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

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Abstract

Technology plays a key role in reducing greenhouse gas emissions from the transportation sector. I estimate 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. Industry competitiveness also affects the two types of technology improvement choices.

Keywords: passenger vehicles, innovation, technology adoption, innovation policy, gasoline taxes

JEL Classifications: L13, L62, O3, Q4, Q55

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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 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 compet-

[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).

itiveness 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; 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 2 presents the empirical model. Section 3 describes the data. Section 4 discusses estimation strategies. Section 5 presents the estimation results. In Section 6, I simulate the model to analyze the effects of policy instruments and market consolidation. Section 8 concludes.

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

[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.

[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.

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 2.1. I present the supply model in Section 2.2 and estimation equations further in the Section 4.1.

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

$$\ln s_{jt} - \ln s_{0t} = \alpha_p p_j + \alpha_g(f p_t \cdot g_{jt}) + \alpha_x x_{jt} + \sigma_{seg} \ln s_{j|seg,t} + \eta^d_{mt} + \xi_{jt} \tag{1}$$

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

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)

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

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).

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

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 frontier* 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 3 and Table 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.

$$c_{ht}(x_{ht}, a_{ht}, i_t) \quad = \quad \gamma_0 + \gamma_x x_{ht} + \gamma_a a_{ht} + \gamma_i ki_t + \eta^c_{seg} + \eta^c_t + \nu_{ht} \tag{3}$$

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)

$$\begin{aligned} H_t(i) &= \lambda_0 + (\lambda_1 + \eta^i_{type} + \lambda_t t + u_t) \cdot i_t + \frac{1}{2}\lambda_2 i_t^2 \\ h_t(i) &= \lambda_1 + \lambda_2 i_t + \eta^i_{type} + \lambda_t t + u_t \end{aligned} \tag{4}$$

$h_t(i)$ 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

$$
\begin{aligned}
F^x_{ht}(x_{ht}) &= \phi^x_0 + (\phi^x_1 + \eta^x_f + \phi^x_t ts + e^x_{ht}) \times x_{ht} + \frac{1}{2}\phi^x_2 x^2_{ht} \\
f^x_{ht}(x_{ht}) &= \phi^x_1 + \phi^x_2 x_{ht} + \eta^x_f + \phi^x_t t + e^x_{ht} \qquad (5) \\
F^a_{ht}(a_{ht}) &= \phi^a_0 + (\phi^a_1 + \eta^a_f + \phi^a_t t + e^a_{ht}) \times a_{ht} + \frac{1}{2}\phi^a_2 a^2_{ht} \\
f^a_{ht}(a_{ht}) &= \phi^a_1 + \phi^a_2 a_{ht} + \eta^a_f + \phi^a_t t + e^a_{ht} \qquad (6)
\end{aligned}
$$

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 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.

[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.

3 Data

In order to estimate the endogenous production choice model described in the Model Section 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 3.1 and other data in Section 3.2.

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 panel B presents summary statistics of technologies adopted. Figure 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 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

[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.

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 panel C presents summary statistics of knowledge capital. Table 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 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

[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.

[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.

of citations a patent receive (i.e. forward citation) [9] following (Trajtenberg, 1990), and I normalize the 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.

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 2; versus (ii) a patent designed for improving engine turbocharging properties, which is categorized under "1.5 Turbocharger" in Table 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

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

[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.

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

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 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 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 Panel A and Panel D.

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

[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).

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 6. In Table 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 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), 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), I find the evidence is the opposite.

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) in Section 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.

4.1 Necessary Equilibrium Conditions and Estimation Equations

Based upon the static model described in the Model Section 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.

$$\begin{aligned} foc_j^{(p)} &: \quad s_j + \sum_{h \in H_f} (p_h - c_h) \frac{\partial s_h}{\partial p_j} = 0 \qquad (7) \\ \mathbf{foc}^{(p)} &: \quad \mathbf{s} + \Delta_{sp}(\mathbf{p} - \mathbf{c}) = 0 \end{aligned}$$

