Peer Review for the Report "The Rebound Effect from Fuel Efficiency Standards: Measurement and Projection to 2035"

United States Environmental Protection Agency

Peer Review for the Report "The Rebound Effect from Fuel Efficiency Standards: Measurement and Projection to 2035"

Assessment and Standards Division
Office of Transportation and Air Quality
U.S. Environmental Protection Agency

Prepared for EPA by
ICF International, L.L.C.
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NOTICE

This technical report does not necessarily represent final EPA decisions or positions. It is intended to present technical analysis of issues using data that are currently available. The purpose in the release of such reports is to facilitate the exchange of technical information and to inform the public of technical developments.

United States Environmental Protection Agency

EPA-420-R-15-013
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Executive Summary

In 2011, EPA contracted with Ken Small of UC Riverside to update and enhance an existing model to estimate the VMT rebound effect for light-duty vehicles, defined as the change in vehicle miles traveled resulting from a change in fuel economy. The updates included using more recent state-level data for travel, as well as methodological enhancements to explore potential asymmetric responses depending on the direction of fuel cost changes, and to evaluate the role of media coverage of energy costs on driver's response. The resulting report by Ken Small, with contributions by Kent Hymel, is entitled "The Rebound Effect from Fuel Efficiency Standards: Measurement and Projection to 2035."

Prior to the release of the Final Report from Small and Hymel, EPA contracted with ICF International to conduct a peer review of the Small and Hymel report. The three peer reviewers selected by ICF were Drs. Kenneth Gillingham (Yale University), David Greene (University of Tennessee), and James Sallee (University of Chicago). EPA would like to extend its appreciation to all three reviewers for their efforts in evaluating this survey. The three reviewers brought useful and distinctive views in response to the charge questions.

This document contains three main components:

I.

Peer Review of Small and Hymel Report on the Rebound Effect for Light-Duty Vehicles, Conducted by ICF International

Peer Review of December 2013 LDV Rebound Report by Small and Hymel

January 31, 2014

Prepared for
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Contents

Tables

Acronyms and Abbreviations

Acronym / Abbreviation	Stands For
3SLS	Three-Stage Least Squares
AEO	Annual Energy Outlook
CAFE	Corporate Average Fuel Economy
EPA	U.S. Environmental Protection Agency
FHWA	Federal Highway Administration
GHG	Greenhouse Gas
ICF	ICF International
NHTSA	National Highway Traffic Safety Administration
OTAQ	Office of Transportation and Air Quality
S&H	Small & Hymel
UKERC	United Kingdom Energy Research Center
VMT	Vehicle Miles Traveled
WAM	Work Assignment Manager

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1. Introduction

The Office of Transportation and Air Quality (OTAQ) of the U.S. Environmental Protection Agency (EPA) is responsible for developing regulations to reduce the emissions of greenhouse gases (GHG) from light-duty vehicles in the U.S. The regulatory option of encouraging the adoption of advanced technologies for improving vehicle efficiency can result in significant fuel savings and GHG emission benefits. At the same time, it is possible that some of these benefits might be offset by additional driving that is encouraged by the reduced costs of operating more efficient vehicles. This so called "rebound effect", the increased driving that results from an improvement in the energy efficiency of a vehicle, must be determined in order to reliably estimate the overall benefits of GHG regulations for light-duty vehicles.

Dr. Ken Small, an Economist at the Department of Economics, University of California at Irvine, with contributions by Dr. Kent Hymel, Department of Economics, California State University at Northridge, have developed a methodology to estimate the rebound effect for light-duty vehicles in the U.S. Specifically, rebound is estimated as the change in vehicle miles traveled (VMT) with respect to the change in per mile fuel costs that can occur, for example, when vehicle operating efficiency is improved. The model analyzes aggregate personal motor-vehicle travel within a simultaneous model of aggregate VMT, fleet size, fuel efficiency, and congestion formation. The model uses three-stage least squares (3SLS) in order to account for the endogeneity of explanatory variables. The results contain both short-run and long-run estimates based upon lagged effects within annual data. For VMT, the behavioral responses underlying short run effects could include changes in travel mode, discretionary trips, destinations, or the combining of several trips into a single chain. Long-run responses might include changes in the vehicle stock, job or residential relocations, and changes in land use.

The model is estimated using a cross-sectional, time series data set with each variable measured for 50 U.S. states, plus District of Columbia, annually for years 1966-2009. Variables are constructed from public sources, mainly the U.S. Federal Highway Administration, U.S. Census Bureau, and U.S. Energy Information Administration.

Since the effectiveness of regulatory efforts to reduce GHG emissions is strongly influenced not only by the technical attributes of vehicles, but also by vehicle usage levels, it is important to assure that the methodologies considered by the U.S. EPA for estimating VMT rebound have been thoroughly examined. Comprehensive, objective peer reviews like the one described here are an important part of that examination process.

This report details the peer review of the subject report, *The Rebound Effect from Fuel Efficiency Standards: Measurement and Projection to 2035 (December 24, 2013)*. A number of independent subject matter experts were identified and the process managed to provide reviews and comments on the methodology of the report. This peer review process was carried out under EPA's peer review guidelines[1].

This report is organized as follows:

- Chapter 2 details the selection of the peer reviewers
- Chapter 3 details the peer review process
- Chapter 4 summarizes the reviews
- Appendix A provides resumes and conflict of interest statements for the three selected reviewers
- Appendix B provides the charge letter sent to the selected reviewers
- Appendix C, D and E provide the actual reviews submitted by the three selected reviewers

[1] U.S. Environmental Protection Agency, Peer Review Handbook, 3rd Edition with appendices. Prepared for the U.S. EPA by Members of the Peer Review Advisory Group, for EPA's Science Policy Council, EPA/100/B-06/002. Available at http://www.epa.gov/peerreview

2. Selection of Peer Reviewers

The EPA and ICF WAM compiled a list of 14 reviewers who would be capable of reviewing the subject report. They are listed in Table 2-1.

Table 2-1. Potential Reviewers

Potential Reviewer	Available	Affiliation	Degree
David Greene	Yes	Senior Fellow in the Howard H. Baker, Jr. Center for Public Policy and a Research Professor of Civil and Environmental Engineering, the University of Tennessee	Ph.D., Geography and Environmental Engineering
Lucas Davis	No – too busy	Associate Professor University of California, Berkeley	Ph.D., Economics
Joshua Linn	Yes	Fellow (indefinite appointment), Resources for the Future	Ph.D., Economics
Jonathan Rubin	Yes	Professor, Margaret Chase Smith Policy Center and School of Economics, University of Maine	Ph.D., Agricultural Economics
Sarah West	Yes	Professor, Macalester College, Economics	Ph. D., Economics
James Sallee	Yes	Assistant Professor, Harris School of Public Policy Studies University of Chicago	Ph.D., Economics
Kenneth Gillingham	Yes	Assistant Professor of Economics, School of Forestry & Environmental Studies, Yale	Ph.D., Management Science & Engineering and Economics
Chris Knittel	No response	William Barton Rogers Professor of Energy Economics Massachusetts Institute of Technology Sloan School of Management	Ph.D., University of California, Berkeley
Mark Jacobson	Yes	Associate Professor, University of California	Ph.D., Economics
David Rapson	Yes	Assistant Professor of Economics, UC Davis	Ph.D., Economics
Soren T. Anderson	No – too busy	Assistant Professor Michigan State University Department of Economics	Ph.D., Economics
Hunt Allcott	Yes	Assistant Professor of Economics, New York University	Ph.D., Public Policy

Potential Reviewer	Available	Affiliation	Degree
Steve Sorrell	Yes	Senior Lecturer (SPRU - Science and Technology Policy Research, The Sussex Energy Group	Ph.D. by publication - Analyzing controversies in energy policy: the evidence for rebound effects and global oil depletion,
Todd Litman	Yes	Executive director of the Victoria Transport Policy Institute	Masters of Environmental Studies

The three selected reviewers are listed in Table 2-2. Each had the necessary expertise, were available to review the report in a timely manner and had no conflict of interest. All were agreed upon by the EPA WAM.

Table 2-2. Final Reviewers

Reviewer	Contact Information	Necessary Expertise	Conflict of Interest
Kenneth Gillingham	Yale University School of Forestry & Environmental Studies P: 203-436-5465 kenneth.gillingham@yale.edu	Yes	No
David Greene	University of Tennessee Howard H. Baker, Jr. Center for Public Policy P: (865) 974-3839 dgreen32@utk.edu	Yes	No
James Sallee	University of Chicago The Harris School of Public Policy Studies P: 773-316-3480 sallee@uchicago.edu	Yes	No

Resumes and conflict of interest statements for the three reviewers can be found in Appendix A.

3. Peer Review Process

Once the three reviewers had been decided upon and approved by the EPA WAM, a charge letter and the subject report were sent to each reviewer via secure email. Shortly after distributing the charge letter (see Appendix B) and supporting materials for the peer review, a teleconference was held between the selected peer reviewers, the EPA WAM, EPA-identified relevant project-related staff and ICF staff to clarify any questions the peer reviewers may have regarding the report/written materials. At the conference call, EPA provided technical and/or background information on the particular report under review.

During the review process, no reviewers had questions. Each reviewer provided a written peer review in a timely manner. These were sent to ICF who forwarded them directly to the EPA WAM.

ICF managed the peer review process to ensure that each peer reviewer had sufficient time to complete their review of the data analysis by the deliverable date specified (January 17, 2014). ICF adhered to the provisions of EPA's Peer Review Handbook guidelines to ensure that all segments of the peer review conformed to EPA peer review policy.

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4. Summary of Review Comments

In this section, review comments from the three reviewers are summarized. Full comments (including those in addition to the charge questions) can be found in Appendix C for Kenneth Gillingham, Appendix D for David Greene and Appendix E for James Sallee. Responses are summarized below relative to the charge questions.

4.1. Responses to Charge Questions

What are the merits and limitations of the authors' approach for estimating the vehicle miles traveled (VMT) rebound effect for light-duty vehicles? Are key assumptions underpinning the methodology reasonable? The VMT rebound effect is defined here as the change in VMT resulting from an improvement in the light-duty efficiency.

The reviewers highlighted a number of merits to the authors' approach. All three reviewers generally agree that authors' selection of FHWA data to be appropriate for this study. Sallee mentioned that the aggregate data used in the report suffer from measurement problems, but due to data gaps in other sources, the data used for this report may be the best available at this time. Other highlighted merits include the authors' accurate understanding of the direct rebound effect and an understanding of estimation issues, resulting in a robust and accurate estimate of the VMT rebound effect.

All three reviewers believed that the assumptions underpinning the methodology were generally reasonable and consistent with the best methods employed in current research in this area. The reviewers did discuss other factors that could be considered or evaluated in more depth. For example Greene noted that the analysis omits part of the effect of increased vehicle prices on the long-run cost per-mile of travel. An increase in the capital cost of a vehicle also affects the long-run cost of vehicle travel via usage-induced capital depreciation. Sallee noted that the data used provides no way to model the relationship between vehicle age and VMT.

Is the implementation of the authors' methodology appropriate for producing estimates of the VMT rebound effect? Specifically, are the input data and the methodology used to prepare the data appropriate? Are sound econometric procedures used? Does the model appropriately reflect underlying uncertainties associated with the assumptions invoked and the parameters derived in the model?

All three reviewers generally thought the authors' approach was appropriate and was representative of best practices. They noted that the research did suffer from some data limitations that the author and the literature more broadly were aware of. A number of tests for robustness and points for additional clarification were suggested.

Sallee noted that most of the independent variables were not independently measured, but imputed using methodologies that may differ across states and over time. On-road fuel economy may vary over time, even for the same vehicle, due to changes in driving conditions, such as congestion or degree of urbanization. While the existing time series data is the best available, there are significant changes that have occurred over time that affect the interpretation of the results. The authors' have documented most of these issues.

Greene notes that "the estimates presented by S&H are based on the maintained hypothesis of economically rational behavior, in the sense that consumers are assumed to respond to changes in fuel cost per mile in the same way whether caused by changes in fuel price or changes in fuel economy", but that the research also demonstrates that the consumer response to fuel economy is less than the response to changes in fuel price, which are more salient to the consumer.

Gillingham notes that standard time series econometric approaches were not used. The paper does account for first order autocorrelation, but second order autocorrelation was not considered, which could introduce some bias into the standard errors.

The methodology used in this report attempts to account for asymmetric responses to increases vs. decreased in per mile fuel costs (and fuel prices). Does the report's finding of an asymmetric response seem reasonable given the methodology that the author's employed? In particular, do the authors' preferred model specifications (3.21 b and 4.21 b) seem appropriate for capturing driver response to an increase in fuel efficiency?

All three reviewers found the authors' finding of an asymmetric response to be reasonable, and that models 3.21b and 4.21b were well chosen as the preferred models. Gillingham raises the following question: If asymmetries come about because of the differing salience of increases and decreases in gasoline prices, should we expect the same effects to apply for changes in vehicle fuel efficiency?

The report describes a methodology for projecting the VMT rebound effect for light-duty vehicles forward in time. The concept of dynamic rebound is introduced to quantify the rebound effect over the period of a vehicle lifetime, during which time the variables that influence the rebound effect are changing. Is this methodology reasonable and appropriate, given the inherent uncertainty in making projections about how future drivers will respond to a change in the fuel efficiency of their vehicles?

All three reviewers agree that the dynamic rebound effect should be used to quantify the rebound effect over the period of a vehicle lifetime. Gillingham suggests that a nonlinear extrapolation (that is asymptotic with 0) may be more appropriate when extrapolating out as far as 2030. Greene and Sallee agree with Gillingham that the rebound effect should not go to 0 and suggest truncating at a value above 0. Sallee notes that it would be instructive to have the authors compare the dynamic rebound forecast to a forecast that assumes a constant rebound over time.

Refer to Appendix C, D, and E for further details on the all the reviewers' comments.

Appendix A. Resumes and Conflict of Interest Statements

Kenneth Gillingham

Contact Information

Yale University
School of Forestry & Environmental Studies
195 Prospect Street
New Haven, CT 06511, USA
phone: (203) 436-5465 *fax:* (203) 436-9135
E-mail: kenneth.gillingham@yale.edu
WWW: www.yale.edu/gillingham

Research Interests

Environmental & Energy Economics, Industrial Organization, Public Economics, Econometrics, Technological Change, Transportation Economics, Energy & Climate Policy Modeling.

Current Position

Yale University, New Haven, CT USA
Assistant Professor of Economics, School of Forestry & Environmental Studies — July 2011-present
Secondary appointment, Department of Economics — May 2012-present
Secondary appointment, School of Management — June 2013-present

Education

Stanford University, Stanford, CA USA

Ph.D., Management Science & Engineering and Economics, 2011

Dissertation: "The Consumer Response to Gasoline Price Changes: Empirical Evidence and Policy Implications"
Committee: Jim Sweeney, Larry Goulder, Matt Harding, John Weyant, Jon Levin (orals chair)
Fields: Public & Environmental Economics, Industrial Organization, Econometrics

M.S., Statistics, 2010

M.S., Management Science & Engineering (Economics & Finance), 2006

Dartmouth College, Hanover, NH USA

A.B., Economics and Environmental Studies (minor in Earth Sciences), 2002

Previous Employment

California Air Resources Board, Sacramento, CA USA
Economist (Graduate Student Assistant) — 2011

Stanford University, Stanford, CA USA
Research Assistant for Prof. Matt Harding, Stanford Economics Department — 2008-2010
Research Assistant for Prof. John Weyant, Stanford Energy Modeling Forum — 2008
Research Assistant for Prof. Jim Sweeney, Precourt Energy Efficiency Center — 2004-2006

Fulbright New Zealand, University of Auckland, Auckland, New Zealand
Fulbright Fellow — 2007

White House Council of Economic Advisers, Washington, DC USA
Fellow for Energy and Environment — 2005

Resources for the Future, Washington, DC USA
Research Assistant — 2002-2004

Dartmouth College, Hanover, NH USA
Research Assistant for Prof. Karen Fisher-Vanden — 1998-2002

Working Papers

Gillingham, K. Selection on Anticipated Driving and the Consumer Response to Changing Gasoline Prices (previously titled: How Do Consumers Respond to Gasoline Price Shocks? Heterogeneity in Vehicle Choice and Driving Behavior)

Gillingham, K., M. Kotchen, D. Rapson, G. Wagner, The Rebound Effect and Energy Efficiency Policy, In preparation for *Review of Environmental Economics & Policy*

Gillingham, K. The Economics of Fuel Economy Standards versus Feebates

Work-in-Progress

Learning-by-Doing in the Solar Photovoltaic Industry (with Bryan Bollinger)

Automaker Responses to Fuel Economy Standards (with Antonio Bento, Kevin Roth, Yiwei Wang)

The Economic Efficiency of Renewable Portfolio Standards in the Presence of Cap-and-Trade (with Arthur van Benthem)

Consumer Welfare and Environmental Effects of Registration Fees and Driving Fees in Denmark (with Bertel Schjerning, Fedor Iskhakov, John Rust, and Anders Munk-Nielsen)

HOV Stickers and the Consumer Adoption of Hybrids: Evidence from California (with Calanit Kamala)

A Dynamic Model of Household Vehicle Choice and Usage (with David Rapson)

Salience and Upstream versus Downstream Cap-and-Trade

The Geographic and Demographic Distributional Effects of Gasoline Taxes

Uncertainty in Integrated Assessment Models of Climate Change Policy (with Bill Nordhaus)

Publications

Gillingham, K. and K. Palmer (2014) Bridging the Energy Efficiency Gap: Policy Insights from Economic Theory and Empirical Analysis. *Review of Environmental Economics & Policy*, forthcoming.

Gillingham, K. (2013) Identifying the Elasticity of Driving: Evidence from a Gasoline Price Shock in California, *Regional Science & Urban Economics*, forthcoming.

Yeh, S., G. Mishra, G. Morrison, J. Teter, R. Quiceno, and K. Gillingham (2013) Long-Term Shifts in Lifecycle Energy Efficiency and Carbon Intensity. *Environmental Science & Technology*, 47(6): 2494-2501.

Gillingham, K., M. Kotchen, D. Rapson, G. Wagner (2013) The Rebound Effect is Over-played. *Nature*, 493: 475-476.

Bollinger, B. and K. Gillingham (2012) Peer Effects in the Diffusion of Solar Photovoltaic Panels. *Marketing Science*, 31(6): 900-912.

Gillingham, K., M. Harding, and D. Rapson (2012) Split Incentives in Household Energy Consumption. *Energy Journal*, 33(2): 37-62.

Gillingham, K. and J. Sweeney (2012) Barriers to Implementing Low Carbon Technologies. *Climate Change Economics*, 3(4), 1-25.

Gillingham, K. and J. Sweeney (2010) Market Failure and the Structure of Externalities. In: Harnessing Renewable Energy, Boaz Moselle, Jorge Padilla, Richard Schmalensee (eds). RFF Press.

Leaver, J. and K. Gillingham (2010) Economic Impact of the Integration of Alternative Vehicle Technologies into the New Zealand Vehicle Fleet. *Journal of Cleaner Production*, 18: 908-916.

Gillingham, K., R. Newell, and K. Palmer (2009) Energy Efficiency Economics and Policy. *Annual*

Review of Resource Economics, 1: 597-619. Reprinted in Italian in Energia (2010).

Gillingham, K. (2009) Economic Efficiency of Solar Hot Water Policy in New Zealand. *Energy Policy*, 37(9): 3336-3347.

Leaver, J., L. Leaver, and K. Gillingham (2009) Assessment of Primary Impacts of a Hydrogen Economy in New Zealand using UNISYD. *International Journal of Hydrogen Energy*, 34(7): 2855-2865.

Gillingham, K., R. Newell, and W. Pizer (2008) Modeling Endogenous Technological Change for Climate Policy Analysis. *Energy Economics*, 30(6): 2734-2753.

van Benthem, A., K. Gillingham, and J. Sweeney (2008) Learning-by-Doing and the Optimal Solar Policy in California. *Energy Journal*, 29(3): 131-151.

Gillingham, K., S. Smith, and R. Sands (2008) Impact of Bioenergy Crops in a Carbon Constrained World: An Application of the MiniCAM Linked Energy-Agriculture and Land Use Model. *Mitigation and Adaptation Strategies for Global Change*, 13(7): 675-701.

Safirova, E., K. Gillingham, and S. Houde (2007) Measuring Marginal Congestion Costs of Urban Transportation: Do Networks Matter? *Transportation Research A*, 41(8): 734-749.

Gillingham, K., R. Newell, and K. Palmer (2006) Energy Efficiency Policies: A Retrospective Examination. *Annual Review of Environment and Resources*, 31: 193-237.

Shih, J-S, W. Harrington, W. Pizer, and K. Gillingham (2006) Economies of Scale in Community Water Systems. *Journal of American Water Works Association*, 98(9): 100-108.

Safirova, E., P. Nelson, W. Harrington, K. Gillingham, and A. Lipman (2005) Choosing Congestion Pricing Policy: Cordon Tolls vs. Link-Based Tolls. *Transportation Research Record*, 1932: 169-177.

Safirova, E., I. Parry, P. Nelson, W. Harrington, K. Gillingham, D. Mason (2004) Welfare and Distributional Effects of HOT Lanes and Other Road Pricing Policies in Metropolitan Washington, DC. *Research in Transportation Economics*, 9(1): 179-206.

Reports & Other Publications

Bollinger, B. and K. Gillingham (2012) Do Peer Effects Matter? Assessing the Impact of Causal Social Influence on Solar PV Adoption, *Photovoltaics International*, 17: 160-165.

Friedland, A. and K. Gillingham (2010) Carbon Accounting is a Tricky Business. Letter to the Editor, *Science*, 327(5964): 411-412.

Sweeney, J., J. Weyant, K. Gillingham, et al. (2008) Analysis of Measures to Meet the Requirements of California's Assembly Bill 32. Precourt Institute for Energy Efficiency Working Paper.

Gillingham, K. (2007) Hydrogen Internal Combustion Engine Vehicles: A Prudent Intermediate Step or a Step in the Wrong Direction? Stanford Global Climate and Energy Project Working Paper.

Gillingham, K., R. Newell, and K. Palmer (2006) The Effectiveness and Cost of Energy Efficiency Programs. In: The RFF Reader in Environmental and Resource Policy, Wallace Oates (ed). RFF Press. 193-201.

Safirova, E., W. Harrington, P. Nelson, and K. Gillingham (2004) Are HOT Lanes a Hot Deal? Analyzing the Potential of HOV to HOT Lanes Conversion in Northern Virginia. RFF Issue Brief 03-03.

Nelson, P., E. Safirova, and K. Gillingham (2003) Revving up the Tax Engine: Gas Taxes and the DC Metro Area's Transportation Dilemma. RFF Issue Brief 03-05.

Grants

"The Influence of Novel Behavioral Strategies in Promoting the Diffusion of Solar Energy," US Department of Energy, PI, 2013-2015 ($1,899,978)

"Density, Walkability, and VMT," Yale Center for Business and the Environment Sobotka Research Fund, PI, 2013-2014 ($10,100)

"Deep Dive Solar Cost Analysis," Lawrence Berkeley National Laboratory/US Department of Energy, PI, 2013-2015 (Yale budget: $74,924)

"Modeling Household and Transportation Vehicle Choice and Usage," California Air Resources Board, co-PI with Dave Rapson, Chris Knittel, and Pat Mokhtarian, 2012-2014 ($300,000)

"Sunrise New England," US Department of Energy, co-PI with Stuart DeCew, 2012-2014 (Yale budget: $215,000)

"The Consumer Response to Gasoline Price Changes," Stanford Institute for Economic Policy Research (SIEPR) Grant, 2010 ($10,000)

"The Consumer Response to Gasoline Price Changes," Shultz Graduate Student Fellowship in Economic Policy, SIEPR, 2010 ($4,000)

"Economics of New Zealand Solar Distributed Generation," Fulbright Fellowship, 2007

"The Effect of Income and Congestion on the Rebound Effect of CAFE Standards," US Environmental Protection Agency STAR Fellowship, 2006-2009 ($111,000)

Heitz Graduate Fellowship, Stanford University, 2006

Battelle Memorial Institute Fellowship, 2001 ($6,000)

Honors and Awards

Full Member, Sigma Xi	2011
Dennis O'Brian Best Student Paper Award, US Association for Energy Economics	2010
Thesis and Research Essay Publication Scholarship, University of Auckland	2008
Outstanding Teaching Assistant Award, Stanford Economics	2006
National Science Foundation Graduate Fellowship, Honorable Mention	2006
American Water Works Association Best Paper Award	2006
Departmental Honors, Dartmouth Economics	2002
Departmental High Honors, Dartmouth Environmental Studies	2002
Associate Member, Sigma Xi	2002
First Prize, Dartmouth Sigma Xi Senior Thesis Competition	2002

Teaching

Yale University

2012-2013: Ph.D. Environmental and Energy Economics, Energy Economics and Policy Analysis (Masters), Yale Environmental Economics Seminar.

2011-2012: Economics of the Environment (Masters), Yale Environmental Economics Seminar.

Stanford University, Teaching Assistant

2009-2010: Ph.D. Microeconomics, Introductory Econometrics, Natural Resource Economics (Graduate).

2008-2009: Transportation Policy (Graduate), Energy Policy Analysis (Graduate), Natural Resource Economics (Graduate).

2007-2008: Energy & Environmental Policy Analysis (Graduate), Climate Policy Analysis (Gradu-

ate), Natural Resource Economics (Graduate).
2005-2006: Principles of Economics

ADVISING

Ph.D. Primary Advisor

Hao Deng (FES 2nd year), Jesse Burkhardt (FES 3rd year; co-advised with Matthew Kotchen)

Ph.D. Committee Member

Laura Bakkensen (FES 5th year), Peter Christensen (FES 5th year), Nathan Chan (FES 5th year), Rich Langford (Yale econ 5th year), Alan Jenn (Carnegie-Mellon 4rd year), Anders Munk-Nielsen (Copenhagen 3rd year), Nikki Springer (FES 3rd year)

M.E.Sc Advisor

Hilary Staver (2nd year), Paige Weber (2nd year)

Masters Independent Research

2012-2013: Vijeta Jangra (MEM '13)
2011-2012: Howard Chang (MEM/MBA '12), Dustin Schinn (MEM '13), Peter Baum (MEM '13)

Undergraduate Senior Thesis Advising

Ana Grajales (economics '13), Daniel Cheng (math-econ '13)

PRESENTATIONS

2013 (scheduled): AEA Meetings (discussant); Modeling Uncertainty Project Meeting (New Haven, CT); FES/SOM Yale Environmental Economics Seminar; Carnegie-Mellon University; Villanova Law; Arizona State University Economics of Water Conference (Keynote); International Industrial Organization Conference (Cambridge, MA); AERE Summer Conference (Banff, AB); Empirical Methods in Energy Economics Workshop (Carlton University, Ottawa); DOE Sunshot Kick-off Meeting; EMF Workshop on Climate Change Impacts and Integrated Assessment (Smowmass, CO); Stanford Institute for Theoretical Economics (SITE) Advances in Environmental Economics Workshop; Columbia University SIPA; Indiana University Kelley School of Business; Tsinghua University Institute of Energy, Environment, and Economy; Fudan University Economics; Indiana University SPEA; Behavior, Energy, and Climate Change (BECC) Conference.

