The Rebound Effect for Automobile Travel: Asymmetric Response to Price Changes and Novel Features of the 2000s

Kent M. Hymel
Kenneth A. Small

August 14, 2014

Hymel: Dept. of Economics, California State University at Northridge;
kent.hymel@csun.edu
Small: Dept. of Economics, University of California at Irvine;
ksmall@uci.edu

JEL Codes: 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.

Acknowledgement

We are grateful to the University of California Center for Energy and Environmental Economics and the Environmental Protection Agency for financial support. 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, Yale, CSU Long Beach, and the International Transportation Economics Association for valuable comments at various stages of the work described here.

The Rebound Effect for Automobile Travel:
Asymmetric Response to Price Changes and Other Quirks of the 2000s

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 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.

[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).

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 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

[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.

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 -0.08 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 one percent increase in

[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).

gasoline price reduces construction over the next four years by one percent, which is 0.03 percent 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.

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.

The standard definition of the direct rebound effect[5] can be derived from a partially reduced form of (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:

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

The VMT elasticity is:

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

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

An important assumption in (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 (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

[5] 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.

between selected exogenous or endogenous variables Z_1^m and fuel cost. Thus we estimate the following system:

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

with autoregressive errors:

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

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, equation (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 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.[6] 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. We have elsewhere compared results with and without these data revisions, ascertaining that they did not have important effects on the results (Small and Hymel 2013). The variable *cafe* measuring stringency of CAFE standards is, as before, constructed by using a reduced-form version of the model system to predict the desired fuel efficiency 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.[7]

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.[8]

3. Empirical Results

[6] See Small and Van Dender (2007) for a full description of data sources and a discussion of possible weaknesses. The two most serious weaknesses are 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, which are what drive our results due to use of state fixed effects.

[7] 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.

[8] 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.

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.[9]

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

[9] Two recent exceptions are the 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 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 (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.

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 they explain about half 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 (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 1shows that the estimated structural elasticity falls in magnitude by 46 percent 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.[10]

[10] In the three-equation models, that coefficient, denoted α^m in (4), varies between 0.82 and 0.84 for the "full" and "early" samples. Applying equations (5) when α^{mv} and/or α^{vm} are small, the ratio of long-run to short-run rebound effect is approximately 1/(1-α^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, eqn 14) and not as easily

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)

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 3.3), in which three variables—income, fuel cost, and urbanization—are interacted with fuel cost, thereby allowing the estimated structural VMT elasticity to vary with those three variables.[11] 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 the interacted variable is pm^2. In each case, the incremental effect of variable Z on the rebound effect

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.

[11] 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.

is given by $\partial(\partial vma/\partial pm)/\partial Z$.[12] 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.

Table 2. Models with interacted coefficients (selected coefficients)

	Model 3.3		Model 3.18	
Variable	Coeff.	Std. Err.	Coeff.	Std. Err.
pm	-0.0466	0.0029	-0.0464	0.0029
*pm*Dummy_2003_09*			-0.0251	0.0076
*pm*inc*	0.0528	0.0108	0.0699	0.0121
pm^2	-0.0124	0.0059	-0.0113	0.0060
*pm*Urban*	0.0119	0.0094	0.0078	0.0096
vma lagged	0.8346	0.0102	0.8279	0.0105
Calculated rebound elasticities:				
1966-2009				
Short run	-0.047		-0.050	
Long run	-0.295		-0.309	
2000-2009				
Short run	-0.028		-0.042	
Long run	-0.178		-0.255	

The results for Model 3.3, our base specification, have only one important difference from the results of using the shorter sample, 1966-2001, of Small and Van Dender (2009). On that shorter sample, the coefficient on pm^2 was estimated to be smaller and statistically insignificant.[13] 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, labeled 3.18, that allows for an additional unexplained shift in the structural VMT elasticity starting in 2003. This starting year, chosen mostly by trial and

[12] Hence if $\gamma_1^m = (\gamma_{1k}^m, k = 1,2,3)$ is the coefficient vector of these three interacted variables, as in (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*.

[13] 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.

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 3.18 due to the boost given by the dummy variable for 2003-2009. Model 3.18 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.[14]

Model 3.18 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.

As detailed in Small and Hymel (2013), we obtain comparable results with the four-equation model of Hymel et al. (2010).[15]

We hoped our longer data set would enable us to better test the assumption implicit in (1) that consumers respond equally, in elasticity terms, to fuel price and fuel intensity (the inverse of

[14] 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.