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 (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)

$$\begin{aligned} R_t^{(i)} &\equiv \left[\sum_{h \in H_f} \left(\frac{\partial p_{ht}}{\partial i_t} - \frac{\partial c_{ht}}{\partial i_t} \right) s_{ht} + \sum_{h \in H_f} (p_{ht} - c_{ht}) \left(\sum_{k \in H_f} \frac{\partial s_{ht}}{\partial g_{kt}} \frac{\partial g_{kt}}{\partial i_t} + \sum_{k \in H_f} \frac{\partial s_{ht}}{\partial p_{kt}} \frac{\partial p_{kt}}{\partial i_t} \right) \right] M_t \\ &= \lambda_1 + \lambda_2 i_t + \eta^i_{type} + \lambda_t t + u_t \qquad (8) \\ R_{jt}^{(a)} &\equiv \left[\sum_{h \in H_f} \left(\frac{\partial p_{ht}}{\partial a_{jt}} - \frac{\partial c_{ht}}{\partial a_{jt}} \right) s_{ht} + \sum_{h \in H_f} (p_{ht} - c_{ht}) \left(\sum_{k \in H_f} \frac{\partial s_{ht}}{\partial g_{kt}} \frac{\partial g_{kt}}{\partial a_{jt}} + \sum_{k \in H_f} \frac{\partial s_{ht}}{\partial p_{kt}} \frac{\partial p_{kt}}{\partial a_{jt}} \right) \right] M_t \\ &= \phi_1^a + \phi_2^a a_{ht} + \eta_f^a + \phi_t^a t + e_{ht}^a \qquad (9) \\ R_{jt}^{(x)} &\equiv \left[\sum_{h \in H_f} \left(\frac{\partial p_{ht}}{\partial x_{jt}} - \frac{\partial c_{ht}}{\partial x_{jt}} \right) s_{ht} + \sum_{h \in H_f} (p_{ht} - c_{ht}) \left(\frac{\partial s_{ht}}{\partial x_{jt}} + \sum_{k \in H_f} \frac{\partial s_{ht}}{\partial g_{kt}} \frac{\partial g_{kt}}{\partial x_{jt}} + \sum_{k \in H_f} \frac{\partial s_{ht}}{\partial p_{kt}} \frac{\partial p_{kt}}{\partial x_{jt}} \right) \right] M_t \\ &= \phi_1^x + \phi_2^x x_{ht} + \eta_f^x + \phi_t^x t + e_{ht}^x \qquad (10) \end{aligned}$$

These optimality conditions illustrate private costs and gains associated with each first-stage choice variables. On the left-hand side of Equations (8)-(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 3.1 for details on continuousness of technology adoption).

I use the first order condition of knowledge capital in Equation (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 (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 (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 function $\{\alpha_p, \alpha_g, \alpha_x, \sigma_{seg}\}$, (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

[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.

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

$$\begin{aligned}
\xi_{jt} &= \xi_{jt}(\cdot\,; \alpha_p, \alpha_g, \alpha_x, \sigma_{seg}) \\
&= \ln s_{jt} - \ln s_{0t} - \alpha_p p_{jt} - \alpha_g (fp_t \cdot g_{jt}) - \alpha_x x_{jt} - \eta_{mt}^d - \sigma_{seg} \ln s_{j|seg,t} \qquad (11)\\
\nu_{jt} &= \nu_{jt}(\cdot\,; \gamma_0, \gamma_x, \gamma_a, \gamma_i;\ \alpha_p, \sigma_{seg}) \\
&= c_{jt} - \gamma_0 - \gamma_x x_{jt} - \gamma_a a_{jt} - \gamma_i ki_t - \eta_{seg}^c - F_t^c \qquad (12)\\
\varepsilon_{jt} &= \varepsilon_{jt}(\cdot\,; \theta_0, \theta_x, \theta_a, \theta_i) \\
&= g_{jt} - \exp\left\{\theta_0 + \theta_x x_{jt} + \theta_a a_{jt} + \theta_i ki_t + F_{seg}^g + F_m^g\right\} \qquad (13)\\
u_t &= u_t(\cdot\,; \lambda_1, \lambda_2;\ \alpha_p, \alpha_g, \sigma_{seg}, \gamma_i, \theta_0, \theta_x, \theta_a, \theta_i) \\
&= R_t^{(i)} - \lambda_1 - \lambda_2 i_t - \eta_{type}^i - \lambda_t t \qquad (14)\\
e_{jt}^a &= e_{jt}^a(\cdot\,; \phi_1^a, \phi_2^a;\ \alpha_p, \alpha_g, \sigma_{seg}\gamma_a, \theta_0, \theta_x, \theta_a, \theta_i) \\
&= R_{jt}^{(a)} - \phi_1^a - \phi_2^a a_{jt} - \eta_f^a - \phi_t^a t \qquad (15)\\
e_{jt}^x &= e_{jt}^x(\cdot\,; \phi_1^x, \phi_2^x;\ \alpha_p, \alpha_g, \alpha_x, \sigma_{seg}, \gamma_x, \theta_0, \theta_x, \theta_a, \theta_i) \\
&= R_{jt}^{(x)} - \phi_1^x - \phi_2^x x_{jt} - \eta_f^x - \phi_t^x t \qquad (16)
\end{aligned}$$

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 (8)-(10).