2012: AEA Meetings; Yale FES Seminar Series; Lawrence Berkeley National Laboratory/DOE Sunshot Initiative Workshop; Triangle Resource & Environmental Economics seminar (Duke, NCSU, UNC); Indiana University Kelley School of Business/Economics/SPEA; University of Massachusetts Amherst Resource Economics; Rice University Economics; Texas A&M Economics; UC Santa Cruz Economics; Naval Postgraduate School Economics; UC Santa Barbara Economics/Bren School; ETH Zurich Economics; University of Lugano Economics; AERE Summer Conference (Asheville, NC); EMF Workshop on Climate Change Impacts and Integrated Assessment (Smowmass, CO); Connecticut Clean Energy Finance & Investment Authority; UC Berkeley/Lincoln Institute of Land Policy Conference; University of Colorado Boulder Economics; University of Wyoming Economics; US Association for Energy Economics (Austin, TX); University of Connecticut ARE; University of Copenhagen Economics.

2011: University of Maryland AREc; Indiana University SPEA; UC Davis Economics; University of Arizona Economics; Arizona State University Economics; University of Illinois Urbana-Champaign Finance; University of Notre Dame Economics; Yale University FES; Informing Green Markets Conference (University of Michigan); Cowles Foundation Structural Microeconometrics Conference (Yale University); Empirical Methods in Energy Economics Workshop (Southern Methodist University); Harvard Seminar on Environmental Economics and Policy; Re-examining the Rebound Effect in Energy Efficiency Workshop (Environmental Defense Fund); RFF-Stanford Workshop on the Next Round of Climate Economics and Policy Research (Washington, DC); US Association for Energy Economics (Washington, DC); Workshop on Environmental and Transportation Policies to Mitigate Climate Change (New York University); Religare Capital Markets (Singapore); Behavior, Economics, and Energy Panel (National University of Singapore Energy Studies Institute); University of Copenhagen Economics.

2010: UC Berkeley Energy Institute; NBER EEE Summer Institute; World Congress Env & Resource Economists (Montreal); US Association for Energy Economics (Calgary); Behavior, Energy & Climate Change (BECC) Conference; 12th Occasional California Workshop on Environmental and Resource Economics; UC Davis ARE; Resources for the Future.

2009: UC Berkeley ARE; Stanford IO Workshop; DOE EIA Advisory Council; US Association for Energy Economics (San Francisco); UC Energy Institute CSEM Conference.

2008: UC Davis ITS; Victoria University, New Zealand.

2007: University of Auckland Energy Centre, New Zealand; Massey University, New Zealand; International Association for Energy Economics (Wellington, New Zealand).

2006: Dartmouth College Workshop on Technological Change & Environment.

2004: Transportation Research Board Annual Meeting.

Referee Service

Economics Journals: *American Economic Journal–Applied, American Economic Review, American Journal of Agricultural Economics, B.E. Journal of Economic Analysis & Policy, Climate Change Economics, Economics of Energy & Environmental Policy, Ecological Economics, Energy Economics, Energy Journal, Journal of the Association of Environmental and Resource Economists, Journal of Economic Surveys, Journal of Environmental Economics & Management, Journal of Institutional & Theoretical Economics, Journal of Public Economics, Management Science, Oxford Economic Papers, Quarterly Journal of Economics, RAND Journal of Economics, Regional Science & Urban Economics, Resource & Energy Economics, Review of Environmental Economics & Policy, Scandinavian Journal of Economics, Southern Economic Journal, The Manchester School.*

Environment/Engineering/Policy/Science Journals: *Building Research, Cityscape, Climatic Change, Energies, Energy, Energy & Fuels, Energy Efficiency, Energy Policy, Environment Development and Sustainability, Environmental Modeling & Assessment, Environmental Research Letters, Environmental Science & Technology, Global Environmental Change, International Journal of Sustainable Transportation, Journal of Cleaner Production, Journal of Environment & Development, Journal of Industrial Ecology, Journal of Policy Analysis & Management, Journal of Sustainable Forestry, Mitigation & Adaptation Strategies for Global Change, Science, Transportation Research A, Utilities Policy.*

Review Service

Alfred P. Sloan Foundation, Alliance for Research on Corporate Sustainability, KU Leuven, MIT Press, National Academy of Sciences Transportation Research Board, National Science Foundation, Swiss National Science Foundation.

Professional Service

US Department of Agriculture NIFA Bioenergy Policy expert review panel (Apr 19-20, 2012), Yale Climate & Energy Institute (YCEI) Steering Committee (2013-present), co-organizer of Modeling Uncertainty in Climate Policy Workshop (Feb 4, 2013 at Yale), US Department of Energy Review Panel (April 26, 2013), co-organizer of Northeast Workshop on Energy Policy & Environmental Economics (May 10-11, 2013 at Cornell), US Department of Agriculture NIFA Climate Change Adaptation expert review panel (Aug 1-2, 2013)

Professional Affiliations

American Economic Association (AEA), Association of Environmental and Resource Economists (AERE), United States Association for Energy Economics (USAEE), Econometric Society, Industrial Organization Society.

Research Cited in the Media

Wall Street Journal *The Numbers Guy* Blog: "The Rebound Effect," May 26, 2009.
Grist: "Making Buildings More Efficient: Looking Beyond Price," Oct 23, 2009.
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Huffington Post: "Solar Panel Installations More Likely In Homes With Energy Efficient Neighbors," Oct 23, 2012.
ClimateWire: "Is Renewable Energy Contagious: Research Shows a 'Peer Effect'," Nov 5, 2012.
Yale Daily News: "Sandy Link to Climate Change Questioned," Nov 9, 2012.
AOL Energy: "The Psychology of Small-Scale Solar," Nov 19, 2012.
New York Times: "Solar Industry Borrows a Page, and a Party, from Tupperware," Dec 1, 2012.
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Washington Square News: "Stern, Yale Professors Team Up To Research Solar Energy," October 1, 2013.

ICF INTERNATIONAL

ORGANIZATIONAL CONFLICT OF INTEREST CERTIFICATE

Customer: U.S. Environmental Protection Agency

Contractor: ICF Incorporated, LLC, 9300 Lee Highway, Fairfax, VA 22031

Prime Contract: EP-C-12-011

Subcontract/Peer Reviewer: Kenneth Gillingham

In accordance with EPAAR 1552.209-70 through 1552.209-73, Subcontractor/Consultant certifies to the best of its knowledge and belief, that:

__X__ No actual or potential conflict of interest exists.

_____ An actual or potential conflict of interest exists. See attached full disclosure.

Subcontractor/Consultant certifies that its personnel, who perform work on this contract, have been informed of their obligations to report personal and organizational conflict of interest to Contractor and Subcontractor/Consultant recognizes its continuing obligation to identify and report any actual or potential organizational conflicts of interest arising during performance under referenced contract.

Kenneth Gillingham

Subcontractor/Consultant

1/17/2014

Date

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PERSONAL

Born: November 18, 1949, New York, New York
Married, two children

EDUCATION

THE JOHNS HOPKINS UNIVERSITY
Ph.D., Geography and Environmental Engineering, 1973–78

UNIVERSITY OF OREGON
M.A., 1972–73

COLUMBIA UNIVERSITY
B.A., 1967–71

EMPLOYMENT

UNIVERSITY OF TENNESSEE, KNOXVILLE — 2010–PRESENT

1/2010–Present	*Senior Fellow, Howard H. Baker, Jr. Center for Public Policy*
10/2013-Present	*Research Professor, Department of Civil and Environmental Engineering*
1/2010-10/2013	*Research Professor, Department of Economics*

INSTITUTE FOR TRANSPORTATION STUDIES, UNIVERSITY OF CALIFORNIA, DAVIS — 2008–2009

9/2008–6/2009	*Visiting Research Faculty*

OAK RIDGE NATIONAL LABORATORY (ORNL) — 1977–PRESENT

1999–Present	*Corporate Fellow, Oak Ridge National Laboratory*
1989–1999	*Senior Research Staff Member II and Manager of Energy Policy Research Programs, Center for Transportation Analysis*
1988–1989	*Senior Research Analyst, Office of Policy Integration, U.S. Department of Energy (On assignment from ORNL)*
1987–1988	*Head, Transportation Research Section*
1984–1987	*Senior Research Staff Member I*
1982–1984	*Research Staff Member*
1980–1982	*Leader, Transportation Energy Group*
1977–1980	*Research Associate*

AWARDS AND HONORS

Distinguished Career Service Award, U.S. Department of Energy, Energy Efficiency and Renewable Energy, 2013
2012 Roy W. Crum Award for Distinguished Achievement, Transportation Research Board of the National Research Council
2011 DOE Vehicle Technologies Program R&D Award, U.S. Department of Energy
2011 Edward L. Ullman Award, Association of American Geographers
2009 Alliance to Save Energy, Energy Efficiency Hall of Fame
2008 Science Communicator Award, UT-Battelle

Recognition by the Intergovernmental Panel on Climate Change for Contributions to the Award of the 2008 Nobel Peace Prize to the IPCC
2007 Department of Energy Hydrogen Program R&D Award (with P.N. Leiby)
Barry D. McNutt Award for Excellence in Automotive Policy Analysis, Society of Automotive Engineers, 2007
Member Emeritus, Transportation Research Board Committee on Alternative Fuels, 2006
Barry D. McNutt Award for best paper of 2004, Energy Committee, Transportation Research Board
Lifetime National Associate of the National Academies, 2002
UT-Battelle Award for Excellence in Science and Technology, 2001
Oak Ridge National Laboratory Significant Event Award, 2001
Corporate Fellow of Oak Ridge National Laboratory, 1999
Outstanding Paper of 1999, *The Energy Journal*, International Association for Energy Economics
Lockheed-Martin Significant Event Award, 1999
Member Emeritus, Transportation Research Board Committee on Transportation Energy, 1998
Lockheed-Martin Significant Event Award, 1996
Distinguished Service Certificate, Transportation Research Board, 1993
ORNL Special Achievement Award, 1991
Distinguished Service Certificate, Transportation Research Board, 1989
Energy Specialty Group Paper Award, Association of American Geographers, 1986
ORNL Special Recognition Award, Oak Ridge National Laboratory, 1986
Technical Achievement Award, Martin Marietta Energy Systems, 1985
Pyke Johnson Award, Transportation Research Board, 1984

PROFESSIONAL ACTIVITIES

- Board of Directors, American Council for an Energy Efficiency Economy, 2010-2013
- Board of Advisors, Institute for Transportation Studies, University of California, Davis
- Editorial Advisory Board, *Transportation Research Part D*, 1996–present
- Editorial Board Member, *Energy Policy*, 2001–present
- Editorial Board Member, *Journal of Transportation and Statistics*, 2001–2006, 2011-present
- Editorial Board Member, *Transportation Quarterly*, 1999–2005
- Editor-in-Chief, *Journal of Transportation and Statistics*, 1997–2000
- Editorial Board Member, Macmillan Encyclopedia of Energy, 1998–2001
- Editorial Advisory Board, *Transportation Research A*, 1986–1997
- National Research Council
  - Transportation Research Board Standing Committees:
    - Committee on Transportation and Sustainability, Member, 2006–present
    - Committee on Energy, A1F01, Chairman 1983–1986, 1986–1990; Member, 1993–1998; Member Emeritus, 1999–present
    - Subcommittee on Forecasting Transportation Energy Demand, A1F01(2), Chairman, 1982–1983
    - Section F, Energy and Environmental Concerns, Chairman, 1990–1992
    - Committee on Alternative Fuels, A1F05, Member, 1993–2006, Member Emeritus, 2006–present
    - Task Force on Freight Transportation Data, A1B51, Secretary, 1989–1996
    - Committee on Transportation Information Systems and Data Requirements, Member, 1983–1986, 1986–1989
  - Ad Hoc Committees:
    - Committee on Assessment of Technologies for Improving Fuel Economy of Light-Duty Vehicles – Phase 2, 2012-2015
    - Committee for Research Perspectives on Sustainable Energy and Transportation: A Conference, 2012-2013
    - Special Task Force on Climate Change and Energy, 4/15/2012-4/14/2015
    - Committee on Transitions to Alternative Vehicles and Fuels, 2011-2012
    - Special Task Force on Energy and Climate Change, 2008–2009
    - Committee on the Assessment of Fuel Economy Technologies for Light-Duty Vehicles, 2007–2010
    - Planning Group for Workshop on Issues Related to Peaking of Global Oil Production, 2005
    - Committee on State Practices in Setting Mobile Source Emissions Standards, 2004–2006

Chair, Committee for the Symposium on Introducing Sustainability into Surface Transportation Planning, 2003–2004
Panel on Combating Global Warming through Sustainable Surface Transportation Policy, TCRP Project Panel H-21A, 2002–2005
Committee on Effectiveness and Impacts of Corporate Average Fuel Economy (CAFE) Standards, 2001
Committee for the Study of the Impacts of Highway Capacity Improvements on Air Quality and Energy Consumption, 1993–1994
Committee on Fuel Economy of Automobiles and Light Trucks, Energy Engineering Board, Commission on Engineering and Technical Systems, 1991–1992
Committee for the Study of High-Speed Surface Transportation in the United States, 1990
Planning Group on Strategic Issues in Domestic Freight Transportation, 1990
Steering Committee for Conference on Transportation, Urban Form, and the Environment, 1990
National Cooperative Highway Research Program, Panel on "Evaluating Alternative Methods of Highway Finance," 1991–1992

- Intergovernmental Panel on Climate Change
  Lead Author, Working Group III, Fourth Assessment Report, 2007
  Lead Author, Working Group III, Third Assessment, 2001
  Lead Author, Working Group III, Aviation and the Global Atmosphere, 1999
  Principal Lead Author, Working Group II, Second Assessment Report, 1995
- Association of American Geographers
  Board of Directors, Transportation Specialty Group, 1989–1991
  Secretary-Treasurer, Transportation Geography Specialty Group, 1980–1982
  Editor, *Transportation Geography Newsletter*, 1980–1982
- Society of Automotive Engineers, member, 1985–present
- International Association for Energy Economics, member
- Consulting
  MacroSys for U.S. Bureau of Transportation Statistics, 2013
  Rand Corporation, 2012-2013
  International Council for Clean Transportation, 2011-present
  International Transport Forum, 2007
  Addx Corporation, 2007
  United Nations Framework Convention on Climate Change, 2007
  Securing America's Future Energy, 2007
  Center for Clean Air Policy, 2007
  Pollution Probe Canada, 2006-2007
  The Energy Foundation China Project, 2005-2011
  The Pew Center on Global Climate Change, 2004-2012
  Eno Transportation Foundation, 1991–1996
  Transportation Research Board, 1996–1997

Books

and D.W. Jones and Mark Delucchi, eds., *The Full Costs and Benefits of Transportation*, Springer-Verlag, Heidelberg, 1997.

Transportation and Energy, Eno Foundation for Transportation, Lansdowne, Virginia, 1996.

and D. J. Santini, eds., *Transportation and Global Climate Change*, American Council for an Energy Efficient Economy, Washington, DC, 1993.

Articles in Professional Journals

D.L. Greene, S. Park and C. Liu, 2013. "Analyzing the Transition to Electric Drive Vehicles in the U.S.", *Futures*, published online, 6 November 2013, http://dx.doi.org/10.1016/j.futures.2013.07.003 .

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Z. Lin and D.L. Greene, "Assessing Energy Impact of Plug-in Hybrid Electric Vehicles: Significance of Daily Distance Variation over Time and Among Drivers", *Transportation Research Record* No. 2252, pp. 99-106, Journal of the Transportation Research Board, Washington, D.C., 2011.

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J.J. Erickson, D.L. Greene and A.J. Sabadell, "An Analysis of Transportation Energy Conservation Projects in Developing Countries," *Transportation*, vol. 15, no. 3, pp. 163–189, 1988.

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ORGANIZATIONAL CONFLICT OF INTEREST CERTIFICATE

Customer: U.S. Environmental Protection Agency

Contractor: ICF Incorporated, LLC, 9300 Lee Highway, Fairfax, VA 22031

Prime Contract: EP-C-12-011

Subcontract/Peer Reviewer: David Greene

In accordance with EPAAR 1552.209-70 through 1552.209-73, Subcontractor/Consultant certifies to the best of its knowledge and belief, that:

__X__ No actual or potential conflict of interest exists.

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Subcontractor/Consultant certifies that its personnel, who perform work on this contract, have been informed of their obligations to report personal and organizational conflict of interest to Contractor and Subcontractor/Consultant recognizes its continuing obligation to identify and report any actual or potential organizational conflicts of interest arising during performance under referenced contract.

David L. Greene
Subcontractor/Consultant

1/17/2014
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EMPLOYMENT AND AFFILIATIONS

Assistant Professor, Harris School of Public Policy Studies
University of Chicago (July 2008 – present)
Faculty Research Fellow, National Bureau of Economic Research
Public Economics and Energy and Environmental Economics Programs (April 2010 – present)
Visiting Researcher, University of California Energy Institute (August 2010 – December 2010)

EDUCATION

University of Michigan, Ph.D. in Economics (2008)
Dissertation: *Three Essays in Public Economics*
Committee: Joel Slemrod (Chair), Rebecca Blank, James Hines, Jeffrey Smith
University of Michigan, M.A. in Economics (2005)
Macalester College, B.A. in Economics and Political Science, *Summa Cum Laude*, ΦΒΚ (2001)

PUBLISHED JOURNAL ARTICLES

"What Do Consumers Believe About Future Gasoline Prices? (with Soren T. Anderson and Ryan Kellogg) *Journal of Environmental Economics and Management* Forthcoming.

"The Value of Honesty: Empirical Estimates from the Case of the Missing Children" (with Sara LaLumia) *International Tax and Public Finance*, 20(2), April 2013, pp. 192-224.

"Car Notches: Strategic Automaker Responses to Fuel Economy Policy" (with Joel Slemrod) *Journal of Public Economics*, 96(11-12), December 2012, pp. 981-999.

"Financial Reporting, Tax, and Real Decisions: Toward a Unifying Framework" (with Douglas A. Shackelford and Joel Slemrod), *International Tax and Public Finance*, 18(4), August 2011, pp. 461-494.

"Using Loopholes to Reveal the Marginal Cost of Regulation: The Case of Fuel-Economy Standards" (with Soren T. Anderson) *American Economic Review* 101(4), June 2011, pp. 1375-1409.

"The Surprising Incidence of Tax Credits for the Toyota Prius" *American Economic Journal: Economic Policy*, 3(2), May 2011, pp. 189-219.

"Fuel Economy Standards: Impacts, Efficiency, and Alternatives" (with Soren Anderson, Carolyn Fischer and Ian Parry), *Review of Environmental Economics and Policy*, 5(1), Winter 2011, pp. 89-108.

"A Cautionary Tale About the Use of Administrative Data: Evidence from Age of Marriage Laws" (with Rebecca M. Blank and Kerwin Kofi Charles), *American Economic Journal: Applied Microeconomics,* 1(2), April 2009, pp. 128 - 149.

"On the Optimal Allocation of Students and Resources in a System of Higher Education" (with Alexandra M. Resch and Paul N. Courant) *The B.E. Journal of Economic Analysis & Policy* (Advances Tier), 8(1), Article 11.

NON-REFEREED PUBLICATIONS

"The Energy Paradox and the Future of Fuel Economy Regulation", working paper, Institute for Policy Integrity at New York University School of Law, December 2011

"Forecasting Gasoline Prices Using Consumer Surveys" (with Soren T. Anderson, Ryan Kellogg and Richard M. Curtin) *American Economic Review Papers & Proceedings* 101(3), May 2011, pp. 110-114.

"The Taxation of Fuel Economy" *Tax Policy and the Economy* v. 25, Editor Jeffrey R. Brown, NBER: University of Chicago Press, 2011, pp. 1-38.

"Consumer Valuation of Fuel Economy: A Microdata Approach" (with Sarah E. West and Wei Fan) *Proceedings of the National Tax Association's 102nd Annual Conference on Taxation*, 2009, pp. 254-259.

WORKING PAPERS

"The Economics of Attribute-Based Regulation: Theory and Evidence from Fuel-Economy Standards" (with Koichiro Ito)

"New Evidence on Taxes and the Timing of Birth" (with Sara LaLumia and Nicholas Turner) *Submitted*

"Rational Inattention and Energy Efficiency" *Submitted*

"The Intergenerational Transmission of Automobile Brand Preferences: Empirical Evidence and Implications for Firm Strategy" (with Soren T. Anderson, Ryan Kellogg and Ashley Langer) *Submitted*

SELECTED WORK IN PROGRESS

"Do Consumers Recognize the Value of Fuel Economy? Evidence from Used Car Prices and Gasoline Price Fluctuations" (with Sarah West and Wei Fan)

AWARDS AND HONORS

Best Teacher in a Core Course, The Harris School (2012, 2013)
W.E. Upjohn Institute Early Career Research Grant (with Reed Walker) (2012)
Certificate of Excellence in Reviewing, *Journal of Public Economics* (2012)
John V. Krutilla Research Award from Resources for the Future (2009 - 2010)
National Tax Association Dissertation Award (2008)
National Science Foundation Graduate Research Fellowship (awarded 2003)
Population Studies Center Trainee Fellowship, University of Michigan (2003-2008)

TEACHING

All for Master of Public Policy Students at the Harris School

Policy Approaches to Mitigating Climate Change

Topics in U.S. Tax Policy

Empirical Methods in Policy Analysis II

Science, Technology and Policy

REFEREE

American Economic Review, Journal of Political Economy, Quarterly Journal of Economics, Journal of Public Economics, American Economic Journal: Economic Policy, American Economic Journal: Applied Economics, RAND Journal of Economics, Journal of Environmental Economics and Management, National Tax Journal, Journal of Labor Economics, International Tax and Public Finance, Journal of Law & Economics, Canadian Journal of Economics, Nature, B.E. Journal of Economic Analysis & Policy, Economic Inquiry, Journal of Human Resources, Economic Letters, Environmental and Resource Economics, Journal of Policy Analysis and Management; ***Grants:*** *National Science Foundation, European Science Foundation, Sloan Foundation, Time-Sharing Experiments for the Social Sciences*

SELECTED PRESENTATIONS

Invited **2013:** University of Pennsylvania (Wharton), Georgetown (Economics), Illinois (Economics), Wisconsin (Economics) **2012:** Maryland (Economics), Northwestern (Law), Universidad de Chile (Business School), Oxford (Business School); **2011:** Columbia (Economics), Maryland (AREC), Syracuse (Maxwell), Illinois (Finance), Ohio State (Economics), Illinois (Sustainability Center), NYU (Law conference), University of Illinois at Chicago (Sustainability workshop), Treasury, EPA, Resources for the Future (Conference); **2010:** MIT (Economics), Yale (Forestry), Berkeley (ARE), Berkeley (UCEI), NBER Tax Policy and the Economy, University of Chile; **2009:** Cornell (Economics), Minnesota (Applied Economics), North Carolina State University (Economics), Berkeley (POWER Conference), University of Illinois at Chicago (Economics), Macalester College (Economics); **2008:** Resources for the Future, University of Chicago (Harris), University of Pennsylvania (Wharton), University of British Columbia (Economics), University of Kentucky (Martin/Economics), University of Indiana (SPEA), University of California, Irvine (Economics), Treasury, Ford Motor Company

Conference **2012:** NBER Public Economics, National Tax Association, Michigan Tax Invitational **2011:** National Tax Association, ASSA, Association of Environmental and Resource Economics, International Institute of Public Finance, University of California Energy Institute; **2010:** NBER Public Economics, Iowa State Bioenergy Camp; **2009:** ASSA, National Tax Association, Heartland Environmental and Resource Economics; **2008:** APPAM, National Tax Association; **2007:** NBER Summer Institute (EEE), National Tax Association, APPAM

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X No actual or potential conflict of interest exists.

_______ An actual or potential conflict of interest exists. See attached full disclosure.

Subcontractor/Consultant certifies that its personnel, who perform work on this contract, have been informed of their obligations to report personal and organizational conflict of interest to Contractor and Subcontractor/Consultant recognizes its continuing obligation to identify and report any actual or potential organizational conflicts of interest arising during performance under referenced contract.

Subcontractor/Consultant

1/17/14

Date

Appendix B. **Charge Letter**

December 18, 2013

Dr. David L. Greene
Senior Fellow, Howard H. Baker, Jr. Center for Public Policy
1640 Cumberland Avenue
Knoxville, TN 37996-3340

Subject: Peer Review of Light-Duty Vehicle Rebound Effect Research

Dear Dr. Greene,

ICF International has been contracted by EPA to facilitate a peer review. In late November we corresponded by email and you indicated your availability to participate as a paid reviewer to review Ken Small and Kent Hymel's report "The Rebound Effect from Fuel Efficiency Standards: Measurements and Projection to 2035". You have been selected to participate on this panel. ICF will compensate you $3,000 for your services. This charge letter provides you with a list of directed questions for your review, the review schedule, and the materials we would like you to send to us at the conclusion of the review. In addition, attached to this letter is a copy of the report that we would like you to review.

Charge Questions
Listed below are the four directed questions we would like you to pay special attention to when conducting your review:

Element 1:
What are the merits and limitations of the authors' approach for estimating the vehicle miles traveled (VMT) rebound effect for light-duty vehicles? Are key assumptions underpinning the methodology reasonable? The VMT rebound effect is defined here as the change in VMT resulting from an improvement in light-duty vehicle efficiency.

Element 2:
Is the implementation of the authors' methodology appropriate for producing estimates of the VMT rebound effect? Specifically, are the input data and the methodology used to prepare the data appropriate? Are sound econometric procedures used? Does the model appropriately reflect underlying uncertainties associated with the assumptions invoked and the parameters derived in the model?

Element3:
The methodology used in this report attempts to account for asymmetric responses to increases vs. decreases in per mile fuel costs (and fuel prices). Does the report's finding of an asymmetric response seem reasonable given the methodology that the authors employed? In particular, do the authors' preferred model specifications (3 .21 b and 4.21 b) seem appropriate for capturing driver response to an increase in fuel efficiency?

Element 4:
The report describes a methodology for projecting the VMT rebound effect for light-duty vehicles forward in time. The concept of dynamic rebound is introduced to quantify the rebound effect over the period of a vehicle lifetime, during which time the variables that influence the rebound effect are changing. Is this methodology reasonable and appropriate, given the inherent uncertainty in making projections about how future drivers will respond to a change in the fuel efficiency of their vehicles?

Schedule
The schedule for this peer review is as follows:

December 18, 2013: Charge letter distributed to reviewers
Early January, 2014: Kick-off conference call with reviewers
January 17, 2014: Comment/review due via email to Larry.orourke@ICFI.com

The kick-off conference call will be an opportunity for you to speak with the other reviewers, ICF and EPA staff to provide you with any clarification you may require.

Materials

Upon completion of your review, you should submit your report under a cover letter that states 1) your name, 2) the name and address of your organization, and 3) a statement of any real or perceived conflict(s) of interest.

Should you have any questions or concerns, feel free to contact me via phone at 617-250-4226 or by email at Larry.orourke@icfi.com. In addition, the EPA project manager for this effort is Jeff Cherry and he may be reached at 734-214-4371. We will send you a meeting request for the kick-off conference call shortly. Thanks for your participation!

Sincerely,

Larry O'Rourke
Manager, ICF International

Attachment: The Rebound Effect from Fuel Efficiency Standards: Measurements and Projection to 2035

Appendix C. Kenneth Gillingham Review Comments

Review of Small and Hymel (2013)

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

By: Kenneth Gillingham, Yale University
January 2014

Overview

This review of the final report by Ken Small and Kurt Hymel "The Rebound Effect from Fuel Efficiency Standards: Measurement and Projections to 2035" first provides a brief overview and then quickly turns to the four charge questions.

The report follows the methodology of Small and Van Dender (2007) and Hymel et al. (2010), with updated data and some minor additions. This is a thoughtful and careful effort aiming to address a difficult question: the change in VMT resulting from an increase in light-duty vehicle efficiency across the entire United States.

