ABSTRACT

Title of dissertation: ESSAYS IN ENERGY, ENVIRONMENT AND TECHNOLOGICAL CHANGE

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This dissertation studies technological change in the context of energy and environmental economics.

Technology plays a key role in reducing greenhouse gas emissions from the transportation sector. Chapter 1 estimates a structural model of the car industry that allows for endogenous product characteristics to investigate how gasoline taxes, R&D subsidies and competition affect fuel efficiency and vehicle prices in the medium-run, both through car-makers' decisions to adopt technologies and through their investments in knowledge capital. I use technology adoption and automotive patents data for 1986-2006 to estimate this model. I show that 92% of fuel efficiency improvements between 1986 and 2006 were driven by technology adoption, while the role of knowledge capital is largely to reduce the marginal production costs of fuel-efficient cars. A counterfactual predicts that an additional $1/gallon gasoline tax in 2006 would have increased the technology adoption rate, and raised average fuel efficiency by 0.47 miles/gallon, twice the annual fuel efficiency improvement

in 2003-2006. An R&D subsidy that would reduce the marginal cost of knowledge capital by 25% in 2006 would have raised investment in knowledge capital. This subsidy would have raised fuel efficiency only by 0.06 miles/gallon in 2006, but would have increased variable profits by $2.3 billion over all firms that year.

Passenger vehicle fuel economy standards in the United States will require substantial improvements in new vehicle fuel economy over the next decade. Economic theory suggests that vehicle manufacturers adopt greater fuel-saving technologies for vehicles with larger market size. Chapter 2 documents a strong connection between market size, measured by sales, and technology adoption. Using variation consumer demographics and purchasing pattern to account for the endogeneity of market size, we find that a 10 percent increase in market size raises vehicle fuel efficiency by 0.3 percent, as compared to a mean improvement of 1.4 percent per year over 1997-2013. Historically, fuel price and demographic-driven market size changes have had large effects on technology adoption. Furthermore, fuel taxes would induce firms to adopt fuel-saving technologies on their most efficient cars, thereby polarizing the fuel efficiency distribution of the new vehicle fleet.

ESSAYS IN ENERGY, ENVIRONMENT AND TECHNOLOGICAL CHANGE

by

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Foreword

The second chapter of this dissertation was co-authored with Thomas Klier at the Federal Reserve Bank at Chicago, and Joshua Linn at Resources for the Future.

Dedication

For Mom and Dad.

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Chapter 1: Knowledge Capital, Technology Adoption and Environmental Policies: Evidence from the US Automobile Industry

1.1 Introduction

Energy efficiency is essential to reducing greenhouse gas emissions (GHG) and mitigating climate change. Policies such as gasoline taxes and R&D subsidies can foster energy-efficient technologies (Acemoglu et al., 2014), but may target technology adoption and R&D differently which may affect fuel efficiency and production costs in different ways. Since the transportation sector contributed 27 percent of the total US GHG emissions in 2011 (EPA, 2013), it has been a primary concern of policymakers.

This paper studies how environmental policies incentivize firms to improve the energy efficiency of their products. In particular, I ask how gasoline taxes, R&D subsidies, and market competitiveness affect vehicle fuel efficiency and private welfare. I propose a model in which firms endogenously choose the adoption of fuel-saving technologies as well as R&D investment in knowledge capital (measured by patents).

The theoretical motivation is the following. Structural studies of how gasoline taxes and other policies affect fuel efficiency have focused on vehicle pricing. However, government policies do more than influence consumer behavior. They may also incentivize firms to change existing products to use fuel more efficiently. Ignoring this channel can lead to a bias in fuel efficiency and welfare implications. In addition to vehicle prices, my paper also endogenizes product characteristics and choices of technology improvements. I then use counterfactuals to understand how different policies would affect fuel efficiency and private welfare through these channels as well as through standard channels of changes in demand and pricing.

My model has a two-stage structure following Fan (2013). In the first stage, automakers choose vehicle performance characteristics (e.g., weight), technologies to adopt, and investment in knowledge capital. In the second stage, automakers take the above choices as given and set prices simultaneously. While the model is static, which reflects the state of the literature for modelling endogenous product characteristics (Fan, 2013; Wollmann, 2014), I interpret my results as reflecting automakers' abilities to update their cars between vehicle model-years as well as changes in price. To relate technology improvements to fuel efficiency, I model fuel efficiency being determined by product characteristics and technology improvements following Knittel (2012).

I assemble a unique panel dataset linking automotive knowledge capital information and automotive technology adoption information, to vehicle characteristics and sales data for new cars in the US over the 1986-2006 period. I measure *technology adoption* by a vector of technology choices, each of which describes the adoption of energy-efficient powertrain or transmission technologies in a specific vehicle. For instance, in the 1991 model-year, 86 percent of Honda Civics sold had multiple valves, and 29 percent had multiport fuel injection. I measure *knowledge capital* by the depreciated number of patents in the automotive engine technologies for which a firm has applied, following Aghion et al. (2012). I allow knowledge capital to benefit all vehicles a firm offers. This scale effect leads to some potential benefits of market concentration.

Using my empirical model, I estimate the components that affect an automaker's profit function. Specifically, I estimate vehicle demand as a function of price, fuel operating cost (depending on fuel efficiency) and performance characteristics. On the supply side, I estimate the marginal cost of vehicle production as a function of performance characteristics, technologies adopted, and knowledge capital stock. The marginal cost is inferred from observed pricing and the demand structure. Similarly, I estimate a cost function for developing knowledge capital in which the marginal return of knowledge capital is inferred from firm's first-order conditions. I address the endogeneity of product characteristics using a set of a plausible exogenous choices of earlier technologies as instruments.

My estimates show that technology adoption has been the main source of fuel efficiency improvements for a vehicle. From 1986 to 2006, adoption of energy-efficient technologies explains 92 percent of fuel efficiency improvements, holding performance characteristics constant. I find that the primary incentive for developing knowledge capital is to reduce the cost of producing a vehicle. Developing an additional 10 patents would lead to a reduction in production costs of $67 per car (in 2006 USD).

Consistent with the estimation results, my counterfactuals show that gas taxes and R&D subsidies can affect fuel efficiency through different channels. Gas taxes mostly incentivize firms to adopt fuel-saving technologies, while R&D subsidies mostly incentivize firms to develop knowledge capital. In turn, gas taxes create sizable fuel efficiency improvements, while R&D subsidies mostly create private benefits for firms via production cost reductions, although some of these are passed to consumers in the form of lower vehicle prices.

A counterfactual increase of gasoline taxes at $1/gallon causes the 2006 fleet to be 0.47 miles/gallon more fuel efficient, twice the observed annual improvement in 2003-2006. This improvement comes from two sources: increases in technology adoption and changes in prices. This shock changes prices disproportionally across cars. While less fuel-efficient cars experience price reductions, more fuel-efficient cars get more expensive, and these changes in prices tend to work against improving fleet fuel efficiency.

In contrast to gasoline taxes, the main effect of R&D subsidies, according to simulations, is to reduce production costs and therefore lower prices by inducing knowledge capital development. I consider a R&D subsidy that reduces the marginal cost of knowledge capital development by 25 percent in 2006. On average, this raises the number of patents applied for by 37%, firms' variable profits by $2.3 billion, and consumer surplus by $20 million (in 2006 USD) (not including the cost to raise the subsidy). The fuel efficiency benefits, however, is very limited. An average vehicle only becomes 0.06 miles/gallon more efficient.

In addition to environmental policies, a further counterfactual suggests that reducing competition can affect technology adoption and knowledge capital, building on (Whinston (2008) Chapter 3). While the scale effect incentivizes merged firms to develop more knowledge capital, the loss of competition discourages them to adopt fuel-saving technologies. This exercise sheds some light on potential situations in which market concentration is important.

My primary contribution is to bridge the gap between the following studies. On the one hand, there is a large literature that estimates structural models of the automobile market to evaluate the effects of gasoline taxes and regulatory standards (Bento et al., 2009; Jacobsen, 2013).[1] These studies typically only allow price effects and treat technological improvements as exogenous. On the other hand, reduced-form studies suggest unignorable improvements in fuel-saving technologies (Newell et al., 1999; Knittel, 2012; Klier & Linn, 2016). Knittel (2012) find that the log of fuel efficiency for passenger cars is 29 percent greater in 2006 than in 1986 holding performance characteristics constant. However, we know little about how policies incentivize automakers to improve fuel efficiency. This study advances these studies by endogenizing technological improvements that are documented in reduced-form studies but not yet incorporated in structural works of policy analysis. Moreover, my work distinguishes between two channels for improving fuel efficiency - knowledge capital and technology adoption - and finds that gas taxes and R&D subsidies have different roles.

This paper also contributes to our understanding of how policies induce investment in knowledge which in turn affects fuel efficiency. Popp (2002), Aghion et

[1] This large literature includes, but is not limited to, Berry (1994), Berry, Levinsohn, & Pakes (1995), Petrin (2002), Austin & Dinan (2005), Busse, Knittel, & Zettelmeyer (2013), Gramlich (2010), Klier & Linn (2012), Reynaert (2015), Whitefoot, Fowlie, & Skerlos (2013), and Wollmann (2014).

al. (2012) and Acemoglu et al. (2014) examine how energy prices and other policies spur the development of clean technologies. They find that higher energy prices tend to direct firms to patent more energy-efficient technologies. However, we know little about the impacts of those policy-induced patents. Moreover, these studies typically assume patents can improve productivity and lower product costs (Popp, 2004; Acemoglu et al., 2014). Despite some limitations, my study examines the impacts of patents on vehicle fuel efficiency, vehicle prices, and private welfare, all of which are either not addressed or are assumed away in previous studies. In addition, my empirical work complements theoretical work that studies how market competitiveness affects the cost-effectiveness of fuel efficiency policies (Fischer, 2010).[2] My study addresses the role of market competitiveness of fuel efficiency using a structural framework of endogenous technological improvements.

The analysis has some limitations. First, in order to have a rich demand and supply structure and to incorporate multiple channels of technological improvements, I set up a two-stage static framework. A static framework reflects the state of emerging literature for modelling endogenous product characteristics (Fan, 2013; Wollmann, 2014). I interpret the framework as indicating automakers' short and medium run adjustment to policy incentives. In addition, in order to simulate counterfactuals for a rich set of product characteristics, I treat my endogenous variables as continuous variables instead of discrete choices following (Fan, 2013;

[2] In addition, Aghion et al. (2005) investigates the inverted-U shape relation of market competitiveness on innovation measured by patents and the total factor productivity in an technological change framework.

Whitefoot et al., 2013). Building on this study, an important extension for future work would be to incorporate dynamic intensive changes for a longer run analysis.[3]

Second, I model the impact of R&D investments as producing a deterministic improvement in practical knowledge that can affect both fuel efficiency and production costs. This reflects the fact that only observed *successful* increases in firms' patent portfolios (but not necessarily the actual spending which includes unsuccessful knowledge development) can affect fuel efficiency and production costs. While the model is deterministic, it allows me to highlight the role of knowledge capital in production cost savings, which previous empirical work has not documented before. To allow patents to have different values, I weight each patent using the number of citations it receives normalized across years.

The rest of the paper is organized as follows. Section 1.2 presents the empirical model. Section 1.3 describes the data. Section 1.4 discusses estimation strategies. Section 2.4 presents the estimation results. In Section 1.6, I simulate the model to analyze the effects of policy instruments and market consolidation. Section 1.8 concludes.

1.2 An Empirical Model of Technology Improvement

In this section, I set up an empirical model of technology improvement in a static framework, which I estimate using panel data. On the demand side, consumers make vehicle purchasing choices based upon vehicle prices, fuel efficiency, and performance

[3]Examples include entries and exits of vehicle models, dynamic positioning of different vehicle segments, entries and exits of automakers, radical technological changes such as a transition to electric/hybrid vehicles.

characteristics. On the supply side, automakers are multi-product firms that can adjust vehicle prices as well as product characteristics.

Automakers engage a two-stage game. In the first stage, firms choose performance characteristics, fuel-saving technologies to adopt, and investment in knowledge capital. In the second stage, firms set vehicle prices simultaneously. Firms make their choices, given other firms' choices. I assume there exists a pure strategy Bertrand-Nash equilibrium, in which first-stage choices are optimal, given what will happen in the second stage.

I feature two types of profitability incentives of technology improvement. The first profitability incentive is to raise revenues and attract vehicle demand by providing fuel-saving cars, through the channel of technology improvement. I also feature the profitability incentive of knowledge capital, which has the potential to make the production process more cost-effective.

I present the demand model and estimation equations in Section 1.2.1. I present the supply model in Section 1.2.2 and estimation equations further in the Section 1.4.1.

1.2.1 New Vehicle Demand

Consumers participate a national market each year. They decide whether to purchase a new vehicle or an outside good, and they choose which vehicle model j (e.g., a Toyota Corolla) to purchase each year. For consumer i, the conditional indirect utility from purchasing the outside good is $u_{i0t} = \omega_{i0t}$. The indirect utility

u_{ijt} from purchasing vehicle model j in year t is

$$u_{ijt} = \alpha_p p_{jt} + \alpha_g(fp_t \cdot g_{jt}) + \alpha_x x_{jt} + \eta^d_{mt} + \xi_{jt} + [\omega_{i,seg,t} + (1 - \sigma_{seg})\omega_{ijt}]$$

where p_{jt} is vehicle price, $fp_t \cdot g_{jt}$ is fuel cost (or fuel economy) measured in dollar-per-mile, and the vector x_{jt} includes performance characteristics (measured in logs) such as horsepower-to-weight and weight. Fuel cost $fp_t \cdot g_{jt}$ is the product of fuel price fp_t (dollar/gallon) in year t and fuel consumption g_{jt} in gallons-per-mile. The lower the fuel consumption rate, the more efficient of the vehicle. I use current fuel price as the best prediction for future fuel prices, as suggested in Anderson, Kellogg, & Sallee (2013). Parameter α_p captures the marginal utility of income foregone from purchasing a vehicle, α_g captures the marginal disutility of expenditures on fuel, and α_x captures the utility received from vehicle performance characteristics. Gasoline taxes will have a sizable effect on consumers' vehicle choices if demand is elastic respect to fuel economy.

η^d_{mt} is the make-by-year (or brand-by-year) fixed effect. A parent automaker f can own several brands (e.g., Honda owns Acura and Honda). (I list vehicle makes and firms in Appendix A.1.) ξ_{jt} is the product characteristics gained from vehicle j. I assume the unobserved individual-specific taste for vehicle j takes a nested logit form $\tilde{\omega}_{ijt} \equiv \omega_{i,seg,t} + (1 - \sigma_{seg})\omega_{ijt}$. It contains a segment-specific common shock $\omega_{i,seg,t}$ and a vehicle-specific shock ω_{ijt}, and the parameter σ_{seg} is the similarity coefficient across vehicles within the same segment. I consider one layer of nests, consisting of seven vehicle segments (small cars, medium cars, large/luxury cars, crossover utility vehicles (CUVs), sport utility vehicles (SUVs), pickup trucks, and vans). I assume that ξ_{jt} and $\tilde{\omega}_{ijt}$ capture unobserved quality and taste attributes that are not related to fuel efficiency (e.g., quality of sound system and vehicle upholstery), and errors $\omega_{i,seg,t}$, ω_{ijt} are i.i.d. with Type I extreme value distributions.

The predicted market share of vehicle j is the probability that vehicle j yields the highest mean utility compared to all alternatives. Under the assumption of nested logit demand, the market share of vehicle model j in segment g takes the form of the logit choice probability $s_{jt} = s_{jt|seg(g)t} \times s_{seg(g)t}$, following (Berry, 1994). Both conditional market share $s_{jt|seg(g)t}$ and segment market share $s_{seg(g)t}$ are functions of the mean utility δ_{jt} (Details in Online Appendix). The mean utility from consuming vehicle j in year t is given by $\delta_{jt} = \alpha_p p_{jt} + \alpha_g f p_t \cdot g_{jt} + \alpha_x x_{jt} + \eta^d_{mt} + \xi_j$. The trans-log version of the conditional predicted market share of vehicle j in year t is

$$\ln s_{jt} - \ln s_{0t} = \alpha_p p_j + \alpha_g (f p_t \cdot g_{jt}) + \alpha_x x_{jt} + \sigma_{seg} \ln s_{j|seg,t} + \eta^d_{mt} + \xi_{jt} \qquad (1.1)$$

In future work, I shall model more flexible demand with random coefficients and supply moments, following (Berry, Levinsohn, & Pakes, 1995; Petrin, 2002).

1.2.2 Automakers' Choice of Technology Adoption and Knowledge Capital

I model automakers' choice problem as a two-stage game that is played each year. To allow tractability, I set up a static model in which I do not formally consider the dynamics in choosing R&D expenditure.

Automakers choose technologies to adopt, knowledge capital to accumulate, and performance characteristics to specify to maximize profits. The profit of automaker f equals the sum of profits from all vehicles produced, less a firm-level cost associated with knowledge accumulation $H(i)$. The profit π_h of vehicle model h depends on vehicle price p_h, knowledge capital i, technologies adopted a_h, and vehicle performance characteristics x_h. Since this framework allows me to model how firms may respond to potential demand and supply shocks by adjusting product characteristics other than prices, my results provide medium run implications.

The timing of the game is the following. Automakers are multiple product firms. They compete in a Bertrand game. In the first stage, automakers choose vehicle performance characteristics, technology adoption, and knowledge capital $\{x, a, i\}$ simultaneously. I model these choices as joint decisions. In the second stage, automakers take the above choices $\{x, a, i\}$ as given and set vehicle prices p simultaneously.

The relevant first stage profit function for automaker f in year t is: (I suppress automaker subscript f and year subscript t for simplicity)

$$\begin{aligned}
\Pi_f^1(\mathbf{p}(\mathbf{x},\mathbf{a},\mathbf{i});\mathbf{x},\mathbf{a},\mathbf{i}) &= \max_{\mathbf{x},\mathbf{a},\mathbf{i}} \sum_{h \in H_f} \pi_h^1(p_h(\mathbf{x},\mathbf{a},\mathbf{i});\ \mathbf{x},\mathbf{a},\mathbf{i}) - H(i) \\
\pi_h^1(p_h(\mathbf{x},\mathbf{a},\mathbf{i});\mathbf{x},\mathbf{a},\mathbf{i}) &= [p_h(\mathbf{x},\mathbf{a},\mathbf{i}) - c_h(x_h, a_h, i)] \cdot s_h\left(\mathbf{p}(\mathbf{x},\mathbf{a},\mathbf{i}), g_h(x_h, a_h, i), x_h\right) M \\
&\quad - F_h^x(x_h) - F_h^a(a_h) \\
&\quad \text{where } g_h = g(x_h, a_h, i)
\end{aligned}$$

Π^1 is the first-stage profit for firm f, π_h^1 is the first-stage profit for vehicle model h, and H_f is the set of vehicle produced by firm f. At the product level, firms face a fixed cost associated with adopting fuel-saving technologies $F_h^a(a_h)$, and a fixed cost associated with improving performance characteristics $F_h^x(x_h)$. At the firm level, automakers face a cost of investment in knowledge capital accumulation $H(i)$. M is the market size. Firms solve their profit maximization problems, internalizing vehicle demand $s_h M$ that depends on vehicle price, fuel efficiency, and performance characteristics.

I observe firms making incremental adjustment of all endogenous variables at the model level between different model-years. I therefore model firms' choices as continuous changes. In addition, I assume firms know the cost errors (unobservable to econometricians) when they make decisions. Thus there are potential endogeneity problems in all cost equations discussed below.

In my empirical work, I assume that the fuel consumption rate g_{ht} is a Cobb-Douglas function of performance characteristics X_{ht}, following (Newell, Jaffe, & Stavins, 1999; Knittel, 2012; Klier & Linn, 2016).

$$
\begin{aligned}
g_h(x_{ht}, a_{ht}, i_t) &= X_{1,ht}^{\theta_{x,1}} X_{2,ht}^{\theta_{x,2}} \exp\{\text{Tech}_{ht}\} + \varepsilon_{ht} \\
\text{where} \qquad & \text{Tech}_{ht} = \theta_0 + \theta_a a_{ht} + \theta_i ki_t + \eta_{seg}^g + \eta_m^g \\
& ki_t = (1-\delta) ki_{t-1} + i_t \\
g_h(x_{ht}, a_{ht}, i_t, t) &= \exp\left\{\theta_0 + \theta_x x_{ht} + \theta_a a_{ht} + \theta_i ki_t + \eta_{seg}^g + \eta_m^g\right\} + \varepsilon_{ht} \qquad (1.2)
\end{aligned}
$$

The function $g_h = g_{ht}(x_{ht}, a_{ht}, i_t)$ approximates an engineering trade-off relation between performance characteristics and fuel efficiency, while technology adoption and knowledge capital can reduce the degree of trade-off. Most studies refer to $g(\cdot)$ as the *technology frontier*, or the *fuel efficiency frontie*r function. The vector of vehicle performance characteristics $x_{ht} \equiv \ln X_{ht}$, including fuel efficiency related characteristics (measured in logs) such as horsepower-to-weight and weight. η^g_{seg} and η^g_m are the segment fixed effect and the make fixed effect.

There are two ways to improve fuel efficiency of a vehicle without sacrificing performance. Automakers could reduce the trade-off between performance and fuel efficiency by adjusting energy-efficient features a_h. (A complete list of technologies a_h is given in Section **??** and Table 1.1). Alternatively, automakers could expand their knowledge pool by developing knowledge capital i. Knowledge depreciates at a rate of δ. I expect $\frac{\partial g_h}{\partial x_h} > 0$, $\frac{\partial g_h}{\partial a_h} < 0$, and $\frac{\partial g_h}{\partial i} < 0$.

The profit from producing vehicle h depends on the marginal cost of producing the vehicle c_{ht}, which is affected by the technology choices that automakers make. I model the marginal cost function as a linear function of performance characteristics, technologies adopted, and knowledge capital accumulated.

$$c_{ht}(x_{ht}, a_{ht}, i_t) \quad = \quad \gamma_0 + \gamma_x x_{ht} + \gamma_a a_{ht} + \gamma_i k i_t + \eta^c_{seg} + \eta^c_t + \nu_{ht} \tag{1.3}$$

where η^c_{seg} and η^c_t are the segment fixed effect and the year fixed effect. Improving vehicle performance and adopting technologies could likely be costly, so I would expect $\frac{\partial c_h}{\partial x_h} > 0$ and $\frac{\partial c_h}{\partial a_h} > 0$. If increasing knowledge capital can improve the cost-effectiveness of the production process, I would expect $\frac{\partial c_h}{\partial ki} < 0$. The error term ν_{ht} captures unobserved cost component. I assume all costs associated with raising fuel efficiency are captured by a_{ht} and ki_t and are not in the error term.

Apart from product characteristics, automakers also decide how much to invest in knowledge capital. I observe the continuous changes in firms' patent portfolios and I model the cost of making these changes in a quadratic form. The firm-level R&D cost associated with developing knowledge capital for firm f in year t is given by: (I suppress firm subscript for simplicity)

$$\begin{aligned} H_t(i) &= \lambda_0 + (\lambda_1 + \eta^i_{type} + \lambda_t t + u_t) \cdot i_t + \frac{1}{2}\lambda_2 i_t^2 \\ h_t(i) &= \lambda_1 + \lambda_2 i_t + \eta^i_{type} + \lambda_t t + u_t \end{aligned} \tag{1.4}$$

$h_t(i)$ is the marginal R&D cost of knowledge capital. u_t is the unobserved first-order cost with respect to knowledge capital. η^i_{ype} indicates whether the automaker is a Japanese firm or a US firm. The omitting category is the European firms and other firms. λ_t is the parameter for the time trend. Expanding knowledge pool could be costly, so that I expect $\lambda_1 > 0$. I also expect a regular convex cost shape so that $\lambda_2 > 0$.

In addition to the marginal cost of production, there can be fixed costs associated with improving performance characteristics F^x_{ht} and adopting fuel-saving technologies F^a_{ht} for each model, regardless of the sales. I assume fixed costs take a conventional quadratic form

$$
\begin{aligned}
F^x_{ht}(x_{ht}) &= \phi^x_0 + (\phi^x_1 + \eta^x_f + \phi^x_t ts + e^x_{ht}) \times x_{ht} + \frac{1}{2}\phi^x_2 x^2_{ht} \\
f^x_{ht}(x_{ht}) &= \phi^x_1 + \phi^x_2 x_{ht} + \eta^x_f + \phi^x_t t + e^x_{ht} \qquad (1.5) \\
F^a_{ht}(a_{ht}) &= \phi^a_0 + (\phi^a_1 + \eta^a_f + \phi^a_t t + e^a_{ht}) \times a_{ht} + \frac{1}{2}\phi^a_2 a^2_{ht} \\
f^a_{ht}(a_{ht}) &= \phi^a_1 + \phi^a_2 a_{ht} + \eta^a_f + \phi^a_t t + e^a_{ht} \qquad (1.6)
\end{aligned}
$$

where f^x_{ht} and f^a_{ht} are the slopes of the fixed costs. e^x_{ht} and e^a_{ht} are the unobserved cost components of performance characteristics and technologies adopted in model h in year t. η^x_f and η^a_f are the firm fixed effects and ϕ^x_t and ϕ^a_t are parameters for the time trends.[4] The signs of ϕ^x_1 and ϕ^a_1 depend on where a model h locates on the cost curves.

In the second stage, automakers choose vehicle prices, taking product characteristics, technology adoption and knowledge capital $\{x, a, i\}$ as given. The relevant second-stage profit function for firm f is: (I suppress the time subscript t for simplicity)

$$
\begin{aligned}
\Pi^2_f(\mathbf{p}; \mathbf{x}, \mathbf{a}, \mathbf{i}) = \; & \max_{\mathbf{p}} \sum_{h \in H_f} \pi^2_h(p_h; x_h, a_h, i) - H(i) \\
\pi^2_h(p_h; \mathbf{x}, \mathbf{a}, \mathbf{i}) = \; & (p_h - c_h(x_h, a_h, i)) \cdot s_h(\mathbf{p}, \mathbf{g}, \mathbf{x}) \cdot M - F^x_h(x_h) - F^a_h(a_h) \\
& \text{where } g_h = g(x_h, a_h, i)
\end{aligned}
$$

Automakers can increase the fleet fuel economy in four ways. First, they can adjust the vehicle prices. Consumers respond to changes of vehicle prices

[4] Improving product quality could be potentially costly, so ϕ^x_0 and ϕ^a_0 can be positive. However, parameters in fixed cost are identified using first stage equations so that I cannot empirically test the signs of ϕ^x_0 and ϕ^a_0.

so that sales of different vehicles will be affected. Second, they can adopt some specific technologies for specific vehicle models, so that models are more fuel-efficient holding performance attributes constant. This is one source of shift of the fuel efficiency frontier. Third, they can increase knowledge capital and apply for more patents in fuel-saving technologies. The improvement of practical knowledge from knowledge capital may also shift the fuel efficiency frontier. Last, automakers can produce at different allocations of fuel economy and vehicle performance attributes, improving fuel efficiency by sacrificing vehicle performance such as horsepower. This is essentially a movement along the fuel efficiency frontier. This study focuses on the second and the third channels while still allowing possibilities of other channels.

1.3 Data

In order to estimate the endogenous production choice model described in the Model Section 1.2, I compile a new dataset of US new vehicle market over 1986-2006. Specifically, the data set contains information of adoption of fuel-saving technologies, automotive patents, vehicle characteristics, and vehicle prices and sales. I describe data for technology adoption and knowledge capital in Section 1.3.1 and other data in Section 1.3.2.

1.3.1 Technology Adoption and Knowledge Capital

Technology Adoption. I link the automotive technology adoption and automotive innovation data to the vehicle sales data for this exercise. I collect data of technology adoption and other vehicle characteristics from the *U.S. EPA Fuel Economy Guide Database* and the *U.S. EPA Fuel Economy Trend Database* over model years 1986-2006.[5] Technology adoption data contain information of whether a vehicle implements certain specific powertrain, transmission, or drivetrain technology. For instance, I observe whether a vehicle has a 5-speed gear box, and whether a vehicle features variable valve timing.

Technology adoption of a model represents the ex-post proportion of vehicle models sold with specific fuel-saving technologies. Table 1.1 panel B presents summary statistics of technologies adopted. Figure 1.1 plots the market penetration trends of five major technologies that is well-adopted over 1986-2006.[6] According to the *Fuel Economy Trend Report* by (EPA, 2008, 2014), there are 6 major technologies that have been penetrating over the sample period 1986-2006. They are (i) multi-point fuel injection (Port/MFI), (ii) torque conversion lock-up, (iii) multi-valve (more than 2 valves per cylinder), (iv) advanced transmission (5-gear transmission), (v) variable valve timing (VVT), and (vi) turbocharger. These technologies play important roles in enhancing vehicle fuel efficiency.

These technologies are well-developed fuel-saving devices installed or fuel-saving specifications featured in the powertrain or gearbox. For example, Figure A.1 in Section A.2 shows an engine with four valves per cylinder. Higher numbers of valves per cylinder can allows a good air and fuel intake and result in significant efficiency

[5] I thank Aaron Hula and other authors of *EPA Fuel Economy Trend Report* for helping me get access to a few technology adoption variables in the Trend database that are not covered in the Guide database.

[6] Turbocharger is a trendy technology adopted over 1986-2006. I do not include it since its market penetration rate is less than 10 percent for all years.

improvements given vehicle power (EPA, 2014). I document descriptions and fuel economy benefits of all the above technologies in Appendix A.2.

I treat these technology adoption choices as *continuous* variables rather than discrete choices variables. Given a specific model, there are a variety of trims, many of which have different technology specifications. Therefore, for a vehicle model j in year t, the proportion of vehicle sold with a specific technology can range from 0 to 1. For example, the technology adoption rate of 5-speed gearbox $a_{h,5speed}$ is 37 percent for Honda Accord in model-year 1997.

Knowledge Capital. I collect automotive knowledge capital data from OECD Triadic Patent Family Database (TPF). In particular, I collect the number of patents applied from each automaker for internal combustion engine technology to measure the knowledge capital i.[7] Table 1.1 panel C presents summary statistics of knowledge capital. Table 1.2 lists a summary of patents in these categories.

These TPF patents represent knowledge of general technologies for practical use. The novelty of most patents are for the "utility" purpose, i.e. they usually innovate to provide better methodologies or better subtle system specifications. A typical patent EP25695518 with patent classification code "F01L: Cyclical operation valves for combustion engines" is titled as "Methods and System for Internal Combustion Engine" (Section A.3). According to the patent description, the novelty of this patent is that it "... improves engine unit to include a separating aperture between cylinders ... and a separating valves". Most patents, just like this one, have the potential to

[7] I also collect the number of patents on alternative fuel vehicle engine technology to measure the cross-category knowledge capital (hereafter AFV knowledge capital). I use them to construct two instrumental variables.

allow cars with given attributes to be more efficient, and allow manufacturers to achieve the same specifications more effortlessly.