4.2 Identification

I estimate Equations (11)-(16) jointly. The identification of parameters comes from the exclusive variables, prices and fuel economy, in the demand equation (11), where fuel price fp_t creates important time varying variations. Identification also comes from stock of knowledge in the marginal production cost equation (12), as well as the functional form assumption in the fuel efficiency frontier equation (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 (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.

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

[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.

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).

Grandfathered technologies. Similar to the idea of longer-run characteristics, I use grandfathered technologies $a^{old}_{f,j}$ to construct my instrument variables, $D(a)^{old}_{f,j} = \left\{a^{old}_{f,j} - a^{old}_{j\in seg},\ a^{old}_{f,j} - a^{old}_{f,-j}\right\}$ 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 $a^{g3}_{f,j}$, (ii) carburetor $a^{c}_{f,j}$, (iii) automatic transmission without lockup $a^{nl}_{f,j}$, and (iv) engines with 8 cylinders $a^{c8}_{f,j}$ as instruments, using reference from EPA (2008, 2014). Figure 1 and Figure 3 illustrate a brief history of technology evolution over 1986-2006 period. Over my sample period, Figure 1 and Figure 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 $a^{old}_{f,j}$ 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^{old}_{j} 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 $D(a)^{old}_{f,j} = \{a^{old}_{f,j} - a^{old}_{j \in seg},\ a^{old}_{f,j} - a^{old}_{f,-j}\}$ 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 (12), (15)-(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 (12) and (15)-(16).

To estimate the R&D cost equation (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.

5 Estimation Results

I estimate parameters using the Generalized Methods of Moments. I present demand estimation in Section 5.1, results of fuel efficiency frontier in Section 5.2, and results of cost structure in Section 5.3. See Online Appendix for the first-stage results.

5.1 Estimation Results of New Cars Demand

In this section, I present estimates of parameters in the model. Table 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 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

[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).

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.

To interpret the estimation results of the demand system, I calculate the willingness-to-pay (WTP) for fuel efficiency improvements in Table 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.

5.2 Estimation Results of the Fuel Efficiency Frontier

In Table 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 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.

[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).

Figure 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 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.

5.3 Estimation Results of Cost Structures

Adopting energy-saving technologies add financial burdens to produce a vehicle. Panel B of Table 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 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 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 4 presents the estimation results of the marginal R&D cost function $h_t(i_t)$. Point estimates suggest that the R&D cost

[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.

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 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 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 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.

6 Counterfactual Simulations

I take the structural model and analyze the consequences of three counterfactual scenarios. In Section 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 6.2, I consider a counterfactual ownership consolidation of two automakers - GM and Chrysler in 2006. In Section 6.3, I investigate the consequences of a potential supply shock in R&D subsidies.

I compute counterfactual equilibrium using best-response functions (7)-(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

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

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 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.

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

[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).

\$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 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 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 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 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 characteris-

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

tics. Second, Table 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 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 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 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

[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.

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. 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.

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 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

[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.

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 11 presents the average simulated choices, responding to the shock. Table 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 7 suggests that merging automakers reduce vehicle prices compared to other players in the economy.

Table 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.

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 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 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 9. The magnitudes of these impacts, however, are negligible. Last, Table 9 suggests vehicles prices drop by \$95 dollars. Prices drop uniformly across different fuel-efficient vehicles (See

Figure 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 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 I 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.

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.

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.

