The Adoption of Fuel-saving Technologies in U.S. Automobile Industry: Regulation Push and Demand Pull

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Abstract

The paper investigates the influence of fuel-price and fuel-economy regulation on the adoption of fuel-saving technologies in the U.S. automobile industry. This question will be addressed with an empirical model of the industry that incorporates demand, supply, technologies, and regulations. The novelty of this model is that it allows for endogenous choices of vehicle fuel efficiency by firms in the form of a fuel-efficiency frontier. The counterfactual studies show that both fuel prices and regulations contribute to the recent acceleration of vehicle fuel economy in the U.S.: consumers are driven by the fluctuation in fuel price and carmakers are driven by stricter regulation when adopting fuel-efficient vehicles.

1 Introduction

The transportation sector is a major consumer of energy and contributor of air pollutants in the U.S. In 2013, its energy consumption and greenhouse gas emission made up 27% of the U.S. total (Environmental Protection Agency, 2015). As a result, it has always been on the list of primary concerns for

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policy-makers regarding energy security and environmental protection. Improving the fuel efficiency of new vehicles is an important part of the U.S. strategy to reduce oil dependency, improve air quality, and slow down climate change.

From 2000 to 2015, the average fuel efficiency of new passenger cars sold in the U.S. increased by 31%, from 28.5 miles per gallon (mpg)[1,2] to 37.24 mpg. Newly sold light-duty trucks also had a similar increase over the same period, from 21.3 mpg to 27 mpg. This was in stark contrast with the situation in the preceding decade, during which the U.S. automobile industry only made meagre improvements in the fuel efficiency of its vehicle fleets (in 1990, the fuel efficiency was 28 mpg for passenger cars and 20.8 mpg for light-duty trucks).

To understand this trend, two crucial factors need to be examined: regulations and fuel prices, not only because they are two of the key incentives for manufacturers and consumers to adopt fuel-efficient vehicles, but also because both have experienced recent changes, the timings of which coincided with the turn of the previously mentioned trend in fuel efficiency. These changes are illustrated in Figure 1. After being frozen for most of the 1990s and the early years of the 2000s, fuel-economy standards started to increase again after 2005, for trucks, and 2011, for cars. Fuel prices, due to the situation in the Middle East post-9/11 and other supply and demand factors, have fluctuated wildly since the start of the millennium. Understanding how much these movements contributed to the increase in vehicle fuel efficiency is an interesting exercise on its own. Even more importantly, however, it has great practical implications for future industry performance. Given that gasoline prices have started to drop substantially since 2014 after reaching their peak in 2012, it is important to assess whether the past performance of improving fuel efficiency can still continue under the new circumstances and the ever-increasing regulatory targets.

The ability of the industry to reduce fuel consumption hinges on its capacity to develop and adopt fuel-saving technologies. The previous empirical literature on the automobile industry often assumes exogeneity of the product characteristics space, including fuel efficiency (Berry et al., 1995; Petrin, 2002). To analyse fuel-saving technology adoption, there is a need to endog-

[1] *Mpg* measures the number of miles over which the vehicle can travel on one gallon of fuel.

[2] The average reported here is the harmonic average weighted by sales.

enize the choice of product characteristic, especially the fuel efficiency of the vehicles. Several recent papers have attempted to do so, such as those by Klier and Linn (2012); Gramlich (2010); Zhou (2016).

This paper assesses the impact of regulatory changes and fuel-price fluctuation on fuel efficiency in the U.S. automobile industry. A model of a differentiated-good oligopoly that allows for automakers endogenous adoption of ready-for-production fuel-saving technologies is structurally estimated with aggregate market data. Counterfactual studies are performed to estimate what would have happened if fuel prices and/or regulations had been kept unchanged, to separately identify the effect of each factor.

The primary contribution of the paper is the development of a structural model of the automobile industry with endogenous choice of vehicle fuel efficiency. In addition to making the model realistic, endogenizing fuel efficiency allows the estimation of the cost of improving fuel efficiency, with which we can conduct various counterfactual analyses quantifying the effects of changes in fuel prices or regulations, or even the interaction of both, on the firms, the consumers, and the environment.

In addition, the paper contributes to the literature on the effects of the Corporate Average Fuel Economy (CAFE) standards on the automobile industry. The model estimates a compliance cost of 230 USD per mpg-vehicle, which is comparable to estimates in previous structural studies[3,4].

This paper also extends the empirical results of the literature on the effects of fuel prices in the automobile markets. The findings here indicate that fuel costs have significant and substantial negative effects on demand for new vehicles, which is consistent with the findings from existing works, which are that consumers care about fuel prices.

The rest of the paper is structured as follows. Section 2 introduces some background information regarding regulations, fuel prices, fuel-saving technologies, and related literature. The structural model is specified in the next section (3), after which the estimation, identification, and estimation results are detailed (Section 4). The counterfactual studies are then described and the results reported (Section 5), after which the final conclusions are presented (Section 6).