[15] We also estimated a version of Model 3.3 adding the national unemployment rate as a variable in each of the three equations (see Appendix Model 3.3c). 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.

fuel efficiency). This 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 different coefficients on both variables.[16] Like Gillingham (2011, Table 3.4 and Section 3.1.3), we find that fuel intensity has a smaller impact on driving than does fuel price.

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.[17] 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.[18] 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:

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

[16] Specifically, when this decomposition of *pm* is applied to the four-equation counterpart of Model 3.3, the coefficient of *pf* is -0.0544 (0.0035) and that of *fint* is -0.0232 (0.0107), with standard errors in parentheses.

[17] 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).

[18] 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.

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):

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

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 3.21b, are summarized in Table 3. The symmetric model 3.3 is shown for comparison. These results suggest that the fuel-cost elasticity of *vma* becomes modestly larger in absolute value when measured only for price increases, and smaller for price cuts. In Model 3.21b, the direct short-run effect of a price rise on driving 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.

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

	Model 3.3		Model 3.21b	
Equation and variable:	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	0.0108
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	0.0105
fint equation:				
pf+vma	-0.0050	0.0041	-0.0097	0.0060
pf_cut+vma			0.0143	0.0123

In the asymmetric model just described (3.21b), 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 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.[19]

The estimated coefficients of the interaction terms from Model 3.21b are similar to those from Model 3.3; 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.[20] [21]

---

[19] 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.

[20] We find very similar behavior if the unemployment rate is included in both the *vma* and *fint* equations, just as in Model 3.3c (as described at the end of Section 3.2). This model is reported in Appendix B as Model 3.21c. Just as with Model 3.3c, 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.

We also estimated Model 3.21b using the generalized method of moments estimator (GMM) 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 3.21b. 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 (3.21b) 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 3.21b; 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 are similar to those obtained from the 3SLS estimator, although the estimated coefficients for the variables used to calculate the rebound effect are smaller in magnitude. Some of the difference in those estimates is a result of excluding the time trend variable while some is attributable to the change in estimator. Nevertheless, the GMM results are more or less consistent with the results for alternate model specifications presented below. Finally, clustering the standard errors at the state level changes the standard errors of coefficients very little, and does not change the statistical significance of any of the variables in the model.

---

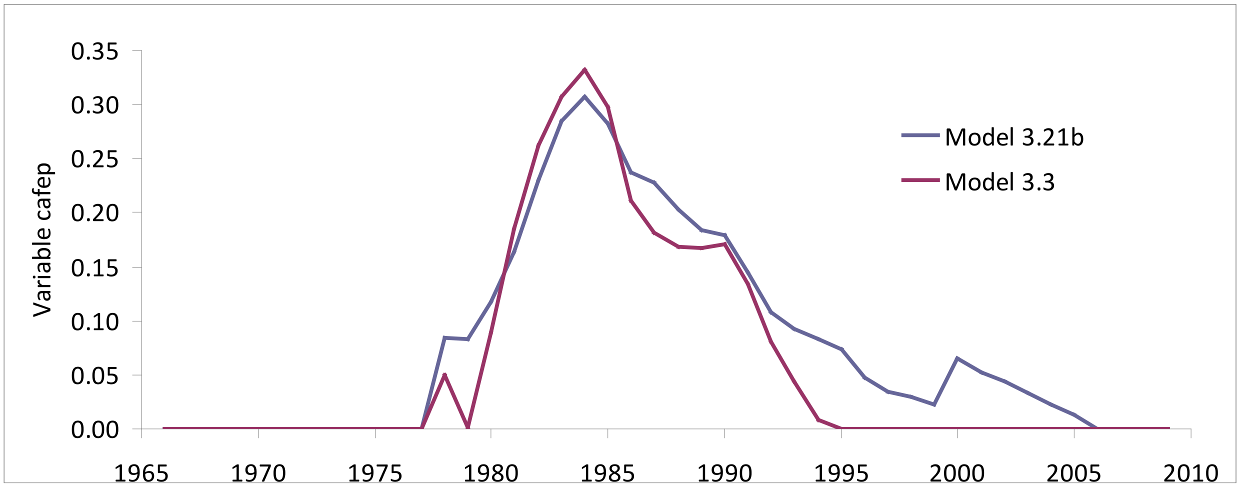
[21] We also estimated a model analogous to 3.21b that included the fuel price variables measured in nominal rather than real dollars; we thank Stuart Rosenthal for this suggestion. The motivation for this model was the possibility that nominal price changes are more noticeable to drivers than real changes. 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.