The primary methodology is to bring together aggregate state-level data on driving per adult M, fuel prices, vehicle stocks , fuel intensity, urbanization, and congestion. The authors then estimate a system of simultaneous equations to address endogeneity in key regressors, such as the cost per mile of driving. The system of equations is clearly summarized in Hymel et al. (2010) as follows:

$$vma_t = \alpha^m vma_{i,t-1} + \alpha^{mv} veh_t + \alpha^{mc} cong_t + \beta_1^m pm_t + \beta_{K1}^m cap1_t + \beta_3^m X_t^m + u_t^m \quad (1)$$
$$veh_t = \alpha^v veh_{t-1} + \alpha^{vm} vma_t + \beta_1^v pv_t + \beta_2^v pm_t + \beta_3^v X_t^v + u_t^v \quad (2)$$
$$fint_t = \alpha^f fint_{t-1} + \alpha^{fm} vma_t + \beta_1^f pf_t + \beta_2^f cafe_t + \beta_3^f X_t^f + u_t^f \quad (3)$$
$$cong_t = \alpha^{cm} vma_t + cap2_t + \beta_3^c X_t^c + \epsilon_t^c. \quad (4)$$

Here vma_t is natural log of the vehicle miles travelled per adult M, veh_t is the natural log of the number of vehicles per adult, $fint_t$ is the natural log of the fuel intensity (i.e., 1/fuel economy), and $cong_t$ is the log of the hours of travel delay per adult. In addition, pm_t is the log price per mile of driving, $cap1_t$ is the log total length of roads divided by state land area, pv_t is the log of an index of the price of a new vehicle, $cafe_t$ is a pre-estimated measure of stringency of CAFE standards, $cap2_t$ is the log of urban lane miles per adult, and the X's are additional variables such as the square of price, interactions between pm and the other variables, time trends, and state fixed effects. All variables are normalized for ease of interpretation.

The approach assumes first order autocorrelation in the error term for equations (1), (2), and (3). Identification of the key parameter of interest (the price elasticity of VMT demand β_1^m) relies primarily on within-state time series variation in M and the price of gasoline (conditional on the other covariates). The fuel cost per mile coefficient β_1^m is potentially endogenous because fuel economy itself is endogenous. This endogeneity is addressed by including another equation for the fuel intensity (3). Equation (2) addresses a potential endogeneity in veh_t and also allows for an interpretation of the effect of a change in fuel economy on the size of the vehicle stock.

If I understand correctly, the model is estimated in the same way as Small and Van Dender (2007), using a modified Cochrane-Orcutt transformation and nonlinear least squares (to address autocorrelation in the context of a lagged dependent variable).

The results are presented with equation (4) (from Hymel et al. (2010)) both included and not included. The results are largely in line with the results in the previous two papers and other previous papers in the literature. With the updated dataset covering 1966-2009, there is a short-run rebound effect on the order of 5%, a long-run effect on the order of 28-30%, evidence of the rebound effect declining with income, and evidence of a greater response when gasoline prices are increasing than decreasing. There is also some evidence of a structural break in 2003, with slightly larger rebound effects after this year. The rebound effect is then projected forward linearly using forecasts of key variables. When this leads to a negative rebound effect, it is replaced by zero.

Now I turn to each of the four charge questions. Since questions 1 and 2 are so closely linked, I will address them together.

Elements 1 and 2

Element 1*: What are the merits and limitations of the authors' approach for estimating the vehicle miles traveled (VMT) rebound effect for light-duty vehicles? Are key assumptions underpinning the methodology reasonable? The VMT rebound effect is defined here as the change in VMT resulting from an improvement in light-duty vehicle efficiency.*

Element 2*: Is the implementation of the authors' methodology appropriate for producing estimates of the VMT rebound effect? Specifically, are the input data and the methodology used to prepare the data appropriate? Are sound econometric procedures used? Does the model appropriately reflect underlying uncertainties associated with the assumptions invoked and the parameters derived in the model?*

There are many merits to the authors' approach for estimating the VMT rebound effect. It tackles a difficult question using what is likely the best data publicly available across all of the United States. It carefully considers many estimation issues and provides estimates that appear to be reasonable. It provides a valiant (and reasonable) attempt at forecasting the VMT rebound effect forward. There is no question that it was a major effort and a thoughtful one at that. It would be difficult to do much better given the task at hand.

As in any study, there are also limitations, most of which the authors recognize. All of these limitations relate to the difficulty of the question being asked. I will address these limitations next, emphasizing unavoidable challenges of estimation and providing a few suggestions.

1. To begin, the definition of the VMT rebound effect is vague. This is not the authors fault, for they are clear about the question they intend to answer. But, the definition, "the change in VMT resulting from an improvement in light-duty vehicle efficiency," provides much room for different interpretations. It provides no guidance on whether the improvement is costly, leading to higher vehicle prices or costless, leading to lower vehicle prices. Similarly, it does not specify whether other attributes of vehicles change along with vehicle efficiency. On one (unlikely) extreme, one could imagine expensive improvements in light-duty vehicle efficiency that also involve a trade-off leading to less desirable characteristics of the vehicles. At this extreme, the number of vehicles in the fleet would decline (vehicles are more expensive and less exciting) and at the same time driving is less exciting, so people drive less. This would suggest a very small rebound effect. Consider another (also unlikely) extreme, where improvements in light-duty vehicle efficiency are free and lead to no change in the attributes of the fleet. This would suggest a larger rebound effect. This extreme is the assumption made in the report. If we are discussing a tightened greenhouse gas (GHG) standard for light-duty vehicles, the truth could be expected to be somewhere in the middle. Put in terms of the notation in the report, the methodology estimates $\varepsilon_{\hat{M},pm}$, where $\hat{M}$ includes both the driving response and the "fleet size" response. In the report, the fleet size response is positive, for vehicles are more efficient and no more expensive. This is entirely consistent with what the authors state they intend to do, but not likely to be the case in the real world. If the vehicle fleet shrinks (or stays constant), we would expect fewer additional miles driven than in the results. Thus, for this reason the results are likely a slight *over-estimate* of the rebound effect from a GHG standard.

2. A second limitation, heterogeneity, is entirely a data limitation. The authors clearly recognize this. The only way data can be assembled on all states in the U.S. over time is to use aggregate data at the state level. Despite improvements in data availability in some states, this is the best we can do for all states. Using aggregate data masks known heterogeneity in the rebound effect, which may be important for projecting the rebound effect forward. This is recognized clearly by the authors on page 3: "In particular, the model assumes that changes in fleet average fuel economy will have the same impact on behavior whether those changes are caused entirely by new vehicles entering the fleet, or partly by new vehicles and partly by the retirement of older ones. It should be adequate insofar as the pattern of mileage driven by vehicle age is reasonably stable; if it is not, a more fine-tuned analysis tracking elasticities by vehicle age would reveal additional effects not captured here." I believe this is an important caveat, given that elasticities do vary by vehicle

age (I can see this in my own work). However, there is not much that can be done about this using aggregate data. Is this a major bias? It's hard to say. It is not even clear what the direction of the bias would be, since it could go either way. I see this as an assumption worth noting, as the authors clearly do, and an area worth researching further in the future. But I don't see any way around this given the current U.S.-wide question being asked.

3. Another limitation is the reliance on within-state time series variation in the study. Relying on time series variation is not necessarily a problem, but using a time series over many years typically lends itself to using time series approaches. For example, testing for the order of autocorrelation and for unit roots are common time series approaches. To its credit, the methodology does account for first-order autocorrelation. But what if the data are second-order autocorrelated? In this case, the coefficients could still be consistently estimated, but the standard errors would be incorrect. This raises a possible issue of incorrect standard errors. It is not clear what the direction of the bias in standard errors would be.

4. Similarly, since the time series econometric approaches are not used, one might have expected the standard panel data approach that includes time fixed effects to be employed. The dataset would make this possible. In this case, the identifying variation would be gasoline price shocks off the mean. I am sure the authors have considered and run such a specification before. I suspect one of two things happened: either there was not enough variation and the estimates were all statistically insignificant, or the results were crazy because the variation identifying the coefficients was not reliable variation. So instead, the paper includes linear time trends in each equation. These are helpful and much better than nothing. They do not control for other changes as flexibly as fixed effects, but they do retain more variation. Another possibility could be decade fixed effects or a quadratic or higher order polynomial in time. Would inclusion of these further time controls make a major difference? Perhaps not, but it could be worth discussing and exploring as further robustness checks. The direction of the bias would again be unclear. One way in which it might not make a difference is if the time-varying unobservables was only correlated with fuel intensity, which is effectively instrumented for in the third equation.

5. Another limitation is the difficulty in finding great instruments for the fuel cost per mile and fuel intensity. The system of equations can be thought of in an instrumental variables context. So the system of equations must have exclusion restrictions (i.e., variables that are not in the first equation, but are in the third equation) in order to address the possible endogeniety of the pm_t variable. In my read of the report and previous papers, it looks to me like the only exclusion restrictions are the CAFE stringency variable $cafe_t$ and lagged fuel intensity $fint_{t-1}$ (although it is a little odd to me that vma_t is in the third equation; usually one would expect to

see vma_{t-1} so that the lagged variable is an instrument for itself). So one way of looking at the results is that we are instrumenting for pm_t with the CAFE variable and lagged fuel intensity. Are these good instruments? Perhaps one could argue so, although they are not obviously so. The identification of the rebound effect does in part rest of this assumption. There is a similar assumption for the vehicle stock variable veh_t, where the price of vehicles and the lagged vehicle stock are the exclusion restrictions that help identify the vehicle stock variable veh_t in equation (1). I am not going to say that these exclusion restrictions are flat-out wrong, for I imagine you could argue for them and I personally would have a very tough time finding much better ones in this context. The bottom line is that β_1^m is a difficult coefficient to reliably identify with aggregate data, so there is reason to be at least somewhat cautious.

6. As the CAFE stringency variable $cafe_t$ is a key exclusion restriction, it is important to understand how it was derived. It was cleverly constructed, as a predicted variable using vehicle efficiency data prior to the implementation of CAFE standards in 1977. In this sense, I like the variable and think it is useful. However, given that it is a predicted variable, we know that using a predicted variable in an estimation means that we really have a two-step estimation approach, which requires adjusting the standard errors for the standard error in the first stage. One could easily get around this (and address any possible autocorrelation without the modified Cochrane-Orcutt approach) using bootstrapped standard errors. This is what I would suggest as another robustness check. Typically, bootstrapped standard errors lead to larger standard errors, but given how statistically significant the coefficients are in the current estimation, I would still expect statistical significance for the key coefficients of interest. Note that the coefficients themselves would not change.

7. A final limitation relates to the assumption of no measurement error in the variables, which may be important given the sources of the data (which to my knowledge are the best available for data of this ilk). Hymel et al. (2010) provide a very clear caveat on this point on page 1227: "Perhaps the greatest danger is that persistent measurement error in a given state (across years) could cause an overestimate of the coefficient in a given equation on the lagged value of the dependent variable. This coefficient is crucial in estimating the relationship between short-run and long-run elasticities. Thus the rather large difference we find between these elasticities (roughly a factor of five in the VMT equation) might be partly caused by measurement error." I think this is a fair caveat that applies equally to this report. If we have classical measurement error in the regressors, we would expect attenuation bias of the coefficients, so β_1^m could be biased downwards; thus it would be an *under-estimate* of the true value. The two things that can be done for this are to use instruments (which is done for some of the variables) and be very careful with the data collection process, which I believe they have been.

8. An assumption (not necessarily limitation) worth highlighting is the choice of a partial-adjustment model with a lagged dependent variable. There is a long history in energy economics using partial-adjustment models. They rely on a few assumptions. First, for consistency, there cannot be autocorrelation in the errors, otherwise there is an endogeneity issue. I believe that the methodology in the report addresses this concern. Second, for the interpretation of long-run elasticities, one must believe that we are in a dynamic system converging to an equilibrium response and that the structure we have put on this dynamic system is correct. Many, if not most applied econometricians today harbor some doubts about this approach, but we cannot rule it out. It relies on variation in the previous year's dependent variable to provide guidance on how quickly we are moving to a hypothetical equilibrium. Is this variation free of confounds? Hard to say. In any event, it is a major assumption that may be reasonable, even if many economists feel more comfortable with research designs where the identification is cleaner and there is no lagged dependent variable. The robustness check that many economists would want to see is the coefficient on pm_t when the first equation is estimated separately and without the lagged dependent variable. From Small and Van Dender (2007), we can see that estimating the first equation separately does not change the coefficient on pm_t much (an increase to -0.085). It would be nice to know what the result would be without the lagged dependent variable as well. At the end of the day though, these assumptions may be defensible.

To summarize, while there are many merits to this study, there are also some limitations. Some are data limitations and some should best be thought of as *possible* concerns that perhaps warrant further robustness checks and thought. I should emphasize that all applied econometric work has possible concerns and it is impossible to address them all. My overall take is that given the state of the literature, the coefficient estimates in this report provide a reasonable sense of what the VMT rebound effect is in the U.S. on average over the period 1966-2009.

Element 3

Element 3*: The methodology used in this report attempts to account for asymmetric responses to increases vs. decreases in per mile fuel costs (and fuel prices). Does the report's finding of an asymmetric response seem reasonable given the methodology that the authors employed? In particular, do the authors' preferred model specifications (3.21 b and 4.21 b) seem appropriate for capturing driver response to an increase in fuel efficiency?*

This report uses a well-established approach to account for asymmetric responses to increases and decreases in per mile fuel costs based on variation in fuel prices. There are many energy economics papers that indicate a greater response to price increases than price decreases, and the authors find results that corroborate this literature. I believe the sign and relative magnitudes of these results, with the caveats above applying of course.

That said, I agree with the authors in questioning whether the driver response to an increase in fuel efficiency would be different than the response to gasoline prices. The asymmetries could come about for two primary reasons. First, gasoline price increases could be more salient than price decreases. Second, investments could be made when gasoline prices are high, limiting a short-run downward response when gasoline prices drop. Both factors probably play a role, and Figures 4.2 and 4.3 may be consistent with both.

But if asymmetries come about because of the differing salience of increases and decreases in gasoline prices, should we expect the same effects to apply for changes in vehicle fuel efficiency? My first inclination is that the answer is "not necessarily." Perhaps the downward price movement would be the better indicator of what the response would be to an increase in fuel efficiency, which is effectively what the asymmetric response results do. But given that saliency of the gasoline price may be different than saliency of the fuel price per mile, I see this as a relatively strong assumption.

The authors clearly recognize this, but must use the variation in the data that they have. Given the strong assumption, I would be more more comfortable using the results assuming the symmetric response. This seems to me to be a more neutral assumption, for it is effectively the mean effect. Fortunately, it does not make a huge difference.

Element 4

Element 4*: The report describes a methodology for projecting the VMT rebound effect for light-duty vehicles forward in time. The concept of dynamic rebound is introduced to quantify the rebound effect over the period of a vehicle lifetime, during which time the variables that influence the rebound effect are changing. Is this methodology reasonable and appropriate, given the inherent uncertainty in making projections about how future drivers will respond to a change in the fuel efficiency of their vehicles?*

Truly projecting the VMT rebound effect for light-duty vehicles forward in time requires a detailed model of the vehicle stock, along with elasticity estimates for each part of the age profile of the vehicle stock. It would involve allowing new vehicles to enter into the stock, which would lead to several dynamics. These new vehicles are more efficient, so they are driven more. Households also switch a bit to these vehicles from others, likely less-efficient vehicles, reducing emissions, but perhaps leading to a slightly more miles driven. Similarly, older vehicles are driven a bit less. As well, different types of people may switch to the new vehicles (e.g., people who have long commutes).

The authors face real data limitations that prevent this ideal modeling of the fleet. Instead they cleverly develop a "dynamic" rebound effect. The dynamic rebound effect attempts to take into account a variety of factors: the transition from the short-run to long-run rebound effect, the change in income, urbanization/congestion over time, and the decrease in driving from vehicles along the vehicle age profile. From my perspective, given the caveat that a true vehicle stock model is unavailable, this approach is sound for estimating the VMT rebound effect going forward in the next several years.

I am less comfortable linearly extrapolating as far out as 2030. It is very likely that the relationship between the rebound effect and income is relatively linear within the observed range of the variables, but moving forward, I believe it is less likely that the relationship would continue. The issue is quite clear in the need to truncate the rebound effect for any given state and year at zero. It seems more likely that there would be a smooth decline in the rebound effect that asymptotes to a level above zero. Congestion would reach saturation. Consumers would be wealthier so perhaps would be driving so much more that the utility of driving on the margin is very low (which could imply a larger rebound effect). These are just two possibilities. Perhaps with some exploration the authors could estimate a non-linear specification a nonlinear effect that asymptotes. If we must extrapolate out to 2030, I would feel more comfortable with this approach than allowing the rebound effect for some states to approach zero and then be zeroed out.

Would such an approach change the results much? I suspect not, but it is worth considering.

Appendix D. David Greene Review Comments

Review of "The Rebound Effect from Fuel Efficiency Standards: Measurement and Projection to 2035" by Kenneth A. Small and Kent Hymel, December 24, 2013.

David L. Greene

January 16, 2014

I have carefully read the paper, "The Rebound Effect from Fuel Efficiency Standards: Measurement and Projection to 2035" by Small and Hymel. This review is based on the December 24, 2013 corrected version.

Element 1:

What are the merits and limitations of Small's approach for estimating the vehicle miles traveled (VMT) rebound effect for light-duty vehicles? Are key assumptions underpinning the methodology reasonable? The VMT rebound effect is defined here as the change in VMT resulting from an improvement in light-duty vehicle efficiency.

Response

The Small & Hymel (S&H) approach for estimating the direct rebound effect is theoretically and methodologically rigorous and has been executed by the researchers without errors, to the best of this reviewer's knowledge. It has both merits and limitations, as do all existing studies of this phenomenon.

Merits

The authors demonstrate an accurate understanding of the direct rebound effect as distinguished from other definitions of the rebound effect. The model they have formulated and the data they use are appropriate for measuring the direct rebound effect.

The system of equations used to estimate the rebound effect allows for fuel intensity (the inverse of miles per gallon)[1] to affect vehicle travel via, 1) the effect of a change in fuel cost per mile on miles traveled per adult person, 2) the effects of fuel cost per mile on automobile ownership and 3) the effect of increased travel on traffic congestion (4-equation model). This formulation allows for quantification of the importance of these potential pathways by which fuel intensity might affect vehicle travel. The general similarity in results between S&H's 4-equation system and their 3-equation system (omitting congestion) adds to the evidence that the estimates are robust.

The lagged adjustment formulation used in the S&H model allows for estimation of both short-run and long-run rebound effects. The authors have used appropriate econometric methods for estimating this

[1] The terms "fuel economy" and "fuel intensity" are used throughout this paper. Fuel economy is defined as miles per gallon of motor fuel. Fuel intensity is the inverse of fuel economy.

type of model in a system of equations, taking into account the possibility that error terms within each equation may be correlated over time, a potentially serious issue for such lagged adjustment models.

The approach makes use of a large volume of data covering the fifty states and the District of Columbia over a period of 44 years. The source of data for vehicle travel is the U.S. Department of Transportation, Federal Highway Administration (FHWA), which collects the data from the individual states. These data have been scrutinized by the FHWA and checked against other data, such as permanent and periodic traffic counts. The data are certainly not ideal (there is no ideal source for VMT data) but are very unlikely to misrepresent year-to-year changes in vehicle travel due to the very large number of permanent and temporary traffic counters in use across the United States. In their estimation methods, the authors have used appropriate statistical procedures to account for any persistent state-specific errors. Aggregate vehicle travel data, such as used in this study, are appropriate for estimating the direct rebound effect since it is the effect of changes in fuel intensity on total vehicle travel that is of greatest relevance to the Environmental Protection Agency's (EPA) and National Highway Traffic Safety Administration's (NHTSA) rulemakings. Other sources of data, such as household travel surveys, cover a large fraction of total vehicle travel but omit vehicle travel by businesses and governments and also by heavier vehicles. Furthermore, models estimated on survey data generally do not insure that the estimated individual household changes integrate to the total national change. Total national vehicle travel as reported in the FHWA's table VM-1 is also a useful data source for estimating the rebound effect but the quantity of data available is smaller by a factor of 50.

There have been many studies of the rebound effect and S&H include the most important research papers in their review. In general, the studies based either on a national vehicle travel data time series, time series cross-sectional state vehicle travel data or panel survey data (covering several years and including significant fuel price changes) are very consistent with the empirical findings of S&H. S&H demonstrate that when their estimation is restricted to the time periods covered by previous studies, the rebound effects estimated by their method are very close to the central tendency of the studies. Higher estimates of the direct rebound effect have come from studies in other countries and from U.S. studies using only a single year of survey data. Statistical analysis based on a single year of survey data is prone to spurious correlations. In general, models attempting to explain variations in vehicle travel based on a single year of survey data have low explanatory power (in the statistical sense, i.e., low R^2). This makes controlling for factors that may influence both fuel economy and vehicle travel critical for obtaining coefficient estimates that are not biased by correlations with omitted variables. More robust estimates are likely to be obtained using time-series, cross-sectional data sources, such as used by S&H.

S&H have carefully investigated the possibility that the rebound effect is not constant over time. They test this possibility first by estimating different rebound effects for different periods of time without consideration of what might be causing any changes. They also test for a varying rebound effect by means of a formulation the authors have used in previously published papers that estimates correlations between the rebound effect and income and fuel price. The limitations of the latter method for forecasting purposes are discussed below. However, the authors have shown significant correlations and have proposed a plausible theoretical explanation for the results.

S&H have also investigated the possibility that fuel price and fuel intensity may affect vehicle travel differently, and that fuel price (or fuel cost per mile) rises and reductions may not have equal effects. This is important because the rebound effect, strictly speaking, pertains only to fuel intensity and not to fuel price yet many studies rely on estimation methods that constrain the elasticities of fuel price and fuel intensity to be equal but opposite in sign. For the purposes of the EPA, it is the effects of fuel intensity reductions that are of interest rather than the effects of fuel intensity increases. In theory, the effects could be symmetrical but, as S&H note, there is a substantial literature that indicates that market responses to fuel price rises and fuel price reductions are not symmetrical. The rigorous investigation of this issue is a valuable contribution about which more will be said below. The results confirm that responses to fuel price or fuel cost per mile reductions are smaller than the responses to increases. They also find that it is not possible to estimate a statistically significant effect of fuel intensity alone using their data and methods. This latter result is consistent with the small number of other studies that have reported on this issue.

The inability to estimate the separate effects of fuel price and fuel efficiency on VMT is worthy of further investigation. The authors' decision to proceed using fuel cost per mile is consistent with the interpretation that this outcome is caused by a poor sample design for the fuel efficiency variable. That is, the fuel efficiency of the on-road vehicle fleet changes very gradually and thus tends to follow a smooth trend, making it difficult to distinguish the effects of fuel intensity from other smoothly trending variables. In addition, state-level fuel economy is not directly measured but estimated by the states by various methods (e.g., by dividing fuel use by vehicle travel). Fuel prices on the other hand, have changed relatively quickly and by relatively large amounts. Fuel prices are also based to a large extent on direct measurements. This makes it easier to accurately estimate at least the short-run price effect. The authors' decision is therefore a prudent one given the information available. It is also appropriate for them to note that, if anything, it is more likely to result in an overestimate of the rebound effect.

Given the above, the authors recommend using the rebound effect estimated using cost per mile, which constrains the price and fuel intensity elasticities to be equal in magnitude and opposite in sign. This is the most important assumption of their study, since without it the estimated rebound effect would not be statistically significant from zero. They also note that this assumption, in all likelihood, leads to an overstatement of the rebound effect. Their decision seems prudent although it is a subjective one and, strictly speaking, not supported by the empirical data. The alternative would be to assign a value of zero to the rebound effect. This, however, would imply that drivers do not behave rationally from an economic perspective, since they would treat changes in cost caused by changes in the price of fuel differently from changes in cost due to changes in fuel intensity. Economic theory suggests that such a conclusion should itself be supported by more evidence than the lack of statistical significance of the fuel intensity coefficient. S&H present their reasoning on this issue transparently, as they should.

Limitations

In their review of the literature, S&H should have included the important review of studies of the rebound effect by Sorrell (2007) and companion reports by the UK Energy Research Center (Sorrell and Dimitropoulos, 2007; Dimitropoulos and Sorrell, 2006). Since the UKERC study is a review of the literature, by itself it does not add much new material to the S&H review but it does cover more of the literature and reaches conclusions that support S&H's interpretation of the literature.

The definition of the rebound effect on p. 6 is the definition appropriate when fuel economy improvements come about due to pure technological change. That is, the improvement in fuel economy does not involve trading off purchase cost or other vehicle attributes (e.g., size, acceleration) for fuel economy. The rebound effects of fuel efficiency due to pure technological change versus fuel economy standards are almost certainly different. Technological change shifts the trade-off between fuel economy and cost (or other attributes) while standards generally cause manufacturers to move to a different location within the same trade-off function. Of course, technological change is always occurring and there is the likelihood that standards induce technological change but the basic point remains valid since standards, in general, will induce a trade-off of fuel economy for other vehicle attributes, especially manufacturing cost. For the purposes of evaluating the EPA/NHTSA rule makings, trade-offs with vehicle cost are highly relevant.

Although the study does a good job of recognizing and describing a wide range of pathways for the rebound effect, it omits part of the effect of increased vehicle prices on the long-run cost per mile of travel. According to all studies of which I am aware, including the rule making itself, the 2025 fuel economy and greenhouse gas (GHG) standards are expected to result in an increase in the long-run cost of manufacturing vehicles. The increased cost will cause an increase in vehicle transaction prices, assuming only that vehicles' selling prices increase with increasing long-run average cost. The S&H model allows the increase in vehicle price to affect VMT through the effect of new vehicle prices on the vehicle stock and the effect of vehicle stock on vehicle travel. But an increase in the capital cost of a vehicle also affects the long-run cost of vehicle travel via usage-induced capital depreciation. This mechanism is not included in either the 3-equation or 4-equation versions of the model and could be important because capital costs are a large fraction of total vehicle ownership costs.

The potential for feedback effects to be generated via institutional processes is appropriately acknowledged but a potentially important one is missing. That is the effect of major fuel economy improvements on highway user fees. In the past, fuel economy improvements have been second only to inflation as a threat to Highway Trust Fund revenues (e.g., Greene, 2011). Historically, motor fuel taxes have been raised by federal and state governments in order to maintain adequate funding for highway construction and maintenance. Whether this will continue to be the case in the future and what type of tax may be used (possibly one that does not fall on motor fuel) are open questions but certainly relevant ones. Raising motor fuel taxes would, *ceteris paribus*, increase the retail price of motor fuel, thereby increasing the fuel cost per mile of travel and partially offsetting the rebound effect of fuel intensity. A careful review and analysis of this subject would likely lead to the conclusion that raising fuel taxes in order to maintain highway user fee revenues should be included in regulatory analyses of the rebound effect. This is not something that S&H need to include in their econometric analysis but it should be mentioned in the discussion of possible institutional effects.

Summary for Element 1

In brief, S&H's study is a technically proficient assessment of the rebound effect of fuel economy on vehicle travel using appropriate state-level vehicle travel and associated data. The conclusions drawn are well supported by the empirical analyses in this paper and, in general, by the previous literature. The authors have made several important contributions:

1. Re-estimating the rebound effect using more recent state-level data and demonstrating the consistency of their historical estimates with the central tendency of the existing literature.
2. Estimating the effects of income and fuel price on the size of the rebound effect over time and showing the ability of these factors to statistically explain a large portion of the apparent changes.
3. Testing the potential asymmetry of response to increases and decreases in fuel cost per mile. The analysis also shows that the asymmetric response to fuel price changes implies a smaller rebound effect than that found assuming a symmetric response to fuel cost per mile.
4. The projections of future rebound effects are useful but may understate the rebound effect in cases where many states' rebound effects approach zero. This is likely a consequence of the linear functional form and truncation rule and could be an artifact of those assumptions.