[3]For example Jacobsen (2013) and Gramlich (2010)

[4]However, Anderson and Sallee (2011), using a loophole in the standards related to flexible fuel vehicles, estimated a much lower compliance cost in the range of $9 to $27.

2 Background

2.1 Regulation

There are two federal government agencies in the U.S. that regulate vehicle fuel efficiency, namely the National Highway Traffic Safety Agency (NHTSA), which oversees vehicle fuel consumption, and the Environmental Protection Agency (EPA), which monitors the emission of greenhouse gases and other pollutants. This paper will focus on the regulations from the NHTSA[5].

The NHTSA regulates vehicle fuel economy using the Corporate Average Fuel Economy (CAFE) standards, which were enacted by Congress in the 1975 Energy Policy and Conservation Act (EPCA) and amended in the 2007 Energy Independence and Security Act (EISA). The standards dictate a set of thresholds for the average fuel economy that all the fleets of new vehicles sold in the U.S. must meet or exceed. Failure to comply with the standards will incur a fine of 55 USD for each mpg below the standard per vehicle[6,7].

Before 2011, there were two separate sets of standards for cars and for trucks. In 2011, each model was assigned its own standard, which was set based on the vehicle footprint (wheelbase multiplied by track width). There is also a system of CAFE credit banking that allows manufacturers who exceed the standards to use the excessive mpg to offset any deficit from other fleets, or from future deficit. Limited borrowing from future credit is also allowed, and trading of CAFE credits between manufacturers has also been allowed since 2011, although the amount that can be traded is limited.

The standards for cars stayed unchanged at 27.5 mpg for two decades, and only have started to increase since 2011. The standards for trucks started to move earlier, rising since 2005 after a 10-year freeze at 20.7 mpg. Under the EISA and the Obama Administration directive in 2009, the two standards are to be increased even more in the future, and are expected to reach 40.3 to 41.0 mpg in 2021 and 48.7 to 49.7 mpg in 2025.

[5] The regulations by the EPA are rarely violated, which may be because either the regulations are too loose or the cost of violation is too high. Lack of variation in compliance status makes identification difficult, and if the regulations are too loose it will not affect the firms decisions anyway

[6] The average used in CAFE calculation is the harmonic average, i.e. the inverse of the production-weighted average of the inverse

[7] There may also be other unobserved cost of violation such as reputation cost, political cost

2.2 Fuel Prices

Purchasers of automobiles care about fuel prices. Busse et al. (2013) found that consumers are forward looking regarding fuel cost, and that a $1 increase in the price of gasoline is associated with a $250 decrease in the prices of new cars in the lowest fuel-economy quartile and a $104 increase in the prices of new cars in the highest quartile. Klier and Linn (2010)) found that the gasoline price explains nearly half of the loss of market share of U.S. manufacturers from 2002 to 2007.

Since 2000, fuel prices have been increasingly volatile, in contrast to the flat and slightly downward trend during the 1990s. They rose quickly from 2000 to 2012, with only a temporary drop in 2008 during the Great Recession (Figure 1). However, since 2013, the trend appears to have been reversed again, reaching a new low point, the lowest in more than a decade.

2.3 Fuel Saving Technologies

Knittel (2011) made two observations regarding vehicle fuel efficiency: first, there is a trade-off between fuel efficiency and performance, and second, if weight, power, and torque had been kept at the same level, fuel efficiency could have improved by nearly 60% from 1980 to 2006. Figure 2 illustrates these two observations. At a given point in time, the scatter-plots between fuel efficiency and performance attributes such as power, torque, weight, or size are all downward sloping, suggesting trade-offs between the two variables. However, from 2006 to 2014, the curves move outward, indicating that, at the same level of performances, fuel efficiency improved over the period.

The improvement in fuel efficiency is due to various fuel-saving technological developments and adoptions over the years. Table 1, which is taken from the National Academy of Sciences (2011), lists some of the technologies, together with the estimated cost. The adoption of these technologies is a lengthy process dependent on both the demand and supply factors of the industry. Figure 3 plots the evolution of the adoption rates of some popular technologies. It takes a decade or more for most technologies to achieve majority adoption by the market.

2.4 Related Work

This paper contributes to a large body of empirical literature studying the U.S. automobile industry. The impact of gasoline prices on vehicle prices, market shares, and fuel efficiency has been studied by Pakes et al. (1993); Bento et al. (2009); Busse et al. (2013); Li et al. (2009), among others. Klier and Linn (2016) studied the effect of the CAFE standard on horsepower and torque, while Jacobsen (2013) emphasizes consumer and producer heterogeneity in studying the distributional effects of CAFE standards.