Table 4. Alternate estimators: selected coefficients from the *vma* equation.

	Model 3.21b		Model 3.21b		Model 3.21b	
	3SLS		3SLS no trend variable		GMM no trend variable	
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
pm2	-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

The asymmetric model implies a somewhat different history of the stringency of the CAFE standards than does our base model. This is because the asymmetric model implies that price cuts and price rises enter separately as explanatory variables in the counter-factual regression explaining fuel efficiency pre-1978, and their different coefficients are carried through in projecting desired fuel efficiency post-1978. Figure 1 shows the variable *cafe* which, as explained earlier, captures the difference between desired fuel efficiency and that mandated under CAFE standards. Using the symmetric model to derive the desired fuel economy, the stringency of CAFE standards drops to zero in 1995 and remains there. Using the asymmetric Model 3.21b, however, the standards remain binding until 2006, with stringency jumping notably upward in 2000 due to the sharp rise in fuel price during that year.

Figure 1. Stringency of CAFE standards



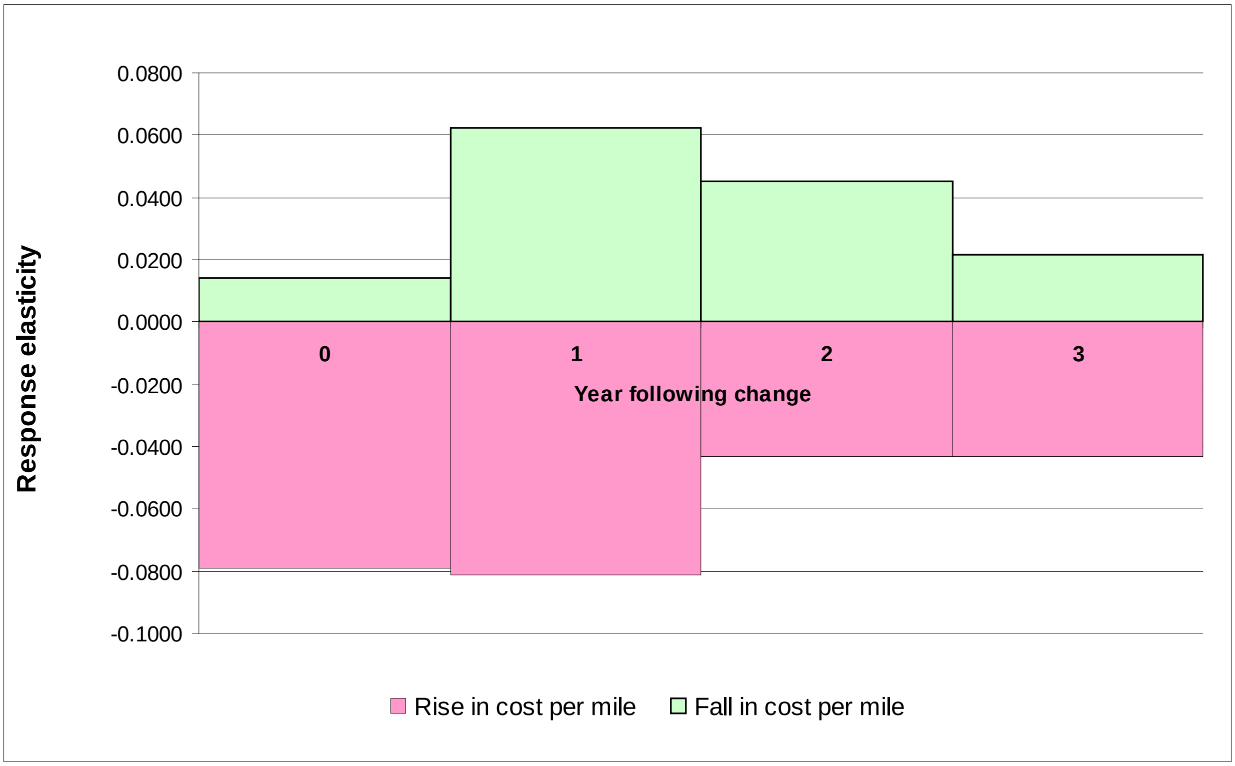
An alternative view of how asymmetry might work is that the difference in response between fuel price rises or cuts is not so much in the *magnitude*, but in the *speed* with which the response occurs. All the models considered in this paper already have an "inertia" built into them, in the form of a lagged dependent variable which governs the speed of response to all variable changes. But in Model 3.29b in Table 5, we allow also for the possibility that the speed of the response differs between rises and cuts in fuel price. This is done by adding various lags of *pf_rise* and *pf_cut*.