Overall, this paper makes an important contribution to the literature and, like the authors' previous work, represents the current state of knowledge about the rebound effect of motor vehicle fuel economy on vehicle travel.

Element 2:

Is the implementation of the Small methodology appropriate for producing estimates of the VMT rebound effect? Specifically, are the input data and the methodology used to prepare the data appropriate? Are sound econometric procedures used? Does the model appropriately reflect underlying uncertainties associated with the assumptions invoked and the parameters derived in the model?

Response

The S&H method represents best practice and is appropriate for producing estimates of the rebound effect. As discussed above, the data used are well suited to the problem. The econometric methods are also appropriate and consistent with the state of practice. Incorporating uncertainty, on the other hand, poses a difficult challenge that has not yet been given much attention in the literature on the rebound effect. There are uncertainties due to data shortcomings, issues with the experimental design available in the historical record, uncertainties due to model formulation, uncertainties inherent in econometric estimation and uncertainties about the future state of the world. S&H have addressed many of these issues by constructing alternative projections based on different assumptions. These are useful. However, adequately addressing uncertainty and incorporating it into a projection methodology requires an identification of the nature of the uncertainties to be included, which should follow from the purpose for representing uncertainty. It is not clear to this reviewer what the goal of including uncertainty is, and therefore it is not possible to give a definitive response concerning the S&H method's handling of uncertainty.

Data Definitions

It would be helpful to the reader for S&H to spend a little more time explaining the nature of the state level data. According to this reviewer's understanding, state level data include VMT and fuel use by all vehicle types, not only the light-duty vehicles affected by past fuel economy regulations. This introduces substantial heterogeneity in the vehicle populations across states, from motorcycles to diesel-powered 18-wheelers, although light-duty vehicles still predominate. Fuel intensity is believed by this reviewer to be total state highway use of motor fuel (not only gasoline) divided by total state highway vehicle travel. It would be helpful to clarify these definitions in the report to alert the reader to the meaning of the data and possibly help interpret the results. It is likely that state-specific constants will account for much of the differences across states in the composition of traffic. Remaining effects of heterogeneity are not likely to cause important problems for estimating the rebound effect.

Cost per Mile versus Fuel Intensity Rebound

The question of whether the data actually support the existence of a rebound effect for fuel economy has been addressed above and is mentioned again here to emphasize its importance and the uncertainty it creates. The estimates presented by S&H are based on the maintained hypothesis of economically rational behavior, in the sense that consumers are assumed to respond to changes in fuel cost per mile in the same way whether caused by a change in fuel price or a change in fuel economy. However, the new research presented by S&H concerning the asymmetry of responses sheds new light on this subject, as explained in greater detail in Element 3. The consequence of the analysis of asymmetry is that there is now strong evidence that the market response to reductions in fuel intensity (a goal of the fuel economy and GHG standards) is less than the response of the market to increases in the price of fuel, and that it is also smaller than estimates of the rebound effect based on the assumption of a symmetrical response to changes in fuel cost per mile. This finding of S&H is potentially of major significance. It implies that the best estimate of the rebound effect for the purpose of estimating the effects of fuel economy and GHG standards is the asymmetric elasticity of reductions in fuel cost per mile. Since it is a relatively novel result with respect to the rebound effect, further research is warranted, yet the results presented by S&H are strong and should now represent the current state of knowledge.

Statistical Insignificance of Endogenous Variables in Some Equations

S&H do not provide an adequate discussion of the fact that some of the endogenous variables in either the 3- or 4-equation models are not statistically significant. For example, in the 3-equation models, *vma* does not appear to be statistically significant at the 0.05 level in any of the equations for vehicle stock, and *pf+vma* is not statistically significant in the equation for *fint* in models 3.3, 3.18, 3.21b, or 3.29 (Table B1). In the 4-equation models, *pf+vma* is not statistically significant in the equation for *fint* in models 4.3, 4.13, 4.21, and possibly 4.23. This calls into question the necessity for the simultaneous equation framework, at least as formulated, and requires explanation. The secondary, simultaneous equation effects are small relative to the direct effect of pm in the *vma* equation and so the empirical significance of these pathways is not great but it would be interesting to see if the hypothesis of simultaneity is rejected by the data or not.

In particular, the equation for *fint* in table 4.2 raises questions. Why it is preferable to interact fuel price and VMT rather than test also for the main effects of the two variables? As explained on p. 30, the interacted fuel cost variable turns out not to be statistically significant. This result increases the need for an explanation of the choice of this formulation. Is this a parsimonious way of getting both variables into the *fint* equation? Would they be less statistically significant individually? And if neither vehicle travel nor the price of fuel is statistically significant in the equation for fuel intensity, doesn't this undermine the rationale for including this equation in a system of equations? If this is the best formulation and yet the log of fuel price times VMT is not statistically significant in the equation for *fint* then it would seem that the data do not support including *fint* in a simultaneous equation formulation. Again, this does not appear to be of great practical importance since the simultaneous equation effects are relatively small.

A Caveat on Long-run and Short-run Effects and Lagged Adjustment Models

The lagged adjustment model used by S&H is a useful formulation and widely adopted for modeling phenomena such as aggregate VMT. However, it implies two important maintained hypotheses. The first is that the correlation between the dependent variable and its lagged value measures only the adjustment process. If there are other causes of a strong positive correlation, the long run elasticities will be overestimated. By using econometric methods that allow for error correlation in the lagged adjustment equation S&H have taken a prudent step to deal with possible correlation between the current and lagged values of the dependent variable from that source. Second, it implies the same adjustment rate for all variables, which would seem to be a special case. These observations do not diminish the value of this analysis or others using the lagged adjustment formulation but are something to be borne in mind when interpreting results.

The Effect of Vehicle Cost on Vehicle Use

The S&H model allows changes in vehicle price to affect vehicle travel via its effect on the size of the vehicle stock. However, this may not be adequate since increased vehicle cost also affects the cost per mile of travel to the extent that use of a vehicle depreciates its value. There is no question that capital depreciation is a component of the long-run cost per mile of travel. The question is how important it is as a determinant of long-run travel demand.

Estimates of the elasticity of total vehicle travel with respect to car purchase cost were found in at least one literature review to have a central tendency of -0.19 in the short run and -0.42 in the long run (Goodwin et al., 2004, table 7). While the plurality of studies reviewed come from the United States, the majority do not. In addition, it is not clear from the study cited how many studies combine the effect of purchase cost via the size of the vehicle stock with the effect of purchase cost via long-run cost per mile. Nonetheless, for illustrative purposes only, I will use the -0.4 elasticity. If a doubling of fuel economy caused a 10-20% increase in VMT at a cost of $2,000 per vehicle for vehicles with a prior average cost of

$25,000, the 8% increase in vehicle cost would reduce VMT by about 3%, offsetting 15-30% of the estimated rebound effect. This reviewer is not arguing here that these numbers correctly represent the magnitude of this possible effect for the United States but rather to illustrate the possibility that there may be an important issue here that is worthy of formal investigation.

Element 3:

The methodology used in this report attempts to account for asymmetric responses to increases vs. decreases in per mile fuel costs (and fuel prices). Does the report's finding of an asymmetric response seem reasonable given the methodology that Small employed? In particular, do the authors' preferred model specifications (3 .21 b and 4.21 b) seem appropriate for capturing driver response to an increase in fuel efficiency?

On this subject, S&H have produced potentially important results. Their analysis supports the inference that rebound estimates based on a symmetric response to fuel cost per mile overstate the rebound effect of fuel intensity. The price asymmetry model has been found in other studies of the response of gasoline demand to gasoline price and petroleum demand to petroleum price. Thus, it is very likely that the difference between rises in fuel cost per mile and decreases in fuel cost per mile is attributable to asymmetric market responses to rises in the price of fuel and not to asymmetric responses to changes in fuel intensity. This would mean that the symmetric model, by estimating an average effect of rises and reductions in fuel cost per mile, would overestimate the effect of reductions in fuel cost per mile. S&H's results confirm this. This result is important because it implies that for purposes of estimating the rebound effect of fuel economy regulations, the asymmetric elasticity of a reduction in fuel cost per mile should be a more accurate estimate of the rebound effect than the fuel cost per mile elasticity estimated assuming a symmetric relationship between fuel cost per mile and vehicle travel.

The analysis of the possibly asymmetric effects of fuel price rises and cuts appears to be separating price effects (which are asymmetric) from fuel intensity effects (which are not asymmetric). As the authors explain, in the asymmetric model the rebound effect is mathematically the sum of the asymmetric effects. The partial effect of fuel efficiency (holding other variables constant) does not depend on whether prices are rising or falling. Rather, it is the effect of the price of gasoline that depends on whether prices rise or fall. Thus, this reviewer concurs with the authors' decision to adopt this result in their preferred models (3.21 b and 4.21 b), especially since these empirical results are also consistent with their earlier inference that by using fuel cost per mile alone (based on a symmetric model) one would almost certainly overestimate the rebound effect.

Generally, two possible explanations are put forward for the asymmetrical response to fuel price rises and cuts. The first is that consumers are more likely to extrapolate fuel price rises than cuts and thus respond more strongly to fuel price rises when purchasing durable goods. The second explains the persistence of asymmetry in the long run as a consequence of technological change or public policy (i.e., efficiency standards) induced by fuel price rises. In either case, the asymmetry method used in this section of the paper should be able to separate these irrelevant effects from the rebound effect. Empirically, the effects of fuel price and fuel intensity changes are not the same (see above). The asymmetric model offers a logical explanation of the conundrum.

Because the media and price volatility effects almost certainly apply to the effects of price but not fuel efficiency, the authors are correct in abandoning the models including these variables. The anomalous results in certain formulations also support this decision. As the authors note, the erratic behavior of the Asymmetry model 3.23 suggests that it is not a plausible model. Because the asymmetric models are also not able to separately estimate the fuel price and fuel efficiency effects, as the authors note, their preference for the models of section 4.4.1 is well reasoned.

In this and previous work, S&H have found that the rebound effect varies with income. In this study, they also found that it varies with the price of fuel. It would be interesting to test whether changes in the distribution of income as well as average income have affected the rebound effect. There is some evidence that the distribution of income has affected the growth rate of aggregate VMT. The result that the rebound effect varies with income and fuel price is both important and useful for analyzing the future costs and benefits of fuel economy and GHG regulations.

Element 4:

The report describes a methodology for projecting the VMT rebound effect for light-duty vehicles forward in time. The concept of dynamic rebound is introduced to quantify the rebound effect over the period of a vehicle lifetime, during which time the variables that influence the rebound effect are changing. Is this methodology reasonable and appropriate, given the inherent uncertainty in making projections about how future drivers will respond to a change in the fuel efficiency of their vehicles?

The dynamic rebound model provides a reasonable method of accounting for the fact that as fuel economy improvements penetrate the vehicle stock, new vehicles have higher fuel economy than older vehicles. What is not clear is how much of an improvement this method makes over basing the rebound effect on the vehicle miles weighted average fuel intensity of the vehicle stock. If distributional effects were important (if it were important to know how much the usage of different vehicles changed), detailed modeling of changes in vehicle use in the vehicle stock by vintage would be necessary. It is not clear that this is necessary for EPA's analysis of the costs and benefits of fuel economy regulations. That said, there is no compelling reason not to use the dynamic method proposed by S&H.

In this and previous papers, the authors have presented strong evidence that the rebound effect has changed over time and that the changes are correlated with changes income and fuel price. The income result was also confirmed in a recent study using national time series data (Greene, 2012). There is also theoretical justification for including these effects, since income affects the value of travelers' time and fuel prices affect the fuel cost share of the long-run cost per mile of travel. Thus, it is appropriate to include these effects in the forecasting model. While there is uncertainty about future incomes and fuel prices, basing the estimated rebound effect on price and income assumptions used elsewhere in the estimation of costs and benefits of the standards will result in a more consistent assessment. That said, the linear extrapolation of the income and price effects is problematic. Whatever the correct functional form may be, it is not linear over the full range of possible future incomes and fuel prices. This leads to the problem of rebound effects with theoretically implausible signs, which the authors have addressed by truncation at zero. Truncation at zero is better than not truncating at zero. A better functional form should be sought that approaches zero as income goes to infinity and fuel price goes to zero.

Final Comments

The S&H analysis is very well done, uses appropriate models, data and econometric methods and makes several important contributions to knowledge of the rebound effect. The results are consistent with both the central tendency of other estimates in the literature and with the best studies contained in the peer-reviewed literature. The range of issues investigated and statistical tests performed is a particular strength of the analysis. The projected rebound effects are useful and plausible. The results are useful to EPA as they now stand. The issues raised in this review and those noted below suggest avenues of additional research and model development that may or may not lead to improvements in the model as currently recommended by S&H.

The chief limitations of the study are the possibly inadequate representation of the effect of vehicle purchase costs on the long-run cost per mile of vehicle travel, the need for an interpretation of the lack of statistical significance of key endogenous variables in many of model equations, and the truncation of the rebound effect in the projecting model when the estimated rebound effect becomes negative.

It is appropriate to adopt the models that include the asymmetric response to reductions in fuel intensity (models 3.21b and 4.21b) as the current best estimates of the rebound effect. The finding of asymmetry in the elasticity of cost per mile should be incorporated in the projection methodology. It is statistically significant and consistent with the peer-reviewed published literature. It also addresses the inability to estimate a significant elasticity for fuel intensity alone and the conclusion that the rebound effect is thereby overestimated. Use of the “price cut” elasticity of fuel cost per mile from the asymmetric model has the advantage of at least removing the fuel price rise asymmetry from the estimated rebound effect.

S&H’s investigation of how the rebound effect may vary systematically with other factors is an important contribution to the understanding of the rebound effect. Incorporating rebound effects that vary with income (value of time) and fuel price (fuel cost share of operating costs) in forecasting the rebound effect is supported both theoretically and empirically. The fact that the rebound effect varies with both income (interpreted as representing the value of time) and fuel price (perhaps representing the fuel cost share of the long-run costs of vehicle travel) suggests that an alternative model formulation explicitly including all the important long-run costs of vehicle travel (and the elasticities of substitution among them) might produce an improved forecasting model. Such an approach might also permit inclusion of use-related depreciation as a component of the cost per mile of travel. Fuel cost is not the only component of the long-run cost of vehicle travel. The short-run cost of travel includes the traveler's time and the long-run cost includes many factors, notably the capital cost of the vehicle.

The assumption of constant elasticity (as a function of income and fuel price) should be considered only one possible functional form. In particular, it is recommended that forecasts of the rebound effect be based on a more explicit representation of the total cost of vehicle travel, including fuel, maintenance, capital and travelers' time costs. Because in the end S&H are left with only a partial explanation for the apparent increase in the rebound effect after 2003, understanding the correct functional form of the rebound effect should be given a higher priority.

It would also be appropriate to update the projected rebound effect estimates using the most recent Annual Energy Outlook (e.g., 2014 Early Release). Undoubtedly this was not available at the time the study was carried out.

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Appendix E. James Sallee Review Comments

THE HARRIS SCHOOL
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January 20, 2014

Larry O'Rourke
ICF International
9300 Lee Highway, Fairfax, VA 22031-1207

Dear Dr. O'Rourke:

Attached to this letter please find my peer review of "The Rebound Effect from Fuel Efficiency Standards: Measurements and Projections to 2035" written by Kenneth Small, with contributions by Kent Hymel.

I have no conflicts of interest relevant to the report or the contents of this review.

Sincerely,

James M. Sallee
Assistant Professor
University of Chicago

Summary statement:

"The Rebound Effect from Fuel Efficiency Standards: Measurement and Projection to 2035", written by Kenneth Small (with contributions from Kent Hymel), uses an appropriate methodology and defensible assumptions. It uses the best available data (given significant constraints on what is available), and emphasizes modeling choices and specifications that are sensible and consistent with both theory and data. As a reviewer, I agree with most of the assumptions and emphases in the paper. Where I do disagree (detailed below), I believe that the preference of one method or specification over the other involves an element of subjective judgment about how to weigh the costs and benefits of different approaches. I did not identify any issues that I believe are objectively incorrect. Thus, while I might have made some different choices myself, I believe that the choices made in the report are *defensible.*

My detailed comments are included below in a numbered list, categorized according to the four charge questions that were given to me by ICF International. I did not restrict myself to comments on how the immediate report ought to be changed given realistic constraints on time and effort; many of my comments are intended to point to areas where future reports could, in my opinion, make the biggest improvements. My comments should be read in that light.

Before proceeding to those comments, two issues are worth highlighting. First is a bi picture question regarding methodology and data. This report uses data aggregated to the state-by-year level over five decades. Recent research (e.g., work by Kenneth Gillingham and joint work by Chris Knittel and Ryan Sandler) has made use of microdata from vehicle odometers, which is available for some cars in some recent years in some states. The aggregate data used in the Small report analyzed here suffer from measurement problems (detailed below, see item 7) and limit the available econometric identification strategies (see items 1-3). The odometer microdata suffer from limited coverage, both across states and over time, and existing estimates are focused on a short-run elasticity that is inconsistent with some of the measures emphasized in the report. In the end, which data and methodology should be preferred likely depends on exactly what specification one wishes to use. I think that a case can certainly be made for sticking with the aggregate data used in the Small report, but I suspect that, in the near future when researchers have gained access to data from a somewhat more representative set of states and have a few more years worth of data, that the case for the microdata will become stronger. In any case, it would be very valuable to know how projections based on the microdata estimates compare to those used here, were it possible to construct such projections.

The second issue worth highlighting is how the report models the relationship between income and the rebound effect for use in projections. In brief, the literature seems consistent in finding evidence that the rebound effect varies over time and that, on a decadal time scale, the effect is smaller in more recent years than in prior decades. The paper posits that this may be due to rising income. This is theoretically sensible in that the total cost of driving involves a cost of time as well as a cost of fuel, and as income rises, so does the wage and hence the time cost of driving, which eventually comes to dominate the price per mile. In the report's projections, with income projected to rise, the rebound effect is quickly driven to zero in many states, which greatly affects the final estimates. But, given the nature of the identification, which relies on time series correlations between income and the rebound effect (see items 1-3), it is difficult to have confidence that income is the driving factor. Even if income is the driving force in the historical data, it is not certain that it will continue to have the same relationship in the future. One must make a stand on the relationship between income and this elasticity, and the one that the paper makes is consistent with economic theory and with the data.

Thus, as with many modeling decisions, I think the paper's choice on how to handle this is defensible, though alternative choices might be defensible as well (see item 11). I highligh this issue in particular because it appears to be pivotal to the results. Below, I include a few thoughts on how the projections might be refined (item 13) and how this issue might affect which results are most useful to report (item 14). Here, I want to make the point that an additional analysis that could corroborate the relationship between income and the VMT elasticity would be very valuable.

I would find it reassuring if the cross-sectional relationship between income and the rebound effect was similar to the estimated aggregate time-series relationship. According to the research cited in the report, the available microdata evidence suggests otherwise; it finds that the rebound effect is U-shaped in income. A rationale for this is that wealthier people have more travel options, which makes them more responsive. This factor competes against the time cost factor, and at different levels of income different factors dominate, resulting in a U-shape. The projections *might* change significantly if the relationship between income and the elasticity is U-shaped in the time series. This depends on whether or not future aggregate income is high enough to reach the upward sloping portion of the U.

Rather than using a cross-section of microdata, one could look at a cross-section of states states (or countries) to see how estimated elasticities are correlated with income. For example, one could estimate the VMT-elasticity separately for each state for some span of years (say, a decade) not controlling for income and then see how that correlates with state income. Are wealthier states less responsive? One might reasonably argue that the cross-sectional relationship between income and the VMT elasticity is a fundamentally different parameter than the over-time relationship, but they seem to me to be based on the same theoretical arguments. As a result, I would like to see some sort of corroborating evidence—either in this report or in a completely separate study—though I recognize that the suggestions made here are themselves far from perfect.

Element 1: *What are the merits and limitations of the authors' approach for estimating the vehicle miles traveled (VMT) rebound effect for light-duty vehicles? Are key assumptions underpinning the methodology reasonable? The VMT rebound effect is defined here as the change in VMT resulting from an improvement in light-duty vehicle efficiency.*

1. The paper uses a panel regression, but it is best understood as deriving results form time-series variation because the panel regressions do not include time period fixed effects and the lion's share of variation in the key measures come from the time-series. In most cases, the extra credibility that is often attributed to panel data models comes from their ability to include both time and entity level fixed effects. The report does *not* use time fixed effects, and generally has very sparse controls for time. The most important variable in the analysis is the price of gasoline. This is measured at the state-year level, but once state fixed effects are controlled for, a vast majority of the variation in the data will be attributable to fluctuations in the global oil price (or national gasoline price).

   I do not necessarily advocate that the paper add time period fixed effects; if year fixed effects were added, the remaining variation in gasoline prices that would identify the coefficients would be state-specific fluctuations in gasoline prices in each time period, which often represent short run imbalances in local supply and demand that should not be expected to persist (and therefore may have a limited impact on behavior). In that sense, the report uses the best available variation, but this implies that the paper's results are largely driven by the national time series in gasoline prices and VMT, which has implications discussed in the next two points.

2. The nature of the panel identification means that, in my judgment, the additional benefit of having 51 states as opposed to 1 national time series may be somewhat overstated. I do not see mention in the paper of any attempt to control for correlation across states in error terms. The standard way of handling this is to cluster standard errors on some larger level of observation, the rule of thumb being "at the level of variation in the key independent variable". Given my argument above that identification is driven primarily by the national price of gasoline, one might interpret this as implying that standard errors should be clustered at the time period level (year), though technically most of the variables vary at the state-by-year level. I suspect that if the standard errors were clustered on time period that much of the added precision that results from moving from a national time series to a panel regression would be lost. To be clear, none of this implies bias in any coefficients, but the confidence one might have in distinguishing between certain specifications might be reduced by attention to the standard errors. As with other issues, I believe there is ambiguity here, and one could perhaps defend more vigorously the decision not to cluster.

3. The nature of the panel identification also opens the possibility for standard omitted variable bias problems. With sparse time controls and trending variables, anything

that is correlated with gasoline prices as well as with VMT per adult could induce bias. Some factors that might be relevant are the fraction of driving that is personal as opposed to work-related,[1] the quality of automobiles,[2] commuting norms, changes in the fraction of families with two wage-earners, the expansion of urban sprawl, etc. This is especially important for an analysis that spans so great a time frame. The report attempts to control for measures of the most important variables, but it is *a priori* difficult to be confident that all such secular trends have been accounted for by a limited number of demographic variables. What is usually done in response is to (a) show precisely how sensitive the coefficients of interest are to the inclusion of the available set of controls and (b) show the robustness of the coefficient to many additional tweaks.

Along these lines, an appealing permutation would be to add state-specific time trends, and to add differential time trends for different periods of time where we have reason to believe that there might be structural breaks. (The appendix to the 2007 working paper indicates that three distinct time trends are used, but this includes a single trend for all years after 1980, which may be inadequate. Moreover, I did not see the set of time controls used spelled out clearly in the current report.) I suspect that the author has tried these permutations, and I recognize that the tests for structural breaks in the data do not yield conclusive results upon which to base these decisions. But, I would hope to see greater evidence of robustness of the results to richer controls for time, and perhaps to a broader set of demographic and vehicle market controls.

4. The report argues that a secondary pathway through which CAFE standards might impact VMT is through the overall size of the car market. The idea is that fuel economy standards will cause people to buy more cars because fuel efficiency standards lower the cost of driving, which thus increases the value of owning a car, holding prices constant. (This is the difference between M and $\widehat{M}$ in the report.) This argument is present in much of the related literature.

   I find this objectionable from a theoretical point of view. In a standard market model, the imposition of fuel economy standards could not *raise* the value of cars (net of price) on average. The market should be offering cars that have a bundle of attributes that maximizes private value to consumers. The introduction of fuel economy standards forces automakers to alter the mix of attributes they offer—perhaps through changes in technology or through a shift from size and

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[1] The price sensitivity of miles driven for work is likely different than miles driven for personal reasons because of the difference in who is paying for fuel and whether time is uncompensated. The data used on VMT do not distinguish these types of driving.
[2] The time cost of driving is a function of the opportunity cost of driving and of the flow utility of being in the car. More comfortable cars with improved media, and cell phones, may substantially lower the cost of driving in that dimension.

performance to economy. If standards force this mix to be altered, it is counter to theory to suggest that this will create attribute mixes that consumers prefer, conditional on price (which is controlled for in the regressions).

This reasoning could be wrong if another market failure exists, such as the idea that consumers are myopic and thereby underappreciate the value of fuel economy. In that case, consumers could conceivably have increased private utility from the standard. But, even this scenario does not rationalize an increase in the size of the vehicle market because, if consumers are myopic, then they won't *recognize* that the new vehicle fleet is preferable—the market was providing the fleet that *seemed to be* value maximizing. This suggests that the market should shrink. It seems to me that the final effect on market size depends on whether the standards raise or lower producer mark-ups over marginal cost in equilibrium, which is theoretically ambiguous.

Importantly, the report de-emphasizes this channel, which is found to be quite small. So, while I disagree at points with the report on this issue, I do not think it has an important impact on the final projections.

5. This report introduces measures of media attention, which are new to the literature. This is used in two ways, one is as an additional regressor, another is as an auxiliary data series useful for aiding interpretation. I agree with the latter usage, but not the former. Media mentions of gasoline prices is not well motivated as an *independent* regressor from a theoretical standpoint. It is meant, I believe, as a measure of the salience of gasoline prices. But, the media surely reflects public attention as much as it dictates it. Thus, it is fundamentally endogeneous. As such, I prefer models that do not include it as a regressor.

   At other times in the report, the media mention series is looked at by itself as an interesting time series that might help interpretation. I think it is appropriate to use in this sense—if it is a proxy for an endogenous measure of salience or awareness, then it may be useful to look at this series and see if it happens to line up with the time pattern of coefficient estimates from the baseline model, as a way of perhaps interpreting what is going on in the main estimates. In the end, the report does not emphasize these results over others, which mitigates my concern.

6. One weakness of the aggregated data used in this report is that it provides no immediate way of modeling the relationship between vehicle age and VMT. Given the lack of data on this, it seems appropriate for the report to abstract from such issues, but this points to another area where the odometer microdata could be useful. Those data could be used to detail the age-VMT relationship and to see how it changes over time and in response to fuel price shocks and regulation. Such information might be especially useful in refining the dynamic rebound effects emphasized in the report.

Element 2: *Is the implementation of the authors' methodology appropriate for producing estimates of the VMT rebound effect? Specifically, are the input data and the methodology used to prepare the data appropriate? Are sound econometric procedures used? Does the model appropriately reflect underlying uncertainties associated with the assumptions invoked and the parameters derived in the model?*

7. The report suffers from crucial data limitations, of which the author and the literature more broadly are well aware. The key problem is that most of the dependent variables are not independently measured, but are instead imputed based on possibly inconsistent procedures across states and over time and through a methodology that is not well explained by the Federal Highway Administration. To recap, states generally have good data on gallons of fuel sold, because they collect taxes by the gallon. States themselves, or the FHWA, use some estimate of fuel efficiency of the vehicles on the road to translate gallons sold into VMT (M), b calculating that M = F / E-hat, where E-hat is their estimate and F is fuel consumed. The fuel intensity is measured in the report as 1/E = F/M, where again VMT is imputed based on E-hat. Then, Gas Price per mile is calculated as Gas Price / E = Gas Price * M/F = Gas Price / E-hat. Thus, the measurement of all of the most important variables depends on some estimate of efficiency that states are using, which may be inconsistent across states and over time, or that the FHWA is using, which at best is based on surveys 5-years apart and may be wiping out differences across states by using national averages for imputation. Any errors in measuring E are being passed through the system because it is an input into all of the relevant variables, which may create mechanical correlations across all of the variables of interest.