This paper is also particularly aligned with a recent trend within the above literature of emphasizing the need to consider endogenous product choice in the automobile industry. Gramlich (2010) assumed a trade-off between fuel efficiency and vehicle quality when studying the effect of gasoline prices on fuel economy. Klier and Linn (2012) studied the medium-run effects of the CAFE standard, making use of engine platformbased instruments to correct for product choice endogeneity. Zhou (2016) studied the effect of R&D and gasoline tax policies on knowledge capital and technology adoption in the automobile industry, using longer-run characteristics and grandfathered technologies as instruments for product choice endogeneity.

On the technical side, the two-stage model presented in this paper loosely follows the work of Eizenberg (2014), using Berry et al. (1995)'s specifications in the second stage and a Nash equilibrium in the first stage to model price competition with product choice. The model is, however, different from that of Eizenberg (2014) in that it focuses on variable cost instead of fixed cost, the decision is continuous so that point-identification is possible, and the first stage decision is not directly observed but only indirectly implied from the observed final fuel efficiency.

This paper also contributes to the studies of the impacts of fuel prices and CAFE standards on the automobile industry with a model that endogenizes technology adoption. It is important to put the two factors fuel prices and standards together because, as shown in Figure 1, the timing of the recent improvement in fuel efficiency coincides with substantial changes in both factors. My treatment of product choice goes beyond the research of Gramlich (2010), and, like the work published by Zhou (2016), considers technological adoption beyond the performancefuel efficiency trade-offs, and also considers the cost of adoption.

3 Model

3.1 Overview

Both supply and demand will be modelled here, and compliance cost due to regulations will also be incorporated. *Demand* will be modelled using a random-coefficient discrete choice specification, similar to that developed by Berry et al. (1995). *Supply* will be modelled with oligopolistic competition between multi-product firms setting not only prices but also fuel efficiency for their vehicles. Firms can improve the fuel efficiency of their vehicles, but need to pay an extra cost per vehicle to install such technology throughout the fleet. *Regulators* set fuel-economy standards each year; firms that violate these standards pay fines. Some firms barely meet the standards, paying no fines, but with the need to optimize under a shadow cost of compliance if they are to maintain their standard-complying status.

3.2 Demand

Consumer utility Market t is populated by M_t consumers. Each consumer is to purchase one vehicle from one of the new models available in the market, or to make no purchase[8]. The consumer derives utility from the characteristics of the purchased model. A subset of characteristics is observed by the econometrician; the rest are not observed. Different consumers may also have different tastes regarding each vehicle characteristic.

Suppose consumer i in market t purchasing vehicle model j receives a utility according to the following equation:

$$u_{ijt} = \alpha_{it} p_{jt} + \gamma_{it} dpm_{jt} + x_{jt}^{u\,\prime} \beta_{it}^{u} + \xi_{jt} + \epsilon_{ijt}$$

p_{jt} denotes the price of model j in market t (in thousands of dollars), dpm_{jt} represents the fuel cost of the same model, expressed in terms of dollars per 100 miles of travel, x_{jt}^{u} is the set of observed vehicle characteristics, ξ_{jt} captures the value from unobserved vehicle characteristics, and ϵ_{ijt} is idiosyncratic shock.

α_{it} and γ_{it} capture consumer marginal disutility from paying for the vehicle purchase and from paying for fuel consumption. β_{it} captures consumers

[8] The no-purchase option includes the choice of purchasing second-hand vehicles, which is not modelled explicitly due to the lack of data.

valuations of the observed vehicle characteristics. These parameters can vary across consumers to capture consumer heterogeneity - the fact that consumers may have different tastes for different vehicle characteristics.

There is substantial variation in income during the sample period, the income effects from which will be accounted for by allowing the coefficients α_{it} and γ_{it} to depend on the median income in each market y_t.

The outside good is assumed to give a zero-mean utility. This is for normalization purposes, as utility is equivalent under translation by a constant.

$$u_{i0t} = \epsilon_{i0t}$$

Distributional assumption The distribution of the parameters on the monetary variables (price and dollars per mile), i.e. α_{it} and γ_{it}, is assumed to be a log-normal distribution. There are two reasons for this choice. First, these parameters are expected to be negative (disutility from losing money), and hence it is necessary to avoid a situation in which consumers may have positive utility for losing money. A log-normal distribution guarantees that the parameters will not change sign. Note that I will allow for a constant to be multiplied with this distribution; the constant can be negative or positive, so I do not impose *a priori* the negativity of these parameters, and only impose the restriction that the parameters do not change sign. The sign of the estimates can therefore still be viewed as a test of the validity of the model. Second, these parameters are expected to interact with income, which empirically follows a log-normal distribution.

Specifically, assume $\alpha_{it} = \frac{\alpha}{y_t}\exp(\sigma_p \nu_{p,it})$ and $\gamma_{it} = \frac{\gamma}{y_t}\exp(\sigma_{dpm}\nu_{dpm,it})$, where α, σ_p, γ, σ_{dpm} are parameters to be estimated, and $\nu_{p,it}$ and $\nu_{dpm,it}$ are unobserved tastes that follow i.i.d standard normal distribution.