Table 5 Selected coefficient estimates: asymmetry in response to fuel price

	Model 3.21b		Model 3.29b	
Equation and variable:	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	0.0099	0.0328	0.0103
vma lagged	0.8334	0.0104	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

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 (0.140); takes its largest value after one year (0.0626, from the sum of the first two coefficients between the dashed lines 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 Figure 2.

Figure 2. Short-run elasticity of VMT with respect to a sustained change in fuel price (Model 3.29b)



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 of *pm* is accounted for as part of the three-equation model.[22] 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 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.

Table 6 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 also contains three interaction variables, whose coefficients are shown just below the dashed line.) 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.

[22] 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 6 Selected coefficient estimates: asymmetry in response to fuel price or fuel cost per mile

	Model 3.21b		Model 3.23	
Equation and variable:	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

In model 3.23, 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 cost per mile. 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.[23] For this reason, we prefer the models of Section 3.3.1.

[23] 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".

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 is variations in media attention to fuel prices and costs. Motor vehicle fuel is a moderately important part of many people's budgets, and crude oil even more so. As a result, there is a tendency for turmoil in gasoline or oil markets to gain much attention in public media.

The second 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.[24]

Data Description

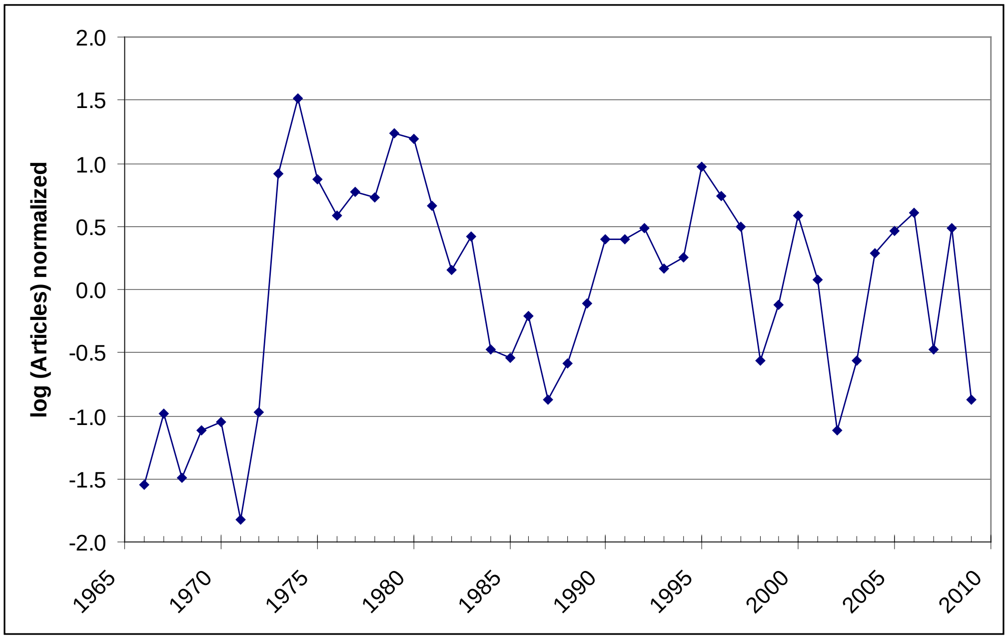
We construct measures of media coverage based upon gas-price-related articles appearing in the *New York Times* newspaper. Using the Proquest historical database , we tally the annual number of article titles containing the words *gasoline* (or *gas*) and *price* (or *cost*). We then form a variable 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 Figure 3. In the specifications shown here, we use a dummy variable *Media_dummy* equal to one when the ratio exceeds its 1996-2009 median value.[25]

---

[24] 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. Anderson et al. (2011) 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.