   The author is aware of these issues and articulates them (although much of the discussion is found only in the working paper version of Small and Van Dender), so raising the issue would be belaboring the point, but for three reasons. One is that this fundamental concern about data is an argument for shifting regulatory impact analysis from the type of methodology used here and towards a reliance on the new odometer-based microdata sooner rather than later.

   A second is that it raises some concerns about the CAFE variable used in the paper, which is imputed based on the relationship between fuel economy and VMT in the years before CAFE. What were states or the FHWA doing to impute fuel economy before EPA ratings existed in 1978? This is especially important because the CAFE variable used in the paper, which is theoretically very clever, is based entirely on a projection forward from data on fuel economy demand for the period before CAFE was in place, which is a period in which there were no government measures of fuel economy. How could states have had meaningful estimates of the on-road fuel economy of the vehicles in their state prior to those years? Why do we think that consumer demand for fuel economy would be the same before and after labels were introduced? How did they even know how efficient were the models in the earlier years?

A third is that it is worth pointing out that the relationship between gallons of gasoline consumed (the only thing actually measured directly) and VMT depends on average *on-road* fuel economy, not EPA ratings. As driving conditions vary, the relationship between VMT and on-road economy will differ. In particular, in observations with greater urbanization and greater congestion, the more miles will be spent in settings that garner lower average mpg for a given vehicle. A recent working paper by Ashley Langer and Shaun McRae suggests that there is huge variation in on-road fuel economy for identical vehicles.

8. There are some important differences in the estimates depending on whether or not the latest years of data are included. I think it is arguably preferable to omit the financial crisis, which would include both 2008 and 2009 in annual data. The paper does not report results that omit only those two years. One might make the case that the baseline specification should include data only up to 2007.

Element3: *The methodology used in this report attempts to account for asymmetric responses to increases vs. decreases in per mile fuel costs (and fuel prices). Does the report's finding of an asymmetric response seem reasonable given the methodology that the authors employed? In particular, do the authors' preferred model specifications (3 .21 b and 4.21 b) seem appropriate for capturing driver response to an increase in fuel efficiency?*

In brief, I agree with the choice of models 3.21b and 4.21b as the preferred model.

9. There are two types of asymmetry discussed in the analysis. One is that drivers may respond differently to changes in fuel economy than to changes in fuel prices, so that price-per-mile is not a sufficient measure of the price to which consumers respond. I am sympathetic to the idea that there could be a difference, primarily because of the salience of the fuel price. However, I think that the appropriate null hypothesis, based on theory, is that consumers make decisions based on price-per-mile. In the absence of compelling evidence that consumers react differently to the two components of price, I think that the report should focus on estimates that assume symmetry in this dimension. This is what the report chooses to do, and it is reflected in the preferred models of 3.21b and 4.21b.

10. The second type of asymmetry is in whether the rebound effect is different for price-per-mile increases as compared to decreases. The report ultimately favors a model in which fuel price increases yield larger responses than fuel price decreases, and it is deemed preferable to use a model based on asymmetry of fuel price, not asymmetry of price per mile.

    Here, I think the preferred specification is more ambiguous than with regard to the other symmetry question, but I am in agreement with the author on the preferred methodology. There does seem to be sufficiently strong evidence of an asymmetric response, in this paper and throughout the literature, to use a model that allows for this difference.

Theoretically, it is sensible to assume that the asymmetry lies in increases or decreases in the cost per mile (e.g., model 3.29), but the added econometric challenge of solving the additional endogeneity problem that is induced by this specification leads me to conclude that models based on asymmetry in fuel prices (not price per mile) are preferable, for practical reasons. Thus, I agree with the report's choice of models 3.21b and 4.21b as the baseline preferred model.

Element 4: *The report describes a methodology for projecting the VMT rebound effect for light-duty vehicles forward in time. The concept of dynamic rebound is introduced to quantify the rebound effect over the period of a vehicle lifetime, during which time the variables that influence the rebound effect are changing. Is this methodology reasonable and appropriate, given the inherent uncertainty in making projections about how future drivers will respond to a change in the fuel efficiency of their vehicles?*

In summary, I think that the paper makes defensible projections. That is, all of the assumptions used in the models that are projected out to 2035 are reasonable. I agree with the report that the baseline statistic should be the dynamic rebound effect, which is the most theoretically relevant statistic for most applications.

11. I do think, however, that an appealing alternative is to simply take the best available estimates of the rebound effect from recent years, say 2000 to 2007, and project this forward as a constant rebound effect over all future years without conditioning on changes in income and other interacted variables. This alternative is dubious in that it assumes that whatever conditions are at work in the most recent decade of data will continue to be true in the future. But, it avoids dangers of extrapolating out of context. That is, in the face of the inherent uncertainty in making projections two decades into the future, a conservative methodology is to simply take the best available recent estimate and assume that it will be constant in the future. If I were the author of the report, I would provide such an estimate alongside the dynamic rebound effects that are reported. An additional benefit of this alternative is that it would allow for direct comparison to the projections that would come from using odometer microdata estimates of the rebound effect, which could be used for this "straight line" projection, but may be harder to integrate into the dynamic estimates emphasized in the report.

12. I do have a question/concern about the way that fuel price volatility is represented in the projections. My understanding is that the AEO projects a smooth gasoline price into the future. This is fine for models that do not include asymmetry, but for models that do include asymmetry, a smoothly evolving gasoline price series and an alternative that has the same average trend but experiences movement up and

down around the trend will not produce the same rebound effect.

If this correct, then it is important for the models using asymmetry of adjustment to fuel price increases and decreases to be based on some reasonable projection of volatility. (I have in mind using the AEO projection of gasoline prices and the annual volatility around a trend from the last 20 or 30 years to draw random forecasted paths of the gasoline price, and then averaging the rebound effect projections that result over many such paths.) I suspect that this will increase the rebound effect for the asymmetric models, but that the effect on the forecasts will be small.

13. With rising income, the rebound effect is driven to zero in the projections, but the effect is truncated at zero so that it cannot become negative. Might it be preferable to truncate at a value above zero? Even as average income rises in the next two decades, many individuals will remain at lower income levels and would therefore be expected to remain responsive to fuel costs. Thus, it is hard to see the logic in expecting that the average rebound effect could go all the way to zero in the near future, so that some baseline above zero may be a more appropriate point of truncation. It would be ad hoc to choose some point, but 0 is actually an ad hoc point itself, given that it is meant to represent an average.

14. There is a great deal of uncertainty surrounding the final projections, due to uncertainty in the estimated coefficients, the possibility of model error, and the uncertainty in the forecasted inputs (like the price of gasoline and future income). The report lists point estimates for forecasts and includes a few different specifications and three forecasted futures that vary the path of the future price of oil. Additional representations of uncertainty might be appropriate.

    A first possibility is to include standard errors around the forecasted values that reflect the sampling uncertainty in the model estimation (i.e., the standard errors on the coefficients). This should be conceptually straightforward, though it multiplies the number of numbers that must be reported in a table by two (though it is just shading in a figure).

    The price of oil makes a substantial difference to the bottom line estimates. Thus, depending on what the EPA foresees as the final use of this report, it may be worth providing additional detail about the oil price scenarios that the AEO is using (are these meant to represent extremes of a spectrum of plausible paths? Or are they likely scenarios?). Or perhaps additional results should be presented. That would depend on the intentions of the user of the report.

    A fuller version way of representing forecast and coefficient uncertainty is to model the uncertainty in the forecasted variables and provide a collection of different model results based on random draws of these variables. I think this would be useful in making clearer which parameters are really pivotal, so users know where to draw their attention. If, for example, all that really matters is income growth relative to oil price growth, then I would like to see a focus on that relative parameter and to have spelled out for me why the range of estimates actually span the useful set of scenarios to study. I recognize that this is a tall order and would perhaps require a substantial separate analysis.

In terms of model error, which is more difficult to represent, the report lists projections for several different specifications, which is useful. The one thing that could perhaps be useful is to provide some explicit comparison, along the lines mentioned above, of how these projections differ from a projection that uses just the VMT elasticity estimate taken from the most recent decade of data and projected forward without reducing it based on income and other demographic trends (the straight line projection).

II.

Draft Report - Peer Reviewed Version, “The Rebound Effect from Fuel Efficiency Standards: Measurement and Projection to 2035”

The Rebound Effect from Fuel Efficiency Standards:

Measurement and Projection to 2035

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Final Report

December 24, 2013

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

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

1. Background and definitions

1.1 Determinants of motor-vehicle travel

The rebound effect is simply a statement of the near-universal economic principle of downward-sloping demand: when the price of a good or service decreases, people purchase more of it. In this case the service is passenger transportation, and its price to the user includes the cost of fuel. If the amount of service is measured as vehicle-miles traveled (VMT), then the component of price accounted for by fuel cost, here called "fuel cost per mile" P_M, is equal to the price of fuel P_f (*e.g.* stated in \$/gallon) divided by fuel efficiency E (*e.g.* stated in vehicle-miles/gallon):

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

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

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

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

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

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

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

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

Table 1.1. Simultaneous Equation Systems

Three-equation system	Four-equation system

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

where:

- α^v is the coefficient of the lagged dependent variable in the equation explaining the logarithm of vehicle stock;
- α^{mv} is the coefficient of vehicle stock in the equation explaining *vma*;
- α^{vm} is the coefficient of *vma* in the equation explaining vehicle stock;
- α_{mc} is the coefficient of congestion in the equation explaining *vma*;
- α_{cm} is the coefficient of *vma* in the equation explaining congestion; and
- β_2^v is the coefficient of *pm* in the equation explaining vehicle stock.

In addition to accounting for lagged values within the system determining our dependent variables, our empirical system accounts for the possibility that the error terms in each equation are correlated over time. That is, for any given state, the unknown random factors affecting a dependent variable may have some elements that are the same year after year. Most of these common factors are accounted for by a "fixed effects" specification, in which a distinct constant term is estimated for every state instead of just one for the entire system.[3] Empirically, the effects of lagged dependent variables are difficult to distinguish from those of autocorrelation, a problem plaguing earlier studies investigating changes over

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

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

time; we are able to distinguish them because of the long time period covered by our panel data set: 36 years in the 2007 published paper, 39 years in the 2010 published paper, and 44 years in this report.

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

1.3 Dynamic rebound effect

A vehicle owner responds to a change in fuel efficiency not just in the first year or some hypothetical year in the distant future, but continuously over that lifetime. Thus, the partial adjustment mechanism postulated here, which is the basis for the distinction between short-run and long-run responses, implies a continuing gradual change in VMT each year over the vehicle's life. But at the same time, the driving force itself, i.e. the short-run rebound effect (5), is changing because the interaction variables that help determine it (income, fuel cost per mile, urbanization, and possibly congestion) are changing. Thus, the vehicle owner adjusts dynamically to both sources of change simultaneously. The results of tracking this process can be expressed as the percentage increase in the vehicle's lifetime VMT divided by the percentage decrease in fuel cost per mile that caused it. That ratio is here called the *dynamic rebound effect*.

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

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

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

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

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

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

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

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

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

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

2. Prior Literature

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

2.1 Earlier Literature

Prior research has measured the rebound effect for passenger transport using a variety of data sources and statistical techniques. Most but not all estimates lie within a range of 10 to 30 percent (expressing the elasticity as an absolute value and as a percentage instead of a fraction). Greening, Greene, and Difiglio

(2000) and Small and Van Dender (2007a) contain more complete reviews of the earlier literature. A few key contributions are highlighted here.

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

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

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

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

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

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

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

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

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

2.2 Recent Literature

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

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

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

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

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

strong during the 1970-2000 period but likely less important during the 2000's. We have not seen any formal argument, either theoretical or empirical, for why these factors should have a major effect in either direction.

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

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

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

The second study using California smog test data is by Gillingham (2013). Gillingham combines the test data for years 2005-2009 with micro observations of new-vehicle registrations in 2001-2003, in order to observe VMT over a several-year period, typically six or seven years due to the requirement that vehicles are tested at those ages. (There are also some observations over four to six years for vehicles that are sold

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

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

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

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

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

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

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

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

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

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

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

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

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

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

3. Data and specification for this report

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

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

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

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

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

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

Independent Variables other than CAFE

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

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

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

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

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

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

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

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

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

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

3.1 Congestion variables (four-equation model)

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

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

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

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

3.2 State population data

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

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

3.3 Variable to measure CAFE regulation (R_E)

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

The calculation proceeds in four steps, described more fully in Small and Van Dender (2007a), Appendix B. First, we estimated a reduced-form equation explaining log fuel intensity from 1966-1977, prior to CAFE regulations.[17] Next, this equation is interpreted as a partial adjustment model, so that the coefficient of lagged fuel intensity enables us to form a predicted desired fuel intensity for each state in each year, including years after 1977. Third, for a given year, we averaged desired fuel intensity (in levels, weighted by vehicle-miles traveled) across states to get a national desired average fuel intensity. Finally, we compared the reciprocal of this desired nationwide fuel intensity to the minimum efficiency mandated under CAFE in a given year (averaged between cars and light trucks using VMT weights, and corrected for the difference between factory tests and real-world driving). The variable *cafe* is defined as the logarithm of the ratio between the mandated and desired fuel efficiency, with that ratio truncated below at one. Thus a value of zero for *cafe* means the constraint is not binding, since desired fuel efficiency is as high as or higher than the mandated level.

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

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

3.4 Variables on media coverage and volatility of gasoline prices

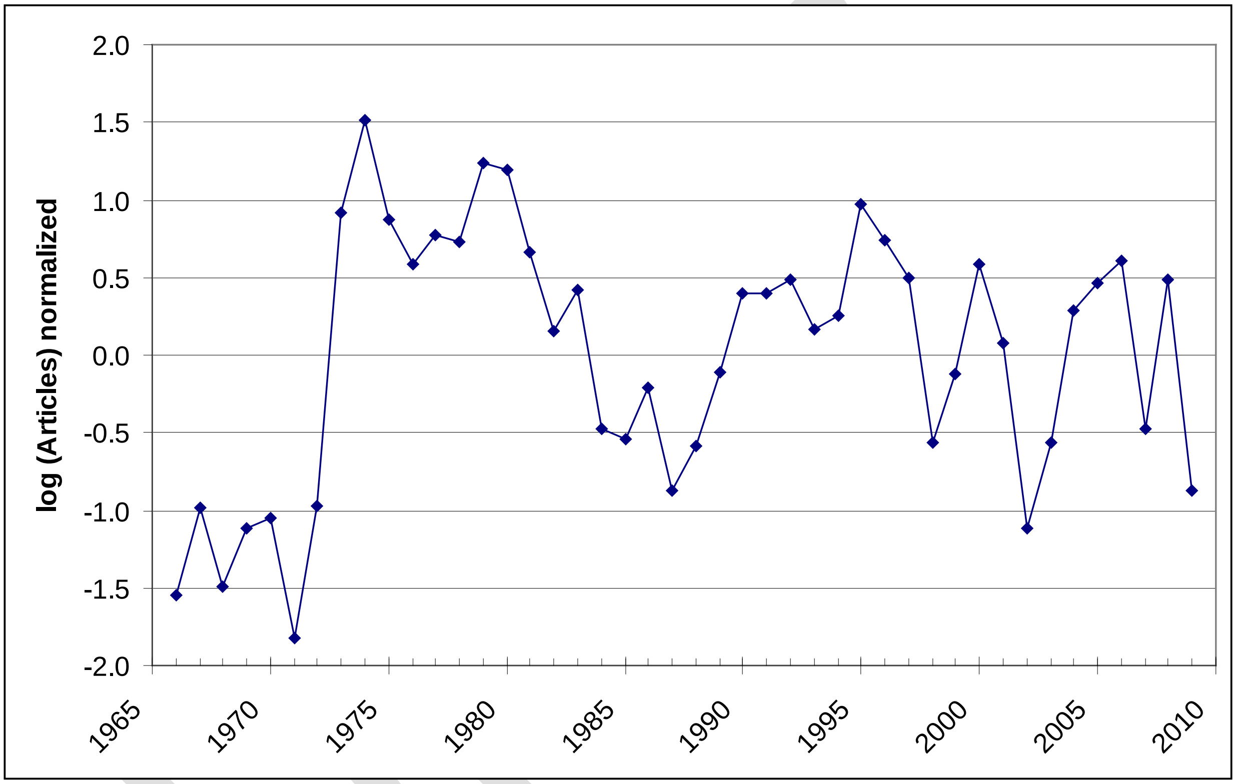
Variables measuring media coverage of gasoline price changes are based upon gas-price related articles appearing in the *New York Times* newspaper. We queried the Proquest historical database for years 1960 to 2009, and tallied the annual number of article titles containing the words *gasoline* (or *gas*) and *price* (or *cost*). This count was the basis for the variable used in the econometric analysis: it is formed from the annual number of gas-price-related articles divided by the annual total number of articles, both in the *New York Times*. This ratio ranged from roughly 1 in 4000 during the 1960s to a high of 1 in 500 in 1974. An

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

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

analogous count of front-page articles yielded a similar pattern of coverage. Its logarithm, after normalization by subtracting its mean, is shown in 3.1. In our specifications, we use either the logarithm of the ratio just defined (called *Media* in the statistical models) or a dummy variable (called *Media_dummy*) defined as one in years where the ratio was greater than the 1996-2009 median value and zero otherwise.[19]

Figure 3.1. Media coverage of gas prices



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

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

even in the absence of direct influence of the New York Times.

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

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

4. Results of the Empirical Analysis

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

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

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

diminution in the rebound effect in the period since 1995; it's harder to say whether it has risen again since 2000.

Second (Section 4.2), we explore income, fuel costs, urbanization, and congestion as the causes of these changes. Each of these factors is entered in the model in such a way that the rebound effect can vary with it rather than varying over time in an unexplained manner, and we do indeed find substantial variation in exactly the manner predicted by theory: the rebound effect (measured as a positive number) declines with increasing income (as well as with either urbanization or congestion), and it increases with increasing fuel cost. By far the most important of these sources of variation is income, which has a profound effect on projections for the rebound effect in future years. In Section 4.3, we consider explicitly how the newer data now available (2002-2009) affect the results from the earlier published studies.

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

4.1. Variation by Time Period

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

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

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

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

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

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

4.2.1 Motivation

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

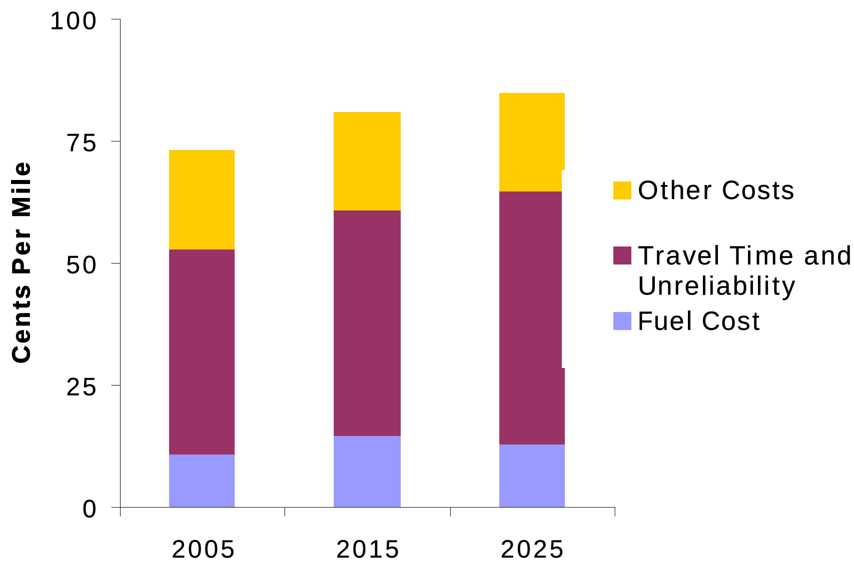
[21] The initial values are for 2005, taken from Small and Verhoef (2007, Table 3.3) and restated at 2007 prices.

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

unreliability increase with rising per capita real income according to an elasticity of 0.8, a recommendation of Mackie *et al.* (2003) based on many studies of how value of time depends on income (Small and Verhoef 2007, Section 2.6.5).

Figure 4.1.

Costs of Driving



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

4.2.2 Implementation

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

In the previous subsection, fuel cost per mile was described as a single variable (*pm* in logarithmic terms) included in the equation for vehicle-miles traveled per adult (*vma* in logarithmic terms). The elasticity was just its coefficient, which we may call β_{pm} for convenience.[23] But it is easy to specify the equation for *vma* so that *pm* appears not only as a single variable, but also interacted with other variables including itself. We define four such variables: $pm{\cdot}inc$, $pm{\cdot}pm \equiv pm^2$, $pm{\cdot}Urban$, and $pm{\cdot}cong$, where *inc* is the logarithm of per capita real income, *Urban* is the fraction of state population that is urbanized, and *cong* is congestion as measured by the logarithm of total congestion delay per adult. We denote the coefficients of these four "interacted variables" by β_1, β_2, β_3, and β_4. In practice, β_4 is set to zero in the three-equation system (since *cong* is not measured there), and β_3 is set to zero in the four-equation system (since its estimates were small and statistically insignificant).

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

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

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

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

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

4.2.3 Estimation results: interaction variables

The models are estimated using the maximum-likelihood simultaneous-equations estimator in Eviews 5 (Quantitative Micro Software 2004). Technical details are provided in Small and Van Dender (2007a) and Hymel, Small, and Van Dender (2010).[24] The full results of estimating the three- and four-equation models on updated data from 1966 through 2009 are presented in Appendix A; some of the most important coefficients are summarized here in Table 4.2.[25]

[24] For this report, however, we have replaced the multiple imputations for the missing data by a single imputation; that is, we predict the values of the missing data only once, rather than multiple times using random draws from the equation estimating them. For this reason, our estimates of standard errors probably understate the true standard errors.

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

Table 4.2. Selected results of main model with updated data, 1966-2009					
		Three-equation model (Model 3.3)		**Four-equation model (Model 4.3)**	
Equation and Variable	Coefficient Symbol	Coefficient Estimate	Standard Error	Coefficient Estimate	Standard Error
Equation for *vma*:					
pm	β_{pm}	-0.047	0.003	-0.046	0.003
*pm*inc*	β_1	0.053	0.011	0.056	0.011
pm^2	β_2	-0.012	0.006	-0.022	0.006
*pm*Urban*	β_3	0.012	0.009		
*pm*cong*	β_4			-0.003	0.002
inc		0.078	0.012	0.083	0.012
lagged *vma*	α^m	0.835	0.010	0.825	0.010
Equation for *fint*:					
pf+vma		-0.005	0.004	-0.007	0.004
cafe		-0.035	0.011	-0.061	0.010
lagged *fint*	α^f	0.904	0.010	0.889	0.010

Notes to Table 4.2:

vma = logarithm of vehicle-miles traveled per adult

pm = logarithm of fuel cost per mile (normalized)

inc = logarithm of income per capita

Urban = fraction of population living in urban areas

cong = logarithm of annual total congestion delay per adult

fint = logarithm of fuel intensity, *i.e.* log $(1/E)$ where E = fuel efficiency

pf = logarithm of fuel price

cafe = variable reflecting how far the CAFE standard is above the desired fuel efficiency based on other variables (Small and Van Dender 2007a, Section 3.3.3)

pf+vma is log (price of fuel * vehicle-miles traveled), representing the natural logarithm of the incremental annual fuel cost of a unit change in fuel intensity; thus it may be interpreted as the logarithm of the "price" the user must pay in annual operating costs, per unit of fuel intensity, for choosing a vehicle with higher fuel intensity.

Most coefficients shown in Table 4.2 easily pass the conventional test of statistical significance, having estimates more than twice the standard deviation of those estimates. Exceptions are β_4, which indicates how the rebound effect varies with congestion, and the coefficient of annual fuel cost (*pf*+*vma* in logarithms) in the equation explaining fuel efficiency. The coefficients α^m of lagged *vma* show that the long-run effect of any variable on VMT is about $1/(1-\alpha^m)$ or roughly six times as large as the corresponding short-run effect. Average fleet fuel efficiency responds to changes with an even longer lag, causing the long-run effects of these variables to be $1/(1-\alpha^f)$ or roughly 9-10 times as large as the corresponding short-run effects.

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

Taking the three-equation model (Model 3.3) for illustration, the short-run rebound effect for average conditions in this sample (1966-2009) is approximately $-\beta_{pm}$=0.047, *i.e.* 4.7%, while the long-run rebound is over six times this value, or about 30%. Furthermore, the coefficients β_1–β_3 for the three interacted variables involving *pm* show that the magnitude of the rebound effect, given approximately by the negative of equation (8), declines with increasing income and urbanization and increases with increasing fuel cost of driving.