The taste parameters for vehicle characteristics are assumed to be normally distributed. Specifically, the taste for the k^{th} characteristics, $\beta^u_{k,it} = \beta^u_k + \sigma_k \nu_{k,it}$. β^u_k will capture the taste of the median consumer, whereas σ_k will capture how dispersed this taste is among all consumers. Note that this specification allows for some consumers to like the characteristics and the others to dislike them. How agreeable the consumers are about certain characteristics depends on how small the dispersion of taste σ_k is.

Choice probability and demand Let $V_{ijt} = \alpha_{it}p_{jt} + \gamma_{it}dpm_{jt} + x^{u}_{jt}{}'\beta^u_{it} + \xi_{jt}$, so that $U_{ijt} = V_{ijt} + \epsilon_{ijt}$. In addition, use t to denote the set of vehicle models available in market t. Consumer i will choose to purchase model

j if $U_{ijt} > U_{ikt}, \forall k \in t$. From the perspective of the econometrician, the probability that consumer i will purchase model j, conditional on observables, is

$$P(U_{ijt} > U_{ikt}, \forall k \in t) = P(\epsilon_{ikt} - \epsilon_{ijt} < V_{ijt} - V_{ikt}, \forall k \in t)$$

Assuming type-1 extreme value for the idiosyncratic shocks $\{\epsilon_{i0t}, ..., \epsilon_{ijt}\}$, the above probability will take on a tractable functional form:

$$s_{ijt} = \frac{\exp(V_{ijt})}{1 + \sum_{k \in t} \exp(V_{ikt})}$$

The market share for model j can be calculated by averaging the choice probability over all consumers:

$$s_{jt} = \int \frac{\exp(V_{ijt})}{1 + \sum_{r \in t} \exp(V_{irt})} dF_t(i)$$

The estimation below simulates a population of N_t representative consumers, and the market share can be obtained by taking the average across all consumers in the simulated population:

$$s_{jt} = \frac{1}{N_t} \sum_{i=1}^{N_t} \frac{\exp(V_{ijt})}{1 + \sum_{r \in t} \exp(V_{irt})}$$

3.3 Cost

As with the work of Berry et al. (1995) and the existing literature, a constant marginal cost of producing vehicles is assumed here. It is also assumed that the marginal cost can be separated into production cost and fuel-saving technological cost (or fuel-tech cost for short). Production cost is the cost of producing one vehicle, and depends on the characteristics of the vehicles. Fuel-tech cost is the amount that firms can spend on each vehicle to improve its fuel efficiency.

$$c_{jt} = c_{jt}^{\text{prod}} + c_{jt}^{\text{fst}}$$

Production cost The production cost depends on vehicle characteristics. To make sure that the cost is positive, its functional form is assumed to be as follows:

$$\ln c_{jt}^{\text{prod}} = x_{jt}^{c}{}'\beta^{c} + \omega_{jt}$$

x_{jt}^{c} is the set of observed vehicle characteristics that affect production cost, and ω_{jt} captures the effect of unobserved cost characteristics and technologies.

Fuel-tech cost Fuel consumption rate gpm_{jt}[9] is assumed to be the outcome of the engineering configuration of the vehicle, i.e. it can be expressed as a function of the vehicle characteristics x_{jt}^{gpm}, subject to random technological shocks τ_{jt}.

$$\ln g\tilde{p}m_{jt} = x_{jt}^{gpm\prime}\beta^{gpm} + \tau_{jt}$$

This is related to the concept of the fuel-efficiency frontier discussed by Knittel (2011) who observed that trade-offs exist between fuel efficiency and performance characteristics of the vehicle, e.g. vehicles with higher horsepower or greater weight tend to consume more fuel.

There exists a spectrum of technologies that can be installed in a vehicle to improve its fuel efficiency beyond what is determined by the above engineering configuration. Let e_{jt} denote the decrease in fuel saving of the vehicle resulting from firms adopting a spectrum of technologies for their vehicles, i.e.

$$\ln gpm_{jt} = \ln g\tilde{p}m_{jt} - e_{jt} = x_{jt}^{gpm\prime}\beta^{gpm} + \tau_{jt} - e_{jt}$$

e_{jt} would be proportionate to the number of technologies that firms used. In fact, given a convex cost curve for fuel-saving improvement, it is likely that there is one-to-one mapping between e_{jt} and the set of technologies that can achieve such improvement. Therefore, the fuel-tech cost can be defined using this variable:

[9]Fuel consumption rate (measured in gallons per 100 miles) is the inverse of fuel efficiency. Fuel consumption rate is linearly proportionate to fuel cost, which is what consumers really care about. Expressing everything in terms of fuel consumption rate is also more tractable, and hence in the model *gpm* instead of *mpg* is used.

$$c_{jt}^{\text{fst}} = c^{\text{fst}}(e_{jt})$$

Flexible specification of this function will be allowed for with the use of a polynomial with a flexible order.