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

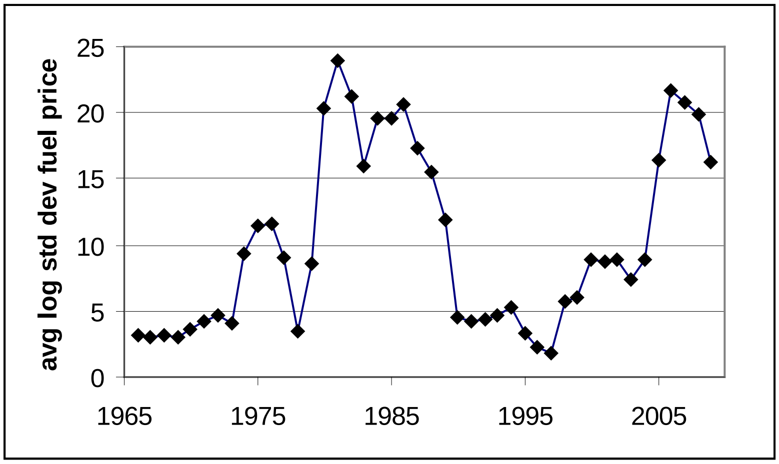
Figure 3
Media coverage of gas prices



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 fuel prices over the years *t*-4 through *t*. (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 Figure 4.

Figure 4
Fuel price volatility



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.[26] 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 3.21b and 3.21d).

[26] 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.

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

	Model 3.21b		Model 3.21d		Model 3.35		Model 3.55		Model 3.55d	
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	-0.0710	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

Models 3.35 and 3.55 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.[27] 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.[28]

Because we specified the media variable to interact with fuel price but volatility to

[27] The base response (coefficient of *pm* is negative, so a negative coefficient on an interaction term mean 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.

[28] These same characteristics persist in the presence of a variable measuring unemployment, and if additional lags are added as with Model 3.29b. (The effects of those additional lags show the same pattern, and nearly the same magnitudes, as in Model 3.29b.)

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 3.21d confirms that this shift exists even in models with asymmetric responses.[29] Model 3.55d reveals, however, that about half this shift can be explained by our media and volatility variables. (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.

For completeness, Table 8 shows the long-run price elasticities of VMT, fuel efficiency, and fuel consumption using our most preferred models. The elasticities are calculated using equations (5) 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.

[29] 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 3.18, it was not normalized.)

Table 8. Long-run elasticities implied by preferred models

Elasticities:	Model 3.3	Model 3.21b Price rising	Model 3.21b Price falling	Model 3.55 Price rising	Model 3.55 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

Notes:
[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.

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 time period, probably due to a combination of higher real incomes, lower real fuel costs, and higher urbanization. Our base model (Model 3.3) 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 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.

References

Allcott, Hunt (2011), “Consumers’ Perceptions and Misperceptions of Energy Costs,” *American Economics Review: Papers and Proceedings*, 101(3): 98-104.

Anderson, Soren T., Ryan Kellogg, James M. Sallee, and Richard T. Curtin (2011), “Forecasting Gasoline Prices Using Consumer Surveys,” *American Economic Review: Papers and Proceedings*, 101(3), 110-114.

Borenstein, Severin (2013), “A Microeconomic Framework for Evaluating Energy Efficiency Rebound and Some Implications,” Working paper 19044, National Bureau of Economics Research, May.

Brons, Martijn, Peter Nijkamp, Eric Pels, and Piet Rietveld (2008), “A meta-analysis of the price elasticity of gasoline demand: A SUR approach,” *Energy Economics*, 30: 2105-2122.

Dargay, J., 2007. The effect of prices and income on car travel in the UK. *Transportation Research Part A: Policy and Practice*, 41(10), 949-960.Davis, Stacy C., Susan W. Diegel, and Robert G. Boundy (2011), *Transportation Energy Data Book*, 30th edition, Oak Ridge National Laboratory, June. http://cta.ornl.gov/data/index.shtml

Dargay, Joyce M., and Dermot Gately, 1997, "The Demand for Transportation Fuels: Imperfect Price-reversibility?" *Transportation Research – Part B*, 31(1):71-82.