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

Table 4.3. Estimated Rebound Effects: Model 3.3

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

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

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

4.2.4 Combined interaction variables and structural breaks

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

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

Table 4.4. Models with interacted coefficients and

structural break starting in 2003

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

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

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

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

4.3 Effects of newer data

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

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

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

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

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

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

Table 4.6. Selected results of model estimated on different versions of data: four-equation model

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

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

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

4.4 Asymmetry in response to price changes

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

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

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

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

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

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

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

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

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

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

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

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

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

Table 4.7. Selected coefficient estimates: asymmetric specifications

(a) Three-equation models

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

(b) Four-equation models

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

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

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

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

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

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

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

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

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

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

Table 4.8. Selected coefficient estimates: asymmetry in response to fuel cost per mile

(a) Three-equation models

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

(b) Four-equation models

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

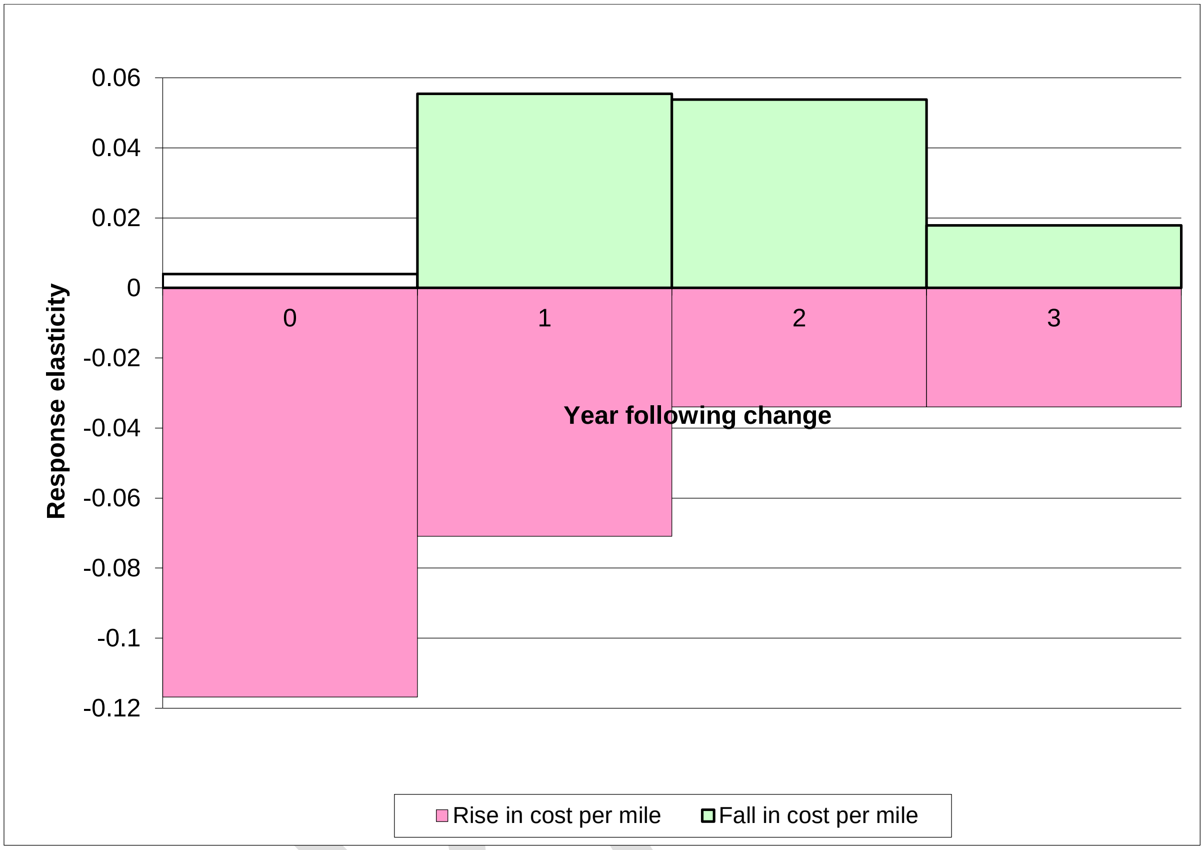
The variable *pm_cut_hat*, just like the previous variable *pf_cut*, is an increasing function of cost per mile.[31] Given its construction, we expect a negative sign on *pm* (which is the direct short-run rebound elasticity if fuel costs are rising) and also on the *sum* of coefficients of *pm* and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

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

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

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

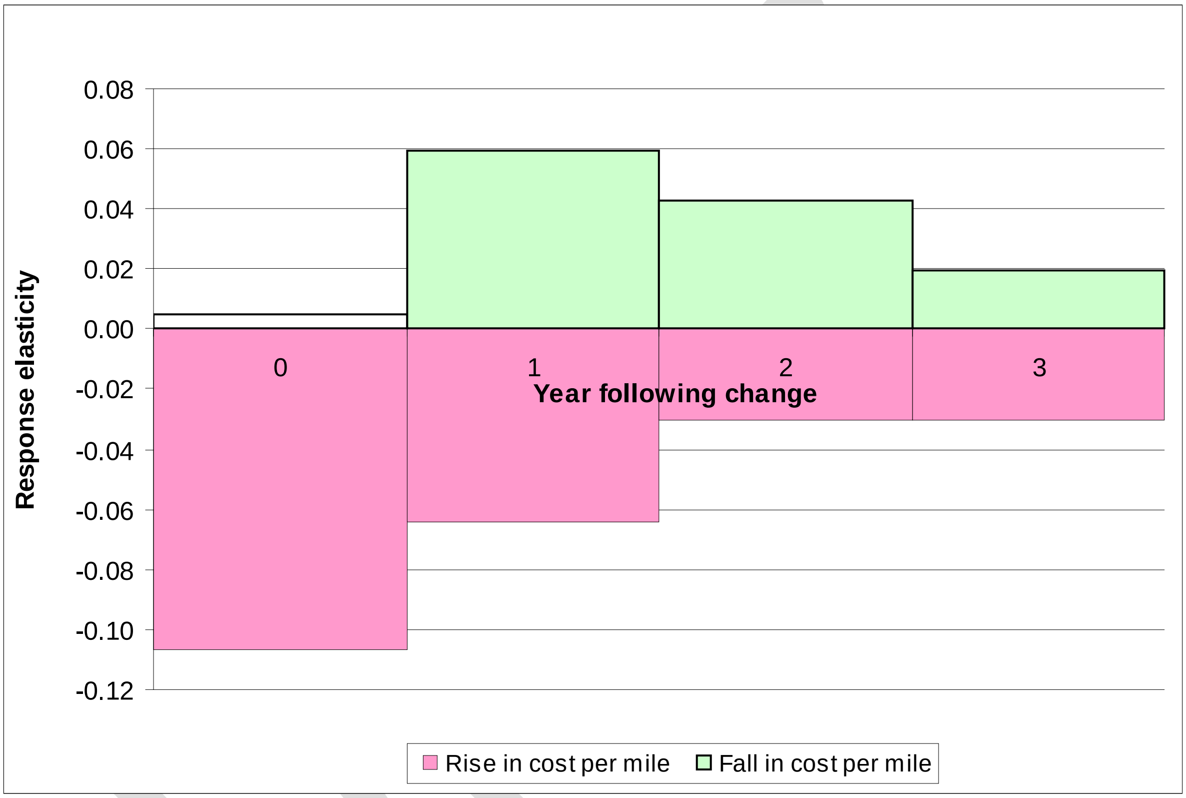
Figure 4.2. Short-run elasticity of VMT with respect to a sustained change in fuel cost per mile (Model 3.29)



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

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

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



4.5 Effects of media attention and expectations

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

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

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

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

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

Table 4.9. Selected coefficient estimates: asymmetry with media coverage or fuel-price uncertainty

(a) Three-equation models

	Model 3.21b		Model 3.35		Model 3.37		Model 3.42		Model 3.45	
Equation and variable:	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
vma equation:										
pm= pf+ fint	-0.0639	0.0049	-0.0587	0.0052	-0.0641	0.0057	-0.0699	0.0069	-0.0666	0.0053
pf_cut + fint	0.0340	0.0078	0.0286	0.0081	0.0332	0.0083	0.0529	0.0091	0.0210	0.0083
*pm*dummy_0309*					-0.0216	0.0079	-0.0265	0.0078	-0.0347	0.0084
pf(Media_dummy)*			-0.0301	0.0101	-0.0319	0.0101	-0.0316	0.0101		
*pf_rise*Media*									-0.2680	0.0544
*pm** log(*fuel price variance*)							0.0028	0.0007	0.0081	0.0024
*pm*inc*	0.0577	0.0107	0.0583	0.0109	0.0711	0.0126	0.0779	0.0124	0.0807	0.0136
pm^2	-0.0207	0.0061	-0.0053	0.0075	-0.0064	0.0075	-0.0126	0.0070	-0.0302	0.0081
*pm*Urban*	0.0131	0.0093	0.0118	0.0094	0.0100	0.0097	0.0091	0.0095	0.0118	0.0106
vma lagged	0.8334	0.0104	0.8325	0.0106	0.8276	0.0109	0.8321	0.0108	0.8247	0.0117
fint equation:										
pf + vma	-0.0097	0.0060	-0.0124	0.0059	-0.0104	0.0058	-0.0079	0.0058	-0.0033	0.0058
pf_cut + vma	0.0143	0.0123	0.0220	0.0120	0.0129	0.0118	0.0031	0.0115	-0.0225	0.0114

(b) Four-equation models

	Model 4.21b		Model 4.35		Model 4.37		Model 4.42		Model 4.45	
Equation and variable:	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
vma equation:										
pm= pf+ fint	-0.0629	0.0049	-0.0638	0.0050	-0.0729	0.0054	-0.0706	0.0054	-0.0719	0.0053
pf_cut + fint	0.0340	0.0079	0.0352	0.0080	0.0420	0.0081	0.0506	0.0083	0.0626	0.0085
*pm*dummy_0309*					-0.0359	0.0071	-0.0308	0.0072	-0.0321	0.0072
pf(Media_dummy)*			0.0061	0.0058	0.0071	0.0058	-0.0080	0.0063		
*pf_rise*Media*									-0.3117	0.0490
*pm** log(*fuel price variance*)							-0.0100	0.0019	-0.0044	0.0019
*pm*inc*	0.0573	0.0110	0.0575	0.0110	0.0825	0.0122	0.0944	0.0124	0.0905	0.0124
pm^2	-0.0275	0.0061	-0.0296	0.0065	-0.0263	0.0066	0.0037	0.0085	-0.0114	0.0074
*pm*Urban*	-0.0016	0.0021	-0.0025	0.0021	-0.0028	0.0021	-0.0044	0.0021	-0.0057	0.0021
vma lagged	0.8305	0.0107	0.8314	0.0106	0.8314	0.0106	0.8275	0.0109	0.8423	0.0112
fint equation:										
pf + vma	-0.0041	0.0058	-0.0060	0.0057	-0.0059	0.0057	-0.0049	0.0057	-0.0035	0.0057
pf_cut + vma	-0.0080	0.0112	-0.0031	0.0110	-0.0022	0.0110	-0.0018	0.0110	-0.0129	0.0111

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

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

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

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

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

5. Implications of the Empirical Analysis: Projections to 2035

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

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

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

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

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

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

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

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

For purposes of regulatory analysis, however, a more relevant measure is how much the path of VMT is shifted by a permanent change in cost per mile in a given year. This measure takes the interacting variables to be changing over time, as in fact they are projected to be, rather than being held constant. It tracks how the VMT changes in the years following a regulatory change from two sources simultaneously: (a) the transition from short to long run, as already described; and (b) the changes in

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

variables that influence the rebound effect. This is what was defined earlier as the *dynamic rebound effect*. (See Section 1 and Appendix C for details of its calculation.)

5.1 Results: Projections using models without media or uncertainty

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

Table 5.1

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

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

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

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

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

Table 5.2

Projection Results: Rebound Effect (expressed as positive percentage) with symmetric models, comparing different oil price cases

(a) Three-equation symmetric model (Model 3.3)

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

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

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

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

Table 5.3

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

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

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

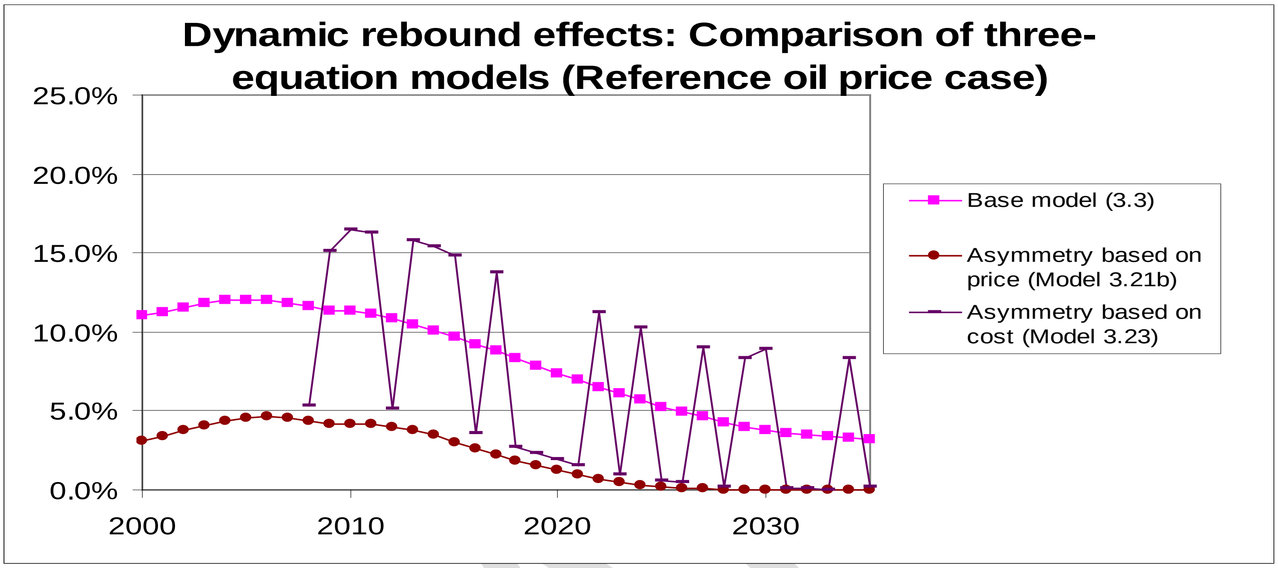
(b) Four-equation asymmetric model (Model 4.21b)

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

Figure 5.1

Selected projection results: Symmetric and two asymmetric models

(a) Three-equation models



(b) Four-equation models

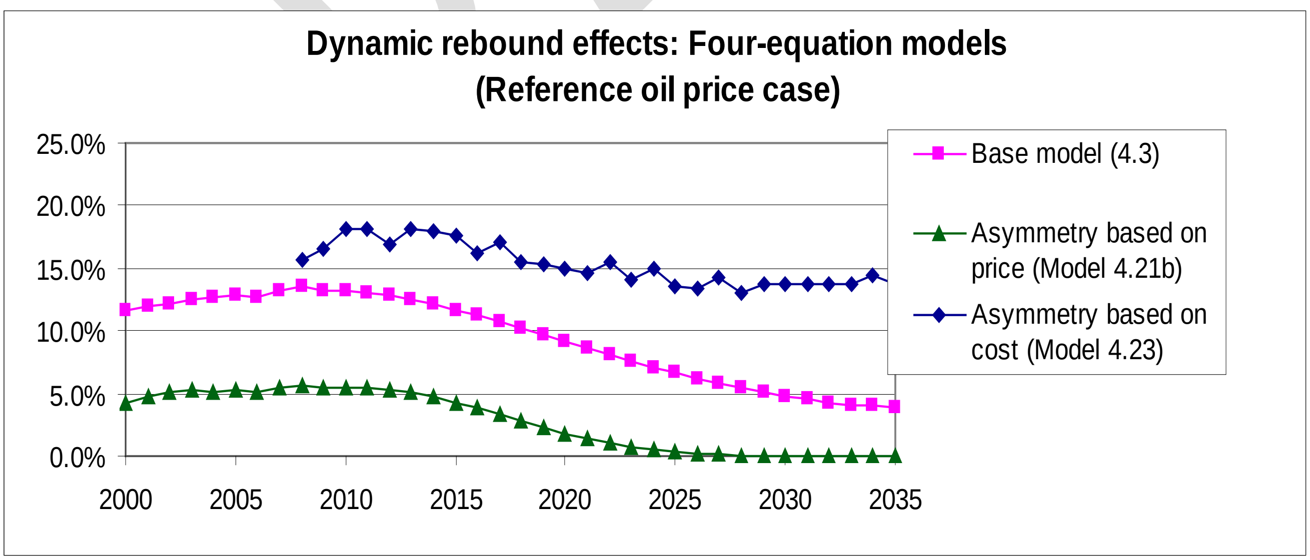
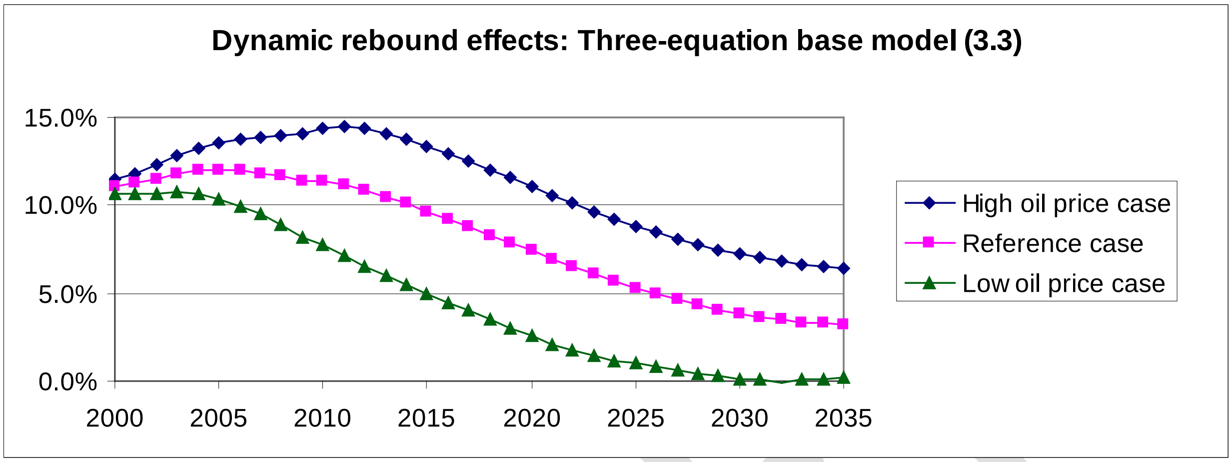


Figure 5.2

Selected Projection Results: Symmetric Models

(a) Three-equation model



(b) Four-equation models

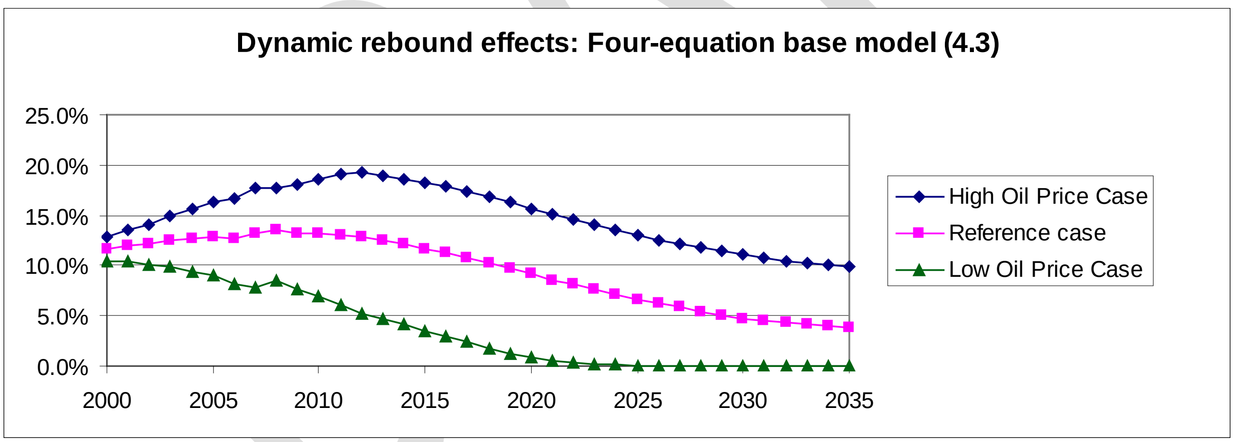
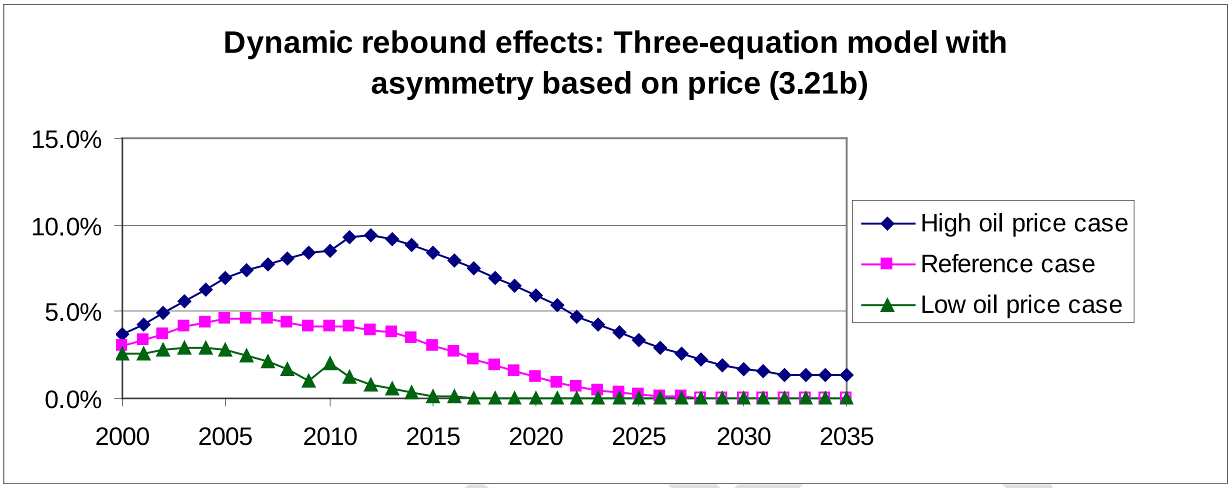


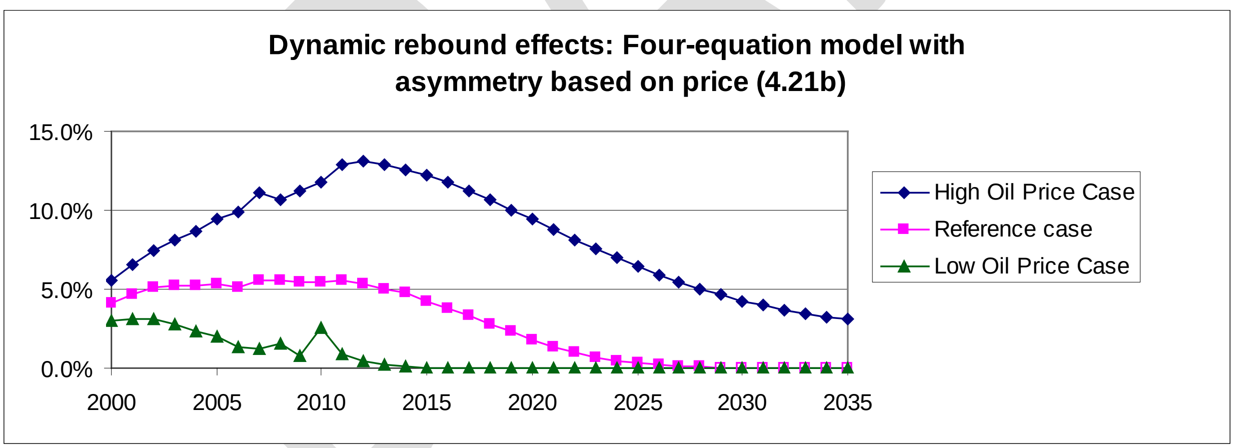
Figure 5.3

Selected projection results: Preferred asymmetric models

(a) Three-equation model



(b) Four-equation models

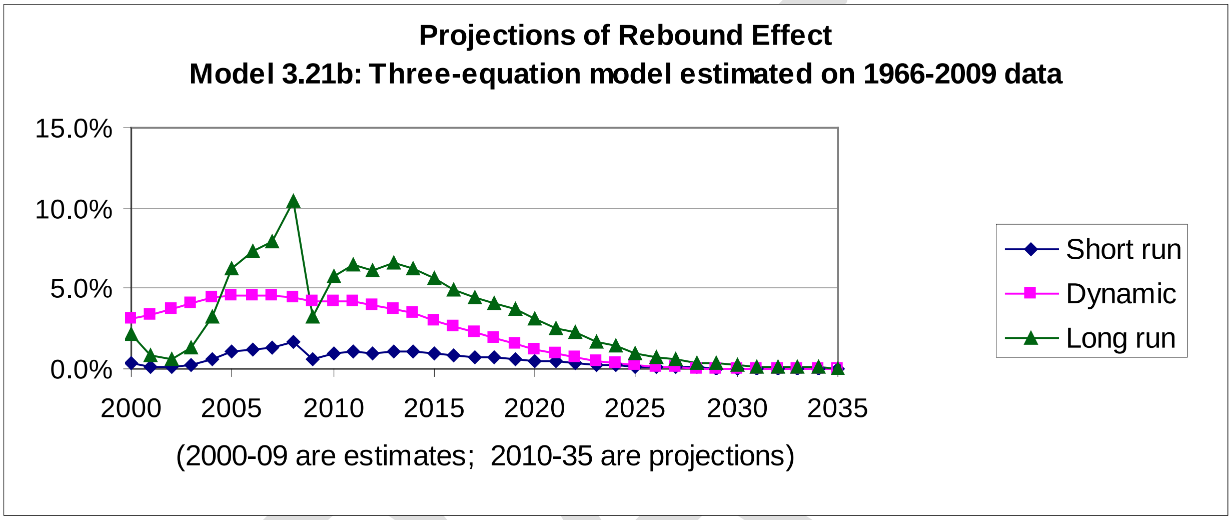


The projections from asymmetric models show more fluctuations than those from symmetric models, because the sharp break between years of rising and falling fuel costs causes jumps in the short-run and long-run rebound effects. This occurs each year when the change in fuel price switches sign, as happened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

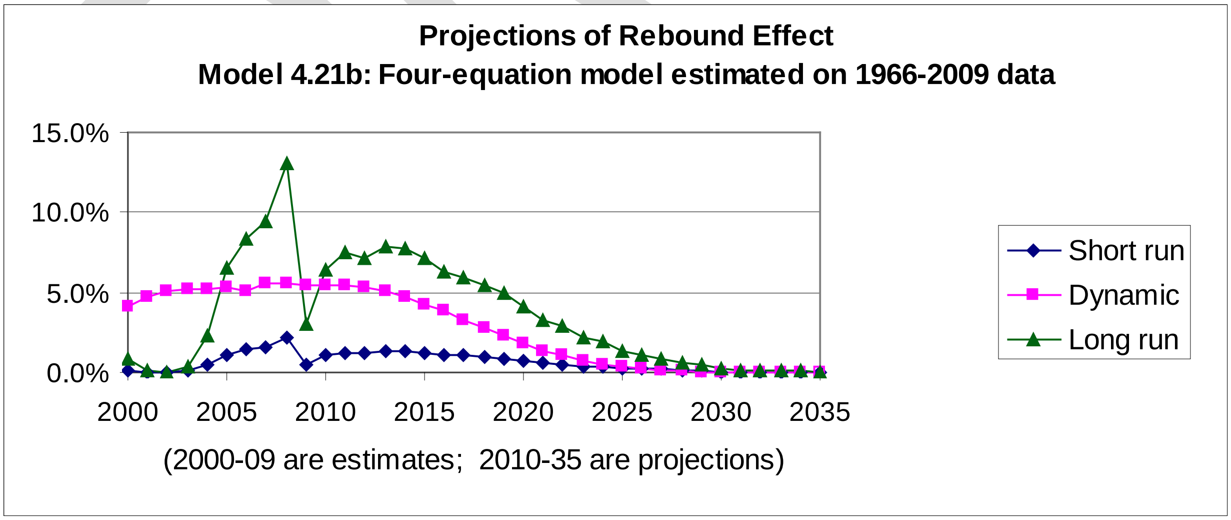
Figure 5.4

Projection results for preferred models with asymmetry

(a) Three-equation model



(b) Four-equation model



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

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

Table 5.4

Selected summary measures

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

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

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

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

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

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

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

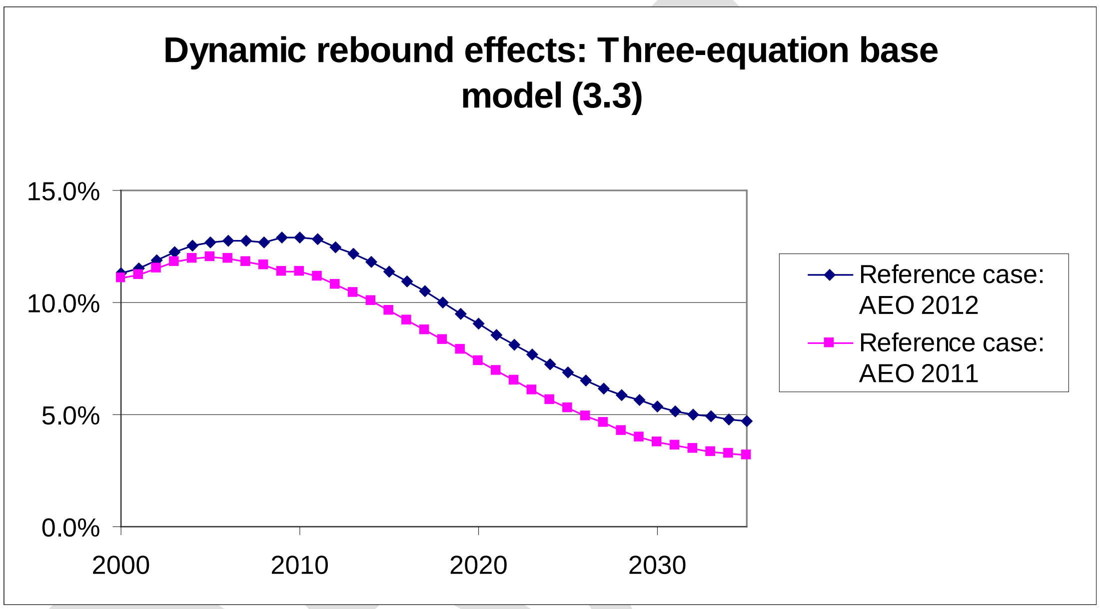
Note: Unlike the dynamic rebound effect, which accounts for changes in fuel prices after a car is purchased, the long-run rebound effect forecasts the result if fuel prices remained the same throughout the life of the vehicle. This is why it can sometimes be smaller than the dynamic rebound effect.

