings of previous studies that the long-run rebound effect, measured over a period of several decades extending back to 1966, is close to 30%. We also find a short-run (one-year) rebound effect, again averaged over that entire period, of about 4.7%.

Furthermore, we confirm earlier findings that the rebound effect became substantially smaller in magnitude over the course of that

[34] As with other interacting variables, we normalize each variable by subtracting its mean value on the entire sample; this is done for convenience so that the coefficient of *pf* or *pm* measures the short-run structural VMT elasticity when all interacting variables take their mean values in the sample.

[35] The base response (coefficient of *pm*) is negative; therefore a negative coefficient on an interaction term means that the magnitude of the response increases with the interacting variable. Because these variables are multiplied by *pf* or by $pm \equiv pf + fint$, and because $pf \equiv pf\_fire + pf\_cut$, the coefficients of the interactions are part of both $\partial vma/\partial pf\_rise$ and $\partial vma/\partial pf\_cut$. The coefficient of *pf_cut* indicates a wedge between the response to price rises and price cuts, a wedge whose size does not depend on the media or volatility variable.

[36] These same characteristics persist in the presence of a variable measuring unemployment, and if additional lags are added as with Model 4. (The effects of those additional lags show the same pattern, and nearly the same magnitudes, as in Model 4.)

[37] The variable *Dummy_0309* is equal to one for years 2003–2009 and zero otherwise, except here it has been normalized (like other variables interacted with *pm*) by subtracting its mean, which is 7 / 44 = 0.159. (In Model 2, it was not normalizEd.)

Table 8
Long-run elasticities implied by preferred models.

Elasticities:	Model 1	Model 3		Model 8	
		Price rising	Price falling	Price rising	Price falling
VMT with respect to fuel efficiency:					
At sample average[a]	−0.295	−0.184	−0.184	−0.052	−0.052
At US 2000–2009 avg.[b]	−0.178	−0.042	−0.042	−0.040	−0.040
VMT with respect to fuel price:					
At sample average[a]	−0.295	−0.397	−0.184	−0.214	−0.052
At US 2000–2009 avg.[b]	−0.178	−0.255	−0.042	−0.202	−0.040
Fuel consumption with respect to fuel price:					
At sample average[a]	−0.322	−0.433	−0.249	−0.279	−0.146
At US 2000–2009 avg.[b]	−0.213	−0.309	−0.130	−0.269	−0.136

[a] Elasticities measured at sample average values of *pm*, *inc*, & *Urban* for years 1966–2009.
[b] Elasticities measured at sample average values of *pm*, *inc*, & *Urban* for years 2000–2009.

time period, probably due to a combination of higher real incomes, lower real fuel costs, and higher urbanization. Our base model (Model 1) implies that the long-run rebound effect is 17.8% when evaluated at average values of income, fuel cost, and urbanization over the years 2000–2009.

We also report some new findings. There is strong evidence of asymmetry in responsiveness to price increases and decreases. This makes interpretation of the rebound effect 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.

In both symmetric and asymmetric response models, there is an upward shift in the rebound effect, of 2.5 to 2.8 percentage points, starting in 2003. We introduce two new variables, which together explain about half of this shift. The first is media coverage of fuel prices; the second is fuel-price volatility. Both substantially increase travelers' responsiveness to changes in fuel price and/or fuel cost. Nevertheless, these influences are small enough in magnitude that they do not fully offset the downward trend in VMT response elasticities due to higher incomes and other factors. Hence even assuming that the variables retain their 2000–2009 values into the indefinite future, they would not prevent a further diminishing of the magnitude of the rebound effect if incomes continue to grow at anything like historic rates.

Acknowledgments

We are grateful for financial support from the University of California Center for Energy and Environmental Economics (project entitled "Response of Light-Duty Vehicle Travel and Fuel Consumption to Fuel Costs") and from the Environmental Protection Agency (Contract EP-W-08-018). We thank Kevin Bolon, Jefferson Cole, Sarah Froman, Kenneth Gillingham, David Greene, Gloria Helfand, Sharyn Lie, James Sallee, Michael Shelby, and seminar participants at Cornell Univ., Yale Univ., and Calif. State Univ. at Long Beach for valuable comments at various stages of the work described here.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2014.12.016.

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