Dargay, Joyce M., Dermot Gately, and Martin Sommer (2007), “Vehicle Ownership and Income Growth, Worldwide: 1960-2030. *Energy Journal*, 28(4): 143-170.

Gately, Dermot, and Hillard G. Huntington, 2002. "The Asymmetric Effects of Changes in Price and Income on Energy and Oil Demand" *Energy Journal*, 23(1), pp. 19-55.

Gillingham, Kenneth (2011), *The Consumer Response to Gasoline Price Changes: Empirical Evidence and Policy Implications*. Ph.D. Dissertation, Dept. of Management Science and Engineering, Stanford University, June. http://purl.stanford.edu/wz808zn3318

Gillingham, Kenneth (2013), “Identifying the Elasticity of Driving: Evidence from a Gasoline Price Shock in California,” working paper, Yale University, February.http://www.yale.edu/gillingham/Gillingham_IdentifyingElasticityDriving.pdf

Golan, Guy (2006), Inter-Media Agenda Setting and Global News Coverage: Assessing the influence of the New York Times on three network television evening news programs,” *Journalism Studies*, 7(2), 323-333.

Goodwin, P., J. Dargay, and M. Hanly (2004). “Elasticities of Road Traffic and Fuel Consumption with Respect to Price and Income: A Review,” *Transport Reviews*, 24 (3), 275-292.

Graham, D.J., Glaister, S., 2004, Road traffic demand elasticity estimates: a review. *Transport Reviews*, 24(3), 261-274.

Greene, D.L. (1992). “Vehicle Use and Fuel Economy: How Big is the Rebound Effect?” *Energy Journal*, 13 (1), 117-143.

Greene, David L. (2012), “Rebound 2007: Analysis of U.S. Light-Duty Vehicle Travel Statistics,” *Energy Policy*, 41: 14–28.

Greene D.L., J.R. Kahn and R.C. Gibson (1999). “Fuel Economy Rebound Effect for US Households, *Energy Journal*, 20 (3), 1-31.

Greening, L.A., D.L. Greene and C. Difiglio (2000). “Energy Efficiency and Consumption – The Rebound Effect – A Survey,” *Energy Policy*, 28, 389-401.

Haughton, J. and S. Sarkar (1996). “Gasoline Tax as a Corrective tax: Estimates for the United States (1970-1991),” *Energy Journal*, 17 (2), 103-126.

Hughes, Jonathan E., Christopher R. Knittel, and Daniel Sperling (2008), “Evidence of a Shift in the Short-Run Price Elasticity of Gasoline Demand,” *Energy Journal*, 29(1): 113-134.

Hymel, Kent, Kenneth A. Small, and Kurt Van Dender (2010). “Induced Demand and Rebound Effects in Road Transport,” *Transportation Research Part B – Methodological*, 44(10), 1220-1241.

Knittel, Christopher R., and Ryan Sandler (2012), “Carbon Prices and Greenhouse Gas Emissions: The Intensive and Extensive Margins,” in Don Fullerton and Catherine Wolfram, eds., *Design and Implementation of U.S. Climate Policy*, University of Chicago Press, ch. 18, pp. 287-299.

Knittel, Christopher R., and Ryan Sandler (2013), “The Welfare Impact of Indirect Pigouvian Taxation: Evidence from Transportation,” Working Paper 18849, National Bureau of Economic Research. http://www.nber.org/papers/w18849

Jones C.T. (1993). “Another Look at U.S. Passenger Vehicle Use and the ‘Rebound’ Effect from Improved Fuel Efficiency,” *Energy Journal*, 14 (4), 99-110.

Litman, Todd (2013), “Changing North American vehicle travel price sensitivities: Implications for transport and energy policy,” *Transport Policy*, 28: 2-10.

Mackie P.J., A.S. Fowkes, M. Wardman, G. Whelan, J. Nellthorp, and J. Bates (2003) *Values of Travel Time Savings in the UK: Summary Report*, report to the UK Department for Transport. Leeds, UK: Institute of Transport Studies, Univ. of Leeds. http://www.dft.gov.uk/pgr/economics/rdg/valueoftraveltimesavingsinth3130?page=1#a1000

Molloy, Raven, and Hui Shan (2013), “The effect of gasoline prices on household location,” *Review of Economics and Statistics* 95(4): 1212–1221.