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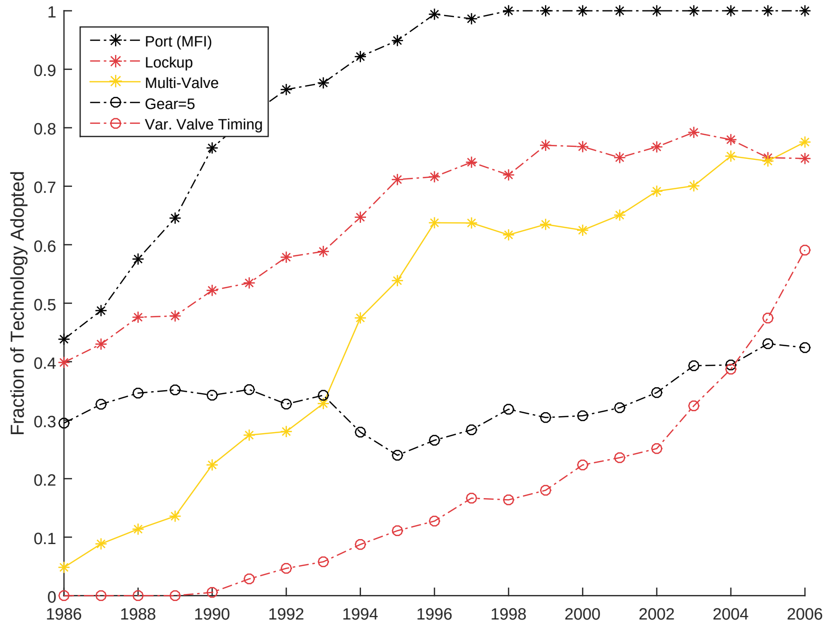
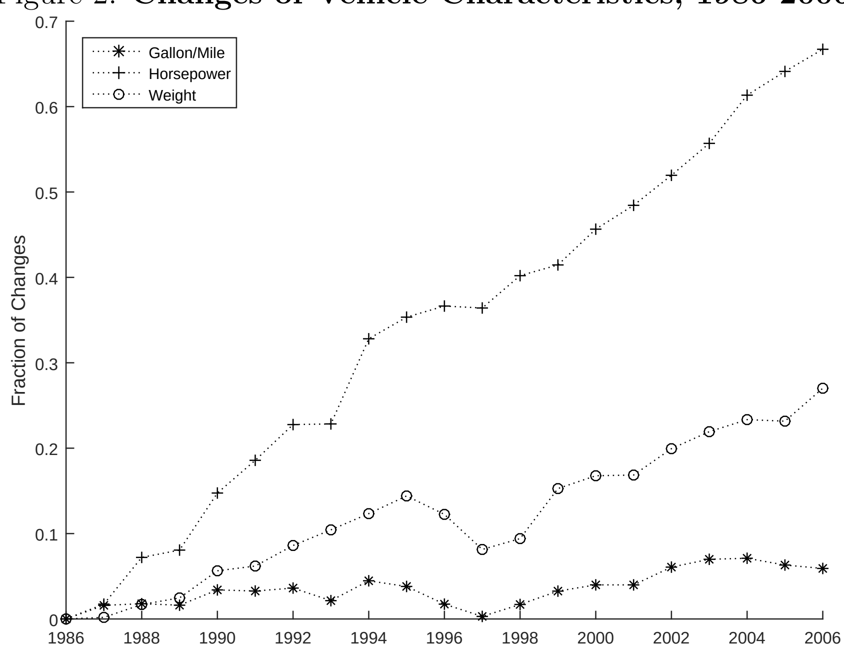
Figures

Figure 1: **Technologies Penetrated the Vehicle Market: 1986-2006**



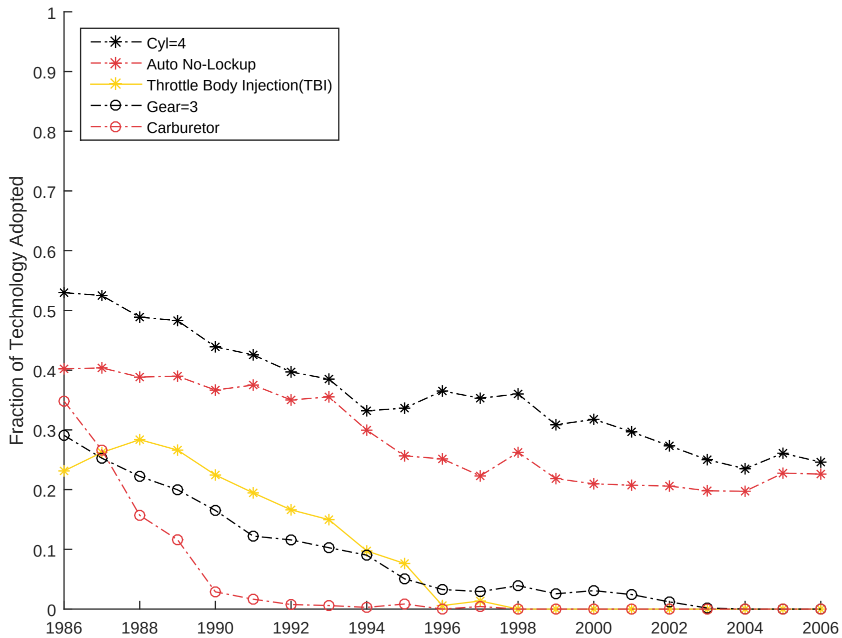
Note: Technology penetration rates are computed as unweighted average.
Source: EPA Fuel Economy Guide Data and EPA Fuel Economy Trend Data.

Figure 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.