3.4 Market Structure and Competition

In each market, a number of firms, each of which manufactures several vehicle models, compete in two stages. In the first stage, without knowing the realization of the market shocks ξ, ω and τ, they simultaneously choose the fuel efficiency for all their models (by choosing the e_{jt} described above) to maximize their expected profits, which they will receive at the end of the second stage. In the second stage, after learning about the values of these shocks, they choose prices simultaneously to maximize the profit, subject to the existing regulations. Each stage is discussed in detail below, beginning with the later stage.

3.4.1 Second stage

Firms learn about market shocks and make their pricing decisions. In doing so, they need to consider their compliance status with regard to the fuel-economy regulations.

Firms are classified into three types according to the status of their compliance with the fuel-economy regulations:

1. *Violating firms*: those whose average fuel economy is below the standard, and that pay the resultant penalty.

2. *Unconstrained firms*: those whose average fuel economy exceeds the standards, and that incur no penalty or compliance cost.

3. *Constrained firms*: those whose average fuel economy is binding at the standard levels, and that pay no penalty but incur a compliance cost when adjusting the fuel economy of their fleets to meet the standards.

The fuel-economy standards are set separately for cars and trucks. Let $\overline{mpg}_{ft}^{car}$ and $\overline{mpg}_{ft}^{truck}$ be the harmonic average fuel efficiency for cars and trucks manufactured by firm f[10] and $\overline{\overline{mpg}}^{car}$ and $\overline{\overline{mpg}}^{truck}$ the standards for cars and trucks respectively. If firms violate the standards they have to pay a fine of \$55 per mpg in violation of the total standards across violating vehicles, i.e. $55(\overline{\overline{mpg}}_t^{car} - \overline{mpg}_{ft}^{car})s_{ft}^{car}$, with s_{ft}^{car} being the share of cars of firm f, and $55(\overline{\overline{mpg}}_t^{truck} - \overline{mpg}_{ft}^{truck})s_{ft}^{truck}$, with s_{ft}^{truck} being the share of trucks. The profit for a violating firm will be

$$\begin{aligned}\pi_{ft} = \sum_{j\in ft} (p_{jt} - c_{jt})\, s_{jt} &- 55(\overline{\overline{mpg}}_t^{car} - \overline{mpg}_{ft}^{car})s_{ft}^{car} \\ &- 55(\overline{\overline{mpg}}_t^{truck} - \overline{mpg}_{ft}^{truck})s_{ft}^{truck}\end{aligned} \tag{1}$$

A constrained firm, i.e. a firm whose average fuel economy is binding at the standard level $\overline{mpg}_{ft}^{car} = \overline{\overline{mpg}}_t^{car}$ and $\overline{mpg}_{ft}^{truck} = \overline{\overline{mpg}}_t^{truck}$, pays no fine, but in optimizing its profit it needs to operate under the constraint of the regulations (assuming the firms compliance is a prior-determined commitment). In other words, the firm is solving a maximization problem under the constraints $\overline{mpg}_{ft}^{car} \geq \overline{\overline{mpg}}_t^{car}$ and $\overline{mpg}_{ft}^{truck} \geq \overline{\overline{mpg}}_t^{truck}$. There will be a shadow associated with each of these constraints, denoted by λ_{kt}^{car} and λ_{kt}^{truck} respectively, and the firm will behave as if it maximizes the Lagrange of the constrained profit:

$$\begin{aligned}\pi_{ft} = \sum_{j\in ft} (p_{jt} - c_{jt})\, s_{jt} &- \lambda_{ft}^{car}(\overline{\overline{mpg}}_t^{car} - \overline{mpg}_{ft}^{car})s_{ft}^{car} \\ &- \lambda_{ft}^{truck}(\overline{\overline{mpg}}_t^{truck} - \overline{mpg}_{ft}^{truck})s_{ft}^{truck}\end{aligned} \tag{2}$$

Maximizing these profits with respect to prices will provide a system of equations that relates prices and costs. For example, for constrained firms, the first-order condition (FOC) will be

$$\begin{aligned}\frac{\partial \pi_{ft}}{\partial p_{kt}} &= \sum_{j\in ft} \left(p_j - c_j - \frac{\lambda_{ft}}{\overline{\overline{gpm}}_{jt}^2} \left(\overline{gpm}_{jt} - \overline{\overline{gpm}}_{jt}\right) - \frac{\lambda_{ft}}{\overline{gpm}_{jt}^2} \left(gpm_{jt} - \overline{gpm}_{jt}\right) \right) \frac{\partial s_{jt}}{\partial p_{kt}} \\ &\quad + s_{kt} \\ &= 0\end{aligned} \tag{3}$$

[10]The harmonic average is used because it is the way the regulator calculates the average fuel economy (in miles per gallon, which is the inverse of the fuel consumption).