The number of patent applied by automaker f in year t is referred to as *knowledge capital* i_{ft}. Knowledge accumulates according to $ki_{ft} = ki_{f,t-1} + i_{ft}$. The cumulative knowledge is referred to as *knowledge stock*, or *stock of knowledge capital.* I model knowledge stock ki to affect production cost $c(\cdot)$ and fuel efficiency $g(\cdot)$. I model the incremental knowledge capital i to enter the R&D cost of knowledge investment.

To account for appropriate energy-efficient patents, I use definitions suggested by Aghion et al. (2012), Haščič et al. (2008), Vollebergh (2010), and Green Inventory developed by the World International Property Organization (WIPO). Appendix A.3 presents the International Patent Classification (IPC) codes of all patents categories selected in this study. To correctly identify patent ownership, I make several assumptions. For examples, I split the ownership of a patent across multiple firms if they collaborate on that patent.[8] To account for heterogeneous values of patents, I weight the importance of a patent using the number of citations a patent receive (i.e. forward citation) [9] following (Trajtenberg, 1990), and I normalize the

[8](1) I assume that if a patent is applied by n co-assignees, then each co-assignees will obtain $1/n$ unit of flow of knowledge as in the innovation literature. (2) I assume that if two firms i and j had merged in year t, then i and j would acquire each others' stock of knowledge after the consolidation. (3) I assume if a firm had separated into i and j in year t, then both won't obtain each others' stock of knowledge from year t onward.

[9]For a patent family k, its forward citation is the number of subsequent patent families that cites patent family k.

numbers of forward citation for each cohort year following Hall et al. (2000, 2001),[10] using citation data from OECD Citation Database.

Here I discuss the advantages and limitations of using the number of patents for internal combustion engines technologies (i.e. powertrain technologies for conventional vehicles) to measure knowledge capital. First, patents are a good measure in terms of representing firms' *own* intellectual property in the automotive industry. Although patents have to be published, intellectual property is rarely shared, traded, or licensed in this industry. There are less than 3% of Triadic Patent Families that are traded over 1978-2006 (Aghion et al., 2012). In addition, the licensing royal rate for automotive inventions is as low as 5%, compared to 8% for pharmaceutical inventions and 12.5% for internet and software/media inventions.[11] Therefore, there is very minimum concern that patents do not include the proportion of knowledge that a firm has from using other firms' patents.

Second, the number of patents for internal combustion engine technologies (i.e. powertrain technologies) is a good approximation for other types of fuel-saving knowledge capital that firm have patented. For example, automakers also patent transmission and drivetrain related technologies. The number of transmission-related patents, for instance, is highly correlated and co-linear with the number of powertrain patents. I therefore model the effects of transmission-related knowledge and other energy-efficient knowledge to be picked up by using powertrain-related patents.

[10]Weighting importance of a patent by the number of forward citations received usually causes dated patents receive more citations compared to recent patents. To correct the truncation issue of patent citations, I normalize patent citation using cohort weights, i.e. total numbers of citation received by all patents applied in year t, following Hall et al. (2000, 2001).

[11]KPMG (2012) Profitability and Royalty Rates Across Industries: Some Preliminary Evidence.

Third, I assume all patents on new powertrain technology have the same effects on cost components and same effects on fuel efficiency. For example, the following two categories of patents affect the system to the same extent in my model: (i) a patent deigned for improving the energy-efficiency of the air-conditioning system, which is categorized under "1.7 General, Improved Fuel Efficiency" in Table 1.2; versus (ii) a patent designed for improving engine turbocharging properties, which is categorized under "1.5 Turbocharger" in Table 1.2. I have incorporate a patent's value by its citation. Investigating the variations of fuel efficiency outcomes and cost implications across different categories of patents is very important, but is beyond the scope of this study.

Here I discuss one misconception about the linkages between technology adoption and knowledge capital. I treat technology adoption and knowledge capital as two types of choices that automakers decide jointly in their profit maximization problems. Automakers do not necessarily have to file patents for a type of technology first, in order to adopt it later. First, technologies adopted in our sample are well-developed technologies that are ready to be adopted. Second, I observe many cases in which firms have adopted a technology first, and then improved their technologies and filed a patent on that technology many years later. For example, Chrysler filed its first Triadic patent on turbocharger in 1997 but it has already installed turbochargers starting in 1985 with 5% penetration rate. Volkswagen filed patents on turbocharger in 1995 but has already adopted this technology in 1986 with 9% adoption rate. Third, three quarters of engine technologies are uncategorized technology for general practical use rather than geared towards specific technology adoption (Table 1.2).

For the above reasons, I treat innovation and technology adoption as separate choices that firms decide jointly.

1.3.2 Other Data

Information on grandfathered technologies are collected for this study. I describe and discuss these technologies in detail when discussing instrumental variables in the Identification Section 1.4.3. This list includes (i) carbureted fuel injection, (ii) 3-speed transmission, (iii) automatic transmission without lockup converter, and (iv) throttle body injection (TBI). This list of technology has been gradually replaced by better technologies over 1986-2006. Summary statistics of grandfathered technologies are on Table 1.1 Panel B.

I aggregate vehicle prices, sales, and characteristics of 24,000 trim-level vehicles over 1986-2006 into 3,700 vehicle models. This study is restricted to conventional vehicles that have internal combustion engines and use gasoline as the primary fuel.[12] Vehicle prices and sales data are from *Ward's Automotive*.[13] Vehicle fuel efficiency and performance characteristics are from *Automotive News*.[14] Performance characteristics include horsepower-to-weight, weight, transmission type, and fuel type. They are produced by 45 brands and 23 parent companies. Summary statistics of vehicle characteristics are on Table 1.1 Panel A and Panel D.

---

[12] I do not include diesel vehicles, which only consist of less than 1 percent of US market shares.

[13] Prices and sales data is kindly shared by Joshua Linn used in Klier & Linn (2010). Vehicle prices are the manufacturer suggested retail prices (MSRP).

[14] This data is provided by Knittel (2012).

I collect tax-inclusive fuel price from *U.S. Energy Information Administration (EIA)* and transportation sector R&D support the *International Energy Agency (IEA)*.

1.3.3 Suggestive Evidence: Effects of Gasoline Taxes, R&D Subsidies, and Competitiveness

This section presents suggestive evidence on the correlations between technological improvements and environmental policies and economic conditions.

I find that knowledge capital is negatively correlated to gasoline prices and HHI, which is consistent with my simulation results in Section 1.6. In Table 1.3, I present the correlation of technology improvement and gasoline prices and market competitiveness. I measure the industry competitiveness using the Herfindahl-Hirschman Index (HHI). The smaller the HHI, the more competitive the market is. I detrend all variables to remove spurious correlations from a common time trend.

Table 1.3 suggests that firms on average may have stronger incentives to expand knowledge pool when the market is more competitive, and weaker incentives to develop knowledge capital and to sit on existing knowledge pool when the industry is less competitive. This correlation only applies to average firms. Consolidated firms however, may find market concentration provide incentives for them to patent more. In addition, higher gasoline prices may discourage firms to patent more, which is consistent to the estimation results later that fuel efficiency benefits from knowledge capital is limited.

In contrast to knowledge capital, I find ambiguous correlation between technology adoption and environmental policies and economic conditions. As for newer technologies such as 5 speed gear and Variable Valve Timing (refereed to Figure 1.1), they are positively correlated to gasoline prices and negatively correlated to HHI. Firms on average may have stronger incentives to adopt these technologies when facing higher gasoline prices and when market is more competitive. As for more matured technologies such as Multi-valve and Multiport Fuel Injection (refereed to Figure 1.1), I find the evidence is the opposite.

1.4 Estimation

I estimate the demand and supply simultaneously using the Generalized Methods of Moments. The unit of an observation is a vehicle model at a model-year. The demand moment follows from the nested logit new car demand, specified in Equation (1.1) in Section 1.2.1. As for the supply moments, they are derived from automakers' first order conditions with respect to prices, performance characteristics, technology adoption, and knowledge capital. Demand parameters, parameters of the fuel efficiency frontier, and variations in the gasoline prices, play important roles in identifying the cost structures.

1.4.1 Necessary Equilibrium Conditions and Estimation Equations

Based upon the static model described in the Model Section 1.2, market equilibrium is described by first-order conditions of automakers' profit maximization problems and market clear conditions. I assume that a pure-strategy Bertrand Nash equilibrium exists. In this section, I present necessary optimality conditions that I use to identify the structure of marginal production cost $c(\cdot)$, marginal R&D cost $h(\cdot)$, and the structure of fuel efficiency frontier $g(\cdot)$.

The first-order condition of the second-stage profit Π_f^2 with respect to vehicle price p_j is the conventional pricing equation. I suppress time subscript t for simplicity.

$$
\begin{aligned}
foc_j^{(p)} &: \quad s_j + \sum_{h \in H_f} (p_h - c_h) \frac{\partial s_h}{\partial p_j} = 0 \\
\mathbf{foc}^{(p)} &: \quad \mathbf{s} + \Delta_{sp}(\mathbf{p} - \mathbf{c}) = 0
\end{aligned}
\tag{1.7}
$$

where Δ_{sp} is the response matrices containing the derivatives of market shares with respect to vehicle prices. Component $\Delta_{sp}(h, j) = \frac{\partial s_h}{\partial p_j}$ depends on predicted market share and demand side price elasticities. With the two-stage optimization, technology adoption choices, stock of knowledge capital, and vehicle performance characteristics are given when automakers choose vehicle prices. This equation is used to compute estimated marginal cost c_h, given data and demand parameters. I use estimated cost c_h to identify parameters in the marginal cost function Equation (1.3).

First-order conditions of the first-stage profit Π_f^1 with respective to knowledge capital, technology adoption, and vehicle characteristics are the following. (I suppress firm subscript f for simplicity)

$$
\begin{aligned}
R_t^{(i)} &\equiv \left[\sum_{h \in H_f} \left(\frac{\partial p_{ht}}{\partial i_t} - \frac{\partial c_{ht}}{\partial i_t} \right) s_{ht} + \sum_{h \in H_f} (p_{ht} - c_{ht}) \left(\sum_{k \in H_f} \frac{\partial s_{ht}}{\partial g_{kt}} \frac{\partial g_{kt}}{\partial i_t} + \sum_{k \in H_f} \frac{\partial s_{ht}}{\partial p_{kt}} \frac{\partial p_{kt}}{\partial i_t} \right) \right] M_t \\
&= \lambda_1 + \lambda_2 i_t + \eta^i_{type} + \lambda_t t + u_t \qquad (1.8) \\
R_{jt}^{(a)} &\equiv \left[\sum_{h \in H_f} \left(\frac{\partial p_{ht}}{\partial a_{jt}} - \frac{\partial c_{ht}}{\partial a_{jt}} \right) s_{ht} + \sum_{h \in H_f} (p_{ht} - c_{ht}) \left(\sum_{k \in H_f} \frac{\partial s_{ht}}{\partial g_{kt}} \frac{\partial g_{kt}}{\partial a_{jt}} + \sum_{k \in H_f} \frac{\partial s_{ht}}{\partial p_{kt}} \frac{\partial p_{kt}}{\partial a_{jt}} \right) \right] M_t \\
&= \phi^a_1 + \phi^a_2 a_{ht} + \eta^a_f + \phi^a_t t + e^a_{ht} \qquad (1.9) \\
R_{jt}^{(x)} &\equiv \left[\sum_{h \in H_f} \left(\frac{\partial p_{ht}}{\partial x_{jt}} - \frac{\partial c_{ht}}{\partial x_{jt}} \right) s_{ht} + \sum_{h \in H_f} (p_{ht} - c_{ht}) \left(\frac{\partial s_{ht}}{\partial x_{jt}} + \sum_{k \in H_f} \frac{\partial s_{ht}}{\partial g_{kt}} \frac{\partial g_{kt}}{\partial x_{jt}} + \sum_{k \in H_f} \frac{\partial s_{ht}}{\partial p_{kt}} \frac{\partial p_{kt}}{\partial x_{jt}} \right) \right] M_t \\
&= \phi^x_1 + \phi^x_2 x_{ht} + \eta^x_f + \phi^x_t t + e^x_{ht} \qquad (1.10)
\end{aligned}
$$

These optimality conditions illustrate private costs and gains associated with each first-stage choice variables. On the left-hand side of Equations (1.8)-(1.10), I compute the firm-level aggregated marginal returns of knowledge capital $R_t^{(i)}$, the model-level marginal returns of technologies adopted $R_{jt}^{(a)}$ and performance characteristics $R_{jt}^{(x)}$. On the right hand side parameters on cost structure are to be estimated. Technology adoption a_{jt} are continuous in this study. (See the Data Section 1.3.1 for details on continuousness of technology adoption).

I use the first order condition of knowledge capital in Equation (1.8) to identify parameters in R&D cost function. I also use this equation as the best-response function to compute counterfactual knowledge capital for simulation exercises. Right hand side of this equation represents the marginal cost from investing in knowledge capital. The left hand side presents the marginal return of doing so. It could reduce the cost of producing a vehicle by $\frac{\partial c_h}{\partial i}$, and it could raise profits through improving fuel efficiency for all vehicle models $\sum_k \frac{\partial s_h}{\partial g_k} \frac{\partial g_k}{\partial i}$. Other terms in this equation account for indirect effects knowledge stock have through affecting vehicle prices.

Similarly, I use the first order condition of technology adoption in Equation (1.9) to estimate fixed cost parameters, and to compute best-response of technology adoption in the counterfactual scenarios. Right hand side of this equation represents the marginal fixed cost of technology adoption. The left hand side presents the marginal return of technology adoption. It includes the additional profit a firm raise through offering energy-efficient cars by adopting fuel-saving technology $\sum_k \frac{\partial s_h}{\partial g_k} \frac{\partial g_k}{\partial a_j}$, accounting for its direct effects on marginal production cost $\frac{\partial c_{ht}}{\partial a_{jt}}$ and indirect effects on vehicle prices. I use the first order condition of performance characteristics in Equation (1.10) in the similar way.

Partial derivatives $\left\{\frac{\partial s_h}{\partial g_k}, \frac{\partial s_h}{\partial x_j}\right\}$ in the above first-order conditions are the responses of market share with respect to fuel consumption (gallon-per-mile) and vehicle characteristics. Gradients $\left\{\frac{\partial p_k}{\partial i}, \frac{\partial p_k}{\partial a_j}, \frac{\partial p_k}{\partial x_j}\right\}$ are responses of second-stage choice prices with respect to first-stage choices. I assume the equilibrium function of vehicle prices are smooth with respect to first-stage choices. Following Villas-Boas (2007)'s methods,[15] I compute gradients$\left\{\frac{\partial p_k}{\partial i}, \frac{\partial p_k}{\partial a_j}, \frac{\partial p_k}{\partial x_j}\right\}$ by applying the implicit function theorem on $foc_j^{(p)}$. (See Online Appendix).

I use the demand moment, marginal cost moment, frontier moment, and R&D cost moment to construct the GMM objective function $G'(\alpha, \gamma, \theta, \lambda, \phi)WG(\alpha, \gamma, \theta, \lambda, \phi)$. Parameters need to identify include (1) parameters in the vehicle demand func-

[15] Villas-Boas (2007) compute second-stage retail pricing choices with respect to first-stage wholesale pricing choices, assuming the second-stage choice is differentiable with respect to first-stage choices.

tion $\{\alpha_p, \alpha_g, \alpha_x, \sigma_{seg}\}$, (2) parameters in the marginal cost of production function $\{\gamma_0, \gamma_x, \gamma_a, \gamma_i\}$, (3) parameters in the fuel efficiency technology frontier function $\{\theta_0, \theta_x, \theta_a, \theta_i\}$, (4) parameters in the cost of knowledge capital function $\{\lambda_1, \lambda_2\}$, (5) parameters associated with fixed cost of adopting technologies and improving vehicle performance $\{\phi_1^a, \phi_2^a, \phi_1^x, \phi_2^x\}$. The values of the structural errors that I use in the moments conditions are

$$
\begin{aligned}
\xi_{jt} &= \xi_{jt}(\cdot\,; \alpha_p, \alpha_g, \alpha_x, \sigma_{seg}) \\
&= \ln s_{jt} - \ln s_{0t} - \alpha_p p_{jt} - \alpha_g (fp_t \cdot g_{jt}) - \alpha_x x_{jt} - \eta_{mt}^d - \sigma_{seg} \ln s_{j|seg,t} \qquad (1.11) \\
\nu_{jt} &= \nu_{jt}(\cdot\,; \gamma_0, \gamma_x, \gamma_a, \gamma_i;\ \alpha_p, \sigma_{seg}) \\
&= c_{jt} - \gamma_0 - \gamma_x x_{jt} - \gamma_a a_{jt} - \gamma_i ki_t - \eta_{seg}^c - F_t^c \qquad (1.12) \\
\varepsilon_{jt} &= \varepsilon_{jt}(\cdot\,; \theta_0, \theta_x, \theta_a, \theta_i) \\
&= g_{jt} - \exp\left\{\theta_0 + \theta_x x_{jt} + \theta_a a_{jt} + \theta_i ki_t + F_{seg}^g + F_m^g\right\} \qquad (1.13) \\
u_t &= u_t(\cdot\,; \lambda_1, \lambda_2;\ \alpha_p, \alpha_g, \sigma_{seg}, \gamma_i, \theta_0, \theta_x, \theta_a, \theta_i) \\
&= R_t^{(i)} - \lambda_1 - \lambda_2 i_t - \eta_{type}^i - \lambda_t t \qquad (1.14) \\
e_{jt}^a &= e_{jt}^a(\cdot\,; \phi_1^a, \phi_2^a;\ \alpha_p, \alpha_g, \sigma_{seg}\gamma_a, \theta_0, \theta_x, \theta_a, \theta_i) \\
&= R_{jt}^{(a)} - \phi_1^a - \phi_2^a a_{jt} - \eta_f^a - \phi_t^a t \qquad (1.15) \\
e_{jt}^x &= e_{jt}^x(\cdot\,; \phi_1^x, \phi_2^x;\ \alpha_p, \alpha_g, \alpha_x, \sigma_{seg}, \gamma_x, \theta_0, \theta_x, \theta_a, \theta_i) \\
&= R_{jt}^{(x)} - \phi_1^x - \phi_2^x x_{jt} - \eta_f^x - \phi_t^x t \qquad (1.16)
\end{aligned}
$$

The firm-level aggregated marginal returns of knowledge capital $R_t^{(i)}$, the model-level marginal returns of technologies adopted $R_{jt}^{(a)}$ and performance characteristics $R_{jt}^{(x)}$ are given in firms' first-order conditions in Equation (1.8)-(1.10).

1.4.2 Identification

I estimate Equations (1.11)-(1.16) jointly. The identification of parameters comes from the exclusive variables, prices and fuel economy, in the demand equation (1.11), where fuel price fp_t creates important time varying variations. Identification also comes from stock of knowledge in the marginal production cost equation (1.12), as well as the functional form assumption in the fuel efficiency frontier equation (1.13) which I adopt from the literature.

All dependent variables in the cost structure are constructed using first order conditions, so that estimation of demand parameters and other moments play important roles in driving the variations. For example, marginal cost c_{jt} in the moment equation (1.12) is solved from the first-order condition with respect to price. Demand parameter α_p and σ_{seg} as well as vehicle prices and sales play key roles in driving variations in the marginal cost, and the marginal cost error is therefore $\nu_{jt} = \nu_{jt}(\cdot\ ; \gamma_0, \gamma_x, \gamma_a, \gamma_i;\ \alpha_p, \sigma_{seg})$. Take the marginal return of knowledge capital as another example. $R_t^{(i)}$ is solved from the first-order condition with respect to knowledge capital. Therefore, marginal cost parameter γ_i (production cost reduction channel), fuel efficiency frontier parameter θ_i (fuel efficiency improvement channel), demand parameter on fuel economy α_g and other parameters play important roles in affecting and driving variations in the marginal return of investment in knowledge capital.

There are, however, still unobserved demand and cost components that may raise endogeneity issues. Most studies of the vehicle demand literature treat vehicle characteristics as exogenous, following the seminal work Berry (1994) and Berry, Levinsohn, & Pakes (1995). In this framework, automakers observe the cost shocks $\{\nu_{jt}, u_t, e^a_{jt}, e^x_{jt}\}$ (unobservable to econometricians) before setting performance characteristics, knowledge capital to develop, and technologies to adopt. Automakers also observe the demand tastes ξ_{jt} (unobserved product quality to econometricians) before setting vehicle prices. Prices and performance characteristics, therefore, could potentially be correlated with unobserved demand shocks. For the same reason, price, performance characteristics, knowledge capital, and technology adoption might be correlated with cost components that are unobservable to econometricians. Vehicle performance characteristics, which are usually used in estimating vehicle demand, are therefore no longer valid instruments in this study. I explain the instrument variables used next.

1.4.3 Instruments

I use three sets of instrumental variables for this study to deal with the endogeneity issue: (i) longer-run characteristics, (ii) grandfathered technologies, and (iii) cross-category knowledge and knowledge spillover. Here I start by explaining my instrumental variables in the context of the demand equation first.

Longer-run characteristics. First, I use longer-term (LR) vehicle characteristics $x^{lr}_{f,j}$ to construct the second set of instruments, $D(x)^{lr}_{f,j} = \left\{x^{lr}_{f,j} - x^{lr}_{j\in seg},\ x^{lr}_{f,j} - x^{lr}_{f,-j}\right\}$, as suggested in (Whitefoot, Fowlie, & Skerlos, 2013). Some vehicle characteristics take longer-run to plan and design, such as drivetrain specification (whether a vehicle is all/4-wheel-drive).[16] This feature is usually determined before a model enters the market and is not changed very often. Still concerning about potential endogeneity from using a model's own variations in longer-run characteristics, I use variations from competing vehicle models and construct the following "difference" measure $D(x)^{lr}_{f,j} = \left\{x^{lr}_{f,j} - x^{lr}_{j\in seg},\ x^{lr}_{f,j} - x^{lr}_{f,-j}\right\}$ as the instrumental variables, following (Whitefoot, Fowlie, & Skerlos, 2013).

The identifying assumption used in BLP and most demand estimation studies is that product characteristics are exogenous. The identifying assumptions here are that longer-run characteristics are per-determined before ξ_j are known to firms, and other products' dated technologies do not affect consumer utility directly, but only affect consumer utility by affecting vehicle h through competition. In addition, I also assume that fuel efficiency term $fp_t \cdot g_{jt}$ captures all fuel-efficiency quality of a car, which I test in the robustness section. This assumption implies that the distance of adoption rates of old technologies from competing models (e.g., 3-speed gear) should be uncorrelated with unobserved non-efficiency related qualities ξ_j (e.g., quality such as sound system, leather seats).

[16] I use do not use vehicle dimension because I only observe them after 1997 in Ward's. Whitefoot et al. (2013) also suggest to use powertrain architecture (diesel engine, hybrid engine) as instruments. I do not use them here because diesel vehicles and hybrid vehicles are thought as on different technology frontier $g_j(\cdot)$ compared with gasoline vehicles. They are likely weak instrument since the market share of diesel and hybrid cars are very small.

Grandfathered technologies. Similar to the idea of longer-run characteristics, I use grandfathered technologies $a_{f,j}^{old}$ to construct my instrument variables, $D(a)_{f,j}^{old} = \{a_{f,j}^{old} - a_{j \in seg}^{old},\ a_{f,j}^{old} - a_{f,-j}^{old}\}$, by utilizing the rich information about the process of technology evolution in the data.

I include the following four grandfathered technologies: (i) 3-speed/gear transmission $a_{f,j}^{g3}$, (ii) carburetor $a_{f,j}^{c}$, (iii) automatic transmission without lockup $a_{f,j}^{nl}$, and (iv) engines with 8 cylinders $a_{f,j}^{c8}$ as instruments, using reference from EPA (2008, 2014). Figure 1.1 and Figure 1.3 illustrate a brief history of technology evolution over 1986-2006 period. Over my sample period, Figure 1.1 and Figure 1.3 suggest that high-speed transmissions such as 5-speed and 6-speed transmissions have gradually replaced 3-speed and 4-speed transmissions. Automatic transmission with lockup and manual transmission with higher gears have gradually replaced automatic transmission without lockup. Multiport fuel injection (Port, or MBI) and variable valve timing (VVT) have gradually replaced carburetor fuel delivery system and throttle body injection (TBI). Engines with multiple valves per cylinders gradually replaced engines with 2 or less valves. Engines with 4 and 6 cylinder gradually replaced engines with 8 cylinders. Similar to longer-run characteristics, dated technologies $a_{f,j}^{old}$ have been introduced to vehicle model j when automakers design the previous generations. So that dated technologies are per-determined features when automakers making choices on new technologies.

There are some potential endogeneity from using a model's own variation. Specifically, variations of dated technologies a_j^{old} can come from variations of technology adoption a_j per see, if the new technologies directly replace those dated technologies. To attenuate this concern, I select dated technologies that is not directly in competition with the new technologies that have been penetrate in 1986-2006. For example, I use 3-speed gearbox transmission to instrument 5-speed transmission. There is an intermediate technology 4-speed transmission that I do not use as instrument since it was in direct competition with 5-speed transmission. Another example is carburetor, which is a dated fuel injection technology that I use to instrument Port (Multiport Fuel Injection). There are intermediate technologies (e.g., single-port and two-port fuel injection) that I do not use as instrumental variables since they can be endogenous.

Still concerning about potential endogeneity from using a model's own variations in technologies, I construct the following "difference" measure $D(a)^{old}_{f,j} = \left\{a^{old}_{f,j} - a^{old}_{j \in seg},\ a^{old}_{f,j} - a^{old}_{f,-j}\right\}$ as the instrumental variables, similar to the idea in (Whitefoot, Fowlie, & Skerlos, 2013). The idea is to exploit both models' own variations and variations from competing models. The intuition is to compare how advanced model j is compared to other models. The former instrument, $(a^{old}_{f,j} - a^{old}_{j \in seg})$, measures the difference between technology adoption rate of a model and other vehicles in the same segment sold by competitors. The latter instrument, $(a^{old}_{f,j} - a^{old}_{f,-j})$, measures the difference between technology adoption rate of a model and other vehicles in the same segment sold by the same firm. Both inform us how far other models are ahead of the game and have a potential to predict choices of price, performance characteristics, and technologies to adopt.

The identifying assumption used here is the same as in the first set of instrument. However, still concerning about remaining endogeneity, I use one-year lag of grandfathered technologies as a robustness checks.

Cross-category knowledge and knowledge spillovers. Third, I use cross-category knowledge stock ki^{afv}, same-category spillover Ski, and cross-category spillover Ski^{afv} to instrument the demand. Same-category refers to patents for internal combustion engines. Cross-category knowledge stock refers to cumulative patents for alternative fuel vehicle (AFV) engines. I construct the spillover variables using each firm's inventors' geographic locations, and using the numbers of patents filed in each region, following Aghion et al. (2012).

This set of instrument assumes the following. Toyota's knowledge about hybrid and electric cars (say Toyota Prius) and spillover in regular cars from the industry can help Toyota improve fuel efficiency of regular vehicles they produce such as Toyota Camry. However, their knowledge about designing engines for Toyota Prius and spillovers they get from the industry are not correlated with unobserved demand taste associated with Toyota Camry. Similar to first two sets of instruments, I assume that fuel efficiency term $fp_t \cdot g_{jt}$ captures all fuel-efficiency quality of a car, which means that the unobserved demand taste associated with Toyota Camry contains only non-efficiency related quality.

First stage results are given in Online Appendix. Standard errors are robust to heteroscedasticity. These three sets of instruments provide enough information in predicting vehicle prices, fuel economy, and performance characteristics in the demand equation. F-statistics for exclusive variables are 56.7 for vehicle price, 228.0 for fuel economy, 40.6 for horsepower-to-weight, and 217.9 for weight.

To estimate the marginal cost and the fixed cost equations (1.12), (1.15)-(1.16), I use the above three sets of instruments. There are more endogenous variables in the marginal cost equations compared to the demand equation. I therefore use, in addition, the interactions of the third set of instruments $\{ki^{afv}, Ski, Ski^{afv}\}$ with dated technologies $D(a)^{old}_{f,j}$, and the interactions of $\{ki^{afv}, Ski, Ski^{afv}\}$ with longer-run characteristics $D(x)^{lr}_{f,j}$ to instrument supply equations (1.12) and (1.15)-(1.16).

To estimate the R&D cost equation (1.14), I use industry-wide spillover and cross-category spillover to predict automakers' choices of knowledge capital accumulation. Since this equation is evaluated at firm-level, I only use the third set of instrument $\{ki^{afv}, Ski, Ski^{afv}\}$ for this equation.

1.5 Estimation Results

I estimate parameters using the Generalized Methods of Moments. I present demand estimation in Section 1.5.1, results of fuel efficiency frontier in Section 1.5.2, and results of cost structure in Section 1.5.3. See Online Appendix for the first-stage results.

1.5.1 Estimation Results of New Cars Demand

In this section, I present estimates of parameters in the model. Table 1.4 includes parameters of the demand system, structures of automakers' marginal cost function, marginal R&D cost function, and the shape of fuel economy frontier.

Panel A of Table 1.4 presents estimates of the demand system. Results suggest that consumers have strong disutility from high vehicle prices and high fuel costs, and they gain utility from better performance characteristics. Parameter α_p is -0.55, which implies that the average own-price elasticity of price is -3.48.[17] The elastic demand suggests that policies that affect vehicle prices via affecting the cost components, such as a R&D subsidy, have a potential in creating incentives for automakers to improve fuel efficiency technologies.

The parameter for fuel cost (dollar-per-mile) α_g is -17.91, which implies that the average own elasticity of fuel cost is -2.05.[18] The elastic demand of fuel cost suggests that policies that affect fuel costs, such as a gasoline tax (a potential carbon tax), have a potential in creating incentives to increase knowledge capital and to adopt better technologies responding to the shifts of demand towards fuel-efficient vehicles.

[17] The average own-price elasticity is comparable to the literature. The average own-price elasticity is around -5.4 in Berry, Levinsohn, & Pakes (1995) (implied using Logit part of the results as a comparison), -1.4 in Klier & Linn (2012) (Nested Logit with BLP IV), -5.4 in Klier & Linn (2012) (Nested Logit with engine-based IV), -1.9 in Whitefoot, Fowlie, & Skerlos (2013) (Random Coefficient), and -1.97 for new cars in Bento et al. (2009) .

[18] Most papers do not report own-product elasticity w.r.t. fuel cost. Here I compare the average elasticity of fuel economy for both own product and cross products. The number is -1.07 here. The imputed average fuel cost elasticity is -1.23~-1.56 in Klier & Linn (2012), -0.20~-0.91 in Gramlich (2010).

To interpret the estimation results of the demand system, I calculate the willingness-to-pay (WTP) for fuel efficiency improvements in Table 1.5, holding price and performance characteristics fixed. I consider two partial-equilibrium cases for the 2006 new cars market. In the first case, I calculate the willingness-to-pay of 1% fuel efficiency improvement at actual gasoline price ($2.16/gallon). In the second case, I calculate the willingness-to-pay for the same amount of fuel efficiency improvement with an increase of gasoline price by $0.5/gallon.

First, I find that consumers have a higher willingness to pay for efficiency improvement in larger vehicles than smaller vehicles in both cases. For instance, consumers are willing to pay an additional $469 for 1% fuel efficiency improvement for a pickup truck at actual 2006 gasoline price, but only $229 for a small car. In addition, I find that consumers are willing to pay higher extra amount for vehicles with worse fuel efficiency when facing higher tax-inclusive gasoline prices. With an increase of gasoline prices by $0.5/gallon, consumer are willing to pay extra $110 dollars for a pickup truck, but only $54 for a small car.

1.5.2 Estimation Results of the Fuel Efficiency Frontier

In Table 1.4 Panel C, I present the estimation results of the fuel economy frontier function $g_{jt} = g(x_{jt}, a_{jt}, i_t)$. g represents the fuel consumption of a vehicle in gallon-per-mile. The smaller the fuel consumption rate g is, the more fuel-efficient a vehicle is. Positive signs of performance characteristics suggest that there is trade-off between performance and fuel efficiency. Negatives signs of technology adoption and knowledge capital suggest that both channels of technology improvement can drive down the fuel consumption and drive up fuel efficiency, holding vehicle performance characteristics constant. Compare to literature benchmark $g_{jt} = g(x_{jt}, t)$ that uses year fixed effects as sources of shift of frontier over time, I use variations in technology adoption and knowledge capital in my specification.

Figure 1.4 Panel A plots the effects of performance characteristics and technology improvement on fuel efficiency. The vertical axis plots the fraction of improvements in fuel efficiency.[19] The downward sloping lines suggest that the improvements in horsepower-to-weight have reduced fuel efficiency by 19 percentage points, and the improvements in weight have reduced fuel efficiency by 6 percentage points over 1986-2006. Part of this trade-off in fuel efficiency is canceled out by technology improvement, which have led to 15 percentage points fuel efficiency improvements over 1986-2006.

Figure 1.4 Panel B plots the separate effects of technology adoption and knowledge capital on fuel efficiency. The solid line presents the estimated autonomous technology progress using similar reduced-form approach as in (Knittel, 2012). Technology adoption and knowledge capital have resulted in 14.5 percentage points of fuel efficiency improvement over 1986-2006, holding performance characteristics constant.

Among the 14.5 percentage points overall improvement, adopting specific technologies is the key driver and accounts for 92% of the fuel efficiency improvements. By

[19]The fraction of improvements in fuel efficiency is the fraction of reduction in fuel consumption. I measure it by $-\log(g)$, following (Knittel, 2012; Klier & Linn, 2016).

itself, technology adoption has led to 13 percentage points of efficiency improvement over 1986-2006. As for knowledge capital, although this framework does not include dynamic decisions and strategic investment, results still suggest that knowledge capital has a solid contribution to fuel efficiency. It accounts for 8% of the 14.5 percentage points fuel efficiency improvement, and by itself contributes to 1.5 percentage points to fuel efficiency improvement. In a longer-run framework, knowledge capital can have higher effects since knowledge capital may affect technology adoption in the long run when technologies invented in patents have matured to penetrate the market.

1.5.3 Estimation Results of Cost Structures

Adopting energy-saving technologies add financial burdens to produce a vehicle. Panel B of Table 1.4 shows the estimated structure of the marginal cost of production $c_{jt}(x_{jt}, a_{jt}, i_t)$. Results suggest that, for instance, one percent increase of the adoption for multi-valve costs additional \$92 per vehicle, and one percent increase of the adoption for port (multiport fuel injection) costs additional \$25 per car.

Although it is costly to adopt fuel-saving technologies, automakers have profitability incentives to do so. Doing so, first, can raise revenues by offering fuel-efficient vehicles, as suggested in the Estimation Section 1.5.2. For example, increasing the adoption of multiport fuel injection by 1 percent would lead to 8 percent reduction in fuel consumption, i.e. 8 percent increase in fuel efficiency. This fuel efficiency improvement may attract extra demand according our demand estimation. Other than the revenue driven incentive, the second reason is related with fixed costs. Panel E of Table 1.4 suggests that fixed costs are non-increasing with respect to technology adoption. Automakers may therefore, have incentive to adopt additional technology when they are more experienced with technology adoption.[20]

Developing knowledge capital is also costly. Panel D of Table 1.4 presents the estimation results of the marginal R&D cost function $h_t(i_t)$. Point estimates suggest that the R&D cost of knowledge capital is increasing and convex with respect to knowledge capital. A partial equilibrium interpretation is that, an extra 10% patents per firm in 2006 (compared to the average level of 32.8 patents per firm in 2006) would cost additional R&D at $516 million a firm in 2006.[21] In my framework, the cost to invest in knowledge capital is the cost to justify the marginal returns from doing so. Given my deterministic framework, however, this cost does not capture the cost accounting for the uncertainty of R&D process. (I discuss the implications and limitations of the deterministic setup in the introduction.)

The profitability incentives to increase knowledge capital are two-fold. The most important incentive is for the sake of production cost reductions. Panel B of Table 1.4 suggests that knowledge capital is valuable in reducing production costs. For instance, knowledge gained from additional 10% patents leads to a $37 saving of producing a vehicle in 2006. Interpreting the $37 per unit cost saving in the partial equilibrium context, it is equivalent to $290 million production cost saving per firm in

[20]Most fixed costs are downward-sloping and weakly convex, suggesting fixed costs are diminishing (with marginal fixed costs are increasing) with respect to with production improvement. One exception is 5-speed gear, where the linear term λ_1^a is not significantly different from zero, suggesting a flat fixed cost.

[21]It is roughly comparable to 0.5 percent of Honda's revenue in 2014.

2006, holding prices and sales constant. In addition, accumulating knowledge capital can raise revenues by improving vehicle fuel efficiency, as in the case of technology adoption.

In addition to technology adoption and knowledge capital, Panel B of Table 1.4 suggests that vehicles with more appealing performance characteristics are more costly to produce. The incentive to improve performance characteristics comes from the vehicle demand, where consumers value appealing vehicle performance.

1.6 Counterfactual Simulations

I take the structural model and analyze the consequences of three counterfactual scenarios. In Section 1.6.1, I study the effects of a hypothetical demand shock from an increase in gasoline taxes. I examine both the equilibrium fuel efficiency outcomes as well as welfare effects. I study the average effects as well as distributional effects across less fuel efficient vehicles. In Section 1.6.2, I consider a counterfactual ownership consolidation of two automakers - GM and Chrysler in 2006. In Section 1.6.3, I investigate the consequences of a potential supply shock in R&D subsidies.

I compute counterfactual equilibrium using best-response functions (1.7)-(1.10). Multiplicity of equilibria is a standard concern of static and dynamic games. To compute desired equilibrium that is close to the observed market equilibrium, I compute equilibrium under small shocks of gasoline taxes and R&D subsidies. Small shocks are also unlikely to trigger radical changes that are not modeled in this framework, such as shifts towards electric vehicles and hybrid vehicles, as well as dramatic entries and exits of vehicle models. For future work, I shall compute counterfactual by iterating best-response functions which is a better method to simulate equilibrium closed to the one played in the data but is much more computational intensive.[22]

Before proceeding further, here I discuss the implications of the counterfactual results. First, my model allows me to quantify the impacts of counterfactual policies in improving automobile fuel efficiency over 1986-2006. The nature of allowing carmakers to choose technological specifications makes this framework suitable to simulate medium-run counterfactuals and draw medium-run policy implications.

Second, I exclude the tax revenue collected from gasoline taxes and the fiscal cost associated with raising R&D subsidies, when evaluating the private welfare of gasoline taxes and R&D subsidies shocks. In addition, since the only inefficiency in this model is imperfect competition, gasoline taxes and R&D subsidies are actually distortionary policies and will create deadweight loss.

Last, the counterfactual exercises is suitable to simulate effects of environmental policies and market competitiveness on fuel-efficient technological choices in 1986-2006, given firms' actual compliance status in Corporate Average Fuel Economy (CAFE) standard. CAFE standard have been constant and ceased to tighten up over 1986-2006.[23] My model, however, is not suitable to predict vehicle fuel efficiency in

[22](Lee & Pakes, 2009) suggest that equilibria under small shocks are likely to be similar to the observed equilibrium qualitatively and quantitatively, so that simulated equilibrium provides similar implications. Alternatively, Aguirregabiria & Ho (2012) suggest to compute equilibrium using Taylor approximation without strategic interaction, but is more computational intensive.

[23]Automakers wouldn't necessarily have to re-adjust sales mix for small shocks. Jacobsen (2013) documents that automakers compliance strategies towards CAFE standard over 1986-2006 are time-invariant. They are either as as a violator, as a binding firm, or as a non-binding firm. And their strategies to meet US fuel economy standard are unlikely to change in the medium to long run (Jacobsen, 2013).

the long run, especially after CAFE standard tighten up dramatically over 2012-2025. Simulation results imply policy effects in the historical 1986-2006 time frame, in addition to the effects of the actual CAFE standard.

1.6.1 An Increase in Gasoline Taxes

In this section, I study the effects of an increase in gasoline taxes. Gasoline taxes have no direct effect on automakers. However, gasoline taxes may create changes consumers' willingness-to-pay for fuel efficiency, which in turn can create incentives for automakers to alter product characteristics, improve fuel-saving technologies, and adjust vehicle prices.

Over 1986-2006, gasoline prices have been taken an upward-sloping trajectory. The tax-inclusive price has reached at $2.1 in 2006 from $1.2 in 1986 according to (US EIA data, all in $2006 USD). The tax proportion has little changes. Federal taxes have increased from $0.17/gallon in 1986 to $0.18 in 2006. Average state tax has declined from $0.22 in 1986 to $0.20 in 2006 (US DOT data, all in $2006 USD).[24]

I consider a scenario where there is a $1/gallon increase in gasoline tax on the new cars market in 2006. An increase of $1/gallon is not a dramatic shock. Gasoline prices have varied by more than $1/gallon. Besides, $1/gallon gasoline tax is roughly $100/metric tons, twice as the level of social cost of carbon.

For this counterfactual exercise, I present two cases as comparison. The first case is the literature benchmark case. Automakers are allowed to reset the

[24] Federal taxes are collected from TaxFoundation.org. State taxes are collected from U.S. DOT Federal Highway Administration *Highway Statistics Yearbook*.

equilibrium prices in a Bertrand game, facing changes of demand due to the shock of the gasoline tax. Automakers will take all first-stage choices variable as given, including performance characteristics, technologies to adopt and knowledge capital. In the second case, I allow automakers to set prices and also choose performance characteristics, technologies to adopt, and knowledge capital.

Table 1.6 presents the equilibrium outcomes under the $1/gallon gasoline tax. I present the literature benchmark case in Panel I and the case allowing endogenous product choices in Panel II. Panel A reports the equilibrium choices and Panel B reports the equilibrium fuel efficiency outcomes.

Under the literature benchmark case, average vehicle prices increase for $50 after the tax (not weighted by sales). Figure 1.5 suggests most price increases are among more fuel efficient vehicles, due to the higher demand of fuel-efficient vehicles. The changes in prices cause the overall 2006 fleet fuel efficiency increases from 20.57 to 21.36 miles/gallon, with 0.85 miles/gallon improvement.

The equilibrium with endogenous product choices tells a different story. Vehicle prices, on average, slightly decrease for $30. This is driven by the firms that engage in more activities in knowledge capital which cause reduction in marginal costs. As for fuel efficiency, the average model-level fuel efficiency increases from 21.06 to 21.20 miles/gallon, with 0.15 miles/gallon improvement. The 2006 fleet, however, only increases from 20.57 to 21.04 miles/gallon, with 0.47 miles/gallon improvement.

This improvement of 0.47 miles/gallon is due to changes in the following channels. First, as in Table 1.6, automakers marginally decrease performance characteristics to trade-off for better fuel efficiency. Literature benchmark case models short-run adjustment in prices, but do not account for the fact that changes in gasoline taxes increase consumers' willingness-to-pay for efficiency but do not affect not their willingness-to-pay for performance characteristics. Second, Table 1.6 suggests that automakers choose to increase technologies to adopt by 0%-1.3%, depending on the specific technology. Third, automakers marginally invest much more in knowledge capital, which in turn can increase fuel efficiency.

The overestimate of fuel efficiency improvement in the literature benchmark case is driven by price effects. Figure 1.5 shows that automakers dramatically increase the prices for more fuel-efficient cars and decrease the prices for less fuel-efficient cars. This effect works against increasing the sales-weighted fleet average fuel efficiency.

Table 1.7 presents the distributional effects. I summarize the unweighted price and fuel efficiency (in miles-per-gallon) across fuel efficiency group, market segment group, and technology group. First, Panel A shows that vehicles with original low efficiency see an reduction of price by 2.3k and a reduction of fuel efficiency by 0.1 mpg. Relatively efficient vehicles see a price increase by 2.4 k and fuel efficiency improvement by 0.39 mpg. This type of fuel efficiency polarization is consistent with Klier et al. (2016). As for distributional effect across market segments in Panel B, vehicles in the car segment get more expensive by 1.8k and more efficient by 0.34 mpg, whereas light-duty trucks become 2.4 less expensive and 0.08 mpg less efficient. Last, I present the distributional effects across firms' technology groups in Panel C. Although firms with different technology background may have improve fuel efficiency differently, I find that vehicle efficiency improves at a similar pace among Japanese manufacturers, US manufacturers and European and other manufacturers.

Compared to other vehicles, US vehicles become cheaper, but this can be explained by the fact that US firms in general take the low efficiency part of the market segment. According to Panel A, these less efficient cars will see a price reduction as a result of a gasoline tax increase.

To evaluate the change of welfare after a shock, I compute changes in consumer surplus[25]. I exclude the present value of future cost savings from using more fuel-efficient cars when evaluating consumer welfare. In addition to consumer welfare, I present changes in producer surplus, and potential externality changes in social cost of carbon dioxide.

Table 1.8 presents the welfare implications in both the short-run scenario and in the medium-run scenario. Both scenarios suggest that an increase in gasoline tax decreases consumers' welfare due to dollars-per-gallon goes up. Both scenarios also suggest that this shock increases producers' welfare since markups increases. However, the welfare distributions between consumers and producers are different. Not allowing automakers to improve fuel efficiency when facing a gasoline price shock, the consumers' welfare lost is predicted to be \$1.57 billion. This is slightly higher than the case allowing endogenous technology improvements, in which consumers' surplus decreases by \$1.56 billion. As for the producers' surplus, short-run simulation suggests a higher increase of variable profits both due to the higher price automakers charge, and due to not accounting for cost burden from adopting costly technologies.

[25] I use compensating variation suggested in (Rosen & Small, 1981) to compute the consumer surplus. The compensating variation is given by $\Delta CV = -\frac{1}{\alpha_p}\left[\ln \sum_j \exp(\delta_j + \xi_j)\right]_0^1$ where α_p is the marginal utility of income forgone from purchasing a vehicle.

Allowing firms to choose technologies and other product characteristics, an increase of gasoline tax at \$1/gallon suggests the variable profits would increase by \$1.44 billion, producers' surplus to increase by \$0.6 billion and the overall private welfare will decrease by \$0.97 billion.

Following EPA's GHG equivalencies calculator, the improvement of 0.47 miles/gallon implies a 0.9 million metric tons CO^2 saved per year.[26] This amount of CO^2 emission reduction is equivalent to putting 0.2 million vehicles off the road per year, which is higher than 1 percent of new car sales in 2006. This efficiency improvement in the 2006 fleet further implies a total \$0.4 billion social benefit from carbon emission reduction over the next 15 years, evaluated at \$40/metric tons CO^2.
[27]

My results agree with existing studies that gasoline taxes have positive effects on fleet average fuel efficiency (Gramlich, 2010). Neglecting the choices that automakers can make other than prices, however, would over predict the fuel-efficient improvement. In addition, I would neglect the distributional effects across consumers buying different fuel-efficient vehicles, and overstate the benefit private welfare.

1.6.2 Consequences of Reducing Competition

In this section, I address the impact of imperfect competition on the vehicle market. Specifically, I investigates what would have happened to technologies

[26]Following EPA's GHG Equivalencies Calculator Website, I assume the average vehicle miles travelled (VMT) per car holds at original 2006 level, 11,318 miles per year.

[27]I assume all cars have a 15 years of lifetime. I evaluate the lifetime social benefit using 6% discount rate and \$40/metric tons social cost of carbon following EPA's Social Cost of Carbon website.

adopted, patents applied, vehicle performance characteristics, vehicle prices, and fuel efficiency if the GM and Chrysler had been merged in 2006.

Evaluating the fuel efficiency consequences (hence also environmental consequences) is important when evaluating an anti-trust policy but is rarely studied. Existing literature on industrial organization focus on the welfare changes due to increase in the market power from ownership consolidations and all types of imperfect competition. Emerging industrial organization studies have started to incorporate endogenous product characteristics to analyze the effects of market consolidation (Fan, 2013). In this section, I would like to address, in addition to the channel of changes of market power, what the effects of reducing competition are in terms of technology improvement of energy efficiency and discouraging production quality improvement.

The effects of imperfect competition on technological improvement is ambiguous. Aghion et al. (2005) find that competition and innovation intensity have an inverse U-shape relation. Monopolists do not have competitive pressure to innovate while intense competition means firms may lack the resource or extra profit for the innovator may be competed away too quickly to be worthwhile. This section relates to existing theoretical work by empirically simulating the effects of reducing competition in automobile industry.

As major US automakers, Chrysler and GM are direct competitors. Chrysler owns 70 models over 1986-2006 sold under 5 makes including Chrysler, Dodge, Plymouth, etc.. GM produce and sell 123 models over 1986-2006 sold under 9 makes including Buick, Chevy, GMC, Saturn, etc.. Chrysler and GM have been rumored to merger in 2008, but they have never actually consolidated. I consider a hypothetical merger that would happen in new cars market in 2006.

Table 1.11 presents the average simulated choices, responding to the shock. Table 1.11 suggests merging firms and other firms respond differently. The outcomes on product characteristics and technology adoption are intuitive. Merged firms choose to offer products with lower quality. The cars they offer come with worse performance characteristics and with lower adoption rates of fuel-saving technologies.

Merging firms, to our surprise, would like to patent slightly more. A reasonable explanation could be the following. After merger, GM and Chrysler have higher incentive to increase knowledge capital since one patent could benefit more lines of vehicles they produce. Besides, after ownership consolidation, GM and Chrysler are able to share the fixed cost of increasing knowledge capital together.

As for the pricing strategy, merging firms increase their markup for \$241 dollars. The prices they charge, however, are contrary to what a short-run simulation would predict. Merged firms mark down vehicles prices for \$142 per car. An explanation is that the effects of the production cost reductions from offering inferior products and from improving knowledge capital dominates the effect from gain of market power. Figure 1.7 suggests that merging automakers reduce vehicle prices compared to other players in the economy.

Table 1.12 presents the equilibrium outcome by market segment. Panel A shows the counterfactual price and fuel efficiency. Panel B summarizes the market specialty of Chrysler and GM compare to one of their biggest competition Ford. First, Panel A suggests that vehicles sold by the merged firms are become less fuel efficient, except for large and luxury cars. This is consistent with Panel B, which suggests that Ford takes much larger market share in this market segment. If Chrysler and GM merge, they will still have to maintain, if not improve their product quality. Second, the two merged firms sell less efficient Vans and Pickups, but only marginally so.

Results suggest that when evaluating anti-trust issues on energy-related products such as vehicle and large residential appliance in the medium run, it is important to account of potential environmental consequence in energy savings and potential welfare consequence from quality improvement. The possibility that merged firms can share their knowledge capital suggest a source of benefit from market consolidation.

1.6.3 An Increase in R&D Subsidies

In this section, I analyze the effects of an increase in R&D subsidies. R&D subsidies would potentially make the research development process less costly, thus creating incentives for firms to engage in more activities in increasing knowledge capital. In most endogenous technological change literature, R&D subsidies are designed to provide long-run incentives of innovation. In this static framework with endogenous product choices, my counterfactual results should capture a proportion of the overall effects of R&D subsidies

I consider a potential shock in R&D subsidies, where all automakers face a 25% reduction in the marginal cost of developing knowledge capital. Specifically, instead of facing λ_2 in the marginal R&D function $h_t(i_t) = \lambda_1 + \lambda_2 i_t + F^i_{type} + T^i$, automakers would face $h_t(i_t) = \lambda_1 + \lambda_2(1 - 25\%)i_t + F^i_{type} + T^i$ as their new cost structure.

Over 1986-2006, US public R&D expenditures in the transportation sector have increased from $107 million in 1986 to $317 million in 2006 (IEA data, $2006 USD). The annual increment rate is 25.4%, ranging from -40% to 100%. In 2007, US public R&D expenditure have increased to $409 million, equivalent to 29% increase from 2006 level.

Table 1.9 presents the simulated outcomes responding to the 25% increase in R&D subsidies. I present equilibrium results in the case of choosing price only in Panel I, as well as in the case considering endogenous product choices in Panel II. I report equilibrium choices in Panel A and corresponding fuel efficiency results in Panel B.

First and for most, Table 1.9 suggests automakers apply for additional 12.1 patents per year, which is equivalent to an average of cost savings at $81.1 of producing a vehicle according to my estimation results. Besides patenting activities, that automakers have marginally less incentives to adopt better technologies and improve performance characteristics as in Table 1.9. The magnitudes of these impacts, however, are negligible. Last, Table 1.9 suggests vehicles prices drop by $95 dollars. Prices drop uniformly across different fuel-efficient vehicles (See Figure 1.6).

On average, a vehicle model is slightly more efficient, increasing from 21.06 to 21.12 miles/gallon, with only 0.06 miles/gallon improvement. Although the fuel-efficiency improvement is small at model level, the improvement at fleet level is much larger, from 20.57 to 21.40 miles/gallon, with 0.83 miles/gallon improvement.

As for the welfare implication, Table 1.10 suggests that a R&D subsidy would increase both consumers' welfare and producers' welfare. On one hand, consumers' welfare marginally increases for \$0.02 billion. The fact that consumers only marginally benefit from a R&D subsidy in the medium run is because knowledge capital has limited fuel efficiency benefits in the medium run, and because technology adoption decreases in this case. The main driver of the increase of consumer surplus comes from the price reduction channel. On the other hand, automakers make profits from the production cost savings due to increase in knowledge capital. Firms in total see an increase in the variable profits for \$2.3 billion, and overall profits for \$0.85 billion in 2006. Accounting for welfare changes for both consumers and producers, the R&D subsidy studied in this exercise results in an increase of private welfare of \$0.88 billion in 2006.

Ignoring the choices of knowledge capital will lead to incorrect evaluations in the effects of R&D subsidies in the transportation sector. Not only will l miss to include the fuel-efficiency benefit from a R&D subsidiary policy, I will also neglect the consumer welfare gain from using more fuel-efficient cars and from paying less for a vehicle. In addition, for producer's surplus, I will miss to include the cost savings raised from such a R&D subsidy.

1.7 Robustness and Additional Results

I perform multiple robust checks in addition to the baseline estimation. Concerning on some assumptions in the identification are too strong, I try alternative specifications to relax those assumptions. Results are included in Online Appendix.

To identify the parameters in the demand system and to correctly predict marginal cost, I assume the demand unobservables are not efficiency-related and all characteristics related with fuel efficiency are picked up fuel cost $fp \cdot g_h$. In Table C.1 Column (4), I include both technology adoption and knowledge capital to test this assumption. Results suggest that I cannot separately identify the coefficient of fuel cost (dollar/mile) from fuel efficiency technology variables. It suggests that it is reasonable to make the above assumption and demand parameters are identified.

Table C.1 includes alternative specifications for the marginal cost of production function. Column (1) shows that the demand is inelastic with respect to vehicle price and fuel cost in OLS. It suggests that a gasoline tax (or carbon tax) has the potential to induce innovation and technology adoption through the channel of shifting demand towards fuel-efficient vehicles. Column (3) includes an alternative specification. I test if consumers make purchasing choices including the technology adoption and innovation. Results suggest that effects of technology adoption and innovation cannot be separately identified from the effect of fuel cost. It provides suggestive evidences that it is reasonable to assume that fuel efficiency and vehicle performance variables fully capture all efficiency-related quality. And demand error only contains non-efficiency related quality.

Table C.2 includes alternative specifications of the fuel efficiency frontier, including a specification using a literature benchmark specification. In Column (1), I estimate the frontier equation allowing fuel efficiency to have trade-off relation with performance, but not allowing the frontier to have different intercept over time. In Column (2), I estimate a well-adopted specification in the literature. I estimate the same trade-off frontier, but allowing the intercepts varies over time using a year fixed effect. The estimated year fixed effect is often referred to as the fuel efficiency *frontier* in the literature. In Column (3), I include the benchmark case. I will refer to $\theta_a a + \theta_i i$ as the fuel efficiency *frontier*. The basic estimation in Column (1) does not pick up the trade-off quite well compared to Column (2) and (3). Our baseline performs as good as the conventional frontier estimates in terms of goodness of fit, yet also with the benefit to allow me to see how different types of technology improvement contributes to the frontier.

In addition, I perform robustness checks using different parameters of depreciation rate δ, which is 20% in the baseline estimation. I show how results could alter in an extreme case of zero depreciation in Table C.2 Column (4), Table C.3 Column (5), and Table C.4 Column (4). I do find in the of lower depreciation rate (0%), that the marginal efficiency gain from additional patents is lower (Table C.2), and that the marginal cost reduction of producing a vehicle is lower (Table C.3). The reason is lower depreciation rate leads to higher existing pool of knowledge so that marginal returns in all channels are lower. Table C.4 also suggests that the marginal cost of increasing knowledge stock is lower. The reason is I use spillovers stocks and cross-categories knowledge stocks to predict current effort of developing knowledge capital i. With higher existing knowledge, it is less difficult for firms to expand their knowledge pool and innovate for more patents. Nonetheless, the qualitative results do not change even in this extreme case.

1.8 Concluding Remarks

Incorporating technological changes is important for understanding the optimal environmental policies needed to combat climate change problems in the medium to long run. However, the link between environmental policies and the different technological choices have not been empirically established. To understand how different types of technological changes respond to environmental policies, this study examines the roles of adopting well-developed technologies versus increasing knowledge capital in improving fuel efficiency and affecting welfare. Using the automobile industry as an example, this paper finds that technology adoption is more sensitive to gasoline prices, whereas knowledge capital responds more to R&D subsidies in the medium run. This paper also highlights two channels of knowledge capital. Increasing knowledge about energy-efficient technologies not only has fuel efficiency benefits, but it also comes with production cost savings.

Carbon policies are designed to combat greenhouse gas emissions in the medium to long run. For this reason, medium-run predictions are more suitable than short-run models for understanding how improvements in low-carbon technologies respond to environmental policies. Moreover, short-run models may overstate the effects of environmental policies on equilibrium outcomes by overstating price effects. To simulate how gasoline taxes, R&D subsidies, and market competitiveness affect fuel efficiency and private welfare, I set up a structural model of technological improvements of the new vehicle market in the US.

My empirical findings suggest that gasoline taxes and R&D subsidies not only trigger different incentives, but these two policies have different fuel efficiency outcomes and implications. To achieve fuel efficiency improvements in the medium run, gasoline taxes are more effective since technology adoption has much greater medium-run fuel efficiency benefits. If, however, the goal is to help automakers become more productive, lower their costs in producing fuel efficient cars, then R&D subsidies are more suitable.

There are many directions in which this study can be extended and re-evaluated for future work. First, this study captures what elements automakers can adjust in addition to short-run price changes, but not what automakers can adjust in the long run. Incorporating radical technological changes (e.g., from conventional internal combustion engine vehicles to hybrid and electric cars) is important for understanding the long-run effects of policy instruments. Second, this study highlights the two channels by which knowledge capital may affect welfare. This framework, however, does not aim to investigate R&D investment strategies facing uncertain outcomes. Addressing these channels my be an important extension for future research.

Tables

Table 1.1: Summary Statistics, 1986-2006

Var	Description	Mean	SD
A. Basic Characteristics			
p_h	Manufacturer suggested retail price (MSRP) in 10k 2006 USD	3.27	2.19
$s_h \cdot M$	Sales in 100k	0.78	0.99
g_h	Fuel efficiency: fuel consumption rate (gallon/mile), i.e. $1/mpg_h$	0.05	0.01
fp_h	Fuel price: dollar/gallon in 2006 USD	1.25	0.31
$fp_h \cdot g_h$	Fuel cost: dollar/mile in 2006 USD	0.06	0.02
$X_{h,hpw}$	Performance: Horsepower-to-weight	0.05	0.02
$X_{h,w}$	Performance: Weight (metric tons)	1.54	0.34
B. Technology			
$a_{h,5g}$	5 speed gear	0.65	0.34
$a_{h,vvt}$	Variable valve timing (VVT)	0.17	0.37
$a_{h,mv}$	Multiple valve (#valve>2)	0.48	0.49
$a_{h,mfi}$	Port (MFI)	0.88	0.32
$a^{old}_{h,cb}$	Grandfathered tech: Carburetor	0.04	0.18
$a^{old}_{h,tbi}$	Grandfathered tech: Throttle body injection (TBI)	0.09	0.28
$a^{old}_{h,a0lk}$	Grandfathered tech:Auto trans. w/o lockup	0.29	0.28
$a^{old}_{h,3g}$	Grandfathered tech:3 speed gear	0.53	0.38
$a^{lr}_{h,4wd}$	Longer-run tech: 4-wheel-drive/all-wheel-drive	0.19	0.31
C. Knowledge Capital			
i_{ft}	Number of patents applied for conventional engines (in 100)	0.47	0.74
ki_{ft}	Accumulated knowledge capital for conventional engines (in 100)	2.01	2.85
Ski_{ft}	Spilled accumu. knowledge cap. for conventional engines (in 100)	7.24	9.54
ki^{afv}_{ft}	Accumulated knowledge capital for AFV† engines (in 100)	0.59	1.27
Ski^{afv}_{ft}	Spilled accumu. knowledge capital for AFV engines (in 100)	1.82	3.20
D. Observations			
	Number of Model-Years	3791	
	Number of Models	502	
	Number of Brands	45	
	Number of Companies	23	
	Number of Segments	7	
	Number of Years	21	

Note: †AFV engine: Alternative Fuel Vehicle engines. See Appendix A.3 for definitions.

Table 1.2: Knowledge Capital: Number of Patents Applied, 1986-2006

Category	Count
A. Engine Tech for Internal Combustion Engines	
1.1 Variable Valve Timing (VVT) and Var. Val. Tim. and Lift (VVLT)	1,398
1.2 Integrated Starter/Generator (ISG)	15
1.3 Cylinder Deactivation (CD)	202
1.4 Direct Fuel Injection (DFI/GDI)	682
1.5 Turbocharger	373
1.6 Supercharger	229
1.7 Other, Improved Fuel Efficiency	5,229
1.8 Other, Uncategorized Engine Technologies	11,697
Total	14,595
B. Engine Tech for Alternative Fuel Vehicles (AFV) Engines	
2.1 Electric Vehicles	863
2.2 Hybrid Vehicles	381
2.3 Hydrogen Vehicles/Fuel Cells	6,661
Total	7,859
	35,464

Note: The count stands for the total number of weighted patent applied in each category. Source: OECD TPF Database. Definition of each broad categories is on Appendix A.3. Definition of each sub-category is available upon request.