NHTSA (National Highway Traffic Safety Administration) (2012), *Corporate Average Fuel Economy for MY 2017-MY 2025 Passenger Cars and Light Trucks: Final Regulatory Impact Analysis*, August. www.nhtsa.gov/staticfiles/rulemaking/pdf/cafe/FRIA_2017-2025.pdf

Schrank, David, Tim Lomax, and Shawn Turner (2010). *Urban Mobility Report 2010*, Texas Transportation Institute, December. http://mobility.tamu.edu

Small K.A. and K. Hymel (2013), *The Rebound Effect from Fuel Efficiency Standards: Measurement and Projection to 2035*, Final report to U.S. Environmental Protection Agency, contract EP-W-08-018, March 26.

Small K.A. and K. Van Dender (2007). "Fuel Efficiency and Motor Vehicle Travel: The Declining Rebound Effect," *Energy Journal* 28: 25-51.

Small K.A. and E.T. Verhoef (2007) *The Economics of Urban Transportation*, London and New York: Routledge, forthcoming.

Wadud Z., D.J. Graham, and R.B. Noland (2007a). "Gasoline demand with heterogeneity in household responses," Working paper, Centre for Transport Studies, Imperial College London.

Wadud Z., D.J. Graham, and R.B. Noland (2007b). "Modelling fuel demand for different socio-economic groups," Working paper, Centre for Transport Studies, Imperial College London.

West, Sarah E. (2004), "Distributional effects of alternative vehicle pollution control policies," *Journal of Public Economic*, 88: 735-757.

Appendix A. Data

A.1 Variables used

Variables used in our base model are described below. For data sources, see Small and Van Dender (2007b) and Hymel et al. (2010).

Dependent Variables

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

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

$1/E$: Fuel intensity, measured as F/M, where F is highway use of gasoline[30] (logarithm: *fint*).

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

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*). [31]

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).

[30] 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.

[31] 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.

A.2 Adjustments to 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 our earlier published papers, 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 paper, the same procedure was applied to the 2001-2009 data using Census counts for 2010. This adjustment was not made for the post-2000 data in the earlier papers due to unavailability at that time of the 2010 Census counts.

Additional references

Small K.A. and K. Van Dender (2007b). “Fuel Efficiency and Motor Vehicle Travel: The Declining Rebound Effect,” Working Paper No. 05-06-03, Department of Economics, University of California at Irvine (revised).

Appendix B. Additional estimation results

B.1 Models including unemployment rate: selected results

Table B1. Three-equation models with and without unemployment variables

	Model 3.3		Model 3.3c		Model 3.18		Model 3.18c		Model 3.21b		Model 3.21c	
Equation and variable:	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
vma equation:												
pm= pf+ fint	-0.0466	0.0029	-0.0416	0.0038	-0.0464	0.0029	-0.0429	0.0031	-0.0639	0.0049	-0.0601	0.0052
pf_cut + fint									0.0340	0.0078	0.0302	0.0079
*pm*dummy_0309*					-0.0251	0.0076	-0.0230	0.0079				
*pf ** (*Media_dummy*)												
*pm ** log(*varpf*)												
*pm*inc*	0.0528	0.0108	0.0521	0.0110	0.0699	0.0121	0.0694	0.0122	0.0577	0.0107	0.0620	0.0107
pm^2	-0.0124	0.0059	-0.0176	0.0060	-0.0113	0.0060	-0.0148	0.0060	-0.0207	0.0061	-0.0242	0.0061
*pm*Urban*	0.0119	0.0094	0.0142	0.0098	0.0078	0.0096	0.0075	0.0097	0.0131	0.0093	0.0117	0.0093
Unemployment rate			-0.0015	0.0005			-0.0017	0.0005			-0.0011	0.0005
vma lagged	0.8346	0.0102	0.8380	0.0104	0.8279	0.0105	0.8306	0.0106	0.8334	0.0104	0.8348	0.0104
veh equation												
Unemployment rate			-0.0029	0.0007			-0.0029	0.0007			-0.0028	0.0007
fint equation:												
pf + vma	-0.0050	0.0041	-0.0143	0.0043	-0.0052	0.0041	-0.0140	0.0043	-0.0097	0.0060	-0.0308	0.0070
pf_cut + vma												
Unemployment rate			0.0047	0.0007			0.0043	0.0007			0.0056	0.0008