3.4.2 First stage

Let $p^*(\xi, \omega, \tau, e)$ be the prices chosen by the firms in the second stage and $\pi^*(\xi, \omega, \tau, e) = \pi(p^*(\xi, \omega, \tau, e), \xi, \omega, \tau, e)$ be the corresponding profit. In the first stage, firms maximize the expected profit, with that profit expectation informed by the distribution of ξ, ω and τ , by choosing the optimal number of fuel-saving technologies:

$$\max_{\{e_{jt}\}_{j \in ft}} E_{(\xi,\omega,\tau)} \left[\pi^*_{ft}(\xi, \omega, \tau, e) \right]$$

The FOC with respect to e_{kt} is as follows:

$$\begin{aligned} \frac{\partial E_{(\xi,\omega,\tau)} \left[\pi^*_{ft}(\xi, \omega, \tau, e) \right]}{\partial e_{kt}} &= E_{(\xi,\omega,\tau)} \left[\frac{\partial \pi^*_{ft}(\xi, \omega, \tau, e)}{\partial e_{kt}} \right] \\ &= E_{(\xi,\omega,\tau)} \left[\frac{\partial \pi_{ft}(p^*(\xi, \omega, \tau, e), \xi, \omega, \tau, e)}{\partial e_{kt}} \right] \end{aligned} \tag{4}$$

The last equation is derived from the envelope theorem and the fact that $p^*(\xi, \omega, \tau)$ maximizes π_{ft}. The above FOCs can be used to solve for the marginal cost of fuel-efficiency improvement.

$$\begin{aligned} c^e_{kt} &= \frac{dc^{FST}_{kt}}{de_{kt}} \\ &= E_{(\xi,\omega,\tau)} \left[\sum_{j \in ft} \left(p_{jt} - c_{jt} - \frac{\lambda_{ft}}{\overline{\overline{gpm}}^2_{jt}} \left(\overline{gpm}_{jt} - \overline{\overline{gpm}}_{jt} \right) \right. \right. \\ &\quad \left. \left. - \frac{\lambda_{ft}}{\overline{gpm}^2_{jt}} \left(gpm_{jt} - \overline{gpm}_{jt} \right) \right) \frac{\partial s_{jt}}{\partial e_{kt}} + \gamma \frac{s_{kt} gpm_{kt}}{\overline{gpm}_{kt}} \right] \Big/ E_{(\xi,\omega,\tau)}[s_{kt}] \end{aligned} \tag{5}$$

4 Data and Estimation

4.1 Data

The model was estimated using the market data of new light-duty vehicles sold in the U.S. from 2006 to 2014. Sales data at the nameplate level (e.g. BMW 3-series, Toyota Camry) were obtained from the Automotive News

Market Data Book. Vehicle characteristics, classification, and manufacturer-suggested retail prices (which were used as a proxy for retail prices) at different trim levels (e.g. BMW 328i XDrive 2dr Coupe AWD (3.0L 6cyl 6M), Toyota Camry SE 4dr Sedan (2.5L 4cyl 6A)) were drawn from www.msn.com/en-us/autos. The annual average motor gasoline regular retail prices from the EIA were used as a proxy for fuel prices faced by consumers. The number of households from the U.S. Census Bureau was used as a measure of market size, and household median income from Fred St Louis was used for consumer income. The CAFE standards were taken from the National Highway Traffic Safety Agency.

Vehicle models with sales fewer than 1000 were excluded, resulting in a total of 2,284 model-year observations from 40 manufacturers[11]. The data on vehicle characteristics and prices were matched to the sales data using year, make, and nameplate, and the corresponding average values of all the trim levels of the same nameplate were used for estimation.

Table 2 shows the summary statistics, grouped into Passenger Car and Light-duty Truck categories. On average, trucks have lower fuel efficiency, larger size, and higher horsepower, weight, and torque, and account for approximately 47% of the sales during the period.

Figure 4 plots the evolution of the sales-weighted average vehicle characteristics over the period. Weight and size stay relatively flat[12], while fuel efficiency and horsepower trend upward.

4.2 Identification

In addition to the usual price endogeneity, there is another source of endogeneity that needs to be corrected for. In the first stage, the set of fuel-saving technologies installed in each vehicle is unknown. The selection of these technologies depends on the vehicle characteristics, and hence may potentially bias the estimation of the fuel-efficiency frontier equation.

The first stage of the model closely follows the BLP (1995), as the BLP-

[11]There were several mergers and splits between firms during the period. These firms will be treated as distinct. In fact, due to the static nature of the model, the same firm from different years will be treated as unrelated in the estimation

[12]In the 1990s the opposite was true, i.e. the weight trend was upward and the fuel-efficiency trend was flat. The changes suggest that manufacturers have arrived at a new set of strategic product choices, potentially in response to new fuel prices and a new regulatory environment

type is a natural set of instruments commonly used in the literature to correct for price endogeneity. The average characteristics of other models from the same manufacturer, and those of other models from the same market, are used as instruments for the demand and cost equations.