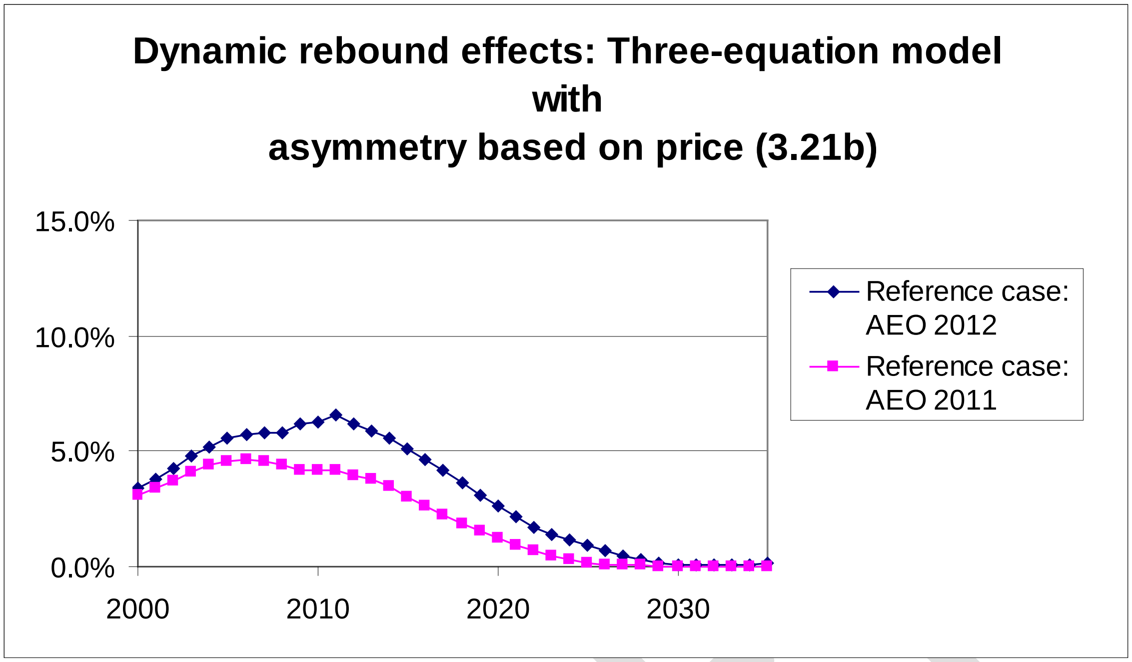
Recently, a Reference Case projection has become available using the 2012 version of the Annual Energy Outlook (AEO2012). In order to see whether this substantially affects the projections of the rebound effects, a comparison is presented in Figure 5.5. Using our base models (Models 3.3 and 4.3), the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

Figure 5.5

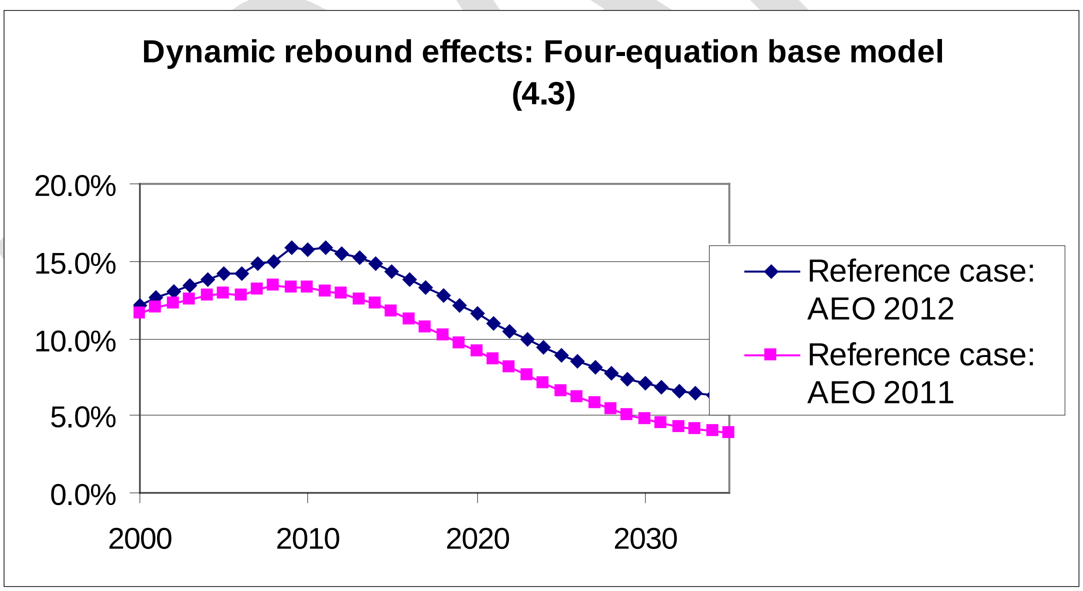
Comparisons of projections using AEO2011 and AEO2012

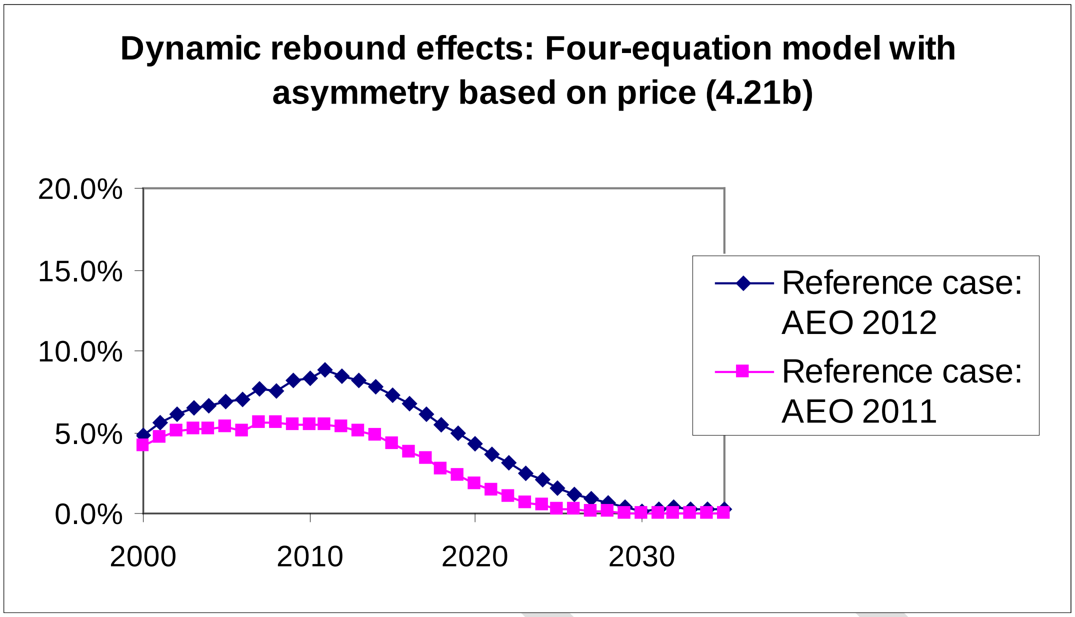
(a) Three-equation models





(b) Four-equation models





5.2 Results: Projections using models with media variable

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

Table 5.5

Projection results for model with media coverage variable:

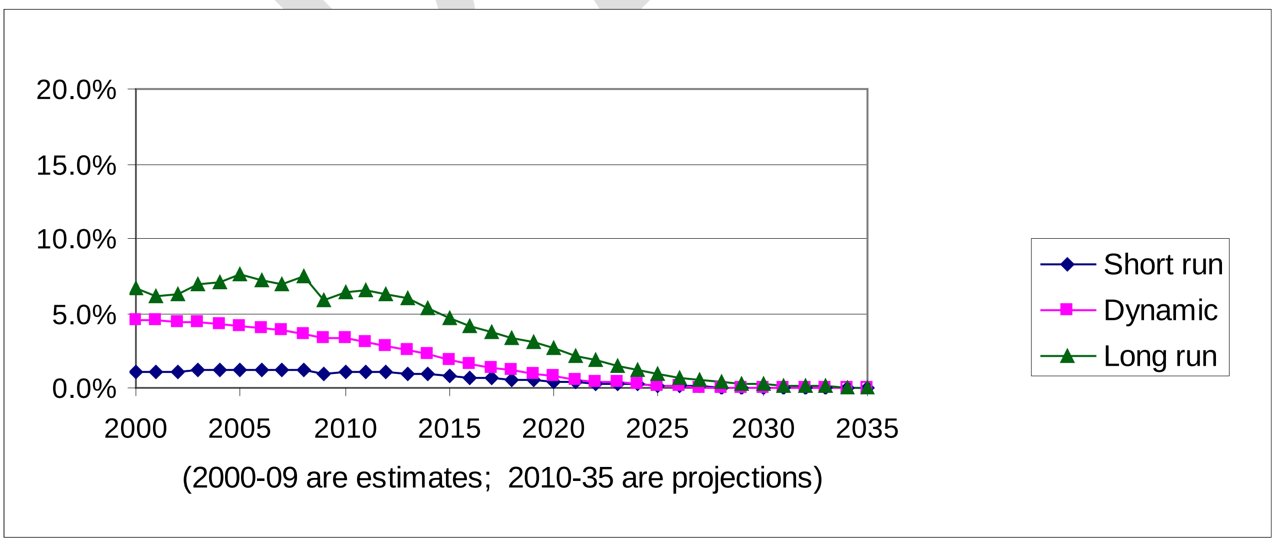
Three-equation model

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

Figure 5.6

Projection results for model with media coverage variable:

Three-equation model



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

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

6. Conclusions

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

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

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

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

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Appendix A. Calculation of Dynamic Rebound Effect

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

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

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

• First, the short-run rebound effect is recomputed for each year assuming that all variables *except fuel efficiency* change as in the projection being considered.[35] This projects the desired short-run response

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

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

that would occur for the owner of a vehicle whose fuel efficiency remains fixed as it ages, but who faces other changes (income, fuel price, urbanization, congestion) that affect the owner's response. [36] The resulting change over the vehicle's lifetime is denoted by $\Delta\breve{b}^{S}{}_{t,\tau} = \breve{b}^{S}{}_{t+\tau} - \breve{b}^{S}{}_{t}$, where *t* is the year of purchase and τ is the vehicle's age.

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

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

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

• Finally, the baseline age-mileage profile mentioned earlier, denoted by $M_{\tau}{}^{0}$ for ages τ=0,1, …, 15, is used as the starting point for changes in mileage over each year of the vehicle's age.[38] The computation assumes a unit increase in fuel cost per mile. (The size and sign of the change in fuel cost per mile is immaterial because the equations are linear so they lead to the same answer once one divides by that

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

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

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

change.) The projected mileage after response to the change in fuel cost per mile, for a new car purchased in year *t*, is the weighted average described earlier:

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

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

$$M_{0} = (1-b^{S}{}_{t}) M^{0}{}_{t}$$

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

Appendix B. Coefficient estimates

Table B1. Coefficient estimates: Symmetric and asymmetric models

(a) Three-equation models

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

(b) Four-equation models

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

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

(a) Three-equation models

		Model 3.21b			Model 3.35			Model 3.37			Model 3.42	
Equation	Variable	Coeff.	Std. Error		Coeff.	Std. Error		Coeff.	Std. Error		Coeff.	Std. Erro
vma	intercept	3.1468	0.3541		2.9103	0.3668		3.1487	0.3810		3.9416	0.40
vma	inc	0.0770	0.0118		0.0830	0.0121		0.0828	0.0123		0.0746	0.01
vma	Adults / road mile	-0.0151	0.0037		-0.0142	0.0038		-0.0145	0.0039		-0.0140	0.00
vma	popratio	0.0630	0.0323		0.0725	0.0328		0.0786	0.0334		0.1462	0.03
vma	Urban	-0.0061	0.0395		-0.0114	0.0400		-0.0231	0.0407		-0.0132	0.04
vma	Railpop	-0.0082	0.0042		-0.0084	0.0043		-0.0076	0.0044		-0.0065	0.00
vma	D7479	-0.0445	0.0035		-0.0440	0.0035		-0.0436	0.0035		-0.0429	0.00
vma	Trend	0.0013	0.0004		0.0011	0.0005		0.0014	0.0005		0.0024	0.00
vma	vma(-1)	0.8334	0.0104		0.8325	0.0106		0.8276	0.0109		0.8321	0.01
vma	vehstock	0.0161	0.0067		0.0162	0.0068		0.0181	0.0070		0.0185	0.00
vma	pf+fint	-0.0639	0.0049	pf +fint	-0.0587	0.0052	pf +fint	-0.0641	0.0057	pf +fint	3.9959	0.00
vma	pm^2	-0.0207	0.0061		-0.0053	0.0075		-0.0064	0.0075		-0.0126	0.00
vma	pm*inc	0.0577	0.0107		0.0583	0.0109		0.0711	0.0126		0.0779	0.01
vma	pm*Urban	0.0131	0.0093		0.0118	0.0094		0.0100	0.0097		0.0091	0.00
vma	pfcut + fint	0.0340	0.0078	pfcut + fint	0.0286	0.0081	pfcut + fint	**0.0332**	0.0083	pfcut + fint	**0.0529**	0.00
vma	Media variable			pf * Media_dummy	-0.0301	0.0101	pf * Media_dummy	**-0.0319**	0.0101	pf*Media_dummy	**-0.0316**	0.01
vma	pm*(dummy 2003-09)[a]							-0.0216	0.0079		-0.0265	0.00
vma	Fuel price variance									pm*log(pf_var)	**0.0028**	0.00
vma	AR(1)	-0.1021	0.0204		-0.0969	0.0206		-0.0894	0.0209		-0.0960	0.02
veh	intercept	-0.2188	0.1449		-0.2117	0.1449		-0.1996	0.1445		-0.2249	0.14
veh	pnewcar	0.0460	0.0317		0.0449	0.0317		0.0434	0.0317		0.0423	0.03
veh	interest	-0.0004	0.0042		-0.0002	0.0042		-0.0004	0.0042		-0.0004	0.00
veh	income	0.0038	0.0146		0.0039	0.0146		0.0043	0.0146		0.0033	0.01
veh	adults / road mile	-0.0137	0.0060		-0.0139	0.0060		-0.0139	0.0060		-0.0136	0.00
veh	licenses/adult	0.0349	0.0183		0.0348	0.0183		0.0346	0.0183		0.0355	0.01
veh	trend	0.0004	0.0007		0.0004	0.0007		0.0003	0.0007		0.0003	0.00
veh	vehstock(-1)	0.9316	0.0104		0.9316	0.0104		0.9319	0.0104		0.9314	0.01
veh	vma	0.0281	0.0146		0.0274	0.0146		0.0262	0.0146		0.0289	0.01
veh	pm	0.0019	0.0058		0.0016	0.0058		0.0012	0.0058		0.0014	0.00
veh	AR(1)	-0.1469	0.0230		-0.1469	0.0230		-0.1475	0.0230		-0.1466	0.02
fint	intercept	0.9282	1.0517		1.6171	1.0241		0.8319	1.0025		0.0017	0.98
fint	pf + vma	-0.0097	0.0060	pf + vma	-0.0124	0.0059	pf + vma	-0.0104	0.0058	pf + vma	-0.0079	0.00
fint	inc	0.0000	0.0146		-0.0031	0.0145		-0.0003	0.0145		0.0050	0.01
fint	fint(-1)	0.8977	0.0115		0.9070	0.0115		0.9009	0.0115		0.8930	0.01
fint	popratio	-0.0005	0.0586		-0.0391	0.0590		0.0020	0.0585		0.0070	0.05
fint	Trend66-73	-0.0005	0.0011		0.0000	0.0011		-0.0002	0.0011		-0.0017	0.00
fint	Trend74-79	-0.0061	0.0011		-0.0075	0.0011		-0.0063	0.0011		-0.0045	0.00
fint	Trend80+	-0.0002	0.0007		0.0005	0.0007		-0.0001	0.0007		-0.0009	0.00
fint	D7479	-0.0032	0.0048		-0.0015	0.0048		-0.0031	0.0048		-0.0049	0.00
fint	Urban	-0.0890	0.0471		-0.0872	0.0470		-0.0876	0.0468		-0.0920	0.04
fint	cafe	-0.0256	0.0183		-0.0023	0.0172		-0.0210	0.0169		-0.0592	0.01
fint	pfcut	0.0143	0.0123	pfCut + vma	0.0220	0.0120	pfCut + vma	0.0129	0.0118	PFCut + VMA	0.0031	0.01
fint	AR(1)	-0.1804	0.0202		-0.1851	0.0202		-0.1810	0.0202		-0.1786	0.02

[a]dummy is normalized

(b) Four-equation models

Equation	Variable	Model 4.21b Coeff.	Std. Error	Model 4.35	Coeff.	Std. Error	Model 4.37	Coeff.	Std. Error	Model 4.42	Coeff.	Std. Err
vma	intercept	3.1388	0.3529		3.1737	0.3555		3.5432	0.3653		3.8758	0.371
vma	inc	0.0807	0.0119		0.0791	0.0119		0.0794	0.0119		0.0652	0.012
vma	cong	0.0016	0.0026		0.0011	0.0027		0.0006	0.0027		-0.0004	0.002
vma	cong*income	-0.0131	0.0031		-0.0144	0.0032		-0.0128	0.0032		-0.0117	0.003
vma	cong*pm	-0.0016	0.0021		-0.0025	0.0021		-0.0028	0.0021		-0.0044	0.002
vma	7479 dummy	-0.0441	0.0035		-0.0445	0.0035		-0.0444	0.0035		-0.0467	0.003
vma	trend	0.0013	0.0005		0.0014	0.0005		0.0019	0.0005		0.0024	0.000
vma	vma(-1)	0.8305	0.0107		0.8314	0.0106		0.8221	0.0109		0.8275	0.010
vma	vehstock	0.0242	0.0066		0.0236	0.0065		0.0277	0.0066		0.0268	0.006
vma	pm	-0.0629	0.0049	PM	-0.0638	0.0050	PM	-0.0729	0.0054	PM	-0.0706	0.005
vma	pm^2	-0.0275	0.0061		-0.0296	0.0065		-0.0263	0.0066		0.0037	0.008
vma	pm*inc	0.0573	0.0110		0.0575	0.0110		0.0825	0.0122		0.0944	0.012
vma	popratio	0.1010	0.0410		0.1093	0.0397		0.1248	0.0399		0.0669	0.041
vma	urban	-0.0589	0.0415		-0.0639	0.0415		-0.0828	0.0419		-0.0967	0.042
vma	road miles/state land area	0.0155	0.0066		0.0148	0.0065		0.0133	0.0066		0.0111	0.006
vma	pfcut + fint	0.0340	0.0079	pfcut+fint	0.0352	0.0080	pfcut+fint	0.0420	0.0081	pfcut+fint	0.0506	0.008
vma	Media variable			pf * Media_dummy	0.0061	0.0058	pf * Media_dummy	0.0071	0.0058	pf*Media_dummy	**-0.0080**	0.006
vma	pm*(dummy 2003-09)[a]							-0.0359	0.0071		-0.0308	0.007
vma	Fuel price variance									pm*log(pf_var)	**-0.0100**	0.001
vma	AR(1)	-0.0888	0.0206		-0.0913	0.0206		-0.0840	0.0207		-0.0849	0.020
vehstock	intercept	-0.3554	0.1421		-0.3577	0.1421		-0.3557	0.1420		-0.3592	0.142
vehstock	pnewcar	0.0445	0.0317		0.0443	0.0317		0.0412	0.0317		0.0403	0.031
vehstock	interest	-0.0030	0.0040		-0.0030	0.0040		-0.0035	0.0040		-0.0038	0.004
vehstock	income	0.0044	0.0146		0.0043	0.0146		0.0042	0.0146		0.0041	0.014
vehstock	urban	-0.0416	0.0465		-0.0417	0.0465		-0.0421	0.0465		-0.0425	0.046
vehstock	licenses/adult	0.0445	0.0178		0.0446	0.0178		0.0445	0.0178		0.0444	0.017
vehstock	trend	0.0000	0.0007		0.0000	0.0007		-0.0001	0.0007		-0.0001	0.000
vehstock	vehstock(-1)	0.9351	0.0102		0.9350	0.0102		0.9354	0.0102		0.9354	0.010
vehstock	vma	0.0384	0.0143		0.0387	0.0143		0.0387	0.0143		0.0391	0.014
vehstock	pm	0.0032	0.0057		0.0031	0.0057		0.0028	0.0057		0.0028	0.005
vehstock	rho	-0.1471	0.0230		-0.1469	0.0230		-0.1474	0.0230		-0.1467	0.023
fint	intercept	-1.0263	0.9488		-0.6026	0.9380		-0.5382	0.9373		-0.5531	0.935
fint	pf + vma	-0.0041	0.0058	pf + vma	-0.0060	0.0057	pf + vma	-0.0059	0.0057	pf + vma	-0.0049	0.005
fint	inc	0.0064	0.0144		0.0064	0.0144		0.0066	0.0144		0.0046	0.014
fint	fint(-1)	0.8805	0.0111		0.8833	0.0110		0.8823	0.0110		0.8749	0.011
fint	Trend66-73	0.0001	0.0010		0.0002	0.0010		0.0000	0.0010		0.0009	0.001
fint	Trend74-79	-0.0034	0.0009		-0.0037	0.0009		-0.0035	0.0009		-0.0036	0.000
fint	Trend80+	-0.0014	0.0006		-0.0010	0.0006		-0.0010	0.0006		-0.0010	0.000
fint	7479 dummy	-0.0078	0.0047		-0.0069	0.0047		-0.0068	0.0047		-0.0071	0.004
fint	urban	-0.0919	0.0471		-0.0896	0.0470		-0.0894	0.0470		-0.0898	0.047
fint	cafep	-0.0714	0.0155		-0.0585	0.0148		-0.0583	0.0148		-0.0554	0.014
fint	popratio	0.1302	0.0556		0.1330	0.0553		0.1360	0.0553		0.1700	0.055
fint	pfcut+vma	-0.0080	0.0112	pfcut+vma	-0.0031	0.0110	pfcut+vma	-0.0022	0.0110	pfcut+vma	-0.0018	0.011
fint	rho	-0.1691	0.0202		-0.1706	0.0202		-0.1704	0.0202		-0.1697	0.020
cong	intercept	-4.0860	0.9273		-3.9180	0.9530		-3.8896	0.9664		-3.8874	0.965
cong	urban-lane-miles/adult	-0.6058	0.1102		-0.6394	0.1176		-0.6352	0.1217		-0.6311	0.120
cong	(vehicle miles/adult)+log(ur	0.2799	0.0860		0.2546	0.0872		0.2533	0.0872		0.2552	0.087
cong	population / state land are	0.5908	0.0490		0.6062	0.0502		0.6088	0.0504		0.6103	0.050
cong	percent trucks	0.4634	0.1983		0.4554	0.2016		0.4506	0.2020		0.4493	0.201
cong	urban	-4.0331	0.3434		-4.2241	0.3484		-4.2191	0.3485		-4.2251	0.348

[a]dummy is normalized

Appendix C. Detailed yearly projections

Model 3.3:

	---Calculated using values of variables from historical data---								---Calculated using values of variables from AEO-------------------------																
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Reference Case																									
Short Run Rebound	2.3%	2.1%	2.1%	2.4%	2.6%	2.9%	3.0%	3.0%	3.3%	2.5%	2.8%	2.9%	2.8%	2.8%	2.8%	2.7%	2.5%	2.4%	2.4%	2.3%	2.2%	2.0%	2.0%	1.8%	1.8%
Dynamic Rebound	11.1%	11.3%	11.5%	11.8%	12.0%	12.0%	12.0%	11.8%	11.7%	11.4%	11.4%	11.1%	10.8%	10.5%	10.1%	9.6%	9.2%	**8.8%**	**8.3%**	**7.9%**	**7.4%**	**6.9%**	**6.5%**	**6.1%**	**5.7%**
Long Run Rebound	14.7%	13.1%	13.0%	14.9%	16.4%	18.4%	18.8%	19.0%	20.7%	15.9%	17.6%	18.1%	17.7%	17.9%	17.4%	16.7%	15.9%	15.4%	14.9%	14.4%	13.7%	12.9%	12.3%	11.5%	11.0%
High Oil Price Case																									
Short Run Rebound	2.3%	2.1%	2.1%	2.4%	2.6%	2.9%	3.0%	3.0%	3.3%	2.5%	2.8%	3.3%	3.5%	3.6%	3.5%	3.4%	3.3%	3.3%	3.2%	3.2%	3.1%	2.9%	2.8%	2.7%	2.6%
Dynamic Rebound	11.5%	11.8%	12.3%	12.8%	13.2%	13.5%	13.7%	13.9%	14.0%	14.1%	14.4%	14.5%	14.4%	14.1%	13.7%	13.3%	12.9%	12.5%	12.0%	11.6%	11.1%	10.6%	10.1%	9.6%	9.3%
Long Run Rebound	14.7%	13.1%	13.0%	14.9%	16.4%	18.4%	18.8%	19.0%	20.7%	15.9%	17.6%	20.8%	22.1%	22.6%	22.2%	21.7%	21.0%	20.8%	20.4%	19.9%	19.3%	18.6%	17.6%	17.0%	16.3%
Low Oil Price Case																									
Short Run Rebound	2.3%	2.1%	2.1%	2.4%	2.6%	2.9%	3.0%	3.0%	3.3%	2.5%	2.8%	2.4%	2.2%	2.1%	1.9%	1.7%	1.5%	1.4%	1.3%	1.2%	1.2%	0.9%	0.8%	0.7%	0.6%
Dynamic Rebound	10.6%	10.6%	10.7%	10.7%	10.6%	10.4%	10.0%	9.5%	8.9%	8.2%	7.8%	7.1%	6.5%	6.0%	5.5%	4.9%	4.5%	**4.0%**	**3.5%**	**3.0%**	**2.6%**	**2.1%**	**1.8%**	**1.4%**	**1.2%**
Long Run Rebound	14.7%	13.1%	13.0%	14.9%	16.4%	18.4%	18.8%	19.0%	20.7%	15.9%	17.6%	14.8%	13.8%	12.9%	11.8%	10.6%	9.6%	8.7%	8.1%	7.4%	7.4%	5.5%	4.7%	4.0%	3.7%

Model 3.21b:

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

Model 3.35 (Reference case):

	---Calculated using values of variables from historical data---																	----------------Calculated using values of variables from AE							
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	202
Short Run Rebound	1.1%	1.0%	1.0%	1.1%	1.2%	1.3%	1.2%	1.2%	1.2%	1.0%	1.1%	1.1%	1.0%	1.0%	0.9%	0.8%	0.7%	0.6%	0.6%	0.5%	0.4%	0.4%	0.3%	0.3%	0.2
Dynamic Rebound	4.5%	4.5%	4.4%	4.4%	4.3%	4.2%	4.0%	3.8%	3.6%	3.4%	3.3%	3.0%	2.8%	2.5%	2.2%	1.9%	1.6%	1.4%	1.2%	1.0%	0.8%	0.6%	0.5%	0.3%	0.2
Long Run Rebound	6.6%	6.1%	6.3%	6.9%	7.0%	7.6%	7.3%	7.0%	7.5%	5.9%	6.4%	6.5%	6.3%	6.0%	5.4%	4.7%	4.1%	3.7%	3.3%	3.0%	2.6%	2.2%	1.8%	1.5%	1.2