Table 1.3: Suggestive Evidence: Gasoline Prices and Competitiveness

	Gasoline Prices	Competitiveness (HHI)
Knowledge Capital Stock	-0.40	-0.26
Technology Adoption		
5 Gear Trans.	0.72	-0.52
Var. Valve Timing	0.89	-0.52
Multi. Valve	-0.65	0.54
Port (MFI)	-0.62	0.67

Note: 1. All variables (knowledge capital, technology adoption, gasoline prices, and HHI) are detrended.

Table 1.4: Estimation Results

(Table continues next page)

Parameters		Estimates	Standard Errors
A. Demand Side Parameters ln($share$)			
α_p: Price	Veh. Price, $10k, 2006 USD	-0.5483***	(0.1134)
α_g: Fuel Cost	Dollar/Mile, 2006 USD	-17.9060***	(6.3303)
α_x: Veh. Performance Char.	ln(Weight)	1.7077***	(0.4448)
	ln(Horsepower/Weight)	1.0533***	(0.3353)
σ_{seg}: Segment Similarity	ln(share|seg)	0.4949***	(0.0881)
	Model by Year FE	Yes	
B. Marginal Cost of Production $c_{jt}(x_{jt}, a_{jt}, i_t)$			
γ_x : Performance Char.	ln(Weight)	4.8700***	(0.3141)
	ln(Hp/Weight)	2.3446***	(0.3967)
γ_a: Technology Adoption	5 Gear Trans.	1.3018***	(0.1464)
	Var. Valve Timing	0.2542	(0.2376)
	Multi. Valve	0.9221***	(0.1623)
	Port (MFI)	0.2547**	(0.1163)
γ_i: Innovation	Ki: Knowledge Stock	-0.0668***	(0.0160)
	(100 Engine Patents)		
γ_0: Constant		2.7747*	(1.3542)
	Segment FE, Year FE	Yes	
C. Fuel Efficiency Technology Frontier: *Fuel Consumption Rate* $g_j(x_{jt}, a_{jt}, i_t)$			
θ_x: Performance Trade-off	ln(Weight)	0.4962***	(0.0102)
	ln(Horsepower/Weight)	0.2412***	(0.0084)
θ_a: Technology adoption	5 Gear Transmission	-0.0716***	(0.0051)
	Var. Valve Timing (VVT)	-0.0450***	(0.0053)
	Multi. Valve (#valve>2)	-0.0875***	(0.0043)
	Port (MFI)	-0.0846***	(0.0054)
θ_i: Innovation	Ki: Knowledge Stock	-0.0090***	(0.0009)
	(100 Engine Patents)		
θ_0 : Constant		-2.7074***	(0.0330)
	Segment FE, Make FE	Yes	
D. Marginal R&D Cost of Innovation $h_t(i_t)$ ***in*** ($Billion 2006 USD)			
λ_1: Slope of R&D cost	Constant	12.1032***	(2.2785)
λ_2: Slope of R&D cost	i: Knowledge Flow i	8.3001***	(1.9750)
	(100 Engine Patents)		
λ_{jp}: Japanese Mfr.		-10.3401***	(2.3793)
λ_{us}: US Mfr.		60.0487***	(3.0349)
λ_0: Constant		-0.4044***	(0.1608)
	Time Trend	Yes	

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.4: Estimation Results (cont.)

Parameters		Estimates	Standard Errors
E.1 Marginal fixed cost associated with technology adoption: $F^a_{jt}(a_{jt})$			
5 Gear Transmission			
ϕ^{a1}_1: Slope of fixed cost	Constant	-0.1016	(0.1563)
ϕ^{a1}_2: Slope of fixed cost	5 Gear Transmission	-0.5286***	(0.0954)
	Company FE, Time Trend	Yes	
Var. Valve Timing (VVT)			
ϕ^{a2}_1: Slope of fixed cost	Constant	-0.0722**	(0.0294)
ϕ^{a2}_2: Slope of fixed cost	Var. Valve Timing (VVT)	0.0097	(0.0263)
	Company FE, Time Trend	Yes	
Multi. Valve (#valve>2)			
ϕ^{a3}_1: Slope of fixed cost	Constant	-0.3118***	(0.1087)
ϕ^{a3}_2: Slope of fixed cost	Multi. Valve (#valve>2)	0.1703***	(0.0877)
	Company FE, Time Trend	Yes	
Port (MFI)			
ϕ^{a4}_1: Slope of fixed cost	Constant	-0.0878**	(0.0305)
ϕ^{a4}_2: Slope of fixed cost	Port (MFI)	0.0253	(0.0153)
	Company FE, Time Trend	Yes	
E.2 Marginal fixed cost associated with performance: $F^x_{jt}(x_{jt})$			
Weight			
ϕ^{x1}_1: Slope of fixed cost	Constant	-1.7416***	(0.2773)
ϕ^{x1}_2: Slope of fixed cost	ln(Weight)	1.1965***	(0.1752)
	Company FE, Time Trend	Yes	
Horsepower-to-weight			
ϕ^{x2}_1: Slope of fixed cost	Constant	1.2406***	(0.1934)
ϕ^{x2}_2: Slope of fixed cost	ln(Hp/Weight)	0.4286***	(0.0588)
	Company FE, Time Trend	Yes	

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Note: This table reports baseline estimated parameters for the demand system, cost structure equations, and the fuel efficiency frontier equation. Panel A: Demand is estimated using a Nested Logit demand. Panel B: Model-level marginal costs of production are derived and estimated using automakers' first order condition w.r.t price under the assumption of Bertrand-Nash equilibrium. Panel C: Fuel economy frontier are estimated using a nonlinear least square. Panel D: Firm-level marginal costs of accumulating knowledge capital are derived from first order condition w.r.t. knowledge capital. Panel E: Model-level fixed costs of adopting technologies and improving performance are derived from first order condition w.r.t. technology adoption and first order condition w.r.t performance characteristics.

Table 1.5: Willingness-to-Pay for 1% Fuel Efficiency Improvement in 2006

	Passenger Cars			Light-duty Trucks			
	Small	Medium	Lrg./Lux	CUV	SUV	Van	Pickup
Fuel Efficiency (miles/gal.)	29.8	24.0	22.0	21.7	17.1	19.4	17.0
Fuel Efficiency with 1% Improvement	30.1	24.2	22.2	21.9	17.3	19.6	17.2
Willingness-to-Pay for 1% Fuel Efficiency Improvement (in 2006 USD)							
with 2006 gas price ($2.13/gallon)	229	236	281	289	464	361	469
with $0.5 gas tax shock ($2.63/gallon)	283	292	347	356	573	445	579
additional WTP	54	56	66	67	109	84	110

Note: 1. Fuel efficiency in 2006 are the sales-weighted fuel efficiency. 2. Willingness-to-pay is computed holding price and characteristics fixed.

Table 1.6: Simulation I: A $1/gallon Increase in Gasoline Tax in 2006

Equilibrium Outcomes

	Scenario I: Choose p			Scenario II: Choose $\{p, x, a, i\}$		
	Actual	Sim.	Diff.	Actual	Sim.	Diff.
A. Equilibrium Choices						
p: Price (2006 USD)	35,435	35,485	50	35,435	35,405	-30
x: Performance Characteristics (log)						
Weight				1.347	1.346	-0.001
Hp/Weight				-2.812	-2.812	-0.000
a: Tech. Adopt Rate (Percent)						
5 Gear Trans				42.4	42.4	0.0
Var. Val. Timing				58.8	60.0	1.3
Multi. Valve				77.6	77.8	0.2
Port (MFI)				100.0	100.0	0.1
i: Knowl. (# of Patents)				32.88	33.61	0.73
B. Fuel Efficiency (miles/gallon)						
Unweighted Average	21.05	21.05	0.00	21.05	21.20	0.15
2006 Fleet Average	20.57	21.42	0.85	20.57	21.04	0.47

Note: 2006 Fleet average is sales weighted, computed using harmonic mean.

Table 1.7: Simulation I: A \$1/gallon Increase in Gasoline Tax in 2006

Distributional Effects

	Actual	Sim.	Diff.	Actual	Sim.	Diff.
	Panel A. By Original MPG Efficiency Distribution					
	1: Efficiency < Mean			2: Efficiency ≥ Mean		
Price (2006 USD)	42,920	40,575	-2,345	27,950	30,235	2,385
Fuel Efficiency, Unweighted	18.01	17.92	-0.10	24.09	24.48	0.39
	Panel B. By Segment					
	1. Passenger Cars			2. Light Duty Trucks		
Price (2006 USD)	37,843	39,707	1,863	32,474	30,117	-2,357
Fuel Efficiency, Unweighted	22.96	23.30	0.34	18.70	18.62	-0.08
	Panel C. By Technology Group					
	1. Japanese Mfr.			2. European & Other		
Price (2006 USD)	29,001	30,345	1,343	58,183	59,790	1,607
Fuel Efficiency, Unweighted	22.39	22.57	0.18	20.38	20.60	0.22
	3. US Mfr.					
Price (2006 USD)	32,134	30,709	-1,426			
Fuel Efficiency, Unweighted	20.04	20.23	0.18			

Note: Fuel Economy here is unweighted miles-per-gallon. It does not reflect the sales weighted fleet average fuel economy.

Table 1.8: Simulation I: A \$1/gallon Increase in Gasoline Tax in 2006

Panel A. Welfare Effects

Items	Scenario I Choose p	Scenario II Choose $\{p, x, a, i\}$
A. Welfare (\$Billion, 2006 USD):		
ΔConsumers Surplus	-1.5680	-1.5639
ΔProfits		
ΔVariable Profit	3.3642	1.4417
ΔFixed Costs	0	-0.2432
ΔR&D Costs	0	1.0886
ΔTotal Private Welfare	1.7962	-0.9676
Externalities		
ΔCO_2 Savings	0.0045	0.0034
ΔTotal Welfare	1.8007	-0.9642
B. Other Cost Components (in \$):		
ΔMarkup/Vehicle	50	92
ΔMarginal Cost/Vehicle	0	-122

Table 1.9: Simulation II: A 25% Reduction in Marginal R&D Cost in 2006

Equilibrium Outcomes

	Scenario I: Choose p			Scenario II: Choose $\{p, x, a, i\}$		
	Actual	Sim.	Diff.	Actual	Sim.	Diff.
A. Equilibrium Choices						
p: Price (2006 USD)	35,435	35,435	0	35,435	35,340	-95
x: Performance Characteristics (log)						
Weight				1.347	1.347	0.000
Hp/Weight				-2.812	-2.817	-0.001
a: Tech. Adopt Rate (Percent)						
5 Gear Trans				42.41	42.41	-0.00
Var. Val. Timing				58.77	59.03	0.26
Multi. Valve				77.56	77.55	-0.01
Port (MFI)				100.0	99.96	-0.04
i: Knowl. (# of Patents)				32.88	45.09	12.21
B. Fuel Efficiency (miles/gallon)						
Unweighted Average	21.051	21.051	0.000	21.051	21.114	0.063
2006 Fleet Average	20.569	20.569	0.000	20.569	20.572	0.003

Note: 2006 Fleet average is sales weighted, computed using harmonic mean.

Table 1.10: Simulation II: A 25% Reduction in Marginal R&D Cost in 2006

Welfare Effects

Items	Scenario I Choose p	Scenario II Choose $\{p, x, a, i\}$
A. Welfare ($Billion, 2006 USD):		
ΔConsumers Surplus	0	0.0220
ΔProfits		
ΔVariable Profit	0	2.2696
ΔFixed Costs	0	0.0164
ΔR&D Costs	0	1.3987
ΔTotal Private Welfare	0	0.8765
Externalities		
ΔCO_2 Savings	0	0.0006
Δ Total Welfare	0	0.8777
B. Other Cost Components (in $):		
ΔMarkup/Vehicle	0	130
ΔMarginal Cost/Vehicle	0	-224

Table 1.11: Simulation III: Merger of GM and Chrysler in 2006

Equilibrium Outcomes

	Type of firms	Scenario I: Choose p Actual	Sim.	Diff.	Scenario II: Choose $\{p, x, a, i\}$ Actual	Sim.	Diff.
A. Equilibrium Choices							
p: Price (2006 USD)		35,435	36,059	625	35,435	35,684	249
	Merged	32,039	33,886	1,847	32,039	31,897	-142
	Other	36,884	39,987	103	36,884	37,299	415
x: Performance Characteristics (log)							
Weight					1.3467	1.3465	0.0002
Hp/Weight					-2.8122	-2.8118	0.0004
Weight	Merged				1.3997	1.3915	-0.0082
Hp/Weight	Merged				-2.8241	-2.8280	-0.0039
Weight	Other				1.3241	1.3273	0.0036
Hp/Weight	Other				-2.8073	-2.8049	0.0024
a: Tech. Adopt Rate (Percent)							
5 Gear Trans					42.41	42.41	0.00
Var. Val. Timing					58.77	59.13	0.36
Multi. Valve					77.55	77.56	0.01
Port (MFI)					100.00	100.00	0.00
5 Gear Trans	Merged				28.85	30.00	1.19
Var. Val. Timing	Merged				31.02	21.31	-9.71
Multi. Valve	Merged				45.86	43.25	-2.61
Port (MFI)	Merged				100.00	95.45	-4.55
5 Gear Trans	Other				48.19	47.68	-0.51
Var. Val. Timing	Other				70.61	75.27	4.66
Multi. Valve	Other				91.11	92.20	1.12
Port (MFI)	Other				100.00	100.00	2.00
i: Knowl. (# of Patents)					32.89	32.89	0.00
	Merged				3.79	3.92	0.13
	Other				36.52	36.50	-0.02
B. Fuel Efficiency (miles/gallon)							
Unweighted Average		21.05	21.05	0.000	21.05	21.06	0.01
2006 Fleet Average		20.57	22.97	2.40	20.57	20.52	-0.05
	Merged	19.03	19.59	0.56	19.03	18.87	-0.16
	Other	21.54	24.14	2.63	21.54	21.56	0.02

Note: 2006 Fleet average is sales weighted, computed using harmonic mean.

Table 1.12: Simulation I: A $1/gallon Increase in Gasoline Tax in 2006

Distributional Effects

Panel A. Equilibrium Outcome By Segment

	Actual	Sim.	Diff.	Actual	Sim.	Diff.
	1. Small Car			2. Medium Car		
Price (2006 USD)	16,097	15,915	-183	23.331	23.173	-157
Fuel Efficiency	28.48	28.34	-0.14	23.33	23.17	-0.16
	3. Large/Lux Car			4. Crossover (CUV)		
Price (2006 USD)	23,986	23,693	-293	27,061	26,286	-775
Fuel Efficiency	19.69	19.71	0.02	21.32	21.14	-0.18
	5. Sport Utility (SUV)			6. Vans		
	36,403	35,846	-557	27,533	27,073	-459
	16.82	16.69	-0.13	19.20	19.11	-0.08
	7. Pickup Trucks					
Price (2006 USD)	30,796	30,720	-73			
Fuel Efficiency	17.61	17.54	-0.07			

Note: Fuel efficiency reported above are unweighted, distinct from fleet average fuel efficiency.

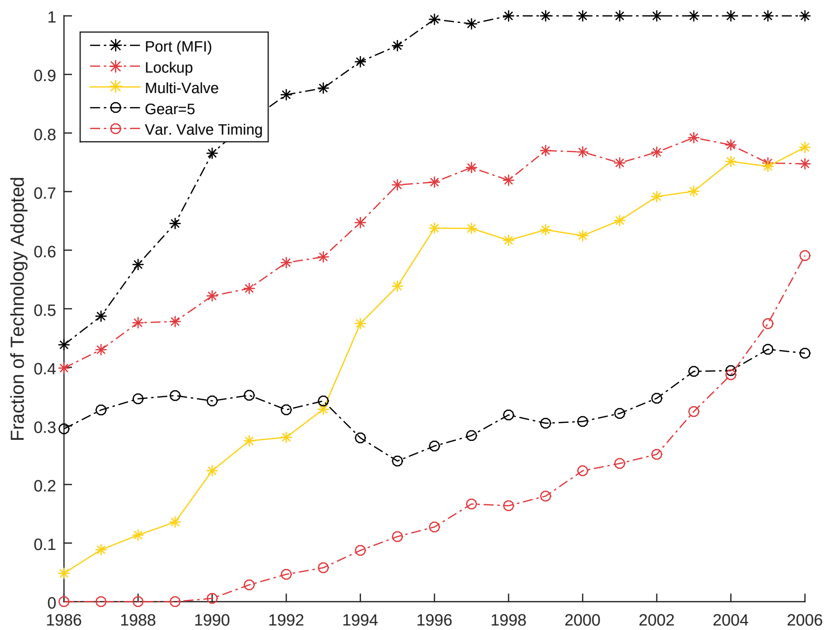
Panel B. Sales of Merged Firms (Chrysler and GM), and Ford by Segment

Selected Firms	Sales in 2006 (in 100k)		
	1. Small Car	2. Medium Car	3. Large/Lux Car
Chrysler	0	1.52	0.81
GM	2.86	6.96	1.63
Ford	1.58	2.16	3.83
	4. CUV	5. SUV	6. Vans
Chrysler	2.18	4.76	3.72
GM	2.47	5.62	2.02
Ford	1.81	3.17	2.43
	7. Pickup Trk.		
Chrysler	4.51		
GM	9.02		
Ford	8.71		

Note: Fuel Economy here is unweighted miles-per-gallon. It does not reflect the sales weighted fleet average fuel economy.

Figures

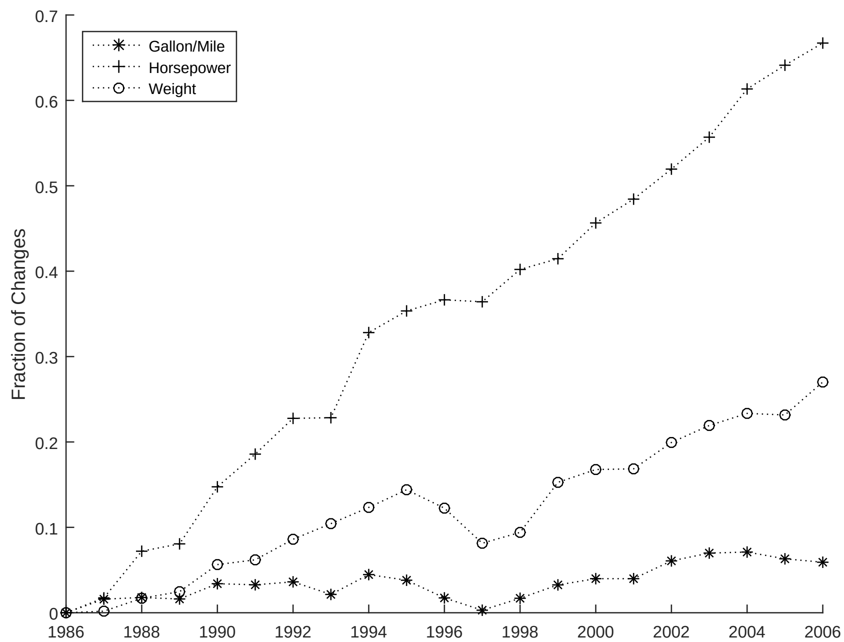
Figure 1.1: Technologies Penetrated the Vehicle Market: 1986-2006



Note: Technology penetration rates are computed as unweighted average.

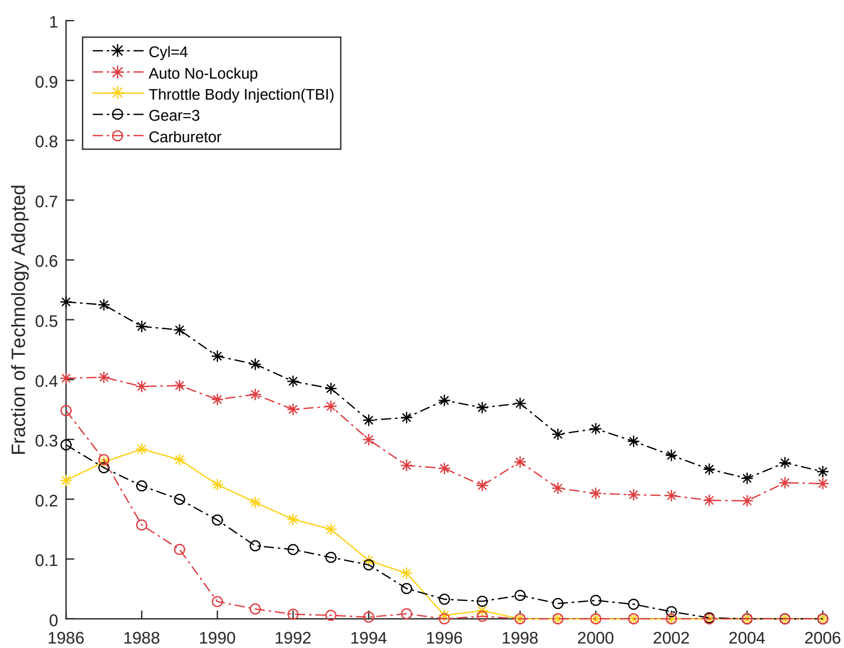
Source: EPA Fuel Economy Guide Data and EPA Fuel Economy Trend Data.

Figure 1.2: Changes of Vehicle Characteristics, 1986-2006



Note: This figure plots the fraction changes (as in logarithm terms) of fuel efficiency (gallon/mile), weight, horsepower since 1986.

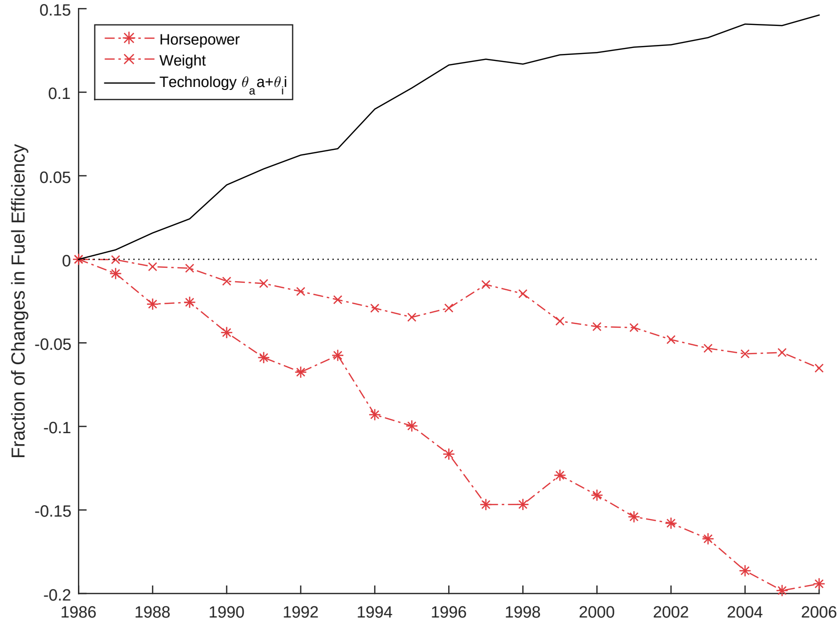
Figure 1.3: Grandfathered Technologies Exited from the Market, 1986-2006



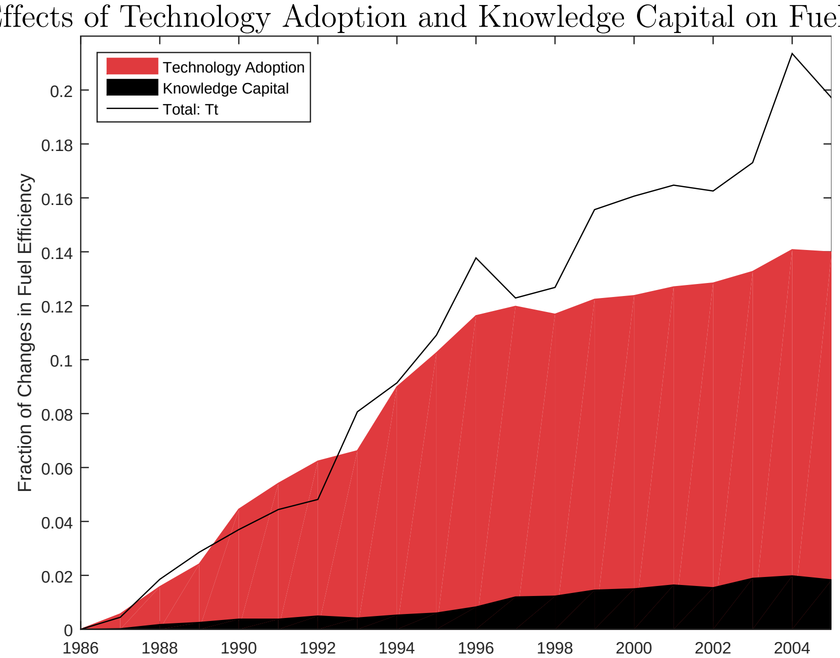
Note: Technology penetration rates are computed as unweighted average.
Source: EPA Fuel Economy Guide Data and EPA Fuel Economy Trend Data.

Figure 1.4: Fuel Efficiency Improvement from Innovation and Technology Adoption

Panel A. Effects of Performance and Technology on Fuel Efficiency



Panel B. Effects of Technology Adoption and Knowledge Capital on Fuel Efficiency



Note: Fraction of Changes in Fuel Efficiency is $-\ln(gallon/mile)$.

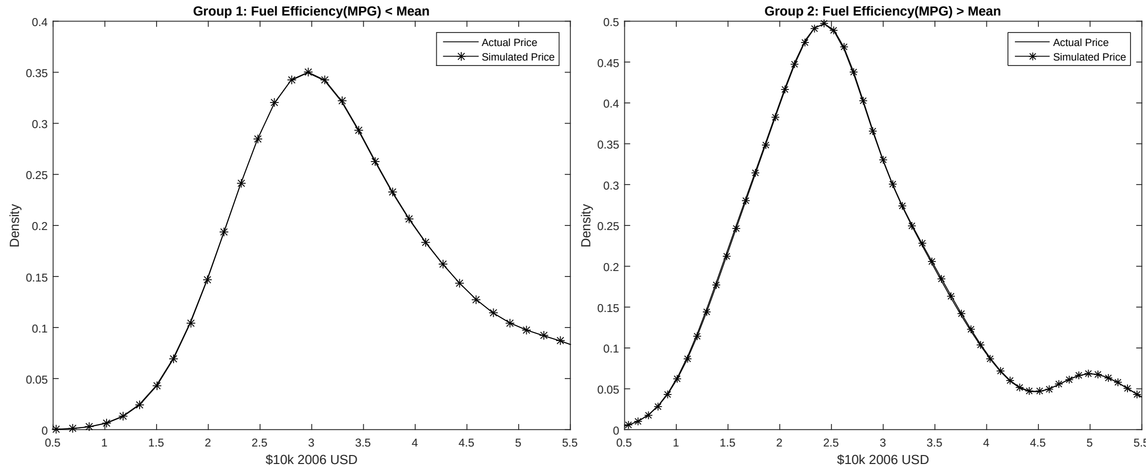
Panel A plots effects of performance and technology improvement on fuel efficiency, using estimates from $g(x,a,i) = \exp\{\theta_0 + \underbrace{\theta_{x,hpw} \ln x_{hpw}} + \underbrace{\theta_{x,wt} \ln x_{wt}} + \underbrace{\theta_a a + \theta_i i}\} + \varepsilon$.

Panel B plots effects of technology adoption and knowledge capital on fuel efficiency, using estimates from $g(x,a,i) = \exp\{\theta_0 + \theta_x \ln x + \underbrace{\theta_a a} + \underbrace{\theta_i i}\} + \varepsilon$.

Panel B also plots the autonomous technology frontier on fuel efficiency improvement is obtained from $g(x,T_t) = \exp\{\theta_0 + \theta_x \ln x + \underbrace{T_t}\} + \varepsilon$ as comparison.