To identify the level of fuel-saving-technology adoption, it is assumed that the fuel-saving-technology cost is convex, so that the marginal cost of fuel-efficiency improvement is monotonic to the level of fuel-saving technology adoption, which enables one-to-one mapping between one variable and another. Specifically, if $c^e_{jt} = c^e(e_{jt}) = \frac{dc^{FST}(e_{jt})}{de_{jt}}$ is monotonic, it can also be written as $e_{jt} = e(c^e_{jt})$, and the fuel-efficiency frontier equation becomes $gpm_{jt} = gpm\left(x^{gpm}_{jt}, \tau_{jt}\right) \exp\left(-e\left(c^e_{jt}\right)\right)$.. A flexible function can be specified to approximate $e\left(c^e_{jt}\right)$.

τ_{jt} may contain unobserved characteristics that affect fuel efficiency and hence can be correlated with c^e_{jt}. Instruments can be used to adjust for such omitted variable bias, but because c^e_{jt} enters the fuel-efficiency frontier equation via a flexible function specification, instruments of higher-order polynomial power may be needed to correct for the endogeneity from the additional terms in the flexible function. A more elegant solution is to use a control function. Suppose we have a set of instrumental variables Z^e for c^e_{jt} and assume that $c^e_{jt} = z^{e\prime}_{jt}\iota^z + \chi_{jt}$ and $\tau_{jt} = \chi_{jt}\iota^\chi + \epsilon_{jt}$ with ϵ_{jt} being uncorrelated with c^e_{jt}, the frontier becomes $gpm_{jt} = gpm\left(x^{gpm}_{jt}, \chi_{jt}, \epsilon_{jt}\right) \exp\left(-e\left(c^e_{jt}\right)\right)$ with χ_{jt} being estimable by the regression of Z^e on c^e_{jt}, and ϵ_{jt} being an exogenous error term. The instruments used are also of the BLP-type, i.e. the average fuel-related vehicle characteristics of other models manufactured by the same firm.

To identify the compliance cost, firms need to be classified according to their compliance status - standard violating, constrained, or unconstrained. Because of the system of credit trading, averaging, banking, and borrowing, the status is not obvious from the data on average fuel economy itself. Jacobsen (2013) developed a dynamic model of credit banking and borrowing to account for such complications. Gramlich (2010), using data from 1971 to 2007, assumed that European manufacturers were always violating, while their domestic and Asian counterparts were always constrained and unconstrained, respectively. Using a dynamic model, like Jacobsen (2013), is too computationally intensive, while the assumptions that Gramlich (2010) used no longer holdhold[13]. Instead, I will manually go through the times series of

[13]For example, BMW, a European manufacturer, previously chose to violate the stan-

the average fuel economy for each manufacturer to identify whether: 1. The firm pays any fine; 2. The average fuel economy of the firm is consistently above or below the standards; or 3. The average fuel economy fluctuates at about the same level as the standards.

4.3 Estimation

Assume the following functional forms:

$$\begin{aligned} \ln gpm_{jt} &= x_{jt}^{gpm\prime}\beta^{gpm} - e_{jt} + \tau_{jt} \\ \ln c_{jt}^{prod} &= x_{jt}^{c\,\prime}\beta^{c} + \omega_{jt} \end{aligned}$$

Let ι^e be the parameters that specify the flexible functions $e(\cdot)$. Given a vector of parameters $\theta = (\alpha, \gamma, \sigma_{price}, \sigma_{dpm}, \lambda, \beta, \beta^c, \beta^{gpm}, \iota^z, \iota^\chi, \iota^e)$, we can

- solve for $\{\xi_{jt}\}$ that equates the model-predicted share with the observed shares $s_{jt}(\xi, p, dpm, X^u; \theta_u) = \hat{s}_{jt}$
- solve for $\{c_{jt}\}$ using the second-stage system of FOCs, from which we derive ω_{jt}
- solve for $\{c_{jt}^e\}$ using the systems of FOCs of the first-stage, from which we derive $\chi_{jt} = c_{jt}^e - z_{jt}^{e\,\prime}\iota^z$ and $\tau_{jt} = \ln gpm_{jt} - x_{jt}^{gpm\prime}\beta^{gpm} - e(c_{jt}^e; \iota^e) - \chi_{jt}\iota^\chi$

The following moment conditions are assumed:

$$\begin{cases} E[\xi_{jt} \mid z_{jt}^u] &= 0 \\ E[\omega_{jt} \mid z_{jt}^c] &= 0 \\ E[\tau_{jt} \mid z_{jt}^e] &= 0 \end{cases}$$

There are two complications in estimating the above system of moments. First, the estimation of the second stage of the model requires the calculation of an expectation about the distribution of the random market shocks, which is unknown. Following Eizenberg (2014), there are two approaches: either approximating the expectation of the function by the function value at the

dards and pay the fine, but since 2008 have consistently met and sometimes exceeded the standards.

expected value of the shocks, i.e. $E_(\xi, \omega, \tau)[f(\xi, \omega, \tau)] \approx f(E[\xi, \omega, \tau])$, or drawing from the empirical distribution estimated in the first stage. Due to computational constraints, in this version of the paper, the first approach is employed.