Model 4.3:

	---Calculated using values of variables from historical data---								--Calculated using values of variables from AEO----------------------------	
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Reference Case										
Short Run Rebound	2.0%	1.6%	1.4%	1.9%	2.5%	3.1%	3.3%	3.4%	3.9%	2.5%
Dynamic Rebound	11.7%	12.0%	12.2%	12.5%	12.7%	12.9%	12.8%	13.1%	13.5%	13.2%
Long Run Rebound	12.1%	9.2%	8.0%	11.4%	14.7%	18.6%	20.0%	20.8%	23.5%	14.9%
High Oil Price Case										
Short Run Rebound	2.0%	1.6%	1.4%	1.9%	2.5%	3.1%	3.3%	3.4%	3.9%	2.5%
Dynamic Rebound	12.8%	13.5%	14.1%	14.9%	15.6%	16.3%	16.7%	17.7%	17.7%	18.1%
Long Run Rebound	12.1%	9.2%	8.0%	11.4%	14.7%	18.6%	20.0%	20.8%	23.5%	14.9%
Low Oil Price Case										
Short Run Rebound	2.0%	1.6%	1.4%	1.9%	2.5%	3.1%	3.3%	3.4%	3.9%	2.5%
Dynamic Rebound	10.4%	10.3%	10.1%	9.8%	9.5%	9.1%	8.2%	7.9%	8.6%	7.6%
Long Run Rebound	12.1%	9.2%	8.0%	11.4%	14.7%	18.6%	20.0%	20.8%	23.5%	14.9%

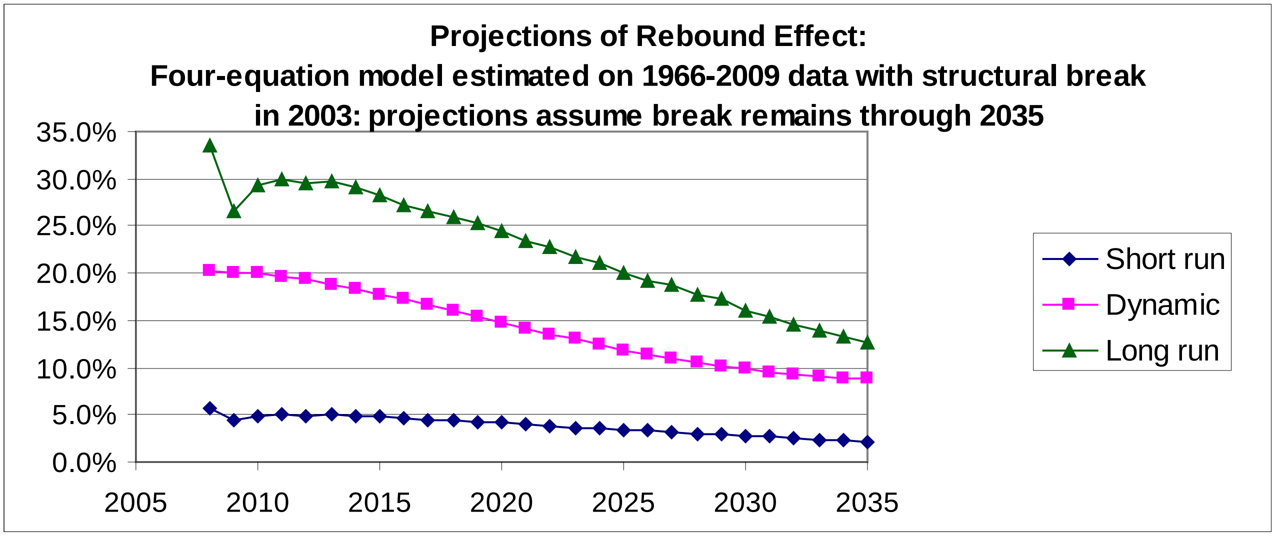
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Reference Case															
Short Run Rebound	3.0%	3.2%	3.1%	3.2%	3.2%	3.1%	2.9%	2.9%	2.8%	2.7%	2.6%	2.4%	2.3%	2.2%	2.1%
Dynamic Rebound	13.2%	13.1%	12.9%	12.5%	12.2%	11.7%	11.2%	10.7%	10.2%	9.7%	9.1%	8.6%	8.1%	7.6%	7.1%
Long Run Rebound	18.2%	19.0%	18.7%	19.3%	19.0%	18.4%	17.6%	17.2%	16.6%	16.2%	15.4%	14.4%	13.9%	13.0%	12.5%
High Oil Price Case															
Short Run Rebound	3.0%	3.9%	4.3%	4.5%	4.5%	4.5%	4.3%	4.4%	4.3%	4.2%	4.1%	4.0%	3.8%	3.7%	3.6%
Dynamic Rebound	18.6%	19.1%	19.2%	19.0%	18.6%	18.3%	17.8%	17.4%	16.8%	16.3%	15.7%	15.1%	14.5%	14.0%	13.5%
Long Run Rebound	18.1%	23.8%	26.2%	27.5%	27.3%	27.1%	26.3%	26.5%	26.1%	25.7%	25.1%	24.3%	23.1%	22.5%	21.7%
Low Oil Price Case															
Short Run Rebound	3.0%	2.2%	2.0%	1.8%	1.6%	1.4%	1.2%	1.0%	0.9%	0.8%	0.9%	0.4%	0.3%	0.2%	0.2%
Dynamic Rebound	6.9%	6.0%	5.3%	4.7%	4.1%	3.4%	2.9%	2.4%	1.8%	1.3%	0.8%	0.4%	0.3%	0.2%	0.1%
Long Run Rebound	18.1%	13.3%	11.7%	10.6%	9.4%	7.9%	6.8%	5.8%	5.1%	4.2%	4.7%	2.0%	1.4%	1.0%	0.9%

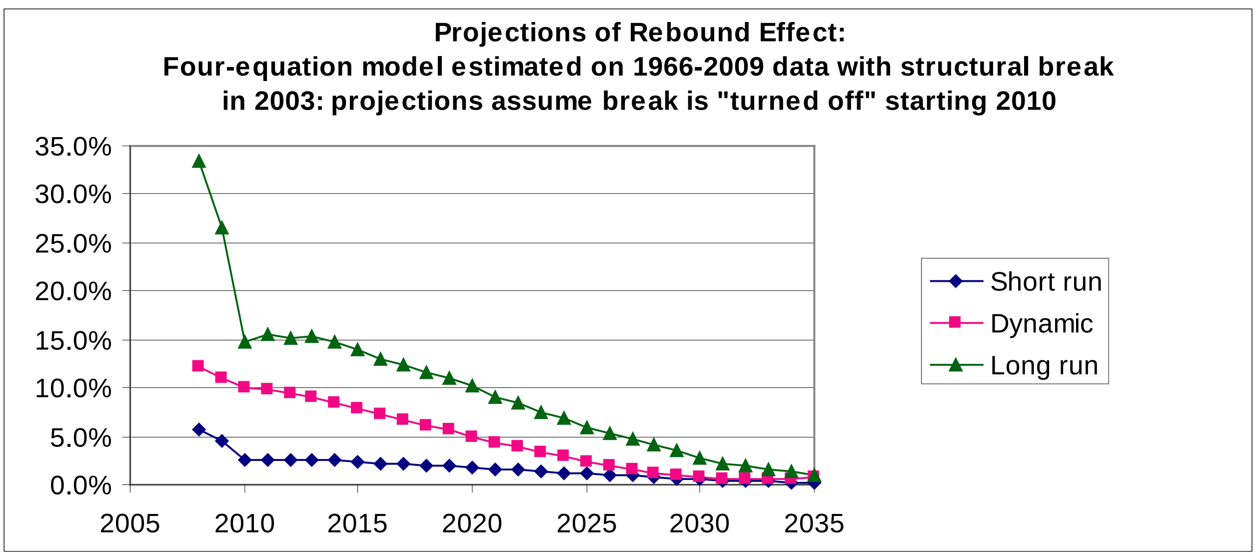
Model 4.21b:

	---Calculated using values of variables from historical data---								------------Calculated using values of variables from AEO---------------	
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Reference Case										
Short Run Rebound	0.2%	0.0%	0.0%	0.1%	0.4%	1.1%	1.4%	1.6%	2.1%	0.5%
Dynamic Rebound	4.1%	4.7%	5.1%	5.2%	5.2%	5.3%	5.1%	5.5%	5.6%	5.4%
Long Run Rebound	0.9%	0.1%	0.0%	0.4%	2.2%	6.5%	8.4%	9.5%	13.0%	3.0%
High Oil Price Case										
Short Run Rebound	0.2%	0.0%	0.0%	0.1%	0.4%	1.1%	1.4%	1.6%	2.1%	0.5%
Dynamic Rebound	5.5%	6.5%	7.4%	8.1%	8.7%	9.4%	9.9%	11.1%	10.7%	11.3%
Long Run Rebound	0.9%	0.1%	0.0%	0.4%	2.2%	6.5%	8.4%	9.5%	13.0%	3.0%
Low Oil Price Case										
Short Run Rebound	0.2%	0.0%	0.0%	0.1%	0.4%	1.1%	1.4%	1.6%	2.1%	0.5%
Dynamic Rebound	2.9%	3.1%	3.1%	2.8%	2.3%	2.0%	1.3%	1.2%	1.6%	0.8%
Long Run Rebound	0.9%	0.1%	0.0%	0.4%	2.2%	6.5%	8.4%	9.5%	13.0%	3.0%

													---------------Calculated u		
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Reference Case															
Short Run Rebound	1.1%	1.3%	1.2%	1.3%	1.3%	1.2%	1.1%	1.0%	0.9%	0.9%	0.7%	0.6%	0.5%	0.4%	0.4%
Dynamic Rebound	5.4%	5.5%	5.3%	5.1%	4.8%	4.3%	3.8%	3.3%	2.8%	2.3%	1.8%	1.4%	1.0%	0.7%	0.5%
Long Run Rebound	6.4%	7.4%	7.1%	7.9%	7.7%	7.1%	6.3%	5.9%	5.4%	4.9%	4.2%	3.3%	2.9%	2.2%	1.9%
High Oil Price Case															
Short Run Rebound	1.1%	2.2%	2.7%	2.9%	2.9%	2.9%	2.8%	2.8%	2.8%	2.7%	2.6%	2.5%	2.3%	2.2%	2.0%
Dynamic Rebound	11.8%	12.9%	13.1%	12.9%	12.5%	12.2%	11.7%	11.3%	10.6%	10.0%	9.4%	8.8%	8.1%	7.5%	7.0%
Long Run Rebound	6.3%	13.3%	16.4%	18.1%	18.0%	17.8%	17.0%	17.4%	16.9%	16.5%	15.9%	15.1%	13.8%	13.1%	12.2%
Low Oil Price Case															
Short Run Rebound	1.1%	0.3%	0.2%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Dynamic Rebound	2.5%	0.9%	0.4%	0.2%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Long Run Rebound	6.3%	1.6%	0.7%	0.4%	0.2%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Appendix D. Projections from model with structural break in 2003





III. EPA's Response to Peer Review Comments

General Comments

The reviewers expressed overall support for the methodology described in the report, as well as support for the implementation of the methodology to derive empirical estimates of the rebound effect for passenger vehicles. Gillingham: "This is a thoughtful and careful effort aiming to address a difficult question…tackles a difficult question using what is likely the best data publicly available…provides estimates that appear to be reasonable…provides a valiant (and reasonable) attempt at forecasting the VMT [vehicle miles traveled] rebound effect forward…It would be difficult to do much better given the task at hand." Greene: "The S&H [Small and Hymel] analysis is very well done, uses appropriate models, data and econometric methods…makes several important contributions to knowledge of the rebound effect…results are consistent with both the central tendency of other estimates in the literature and with the best studies in the peer-reviewed literature… projected rebound effects are useful and plausible…results are useful to EPA as they now stand." Sallee: The Small/Hymel report "…uses an appropriate methodology and defensible assumptions…Where I do disagree…I believe that the preference of one method or specification over the other involves an element of subjective judgment about how to weigh the costs and benefits of different approaches…I did not identify any issues that I believe are objectively incorrect"

Comment: Gillingham commented that in the task given to the authors, the definition of VMT rebound effect was vague and required that certain assumptions be made about how the adoption of fuel efficient technologies will influence other vehicle characteristics. Gillingham noted how an increase in vehicle price or a trade-off leading to less desirable vehicle characteristics could lead to fewer vehicles in the fleet and a reduction in VMT. Gillingham also concludes that the authors' assumption that vehicle price and other attributes remained fixed while vehicle efficiency improved would result in a slight overestimate of the rebound effect.

EPA Response: The Small and Hymel methodology accounts for the VMT rebound effect from two pathways. The first is the increase in the average fuel economy of the vehicle fleet, and that in turn reduces the cost per mile of travel. The second is that the size of the vehicle fleet may increase because vehicles are now more useful, in the sense that they can be driven more cheaply. This change in vehicle fleet size may further affect the amount of overall driving. Empirically, they find that the first path is by far the dominant one, so that one could ignore the second pathway as an approximation. The full effect on vehicle sales and fleet size will also be influenced by any change in vehicle prices due to regulation. This effect on fleet size would likely work in the opposite direction to that arising from a change in fuel cost: if regulations result in manufacturers raising vehicle prices along with reduced fuel costs, those higher prices would tend to mitigate any tendency for the size of the fleet to increase.

EPA agrees that there are potentially other aspects of our rule that may affect VMT besides the rule's impact on fuel costs, which is the focus of the Small and Hymel report. For example, effects on vehicle sales, due to changes in price, fuel economy, or other vehicle attributes could affect total VMT. In EPA's analysis of the effects of greenhouse gas (GHG) standards on light-duty vehicle sales, it sees counterbalancing forces: sales may increase due to improved fuel economy, but may decrease due to increased costs. The agency has not concluded whether the net effect on vehicle sales will be positive or negative. In turn, vehicle sales impacts could affect rates of vehicle scrappage. Given the complications in just assessing the directional impact of EPA standards on vehicle sales, focusing on the direct effects of reduced fuel costs on VMT seems like a reasonable approach.

Comment: Greene noted that both 3-equation and 4-equation versions of the model do not consider usage-induced capital depreciation, which will increase as efficiency technologies are adopted that increase the price of the vehicle.

EPA Response: We are not sure of the causal linkage between higher vehicle prices and usage-induced depreciation of vehicles. Furthermore, there is little evidence that drivers, in general, take capital cost into account in decisions relating to amount of driving. Most choice models, for example those used in practical urban transportation planning, assume that the cost variable affecting consumers' decisions excludes capital cost entirely. In any case, we don't believe that this effect would have much quantitative impact on VMT rebound estimates.

Comment: Greene and Gillingham commented that aggregate state input data may mask some of the heterogeneity in the rebound effect, such as VMT rebound elasticities that vary by vehicle age.

EPA Response: We agree with the Greene and Gillingham that the use of aggregate VMT data does not allow for the identification of some aspects of heterogeneity in the rebound effect. Alternative approaches, focusing for example on travel survey data, may help address some of these heterogeneity questions. But there are trade-offs between using more aggregate data (i.e., state level data) and travel survey data. For example, Greene noted that, unlike travel survey data, studies based upon aggregate data do not face the risk that observations of individual responses may fail to add up to a national-level change. As another example, it can be difficult to control for important factors other than fuel prices and fuel efficiency that may make one household drive more than the other (e.g., job location, after school activities, etc.). EPA believes that the aggregate approach is appropriate for the purpose of estimating the overall nationwide increase in driving that would result from a given reduction in fuel operating costs.

Comment: Gillingham and Sallee raised the issue of the potential problem of measurement error with the use of aggregate data in the report. Sallee commented that the VMT variable is not directly measured, but is imputed based on fuel sales and estimates of fuel efficiency that may be inconsistent across states and over time. Sallee suggested that using VMT readings from odometer readings from smog checks may be one way to avoid the issues associated with using state level aggregate data.

EPA Response: As Small and Hymel state, there are potential problems with the VMT data collected by the US Federal Highway Administration. These data are reported by states, which lack a uniform methodology for estimating them. For example, some states rely on periodic vehicle counts, while others multiply fuel consumption (measured from tax records) by an independent estimate of fleet fuel efficiency. However, Small and Hymel do not think that these potential problems bias their results. They posited that sources of measurement error are mostly unrelated to their independent variables. Even if there are sources of measurement error, the use of fixed effects eliminates the spurious effect of any cross-state relationship that is consistent over time. One might worry that errors in measuring fuel consumption by state could appear in both VMT data (in those states where the VMT estimate is based on fuel consumption) and in fuel efficiency. This would bias OLS estimates, but not 2SLS and 3SLS, which are specifically designed to eliminate asymptotic bias resulting from correlated errors in the dependent variables.

We agree with Sallee that smog check odometer travel data would be another source of information about travel behavior that could be useful in attempting to estimate VMT rebound effects. We also note that Gillingham has undertaken work estimating the VMT rebound effect with California smog check data. The Gillingham study is quite useful in providing another "data point" to assess VMT rebound effects. However, there are trade-offs between using more aggregate data (i.e., state level data) and disaggregate data (e.g., travel survey data, or smog check odometer readings). For example, as mentioned above, Greene noted one advantage of using aggregate data for estimating the rebound effect is that it covers the totality of vehicle travel. Unlike travel survey data, studies based upon aggregate data do not face the risk that observations of individual responses fail to integrate to national-level change. Also, only a limited amount of smog check data is available for specific states or cities, which limits the usefulness of this approach to obtaining national estimates of VMT rebound.

Comment: Gillingham noted that while the report assumed no measurement error, if classical measurement error in the regressors existed, the result would be a downward bias of the coefficients (i.e. attenuation bias).

EPA Response: Attenuation bias is a common problem in econometric studies. The reviewer is correct that measurement error in the regressors might lead to a downward bias in the coefficients estimated. This is one of several sources of uncertainty in the results.

Soundness of econometric procedures

Comment: Gillingham commented that linear time trends are used instead of a standard panel data approach with fixed time effects, and that if fixed time effects had been used, the model would control for other changes more flexibly. Sallee commented similarly that there was apparently no attempt to control for correlation across states in the error terms, and suggested clustering standard errors by year.

EPA Response: These comments raise the questions on how the time trend should be better represented in the model and what the impact is on the standard errors if the time trend is treated differently in the model. Due to limitations of the software used to estimate the model in the report, the authors were not able to compute clustered standard errors along with the other two time-related effects it takes into account, namely autoregressive errors and a lagged dependent variable. However, subsequent to this report, the authors conducted two experiments to see if clustering the standard errors makes a difference. First, they estimated a slightly different model, identical except omitting the time trends. They also estimated this model with a different estimator, Generalized Method of Moments (GMM), which was also used for a comparison in the Small and Van Dender paper. The comparison was just to see whether this different method gave different results, which for the most part it did not.

Using this slightly modified model, standard errors were computed both with and without clustering. The clustering was done at both at the state level, as the authors initially thought correlations across time would be the main problem with standard errors, and also at the level of a year, as suggested by the commenter. The results showed virtually no change in standard errors. This is somewhat surprising, but with two time-related correlations already handled in the model (autoregressive errors and lagged dependent variables), it is difficult to develop trustworthy intuition about what to expect from a time-related clustering calculation.

The authors do not think the failure to cluster during the calculation of standard errors makes any significant difference, and in particular they cannot find any evidence that the reported standard errors are understated as a result. A more thorough description of these experiments is described in their working paper.[39]

Comment: Gillingham suggested that when relying on time series variation over many years, testing for autocorrelation and unit roots is a common approach, and noted that while the authors did consider 1st order autocorrelation, that second-order order autocorrelation was not considered.

EPA Response: In the judgment of the authors, the time series variation in the data was too limited to make it likely that both first-order and second-order correlation could be accurately measured. Measuring first-order autocorrelation already is a major advance over much of the literature.

Comment: Sallee noted that panel identification may introduce the problem of omitted variable bias if there are other factors that are correlated with gasoline price and VMT per adult, such as personal vs. work driving, the quality of automobiles, commuting norms, fraction of two-earner families, expansion of urban sprawl and that other factors that may also be correlated with VMT. Along this same line of argument, Sallee noted that the price of gasoline is the most important variable in the analysis, and adding time period fixed effects would remove the vast majority of variation in gasoline prices due to fluctuations in global oil price. The remaining state-specific variations in price would be the result of short term imbalances in supply and demand, and therefore may have limited impact on behavior. Thus, Sallee suggested adding time dummies to distinguish between periods where there may be structural breaks.

EPA Response: Using dummy variables for years better controls for changes over time for factors that Sallee raises (e.g., quality of cars, commuting norms, etc), whereas a linear time trend will not be as effective. But reducing omitted variable bias with fixed effects comes at a cost. As Sallee mentions, the problem is that every time you add in a fixed effect, you are removing some kind of variation from the data. Having both time and state dummies would mean that you are using only variation in prices within a given state in a single year. And if most of the variation is coming from national trends, or fluctuations

[39] Hymel, Kent, and Kenneth A. Small, "The Rebound Effect for Automobile Travel: Asymmetric Response to Price Changes and Novel Features of the 2000s," Working paper 14-15-03, UC Irvine (May 2014). http://www.economics.uci.edu/files/economics/docs/workingpapers/2014-15/14-15-03.pdf

in the global oil price, then time fixed effects will remove that variation, leaving you with very little to identify the coefficients.

At an earlier stage of the research the authors attempted to estimate a model with individual dummies for each year. The result was very imprecise coefficient estimates, and sometimes failure of the iterative nonlinear estimation routine to converge. It is for this reason that this approach was not included in the results. An additional reason to forego year dummies is the possible anomalous causes of year-to-year changes in state-level fuel prices, as noted by this same commenter. As for more complex time trends, the authors did try a number of time-trend variables with structural breaks. No significant breaks were found in time trends in the VMT equation, but there were identifiable breaks in the equation for fuel intensity, resulting in the use of three time trend variables in the latter equation. This is not mentioned in the text of the paper but can be seen in the detailed appendix results.

Consideration of uncertainties

Comment: All of the reviewers suggested that more treatment of uncertainty would be useful. Sallee suggested that a fuller way of representing forecast and coefficient uncertainty would be to model the uncertainty in the forecasted variables and provide a collection of different model results based on random draws of these variables. If this was done, he suggested, it would make clearer which parameters are pivotal, so users know where to focus their attention.

EPA Response: Incorporating uncertainty is a difficult challenge that has not been given much attention in the literature on the VMT rebound effect. There are many different types of uncertainties: (1) uncertainties due to data shortcomings, (2) issues with the experimental design available in the historical record, (3) uncertainties due to model formulation, (4) uncertainties inherent in econometric estimation, and (5) uncertainties about the future state of the world. Small and Hymel attempt to address many of these issues by constructing alternative projections based on different assumptions. While a formal uncertainty analysis might be useful to undertake in the context of the VMT rebound issue, such an effort would be a significant and complex task in its own right. Given the complexities associated with undertaking this type of analysis, a formal uncertainty analysis is beyond the scope of this current effort.

Finding of asymmetric response

Comment: All reviewers believe Small and Hymel use a well-established approach to account for asymmetric responses to increases/decreases in per mile fuel costs based on variation in fuel prices. Greene and Sallee believe that there is sufficiently strong evidence of an asymmetric response in the paper and the literature to use a model that allows for this difference, and agree with Small and Hymel's decision to use 3.21b and 4.21b as their preferred model specifications. Gillingham, however, believes that the saliency of gasoline prices may be different than the saliency of fuel price per mile, so he would be more comfortable using results that assume a symmetric response.

EPA Response: Small and Hymel find a significant asymmetric VMT response to fuel cost increases and decreases based upon fuel price changes. While we agree with Gillingham that the saliency of gasoline prices may be different than the saliency of fuel costs, Greene and Sallee suggest that an asymmetric VMT response to fuel costs based on fuel price increases and decreases (i.e., models 3.21b and 4.21b) seems reasonable in Small and Hymel's work. Small and Hymel suggest in their report that their estimates of the impact on VMT from fuel costs may actually measure the response to changes in fuel price rather than fuel efficiency because they are unable to find a statistically significant influence on VMT from fuel efficiency alone. For this reason, as well as endogeneity concerns discussed in their report, they prefer the model that captures asymmetry based on fuel price increases vs. decreases (3.21b, 4.21b) rather than fuel costs (3.23 and 3.24). In models 3.21b and 4.21b, an increase in fuel economy (which would by itself reduce fuel costs) behaves like a decrease in fuel price, with a smaller response than when the fuel price increases. It should be noted that they also found a statistically significant difference in the impact on VMT from fuel cost increases and decreases, too (models 3.23 and 3.24).

Appropriateness of dynamic rebound to account for variables that change over vehicle lifetime

Comment: All three reviewers agree that the dynamic rebound effect (i.e., which accounts for how income, congestion, and other variables that influence vehicle travel vary over time) is a useful way to summarize the rebound effect through time. They also agree that the dynamic rebound effect should be used to quantify the rebound effect over the period of a vehicle's lifetime.

EPA Response: We agree with the reviewers that the dynamic rebound effect is a useful summary statistic for quantifying vehicle rebound effects over time and should be used to estimate the rebound effect over the period of a vehicle's lifetime.

Appropriateness of methodology for projecting VMT

Comment: The reviewers are generally in agreement that there is strong evidence that the rebound effect has changed over time and that changes are correlated with changes in income and fuel prices. They also agree that there is a theoretical justification for including these effects, since income affects the value of travelers' time and fuel prices affect the fuel cost share of the long-run cost per mile of travel. Thus, they agree that it is appropriate to include these effects in the forecasting model.

Sallee suggested that one alternative to forecasting the rebound effect would be to take the best available estimate of the rebound effect from recent years, say 2000 to 2007, and project these estimates forward as a constant rebound effect over all future years without changing income and fuel prices. Similarly, Sallee suggested that one way to judge the importance of the decline in the rebound effect with income is to provide a comparison projection using a constant rebound effect.

The reviewers provided some additional considerations and recommendations regarding the extrapolation approach. For example, Sallee raised questions about the way that fuel price volatility is represented in the projections. Sallee and Greene suggested using a nonlinear extrapolation approach that is asymptotic above zero. Greene commented that a linear extrapolation of the income and price effects could be improved upon by using a better functional form. Greene suggested an alternative approach where the rebound approaches zero as income goes to infinity and fuel prices go to zero.

<u>EPA Response</u>: We agree with the reviewers that there is strong evidence that the rebound effect has changed over time and that changes may be caused by changes in income and fuel prices. Thus, it is appropriate to include these effects in the forecasting model. We believe that it is possible to judge the importance of income without formal projections. One only needs to compare the rebound effect estimated year by year with the estimated rebound effect for the entire time frame of the analysis to see the impact of income on the rebound effect.

According to Small and Hymel, they attempted in earlier phases of this research to estimate a model with a built-in nonlinear response that tends toward an asymptote of zero rebound (when incomes are very high), but were unsuccessful. The procedure currently used truncates the rebound effect at zero state by state, and has the effect of making the aggregate rebound nonlinear with a zero asymptote. This seems like a reasonable way to project the rebound effect into the future when, as happened here, using a nonlinear form ended up being intractable to implement. While the truncation procedure is undoubtedly inaccurate at a fine level of detail (e.g., a given state in a given year), the errors are likely to average out and so it can produce a satisfactory aggregate analysis. If an asymptotic value above zero is used as suggested by Gillingham and Sallee, other issues would need to be addressed. For example, what value should be chosen and what is the basis for the new chosen value? The choice of a positive asymptotic value may be considered arbitrary and difficult to defend.