Figure 1.5: Simulation I: A $1/gallon Increase in Gasoline Tax in 2006

Scenario I. Choose Price p



Scenario II. Choose $\{p, x, a, i\}$

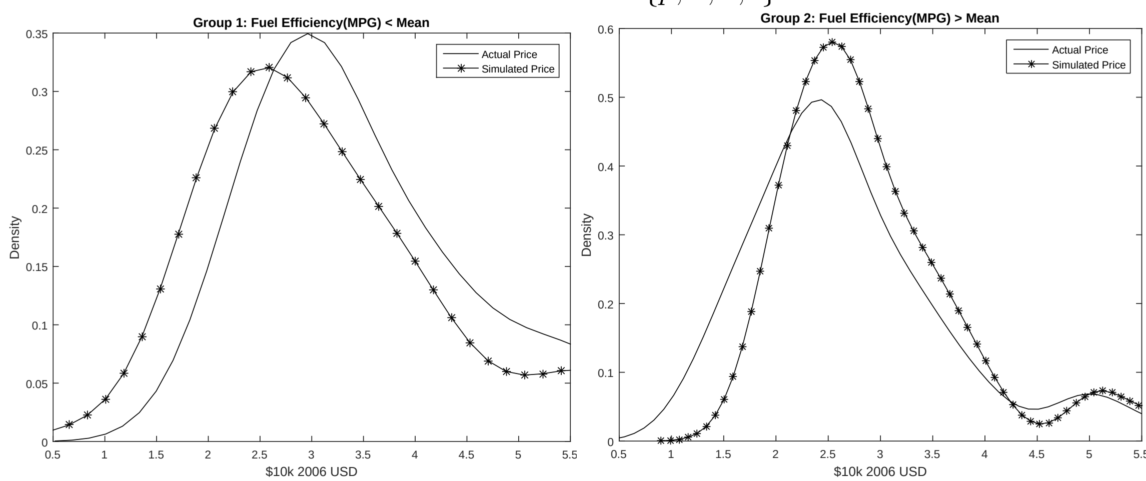


Figure 1.6: Simulation II: A 25% Reduction in Marginal R&D Cost in 2006

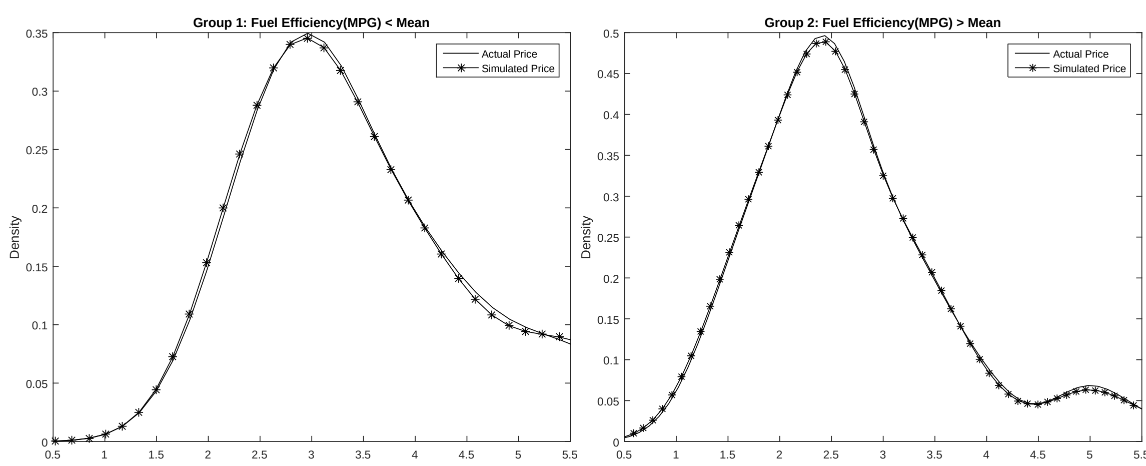
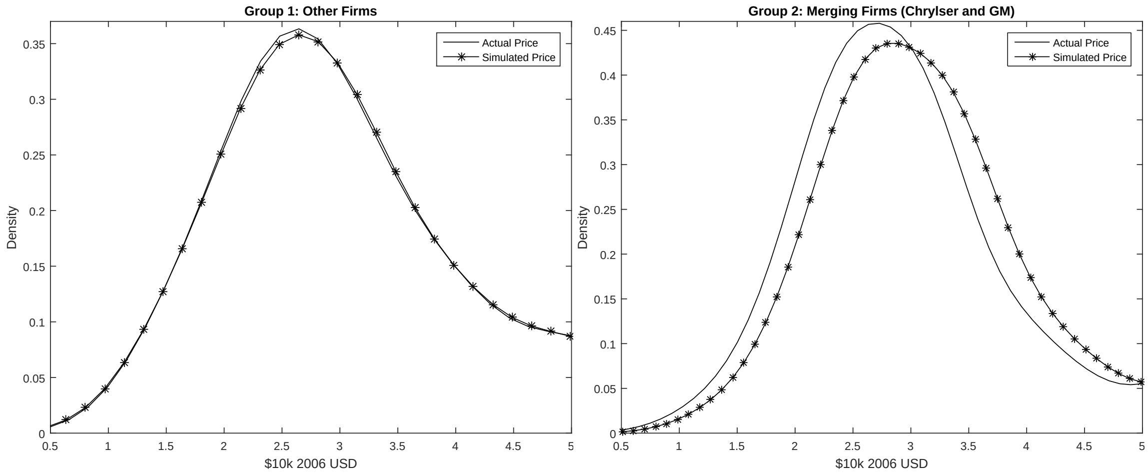
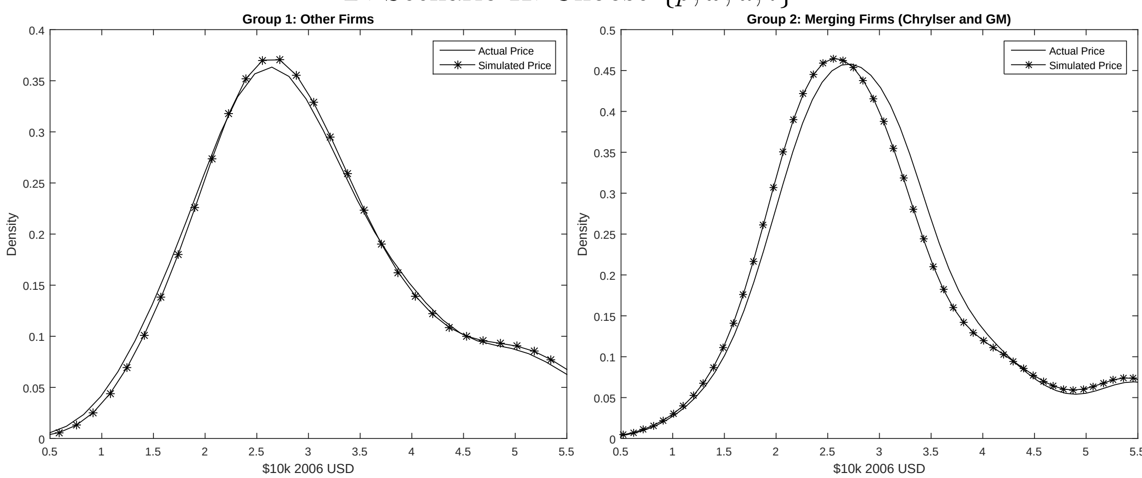


Figure 1.7: Simulation III: Merger of GM and Chrysler in 2006

Panel A. Scenario I. Choose Price p



B. Scenario II. Choose $\{p, x, a, i\}$



A.1 Data Sources and Definitions of Variables

Table A.1: Data Description and Sources

Var	Data Description	Source
A. Basic Vehicle Characteristics		
p_h	Manufacturer suggested retail price (MSRP) in 10k 2006 USD	Ward's Auto
s_h	Market share	Ward's Auto
$s_{h\|seg}$	Market share in the segment	Ward's Auto
$X_{h,hpw}$	Performance: Horsepower-to-weight	Automotive News
$X_{h,w}$	Performance: Weight (metric tons)	Automotive News
g_h	Fuel consumption rate (Gallon/mile), i.e. $\frac{1}{mpg}$	EPA FE Guide
fp_h	Tax-inclusive national gasoline price. (Dollar/gallon in 2006 USD)	EIA
B. Technology		
$a_{h,5g}$	5 speed gear	EPA FE Guide
$a_{h,vvt}$	Variable valve timing (VVT)	EPA FE Trend
$a_{h,mv}$	Multiple valve (#valve>2)	EPA FE Trend
$a_{h,mfi}$	Port (MFI)	EPA FE Trend
$a^{old}_{h,cb}$	Grandfathered tech: Carburetor	EPA FE Trend
$a^{old}_{h,tbi}$	Grandfathered tech: Throttle body injection (TBI)	EPA FE Trend
$a^{old}_{h,a0lk}$	Grandfathered tech:Auto trans. w/o lockup	EPA FE Guide
$a^{old}_{h,3g}$	Grandfathered tech:3 speed gear	EPA FE Guide
$a^{lr}_{h,4wd}$	Longer-run tech: 4-wheel-drive/all-wheel-drive	EPA FE Guide
C. Knowledge Capital		
i_{ft}	Number of patents applied for conventional internal combustion engines	OECD TPF, Citation
ki_{ft}	Accumulated knowledge capital for internal combustion engines	OECD TPF, Citation
ki^{afv}_{ft}	Accumulated knowledge capital for alternative fuel vehicle(AFV) engines	OECD TPF, Citation
Ski_{ft}	Spilled accumulated knowledge capital for internal combustion engines	OECD TPF, Citation
Ski^{afv}_{ft}	Spilled accumulated knowledge capital for AFV engines	OECD TPF, Citation

Technology Adoption.- Data are collected from *EPA Fuel Economy Guide Data.* I supplement technology adoption variables using *EPA Fuel Economy Trend Data.* Selection of trendy technologies over 1986-2006 is based on EPA Fuel Economy Trend

Report (2008; 2013; 2014). The *Guide* data is the public version of *Trend* data with much fewer variables. Therefore, matching two data set causes very minimum inconsistency.

Knowledge Capital.- Appendix A.3 for detail.

Segment.- There are 7 segments-small car, medium car, large/luxury car, crossover, SUV, van, and pickup trucks.

Company.-Each company is a parent company including one brand to multiple brands. Knowledge capital varies at company level. There are 23 companies-AMC, BMW, Chrysler, Daewoo, Daimler, Fiat, Ford, GM, Honda, Hyundai, Isuzu, Mazda, Mitsubishi, Nissan, Peugeot, Porsche, Saab, Suzuki, Rover Group, Toyota, Volkswagen, and Volve.

Brand/Make.- There are 45 brands-Acura, Alfa, AMC, Audi, BMW, Buick, Cadillac, Chevy, Chrysler, Daewoo, Dodge, Eagle, Ford, GMC, Honda, Hummer, Hyundai, Infiniti, Isuzu, Jaguar, Jeep, Kia, Lexus, Lincoln, Mazda, Mercedes, Mercury, Merkur, Mini, Mitsubishi, Nissan, Olds, Peugeot, Plymouth, Pontiac, Porsche, Saab, Saturn, Scion, Subaru, Suzuki, Toyota, Volvo, and Volkswagen.

A.2 Fuel Efficiency Benefits of Technologies Adopted

Multipoint Fuel Inject (Port/MFI).- A fuel injector is placed at each of the intake ports. This control increases the manufacturer's ability to optimize the air-fuel ratio for emissions, performance, and fuel consumption.[28]

Lockup.- Fuel consumption can be further reduced by locking up the torque converter at lower vehicle speeds, provided there is sufficient power to propel the

[28]EPA (2001) *Draft Regulatory Support Document: Control of Emission from Unregulated Nonroad Engines*. #EPA420-D-01-004. September 2001.

vehicle, and noise and vibration are not excessive. It is applicable to all vehicle types with automatic transmissions (EPA, 2008).

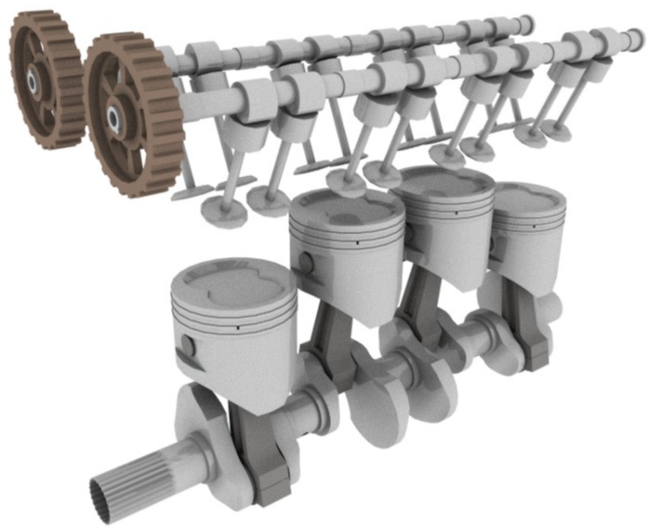
Multiple Valve.- A key aspect of engine design is the valvetrain. The number of valves per cylinder can result in significant power and efficiency improvements (EPA, 2014).

Adding Gears.- "Adding gears allows engine to operate at a more efficient speed more often, and the more gearing options your vehicle has, the more efficient it can be."[29]

Variable Valve Timing.- A key aspect of engine design is the valvetrain. "The ability to control valve timing allows the design of an engine combustion chamber with a higher compression level than in engines equipped with fixed valve timing engines, which in turn provide greater engine efficiency, more power and improved combustion efficiency. VVT also allows the valves to be operated at different point in the combustion cycle, ... i.e. resulting improved engine efficiency under low-load conditions" (EPA, 2008).

[29]EPA's Fuel Economy website: www.fueleconomy.gov

Figure A.1: An Example of Technology Adoption, Multiple Valves

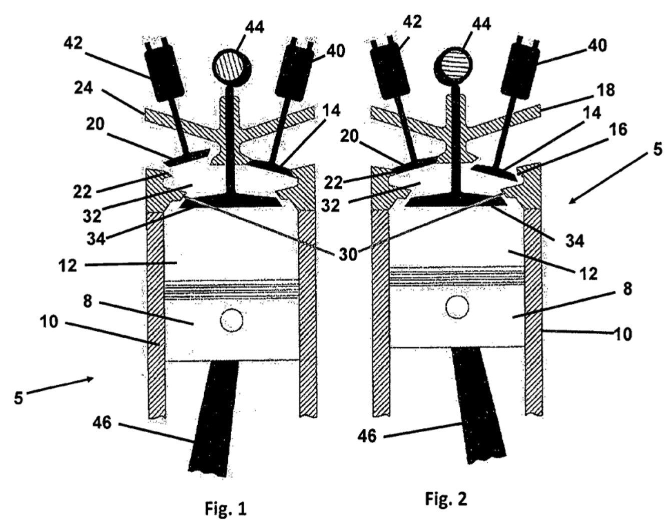


Note: This figure features an inline-four engine with four engine heads, each of which has four valves per cylinder (link).

A.3 Definition of Knowledge Capital

Here I present a typical Patent EP 25695518 (link) with IPC code "FO1L". This patent is on "Methods and Systems for Internal Combustion Engine".

Figure A.2: An Example of Knowledge Capital, A Typical Patent



I select related International Patent Classification (IPC) codes following Aghion et al. (2012), Haščič et al. (2008), Veefkind et al. (2012), Vollebergh (2010), and Green Inventory developed by the World International Property Organization (WIPO).

Table A.2: Definition of Knowledge Capital

Description	IPC Code
Panel A. Engine and Powertrain Technologies	
Cyclical operating valves for machines or engines	F01L
Internal-combustion piston engines; combustion engines in general	F02B
Controlling combustion engines	F02D
Cylinders, pistons, or casings for combustion engines; arrangement of sealings in combustion engines	F02F
Supplying combustion engines with combustible mixtures or constituents thereof	F02M
Starting of combustion engines	F02N
Ignitions (other than compressing ignition) for internal-combustion engines	F02P
Electrical control and monitor of exhaust gasoline treating apparatus	F01N 09
Panel B. Powertrain Technologies for Alternative Fuel Vehicles	
A. Electric Vehicles	
Electric propulsion with power supplied within the vehicle	B60L 11/(02-16)
Electric device on electrically-propelled vehicles for safety purposes; Monitoring operating variables, e.g. speed, deceleration, power consumption	B60L 03
Methods, circuits, or devices for controlling the traction-motor speed of electrically-propelled vehicles	B60L 15
Arrangement or mounting of electrically propulsion units	B60K 01
Conjoint control of vehicle sub-units of different types or different function / including control of electric propulsion units, e.g. motors or generators / including control of energy storage means / for electrical energy, e.g. batteries or capacitors	B60W 10/(08, 24,26)
B. Hybrid Vehicles	
Arrangement or mounting of plural diverse prime-movers for mutual or common propulsion, e.g. hybrid propulsion system comprising electric motors and internal combustion engines	B60K 06 (except 06/387)
Control system specially adapted for hybrid vehicles, i.e. vehicles having two or more prime movers of more than one type, e.g. electrical and internal combustion motors, all used for propulsion of vehicle	B60W 20
Regenerative breaking	
Dynamic electric regenerative braking	B60L 07/01
Braking by supplying regenerated power to the prime mover of vehicles comprising engine-driven generators	B60L 07/20
C. Hydrogen Vehicles/Fuel Cells	
Conjoint control of vehicle sub-units of different type or different function; including control of fuel cells	B60W 10/28
Electric propulsion with power supplied with the vehicle-using power supplied from primary cells, secondary cells, or fuel cells	B60L 11/18
Fuel cells; Manufacture thereof	H01M 08

B.1 Additional Appendix and Supplementary Document

See Online Appendix for:

- Appendix A.4 Adjustment of Patents
- Appendix B. Details in the Moment Equations
- Appendix C. Robustness and First Stage Results

Chapter 2: The Effect of Market Size on Fuel-Saving Technology Adoption in Passenger Vehicles

2.1 Introduction

Improving passenger vehicle fuel economy is a central part of international efforts to reduce the risks of climate change. Passenger vehicles account for about 15 percent of US greenhouse gas emissions and half of transportation sector emissions (IPCC, 2014). US regulations require new vehicle fuel economy to roughly double between 2005 and 2025 to 54 miles per gallon (mpg); fuel economy or carbon dioxide emissions standards are common across developed and developing countries.

Achieving the US fuel economy standards over the next decade requires substantial technology adoption (Knittel, 2012). Over the past several decades numerous fuel-saving technologies, such as advanced transmissions, have been developed that improve the efficiency of gasoline and diesel-powered vehicles. Knittel (2012) and Klier & Linn (2012, 2016) find that the adoption of fuel-saving technologies over time has improved the efficiency by 1 to 2 percent annually since 1980. Historically most of that adoption has been used to improve attributes other than fuel economy, such as horsepower and weight. Klier & Linn (2016) show that fuel economy standards have accelerated the market-wide rate of adoption of fuel-saving technologies, and have caused manufacturers to use fuel-saving technology to raise fuel economy, rather than other attributes such as horsepower.

This paper focuses on a manufacturer's decision to adopt fuel-saving technology for its individual vehicle models. Despite the importance of technology adoption in meeting future standards, the economic factors that drive adoption remain unclear. The literature has focused on the roles of costs and consumer willingness to pay for technology in explaining technology adoption. Welfare analysis of fuel economy standards, fuel taxes or a carbon tax (e.g., (Jacobsen, 2013; Klier & Linn, 2012)), as well as the US regulatory agencies that have estimated the costs and benefits of their fuel economy standards, assume that a manufacturer's technology adoption for each of its vehicles depends solely on technology costs and consumer willingness to pay for the technology.

We depart from the traditional focus, and instead examine the role of market size in explaining technology adoption. Because of fixed costs of technology adoption or other reasons, market size may affect technology adoption according to theories of endogenous technological change, such as directed technological change (Acemoglu, 2002). Carmakers typically redesign vehicles every five to seven years. Technology adoption entails fixed costs, such as spending resources to redesign and test the vehicle with a new technology before production begins. Fixed costs of adoption cause the average cost of technology adoption to decline with a vehicle's market size. A manufacturer can recover fixed adoption costs by charging a markup over marginal costs that depends on willingness to pay for fuel-saving technology and other factors (Berry, Levinsohn, & Pakes, 1995). Comparing two hypothetical vehicles for which consumers have the same willingness to pay for fuel-saving technology, theory predicts that the manufacturer will adopt more technology for the vehicle with the larger market size.[1]

Whether market size affects passenger vehicle technology adoption is important not only for understanding the historical determinants of technology adoption, but also for consumer adoption of new technologies such as electric vehicles, and for the welfare effects of fuel policy. Notwithstanding the media attention around electric vehicles and other alternative technologies, the internal combustion engine continues to dominate the market, accounting for about 97 percent of the US new vehicles market in 2015. Given the market size advantage of gasoline-powered vehicles over alternative fuel technologies such as plug-in electrics, a strong market size effect would imply that manufacturers will continue directing efficiency improvements to gasoline-powered vehicles (Acemoglu et al., 2012). These efficiency improvements will make it more challenging for alternative fuel technologies to compete than in the absence of a market size effect. In addition, the market size effect would have implications for the welfare consequences of fuel policies such as fuel economy standards, fuel or carbon taxes, and alternative fuel vehicle tax credits. The literature has provided evidence of the role of market size in pharmaceutical innovation (Acemoglu & Linn, 2004), and a few studies (e.g., Newell, Jaffe, & Stavins (1999)) document the effects of consumer demand on innovation and technology adoption in other industries.

[1] The US regulatory agencies include fixed costs in their cost benefit analysis of fuel economy standards, but they do not consider the effect of market size on technology adoption.

Although Acemoglu et al. (2016) demonstrate the importance of path dependence and fuel prices on passenger vehicle engine patenting, there is no evidence for the effects of market size or consumer demand on technology adoption among energy-intensive durable goods such as passenger vehicles.[2]

We compare the effect of market size, as measured by vehicle sales, on fuel-saving technology adoption with the effect of fuel-cost driven changes in consumer demand. We focus on fuel-saving technology for the internal combustion engine, including gasoline and diesel-powered engines, and associated transmissions. Using a novel empirical strategy to account for the endogeneity of market size and unique data on vehicle-level technology, consumer preferences, and demographics, we show that market size has a statistically significant effect on fuel-saving technology adoption for individual vehicles, and that this effect explains an economically important share of historical technology adoption across vehicles in the market. Fuel costs affect technology adoption but primarily via their effect on market size. Based on these results we consider several counterfactual scenarios that illustrate the economic and policy implications of the relationship between market size and technology adoption.

More specifically, we construct a unique data set that spans 1997-2013 and that links US new vehicle sales and characteristics with consumer purchasing patterns by demographics groups. We begin by defining a vehicle power train's efficiency, which is distinct from its fuel economy (hereafter we use efficiency, powertrain efficiency and fuel efficiency interchangeably). For a given level of efficiency, a manufacturer

[2]The international trade literature focuses on the the link between market size and productivity (Melitz & Ottaviano, 2008) or product choice (Mayer et al., 2014), but firm-specific productivity and the technology of each product is exogenous in these models.

can trade off fuel economy, horsepower, and weight, analogously to a production possibilities frontier. When a manufacturer adds fuel-saving technology, it can increase fuel economy without affecting the other characteristics. We define the increase in efficiency that results from technology adoption as the increase in fuel economy that is feasible while holding fixed other characteristics. This definition accounts for the possibility that manufacturers adopt fuel-saving technologies and use additional efficiency to boost horsepower or increase weight. We estimate the efficiency of each vehicle model and year similarly to Klier & Linn (2016).

The main empirical challenge is the endogeneity of market size. The endogeneity problem, which is common to nearly all empirical analysis of market-driven technological change, arises from both potential reverse causality and omitted variable bias. Adopting fuel-saving technologies may increase demand for the vehicle, causing sales to increase and creating reverse causality. Furthermore, omitted demand or supply variables, such as a vehicle's acceleration, can be correlated with both market size and efficiency.

To address this challenge we construct an instrumental variable (IV) that takes advantage of variation in consumer demographics over time, combined with variation in purchasing behavior across consumer groups. For example, larger households tend to purchase more minivans than smaller households. The fact that the share of large households in the United States has decreased over the sample reduces demand for minivans relative to other market segments. The validity of the instrument rests on the exogeneity of time series changes in demographics to the vehicle market. Acemoglu

& Linn (2004) and DellaVigna & Pollet (2007) have similarly used demographic trends as exogenous determinants of market size in other industries.[3]

We find that a one standard deviation increase in market size, which corresponds to about a 10 percent increase, raises a vehicle's efficiency by 0.3 percentage points. This estimate constitutes a large increase relative to the average annual efficiency increase of about 1.4 percentage points between 1997 and 2013. We test whether a vehicle's efficiency responds to the efficiency of competing vehicles or to the manufacturer's stock of fuel-saving patents, finding some effect of competing vehicles. However, these effects are less precisely estimated than the primary effect of market size on efficiency. We also find that the main results are robust to alternative functional forms or constructions of the instruments.

We compare the effect of instrumented market size with the effect of fuel-cost driven changes in willingness to pay for fuel economy. Busse et al. (2013) and Allcott & Wozny (2014) demonstrate that high gasoline prices raise the market shares of vehicles with high fuel economy relative to vehicles with low fuel economy, and that consumers value the fuel savings offered by vehicles with high fuel economy. These findings suggest that an increase in fuel costs can affect technology adoption in two ways: first, by affecting market size, and second, by affecting consumers' willingness to pay for fuel-saving technology that raises fuel economy. In contrast to the strong effect of market size on technology adoption, after controlling for market size, fuel costs do not have a statistically significant effect on technology adoption. However, fuel costs strongly predict market size, which is consistent with the literature. The

[3] Other papers have use pre-sample information to address endogeneity (Blundell et al., 1999).

results suggest that fuel costs affect technology adoption via market size, but not via willingness to pay for fuel cost savings. This finding is consistent with Busse et al. (2013), who show that gasoline prices have large effects on market shares but relatively small effects on vehicle prices.

The empirical findings are the basis for four sets of simulations that demonstrate the economic and policy implications of the results. First, historical fuel price-driven changes in market size have had large effects on technology adoption. We illustrate this point by simulating the effects of fuel prices on the cross-sectional distribution of efficiency. The 80 percent increase in real gasoline prices between 2003 and 2007 raised the market size of vehicles with high fuel economy relative to vehicles with low fuel economy. In turn, the changes in market size caused efficiency of the lowest fuel economy vehicles to be lower than if fuel prices had remained at the low 2003 levels. Likewise, efficiency of the highest fuel economy vehicles was higher in 2007 than if fuel prices had remained at 2003 levels.

Second, demographics have had a large effect on the fuel efficiency distribution across models in different market segments. The overall shifts in demographics between 1980 and 2013 caused a shift in efficiency improvements away from light trucks and toward cars.

Third, changes in market size for crossovers and sport utility vehicles (SUVs) affected technology adoption. Between 2000 and 2004, the per-model sales of crossovers increased by 44 percent and per-model sales of SUVs decreased by 25 percent. The increase in crossover market size raised crossover efficiency and the decrease in SUV market size reduced SUV efficiency.

The fourth simulation concerns policies that aim to improve new vehicle fuel economy. Although a carbon price, fuel tax increase, feebate and fuel economy standard affect the vehicle market in different ways, these policies have the common feature that they increase the relative market size of vehicles with high fuel economy. For a carbon or gasoline tax increase, the market shares change because higher tax-inclusive fuel costs cause consumers to choose vehicles with higher average fuel economy (Klier & Linn, 2010; Li, Linn, & Muehlegger, 2014). In the case of fuel economy standards or a feebate (which jointly taxes and subsidizes vehicles according to their fuel economy), manufacturers respond to standards partly by reducing the relative price of vehicles with high fuel economy, raising their market share (Goldberg, 1995).

These policy-induced changes in market size in turn affect the cross-sectional efficiency distribution. In our data, efficiency is positively correlated with fuel economy. These policies would strengthen this positive correlation by shifting sales to vehicles with high fuel economy and causing greater efficiency improvements for those vehicles than for vehicles with lower fuel economy. Because alternative fuel vehicles likely compete with high fuel economy gasoline-powered vehicles, the resulting increase in efficiency for vehicles with high fuel economy will present an even greater challenge for alternative technologies such as electric vehicles to gain market share. The market size effect also introduces an unintended effect of feebates or fuel taxes, which is to decrease the efficiency of vehicle with low fuel economy.

2.2 Data and Summary Statistics

2.2.1 Data

We assemble three data sets for the empirical analysis. The first data set includes vehicle characteristics and sales by model year and model version. This data set is constructed by merging vehicle characteristics by model year and model version with sales by model year, model, and power type. The characteristics are from *Ward's Automotive Annual Yearbooks* from 1997 through 2013.[4] A model year begins in September of the previous calendar year and ends in the current calendar year. A model version refers to a unique model, trim, body type, and fuel type, such as the 2-door gasoline-powered Honda Accord coupe. In addition to these identifying characteristics, other vehicle characteristics include fuel economy, horsepower, torque, weight, transmission type, engine displacement, number of cylinders, and market segment.[5] Our data exclude hybrid and electric vehicles, which accounts for 0.8 percent of sales between 1997 and 2013.[6]

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[4]A change in reporting in 1997 prevents us extending the sample to earlier years.

[5]Market segment is aggregated from the Ward's vehicle classes as in Klier & Linn (2016).

[6]The recent Volkswagen scandal raises some concerns about the accuracy of laboratory testing of vehicle emissions. Laboratory testing of US vehicle fuel economy typically overstates fuel economy by about 20 percent relative to the fuel economy values that appear on window stickers at new car dealerships. There are a few instances of US laboratory tests overstating fuel economy by a substantially greater amount, but these events have affected a smaller number of vehicles than the Volkswagen event. Testing inaccuracies are likely a more important issue for emissions of other pollutants–such as nitrogen oxides–than for fuel economy or greenhouse gases. The reason is that consumers can observe a vehicle's fuel economy (which is directly related to its rate of greenhouse gas emissions) but they cannot directly observe emissions of other pollutants. This makes it easier to detect systematic cheating on fuel economy than on emissions of other pollutants, providing a disincentive for manufacturers to cheat on fuel economy ratings.

The sales data are from *Ward's Automotive InfoBank*, which reports sales by month, model, and fuel type (gasoline, diesel fuel, and flex fuel, which are capable of using gasoline that contains a high percentage of ethanol). Because technology adoption depends on different factors for conventional internal combustion engines and hybrid electric vehicles, our analysis includes only gasoline and diesel fuel vehicles, as well flex-fuel vehicles; these vehicles account for about 97 percent of the US market in 2013 and 99 percent between 1997 and 2013. We aggregate sales by model year, model, and fuel type and merge with the characteristics data. We collect the real average state-level gasoline and diesel fuel prices by model year from the U.S. Energy Information Administration, and merge the fuel prices to the sales and characteristics data.

The second data set contains vehicle purchases by demographic group and year. We use the 1995 National Personal Travel Survey (NPTS) and the 2001 and 2009 National Household Travel Survey (NHTS). The Department of Transportation makes the survey data available to the public and the three waves had similar scope and sampling methodologies. The samples are considerably larger in the latter years. We refer to all surveys as the NHTS for convenience. For each household in the multi-year sample, the survey collects information on demographics (age, income, etc.), vehicle holdings, and vehicle use. We keep vehicles that were purchased new in the survey year.

A demographic group is defined by a unique combination of age group, household income group, household size, education group, urbanization status, and geographic Census division (see Appendix Table A.1 for definitions of the groups).

The age and education groups are based on the attributes of the respondent. Other groups are based on the attributes of the household. Using sample weights for each of the three survey waves we compute the average number of new vehicles purchased per household by market segment and demographic group. For example, we compute the average number of new SUVs purchased by the group defined by households headed by a 26-30 year old with 12 or more years of schooling, with annual household income of $10-20,000, containing two people, and located in an urban area in New England.

The third data set is constructed from the Current Population Survey (CPS), which is available at the National Bureau of Economic Research, from 1980 through 2013. We compute the number of households for each demographic group using the sample weights. We use the same six-dimension demographic groups as we use in the NHTS.

2.2.2 Summary Statistics

In this subsection we present summary statistics of vehicle market trends, consumer purchasing patterns, the evolution of consumer demographics over time, and manufacturer adoption of fuel-saving technologies. Figure 2.1 shows total sales by market segment for model years 1997 through 2013, separately for cars and light trucks. The figure illustrates considerable variation in segment-level sales, such as the growth for crossovers that began in the late 1990s and the decline in sport utility vehicles (SUVs) that began shortly thereafter. This variation is useful in identifying the effect of market size on power train efficiency.

Table 2.1 shows average vehicle characteristics at various times in the sample. Average fuel economy was fairly flat through the mid-2000s, and increased at the end of the sample. Horsepower and weight increased steadily through the sample. Vehicle torque, which represents light truck towing ability, followed a similar pattern.

Figure 2.2 summarizes the variation in vehicle purchasing patterns across demographic groups. The figure indicates a substantial amount of variation in purchase behavior across groups. The variation is largely intuitive. For example, Panel A shows that younger households are more likely to buy small cars than older households, and wealthier households are more likely to buy crossovers and SUVs than small cars. Geographic variables are also correlated with purchase behavior; households in urban areas and the Northeast are much less likely to buy pickup trucks than are other households. The demographic variables are correlated with one another; for example, households with high incomes tend to be well educated. As the next section explains, the IV accounts for this correlation.

Figure 2.3 shows changes in demographics over time from the CPS. Average age, education, and urbanization increased over time, whereas average household size decreased. As the next section explains, we combine this variation with the variation in purchasing patterns across demographics groups illustrated in Figure 2.2 to construct the instrumental variable for market size. The raw data support this approach by indicating that the time series changes in demographics, combined with heterogeneous purchasing patterns across demographic groups, are consistent with changes in market size. For example, the market share of crossovers increased from the late 1990s through the 2000s. This is consistent with the fact that older households are more likely to purchase crossovers than younger households, and that during the same time period the share of older households increased. Likewise, the market size of medium-size cars decreased in the 2000s. This is consistent with the fact that urban consumers tend to purchase more medium cars than other consumers, and that the urbanization rate decreased in the 2000s.

Finally, we present some background information about technology adoption in the US new vehicles market. Manufacturers continually redesign their vehicles, improving power train technologies and other attributes that consumer demand. Many vehicles experience major redesigns at regular intervals, commonly every five to seven years. During a redesign, the manufacturer may make major changes to the power train, cabin, cargo, or exterior. In between redesigns, manufacturers commonly make smaller changes to exterior design, such as offering new options (e.g., paint color) or making small changes to the power train, such as increasing the number of transmission speeds.