Second, if joint GMM were to be carried out, all the parameters in the first stage and most of the parameters in the second stage would enter the GMM objective in a non-linear manner, preventing the use of concentration out of linear parameters to simplify the estimation procedure. This would increase the computational burden substantially. Therefore, for this version of the paper, a two-step estimation strategy is employed to reduce the computational complexity, albeit at the cost of lower estimation efficiency:

1. Estimate the first stage using demand and cost moments to derive the first-stage parameters $(\alpha, \gamma, \sigma_{price}, \sigma_{dpm}, \beta^u, \sigma, \beta^c, \lambda)$ – this is similar to the standard BLP.

2. Using the fitted parameters from the first step, solve the second-stage FOCs for c^e and use it to regress the fuel-efficiency frontier equation with the control function.

4.4 Results and Discussion

Panels A, B, C, and E from Table 3 display the first-step estimation results.

Utility The signs of the coefficients on price and cost of fuel consumption (*dpm* dollars per 100 miles) are negative, as expected. The average consumer values power and size and dislikes greater weight. However, the dispersion of taste for power and weight is relatively large, with the standard deviation of the taste distribution for both characteristics similar in magnitude to that of the mean taste, suggesting that a substantial portion of consumers have opposite tastes to those of the average consumer. Regarding size, consumers are generally agreeable on their liking of larger size, with the standard deviation being small compared with the magnitude of the mean taste.

The model implies an average own-price elasticity of -2. This estimate is comparable to those of the existing literature: Zhou (2016)'s estimate is -2.0, Klier and Linn (2012)'s -3.48, and Klier and Linn (2012)'s -1.4. My estimates imply an average mark-up of 46%.

Production cost Increasing power, weight, and torque increases production cost. This is to be expected, as increasing power and torque generally requires higher-quality components and materials. Increasing size decreases cost, but this effect should be interpreted as conditional on fixing weight and power. Production cost is trending downwards, reflecting a general improvement in manufacturing technologies, among other factors.

Fuel efficient frontier An increase in power, weight, and torque decreases the fuel efficiency of the vehicles. This is similar to the results of Knittel (2011), who found a trade-off between fuel economy and vehicle performance. The time effects are trending up, suggesting an improvement in fuel technology over time. This is also in line with the outward shift of the fuel-efficiency frontier over time reported by Knittel (2011).

Compliance cost The estimated compliance cost for constrained manufacturers is 230 USD per mpg per vehicle. This is higher than the penalty for violating the standard (55 USD per mpg), but comparable with estimates from Jacobsen (2013)), who made estimates in the range of \$157\$264, and Gramlich (2010), who made an estimate of \$347. Reasons for these high compliance costs include reputational cost and political cost (due to damaged relationships with regulators and legislators). However, these estimates are in contrast with the low compliance cost estimated by Anderson and Sallee (2011), who suggested a value of \$9 to \$27.

Marginal fuel-tech cost In the second stage, a polynomial is used to approximate the fuel-tech function $e\left(c_{jt}^{e}\right)$. Polynomials of different order have been tried, from 1 to 7. Figure 5 plots the shape of such functions[14]. A polynomial of order 3 was chosen for the final estimation because going beyond order 3 does not provide significant additional explanatory power to the function.

Panel D from Table 3 displays the results from the second step. The median c^e across all vehicles is 2.88, which means that, on average, manufacturers incur a cost of 288 USD to improve the fuel efficiency of their vehicles by 1% beyond what the vehicle has achieved. To put the numbers

[14]Note that the absolute vertical location of the curve is not important because the constant term of the function $e(c_{jt}^{e})$ is not separately identified from the constant term of the fuel-efficiency frontier equation.

into perspective, for a vehicle with fuel efficiency of 30 mpg equipped with the median amount of fuel-saving technology, it will cost 944 USD to increase its fuel efficiency to 31 mpg.

Figure 6 plots the distribution of c^e separately for cars and trucks. The truck distribution is more skewed to the right, suggesting that trucks have exhausted their fuel-saving options more than cars have. Almost 40% of the car models have a marginal cost of fuel-efficiency improvement of less than 1,000 USD/mpg, and 76% of less than 2,000 USD/mpg, implying that cars still have a lot of room to further adopt more fuel-saving technologies at low cost. The respective numbers for trucks are only 18% and 56%.

Counterfactual Studies This section details the investigation of how fuel prices and CAFE standards, individually and together, have affected the recent changes in fuel economy of new vehicles sold in the U.S. This will be addressed by several counterfactual studies. In particular, the following three counterfactual simulations will be carried out:

1. