ECONOMIC ANALYSIS GROUP
DISCUSSION PAPER

Automobile Prices, Gasoline Prices, and Consumer Demand for Fuel Economy

By

Ashley Langer* and Nathan Miller**

EAG 08-11 December 2008

---

* Department of Economics, University of California, Berkeley. Email: alanger@econ.berkeley.edu.

** Economist, Economic Analysis Group, Antitrust Division, U.S. Department of Justice. Email: Nathan.miller@usdoj.gov. We thank Severin Borenstein, Joseph Farrell, Richard Gilbert, Joshua Linn, Kenneth Train, Clifford Winston, Catherine Wolfram, and seminar participants at the George Washington University and the University of California, Berkeley for valuable comments. Daniel Seigle and Berk Ustun provided research assistance. The views expressed are not purported to reflect those of the United States Department of Justice.

Abstract

The relationship between gasoline prices and the demand for vehicle fuel efficiency is important for environmental policy but poorly understood in the academic literature. We provide empirical evidence that automobile manufacturers price as if consumers respond to gasoline prices. We derive a reduced-form regression equation from theoretical micro-foundations and estimate the equation with nearly 300,000 vehicle-week-region observations over the period 2003-2006. We find that vehicle prices generally decline in the gasoline price. The decline is larger for inefficient vehicles, and the prices of particularly efficient vehicles actually rise. Structural estimation that ignores these effects underestimates consumer preferences for fuel efficiency.

1 Introduction

The combustion of gasoline in automobiles poses some of the most pressing policy concerns of the early twenty-first century. This combustion produces carbon dioxide, a greenhouse gas that contributes to global warming. It also limits the flexibility of foreign policy – more than sixty percent of U.S. oil is imported, often from politically unstable regimes. These effects are classic externalities. It is not clear whether, in the absence of intervention, the market is likely to produce efficient outcomes.

One topic of particular importance for policy in this arena is the extent to which retail gasoline prices influence the demand for vehicle fuel efficiency. If, for example, higher gasoline prices induce consumers to shift toward more fuel efficient vehicles, then 1) the recent run-up in gasoline prices should partially mitigate the policy concerns outlined above and 2) gasoline and/or carbon taxes may be reasonably effective policy instruments. However, a small empirical literature estimates an inelastic consumer response to gasoline prices (e.g., Goldberg 1998; Bento et al 2005; Li, Timmins and von Haefen 2007; Jacobsen 2008). For example, Shanjun Li, Christopher Timmins, and Roger H. von Haefen conclude that:

> [H]igher gasoline prices do not deter American's love affair with large, relatively fuel-inefficient vehicles. Moreover, a politically feasible gasoline tax increase will likely not generate significant improvements in fleet fuel economy.

Interestingly, the findings of the academic literature are seemingly contradicted by a bevy of recent articles in the popular press. Consider Bill Vlasic's article in the *New York Times* titled "As Gas Costs Soar, Buyers Flock to Small Cars":

> Soaring gas prices have turned the steady migration by Americans to smaller cars into a stampede. In what industry analysts are calling a first, about one in five vehicles sold in the United States was a compact or subcompact car...[1]

One might be tempted to point out that four in five vehicles were neither compact nor subcompact cars. But suppose that the spirit of the article is correct. Can its perspective be reconciled with the academic literature?

We approach the topic from a new perspective. We ask the question: "Do automobile manufacturers behave *as if* consumers respond to gasoline price?" Our approach starts with the observation that consumer choices have implications for equilibrium automobile prices: if gasoline price shocks affect consumer choices then one should see corresponding adjustments in automobile prices. We derive the specific form of these adjustments from theoretical micro foundations. In particular, we show that a change in the gasoline price affects an automobile's equilibrium price

[1] The article appeared on May 2, 2008. Other recent press articles include CNN.com's May 23, 2008 article titled "SUVs plunge toward 'endangered' list," the *LA Times*' April 24, 2008 article titled "Fueling debate: Is $4.00 gas the death of the SUV?" and the *Chicago Tribune*'s May 12, 2008 article titled "SUVs no longer king of the road."

through two main channels: its effect on the vehicle's fuel cost and its effect on the fuel cost of the vehicle's competitors.[2]

To build intuition, consider the effect of an adverse gasoline price shock on the price of an arbitrary automobile. If consumers respond to the vehicle's fuel cost, then the gasoline price shock should reduce demand for the automobile. However, the gasoline price shock also increases the fuel cost of the automobile's competitors and should therefore increase demand through consumer substitution. The net effect on the automobile's equilibrium price is ambiguous. Overall, the theory suggests that the net price effect should be negative for most automobiles, but positive for automobiles that are sufficiently more fuel efficient then their competitors. We believe that the framework is quite intuitive. For example, the theory formalizes the idea that an adverse gasoline price shock should reduce demand for fuel inefficient automobiles (e.g., the GM Suburban) more than demand for fuel efficient automobiles (e.g., the Ford Taurus), and that demand for highly fuel efficient automobiles (e.g., the Toyota Prius) may actually increase.

In the empirical implementation, we test the extent to which automobile prices respond to changes in fuel costs. We use a comprehensive set of manufacturer incentives to construct region-time-specific "manufacturer prices" for each of nearly 700 vehicles produced by GM, Ford, Chrysler, and Toyota over the period 2003-2006, and combine information on these vehicles' attributes with data on retail gasoline prices to measure fuel costs. We then regress manufacturer prices on fuel costs and competitor fuel costs and argue that manufacturers set prices as if consumers respond to the gasoline price if the first coefficient is negative while the second is positive. Overall, the estimation procedure uses information from nearly 300,000 vehicle-week-region observations; as we discuss below, identification is feasible even in the presence of vehicle, time, and region fixed effects.

By way of preview, the results are consistent with a strong and statistically significant consumer response to the retail price of gasoline. Manufacturer prices decrease in fuel costs but increase in the fuel costs of competitors. The median net manufacturer price change in response to a hypothetical one dollar increase in gasoline prices is a reduction of \$792 for cars and a reduction of \$981 for SUVs; the median price change for trucks and vans are modest and less statistically significant. Although the fuel cost effect almost always dominates the competitor fuel cost effect, the manufacturer prices of some particularly fuel efficient vehicles do increase (e.g., the 2006 Prius or the 2006 Escape Hybrid). The manufacturer responses that we estimate are large in magnitude. Rough back-of-the-envelope calculations suggest that, for most vehicles, manufacturers substantially offset the discounted future gasoline expenditures incurred by consumers.

The results have important policy implications. The manufacturer price responses that we

[2]By "fuel cost" we mean the fuel expense associated with driving the vehicle. Notably, changes in the gasoline price affect the fuel costs of automobiles differentially – the fuel costs of inefficient automobiles are more responsive to the gasoline prices than the fuel costs of efficient automobiles. One can imagine that the gasoline price may affect equilibrium automobile prices through other channels, perhaps due to an income effect and/or changes in production costs. Our empirical framework allows us to control directly for these alternative channels; we find that their net effect is small.

document should dampen short-run changes in consumer purchase behavior by subsidizing relatively fuel inefficient vehicles when gasoline prices rise. Structural estimation that fails to control for these manufacturer responses may therefore underestimate the short-run elasticity of demand with respect to gasoline prices. Further, counter-factual policy simulations based on such estimation are likely to understate the effects of gasoline prices or gasoline/carbon taxes, even if the *simulations* allow for appropriate manufacturer responses.[3]

Thus, the evidence presented here may help reconcile the academic literature with the perspective of the popular press. That is, consumers may consider gasoline prices when choosing which automobile to purchase but, due to the manufacturer price response, changes in the gasoline price are not fully reflected in observed vehicle purchases. We speculate that a major effect of gasoline price changes (or gasoline/carbon taxes) may occur in the long-run. The manufacturer responses that we estimate reduce the profit margins of fuel inefficient vehicles relative to those of fuel efficient vehicles. It is possible, therefore, that increases in the gasoline price (or in the gasoline/carbon tax) provide a substantial profit incentive for manufacturers to invest in the development and marketing of fuel efficient vehicles.

The paper proceeds as follows. We lay out the empirical model in Section 2, including the underlying theoretical framework and the empirical implementation. We describe the data and regression variables in Section 3. Then, in Section 4, we present the main regression results and discuss a number of extensions related to historical and futures gasoline prices, pricing dynamics, selected demand and cost factors, and manufacturer inventory levels. We conclude in Section 5.

2 The Empirical Model

2.1 Theoretical framework

We derive our estimation equation from a model of Bertrand-Nash competition between multi-vehicle manufacturers. Specifically, we model manufacturers, $\Im = 1, 2, \ldots F$ that produce vehicles $j = 1, 2, \ldots J_t$ in period t. Each manufacturer chooses prices that maximize their short-run profit over all of their vehicles:

$$\pi_{\Im t} = \sum_{j \in \Im} [(p_{jt} - c_{jt}) * q_{jt} - f_{jt}] \tag{1}$$

where for each vehicle j and period t, the terms p_{jt}, c_{jt}, and q_{jt} are the manufacturer price, the marginal cost, and the quantity sold respectively; the term f_{jt} is the fixed cost of production. As we detail in the empirical implementation, we assume that marginal costs are constant in quantity but responsive to certain exogenous cost shifters.[4]

We pair this profit function with a consumer demand function that depends on manufacturer

[3] We formalize this argument in Appendix A.

[4] We abstract from the manufacturers' selections of vehicle attributes and fleet composition, as well as any entry and/or exit, which we deem to be more important in longer-run analysis.

prices, expected lifetime fuel costs, and exogenous demand shifters that capture vehicle attributes and other factors. We specify a simple linear form:

$$q(p_{jt}) = \sum_{k=1}^{J_t} \alpha_{jk}(p_{kt} + x_{kt}) + \mu_{jt}, \tag{2}$$

where the term α_{jk} is a demand parameter and the terms x_{kt} and μ_{jt} capture the fuel costs and the exogenous demand shifters, respectively. One can conceptualize the demand shifters as including the vehicle's fixed attributes and quality, as well as maintenance costs and any other expenses that are unrelated to the gasoline price. We consider the case in which demand is well defined ($\partial q_{jt}/\partial p_{jt} = \alpha_{jj} < 0$) and vehicles are substitutes ($\partial q_{jt}/\partial p_{kt} = \alpha_{jk} \geq 0$ for $k \neq j$). The equilibrium manufacturer prices in each period are then characterized by J_t first-order conditions:

$$\frac{\partial \pi_{\Im t}}{\partial p_{jt}} = \sum_{k} \alpha_{jk}(p_{kt} + x_{kt}) + \mu_{jt} + \sum_{k \in \Im} \alpha_{kj}(p_{kt} - c_{kt}) = 0. \tag{3}$$

We solve these first-order equations for the equilibrium manufacturer prices as a function of the exogenous factors.[5] The resulting manufacturer "price rule" is a linear function of the fuel costs, marginal costs, and demand shifters:

$$\begin{aligned} p^*_{jt} = \phi^1_{jt} x_{jt} + \sum_{k \notin \Im} \phi^2_{jkt} x_{kt} + \sum_{l \in \Im,\ l \neq j} \phi^3_{jlt} x_{lt} \\ + \phi^4_{jt} c_{jt} + \phi^5_{jt} \mu_{jt} + \sum_{k \notin \Im} \left(\phi^6_{jkt} c_{kt} + \phi^7_{jkt} \mu_{kt}\right) + \sum_{l \in \Im,\ l \neq j} \left(\phi^8_{jlt} c_{lt} + \phi^9_{jlt} \mu_{lt}\right). \end{aligned} \tag{4}$$

The coefficients $\phi^1, \phi^2, \ldots, \phi^9$ are nonlinear functions of all the demand parameters. The price rule makes it clear that the equilibrium price of a vehicle depends on its characteristics (i.e, its fuel cost, marginal cost, and demand shifters), the characteristics of vehicles produced by competitors, and the characteristics of other vehicles produced by the same manufacturer.[6] For the time being, we collapse the second line of the price rule into a vehicle-time-specific constant, which we denote γ_{jt}.

The sheer number of terms in Equation 4 makes direct estimation infeasible. With only J_t observations per period, one cannot hope to identify the J_t^2 fuel cost coefficients, let alone the

[5] The solution technique is simple. Turning to vector notation, one can rearrange the first-order conditions such that $Ap = b$, where A is a $J_t \times J_t$ matrix of demand parameters, p is a $J_t \times 1$ vector of manufacturer prices, and b is a $J_t \times 1$ vector of "solutions" that incorporate the fuel costs, marginal costs, and demand shifters. Provided that the matrix A is nonsingular, Cramer's Rule applies and there exists a unique Nash equilibrium in which the equilibrium manufacturer prices are linear functions of all the fuel costs, marginal costs, and demand shifters.

[6] We divide the terms into these three groups because Equation (3) can be rewritten:

$$\alpha_{jj}(2p_{jt} + x_{jt} - c_{jt}) + \sum_{k \notin \Im} \alpha_{jk}(p_{kt} + x_{kt}) + \sum_{l \in \Im,\ l \neq j} \left(\alpha_{jl}(p_{lt} + x_{lt}) + \alpha_{lj}(p_{lt} - c_{lt})\right) = 0,$$

in which each group has a distinctly different functional form.

vehicle-time-specific constant. We move toward the empirical implementation by re-expressing the price rule in terms of weighted averages:

$$p^*_{jt} \quad = \quad \phi^1_{jt} x_{jt} + \phi^2_{jt} \sum_{k \notin \Im} \omega^2_{jkt} x_{kt} + \phi^3_{jt} \sum_{l \in \Im,\ l \neq j} \omega^3_{jlt} x_{lt} + \gamma_{jt}, \tag{5}$$

where the weights ω^2_{jkt} and ω^3_{jlt} both sum to one in each period.[7] Thus, the equilibrium price depends on its fuel cost, the weighted average fuel cost of vehicles produced by competitors, and the weighted average fuel cost of vehicles produced by the same manufacturer. Under a mild regularity condition that we develop in Appendix B, the equilibrium manufacturer price of a vehicle decreases in its fuel cost (i.e, $\phi^1_{jt} \in [-1, 0]$) and increases in the weighted average fuel cost of vehicles produced by competitors (i.e., $\phi^2_{jt} \in [0, 1]$). Further, the equilibrium price of a vehicle is more responsive to changes in its fuel cost than identical changes to the weighted average fuel cost of its competitors (i.e., $|\phi^1_{jt}| > |\phi^2_{jt}|$). The relationship between the equilibrium price of a vehicle and the weighted average fuel cost of vehicles produced by the same manufacturer is ambiguous (i.e., $\phi^3_{jt} \in [-1, 1]$).[8]

The intuition that manufacturer prices can increase or decrease in response to adverse gasoline price shocks can now be formalized. Assume for the moment that the gasoline price does not affect marginal costs or the demand shifters, and therefore does not affect the vehicle-time-specific constant (we relax this assumption in an extension). Denoting the gasoline price at time t as gp_t, the effect of the gasoline price shock on the manufacturer price is:

$$\frac{\partial p^*_{jt}}{\partial \mathrm{gp}_t} = \phi^1_j \frac{\partial x_{jt}}{\partial \mathrm{gp}_t} + \phi^2_{jt} \sum_{k \notin \Im} \omega^2_{jkt} \frac{\partial x_{kt}}{\partial \mathrm{gp}_t} + \phi^3_{jt} \sum_{l \in \Im,\ l \neq j} \omega^2_{jlt} \frac{\partial x_{lt}}{\partial \mathrm{gp}_t}, \tag{6}$$

where fuel costs increase unequivocally in the gasoline price (i.e., $\partial x_{jt} / \partial \mathrm{gp}_t > 0 \ \forall \ j$). The first term captures the intuition that manufacturers partially offset an increase in the fuel cost with a reduction in the vehicle's price. This reduction is greater for vehicles whose fuel costs are sensitive to the gasoline price (e.g., for fuel-inefficient vehicles). The second and third terms capture the intuition that an increases in the fuel costs of other vehicles can increase demand (e.g., through consumer substitution) and thereby raise the equilibrium price. Although the first effect tends to dominate, prices can increase provided that the vehicle is sufficiently more fuel efficient than other vehicles.[9]

---

[7] The weights have specific analytical solutions given by $\omega^i_{jkt} = \phi^i_{jkt} / \phi^i_{jt}$ for $i = 2, 3$, so that closer competitors receive greater weight. The coefficients ϕ^2_{jt} and ϕ^3_{jt} are the sums of the ϕ^2_{jkt} and ϕ^3_{jkt} coefficients, respectively. Mathematically, $\phi^i_{jt} = \sum \phi^i_{jkt}$ for $i = 2, 3$.

[8] As we show in Appendix B, if demand is symmetric (i.e., $\alpha_{jk} = \alpha_{kj} \ \forall \ j, k$), then changes in the fuel costs of other vehicles produced by the same manufacturer have no effect on equilibrium prices, and $\phi^3_{jt} = 0$.

[9] The exact condition for a price increase is:

$$\frac{\partial x_{jt}}{\partial \mathrm{gp}_t} < -\frac{1}{\phi^1_{jt}} \left(\phi^2_{jt} \sum_{k \notin \Im} \omega^2_{jkt} \frac{\partial x_{kt}}{\partial \mathrm{gp}_t} + \phi^3_{jt} \sum_{l \in \Im,\ l \neq j} \omega^2_{jlt} \frac{\partial x_{lt}}{\partial \mathrm{gp}_t} \right).$$

2.2 Empirical implementation

Our starting point for estimation is the reduced-form outlined in Equation 5. The empirical implementation requires that we specify the fuel costs (x_{jt}), the weights (ω^i_{jkt} for $i = 2, 3$), and the vehicle-time-specific constants (γ_{jt}). We discuss each in turn.

We proxy the expected lifetime fuel cost of vehicle j at time t as a function of the vehicle's fuel efficiency and the gasoline price at time t, following Goldberg (1998), Bento et al (2005) and Jacobsen (2007). The specific form is:

$$x_{jt} = \tau * \frac{\mathrm{gp}_t}{\mathrm{mpg}_j},$$

where mpg_j is the fuel efficiency of vehicle j in miles-per-gallon and τ is a discount factor that nests any form of multiplicative discounting; one specific possibility is $\tau = 1/(1-\delta)$, where δ is the "per-mile discount rate."[10] The fuel cost proxy is precise if consumers perceive the gasoline price to follow a random walk because, in that case, the current gasoline price is a sufficient statistic for expectations over future gasoline prices. As we discuss below, we fail to reject the null hypothesis that gasoline prices actually follow a random walk, but also provide some evidence that consumers consider both historical gasoline prices and futures prices when forming expectations.

To construct the weighted average variables, we assume that the severity of competition between two vehicles decreases in the Euclidean distance between their attributes. To that end, we take a set of M vehicle attributes, denoted z_{jm}; $m = 1, \ldots, M$, and standardize each to have a variance of one. Then, for each pair of vehicles, we sum the squared differences between each attribute to calculate the effective "distance" in attribute space. We form initial weights as follows:

$$\omega^*_{jk} = \frac{1}{\sum_{m=1}^{M} (z_{jm} - z_{km})^2}.$$

To form the final weights that we use in estimation, we first set the initial weights to zero for vehicles of different types and then normalize the weights to sum to one for each vehicle-period. We perform this weighting procedure separately for vehicles produced by the same manufacturer and vehicles produced by competitors; the result is a set of empirical weights that we denote $\widetilde{\omega}^2_{jkt}$ and $\widetilde{\omega}^3_{jkt}$.[11] The use of weights based on the Euclidean distance between vehicle attributes is analogous to the

We say that manufacturer prices tend to fall in the gasoline price because $|\phi^1_{jt}| > |\phi^2_{jt}|$ and $\phi^3_{jt} \approx 0$ provided that demand that is approximately symmetric.

[10]It may help intuition to note that the ratio of the gasoline price to vehicle miles-per-gallon is simply the gasoline expense associated with a single mile of travel.

[11]Thus, the weighting scheme is based on the inverse Euclidean distance between vehicle attributes among vehicles of the same type. There are four vehicle types in the data: cars, SUVs, trucks and vans. We use the following set of vehicle attributes in the initial weights: manufacturer suggested retail price (MSRP), miles-per-gallon, wheel base, horsepower, passenger capacity, and dummies for the vehicle type and segment. Although the initial weights are constant across time for any vehicle pair, the final weights may vary due to changes in the set of vehicles available on the market. An alternative weighting scheme based on the inverse Euclidean distance of all vehicles (not just those of the same type) produces similar results.

instrumenting procedures of Berry, Levinsohn, and Pakes (1995) and Train and Winston (2007).

Turning to the vehicle-time-specific constants, recall from that Equation (4) that the constants represent the net price effects of marginal costs and demand-shifters:

$$\gamma_{jt} = \phi_j^4 c_{jt} + \phi_j^5 \mu_{jt} + \sum_{k \notin \Im} \left(\phi_{jk}^6 c_{kt} + \phi_{jk}^7 \mu_{kt} \right) + \sum_{l \in \Im,\ l \neq j} \left(\phi_{jl}^8 c_{lt} + \phi_{jl}^9 \mu_{lt} \right).$$

In the empirical implementation, we decompose this function using vehicle fixed effects, time fixed effects, and controls for the number of weeks that each vehicle has been on the market. Let λ_{jt} denote the number of weeks that vehicle j has been on the market as of period t, and $\bar{\lambda}_{A,t}$ denote the weighted average number of weeks since the vehicles in the set A were first produced. The decomposition takes the form:

$$\gamma_{jt} = \delta_t + \kappa_j + f(\lambda_{jt}) + g(\bar{\lambda}_{k \notin \Im, t}) + h(\bar{\lambda}_{k \in \Im,\ k \neq j, t}) + \epsilon_{jt}$$

where δ_t and κ_j are time and vehicle fixed effects, respectively, and functions f, g, and h flexibly capture the net price effects of learning-by doing and predictable demand changes over the model-year.[12] In the main results, we specify the functions f, g, and h as third-order polynomials; the results are robust to the use of higher-order or lower-order polynomials. The error term ϵ_{jt} captures vehicle-time-specific cost and demand shocks.

Two final adjustments produce the main regression equation that we take to the data. First, we incorporate regional variation in manufacturer prices and gasoline prices and add a corresponding set of region fixed effects.[13] Second, we impose a homogeneity constraint that reduces the total number of parameters to be estimated; the constraint eliminates vehicle-time variation in the coefficients, so that $\phi_{jt}^i = \phi^i \ \forall\ j, t$ (in supplementary regressions we permit the coefficients to vary across manufacturers and vehicle types). The regression equation is:

$$\begin{aligned} p_{jtr} \quad &= \quad \beta^1 \frac{\mathrm{gp}_{tr}}{\mathrm{mpg}_j} + \beta^2 \sum_{k \notin \Im} \widetilde{\omega}_{jkt}^3 \frac{\mathrm{gp}_{tr}}{\mathrm{mpg}_k} + \beta^3 \sum_{l \in \Im,\ l \neq j} \widetilde{\omega}_{jlt}^2 \frac{\mathrm{gp}_{tr}}{\mathrm{mpg}_l} \\ &+ \quad f(\lambda_{jt}) + g(\bar{\lambda}_{k \notin \Im, t}) + h(\bar{\lambda}_{k \in \Im,\ k \neq j, t}) + \delta_t + \kappa_j + \eta_r + \epsilon_{jt}, \end{aligned} \tag{7}$$

where the fuel cost coefficients incorporate the discount factor, i.e., $\beta^i = \tau \phi^i$ for $i = 1, 2, 3$; for reasonable discount factors, these coefficients should be much larger than one in magnitude. Thus, we estimate the average response of a vehicle's price to changes in its fuel costs, changes in the weighted average fuel cost among vehicles produced by competitors, and changes in the weighted average fuel cost among other vehicles produced by the same manufacturer.

[12] Copeland, Dunn and Hall (2005) document that vehicles prices fall approximately nine percent over the course of the model-year.

[13] Adding regional variation in prices does not complicate the weight calculations because there is no regional variation in the vehicles available to consumers.

We estimate Equation 7 using ordinary least squares. We are able to identify the fuel cost coefficients in the presence of time, vehicle, and region fixed effects precisely because changes in the gasoline price across time and regions affects manufacturer prices differentially across vehicles. We argue that manufacturers price as if consumers respond to gasoline prices if the fuel cost coefficient is negative (i.e., $\beta^1 < 0$) and the competitor fuel cost coefficient is positive (i.e., $\beta^2 > 0$). The theoretical results suggest that the fuel cost coefficient should be larger in magnitude than the competitor fuel cost coefficient (i.e., $|\beta^1| > |\beta^2|$); more generally, the relative magnitude of these coefficients determines the extent to which average manufacturer prices fall in response to an adverse gasoline shock. We cluster the standard errors at the vehicle level, which accounts for arbitrary correlation patterns in the error terms.[14]

3 Data Sources and Regression Variables

3.1 Data sources

Our primary source of data is Autodata Solutions, a marketing research company that maintains a comprehensive database of manufacturer incentive programs. We have access to the programs offered by Toyota and the "Big Three" U.S. manufacturers – GM, Ford, and Chrysler – over the period 2003-2006.[15] There are just over 190,000 cash incentive-vehicle pairs in the data. Each lasts a fixed period of time, and provides cash to consumers ("consumer-cash") or dealerships ("dealer-cash") at the time of purchase.[16] The incentive programs may be national, regional, or local in their geographic scope; we restrict our attention to the national and regional programs.[17] Thus, we are able to track how manufacturer incentives change over time and across regions for each vehicle in the data.

By "vehicle," we mean a particular model in a particular model-year. For example, the 2003 Ford Taurus is one vehicle in the data, and we consider it as distinct from the 2004 Ford Taurus. Overall, there are 681 vehicles in the data – 293 cars, 202 SUVs, 105 trucks, and 81 vans. The data have information on the attributes of each, including MSRP, miles-per-gallon, horsepower, wheel base, and passenger capacity.[18] We impute the period over which each vehicle is available to

[14]The results are robust to the use of brand-level or segment-level clusters. Brands and vehicle segments are finer gradations of the manufacturers and vehicle types, respectively. There are 21 brands and 15 vehicle segments in the data. Examples of brands (and their manufacturer) include Chevrolet (GM), Dodge (Chrysler), Mercury (Ford), and Lexus (Toyota). Examples of vehicle segments include compact cars, luxury SUVs, and large pick-ups. The results are also robust to the use of manufacturer and vehicle type clusters, though the small number of manufacturers and vehicle types makes the asymptotic consistency of the standard errors suspect.

[15]The German manufacturer Daimler owned Chrysler over this period. We exclude Mercedes-Benz from this analysis since it is traditionally associated with Daimler rather than Chrysler.

[16]Consumer cash includes both "Stand-Alone Retail Cash" and "Bonus Cash."

[17]We consider an incentive to be regional if it is available across an entire Energy Information Agency region. We exclude incentives that are available in only a single city or state.

[18]Attributes sometimes differ for a given vehicle due to the existence of different option packages, also known as "trim." When more than one set of attributes exists for a vehicle, we use the attributes corresponding to the trim

consumers as beginning with the start date of production, as given in Ward's Automotive Yearbook, and ending after the last incentive program for that vehicle expires.[19] For each vehicle, we construct observations over the relevant period at the week-region level.

We combine the Autodata Solutions data with information from the Energy Information Agency (EIA) on weekly retail gasoline prices in each of five distinct geographic regions. The EIA surveys retail gasoline outlets every Monday for the per gallon pump price paid by consumers (inclusive of all taxes).[20] In addition to the regional measures, the EIA calculates an average national price. Figure 1 plots these retail gasoline prices over 2003-2006 (in real 2006 dollars). A run-up in gasoline prices over the sample period is apparent. For example, the mean national gasoline price is 1.75 dollars-per-gallon in 2003 and 2.57 dollars-per-gallon in 2006. The sharp upward spike around September 2005 is due to Hurricane Katrina, which temporarily eliminated more than 25 percent of US crude oil production and 10-15 percent of the US refinery capacity (EIA 2006). Although gasoline prices tend to move together across regions, we are able to exploit limited geographic variation to strengthen identification.