These regularities yield a process of steady technology adoption over time. Figure 2.4 shows the share of vehicles in the market with the indicated fuel-saving engine or transmission technologies. The data cover 1986 through 2014, and are from the EPA Annual Fuel Economy Guides and Trend Reports. For many of these technologies, the figure suggests fairly typical patterns in the technology adoption literature, in which the penetration rate is very low initially, subsequently increases steeply, and then levels off–that is, an S-curve. Note that the penetration rate of multiport fuel injection decreases in the late 2000s, which is because many manufacturers have begun to replace this technology with other fuel injection technologies.

2.3 Empirical Strategy

In this section we motivate the reduced-form estimation equation using a simple model of technology adoption with fixed costs. Then, we estimate efficiency of each vehicle in the sample, and finally we derive the estimating equation and explain the IV strategy.

2.3.1 Technology Adoption with Fixed Costs

In this subsection we outline a simple model of technology adoption with fixed costs. In practice, manufacturers can improve efficiency by adding technologies such as those depicted in Figure 2.4. Adoption entails fixed costs because of the need to redesign and test the vehicle before commencing production of vehicles that include the new technology. Many efficiency-improving technologies also increase marginal costs because adoption requires that new parts be installed in the power train. For example, NAS (2015) estimates that adding cylinder deactivation, which effectively shuts off a subset of a vehicle's cylinders when the vehicle is operating under a light load, increases production costs by $118-133 per vehicle. To approximate these aspects of technology adoption, we assume that both marginal costs, c, and fixed costs, F, have positive first and second derivatives with respect to efficiency, τ.

The analysis focuses on a firm that sells one type of vehicle. The firm chooses the vehicle's price p and efficiency to maximize profits:

$$\pi(p, \tau) = \max_{p,\tau} (p - c(\tau))\, q(\tau, p) - F(\tau)$$

where q is the quantity of vehicles demanded, which equals quantity supplied in equilibrium. We assume quantity demanded decreases with price and increases with efficiency (that is, $\frac{\partial q}{\partial p} < 0$ and $\frac{\partial q}{\partial \tau} > 0$).

This setup introduces the simplification that vehicle demand depends on the vehicle's efficiency. Most consumers likely care about fuel economy, horsepower, and other vehicle characteristics that affect efficiency, rather than efficiency per se. As we discuss in Section 2.3.2, for a vehicle with a particular level of efficiency there exist trade-offs between fuel economy, horsepower, and weight. Consequently, manufacturers will choose efficiency and then select fuel economy, horsepower, and characteristics that affect weight (such as electronic accessories). For simplicity we abstract from those subsequent decisions and instead focus on the choice of fuel efficiency. We assume that quantity demanded increases with efficiency because a vehicle with higher efficiency allows the manufacturer to increase fuel economy without sacrificing other characteristics (or likewise, increase horsepower or weight, without sacrificing other characteristics). Jointly modeling the manufacturer's choice of efficiency, horsepower, and fuel economy, as in Klier & Linn (2012), would not affect the main conclusions but would increase the complexity of the expressions below.

The first order conditions for price and efficiency are

$$\begin{aligned}
\text{price:} \qquad & (p-c)\frac{\partial q}{\partial p} + q = 0 \\
\text{efficiency:} \qquad & (p-c)\frac{\partial q}{\partial \tau} - c'q - F' = 0
\end{aligned}$$

where $c'$and F' indicate the first derivatives with respect to efficiency. Combining the two first order conditions and rearranging them yields

$$F'(\tau) = q(-c' - \eta) \tag{2.1}$$

where $\eta = \frac{\partial q/\partial \tau}{\partial q/\partial p} < 0$, and η increases the more sensitive is quantity demanded to efficiency than to price. Provided that η does not decrease quickly with quantity (i.e., $\partial\eta/\partial q > -1$), and c' is relatively small in magnitude, equation (2.1) shows that equilibrium efficiency increases with vehicle sales. That is, vehicles with higher equilibrium market size have higher efficiency. In addition, η captures the willingness to pay for efficiency, and equation (2.1) shows that higher willingness to pay raises efficiency. Although we do not show it here, this conclusion is unaffected if the firm sells multiple vehicles (provided that fixed costs are vehicle-specific) or faces a fuel economy standard. The positive relationship between sales and efficiency is more general than the simple model implies.

2.3.2 Estimating Power Train Efficiency

The empirical objective is to estimate the effect of market size on power train efficiency. In this subsection we describe the construction of the dependent variable, which is power train efficiency.

We do not directly observe a vehicle's efficiency. The data do not contain efficiency per se, but they do include fuel economy and a number of other observable variables that affect efficiency, such as the number of engine cylinders.

We follow Knittel (2012) and Klier & Linn (2016) and estimate efficiency from the available data. We begin by defining a power train's efficiency as the amount of useful energy it produces per unit of fuel consumption. Fuel economy (miles per gallon) is distinct from fuel efficiency. A vehicle's fuel economy depends on the efficiency of its power train as well as characteristics such as horsepower, weight, and body type (which affects air resistance). As in Klier & Linn (2016), we conceive of an efficiency frontier defined in fuel economy-horsepower-weight space. The frontier represents the maximum fuel economy that can be achieved given any particular level of horsepower and weight, and holding efficiency fixed along the frontier. That is, for a particular level of efficiency, as it moves along the frontier, the manufacturer can trade off fuel economy for weight and horsepower.

This framework yields a straightforward identification of efficiency improvements over time. Specifically, we estimate the shape of the frontier using within-model variation in horsepower, weight, and fuel economy. In the baseline we assume that the shape of the frontier does not change over time. In that case, if we control for the effects of weight, horsepower, and other attributes on fuel economy, an increase in fuel economy is equivalent to an increase in efficiency. To implement this approach, we estimate an equation similar to Klier & Linn (2016)

$$\ln e_{jt} = \lambda_h \ln h_{jt} + \lambda_w \ln w_{jt} + \tau_{mt} + X_{jt}\delta + \varepsilon_{jt}, \tag{2.2}$$

where e_{jt} is the fuel economy of vehicle j in model year t, h_{jt} is horsepower for passenger cars (and torque for light-duty trucks), w_{jt} is weight, τ_{mt} is a set of interactions of model by model year, X_{jt} includes a vector of vehicle attributes, ε_{jt} is an error term, and the λ's and δ are coefficients to be estimated. The coefficients on weight and horsepower capture trade-offs between these characteristics and fuel economy. We expect both coefficients to be negative. The controls in X_{jt} include fixed effects for whether the vehicle uses diesel fuel, whether the vehicle is flex-fuel capable, whether the vehicle has a manual transmission, as well as fixed effects for the number of doors and the number of cylinders. Together, these variables allow for the fact that versions of a particular model sold in the same model year have different efficiency depending on fuel type and body type (as approximated by the number of doors). We estimate the equation separately for cars and light trucks to allow the coefficients to vary across the two classes.

We interpret the interactions of model by model year, τ_{mt}, as the average efficiency of vehicles belonging to the model, and sold in model year t. The difference between τ_{mt} and $\tau_{m(t-1)}$ is the change in efficiency of model m between model years

$t-1$ and t. Equation (2.2) thus allows us to identify changes in efficiency over time, where efficiency is measured in units of fuel economy.

Before presenting the results from estimating equation (2.2) we briefly discuss identification and potential sources of bias. The equation characterizes a technical relationship between vehicle characteristics and fuel economy. The equation does not include certain vehicle attributes that consumers care about, such as seating comfort. Such attributes could be correlated with variables that are included in equation (2.2), but in this context that would not bias the coefficients as long as the omitted variables affect fuel economy via horsepower or weight, and not independently of the included variables. In other words, identification rests on the ability to include the variables that directly determine a vehicle's fuel economy. The high R-squared value reported below supports this estimation approach. See Klier & Linn (2016) for additional discussion of identification of equation (2.2).

Table 2.2 reports the main coefficient estimates from equation (2.2). Because fuel economy, horsepower, and weight enter equation (2.2) in logs, the horsepower and weight coefficients are elasticities. The coefficients on diesel fuel and flex fuel are the difference between log fuel economy of a vehicle that uses diesel fuel or is flex fuel-capable, and the log fuel economy of an otherwise comparable gasoline-powered vehicle. Diesel fuel vehicles achieve about 30 percent higher fuel economy, and flex-fuel light trucks achieve about 27 percent worse fuel economy than gasoline-powered vehicles. The negative coefficient on flex-fuel vehicles reflects the lower energy content of ethanol compared to gasoline. Overall, the estimates in Table 2.2 have the expected signs and are statistically significant at the one percent level. The magnitudes are similar to those reported in Klier & Linn (2016) for both cars and light trucks.

Because of the large number of estimated model by model year interactions, we aggregate across observations before reporting those estimates. Figure 2.5 plots the change in power train efficiency, averaged across cars and light trucks. The figure shows steady efficiency improvements for both vehicle classes. Table 2.3 shows the average change in efficiency by 5-year time period, separating models with sales above the median level of sales for the corresponding period and vehicles with sales below the median level of sales. Efficiency improvements are generally higher for the higher-selling models, which previews the main empirical finding that market size has a positive effect on efficiency-improving technology adoption.

2.3.3 Empirical Strategy for Estimating the Effect of Market Size on Efficiency

This section presents the strategy for estimating the effect of market size on efficiency. We assume a log-linear relationship between market size and efficiency that can be derived from equation (2.1) if we assume that fixed costs of technology adoption are iso-elastic (i.e., $F(\tau) \propto \tau^{\alpha}$, where $\alpha > 1$). Alternatively, a log-linear functional form can be derived from a model in which marginal costs decrease with production, because of learning by doing or scale economies in vehicle production.

The estimating equation is

$$\hat{\tau}_{mt} = \gamma_1 \ln Q_{mt} + \gamma_2 \bar{C}_{mt,s} + \phi_t + \phi_b + \phi_b \times t + \varepsilon_{mt} \tag{2.3}$$

where $\hat{\tau}_{mt}$ is powertrain efficiency estimated from equation (2.2), Q_{mt} is sales, $\bar{C}_{mt,s}$ is fuel costs per mile (dollars-per-mile)[7], ϕ_t and ϕ_b are sets of year and brand fixed effects, $\phi_b \times t$ is the interaction of brand fixed effects with a linear time trend, and ε_{mt} is an error term. The two parameters of interest are γ_1 and γ_2, which are the effects of log sales and fuel costs on efficiency. Equation (2.1) implies a positive coefficient on log sales, which would indicate that manufacturers adopt more efficiency for high-selling vehicles. The coefficient on fuel costs is the effect of fuel costs on efficiency, holding market size fixed. We discuss the identification and interpretation of this coefficient at the end of the subsection. The year fixed effects control for aggregate demand or supply shocks and the brand fixed effects control for brand-level supply or demand shocks, such as consumer perceptions of brand quality. The interactions of the brand fixed effects with a linear time trend allows brand-specific demand and supply shocks to vary linearly over time. For example, the time trends control for changes in consumer preferences for brands as well as changes in brand quality.

Estimating equation (2.3) by ordinary least squares (OLS) is likely to yield biased estimates for three main reasons. First, there would be reverse causality if increasing a vehicle's efficiency raises a vehicle's demand and equilibrium sales.

[7]We explain at the end of this section that fuel cost $\bar{C}_{mt,s}$ depends on gas prices at each geographic division collected from each survey round year s.

Second, sales may be correlated with unobserved supply or demand determinants of fuel-saving technologies. The brand fixed effects and time trends control for brand-level supply or demand shocks, but efficiency could be correlated with within-brand variation in vehicle characteristics. For example, there is anecdotal evidence that manufacturers test efficiency-improving technologies on luxury or performance vehicles before installing the technologies more broadly. This practice would cause sales and efficiency to be correlated with (omitted) characteristics such as seating quality or cabin space. Note that we could control flexibly for omitted model-level characteristics by including model fixed effects in equation (2.3). That approach would yield an undesirable interpretation of γ, however. The coefficient would be identified by within-model variation over time in sales and efficiency. In practice, manufacturers face choices not only about when to adopt technologies for a particular model but also, given time and resource costs, for which of its models to improve technologies at a particular time. Including model fixed effects would identify the former choice but not the latter, and therefore might omit an important role of market size in technology adoption across vehicle models.

A final source of bias is that technology adoption is a dynamic decision that includes fixed and irreversible costs. Efficiency may therefore depend on current sales as well as expected future sales. We use current sales in equation (2.3) as a proxy for expected sales, but this introduces measurement error that biases the estimated sales coefficient.

We instrument for sales and address all three sources of bias. The IV is the vehicle's potential market size, which depends on cross-sectional variation in consumer purchasing patterns and time series variation in demographics. We define demographic group cell, g, by age, income, education, household size, urbanization, and Census division. In total, we have 2,700 group cells, each represents 300 households over 1997-2013 in average. (see Appendix Table A.1 for definitions of the groups).[8] To measure purchasing behavior by group, we compute q_{mgs} as the number of vehicles of model m purchased per household by demographic group cell g in NHTS survey year s (recall that we use data from the NHTS survey years 1995, 2001, and 2009).[9] To measure time-series variation in demographics, we compute the number of households in demographic group cell g in year t,w_{gt} , using CPS data. The potential market size is the product of NHTS vehicle purchases per household and CPS number of households, summed across demographic group cells

$$\tilde{Q}_{mt;s} = \sum_{g} (q_{mgs} \times w_{gt})$$

The subscript s in potential market size reflects the fact that q_{mgs} varies across NHTS survey waves. The IV is based on the assumption that w_{gt} is exogenous to the demand and supply of new vehicle technologies. Changes in educational attainment, labor participation and the US income distribution are driven by broad technological developments (such as information technology), the decrease in unionization, and other factors that are largely unrelated to the new vehicle market (Black & Lynch,

[8] We aggregate 817,000 household between 1997 and 2013 to 2,700 cells. Alternatively, we have specified demographic cells with higher level of aggregation and lower level of aggregation. Point estimate and standard errors are barely affected.

[9] Alternatively, we hold vehicle purchase pattern unchanged NHTS 2009 survey round only as a robust check.

2001; Bresnahan et al., 2002; Jorgenson, 2001; Johnson & Mieszkowski, 1970; Autor et al., 2008). Likewise, the overall increase in age depicted in Figure 2.3 arises from the aging of the baby boom generation. Household size, urbanization, and migration trends are similarly driven by changing preferences and other factors that are unrelated to demand and supply of new vehicle technologies. The assumed exogeneity of these demographics follows assumptions made by Acemoglu & Linn (2004) and DellaVigna & Pollet (2007) for consumer demand in other industries. The IV also addresses potential classical measurement error; we discuss non-classical measurement error in the next section.

We would be concerned about using the average per-household vehicle purchases, q_{mgs}, however, because this variable is likely to be correlated with demand and supply factors omitted from equation (2.3). For example, an increase in the efficiency of crossovers would increase per-household purchases of crossovers as measured in the NHTS, creating reverse causality between the dependent variable and the NHTS weights.

We make two refinements to the instrument to address this issue. First, we define time periods based on the NHTS survey waves: 1997-2000, 2001-2008, and 2009-2013. The variable q_{mgs} is measured at the beginning of each time period and does not vary across years within a period. Returning to the example of an efficiency improvement of crossovers, the fact that q_{mgs} is constant within a time period reduces the likelihood that efficiency improvements that occur within the period are correlated with q_{mgs} because the variable is measured at the beginning of the period and does not change in response to efficiency improvements.

However, there could be unobserved and time-invariant characteristics of the vehicle that are correlated with efficiency and q_{mgs}. We use a second refinement to address this possibility, and demean $\tilde{Q}_{mt;s}$ by period and vehicle model. The demeaned value $\bar{Q}_{mt;s}$, is the instrument. This refinement eliminates correlation between the IV and unobserved model characteristics that are time invariant. Note that rather than demeaning the instrument we could add model by period interactions to equation (2.3), but this would affect the interpretation of the log market size coefficient as discussed above.

The demeaned potential market size, $\bar{Q}_{mt;s}$, is the IV in the first stage for market size in equation (2.3), which also contains fuel costs

$$\ln Q_{mt} = \beta_1 \ln \bar{Q}_{mt;s} + \beta_2 \bar{C}_{mt,s} + \beta_3 I_{mt}^{imp} + \phi_t + \phi_b + \phi_b \times t + u_{mt} \tag{2.4}$$

where I_{mt}^{imp} is an indicator variable equal to one if the instrument is imputed using brand-segment-year means.[10] As we show below, the instrument is a strong predictor of log sales, reducing concerns about weak instruments bias. Because the instrument is demeaned by time period, the identifying assumption is that within-period variation in demographics is uncorrelated with omitted demand and supply shocks. Supporting this assumption is the fact that demographic shifts are slow-moving and are driven by factors such as the aging of the baby-boom generation and macroeconomic factors.

[10]Some vehicle models appear in the sales and characteristics data but not in the NHTS data. Most of these are low-selling models. In these cases, we impute the instruments using brand-level average NHTS weights.

Under this identifying assumption the IV strategy addresses reverse causality and omitted variables bias. The instrument is plausibly uncorrelated with measurement error in actual market size, addressing bias due to classical measurement error (we discuss non-classical measurement error in Section 2.4.2).

We interpret the coefficient on log sales in equation (2.3) as the effect on efficiency of a change in market size induced by a change in potential market size. In practice, changes in potential market size may affect equilibrium sales as well as vehicle prices. We do not control for vehicle prices in equation (2.3) because prices are likely to be correlated with unobserved demand or supply factors, and we lack suitable price instruments in this context in which technology and vehicle characteristics are endogenous (Klier & Linn, 2012). If the potential market size is a valid instrument, it is uncorrelated with unobserved supply or demand factors that affect vehicle price (and sales), and omitting the vehicle's price would not cause spurious results.

Next, we discuss the identification and interpretation of the vehicle's fuel cost per mile. The coefficient on fuel cost per mile is identified by fuel price and fuel economy variation across vehicles and over time. As in recent research we use the contemporaneous fuel price under the assumption that price shocks are fully persistent. Previous research (Klier & Linn, 2010) has used the ratio of the national average fuel price to the vehicle's fuel economy to approximate per-mile fuel costs. Using this approach, fuel cost per mile varies because of time-series variation in fuel prices and cross-model variation in fuel economy. We slightly refine our previous approach and introduce additional variation by exploiting geographic variation in fuel prices and vehicle purchases. For example, fuel prices tend to be higher in the Northeast than the Midwest. Households purchase more small cars relative to pickup trucks in the Northeast than the Midwest, which causes the national average fuel price for households that purchase small cars to be higher than the national average fuel price for households that purchase pickup trucks. Formally, we compute a model-specific fuel price using NHTS data on vehicle purchases and EIA data on fuel prices by Census division, d

$$p_{mt;s} = \sum_{g} \left(p_{dt} \times q_{mgs} \times w_{gt} \right) / \tilde{Q}_{mt}$$

We calculate the fuel cost per mile as the ratio of the model's fuel price to its fuel economy e_{m0}, which is measured in the first year the model is observed in the sample

$$\widetilde{C}_{mt;s} = \frac{p_{mt}}{e_{m0}}$$

In the cross section, $\widetilde{C}_{mt;s}$ is correlated with the vehicle's fuel economy (by construction), and may therefore be correlated with vehicle characteristics that are correlated with fuel economy, such as horsepower. Including $\widetilde{C}_{mt;s}$ in equation (2.3) as an independent variable would yield biased estimates because the variable would be correlated with the error term in equation (2.3). Similarly to the potential market size instrument, we eliminate this possibility by subtracting the mean fuel cost by model and period to obtain the demeaned independent variable $\bar{C}_{mt;s}$, which we include in equation (2.3). Note that demeaning this variable reduces concerns about the potential endogeneity of the NHTS weights in the fuel price.

The coefficient on log fuel costs is the effect of fuel costs on efficiency after controlling for market size. Because the estimating equation includes year fixed effects, the coefficient is identified by within-year variation in fuel costs. We expect the coefficient to be positive because higher fuel costs raise the value of an efficiency improvement of a particular magnitude.

We interpret this coefficient as capturing the effect of consumer willingness to pay for fuel-saving technology. The coefficient on log sales is identified by variation in the IV as well as all of the other independent variables, which includes fuel costs. Therefore, fuel costs can affect efficiency via market size, as well as having a direct effect on efficiency.

2.4 Estimation Results

2.4.1 Main Results

Table 2.4 shows the main estimation results. Column 1 reports the OLS estimates of equation (2.3) for comparison with the IV estimates in column 2. In all columns of Table 2.4, the dependent variable is the efficiency estimated in Table 2.2 and observations are by model and model year from 1997 through 2013. To control for aggregate demand or supply shocks as well as brand-specific shocks, the regression includes year fixed effects, brand fixed effects, and the interaction of a linear time trend with brand fixed effects. The table reports the estimated coefficient on log sales with the bootstrapped standard error in parentheses, clustered by brand (make) to allow for arbitrary correlation of the error terms within manufacturers and over time. The estimated coefficient on log sales is 0.006 and the estimate is statistically significant at the five percent level. The coefficient on fuel costs is negative, and the estimate is statistically significant at the one percent level.

The OLS estimates in column 1 are likely to be biased because of reverse causality, omitted variable bias, and measurement error (see Section 2.3.3). To address all three issues, we instrument for log sales using the log of demographics-driven potential market size, $\ln \bar{Q}_{mt;s}$. Column 2 in Panel B of Table 2.4 shows the results from the first stage. The instrument is a strong predictor of market size. The coefficient has the expected positive sign, and is statistically significant at the 1 percent level.

The magnitude of the IV estimate in Panel A is statistically and economically significant. Between 1997 and 2013, the average annual efficiency improvement is about 1.4 percent (see Figure 2.5). As shown in column 2, the estimated sales coefficient implies that a one standard deviation increase in log sales, or a 10 percent increase, raises efficiency by 0.3 percent. This estimate is substantially larger than the OLS estimate in column 1. It suggests that omitted variables or measurement error biases the OLS estimate towards zero. The fact that the OLS estimates is biased towards zero also suggests that main endogeneity issue is omitted variable bias rather than reverse causality. In the following subsections we present a variety of additional estimation results and we refer to column 2 in Table 2.4 as our baseline estimate.

The coefficient on fuel costs in the second stage is negative, but the estimate is much smaller than in column 1 and it is not statistically significant. In addition to the lack of statistical significance, the results in Section 2.5.1 show that the magnitude is small. Comparing this estimate with the OLS estimate suggests that fuel costs affect fuel-saving technology adoption primarily via market size. The negative and statistically significant negative coefficient on fuel costs in column 1 likely reflects the correlation between sales and fuel costs. The negative OLS coefficient may also reflect a negative correlation between fuel economy and other vehicle attributes such as horsepower. After controlling for fuel-cost driven changes in market size in the first stage, fuel costs do not affect efficiency. Nevertheless, fuel costs affect market size, as the first-stage coefficient on fuel costs indicates. The importance of market size in determining the adoption of fuel-saving technology, relative to the direct effect of fuel costs, is confirmed in column 3, in which we omit fuel costs from the first and second stages. In this case, the coefficient on log sales is nearly identical to that in column 2.

2.4.2 Alternative Estimation Models

As discussed above, the IV addresses the main potential sources of bias. In this subsection we show that the results are robust to adding further controls and alternative procedures for estimating efficiency and market size.

The baseline includes controls for brand-level demand or supply shocks, but there may also be segment-level shocks. For example, the increase in market shares of crossovers in the late 1990s and early 2000s, along with the decrease in market share of SUVs during the same period, could reflect a shift in consumer preferences toward smaller light trucks. Although we subtract mean preferences by model and period from the instruments, causing them to be orthogonal to segment-level shocks, there could be within-period preference changes correlated with the within-period demographic changes. Such a correlation would bias the IV estimate, but column 3 shows that the log sales coefficient is very similar if we add to the baseline the interactions of market segment fixed effects and a linear time trend.

Fuel economy standards have varied over the data sample in stringency and form. The standards were roughly constant in the 1990s and early 2000s, began increasing for light trucks in 2005, and then for both cars and light trucks in 2011. Because of differences in fleet composition and market positioning, the standards impose varying degrees of pressure across manufacturers to improve fuel economy over time, which has affected the adoption of energy efficiency-improving technologies (Klier & Linn, 2016). The interactions of brand fixed effects with a linear time trend control for this varying pressure to some extent, because the standards require manufacturers to achieve fleet-wide levels of fuel economy. We have tried several semi-parametric approaches to controlling for fuel economy standards, in addition to using brand fixed effect and the interactions of brand fixed effects with a linear time trend. In particular, column 4 includes the interactions of brand fixed effects with a quadratic time trend. This controls for the nonlinear changes in the stringency of the standards over time across manufacturers. Historically the standards applied separately for cars and light trucks, but since 2011 manufacturers can average across their entire fleet (Leard & McConnell, 2016). To account for the differing regulatory pressure across cars and light trucks, column 5 includes triple interactions of brand fixed effects, vehicle class fixed effects (i.e., passenger car or light-duty truck), and a linear time trend. This controls for changes in stringency of standard over time across vehicle class. The results are similar to our baseline in column 2. Note that these specifications also address the potential bias caused by unobserved demand or supply shocks at the brand, market segment, or class level. The results are also similar to the baseline if we control directly for the stringency of the standards as in Klier & Linn (2016). In Table 2.4 column 7, e the coefficient on log sales is 0.30, with standard error 0.15, which is statistically significant at the 5 percent level and very similar to the baseline estimate. It is possible that there are remaining unobservable taste and cost components correlated with shadow costs complying to CAFE standard that varies at vehicle model level. To account for that, we interact CAFE stringency variable with fuel cost savings. As shown in column 8, the results is similar to our baseline.

Table 2.5 reports estimates of equation (2.3) using alternative measures of efficiency as the dependent variable. In the baseline specification (repeated in column 1 for convenience), we estimate efficiency by model and model year τ_{mt} using equation (2.2), implicitly assuming that efficiency is constant across versions of the same model and model year. This assumption is supported by the fact that versions of the same model, such as the Honda Accord, typically include the engines produced on the same or very similar production platform. However, because many technologies are installed at the engine platform rather than the model level and some models share an engine platform (Klier & Linn, 2012), platform-level market size could affect efficiency. To assess whether engine platform-level market size affects efficiency, columns 2 and 3 report estimates of equation (2.3) that are the same as the baseline, except for the estimation of the dependent variable. These specifications take advantage of highly detailed engine platform data, which allow us to identify the specific engine sold with each version. In column 2 we estimate efficiency in equation (2.2) by engine platform and model year rather than by model and model year, and use the estimated efficiency as the dependent variable in equation (2.3). The estimated coefficient on log sales is similar to the baseline. In column 3 we estimate efficiency by model and platform generation (such that a redesign of the engine constitutes a new generation).[11] The log sales coefficient is larger than the baseline. Thus, there is some evidence that the baseline understates the effect of market size on efficiency, but no evidence of a spurious estimate in the baseline specification.

As noted in Section 2.2.1, manufacturers typically make large changes to the power train or vehicle during major redesigns, and smaller changes between redesigns. The baseline estimates include efficiency improvements that occur both within and across redesigns, but the relationship between log sales and efficiency may be different across redesigns from the relationship within redesigns. To allow for this possibility we define a change in model generation as occurring when the model is redesigned, and in column 4 we estimate efficiency by model and generation (we collect model

[11] Different models in the same year from the same brand could share a platform. One model in consecutive model years could share one platform. Different models from different brand in a year could share a platform if there is collaboration in the design process.

generation information from Automotive News). The estimated coefficient on log sales is slightly smaller than the baseline estimate, but there appears to be less variation with which to identify the market size effect in this specification than the baseline.

Finally, because of regular production and redesign cycles in the vehicles market, efficiency may respond gradually to market size. Column 4 represents one approach to allowing for this possibility, by focusing on efficiency improvements across generations. Column 5 represents an alternative. In this case we use as the dependent variable the three-year moving average of efficiency. The estimate is close to the baseline, which is also the case if we use the three-year moving average of the model's sales (not reported).

Given the time required to redesign and test a vehicle before beginning production of a new generation, there could be a lag between market size and adoption. The fact that shifts in demographics and potential market size can be forecasted to some extent mitigates the lag between demographics-driven changes in market size and adoption, but there could nonetheless be a lag. We can consider this possibility empirically by replacing current log sales with one or two year lags. We find [12]

[12] Another source of measurement error for market size is that some vehicle models are produced on global platforms and in principle technology could respond to global market size for these models. However, even in such cases manufacturers commonly select engines and transmissions that are specific to the market, in which case the US market size would be most relevant to the chosen engine and transmission technologies. In addition, the United States represents about 20 percent of global sales.

2.4.3 Additional Channels of Technology Adoption

So far we have focused on the link between a vehicle's market size and its efficiency. In this subsection we consider possible indirect effects on efficiency, such as competitors' behavior. We report these results in Table 2.6. For comparison, column 1 repeats the baseline specification from column 2 of Table 2.4.

First, manufacturers may respond to the efficiency of competing models (Fischer, 2010). Because consumers have heterogeneous preferences for efficiency and other vehicle attributes, the efficiency of competing models could have a positive or negative effect on a particular model's efficiency. On the one hand, if a manufacturer's competitors increase the efficiencies of their competing vehicles, the manufacturer might increase the efficiency of its vehicles to avoid losing customers to the other manufacturers' vehicles. On the other hand, instead of increasing efficiency in response to competitors' efficiency improvements, the manufacturer might not adopt efficiency or even decrease efficiency and instead improve other attributes such as cabin size. These changes would attract customers with low valuation of efficiency and high valuation of cabin size. In column 2 of Table 2.6 we add to the baseline specification the mean efficiency of other vehicles in the same market segment and technology group, where we assign each manufacturer to one of three technology groups (Japanese, US, and other). This efficiency variable may be endogenous because of reverse causality and perhaps other reasons, and we instrument for it using the mean potential market size of the corresponding vehicles. Column 2 provides some evidence that efficiency of competing models has a positive effect on technology adoption; in column 2 the coefficient on competing vehicle efficiency is positive. The coefficient on competing efficiency suggests a more than one-for-one effect of competing vehicle efficiency, but the large standard errors reflect the limited variation of this variable.

Second, manufacturers could adopt efficiency-improving technologies at the brand rather than the model level. This could occur if models share engine platforms or because of scale economies in redesigning vehicles. Table 5 address the former possibility but not the latter. We add to column 3 the mean frontier of other models sold under the same brand in the same market segment, and using mean potential market size of the corresponding models as an instrument. It is perhaps somewhat surprising that brand-level efficiency has a small and negative effect on efficiency, but this result could arise from the limited variation in this variable (as indicated by the large standard error).