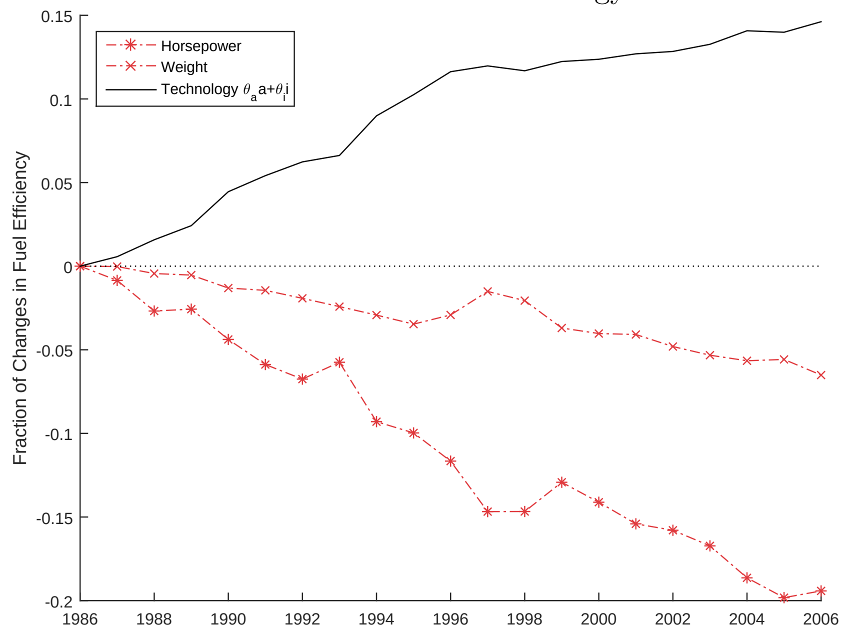
Figure 3: **Grandfathered Technologies Exited from the Market, 1986-2006**



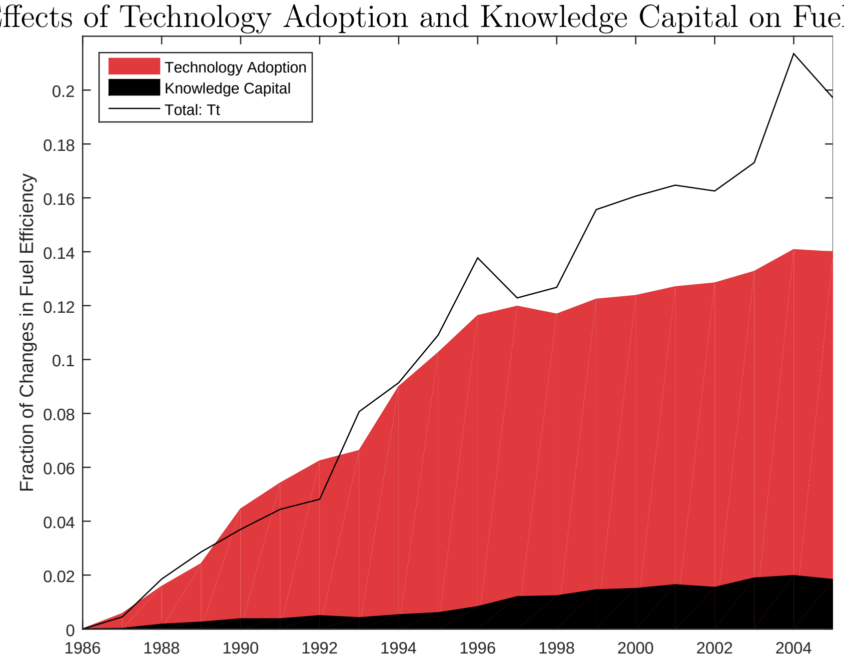
Note: Technology penetration rates are computed as unweighted average.
Source: EPA Fuel Economy Guide Data and EPA Fuel Economy Trend Data.

Figure 4: **Fuel Efficiency Improvement from Innovation and Technology Adoption**