We purge the gasoline prices of seasonality prior to their use in the analysis. Since automobile manufacturers adjust their prices cyclically over vehicle model-years (e.g., Copeland, Hall, and Dunn 2005), the presence of seasonality in gasoline prices is potentially confounding. Further, the use of time fixed effects alone may be insufficient in dealing with seasonality because gasoline prices affect the fuel costs of each vehicle differentially (e.g., Equation 7). We employ the X-12-ARIMA program, which is state-of-the-art and commonly employed elsewhere, for example by the Bureau of Labor Statistics to deseasonalize inputs to the consumer price index.[21] Figure 2 plots the resulting deseasonalized national gasoline prices together with the seasonal adjustments. As shown, the program adjusts the gasoline price downward during the summer months and upwards during the winter months. The magnitude of the adjustments increases with gasoline prices.

In an extension (presented in Section 4.2), we explore whether consumers consider historical and futures prices when forming expectations about future gasoline prices. Interestingly, statistical tests based on Dicky and Fuller (1979) fail to reject the null that gasoline prices follow a random walk – the p-statistic for the deseasonalized national time-series is 0.7035 and the p-statistics for the deseasonalized regional time-series are similar. These tests suggest that knowledge of the current

with the lowest MSRP.

[19]The start date of production is unavailable for some vehicles. For those cases, we set the start date at August 1 of the previous year. For example, we set the start date of the 2006 Civic Hybrid to be August 1, 2005. We impose a maximum period length of 24 months. In robustness checks, we used an 18 month maximum; the different period lengths did not affect the results.

[20]The survey methodology is detailed online at the EIA webpage. The regions include the East Coast, the Gulf Coast, the Midwest, the Rocky Mountains, and the West Coast.

[21]We use data on gasoline prices over 1993-2008 to improve the estimation of seasonal factors, and adjust each national and regional time-series independently. We specify multiplicative decomposition, which allows the effect of seasonality to increase with the magnitude of the trend-cycle. The results are robust to log-additive and additive decompositions. For more details on the X-12-ARIMA, see Makridakis, Wheelwright and Hyndman (1998) and Miller and Williams (2004).

gasoline price is sufficient to inform predictions over future gasoline prices. The result is consistent with the academic literature and statements of industry experts. For example, Alquist and Kilian (2008) find that the current spot price of crude oil outperforms sophisticated forecasting models as a predictor of future spot prices, and Peter Davies, the chief economist of British Petroleum, has stated that "we cannot forecast oil prices with any degree of accuracy over any period whether short or long..." (Davies 2007). If consumers form expectations efficiently, therefore, one would not expect historical and/or futures prices of gasoline to influence vehicle purchase decisions.

3.2 Regression variables

The two critical variables that enable regression analysis are manufacturer price and fuel cost. We discuss each in turn. To start, we measure the manufacturer price of each vehicle as MSRP minus the mean incentive available for the given week and region. We also show results in which the variable includes only regional incentives and only national incentives, respectively. From an econometric standpoint, the MSRP portion of the variable is irrelevant for estimation because the vehicle fixed effects are collinear (MSRP is constant for all observations on a given vehicle). It is the variation in manufacturer incentives across vehicles, weeks, and regions that identifies the regression coefficients.

At least two important caveats apply to our manufacturer price variable. First, the variable does not capture any information about final transaction prices, which are negotiated between the consumers and the dealerships. Changes in negotiating behavior could dampen or accentuate the effect we estimate between gasoline prices and manufacturer prices. Second, although we observe the incentive programs, we do not observe the actual incentives selected. In some circumstances, it is possible that consumers may stack multiple incentives or choose between different incentives. To the extent that manufacturers are more lenient in allowing consumers to stack incentives when gasoline prices are high, our regression estimates are conservative relative to the true manufacturer response.[22]

We measure the fuel costs of each vehicle as the gasoline price divided by the miles-per-gallon of the vehicle. As discussed above, this has the interpretation of being the gasoline expense associated with a single mile of travel. Since the gasoline price varies at the week and region levels and miles-per-gallon varies at the vehicle level, fuel costs vary at the vehicle-week-region level. In an extension, we construct alternative fuel costs based on 1) the mean of the gasoline price over the previous four weeks and 2) the price of one-month futures contract for retail gasoline. The futures data are derived from the New York Mercantile Exchange (NYMEX) and are publicly available from the EIA.[23] The alternative variables permit tests for whether consumers are backward-looking

[22]To check the sensitivity of the results, we construct a number of alternative variables that measure manufacturer prices: 1) MSRP minus the maximum incentive, 2) MSRP minus the mean consumer-cash incentive, 3) MSRP minus the mean dealer-cash incentive, and 4) MSRP minus the mean publicly available incentive. None of these alternative dependent variables substantially change the results.

[23]We use one-month futures contracts for reformulated regular gasoline at the New York harbor. In order to ensure

and forward-looking, respectively.

Table 1 provides means and standard deviations for the manufacturer price and the gasoline price variables, as well as for five vehicle attributes used in the weighting scheme – MSRP, miles-per-gallon, horsepower, wheel base, and passenger capacity. The statistics are calculated from the 299,855 vehicle-region-week observations formed from the 681 vehicles, 208 weeks, and five regions in the data. As shown, the mean manufacturer price is 30.344 (in thousands). The mean fuel cost is 0.108, so that gasoline expenses average roughly eleven cents per mile. The means of MSRP, miles-per-gallon, horsepower, wheel base, and passenger capacity are 30.782, 21.555, 224.123, 115.193, and 4.911, respectively.

Table 2 shows the means of these variables, calculated separately for each vehicle type. On average, cars are less expensive than SUVs but more expensive than trucks and vans. The mean manufacturer price for the four vehicle types are 30.301, 35.301, 24.482, and 24.658, respectively. Cars also require far less gasoline expense per mile. The mean fuel cost of 0.087 is nearly thirty percent smaller than the means of 0.121, 0.133, and 0.120 for SUVs, trucks, and vans, respectively. The means of the attributes used in the weights also differ across type, and reflect the generalization that cars are smaller, more fuel efficient, and less powerful than SUVs, trucks, and vans. Of course, the vehicles also differ along unobserved dimensions. We use vehicle fixed effects to control for all these differences – observed and unobserved – in our regression analysis.

4 Empirical Results

4.1 Main regression results

We regress manufacturer prices on fuel costs, as specified in Equation 7. To start, we impose the full homogeneity constraint that all vehicles share the same fuel cost coefficients. The estimated coefficients are the average response of manufacturer prices to fuel costs. Table 3 presents the results. In Column 1, we use the baseline manufacturer price – MSRP minus the mean of the regional and national incentives. In Columns 2 and 3, we use MSRP minus the mean regional incentive and MSRP minus the mean national incentive, respectively. Although the first column may provide more meaningful coefficients, we believe that the second and third columns are interesting insofar as they examine whether manufacturers respond at the regional and national levels, respectively.

As shown, the fuel cost coefficients of -55.40, -56.96, and -63.75 are precisely estimated and capture the intuition that manufacturers adjust their prices to offset changes in fuel costs. The competitor fuel cost coefficients of 50.76, 50.16, and 50.09 are also precisely estimated and support the idea that increases in competitors' fuel costs raise demand due to consumer substitution. In each regression, the magnitude of the fuel cost coefficient exceeds that of the competitor fuel cost

that the regression coefficients are easily comparable, we normalize the futures price to have the same global mean over the period as the national retail gasoline price.

coefficient, which is suggestive that the first effect dominates for most vehicles.[24] We make this more explicit shortly. The same-firm fuel cost coefficients are nearly zero and not statistically significant.[25] Finally, a comparison of coefficients across columns suggests that manufacturers adjust their prices similarly at the regional and national levels in response to changes in fuel costs.[26]

We explore the effect of retail gasoline prices on manufacturer prices in Figure 3. The gasoline price enters through the fuel costs, average competitor fuel costs, and average same-firm fuel costs. We calculate the effect of a one dollar increase in the gasoline price for each vehicle-week-region observation:

$$\frac{\partial p_{jrt}}{\partial \mathrm{gp}_{rt}} = \frac{\widehat{\beta}_1}{\mathrm{mpg}_j} + \widehat{\beta}_2 \sum_{k \neq j} \frac{\widetilde{\omega}^2_{jkt}}{\mathrm{mpg}_k} + \widehat{\beta}_3 \sum_{k \neq j} \frac{\widetilde{\omega}^2_{jkt}}{\mathrm{mpg}_k}.$$

We plot these derivatives (in thousands) on the vertical axis against vehicle miles-per-gallon on the horizontal axis. We focus on the first dependent variable, i.e., MSRP minus the mean regional and national incentive.[27] The median effect of a one dollar increase in the gasoline price per gallon is a reduction in the manufacturer price of \$171. The calculation varies greatly across vehicles – for example, the effects range from a reduction of \$1,506 for the 2005 GM Montana SV6 to a rise of \$998 for the 2006 Toyota Prius. Although the manufacturer price drops for 83 percent of the vehicles, the price response for fuel efficient vehicles tends to be less negative, and the prices of extremely fuel efficient vehicles such as hybrids actually increase. Overall, the own fuel cost effect dominates the competitor fuel cost effect for most vehicles; the converse is true only for vehicles that are substantially more fuel efficient than their competitors.

We use sub-sample regressions to relax the homogeneity constraint that all vehicles share the same fuel cost coefficients. In particular, we regress manufacturer prices on the fuel cost variables for each combination of vehicle type (cars, SUVs, trucks, and vans) and manufacturer (GM, Ford, Chrysler, and Toyota). The sub-sample regressions may be informative, for example, if the market for cars is more (or less) competitive than the market for SUVs, if region- and time-specific cost and demand shocks affect cars and SUVs differentially, or if consumers who purchase different vehicle types are heterogeneous (for instance if they drive different mileage or have different discount factors).[28] For expositional brevity we focus solely on the baseline manufacturer price and present

[24]The fuel cost coefficients contribute substantially to the regression fits. For example, the R^2 of Column 1 is reduced from 0.5260 to 0.4133 when the fuel cost variables are removed from the specification, so that changes in vehicle fuel costs explain more than ten percent of the variance in manufacturer prices.

[25]As we develop in Appendix B, this is consistent with demand being roughly symmetric.

[26]The results to not seem to be driven by outliers; the coefficients are similar when we exclude the extremely fuel efficient or fuel inefficient vehicles from the sample.

[27]We plot each vehicle only once because the derivatives do not vary substantially over time or regions. Indeed, the only variation within vehicles is due to changes in the set of other vehicles available.

[28]One might additionally suspect that the response of manufacturer prices to fuel costs changes over time. To test for such heterogeneity, we split the observations to form one sub-sample over the period 2003-2004 and another over the period 2005-2006; the results from each sub-sample are quite close. Similarly, we divide the sample between the 2003-2004 model-years and the 2005-2006 model-years without substantially changing the results. We conclude that

the results using figures. The regression coefficients appear in Appendix Table A-1.

Figure 4 plots the estimated effects of a one dollar increase in the gasoline price on manufacturer prices against vehicle miles-per-gallon, separately for each vehicle type.[29] Converted into dollars, the median estimated effect is a reduction in the manufacturer price of \$779, \$981, and \$174 for cars, SUVs, and trucks, respectively, and an increase of \$91 for vans. Among cars and SUVs, the fuel cost effect almost always dominates the competitor fuel cost effect: 91 percent of the cars and 95 percent of the SUVs feature negative net effects. Still, the estimated manufacturer price response is less negative for more fuel efficient vehicles, so that the univariate correlation coefficient between the price response and miles-per-gallon is 0.6610 for cars and 0.7521 for SUVs.[30] By contrast, the magnitude of the estimated effects are much smaller for trucks and vans, as is the strength of the relationship between the effects and vehicle fuel efficiency.

In order to provide some sense of the economic magnitude of these results, we use back-of-the-envelope calculations to (roughly) estimate the extent to which manufacturers offset changes in consumers' cumulative gasoline expenses. We assume an annual discount rate of five percent, a vehicle holding period of thirteen years, and a utilization rate of 11,154 miles per year (the Department of Transportation estimates an average vehicle lifespan of thirteen years and 145,000 miles). Under these parameters, the cumulative gasoline expense associated with a one dollar increase in the gasoline prices ranges between \$1,972 and \$7,953 among the sample vehicles; the expense for the median vehicle (miles-per-gallon of 21.40) is \$5,073. We divide the estimated manufacturer responses, based on the regression coefficients shown in Appendix Table A-1, by the computed cumulative gasoline expense. The resulting ratio is the percent of cumulative gasoline expenses, due to a change in the retail gasoline price, that is offset by changes in the manufacturer price.

Figure 5 plots this "offset percentage" against vehicle miles-per-gallon, separately for each vehicle type. The median offset percentage is 18.17 and 15.27 for cars and SUVs, respectively, but climbs as high as 52.17 for cars (the 2006 Ford GT) and as high as 33.92 for SUVs (the 2004 GM Envoy XUV). These percentages fall in vehicle fuel efficiency, so that the univariate correlation coefficients between the offset percentage and miles-per-gallon for cars and SUVs are -0.6292 and -0.6681, respectively. By contrast, the offset percentage is smaller for trucks and vans. We wish to emphasize that these numbers should be interpreted with considerable caution. Alternative assumptions regarding the discount rate, the vehicle holding period, and the utilization rate could push the offset percentages higher or lower. Further, as previously discussed, the manufacturer price we use to estimate the regressions – MSRP minus the mean available incentive – could understate the manufacturer responses and the offset percentages if some consumers stack multiple incentives.

Returning the regression results of Appendix Table A-1, in Figure 6 we plot the estimated

the effects of any time-related heterogeneity are relatively small.

[29] Each plot combines the results of four regressions, one for each manufacturer.