Third, we consider the effect of the knowledge stock on technology adoption. To improve efficiency, manufacturers could adopt technologies that are already widely used in the market–either in their own vehicles or in those of competing manufacturers. Alternatively, they could innovate and adopt new technologies. We construct a proxy for the effect of innovation and adoption of new technologies by adding to equation (2.3) an estimate of a manufacturer's knowledge stock based on its historical patents. The variable is the cumulative number of fuel-saving patents that a parent company has applied for. The variable, which is sometimes referred to as the knowledge stock, is the sum of the depreciated patent stock from the previous period and the flow of patents in the current period (see Zhou (2016) for details on variable construction). Column 4 controls for knowledge stock between 1997-2010 and shows that knowledge stock has a positive effect on efficiency, but the estimate is not statistically significant.[13]

Forth, we have focused on the role of market size and fuel cost-driven willingness to pay for technology. Consumer demand for other vehicle attributes, such as horsepower, may also affect the adoption of fuel-saving technology. If the IV strategy is valid, such omitted factors would not bias the estimated market size effect. To demonstrate this point and consider the role of other factors driving technology adoption, we add to the main regression the vehicle's price as a proxy for consumers' overall willingness to pay for the vehicle. Column 5 shows that adding the vehicle price does not affect the estimate of log sales, supporting the validity of the IV strategy. The price coefficient is positive which suggests that vehicle demand affects technology adoption, but this coefficient is likely to be biased.

In addition, we consider lagged log sales as an alternative measure of market size in column 6. We instrument lagged log sales using lagged instruments and we use lagged fuel cost as potential willingness to pay for fuel cost savings. Results are similar to our baseline. Compare to lagged sales, our baseline presents a relatively conservative estimate of the market size effect.

In column 7, we hold vehicle purchasing pattern for each demographic cell unchanged using vehicle purchasing information from only 2009 NHTS survey round. Results are similar to our baseline. This result suggest that vehicle purchasing pattern

[13]The stock of patent variable stops at 2010. OECD Triadic Patent Family data are available up to 2015. However, it is common knowledge not to use the last 4-5 years of TPF data due to reporting lag from USPTO.

by demographic groups do not vary much over our sample period, which reduces the concern that there are omitted variable that correlate with vehicle purchasing pattern and efficiency.

Finally, we analyze if there are heterogeneous effects of market size. In column 5, we interact market size with truck dummy. We find the point estimate of market size effect is barely affected although it is not precisely estimated. We do not find market size influences vehicle efficiency differently between truck and car segments.[14] In column 8, we interact market size with US firm dummy. Similar to our exercise in column 9, we do not find market size effect different across firm types.[15] Both columns suggest that there is lack of evidence of heterogeneity in market size effect and therefore we still take column 1 as our preferred baseline results.

2.5 Implications

This section discusses four implications of the main estimates from Section 2.4. We quantify the effect of past variation in fuel prices on efficiency; the effect of changes in demographics on efficiency; the effect of sales of crossovers and SUVs on efficiency; and estimate the effect of a fuel tax, feebate or fuel economy standards on the variation in efficiency across models sold in the market.

[14] We have also tried to interact market size with all segment dummies. Results are similar.

[15] We have also tried to interact market size with other firm dummies such as Japanese firm dummy. Results are similar.

2.5.1 Effects of Gasoline Prices on Efficiency

In Section 2.4 we quantified the economic significance of the magnitude of the log market size coefficient by comparing the effect of a one standard deviation market size increase with the average efficiency improvement observed in the sample. To further illustrate the economic importance of this estimate, we compare efficiency levels across scenarios of low and high gasoline prices.

Between 2003 and 2007 the real price of gasoline price increased almost 80 percent. Klier & Linn (2010) show that this price change increased sales of vehicles with high fuel economy at the expense of sales of vehicles with low fuel economy. The shifts in market shares increased sales-weighted average fuel economy by about 0.5 mpg.

We use equation (2.3) to estimate the effect of the resulting changes in market shares on efficiency, and report the results in Figure 2.6. We assign each model in the data to one of five fuel economy quintiles, based on each model's initial fuel economy when it first appears in the data. The first quintile includes vehicles with the lowest fuel economy, and the fifth quintile includes vehicles with the highest fuel economy. The colored bars show the average predicted efficiency increase for each quintile using the actual fuel prices between 2003 and 2007 and the baseline estimates of equation (2.3). The clear bars show the average predicted efficiency increase assuming fuel prices had remained at 2003 levels.

For this exercise, we hold the market-wide average efficiency increase equal in the two scenarios. To maintain consistency with equation (2.3), which includes year fixed effects that control for the market-wide average efficiency increase, we assume that fuel prices do not affect the market-wide average rate of efficiency changes. We do allow fuel prices to affect the cross-sectional distribution of sales, which in turn affects the cross-sectional distribution of efficiency. We use equations (2.3) and (2.4) to generate the counterfactual efficiency each year from 2003-2007. Because gasoline prices are lower in the counterfactual scenario, we expect counterfactual efficiency to be higher than predicted efficiency for the first quintile, which represents the lowest fuel economy vehicles.

In this counterfactual exercise, we focus on the effect of fuel prices on efficiency via market size, rather than the direct effect via consumer demand. Therefore, we adjust fuel prices for the first stage equation (2.4) but not the second stage equation (2.3). As a sensitivity check, Figure A.2 shows minimal differences if we also adjust fuel prices in the second stage.

Comparing the predicted and counterfactual cumulative efficiency improvements across quintiles, we observe that if fuel prices had remained at 2003 levels efficiency would have improved 0.44 percentage points more for the lowest fuel economy quintile, and by 0.37 percentage points less for the highest fuel economy quintile. These effects are consistent with expectation and they are large relative to the predicted cumulative 6.8 percentage points efficiency improvements that actually occurred between 2003 and 2007.

2.5.2 Effects of Demographics on Efficiency

Next we analyze how demographics affect market size and the cross-sectional distribution of efficiency. As a counterfactual scenario, we suppose that all demographics remain unchanged at 1980 levels. The counterfactual reflects the changes in income, age, and other demographics over the 33 years between 1980 and 2013. In Figure 2.7, we compare predicted changes in efficiency using actual demographic changes in the colored bars, with counterfactual efficiency changes that would have occurred if demographics had remained fixed at 1980 levels in the clear bars.

Similarly to the fuel price exercise, we use equations (2.3) and (2.4) to predict counterfactual efficiency improvements each year from 1997 through 2013, again assuming that annual market-wide average efficiency improvements are unchanged from their observed levels. Figure 2.7 compares the predicted and counterfactual cumulative efficiency improvements from 1997 through 2013. The figure shows that if demographics had remained constant at 1980 levels, small cars would have been 0.25 percentage points less efficient, medium cars would have been 0.67 percentage points less efficient, SUVs would have been be 0.7 percentage points more efficient, and pickup trucks would have been 0.54 percentage points less efficient, while other segments are less affected. For context, the overall change between 1997 and 2013 was 24 percentage points. Thus, demographics explain some of the cross-sectional variation in efficiency changes over the sample period.

2.5.3 Effects of Crossover and SUV Market Size on Efficiency

Figure 2.1 shows the large shifts in sales for crossovers and SUVs that occurred in the early 2000s. Those shifts reflect segment-level sales changes, and underlying model-level sales changed in the same directions. Between 2000 and 2004, the average sales per model of crossovers increased by 44 percent and average sales per model of SUVs decreased by 25 percent. The empirical results suggest that these changes in market size caused efficiency to increase for crossovers and to decrease for SUVs, relative to a counterfactual in which market size had remained constant.

To quantify these effects, we analyze how cumulative efficiency would have been affected if the market size of crossovers and SUVs remain at 2000 levels through 2004.[16] In the left side of Figure 2.8 we compare the predicted and counterfactual efficiency of crossovers (CUVs). The colored bar shows predicted cumulative efficiency improvement over 2000-2004. The clear bar shows the simulated result holding market size of crossovers at 2000 levels. In the counterfactual scenario, the lower market size of crossovers causes efficiency to be 0.44 percentage points lower. This is economically significant compared to a cumulative change of 3.6 percentage points for crossovers.

As shown in the right of Figure 2.8, the counterfactual scenario causes SUVs to be 0.34 percentage points higher than is predicted using the actual market size in 2004. This is substantial in magnitude compared to cumulative changes between

[16]Because we are only interested in the effect of market size on crossover and SUV efficiency, our counterfactual represents a partial equilibrium outcome in which the market size of crossovers and SUVs do not affect total vehicle sales or total cumulative efficiency across the market (that is, total vehicle sales and average cumulative efficiency across all segments are identical in the predicted and counterfactual scenarios).

2000 and 2004 of 2.9 percentage points for SUVs. In short, comparing the simulations for fuel prices, demographics, crossovers, and SUVs, we observe that market size and fuel prices have had economically significant effects on the adoption of fuel-saving technology.

2.5.4 Effects of Taxes, Feebates, and Fuel Economy Standards on the Efficiency Distribution

Raising fuel taxes, introducing a carbon tax or feebate, or imposing fuel economy standards all increase sales of vehicles with high fuel economy at the expense of vehicles with low fuel economy. In this subsection we discuss the mechanism by which the policies affect market size and technology adoption, and use a hypothetical feebate to illustrate the magnitude of this effect.

A fuel tax increase or carbon price raises per-mile driving costs of all vehicles, but more so for vehicles with low fuel economy than vehicles with high fuel economy. The increase in relative driving costs of the low fuel economy vehicles decreases their market size compared to those of high fuel economy vehicles.

The effect of fuel economy standards on vehicle sales arises from a different mechanism but nonetheless has the same qualitative effect on market size. If the standard applies to the sales-weighted mean fuel economy of a manufacturer's vehicles, as with the US standards and those in other regions, one compliance strategy available to manufacturers is to reduce the prices of vehicles with high fuel economy relative to vehicles with low fuel economy (Goldberg, 1995). The relative vehicle price change induces consumers to substitute from vehicles with low fuel economy to vehicles with high fuel economy. Consequently, standards cause the sales of low fuel economy vehicles to decrease relative to sales of high fuel economy vehicles. The shift in market size raises the manufacturer's sales-weighted average fuel economy.

Finally, a feebate refers to a system of taxes and rebates that jointly offers subsidies to vehicles with high fuel economy and imposes taxes on vehicles with low fuel economy. The taxes and rebates therefore mimic the pricing behavior of manufacturers facing fuel economy standards, and a feebate can be designed to achieve the outcomes that are identical to a fuel economy standard (Roth, 2014).

Thus, taxes, feebates, and fuel economy standards increase sales of vehicles with high fuel economy relative to sales of vehicles with low fuel economy. Figure 2.6 showed that historical fuel price increases have affected the efficiency of vehicles in the market, and we would expect a carbon price, fuel tax increase, feebate or standard to affect efficiency.

In principle, these policies could widen or narrow the distribution of efficiencies of vehicles in the market. If, in the absence of any policy, fuel economy is positively correlated with efficiency, the policies would widen the distribution. This is because the market size of vehicles with high fuel economy would increase, raising their efficiency, and the market size of vehicles with low fuel economy would decrease, reducing their efficiency. Both changes would strengthen the positive correlation between fuel economy and efficiency. If, on the other hand, fuel economy is negatively correlated with efficiency, the policies would narrow the efficiency distribution. In practice, the correlation is positive, 0.29, in which case we expect the policies to increase the variance of efficiency across vehicles in the market.

In this simulation we focus on a feebate (the other policies discussed above would have qualitatively similar effects). A feebate is determined by a pivot, which is the fuel economy level above which vehicles receive a subsidy and below which vehicles are taxed; and a rate of subsidy and taxation per unit of fuel economy. We set the pivot equal to the sales-weighted mean fuel economy in year t, e_t. For comparability with the fuel price counterfactual in Figure 2.6, the rate of taxation is chosen such that the sales-weighted average fuel economy increases by 0.5 mpg, which is the same fuel economy change as occurred in the counterfactual scenario considered in Figure 2.6. Here we consider a per-mile feebate rather than a lump-sum feebate, such that a model with fuel economy e_{jt} has a feebate of $(1/e_{jt} - 1/e_t) \times 1.53$. The counterfactual scenario includes a fee-bate for the years 2010-2013, and market conditions (e.g., fuel prices) are otherwise unchanged. We compute the predicted and counterfactual efficiency of each model in the sample for the years 2010 through 2013, and compute the cumulative predicted and counterfactual efficiencies for each model. As explained above, because of the feebate's effect on market size, we expect the feebate to increase the variance of efficiency across vehicles in the market.

Panel A of Figure 2.9 compares the cross-model distribution of predicted and counterfactual efficiencies, using the cumulative efficiency changes over 2010 through 2013. The solid line shows the estimated density function of the predicted efficiency, and the dashed line shows the estimated density function of the counterfactual efficiency had the feebate in place. Consistent with expectations, the figure shows that the feebate increases the variance of efficiency across vehicles in the market.

Further illustrating the effects of the feebate on the distribution of efficiency in the market, Panel B of Figure 2.9 presents a scatter plot of efficiency and fuel economy for each model in the sample. The solid dots represent the predicted cumulative efficiencies of models sold in 2013 and the black circles are counterfactual cumulative efficiencies. Because the feebate reduces the market size of vehicles with fuel economy below the pivot, the counterfactual efficiency lies below the predicted efficiency for models with fuel economy below the pivot. In contrast, the feebate increases the market size of vehicles with fuel economy above the pivot, and causes counterfactual efficiency to lie above predicted efficiency for such vehicles. The lines in Panel B represent the fitted values of a linear regression of efficiency on fuel economy. The counterfactual line is steeper than the predicted line, which indicates that the feebate strengthens the positive relationship between efficiency and fuel economy.

Previous welfare analysis of these policies has not considered their effects on market size and technology adoption, which have several implications both for the cost effectiveness of the policies as well as their distributional effects. First, the feebate introduces a shadow cost of fuel economy, inducing manufacturers to increase the fuel economy of all vehicles. Our analysis illustrates an unintended consequence of the feebate, which is that because of the feebate's effect on market size, the feebate causes manufacturers to decrease the efficiency of their vehicles with fuel economy below the pivot. The market size effect lies behind this unintended effect, which could undermine the effectiveness of feebates or taxes at reducing fuel consumption.[17] Second, and following from the first, by affecting the distribution of efficiency across vehicles in the market, these policies will cause consumers to purchase different vehicles than they would have if market size did not affect efficiency. Because each vehicle's fuel economy required by the standards depends on its footprint (roughly, the area defined by the four wheels), changes in consumer purchase decisions will affect market-wide average fuel economy and therefore the effectiveness of the policies at reducing fuel consumption and greenhouse gas emissions. While estimating the welfare consequences of these efficiency improvements lies outside the scope of this paper, the scenario considered here illustrates the effects of these policies on the distribution of efficiency across vehicles in the market. Third, alternative fuel technologies likely are closest substitutes to gasoline-powered vehicles with high fuel economy. If a policy raises the efficiency of high fuel economy gasoline-powered vehicles, it would reduce consumer demand for alternative fuel vehicles.

2.6 Conclusion

Current US fuel economy standards will dramatically increase the average fuel economy of new vehicles over at least the next decade. Despite the magnitude of this fuel economy change and the importance of technology adoption for meeting the standards, there is little empirical evidence on which factors determine a man-

[17] Although our analysis suggests that the market size effect undermines the effectiveness of fuel consumption policies, the market size effect does not necessarily undermine the economic efficiency of these policies. It may be economic efficient to have the most efficient cars improved the most and least efficient cars improved the least.

ufacturer's adoption of fuel-saving technologies. This paper analyzes the effect of market size, as approximated by vehicle sales, on the adoption of efficiency-improving technologies in the US passenger vehicle market. We show that market size has a substantial effect on technology adoption and discuss implications for the evolution of technology adoption and fuel policies.

We motivate the empirical analysis using a simple model of energy efficiency technology adoption, which shows that fixed costs of technology adoption cause adoption to depend on a vehicle's market size. The empirical analysis uses a unique data set that combines vehicle characteristics and sales with vehicle purchasing patterns by demographic group from 1997-2013. We address the endogeneity of market size by instrumenting for vehicle sales using potential market size. Variation in potential market size arises from changes in demographics over time and cross-sectional heterogeneity in purchasing patterns across demographic groups. In the preferred specification we find that a 10 percent increase in sales (corresponding to about one standard deviation) increases efficiency by 0.3 percentage points, compared to a mean annual efficiency improvement of about 1.4 percentage points in the sample. Fuel costs affect efficiency via market size but not independently of market size. Acemoglu et al. (2016) find that high fuel prices increase clean technology innovation, and given our findings that fuel prices affect technology adoption primarily via innovation, future research can address whether innovation responds directly to fuel prices or to fuel price-driven changes in market size.

The results have four main implications. The first is that historical variation in fuel prices has had a substantial effect on new vehicle technologies. Real fuel prices nearly doubled between 2003 and 2007. If gasoline prices had remained at 2003 levels, the efficiency of vehicles with low fuel economy would have increased 0.5 percentage points more between 2003 and 2007 than it did. Efficiency of the highest fuel economy vehicles would have increased by 0.2 percentage points less than it did.

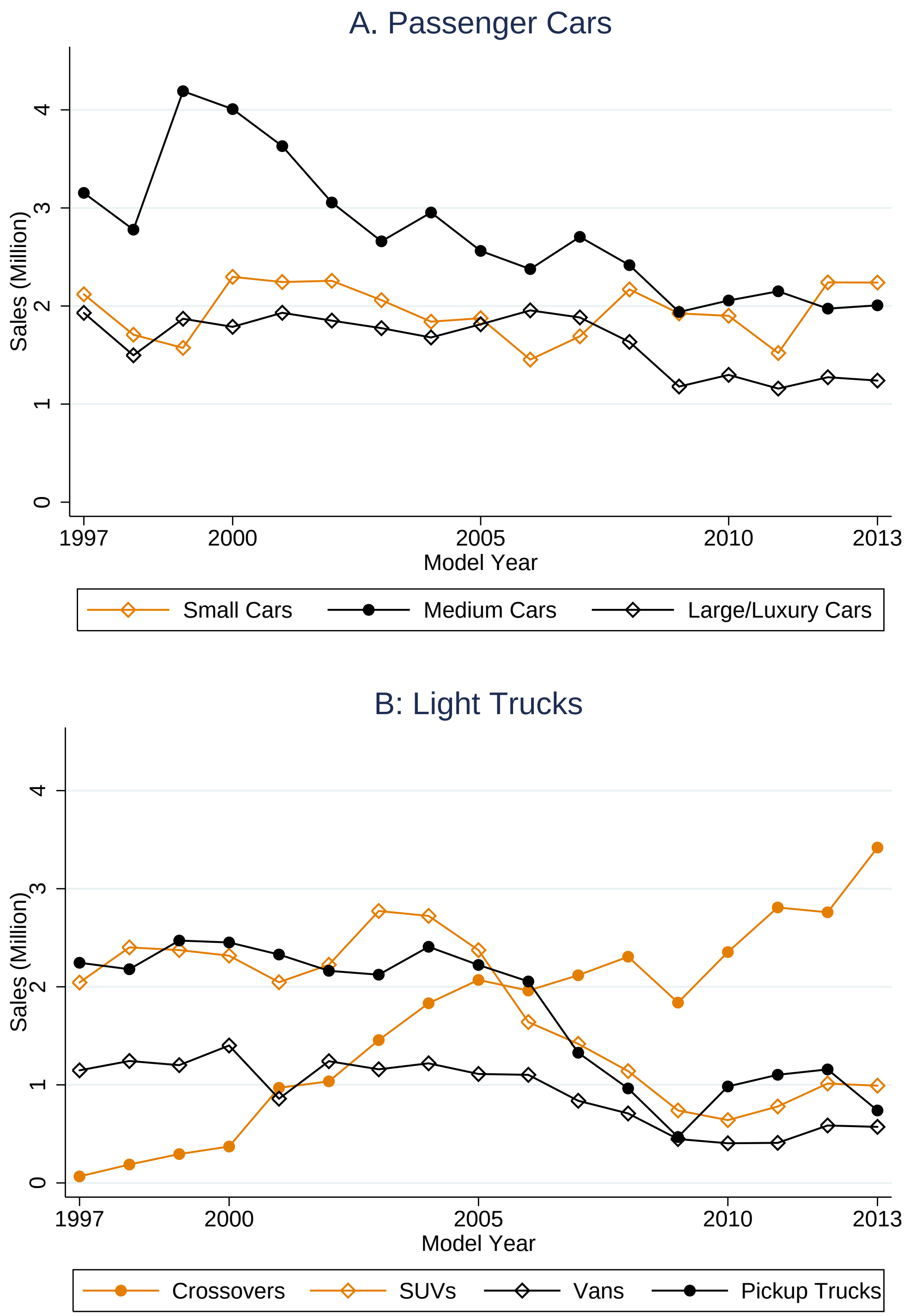
Second, demographics have had a large effect on vehicle efficiency. Shifts in demographics increased efficiency of cars relative to light trucks. Third, shifts in market size of crossovers and SUVs have caused large changes in the efficiency of these vehicles. These three results imply that market size and fuel costs have had economically significant effects on technology adoption in the new vehicles market.

The final implication is that a fuel tax, feebate, or fuel economy standard increases the cross-sectional variation in efficiency by raising the efficiency of vehicles with high fuel economy relative to vehicles with low fuel economy. Because the existing literature on the welfare effects of these policies has not considered this effect, we suggest that future research should consider it. Accounting for the effects of market size and fuel costs on technology adoption would affect the estimated cost effectiveness and the distributional consequences of these policies, as well as the demand for alternative fuel vehicles such as plug-in electrics.

The empirical analysis does not identify the underlying reasons why market size affects efficiency. The simple model we introduced to motivate the empirical analysis emphasizes the role of fixed costs in vehicle production, but other factors could contribute to the positive relationship between market size and technology adoption, such as scale economies in vehicle production. Future work may address this question, which has important implications for the welfare effects of fuel economy standards or taxes.

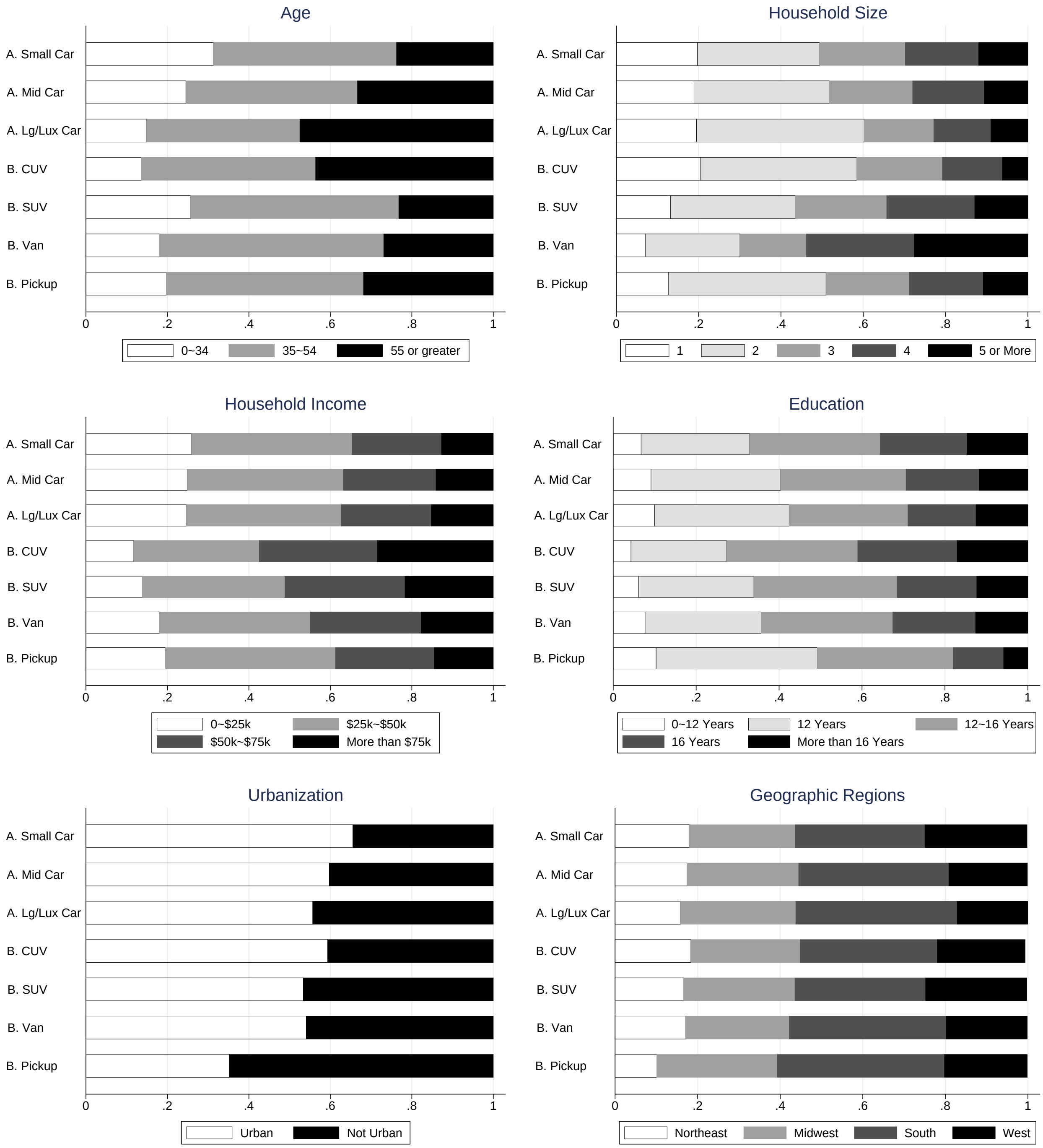
Figures

Figure 2.1: Vehicle Sales by Segment, 1997-2013



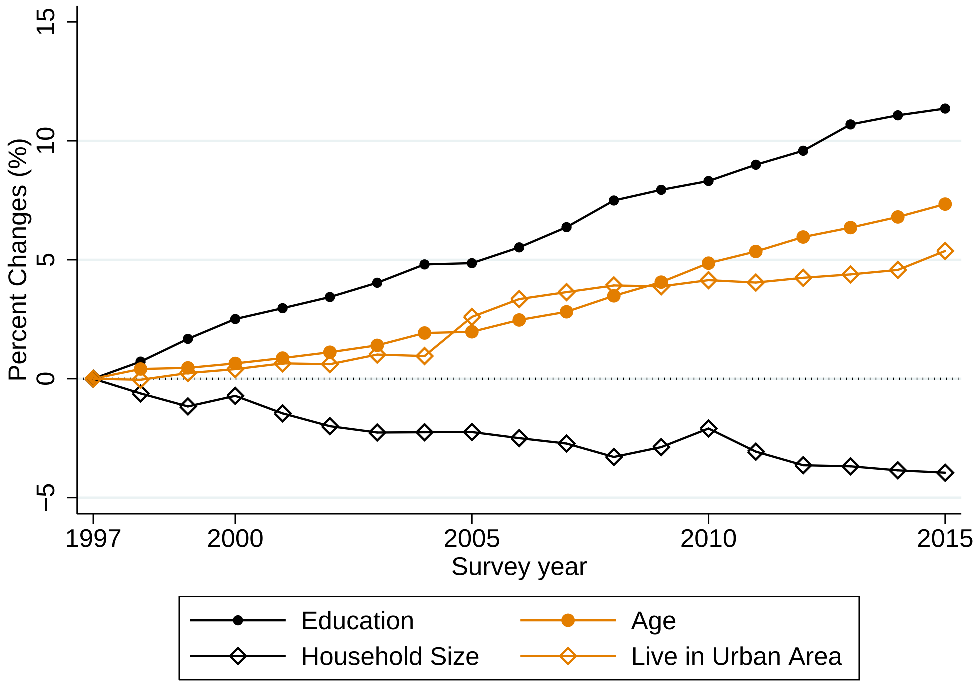
Notes: For each market segment, the figure plots the total model year sales. Panel A includes passenger cars and Panel B includes light-duty trucks.

Figure 2.2: Vehicle Purchase Patterns by Demographic Group



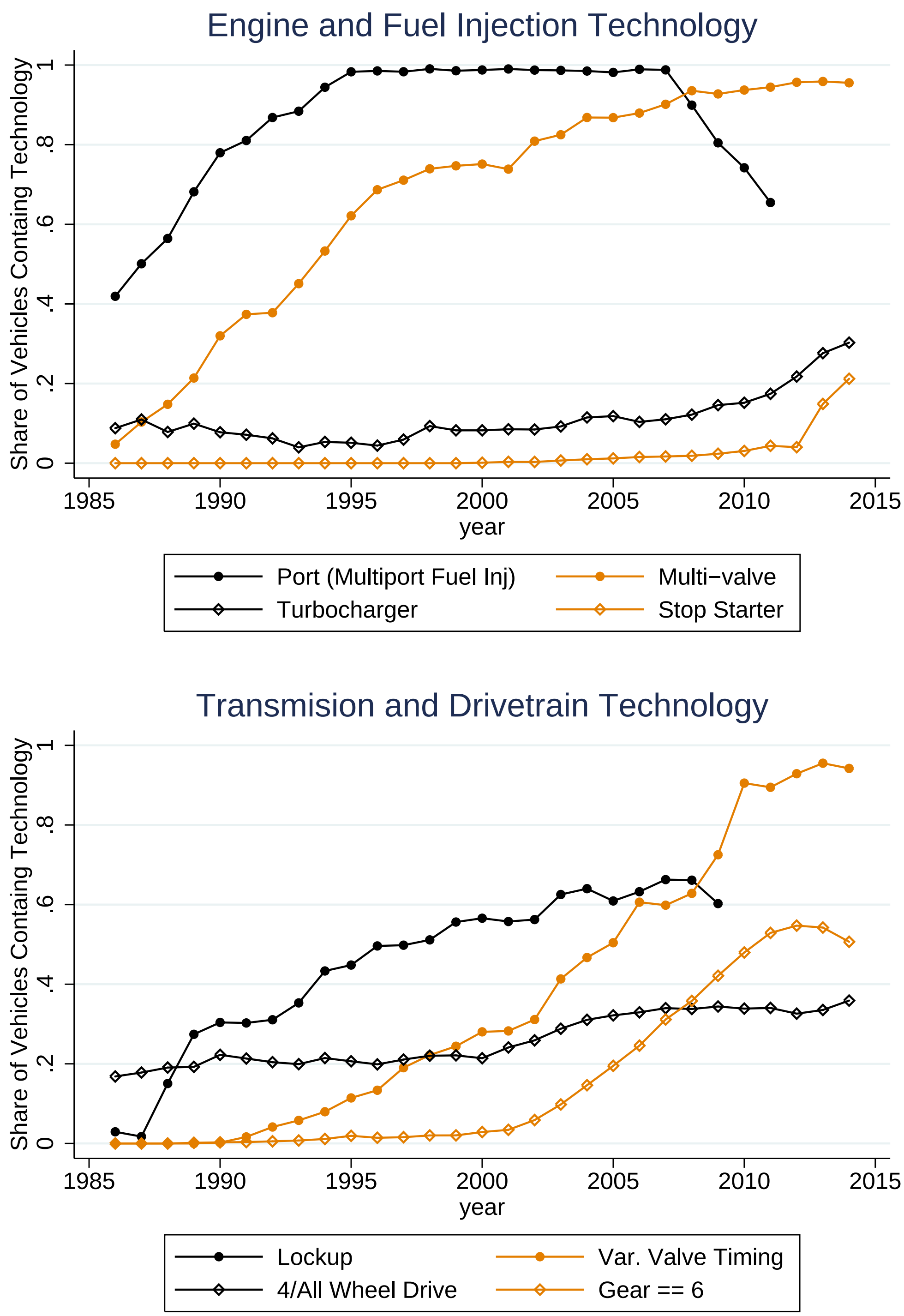
Notes: The figure is constructed using the NHTS survey data from the 1995, 2001, and 2009 survey waves. Each panel illustrates purchasing patterns for the indicated demographic variable. For households purchasing vehicles in a particular market segment, we compute the share of those households belonging to each category of the demographic variable, using the NHTS household survey weights. For example, among the households that purchase small cars, 64% of them live in urban areas.