Panel A. Effects of Performance and Technology on Fuel Efficiency



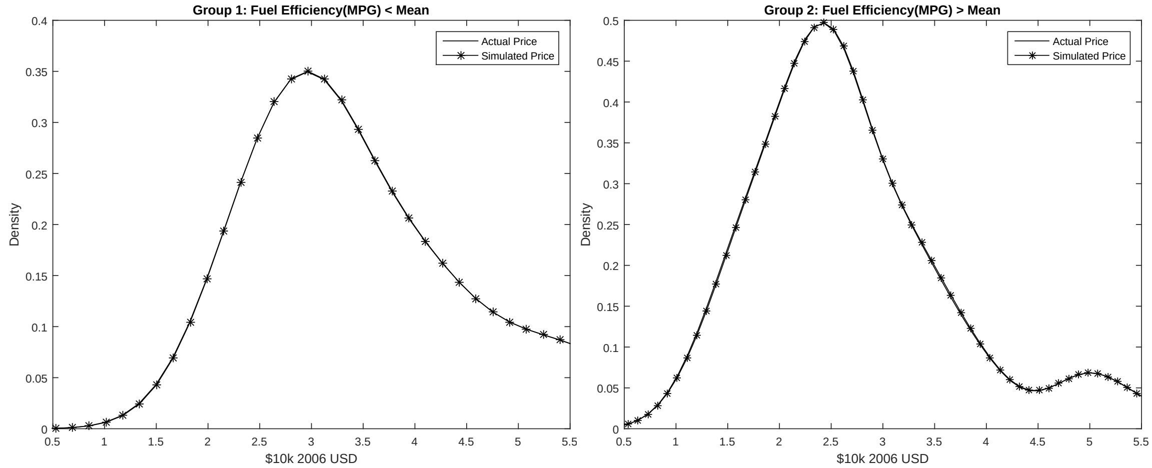
Panel B. Effects of Technology Adoption and Knowledge Capital on Fuel Efficiency



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 5: **Simulation I: A \$1/gallon Increase in Gasoline Tax in 2006**