[30] Appendix Table A-2 lists the largest positive and negative price effects for both cars and SUVs.

manufacturer price effects against vehicle miles-per-gallon for cars, separately for each manufacturer. The estimated effects are negative for all GM and Ford cars, and negative for 92 percent of the Toyota cars (all but the 2003 Echo and the four Prius vehicles). Converted into dollars, the median estimated effect for these manufacturers is a reduction in price of $610, $1180, and $758, respectively. By contrast, only 38 percent of the Chrysler estimated effects are negative and the median effect is an increase of $107. This difference between Chrysler and the other manufacturers remains even for a given level of fuel efficiency. For example, the mean effects for cars with between 25 and 35 miles-per-gallon are reductions of $529, $843, and $719, respectively, for GM, Ford and Toyota, but an increase of $239 for Chrysler. One might conclude that Chrysler pursues a different pricing strategy than GM, Ford, and Toyota. However, an alternative explanation is that Chrysler vehicles are simply more fuel efficient than their competitors (e.g., Chrysler vehicles could be closer to inefficient vehicles in attribute space). We compare the manufacturers' pricing rules more explicitly in Section 4.2.

We plot the estimated manufacturer price effects among SUVs separately for each manufacturer in Figure 7. Among the GM, Ford, and Toyota SUVs, the estimated price effects are positive for only four vehicles: the 2006 (Ford) Mercury Mariner Hybrid, the 2006 Ford Escape Hybrid, the 2006 Toyota Highlander Hybrid and the 2006 Lexus RX 400 Hybrid. The median estimated effects for GM, Ford, and Toyota are reductions in price of $1315, $663, and $754, respectively. The price effects are more negative for fuel inefficient SUVs. By contrast, the estimated price effects are positive for nearly 30 percent of the Chrysler SUVs and the price effects are actually more negative for fuel efficient SUVs.[31] The unexpected pattern among Chrysler SUVs exists because the estimated fuel cost coefficient is positive and the competitor fuel cost coefficient is negative (see Appendix Table A-1), inconsistent with the profit maximizing pricing rule derived in the theoretical framework.

4.2 Extensions

4.2.1 Lagged retail gasoline prices and gasoline futures

The main results are based on the premise that consumers form expectations about future retail gasoline prices based on current retail gasoline prices. We explore that premise here. In particular, we examine whether manufacturers set vehicle prices in response to information on historical gasoline prices and gasoline futures prices. We construct two new sets of fuel cost variables. The first uses the mean retail gasoline price over the previous four weeks, and the second uses the one-month futures price for retail gasoline. To the extent that consumers are backward-looking and forward-looking, respectively, manufacturers should adjust vehicle prices to these new fuel cost variables. The units of observation are at the vehicle-week level; we discard regional variation because futures

[31]The univariate correlation coefficients between the price effects and miles-per-gallon are 0.9062, 0.8584, and 0.9447 for GM, Ford, and Toyota, respectively, and -0.1765 for Chrysler.

prices are available only at the national level. The results are therefore comparable to Column 3 of Table 3.

Table 4 presents the regression results. Columns 1 and 2 include variables based on mean lagged gasoline prices and gasoline futures prices, respectively. The fuel cost coefficients are -64.55 and -47.66; the competitor fuel cost coefficients are 50.01 and 63.32. The coefficients are statistically significant and consistent with the theoretical model. Still, the more interesting question is whether these variables matter after controlling for the current price of retail gasoline. Columns 3 and 4 include variables based on mean lagged gasoline prices and gasoline futures prices, respectively, together with variables based on the current gasoline price. Each of the coefficients takes the expected sign and statistical significance is maintained for all but two coefficients. Finally, Column 5 includes variables based on mean lagged gasoline prices and variables based on gasoline futures prices. The coefficients are precisely estimated and again take the correct sign.

The finding that consumers may use historical gasoline prices and gasoline futures prices to form expectations for gasoline prices is interesting, in part because both the empirical evidence and the conventional wisdom of industry experts suggest that gasoline prices follow a random walk (as we outline Section 3). One could argue that some consumers form inefficient expectations for future gasoline prices. Alternatively, some consumers may be imperfectly informed about the current gasoline price; these consumers could rationally turn to alternative sources of information, such as historical prices and/or futures prices. We are skeptical that our data can untangle these informal hypotheses and hope that future research better addresses the topic.

4.2.2 Impulse Response Functions

In this section, we examine manufacturer price responses for hypothetical, "perfectly average" vehicles. We define a perfectly average vehicle as one whose miles-per-gallon, weighted-average competitor miles-per-gallon, and weighted-average same-firm miles-per-gallon are all at the mean (for cars the mean is 25.99; for SUVs it is 18.80). Hypothetical vehicles are advantageous for comparisons of manufacturers because they strip away the vehicle heterogeneity that may not be apparent in the main results (e.g., Figures 6 and 7); one can essentially compare the performance of manufacturer price rules under identical circumstances.[32]

We use impulse response functions to track the effects of a gasoline price shock, during the week of the shock and each of the following ten weeks. The approach may be of additional interest to the extent that it captures dynamics. To compute the impulse response function, we add ten lags of each fuel cost variable to the baseline specification, and estimate the specification separately for the cars and SUVs of each manufacturer. We then calculate the predicted effects of a one dollar increase in the gasoline price for the perfectly average car and SUV (in principle, one could examine

[32]For example, based on Figure 6 alone, it is not clear whether Chrysler employs a fundamentally different pricing rule than GM, Ford, and Toyota, or whether its vehicles are simply more fuel efficient than their competitors (e.g., they could be closer to inefficient vehicles in attribute space).

any hypothetical vehicle).

Figure 9 shows the results.[33] Starting with the cars, GM, Ford, and Toyota reduce prices by \$516, \$495, and \$691, respectively, immediately following the gasoline price shock, while Chrysler increases prices by \$106. The discrepancies between the manufacturer grow steadily over the following ten weeks; by the final week, the net price changes are reductions of \$1,495, \$2,767, \$1,673, and \$21 for GM, Ford, Toyota, and Chrysler, respectively. Turning to the SUVs, GM, Ford, and Toyota reduce their prices by \$121, \$105, and \$569, respectively, immediately following the gasoline shock, while Chrysler increases prices by \$63. Again, the discrepancies between the manufacturer grow steadily over the following weeks; by the final week, the net price changes are reductions of \$831, \$612, \$1,422, and \$72 for GM, Ford, Toyota, and Chrysler, respectively. Overall, Ford reacts most aggressively relative to the other manufacturers in adjusting its car prices; Toyota reacts most aggressively for SUVs. Chrysler's reactions are negligible for both vehicle types.

Two of the results merit further discussion. First, we find Chrysler's price responses puzzling because the theoretical framework indicates that demand for the perfectly average vehicle *must fall* in response to an adverse gasoline shock.[34] We are reticent to conclude that Chrysler's pricing rule is suboptimal, however, in the absence of more sure evidence. It is possible that Chrysler's consumers are distinctly unresponsive to fuel costs, or that Chrysler adjusts its prices without using incentives.[35] Second, the result that manufacturer prices continue to fall after the initial gasoline price shock is consistent with the hypothesis that consumers internalize gasoline price shocks slowly over time. The result could also be consistent with some forms of dynamic competition or certain supply-side frictions; we leave the exploration of these possibilities to future research.

4.2.3 Demand and cost factors

In the main regressions we estimate a separate time fixed effect for each of the 208 weeks in the data. These fixed effects capture the combined influence of demand and cost factors that change over time through the sample period. In this section, we use a second-stage regression to decompose the fixed effects into contributions from specific time-varying demand and cost factors. We are particularly interested in whether the retail gasoline price affects manufacturer prices after having controlled for its impact on vehicle fuel costs. Such an effect could be present if higher gasoline prices increase manufacturer production costs or reduce consumer demand through an income effect.[36] One might

[33] Appendix Tables A-3 and A-4 provide the regression coefficients. The individual coefficients are difficult to interpret due to the high degree of co-linearity among the 33 fuel cost regressors, but the net manufacturer price effects are reasonable, easily interpretable, and consistent with the main results.

[34] A corollary is that the fuel cost coefficient should be larger in magnitude than the competitor fuel cost coefficient, i.e., $|\phi^1_{jt}| > |\phi^2_{jt}|$. In the main regression results, shown in Table A-1, this holds for GM, Ford, and Toyota, but not for Chrysler.

[35] Chrysler dealerships may adjust prices. We note, however, that our data include cash incentives paid to both consumers ("consumer-cash") and dealerships ("dealer-cash").

[36] For example, Gicheva, Hastings, and Villas-Boas (2007) identify an income effect of gasoline prices using scanner data on grocery purchases.

expect these two channels to partially offset; we can identify only the net effect.

Figure 8 plots the time fixed effects estimated in Column 3 of Table 3, together with the prime interest rate and the unemployment rate (which may shift demand), price indices for electricity and steel (which may shift manufacturer costs), and the retail gasoline price (which may shift demand and costs). The fixed effects units are in thousands, so that a fixed effect of 0.25 represents manufacturer prices that are $250 on average higher than manufacturer prices during the first week of 2003 (the base date). The fixed effects are higher in the winter months than in the summer months, consistent with the notion that manufacturer prices fall as consumers anticipate the arrival of new vehicles to the market in the summer months (e.g., Copeland, Dunn, and Hall 2005). The prime interest rate increases over the sample while unemployment decreases; the means of these variables are 5.64 and 5.30, respectively. The electricity and steel indices are defined relative to January 1, 2003; the prices of these cost factors increase over the sample by 10 and 61 percent, respectively. The mean gasoline price is $2.16 per gallon, and gasoline prices increase over the sample.[37]

We regress the estimated time fixed effects on different combinations of the demand and cost factors.[38] Table 5 presents the results. Column 1 features only the gasoline price, Column 2 features the gasoline price and the other demand factors, Column 3 features gasoline price and the other cost factors, and Column 4 features all five demand and cost factors. The coefficients are remarkably stable across specifications. In each column, the gasoline price coefficient is small and statistically indistinguishable from zero; gasoline prices appear to have little effect on manufacturer prices after controlling for vehicle fuel costs. The remaining coefficients take the expected signs. Based on the Column 4 regression, a one percentage point increase in prime interest rate reduces manufacturer prices by $164 and a one percentage point increase in the unemployment rate reduces manufacturer prices by $104 (though the latter effect is not statistically significant). Similarly, ten percent increases in the prices of electricity and steel raise manufacturer prices by $283 and $55, respectively.

4.2.4 Vehicle inventories

We use the assumption that manufacturers have full information about consumer demand conditions to generate a simple linear pricing rule. It is not clear whether the assumption is appropriate. For example, manufacturers may receive only noisy signals about demand, and accurate informa-

[37]The electricity index is publicly available from the EIA, and the steel index is publicly available from Producer Price Index maintained by the Bureau of Labor Statistics. We deseasonalize both indices using the X12-ARIMA prior to their use in analysis.

[38]Each regression includes week fixed effects to help control for seasonality. To be clear, we estimate 52 week fixed effects using 208 weekly observations; equivalent weeks in each year are constrained to have the same fixed effect. We use the Newey and West (1987) variance matrix to account for first-order autocorrelation. The standard errors do not change substantially when we account for higher-order autocorrelation. We are unable to use the more general clustering correction because the data lack cross-sectional variation. Of course, the standard errors may be too small because the dependent variable is estimated in a prior stage.

tion may be costly to obtain. In such an environment, one might expect manufacturers to set their prices primarily based on their observed inventories; demand conditions would affect prices only indirectly. As a specification test, we re-estimate the empirical model controlling for inventories. The main theoretical framework – and its simple pricing rule – should gain credibility if the fuel cost coefficients remain important.

To implement the test, we collect data on the "days supply" of inventory from Automotive News, a major trade publication. Days supply is the current inventory divided by sales during the previous month (the units are easily converted from months to days). The measure is frequently used in industry analysis (e.g., Windecker 2003). Intuitively, the days supply should be high when demand is sluggish and low when demand is great. The units of observation are at the month-model level. To be clear, the inventories data do not vary across weeks within a month, and the data lump all vehicles within a given model (e.g., the 2003 Dodge Neon and 2004 Dodge Neon). We map the data into the main regression sample by using cubic splines to interpolate weekly observations. We then apply the days supply to every vehicle in the model category. The procedure generates a regression sample of 500 vehicles and 41,822 vehicle-week observations.[39]

Table 6 presents the regression results. In Column 1, we re-estimate the same specification as in Table 3, Column 3 using only those observations for which we have information on inventories. The fuel cost and competitor fuel cost coefficients are -69.23 and 53.16, respectively.[40] We add the days supply measure to the specification in Column 2. The fuel cost and competitor fuel cost coefficients of -69.11 and 53.00 are virtually unchanged.[41] The result suggests that manufacturers respond to changes in demand conditions before these changes affect inventories; one might infer that manufacturers are well informed about consumer preferences. The result also strengthens our interpretation of the main empirical results: manufacturers intentionally set prices as if consumers respond to gasoline prices.

5 Conclusion

We provide empirical evidence that automobile manufacturers adjust vehicle prices in response to changes in the price of retail gasoline. In particular, we show that the vehicle prices tend to decrease in their own fuel costs and increase in the fuel costs of their competitors. The net effect is such that adverse gasoline price shocks reduce the price of most vehicles but raise the price of particularly fuel efficient vehicles. We argue, based on theoretical micro foundations, that these empirical results are

[39] We have inventory data for 500 of the 589 domestic vehicles in the data; the Toyota data are insufficiently disaggregated to support analysis. The mean days supply among the 41,822 vehicle-week observations is 92.18. The 25^{th}, 50^{th}, and 75^{th} percentiles are 62.26, 84.63, and 109.42, respectively.

[40] The fact that these coefficients are close to those produced by the full sample provides some comfort that the smaller inventory sample does not introduce sample selection problems or other complexities.

[41] The days supply coefficient is small and statistically indistinguishable from zero. We are wary of interpreting this coefficient too strongly because inventories may be correlated with the vehicle-time specific cost and demand shocks that compose the error term in the regression equation.

consistent with the notion that automobile manufacturers set prices as if consumers value (low) fuel costs. In terms of policy implications, the results suggest that gasoline and/or carbon taxes may be effective instruments in mitigating the negative externalities associated with gasoline combustion in automobiles. The results do not speak, however, to the optimal magnitude of any policy responses; we leave that important matter to future research.

References

[1] Alquist, Ron and Lutz Kilian. 2008. What do we learn from the price of crude oil futures? Mimeo.

[2] Bento, Antonio, Lawrence Goulder, Emeric Henry, Mark Jacobsen, and Roger von Haefen. 2005. Distributional and efficiency impacts of gasoline taxes: an econometrically based multi-market study. *American Economic Review – Papers and Proceedings*, 95.