Figure 2.3: Changes in Demographics, 1997-2013



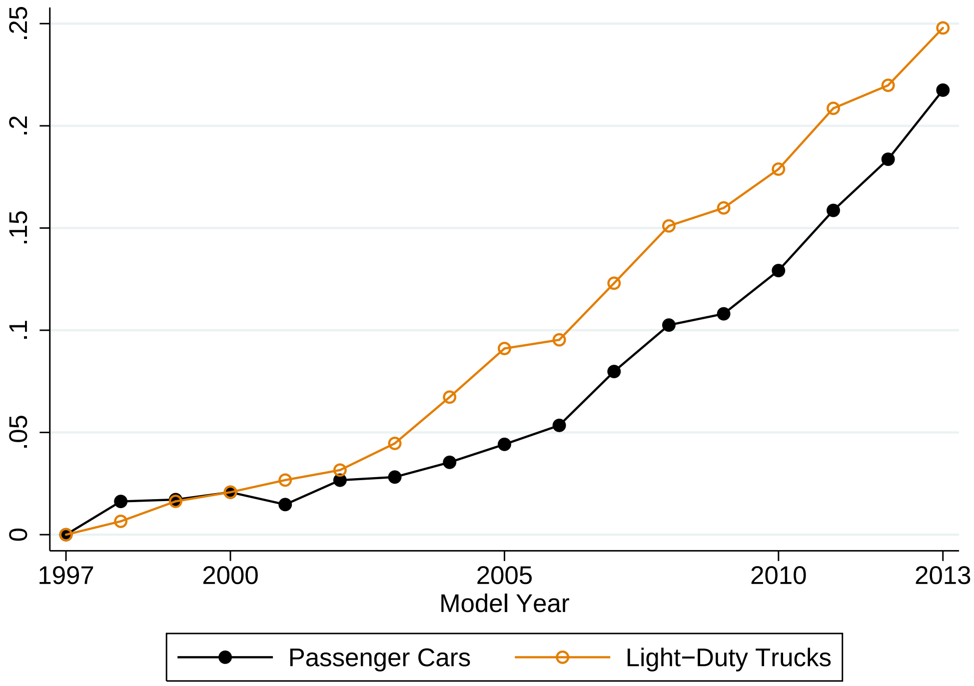
Notes: Using household survey weights from the CPS, we compute the weighted average of each demographic variable by year. The figure plots the percentage change since 1997 of each variable.

Figure 2.4: Market Penetration of Selected Fuel-Saving Technologies, 1986-2014



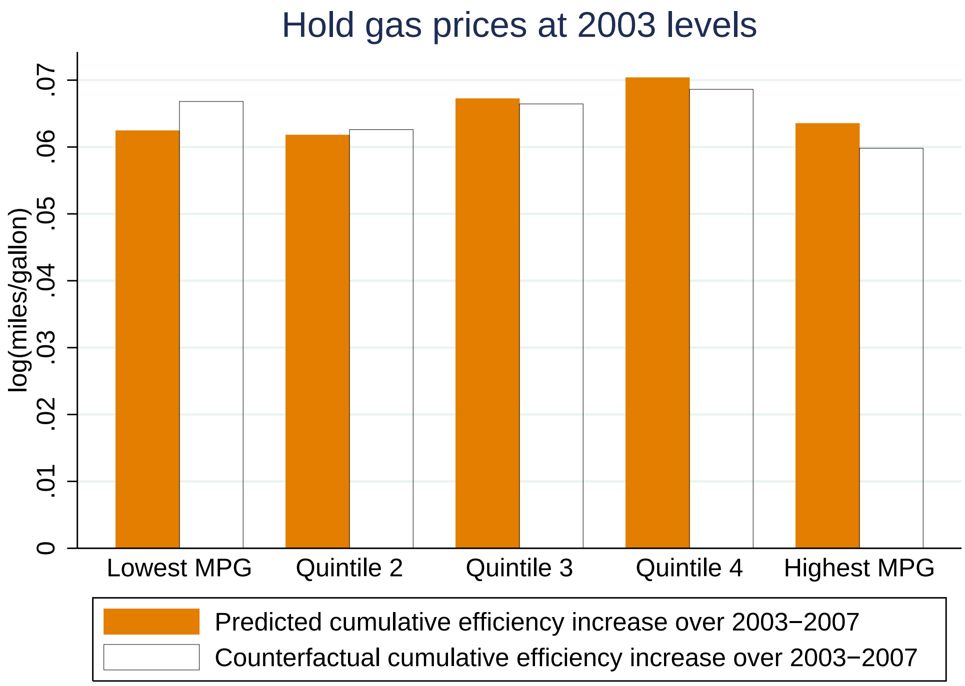
Notes: The figure is constructed from the EPA Fuel Economy Guide and EPA Fuel Economy Trends data. Technology penetration rates are the unweighted average across all vehicles in the corresponding model year.

Figure 2.5: Estimated Power Train Efficiency, 1997-2013



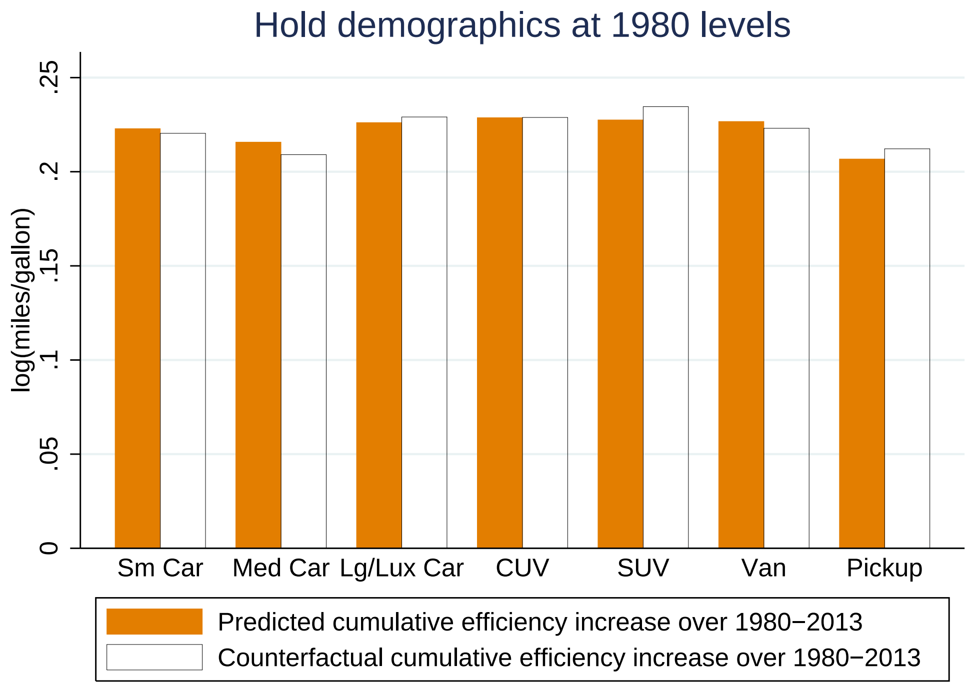
Notes: The figure plots the mean estimated efficiency across passenger cars and light trucks estimated from equation (2.2). To construct this figure, efficiency is normalized to zero for all observations in 1997.

Figure 2.6: Effect of 2003-2007 Gas Price Increase on Efficiency



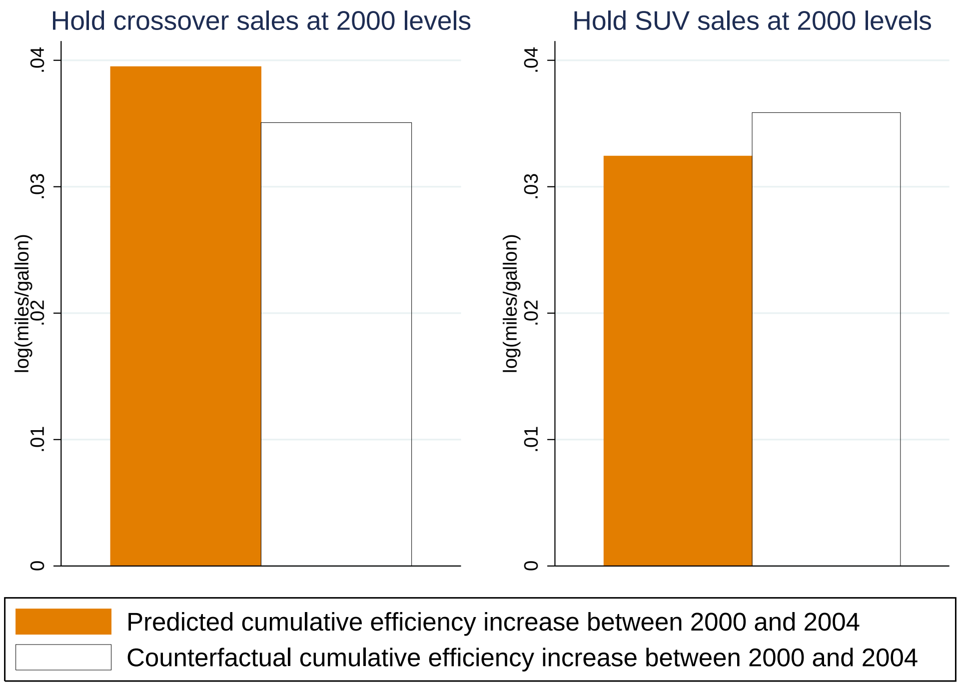
Notes: For each observation in equation (2.3), the frontier is predicted using the estimates reported in column 2 of Table 2.4. All observations are assigned to a fuel economy quintile based on the fuel economy distribution across observations between 2003 and 2007, using each vehicle model's initial fuel economy when the model enters the market. The predicted frontier in each colored bar is the mean cumulative predicted efficiency change between 2003 and 2007 for each quintile. The clear bars show the cumulative counterfactual efficiency change by quintile. Counterfactual efficiency changes are computed by holding fixed fuel prices at 2003 levels and using equations (2.3) and (2.4) to predict the efficiency change for each observation between 2003 and 2007.

Figure 2.7: Effect of Demographics on Efficiency, 1980-2013



Notes: The colored bars show the mean cumulative predicted efficiency increase between 1980 and 2013, for each market segment. Predicted values are obtained from the estimation of equation (2.3) reported in column 2 of Table 2.4. The clear bars show the cumulative counterfactual efficiency change by market segment. The counterfactual holds fixed demographics at 1980 levels and uses equations (2.3) and (2.4) to predict the counterfactual efficiency change for each observation between 1980 and 2013.

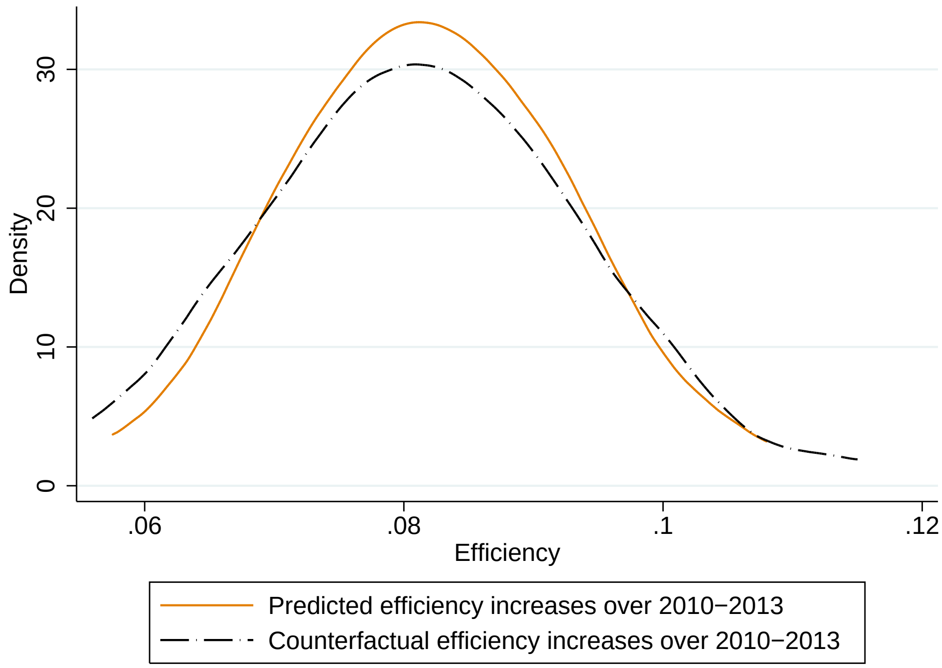
Figure 2.8: Effect of Sales on Efficiency, 2000 - 2004



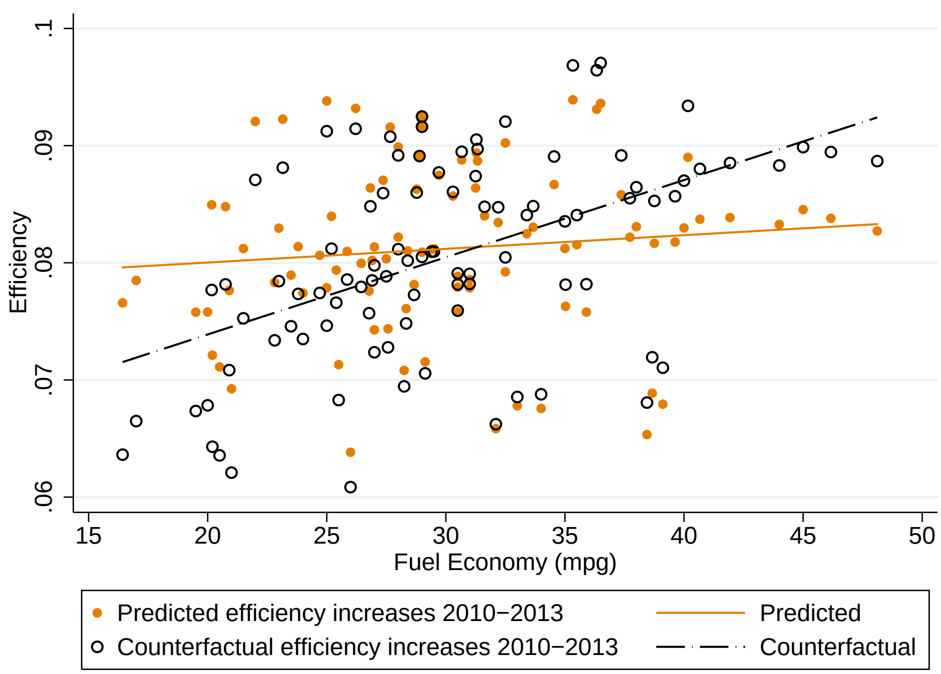
Notes: The colored bars show the mean cumulative predicted efficiency increase between 2000 and 2004 for crossovers (left panel) and SUVs (right panel). Predicted values are obtained from the estimation of equation (2.3) reported in column 2 of Table 2.4. The clear bars show the cumulative counterfactual efficiency changes for crossovers and SUVs. The counterfactual holds fixed crossover sales at 2000 levels and uses equation (2.3) to predict the counterfactual efficiency change for each crossover and SUV between 2000 and 2004.

Figure 2.9: Effect of Feebate on Efficiency

A. Distribution of Efficiency



B. Correlation of Fuel Economy and Efficiency



Notes: For each observation in equation (2.3), the frontier is predicted using the estimates reported in column 2 of Table 2.4. The counterfactual efficiency of each vehicle is computed from the market size caused by introducing a feebate of $(1/e_{jt} - 1/e_t) \times 1.53$, where e_{jt} is the fuel economy of model j in year t and e_t is the harmonic mean of fuel economy in year t. Panel A shows the estimated density functions of cumulative predicted and counterfactual efficiencies over the period 2010 through 2013. Panel B is a scatter plot of efficiency and fuel economy for each model in the sample. The solid dots represent cumulative predicted efficiency and the circles represent cumulative counterfactual efficiency. The two lines are the linear prediction of efficiency on fuel economy.

Tables

Table 2.1: Average Vehicle Characteristics over 1997-2013

Model Year	Fuel economy (miles per gallon)	Horsepower	Torque (newton-meters)	Weight (pounds)	Number of cylinders
1997	25.4	184	301	3607	6.0
2000	24.9	201	317	3746	6.2
2005	24.9	232	344	4028	6.3
2010	26.3	262	368	4230	6.2
2013	29.1	275	377	4226	6.0

Notes: The table reports the sales-weighted average of fuel economy (in miles per gallon), horsepower, torque (maximum torque in newton-meters), weight (in pounds), and number of cylinders for the indicated years.

Table 2.2: Estimated Tradeoffs Between Fuel Economy and Other Characteristics

Dependent variable: Log fuel economy	Passenger Cars	Light-Duty Trucks
Log horsepower	-0.224***	-
	(0.014)	-
Log torque	-	-0.157***
	-	(0.016)
Log weight	-0.317***	-0.424***
	(0.037)	(0.034)
Diesel	0.336***	0.260***
	(0.017)	(0.015)
Manual transmission	0.008	-0.004
	(0.004)	(0.004)
Flex fuel	-	-0.272***
	-	(0.012)
Observations	8676	15836
R-squared	0.95	0.93

* p<0.10 ** p<0.05 *** p<0.01.

Notes: The table reports coefficient estimates from equation (2.2), with standard errors in parentheses, clustered by model and model year. Observations are by model year and model version. The sample in column 1 includes passenger cars and the sample in column 2 includes light-duty trucks. In addition to the reported coefficients, the regressions include model by model year interactions, fixed effects for the number of cylinders, and fixed effects for the number of doors, similarly to Klier & Linn (2016).

Table 2.3: Estimated Efficiency for High and Low-Selling Vehicles

Time Period	High-Selling Vehicles			Low-Selling Vehicles		
	Efficiency in starting year	Efficiency in ending year	Cumulative change	Efficiency in starting year	Efficiency in ending year	Cumulative change
1997-2000	0	0.017	0.017	0	0.0126	0.012
2001-2005	0.019	0.069	0.050	0.006	0.057	0.050
2006-2009	0.067	0.140	0.072	0.078	0.134	0.056
2010-2013	0.156	0.239	0.083	0.160	0.232	0.072

Notes: Efficiency is estimated by model, market segment, and model year in equation (2.2), using the specification reported in Table 2.2. Models are assigned one of two categories depending on whether their sales are above the median sales in the initial year of the indicated time period. The table reports the mean estimated efficiency across the two groups and time periods in the first and last years of each period, as well as the cumulative change in mean efficiency over the time period.

Table 2.4: Estimation Results: Effect of Market Size and Fuel Costs on Efficiency

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Dependent variable: Efficiency								
Log sales	0.006***	0.030***	0.030***	0.029***	0.025***	0.034***	0.032***	0.030***
	(0.001)	(0.007)	(0.007)	(0.007)	(0.007)	(0.005)	(0.008)	(0.008)
Fuel costs	-0.410***	-0.168		-0.178*	-0.153	0.201	-0.178	-0.306***
	(0.052)	(0.110)		(0.099)	(0.144)	(0.162)	(0.127)	(0.115)
CAFE Stringency							0.048	-0.126
							(0.033)	(0.087)
Fuel costs×CAFE Stringency								1.306**
								(0.648)
Panel B. First Stage Estimate. Dependent variable: Log sales								
Potential market size (log)		0.139***	0.112***	0.117***	0.179***	0.161***	0.115***	0.159***
		(0.037)	(0.039)	(0.040)	(0.036)	(0.037)	(0.039)	(0.042)
Fuel costs		-12.017***		-8.800***	-16.544***	-14.133***	-10.759***	-10.527***
		(1.155)		(1.164)	(1.570)	(1.812)	(1.277)	(1.717)
If market size is imputed		-0.391***	-0.385***	-0.506***	-0.521***	-0.389***	-0.398***	-0.432***
		(0.053)	(0.056)	(0.053)	(0.053)	(0.053)	(0.053)	(0.058)
Estimated by:	OLS	IV, Baseline	IV	IV	IV	IV	IV	IV
Brand FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Brand FE×t	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Brand FE×t^2				Yes				
Brand FE×t×Truck					Yes			
Segment FE						Yes		
SegmentFE×t						Yes		
Obs.	2,722	2,722	2727	2,722	2727	2,722	2,722	2,722
RMSE	0.07	0.07	0.07	0.06	0.06	0.06	0.07	0.07
F (1st stg. excl. var.)	NA	32.69	31.76	31.96	43.42	29.73	27.40	25.96

* p<0.10 ** p<0.05 *** p<0.01.

Notes: The table reports coefficient estimates from equation (2.3), with bootstrapped standard errors in parentheses, clustered by brand (make). Observations are by model and model year. Column 1 is estimated by ordinary least squares (OLS) and columns 2-5 are estimated by instrumental variables, using potential market size and the imputation dummy as instruments according to equation (2.4). The bottom of the table reports the F statistics of a joint test of the significance of the excluded variables. All regressions include brand fixed effects, year fixed effects, and brand fixed effects interacted with a linear time trend. Column 4 includes brand fixed effects interacted with a quadratic time trend. Column 6 includes the triple interaction of brand fixed effects by light-duty truck class by linear time trend. Column 7 includes a set of segment fixed effects with a linear time trend. Column 4 include additional CAFE stringency control as described in (Klier & Linn, 2016).

Table 2.5: Alternative Methods for Estimating Efficiency

Efficiency estimated by:	(1) Model by year (baseline)	(2) Platform by year	(3) Model by platform generation	(4) Model by model generation	(5) Model by year (3-yr moving average)
Log sales	0.030***	0.041***	0.039**	0.035***	0.040***
	(0.007)	(0.009)	(0.018)	(0.013)	(0.010)
Fuel costs	-0.168	-0.033	-0.554***	-0.560***	0.083
	(0.110)	(0.144)	(0.171)	(0.200)	(0.141)
Brand FE	Yes		Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Brand FE$\times t$	Yes		Yes	Yes	Yes
Company FE		Yes			
Company$\times t$		Yes			
Observations	2722	1953	526	541	2084
RMSE	0.07	0.07	0.06	0.07	0.06
F (1st stg. excl. var.)	32.69	16.23	7.74	11.64	20.32

* p<0.10, ** p<0.05, *** p<0.01.

Notes: The table reports coefficient estimates with bootstrapped standard errors in parentheses, clustered by brand (make). In column 2 efficiency is estimated by platform and model year. In column 3 efficiency is estimated by model and platform generation. In column 4 efficiency is estimated by model generation and model year. In column 5 efficiency is estimated by model and model year, as in the baseline, but the dependent variable is the three-year moving average of efficiency. In all columns, the independent variables are aggregated to match the aggregation of the dependent variable. All regressions are estimated by instrumental variables using potential market size as an instrument, as in Table 2.4.

Table 2.6: Additional Factors Affecting Efficiency

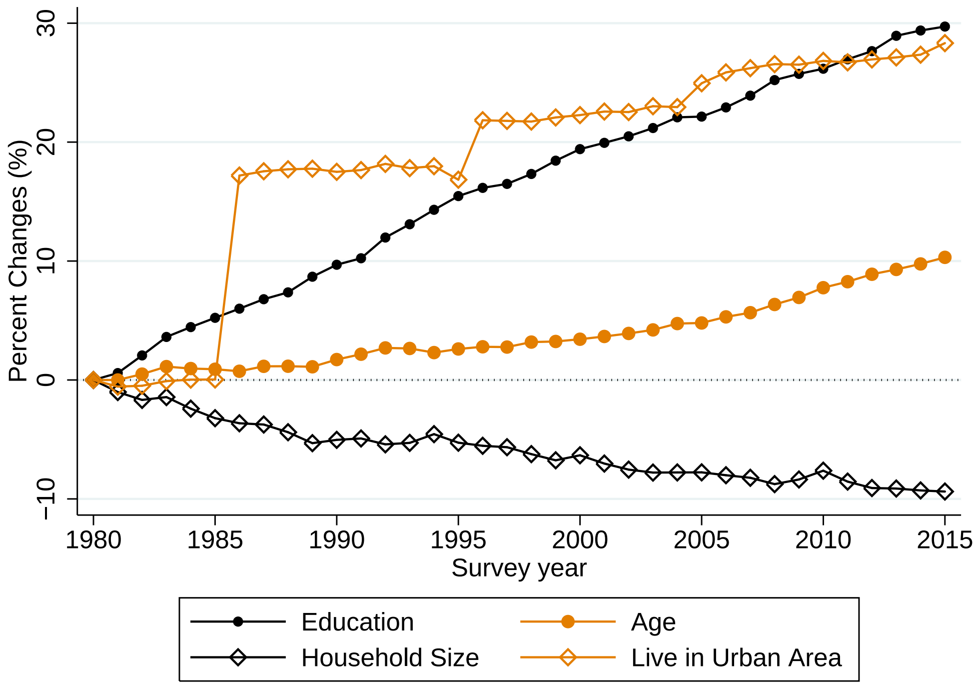
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Baseline					Lagged log sales	NHTS 09 round	Truck	US firm
Log sales	0.030***	0.034	0.023*	0.028*	0.031***	0.040***	0.025***	0.026	0.035*
	(0.007)	(0.023)	(0.011)	(0.011)	(0.007)	(0.009)	(0.010)	(0.022)	(0.012)
Fuel costs	-0.168	1.156	-0.239	-0.237	-1.026***	0.036	0.062	0.408	-0.157
	(0.110)	(1.305)	(0.153)	(0.150)	(0.075)	(0.138)	(0.099)	(2.574)	(0.141)
Efficiency of competing models		3.527							
		(3.058)							
Efficiency of models by same brand and segment			-1.722						
			(1.233)						
Knowledge stock				0.003					
				(0.009)					
Log price					0.089***				
					(0.012)				
Log sales$\times$Truck								-0.004	
								(0.018)	
Log sales$\times$US firm									-0.051
									(0.075)
Brand FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Brand FE$\times t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2722	2722	2722	2318	2722	2384	2727	2727	2727
RMSE	0.07	0.06	0.06	0.06	0.06	0.07	0.06	0.06	0.06
F (1st stg. excl. var.)	32.69	25.17	22.92	20.91	35.32	27.39	25.33	22.07	21.90

* p<0.10 ** p<0.05 *** p<0.01.

Notes: The table reports coefficient estimates with bootstrapped standard errors in parentheses, clustered by brand (make). Column 1 repeats the baseline regression from column 2 of Table 2.4. We assign each manufacturer to one of three technology groups: Japanese, US, and other. Column 2 includes the average efficiency by technology group as an independent variable. This variable is instrumented using the corresponding average potential market size of those models. Column 3 includes the average efficiency of other models sold under the same brand in the same market segment, using the average potential market size as an instrument. Column 4 includes the manufacturer's knowledge stock, which is the cumulative number of fuel-saving patents that a parent company has applied for. Column 5 includes the log of the vehicle's price as an independent variable. Columns 1-3 and 5-7 include observations from 1997-2013 and column 4 includes observations from 1997-2010. Columns 2 and 3 use the potential market size of the corresponding vehicles to instrument for competing models and models sold under the same brand. Column 6 presents results if we use lagged market size, as well as lagged fuel cost, potential market size, and impute dummy. In Column 7, we hold vehicle purchasing pattern for each demographic cell unchanged using vehicle purchasing information from 2009 NHTS survey round only. In Column 8, we interact market size with truck dummy. In Column 9, we interact market size with US firm dummy.

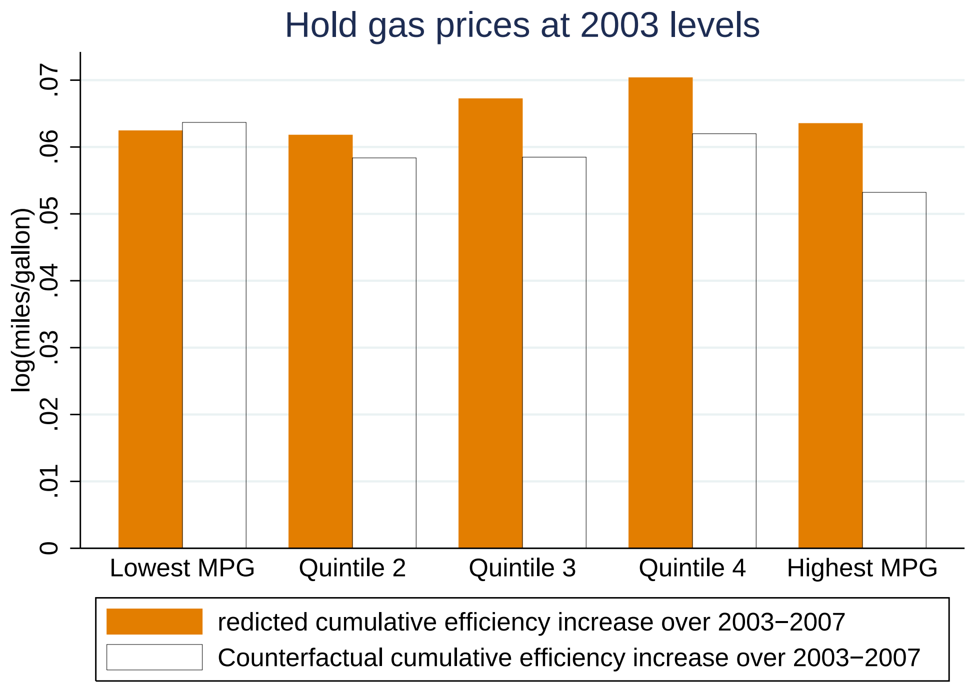
Appendix

Figure A.1: Changes in Demographics, 1980-2013



Notes: Using household survey weights from the CPS, we compute the weighted average of each demographic variable by year. The figure plots the percentage change since 1980 of each variable.

Figure A.2: Effect of 2003-2007 Gas Price Increase on Efficiency



Notes: Notes: For each observation in equation (2.3), the frontier is predicted using the estimates reported in column 3 of Table 2.4. All observations are assigned to a fuel economy quintile based on the fuel economy distribution across observations between 2003 and 2007, using each vehicle model's initial fuel economy when the model enters the market. The predicted frontier in colored bar is the mean cumulative predicted efficiency change between 2003 and 2007 for each quintile. The clear bars show the cumulative counterfactual efficiency change by quintile. Counterfactual efficiency changes are computed by holding fixed fuel prices at 2003 levels and using equations (2.3) and (2.4) to predict the efficiency change for each observation between 2003 and 2007.

Table A.1: Definitions of Demographic Groups

Group Number	Age (years)	Household Income (1k nominal dollars)	Education (years)	Household Size	Urban	Census Division
1	0-34	0-25	0-12	1	urban	New England
2	35-54	25-50	12 +	2	not urbanized	Middle Atlantic
3	55+	50-75		3		East North Central
4		75-100		4		West North Central
5		100+		5 +		South Atlantic
6						East South Central
7						West South Central
8						Mountain
9						Pacific
Num. of Groups	3	9	2	5	2	9
Total Number of Groups:						2,700

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