Scenario I. Choose Price p



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

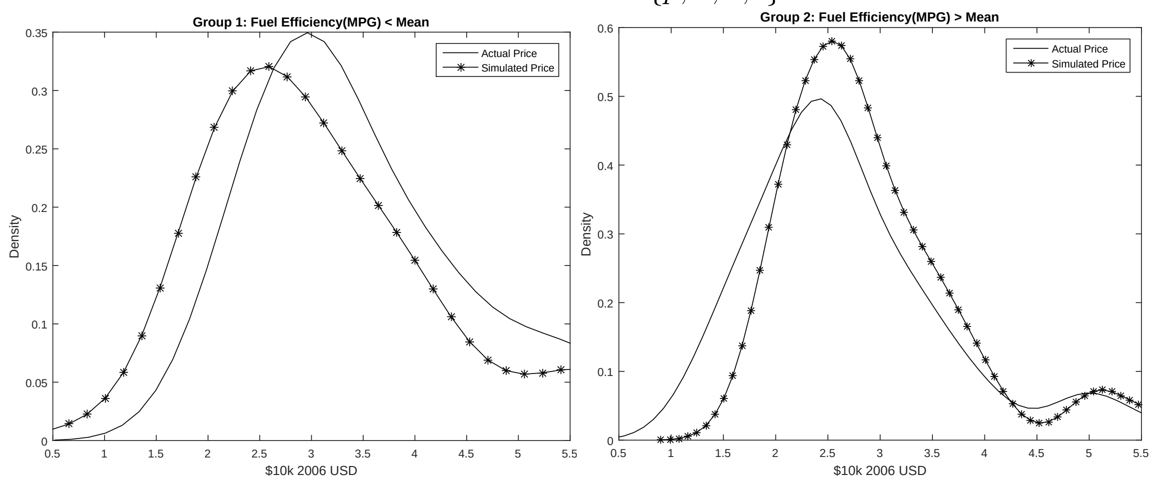


Figure 6: **Simulation II: A 25% Reduction in Marginal R&D Cost in 2006**

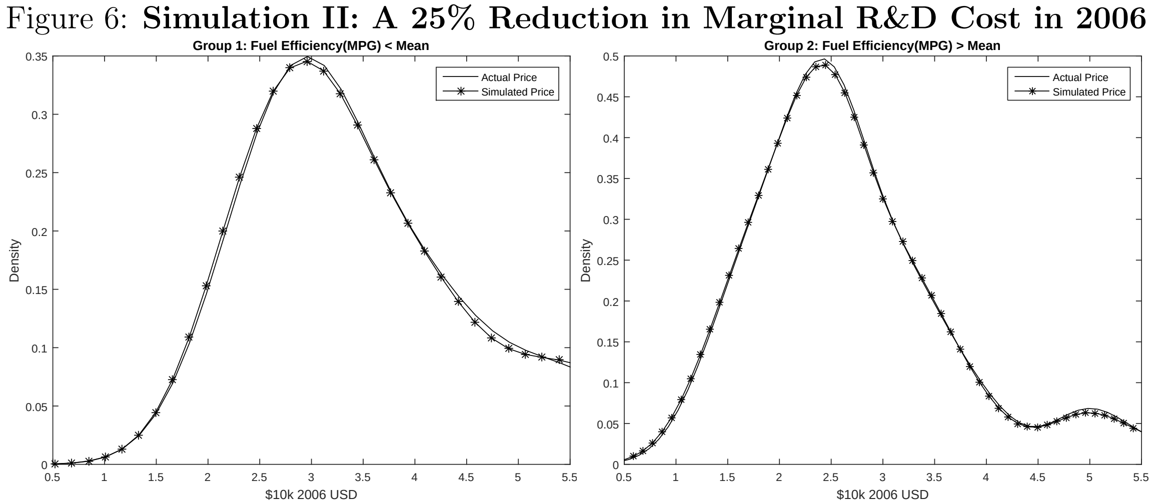
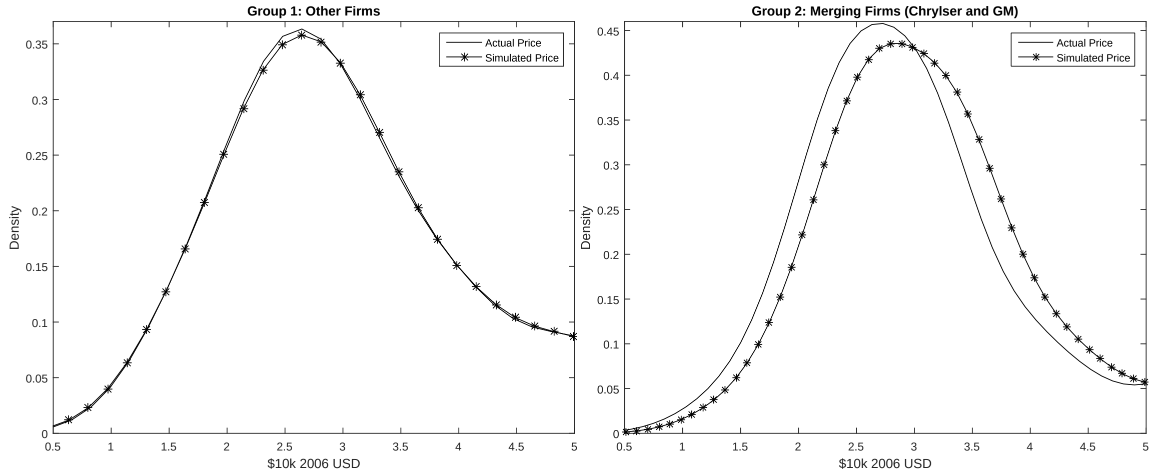
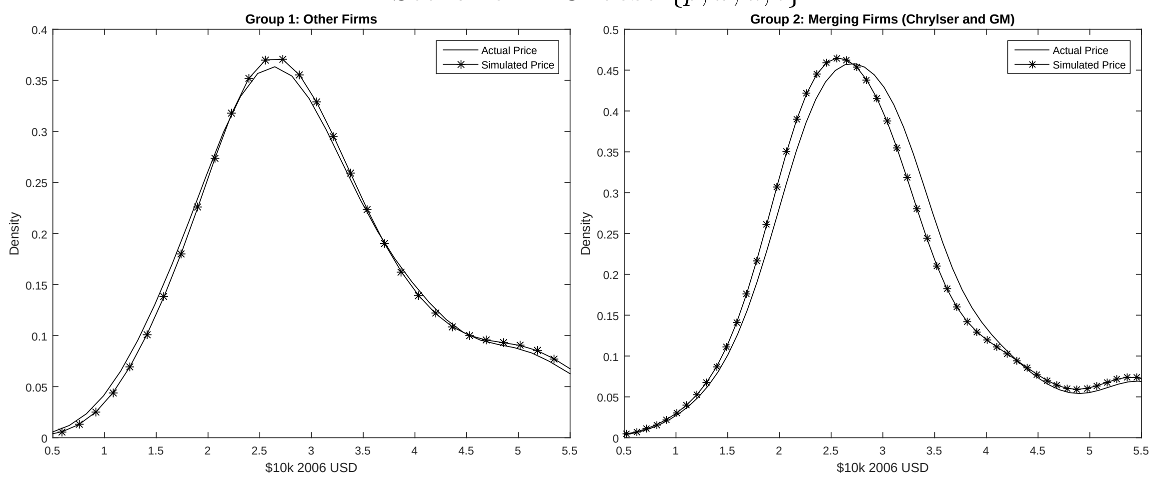


Figure 7: **Simulation III: Merger of GM and Chrysler in 2006**

Panel A. Scenario I. Choose Price p



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



Tables

Table 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 accumulated knowledge capital 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 accumulated 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 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 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 4: **Estimation Results**

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 (100 Engine Patents)	-0.0668***	(0.0160)
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 (100 Engine Patents)	-0.0090***	(0.0009)
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 (100 Engine Patents)	8.3001***	(1.9750)
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 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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.