[3] Berry, Steve, Jim Levinsohn, and Ariel Pakes. 2004. Estimating differentiated product demand systems from a combination of micro and macro data: the market for new vehicles. *Journal of Political Economy*, 112: 68-105.

[4] Copeland, Adam, Wendy Dunn, and George Hall. 2005. Prices, production and inventories over the automotive model year. NBER Working Paper 11257.

[5] Corrado, Carol, Wendy Dunn, and Maria Otoo. 2006. Incentives and prices for motor vehicles: what has been happening in recent years. FEDS Working Paper.

[6] Davies, Peter. 2007. What's the value of an energy economist? Speech presented at the International Association of Energy Economics, Wellington, New Zealand.

[7] Dickey, D. A., and W. A. Fuller. 1979. Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74: 427431.

[8] Department of Energy, Energy Information Agency. 2006. A primer on gasoline prices.

[9] Gicheva, Dora, Justine Hastings, and Sofia Villas-Boas. 2007. Revisiting the income effect: gasoline prices and grocery purchases. CUDARE Working Paper.

[10] Goldberg, Pinelopi. 1998. The effects of the corporate average fuel economy standards in the automobile industry. *Journal of Industrial Economics*, 46: 1-33.

[11] Jacobsen, Mark. 2008. Evaluating U.S. fuel economy standards in a model with producer and household heterogeneity. Mimeo.

[12] Li, Shanjun, Christopher Timmins, and Roger H. von Haefen. 2007. Do gasoline prices affect fleet fuel economy? Mimeo.

[13] Makridakis, Spyros, Steven C. Wheelwright, and Rob J. Hyndman. 1998. *Forecasting Methods and Applications*. (3^{rd} ed.). New York: Wiley.

[14] Miller, Don M. and Dan Williams. 2004. Damping seasonal factors: Shrinkage estimators for the X-12-ARIMA program. *International Journal of Forecasting*, 20: 529-549.

[15] Newey, Whitney K., and Kenneth D. West. 1987. A simple positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55: 703-708.

[16] Windecker, Ray. 2003. The battle of the bulge: the intricacies and lessons of days supply. *Automotive Industries*, November.

[17] Train, Kenneth and Cliff Winston. 2007. Vehicle choice behavior and the declining market share of U.S. automakers. *International Economic Review*, 48: 1469-1496.

A Elasticity Bias

In our introductory remarks, we argued informally that structural estimation can understate consumer responsiveness to fuel costs if it fails to account for manufacturer price responses. We formalize our argument here in the context of logit demand. In particular, we demonstrate that 1) estimation yields a fuel cost coefficient that is biased downwards and 2) one can estimate the magnitude of bias with data on gasoline and manufacturer prices.

Under a set of standard (and restrictive) assumptions, the logit demand system generates the well-known regression equation:

$$\log(s_{jt}) - \log(s_{0t}) = \psi(p_{jt} + x_{jt}) + \kappa_j + \nu_{jt}, \tag{A-1}$$

where s_{jt} and s_{0t} are the market shares of vehicle j and the outside good, respectively, p_{jt} is the vehicle price, x_{jt} captures the expected lifetime fuel costs, κ_j is vehicle "quality," and ν_{jt} is an error term that captures demand shocks.

Assuming away the obvious endogeneity issues, one can use OLS with vehicle fixed effects to obtain consistent estimates of ψ, the parameter of interest. However, suppose that one observes the mean price of each vehicle rather than the true price. The regression equation becomes:

$$\log(s_{jt}) - \log(s_{0t}) = \psi x_{jt} + \kappa_j^* + \nu_{jt}^*, \tag{A-2}$$

where $\kappa_j^* = \kappa_j + \psi \overline{p}_j$ and $\nu_{jt}^* = \nu_{jt} + \psi(p_{jt} - \overline{p}_j)$. The problem is now apparent. Gasoline price shocks affect not only x_{jt} but also the composite error term ν_{jt}^* through the manufacturer response. Since, as we document above, adverse gasoline shocks typically induce manufacturers to lower prices, the OLS estimate of ψ is biased downwards. Going further, the regression coefficient has the expression:

$$\begin{aligned} \widehat{\psi} &= \psi + \frac{\sum(x_{jt} - \overline{x}_j)\nu_{jt}}{\sum(x_{jt} - \overline{x}_j)^2} + \frac{\sum(x_{jt} - \overline{x}_j)\psi(p_{jt} - \overline{p}_j)}{\sum(x_{jt} - \overline{x}_j)^2} \\ &\rightarrow^p \psi\left(1 + \frac{\sum(x_{jt} - \overline{x}_j)(p_{jt} - \overline{p}_j)}{\sum(x_{jt} - \overline{x}_j)^2}\right). \end{aligned} \tag{A-3}$$

Thus, it is possible to estimate the magnitude of bias simply by regressing vehicle prices on expected lifetime fuel costs and a set of fixed effects; one need not have market share data or any other inputs to the structural model.

Such a procedure has its difficulties. Perhaps the most central is constructing an appropriate proxy for expected lifetime fuel costs.[42] We use the discounted price-per-mile, i.e., $x_{jt} = (\text{gp}_t/\text{mpg}_j)/(1-\delta)$, and impose a per-mile discount rate of $\delta = 0.999995401$; this corresponds to an annual discount rate of 0.95, assuming 11,154 miles per year.[43] We measure manufacturer prices in dollars, rather than thousands of dollars, to sidestep any problems associated with unit conversion. We then regress manufacturer prices on lifetime fuel costs, vehicle fixed effects, and time fixed effects. The resulting coefficient of -0.141 (standard error = 0.019) corresponds to a downward bias of 14 percent.[44]

[42] Of course, structural estimation also requires one to proxy fuel costs. Goldberg (1998), Bento et al (2005) and Jacobsen (2007) all use measures based on price-per-mile.

[43] The Department of Transportation estimates the average vehicle lifespan to be thirteen years and 145,000 miles; based on these data, the average number of miles per year is 11,154.

[44] The calculation is sensitive to the discount rate. An annual discount rate of 0.99 produces a bias of 2.7 percent;

Although we hope our empirical estimate of bias provides a useful benchmark, we caution against taking the calculation too literally. Data imperfections and/or specification errors could result in an estimate that is too high or too low. For example, our measure of manufacturer prices is based on incentives offered to consumers and does not fully capture transaction prices or even the actual incentives selected. Our proxy for expected lifetime fuel costs imposes both a specific form of multiplicative discounting and an arbitrary discount rate. Aside from these estimation issues, the bias formula itself is based on logit assumptions that are generally considered too restrictive. More flexible structural models still understate consumer responsiveness to fuel costs – the negative correlation between fuel costs and unobserved price responses remains – but the bias is nonlinear and could be substantially larger or smaller than what we estimate here.

B Analytical solutions to the theoretical model

B.1 Three single-vehicle manufacturers

We derive analytical solutions to the theoretical model for the specific case of three single-product manufacturers that compete in prices. The profit equation specified in Equation 1 takes the form:

$$\pi_j = (p_j - c_j) * q_j(\widetilde{p}_\cdot) - f_j, \tag{B1-1}$$

where p_j is the price of vehicle j, the scalar c_j captures the marginal cost of production, the quantity demanded q_j is a function of the "full" vehicle price, inclusive of fuel costs, and f_j is a fixed cost. We specify the linear demand system:

$$q_j = \alpha_{jj}(p_j + x_j) + \sum_{k \neq j} \alpha_{jk}(p_k + x_k) + \mu_j \tag{B1-2}$$

in which the scalar x_j is the fuel cost of vehicle j, and the scalar μ_j is an exogenous demand shifter. We are concerned with the case in which demand is well-defined (so that $\alpha_{jj} < 0 \; \forall j$) and vehicles are substitutes (so that $\alpha_{jk} > 0 \; \forall j \neq k$). The first-order condition for the equilibrium price of vehicle j can be expressed as follows:

$$p_j^* = \frac{1}{2}\left(c_j - \frac{1}{\alpha_{jj}}\mu_j\right) - \frac{1}{2}x_j - \frac{1}{2}\sum_{k \neq j} \frac{\alpha_{jk}}{\alpha_{jj}}(p_k + x_k) \tag{B1-3}$$

an annual discount rate of 0.90 produces a bias of 28.9 percent.

We solve the system of equations for the equilibrium vehicle prices as functions of the non-price variables. The equilibrium price for vehicle 1 has the expression:

$$
\begin{aligned}
p_1^* \quad * & \quad \left[1 - \frac{1}{4}\frac{\alpha_{23}}{\alpha_{22}}\frac{\alpha_{32}}{\alpha_{33}} - \frac{1}{4}\frac{\alpha_{12}}{\alpha_{11}}\frac{\alpha_{21}}{\alpha_{22}} - \frac{1}{4}\frac{\alpha_{13}}{\alpha_{11}}\frac{\alpha_{31}}{\alpha_{33}} + \frac{1}{8}\frac{\alpha_{12}}{\alpha_{11}}\frac{\alpha_{23}}{\alpha_{22}}\frac{\alpha_{31}}{\alpha_{33}} + \frac{1}{8}\frac{\alpha_{13}}{\alpha_{11}}\frac{\alpha_{32}}{\alpha_{33}}\frac{\alpha_{21}}{\alpha_{22}}\right] \\
= & \quad -\frac{1}{2}\left[1 - \frac{1}{4}\frac{\alpha_{23}}{\alpha_{22}}\frac{\alpha_{32}}{\alpha_{33}} - \frac{1}{2}\frac{\alpha_{12}}{\alpha_{11}}\frac{\alpha_{21}}{\alpha_{22}} - \frac{1}{2}\frac{\alpha_{13}}{\alpha_{11}}\frac{\alpha_{31}}{\alpha_{33}} + \frac{1}{4}\frac{\alpha_{12}}{\alpha_{11}}\frac{\alpha_{23}}{\alpha_{22}}\frac{\alpha_{31}}{\alpha_{33}} + \frac{1}{4}\frac{\alpha_{13}}{\alpha_{11}}\frac{\alpha_{32}}{\alpha_{33}}\frac{\alpha_{21}}{\alpha_{22}}\right] * x_1 \\
& \quad -\frac{1}{4}\left[\frac{\alpha_{12}}{\alpha_{11}} - \frac{1}{2}\frac{\alpha_{13}}{\alpha_{11}}\frac{\alpha_{32}}{\alpha_{33}}\right] * x_2 - \frac{1}{4}\left[\frac{\alpha_{13}}{\alpha_{11}} - \frac{1}{2}\frac{\alpha_{12}}{\alpha_{11}}\frac{\alpha_{23}}{\alpha_{22}}\right] * x_3 \qquad \text{(B1-4)} \\
& \quad +\frac{1}{2}\left[1 - \frac{1}{4}\frac{\alpha_{23}}{\alpha_{22}}\frac{\alpha_{32}}{\alpha_{33}}\right] * \left(c_1 - \frac{1}{\alpha_{11}}\mu_1\right) \\
& \quad -\left[\frac{1}{4}\frac{\alpha_{12}}{\alpha_{11}} - \frac{1}{8}\frac{\alpha_{13}}{\alpha_{11}}\frac{\alpha_{32}}{\alpha_{33}}\right] * \left(c_2 - \frac{1}{\alpha_{22}}\mu_2\right) - \left[\frac{1}{4}\frac{\alpha_{13}}{\alpha_{11}} - \frac{1}{8}\frac{\alpha_{12}}{\alpha_{11}}\frac{\alpha_{23}}{\alpha_{22}}\right] * \left(c_3 - \frac{1}{\alpha_{33}}\mu_3\right)
\end{aligned}
$$

The equilibrium prices for vehicles 2 and 3 are analogous. One can combine the two competitor fuel cost terms into a single term that captures the influence of the weighted average competitor fuel cost. This single term has the expression:

$$
-\frac{1}{4}\left[\frac{\alpha_{12}}{\alpha_{11}} + \frac{\alpha_{13}}{\alpha_{11}} - \frac{1}{2}\frac{\alpha_{12}}{\alpha_{11}}\frac{\alpha_{23}}{\alpha_{22}} - \frac{1}{2}\frac{\alpha_{13}}{\alpha_{11}}\frac{\alpha_{32}}{\alpha_{33}}\right] * \left(\omega_{12}x_2 + \omega_{13}x_3\right), \qquad \text{(B1-5)}
$$

where the weights w_{12} and w_{13} sum to one. The weights are functions of the demand parameters:

$$
\begin{aligned}
\omega_{12} &= \frac{\frac{\alpha_{12}}{\alpha_{11}} - \frac{1}{2}\frac{\alpha_{13}}{\alpha_{11}}\frac{\alpha_{32}}{\alpha_{33}}}{\frac{\alpha_{12}}{\alpha_{11}} + \frac{\alpha_{13}}{\alpha_{11}} - \frac{1}{2}\frac{\alpha_{12}}{\alpha_{11}}\frac{\alpha_{23}}{\alpha_{22}} - \frac{1}{2}\frac{\alpha_{13}}{\alpha_{11}}\frac{\alpha_{32}}{\alpha_{33}}} \\
& \qquad \text{(B1-6)} \\
\omega_{13} &= \frac{\frac{\alpha_{13}}{\alpha_{11}} - \frac{1}{2}\frac{\alpha_{12}}{\alpha_{11}}\frac{\alpha_{23}}{\alpha_{22}}}{\frac{\alpha_{12}}{\alpha_{11}} + \frac{\alpha_{13}}{\alpha_{11}} - \frac{1}{2}\frac{\alpha_{12}}{\alpha_{11}}\frac{\alpha_{23}}{\alpha_{22}} - \frac{1}{2}\frac{\alpha_{13}}{\alpha_{11}}\frac{\alpha_{32}}{\alpha_{33}}}.
\end{aligned}
$$

A single regularity condition generates the following results regarding the relationship between equilibrium prices and fuel costs:

Result A1-1: $\dfrac{\partial p_1^*}{\partial x_1} \in [-1, 0]$ and $\dfrac{\partial p_1^*}{\partial(\omega_{12}x_2 + \omega_{13}x_3)} \in [0, 1]$

Result A1-2: $\left|\dfrac{\partial p_1^*}{\partial x_1}\right| > \left|\dfrac{\partial p_1^*}{\partial(\omega_{12}x_2 + \omega_{13}x_3)}\right|$

Thus, in any empirical implementation, one should expect that the regression coefficient on fuel costs should be negative, that the coefficient on the weighted average competitor fuel costs should be positive, and that the first coefficient should be larger in magnitude than the second. If one proxies cumulative fuel costs using a measure of current fuel costs – for example, the "price per-mile" variable that we employ – then the coefficients may be much larger than one in magnitude.