B.2 Full estimation results for preferred models

Table B2 Full estimation results for preferred models

		Model 3.3		Model 3.21b		Model 3.55	
Equation	Variable	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
vma	intercept	1.6261	0.1022	3.1468	0.3541	2.6249	0.4077
vma	inc	0.0781	0.0117	0.0770	0.0118	0.0667	0.0129
vma	Adults / road mile	-0.0149	0.0038	-0.0151	0.0037	-0.0133	0.0039
vma	popratio	0.0726	0.0322	0.0630	0.0323	-0.0024	0.0364
vma	Urban	-0.0205	0.0391	-0.0061	0.0395	-0.0122	0.0406
vma	Railpop	-0.0067	0.0043	-0.0082	0.0042	-0.0075	0.0044
vma	D7479	-0.0439	0.0034	-0.0445	0.0035	-0.0490	0.0038
vma	Trend	-0.0004	0.0002	0.0013	0.0004	0.0011	0.0005
vma	vma(-1)	0.8346	0.0102	0.8334	0.0104	0.8439	0.0108
vma	vehstock	0.0209	0.0067	0.0161	0.0067	0.0142	0.0069
vma	pm = pf + fint	-0.0466	0.0029	-0.0639	0.0049	-0.0325	0.0088
vma	pm^2	-0.0124	0.0059	-0.0207	0.0061	0.0204	0.0100
vma	pm*inc	0.0528	0.0108	0.0577	0.0107	0.0620	0.0113
vma	pm*Urban	0.0119	0.0094	0.0131	0.0093	0.0025	0.0099
vma	pfcut + fint			0.0340	0.0078	0.0242	0.0089
vma	pf*Media_dummy					-0.0412	0.0102
vma	pm*Price_volatility					-0.0018	0.0005
vma	AR(1)	-0.1018	0.0204	-0.1021	0.0204	-0.1012	0.0208
vma	State fixed effects	yes		yes		yes	
veh	intercept	-0.2253	0.1452	-0.2188	0.1449	-0.2206	0.1448
veh	pnewcar	0.0400	0.0317	0.0460	0.0317	0.0458	0.0317
veh	interest	-0.0008	0.0042	-0.0004	0.0042	-0.0006	0.0042
veh	income	0.0032	0.0146	0.0038	0.0146	0.0038	0.0146
veh	adults / road mile	-0.0136	0.0060	-0.0137	0.0060	-0.0137	0.0060
veh	licenses/adult	0.0345	0.0184	0.0349	0.0183	0.0351	0.0183
veh	trend	0.0002	0.0007	0.0004	0.0007	0.0004	0.0007
veh	vehstock(-1)	0.9318	0.0104	0.9316	0.0104	0.9317	0.0104
veh	vma	0.0291	0.0147	0.0281	0.0146	0.0283	0.0146
veh	pm	0.0013	0.0058	0.0019	0.0058	0.0018	0.0058
veh	AR(1)	-0.1461	0.0230	-0.1469	0.0230	-0.1467	0.0230
veh	State fixed effects	yes		yes		yes	
fint	intercept	-0.2447	0.0631	0.9282	1.0517	1.4590	1.0132
fint	pf + vma	-0.0050	0.0041	-0.0097	0.0060	-0.0109	0.0058
fint	inc	-0.0016	0.0144	0.0000	0.0146	-0.0017	0.0144
fint	fint(-1)	0.9040	0.0100	0.8977	0.0115	0.8947	0.0115
fint	popratio	-0.0168	0.0603	-0.0005	0.0586	0.0300	0.0600
fint	Trend66-73	0.0005	0.0011	-0.0005	0.0011	0.0001	0.0011
fint	Trend74-79	-0.0068	0.0010	-0.0061	0.0011	-0.0063	0.0011
fint	Trend80+	-0.0007	0.0003	-0.0002	0.0007	0.0002	0.0007
fint	D7479	-0.0070	0.0048	-0.0032	0.0048	-0.0022	0.0048
fint	Urban	-0.0905	0.0467	-0.0890	0.0471	-0.0863	0.0467
fint	cafe	-0.0345	0.0108	-0.0256	0.0183	-0.0103	0.0171
fint	pfcut + vma			0.0143	0.0123	0.0210	0.0119
fint	AR(1)	-0.1773	0.0201	-0.1804	0.0202	-0.1858	0.0202
fint	State fixed effects	yes		yes		yes	