Table 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 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 5: **Willingness-to-Pay for 1% Fuel Efficiency Improvement in 2006**

	Passenger Cars			Light-duty Trucks			
	Small	Medium	Large/Lux	CUV	SUV	Van	Pickup
Fuel Efficiency (miles/gallon)	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 gasoline price ($2.13/gallon)	229	236	281	289	464	361	469
with $0.5 gasoline 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 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 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 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 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 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 11: **Simulation III: Merger of GM and Chrysler 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	36,059	625	35,435	35,684	249
	Merging Firms	32,039	33,886	1,847	32,039	31,897	-142
	Other Firms	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	Merging Firms				1.3997	1.3915	-0.0082
Hp/Weight	Merging Firms				-2.8241	-2.8280	-0.0039
Weight	Other Firms				1.3241	1.3273	0.0036
Hp/Weight	Other Firms				-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	Merging Firms				28.85	30.00	1.19
Var. Val. Timing	Merging Firms				31.02	21.31	-9.71
Multi. Valve	Merging Firms				45.86	43.25	-2.61
Port (MFI)	Merging Firms				100.00	95.45	-4.55
5 Gear Trans	Other Firms				48.19	47.68	-0.51
Var. Val. Timing	Other Firms				70.61	75.27	4.66
Multi. Valve	Other Firms				91.11	92.20	1.12
Port (MFI)	Other Firms				100.00	100.00	2.00
i: Knowl. (# of Patents)					32.89	32.89	0.00
	Merging Firms				3.79	3.92	0.13
	Other Firms				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
	Merging Firms	19.03	19.59	0.56	19.03	18.87	-0.16
	Other Firms	21.54	24.14	2.63	21.54	21.56	0.02

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

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

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	7. Pickup Trk.
Chrysler	2.18	4.76	3.72	4.51
GM	2.47	5.62	2.02	9.02
Ford	1.81	3.17	2.43	8.71

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

Appendix A. Data and Additional Results

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 efficiency: 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 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).

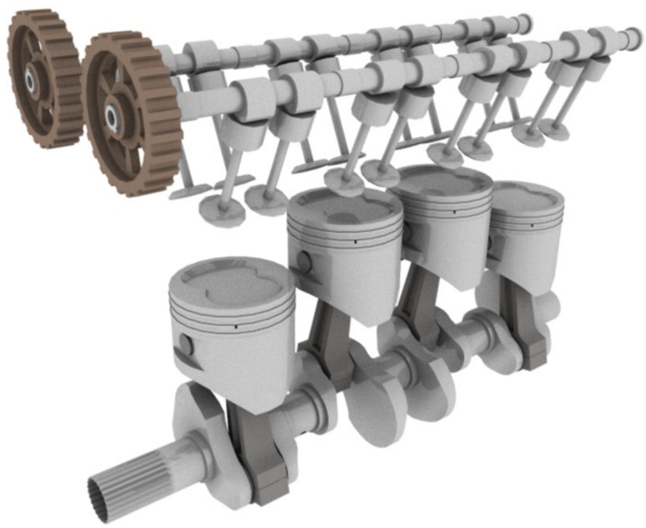
Adding Gears.- "Adding gears allows engine to operate at a more efficient speed more often, and the more gearing options your vehicle has, the more efficient it can be."[29]

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).

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

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

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

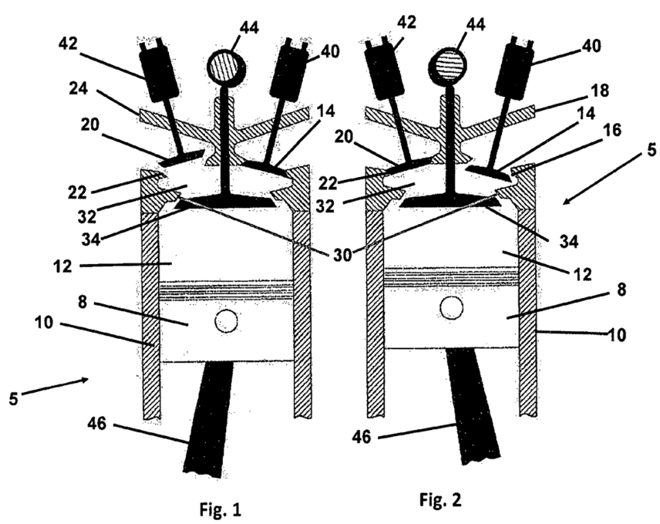


Note: This figure features an inline-four engine with four engine heads, each of which has four valves per cylinder (link).

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

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