The same regularity condition generates the following results regarding the weights:

$$\text{Result A1-3:} \qquad \omega_{12} \in (0,1) \text{ and } \omega_{13} \in (0,1)$$

$$\text{Result A1-4:} \qquad \frac{\partial \omega_{12}}{\partial \alpha_{12}} > 0 \text{ and } \frac{\partial \omega_{13}}{\partial \alpha_{13}} > 0$$

Since the parameters α_{12} and α_{13} govern the severity of competition between vehicles, it is appropriate to weight "closer" competitors more heavily when constructing the empirical proxies for the weights. The regularity condition that generates these results is:

$$\begin{aligned} 1 > \quad & -\frac{1}{2}\frac{\alpha_{12}}{\alpha_{11}} - \frac{1}{2}\frac{\alpha_{13}}{\alpha_{11}} + \frac{1}{2}\frac{\alpha_{12}}{\alpha_{11}}\frac{\alpha_{21}}{\alpha_{22}} + \frac{1}{2}\frac{\alpha_{13}}{\alpha_{11}}\frac{\alpha_{31}}{\alpha_{33}} + \frac{1}{4}\frac{\alpha_{23}}{\alpha_{22}}\frac{\alpha_{32}}{\alpha_{33}} \\ + \quad & \frac{1}{4}\frac{\alpha_{12}}{\alpha_{11}}\frac{\alpha_{23}}{\alpha_{22}} + \frac{1}{4}\frac{\alpha_{13}}{\alpha_{11}}\frac{\alpha_{32}}{\alpha_{33}} - \frac{1}{4}\frac{\alpha_{12}}{\alpha_{11}}\frac{\alpha_{23}}{\alpha_{22}}\frac{\alpha_{31}}{\alpha_{33}} - \frac{1}{4}\frac{\alpha_{13}}{\alpha_{11}}\frac{\alpha_{32}}{\alpha_{33}}\frac{\alpha_{21}}{\alpha_{22}}. \end{aligned} \tag{B1-7}$$

The condition holds provided that the own-price parameters are sufficiently large relatively to the cross-price parameters. For intuition, it may be useful to note that each right-hand-side term enters as a positive because the own-price parameters are negative and the cross-price parameters are positive. Although these results extend naturally to cases with $J > 3$ manufacturers, the algebraic burden associated with obtaining analytical solutions increases exponentially with J.

B.2 One manufacturer with three vehicles

We derive analytical solutions to the theoretical model for the specific case of a single manufacturer that produces three distinct products. The first-order conditions for profit maximization are identical to those presented in Section 2, i.e.,

$$\frac{\partial \pi_{\Im t}}{\partial p_{jt}} = \sum_k \alpha_{jk}(p_{kt} + x_{kt}) + \mu_{jt} + \sum_k \alpha_{kj}(p_{kt} - c_{kt}) = 0. \tag{B2-1}$$

We solve the system of equations for the equilibrium vehicle prices as functions of the non-price variables. The equilibrium price for vehicle 1 has the expression:

$$
\begin{aligned}
p_1^* \quad * \quad & \left[1-\frac{1}{4}\frac{(\alpha_{23}+\alpha_{32})^2}{\alpha_{22}\alpha_{33}}-\frac{1}{4}\frac{(\alpha_{12}+\alpha_{21})^2}{\alpha_{11}\alpha_{22}}-\frac{1}{4}\frac{(\alpha_{13}+\alpha_{31})^2}{\alpha_{11}\alpha_{33}}+\frac{1}{4}\frac{\alpha_{12}+\alpha_{21}}{\alpha_{11}}\frac{\alpha_{23}+\alpha_{32}}{\alpha_{22}}\frac{\alpha_{13}+\alpha_{31}}{\alpha_{33}}\right] \\
= \quad & -\frac{1}{2}\left[1-\frac{1}{4}\frac{(\alpha_{23}+\alpha_{32})^2}{\alpha_{22}\alpha_{33}}-\frac{1}{2}\frac{\alpha_{12}+\alpha_{21}}{\alpha_{11}}\frac{\alpha_{21}}{\alpha_{22}}-\frac{1}{2}\frac{\alpha_{13}+\alpha_{31}}{\alpha_{11}}\frac{\alpha_{31}}{\alpha_{33}}\right. \\
& \qquad \left.+\frac{1}{4}\frac{\alpha_{12}+\alpha_{21}}{\alpha_{11}}\frac{\alpha_{23}+\alpha_{32}}{\alpha_{22}}\frac{\alpha_{31}}{\alpha_{33}}+\frac{1}{4}\frac{\alpha_{13}+\alpha_{31}}{\alpha_{11}}\frac{\alpha_{23}+\alpha_{32}}{\alpha_{33}}\frac{\alpha_{21}}{\alpha_{22}}\right]*x_1 \\
& -\frac{1}{2}\left[\frac{\alpha_{12}}{\alpha_{11}}-\frac{1}{2}\frac{\alpha_{12}+\alpha_{21}}{\alpha_{11}}-\frac{1}{2}\frac{\alpha_{13}+\alpha_{31}}{\alpha_{11}}\frac{\alpha_{32}}{\alpha_{33}}+\frac{1}{4}\frac{\alpha_{13}+\alpha_{31}}{\alpha_{11}}\frac{\alpha_{32}+\alpha_{23}}{\alpha_{33}}\right. \\
& \qquad \left.+\frac{1}{4}\frac{\alpha_{12}+\alpha_{21}}{\alpha_{11}}\frac{\alpha_{23}+\alpha_{32}}{\alpha_{22}}\frac{\alpha_{32}}{\alpha_{33}}-\frac{1}{4}\frac{\alpha_{23}+\alpha_{32}}{\alpha_{22}}\frac{\alpha_{23}+\alpha_{32}}{\alpha_{33}}\frac{\alpha_{12}}{\alpha_{11}}\right]*x_2 \\
& -\frac{1}{2}\left[\frac{\alpha_{13}}{\alpha_{11}}-\frac{1}{2}\frac{\alpha_{13}+\alpha_{31}}{\alpha_{11}}-\frac{1}{2}\frac{\alpha_{12}+\alpha_{21}}{\alpha_{11}}\frac{\alpha_{23}}{\alpha_{22}}+\frac{1}{4}\frac{\alpha_{12}+\alpha_{21}}{\alpha_{11}}\frac{\alpha_{23}+\alpha_{32}}{\alpha_{22}}\right. \\
& \qquad \left.+\frac{1}{4}\frac{\alpha_{13}+\alpha_{31}}{\alpha_{11}}\frac{\alpha_{23}+\alpha_{32}}{\alpha_{33}}\frac{\alpha_{23}}{\alpha_{22}}-\frac{1}{4}\frac{\alpha_{23}+\alpha_{32}}{\alpha_{33}}\frac{\alpha_{23}+\alpha_{32}}{\alpha_{22}}\frac{\alpha_{13}}{\alpha_{11}}\right]*x_3 \\
& +f(c_1,c_2,c_3,\mu_1,\mu_2,\mu_3),
\end{aligned}
\tag{B2-2}
$$

where, for brevity, we focus on the fuel cost terms. Again, one can combine the fuel cost terms of vehicles 2 and 3 into a single term that captures the weighted average influence of these vehicles. A single regularity condition, slightly stronger than that presented in Equation B2-4, generates the following results:

Result A2-1: $\dfrac{\partial p_1^*}{\partial x_1} \in [-1,0]$; $\dfrac{\partial p_1^*}{\partial x_2} \in [-1,1]$ and $\dfrac{\partial p_1^*}{\partial x_3} \in [-1,1]$

Result A2-2: $\left|\dfrac{\partial p_1^*}{\partial x_1}\right| \leqslant \left|\dfrac{\partial p_1^*}{\partial x_2}\right| \leqslant \left|\dfrac{\partial p_1^*}{\partial x_3}\right|$

Thus, the manufacturer partially offsets changes in fuel costs of a specific vehicle with changes in price of that vehicle. Changes in the fuel costs of *other* vehicles produced by the same manufacturer, however, have ambiguous implications for the vehicle price. Interestingly, in the specific case of symmetric demand (i.e., $\alpha_{jk} = \alpha_{kj} \ \forall \ j,k$), changes in the fuel costs of other vehicles produced by the same manufacturer have no effect on the equilibrium price. The regularity condition that generates these results is:

$$
\begin{aligned}
1 \quad > \quad & \frac{1}{4}\frac{(\alpha_{12}+\alpha_{21})^2}{\alpha_{11}\alpha_{22}} + \frac{1}{4}\frac{(\alpha_{13}+\alpha_{31})^2}{\alpha_{11}\alpha_{33}} + \frac{1}{4}\frac{(\alpha_{23}-\alpha_{32})^2}{\alpha_{22}\alpha_{33}} \\
+ \quad & \frac{1}{2}\frac{\alpha_{12}+\alpha_{21}}{\alpha_{11}}\frac{\alpha_{21}}{\alpha_{22}} + \frac{1}{2}\frac{\alpha_{13}+\alpha_{31}}{\alpha_{11}}\frac{\alpha_{31}}{\alpha_{33}} \qquad \text{(B2-3)} \\
- \quad & \frac{1}{4}\frac{\alpha_{12}+\alpha_{21}}{\alpha_{11}}\frac{\alpha_{23}+\alpha_{32}}{\alpha_{22}}\frac{\alpha_{31}}{\alpha_{33}} - \frac{1}{4}\frac{\alpha_{13}+\alpha_{31}}{\alpha_{11}}\frac{\alpha_{23}+\alpha_{32}}{\alpha_{33}}\frac{\alpha_{21}}{\alpha_{22}}
\end{aligned}
$$

The condition holds provided that the own-price parameters are sufficiently large relatively to the cross-price parameters. Again, the intuition underlying these results extends naturally to cases with $J > 3$ vehicles.

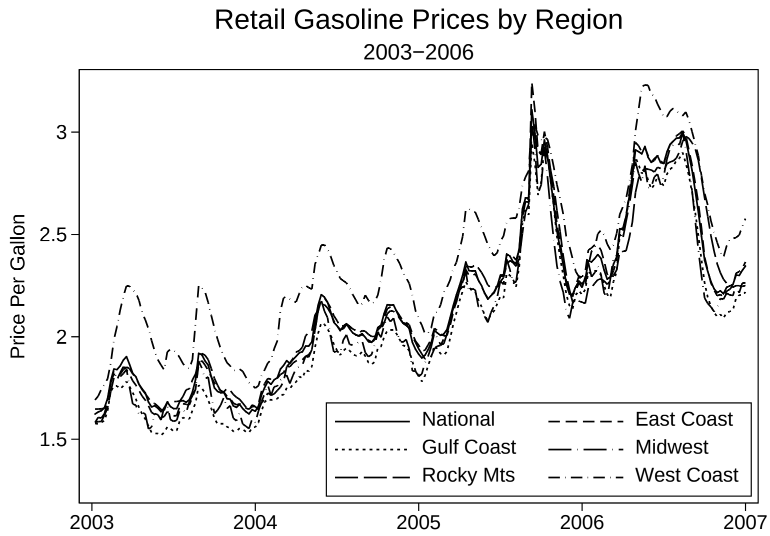

Figure 1: The weekly retail price of gasoline by region over 2003-2006, in real 2006 dollars.

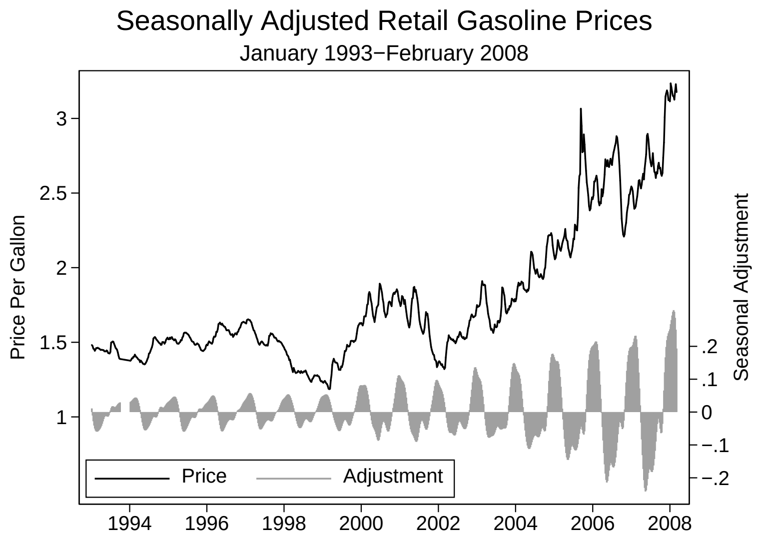

Figure 2: Seasonally adjusted retail gasoline prices at the national level over 1993-2008, in real 2006 dollars. Seasonal adjustments are calculated with the X-12-ARIMA program.

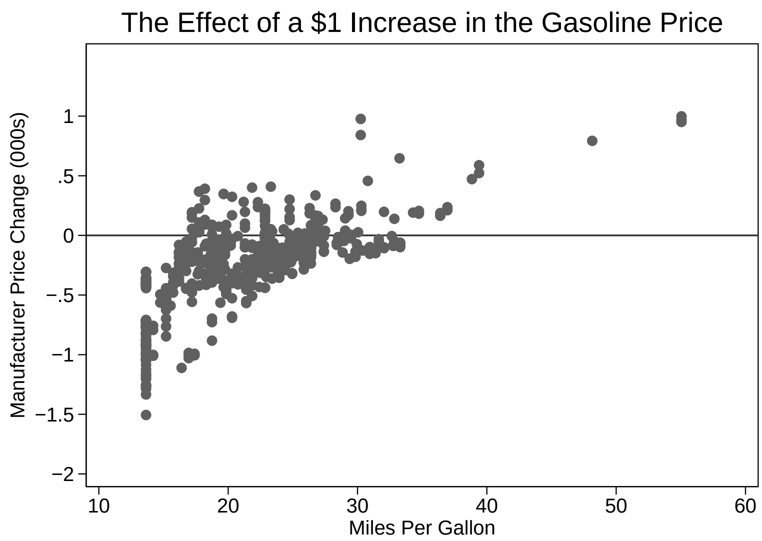

Figure 3: The estimated effects of a one dollar increase in the retail gasoline price on the manufacturer price, based on the regression results in Column 1 of Table 3. Each point represents the price effect for a single vehicle. See text for details.

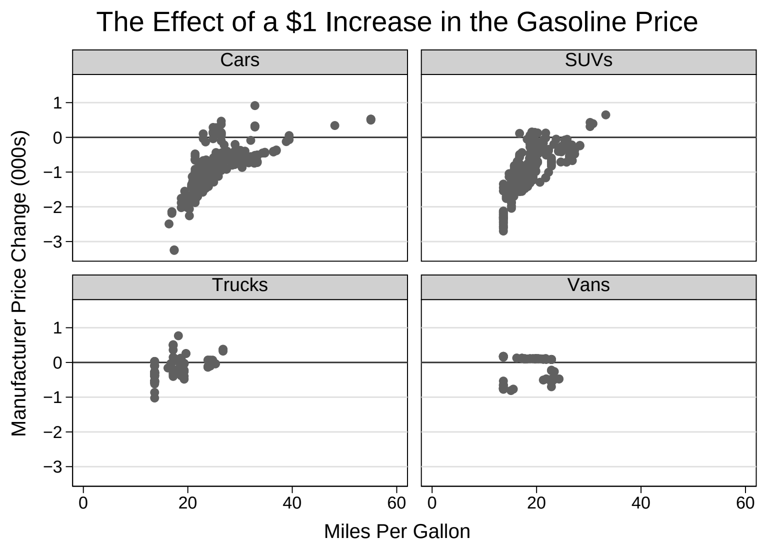

Figure 4: The estimated effects of a one dollar increase in the retail gasoline price on the manufacturer price, based on the regression results of Appendix Table A-1. Each point represents the price effect for a single vehicle. See text for details.

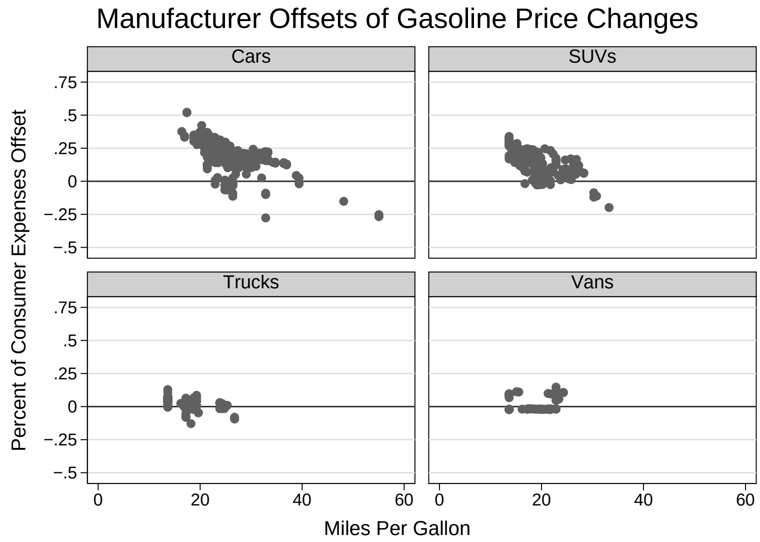

Figure 5: The percentages of consumer cumulative gasoline expenses, due to changes in the retail gasoline price, that are offset by changes in the manufacturer price. Each point represents the percentage for a single vehicle. Based on back-of-the-envelope calculations and the regression results of Appendix Table A-1.

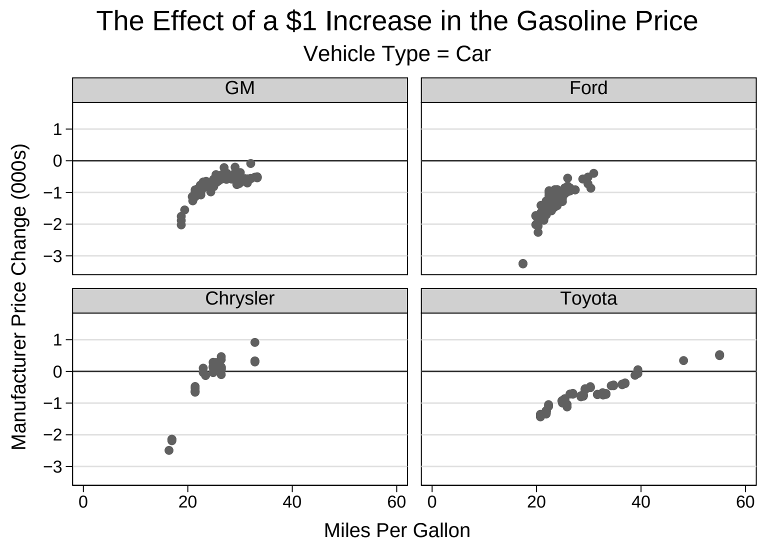

Figure 6: The estimated effects of a one dollar increase in the retail gasoline price on the manufacturer price, based on the regression results of Appendix Table A-1. Each point represents the price effect for a single vehicle. See text for details.

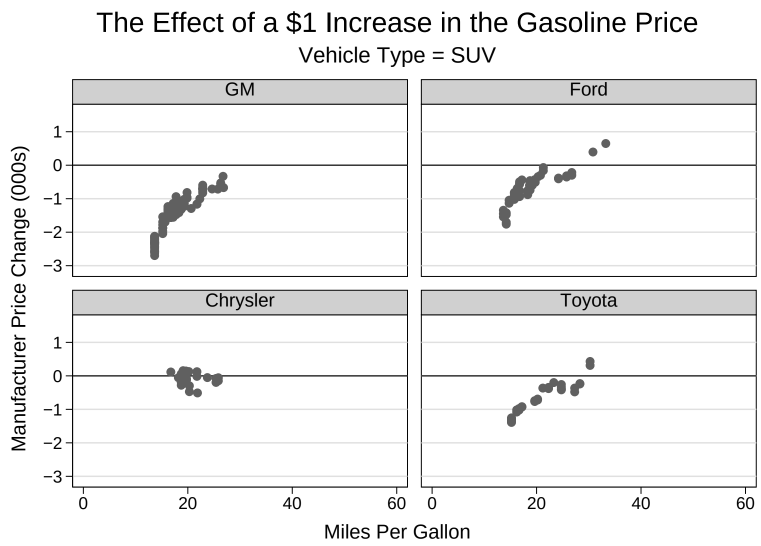

Figure 7: The estimated effects of a one dollar increase in the retail gasoline price on the manufacturer price, based on the regression results of Appendix Table A-1. Each point represents the price effect for a single vehicle. See text for details.

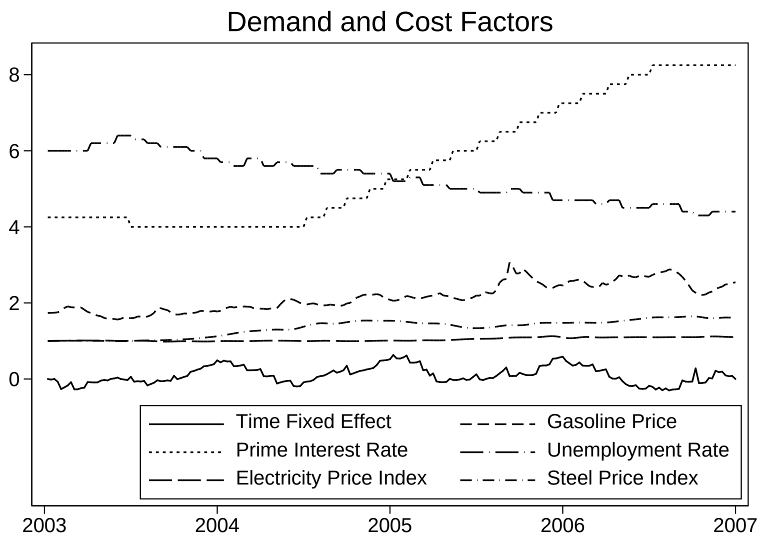

Figure 8: Time-series plots of time fixed effects together with selected demand and cost factors. There are 208 weekly values over 2003-2008. The time fixed effects are estimated in the regression presented in Table 3, Column 3.

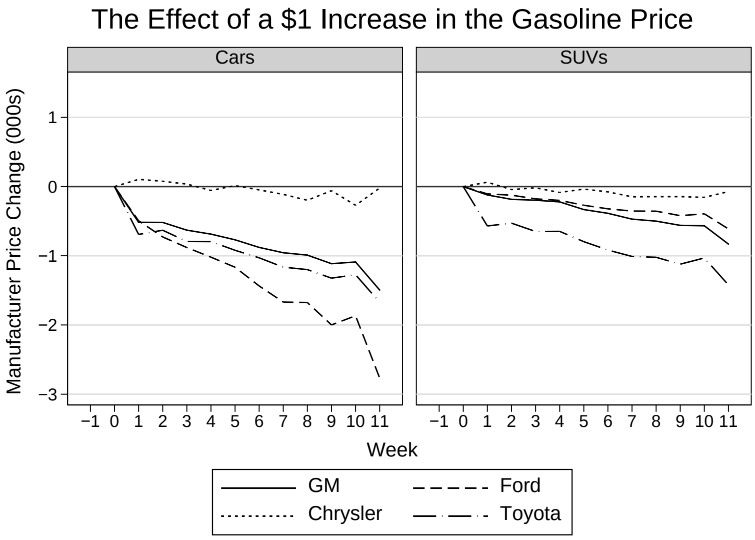

Figure 9: The estimated effects of a one dollar increase in the retail gasoline price for a hypothetical, "perfectly average" vehicle, in the ten weeks following a gasoline price shock. A perfectly average vehicle is one whose miles-per-gallon, weighted-average competitor miles-per-gallon, and weighted-average same-firm miles-per-gallon are all at the mean (for cars the mean is 25.99; for SUVs it is 18.80). The impulse response function is calculated based on the regression coefficients shown in Appendix Tables A-3 and A-4.

Table 1: Summary Statistics

Variables	Definition	Mean	St. Dev.
Manufacturer price	$\text{MSRP}_j - \overline{\text{INC}}_{jrt}$	30.344	16.262
Fuel cost	$\text{gp}_{rt}/\text{mpg}_j$	0.108	0.034
MSRP	MSRP_j	30.782	16.299
Miles-per-gallon	mpg_j	21.555	5.964
Horsepower		224.123	71.451
Wheel base		115.193	12.168
Passenger capacity		4.911	1.633

Means and standard deviations based on 299,855 vehicle-region-week observations over the period 2003-2006. The manufacturer price is defined as MSRP minus the mean regional and national incentives (in thousands). The fuel cost is the gasoline price divided by miles-per-gallon, and captures the gasoline expense per mile. The manufacturer price, the fuel cost, and MSRP (in thousands) are in real 2006 dollars; wheel base is measured in inches.

Table 2: Means by Vehicle Type

Variables	Cars	SUVs	Trucks	Vans
Manufacturer price	30.301	35.782	24.482	24.658
Fuel cost	0.087	0.121	0.133	0.120
MSRP	30.835	36.124	24.881	25.048
Miles-per-gallon	25.991	18.803	17.121	18.815
Horsepower	209.947	241.858	254.383	191.152
Wheel base	107.723	114.880	129.527	123.196
Passenger capacity	4.799	5.849	3.763	4.451
# of observations	125,660	90,270	46,615	37,310

Means based on vehicle-region-week observations over the period 2003-2006. The manufacturer price is defined as MSRP minus the mean regional and national incentives (in thousands). The fuel cost is the gasoline price divided by miles-per-gallon, and captures the gasoline expense per mile. The manufacturer price, the fuel cost, and MSRP (in thousands) are in real 2006 dollars; wheel base is measured in inches.

Table 3: Manufacturer Prices and Fuel Costs

	Incentive level:		
	Regional+ National	Regional Only	National Only
Variables	(1)	(2)	(3)
Fuel cost	-55.40***	-56.96***	-63.75***
	(7.73)	(7.86)	(8.77)
Average competitor fuel cost	50.76***	50.16***	50.09***
	(7.15)	(7.39)	(8.12)
Average same-firm fuel cost	1.15	2.62	1.31
	(2.29)	(1.78)	(2.30)
R^2	0.5260	0.6763	0.5289
# of observations	299,855	299,855	59,971
# of vehicles	681	681	681

Results from OLS regressions. The dependent variable is the manufacturer price, i.e., MSRP minus the mean regional and/or national incentives (in thousands). The units of observation in Columns 1 and 2 are at the vehicle-week-region level. The units of observation in Column 3 are at the vehicle-week level. All regressions include vehicle and time fixed effects, and Columns 1 and 2 include region fixed effects. The regressions also include third-order polynomials in the vehicle age (i.e., weeks since the date of initial production), the average age of vehicles produced by different manufacturers, and the average age of other vehicles produced by the same manufacturer. Standard errors are clustered at the vehicle level and shown in parenthesis. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 4: Gasoline Price Lags and Futures Prices

Variables	Metric	(1)	(2)	(3)	(4)	(5)
Fuel cost	Lagged	-64.55***		-36.51***		-30.08***
	Retail	(8.77)		(10.65)		(8.42)
Average competitor	Lagged	50.01***		23.19**		30.24***
fuel cost	Retail	(8.16)		(10.09)		(9.93)
Fuel cost	Futures		-47.66***		-35.52**	-31.69***
			(7.11)		(16.42)	(9.39)
Average competitor	Futures		63.32***		19.87	27.73**
fuel cost			(10.44)		(24.95)	(13.21)
Fuel cost	Retail			-29.70***	-22.58	
				(10.83)	(16.46)	
Average competitor	Retail			27.70***	33.38*	
fuel cost				(8.14)	(18.87)	
R^2		0.5291	0.5286	0.5295	0.5295	0.5305

Results from OLS regressions. The dependent variable is the manufacturer price, i.e., MSRP minus the mean national incentive (in thousands). The sample includes 59,971 observations on 681 vehicles at the vehicle-week level. Fuel cost variables labeled "lagged retail" are constructed using the mean retail gasoline price over the previous four weeks. Fuel cost variables labeled "futures" are constructed using the one-month futures price of retail gasoline. Fuel cost variables labeled "retail" are constructed using the current retail gasoline price. All regressions include the appropriate average same-firm fuel cost variable(s). The regressions also include vehicle and time fixed effects, as well as third-order polynomials in the vehicle age (i.e., weeks since the date of initial production), the average age of vehicles produced by different manufacturers, and the average age of other vehicles produced by the same manufacturer. Standard errors are clustered at the vehicle level and shown in parenthesis. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 5: Demand and Cost Factors

Variables	(1)	(2)	(3)	(4)
Gasoline Price	-0.015	0.011	-0.102	-0.096
	(0.036)	(0.059)	(0.088)	(0.067)
Interest Rate		-0.128***		-0.164***
		(0.027)		(0.034)
Unemployment Rate		-0.315***		-0.104
		(0.073)		(0.091)
Electricity Price Index			0.950*	2.832***
			(0.540)	(0.726)
Steel Price Index			0.405***	0.549***
			(0.113)	(0.152)
R^2	0.5160	0.6117	0.5829	0.6454

Results from OLS regressions. The data include 208 weekly observations over the period 2003-2006. The dependent variable is the time fixed effect estimated in Column 3 of Table 3. The regressions also include 52 week fixed effects; equivalent weeks in each year are constrained to have the same fixed effect. Standard errors are robust to the presence of heteroskedasticity and first-order autocorrelation. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 6: Manufacturer Prices, Fuel Costs, and Inventories

Variables	(1)	(2)
Fuel cost	-69.23***	-69.11***
	(11.57)	(11.54)
Average competitor fuel cost	53.16***	53.00***
	(9.79)	(9.76)
Average same-firm fuel cost	1.95	1.94
	(3.36)	(3.36)
Vehicle inventory		0.0001
		(0.0001)
R^2	0.6202	0.6203

Results from OLS regressions. The dependent variable is the manufacturer price, i.e., MSRP minus the mean national incentive (in thousands). The sample includes 41,822 observations on 500 vehicles over the period 2003-2006, at the vehicle-week level. The regressions include vehicle and time fixed effects, as well as third-order polynomials in the vehicle age (i.e., weeks since the date of initial production), the average age of vehicles produced by different manufacturers, and the average age of other vehicles produced by the same manufacturer. Standard errors are clustered at the vehicle level and shown in parenthesis. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table A-1: Manufacturer Prices by Vehicle Type and Manufacturer

Vehicle Type:	Cars				SUVs			
Manufacturer:	GM	Ford	Chrysler	Toyota	GM	Ford	Chrysler	Toyota
Fuel cost	-97.52***	-146.80**	-152.09***	-77.13***	-75.98***	-72.10***	45.87*	-62.11***
	(17.85)	(71.68)	(30.81)	(21.55)	(23.26)	(23.50)	(24.92)	(17.82)
Average competitor fuel cost	85.78***	80.61	159.99***	46.38***	64.08***	66.75***	-29.56	44.25***
	(18.25)	(57.25)	(41.91)	(18.52)	(21.67)	(23.79)	(19.01)	(16.41)
Average same-firm fuel cost	-6.47	41.10	-2.56	6.12	8.19	-1.51	-17.88*	1.73
	(8.79)	(29.64)	(11.33)	(4.48)	(9.02)	(6.28)	(10.42)	(4.27)
R^2	0.6173	0.5254	0.5294	0.7282	0.7861	0.6758	0.7126	0.8352
# of vehicles	101	92	34	66	94	50	24	34
Vehicle Type:	Trucks				Vans			
Manufacturer:	GM	Ford	Chrysler	Toyota	GM	Ford	Chrysler	Toyota
Fuel cost	-43.10***	-61.49***	26.07	2.70	2.26	4.02	8.60	30.47
	(5.46)	(17.91)	(20.50)	(15.35)	(1.75)	(6.93)	(8.61)	(14.26)
Average competitor fuel cost	37.77***	57.54***	-30.63	-0.68	-1.12	-1.51	-4.40	-28.52*
	(5.74)	(17.39)	(19.31)	(14.07)	(3.51)	(7.48)	(10.78)	(11.91)
Average same-firm fuel cost	2.70*	5.13	-1.69	-0.36	0.88	-0.39	-15.33***	-5.33
	(1.44)	(3.49)	(2.27)	(1.18)	(2.28)	(1.50)	(4.84)	(3.65)
R^2	0.8946	0.7959	0.8248	0.5659	0.9051	0.8610	0.7074	0.8769
# of vehicles	59	22	16	8	30	19	28	4

Results from OLS regressions. The dependent variable is the manufacturer price, i.e., MSRP minus the mean regional and national incentives (in thousands). The units of observation are at the vehicle-week-region level. All regressions include vehicle, time, and region fixed effects, as well as third-order polynomials in the vehicle age (i.e., weeks since the date of initial production), the average age of vehicles produced by different manufacturers, and the average age of other vehicles produced by the same manufacturer. Standard errors are clustered at the vehicle level and shown in parenthesis. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table A-2: Fuel Efficient and Inefficient Vehicles

The Most Positive Manufacturer Price Responses							
Cars	Brand	mpg	$\widehat{\frac{\partial p}{\partial gp}}$	SUVs	Brand	mpg	$\widehat{\frac{\partial p}{\partial gp}}$
2003 SRT4	Dodge	32.85	0.9148	2006 Escape Hybrid	Ford	30.25	0.6485
2004 Prius	Toyota	55.05	0.5268	2006 RX 400h	Lexus	30.25	0.4304
2006 Prius	Toyota	55.05	0.5227	2006 Mariner Hybrid	Mercury	30.80	0.3944
2005 Prius	Toyota	55.05	0.4971	2006 Highlander Hybrid	Toyota	30.25	0.3111
2005 SRT4	Dodge	26.40	0.4661	2003 Wrangler	Jeep	19.10	0.1551
2004 SRT4	Dodge	26.40	0.3740	2005 Wrangler	Jeep	19.65	0.1442
2003 Prius	Toyota	48.15	0.3414	2006 Liberty	Jeep	20.20	0.1284
2004 Neon	Dodge	32.85	0.3305	2003 Liberty	Jeep	21.75	0.1246
2003 Neon	Dodge	32.85	0.3244	2003 Durango	Dodge	16.75	0.1155
2005 Neon	Dodge	32.85	0.2981	2006 Wrangler	Jeep	19.65	0.0691
The Most Negative Manufacturer Price Responses							
Cars	Brand	mpg	$\widehat{\frac{\partial p}{\partial gp}}$	SUVs	Brand	mpg	$\widehat{\frac{\partial p}{\partial gp}}$
2003 XKR	Jaguar	19.85	-2.0168	2003 H2	Hummer	13.65	-2.3293
2004 GTO	Pontiac	18.75	-2.0239	2006 H2 SUV	Hummer	13.65	-2.3618
2004 Marauder	Mercury	20.30	-2.0617	2004 H1	Hummer	13.65	-2.3711
2005 Viper	Dodge	16.95	-2.1401	2003 9-7X	Saab	13.65	-2.4298
2003 Viper	Dodge	16.95	-2.1462	2003 H1	Hummer	13.65	-2.4511
2004 Viper	Dodge	16.95	-2.1880	2003 Escalade	Cadillac	13.65	-2.5031
2003 Marauder	Mercury	20.30	-2.2581	2006 H2 SUT	Hummer	13.65	-2.5640
2006 Viper	Dodge	16.40	-2.4917	2005 H2 SUT	Hummer	13.65	-2.578
2005 GT	Ford	17.40	-3.2390	2006 H1	Hummer	13.65	-2.6173
2006 GT	Ford	17.40	-3.2552	2005 Envoy XUV	GMC	13.65	-2.6979

Based on Appendix Table A-1 and Figures 6 and 7.

Table A-3: Multiple Fuel Cost Lags – Cars

Variables	Weeks Lagged	GM	Ford	Chrysler	Toyota
Fuel cost	0	-37.39	-50.31	-46.24	-81.33***
Fuel cost	1	-3.56	-13.28	5.21	22.78*
Fuel cost	2	-19.01	-36.08**	-78.41*	-2.99
Fuel cost	3	17.41	-46.24**	-18.12	17.15
Fuel cost	4	18.63	-5.47	-17.10	-18.97
Fuel cost	5	8.79	7.48	18.23	11.85
Fuel cost	6	-29.07***	21.31**	66.43*	-26.99***
Fuel cost	7	13.72	8.66	29.70	-0.59
Fuel cost	8	9.20	-55.16***	-29.28	-2.15
Fuel cost	9	38.37**	61.03***	87.15	15.40
Fuel cost	10	-128.67***	-76.56*	-186.37*	-19.28
Competitor fuel cost	0	62.56**	96.30	179.61**	39.14**
Competitor fuel cost	1	-6.61	-50.99	-33.56**	-8.47
Competitor fuel cost	2	14.27	13.95	-0.29	4.88
Competitor fuel cost	3	8.94	-0.07	-29.92	-4.58
Competitor fuel cost	4	-7.34	-12.45	17.16**	-5.11*
Competitor fuel cost	5	4.24	-4.73	0.70	6.23
Competitor fuel cost	6	-14.43	-11.32	3.00	3.67
Competitor fuel cost	7	11.55	18.85	-8.89	1.24
Competitor fuel cost	8	0.78	-30.56	39.08	1.67
Competitor fuel cost	9	-19.88	38.13	-48.17	-5.92*
Competitor fuel cost	10	24.95	16.55	53.38	2.42
Same-firm fuel cost	0	-38.58	-58.84	-130.65	24.22
Same-firm fuel cost	1	10.12	58.21***	27.63	-12.61
Same-firm fuel cost	2	1.84	18.16	77.65	-6.11
Same-firm fuel cost	3	-27.85	42.70*	45.63	-12.74
Same-firm fuel cost	4	-13.41	14.15	1.77	20.82
Same-firm fuel cost	5	-15.89	-9.79	-20.53	-20.91
Same-firm fuel cost	6	41.49***	-16.04	-71.12*	19.82**
Same-firm fuel cost	7	-26.16	-27.69	-23.03	-1.58
Same-firm fuel cost	8	-13.21	77.31***	-6.22	-2.72
Same-firm fuel cost	9	-17.86	-95.73***	-44.45	-8.20
Same-firm fuel cost	10	93.18**	36.61	139.47	5.50

Results from four OLS regressions. The dependent variable is the manufacturer price, i.e., MSRP minus the mean regional and national incentives (in thousands). The units of observation are at the vehicle-week-region level. All regressions include vehicle, time, and region fixed effects, as well as third-order polynomials in the vehicle age (i.e., weeks since the date of initial production), the average age of vehicles produced by different manufacturers, and the average age of other vehicles produced by the same manufacturer. Standard errors are clustered at the vehicle level but omitted for brevity. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table A-4: Multiple Fuel Cost Lags – SUVs

Variables	Weeks Lagged	GM	Ford	Chrysler	Toyota
Fuel cost	0	-71.20**	-43.14*	-83.16**	-53.31***
Fuel cost	1	19.08*	14.33	57.27**	8.93
Fuel cost	2	-7.88	-26.46	24.12	-3.87
Fuel cost	3	-17.00	1.86	7.55	-0.311
Fuel cost	4	15.59	-10.92	22.44**	5.93
Fuel cost	5	-11.67	9.79	3.11	-8.23**
Fuel cost	6	14.21	-5.77	3.41	-26.99***
Fuel cost	7	12.78	4.16	0.93	6.12
Fuel cost	8	-26.82**	-2.80	-3.14	-2.73
Fuel cost	9	16.32	9.02	11.18	7.51
Fuel cost	10	-26.35	-31.32	13.24	-31.48***
Competitor fuel cost	0	54.88***	51.93**	-47.89	19.78
Competitor fuel cost	1	-17.24***	-2.81	26.82	7.39
Competitor fuel cost	2	13.70**	-1.54	5.40	1.49
Competitor fuel cost	3	0.64	1.41	-4.15	-8.32
Competitor fuel cost	4	-10.06	-12.30	7.75	6.37
Competitor fuel cost	5	1.93	3.82	-14.28	-4.54
Competitor fuel cost	6	-1.86	4.04	16.51	10.18**
Competitor fuel cost	7	-3.10	13.56*	-9.35	4.41
Competitor fuel cost	8	5.59	3.78	-7.94	12.13**
Competitor fuel cost	9	7.89	6.02	22.83	-10.01
Competitor fuel cost	10	23.06*	0.60	-36.55	6.40
Same-firm fuel cost	0	14.05	-10.78	132.23*	22.83
Same-firm fuel cost	1	-3.03	-11.78	-86.08*	-15.56
Same-firm fuel cost	2	-6.04	27.00	-29.04	0.12
Same-firm fuel cost	3	15.90	-3.69	-4.66	8.66
Same-firm fuel cost	4	-7.62	21.91	-29.28*	-15.09*
Same-firm fuel cost	5	8.73	-14.59	10.42	10.50
Same-firm fuel cost	6	-13.94	1.12	-21.26	-9.30
Same-firm fuel cost	7	-10.22	-17.76	8.46	-10.77
Same-firm fuel cost	8	20.09	2.19	11.08	-11.27
Same-firm fuel cost	9	-8.55	-14.54	-34.20	4.19
Same-firm fuel cost	10	-1.68	26.61	24.88	17.74

Results from four OLS regressions. The dependent variable is the manufacturer price, i.e., MSRP minus the mean regional and national incentives (in thousands). The units of observation are at the vehicle-week-region level. All regressions include vehicle, time, and region fixed effects, as well as third-order polynomials in the vehicle age (i.e., weeks since the date of initial production), the average age of vehicles produced by different manufacturers, and the average age of other vehicles produced by the same manufacturer. Standard errors are clustered at the vehicle level but omitted for brevity. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.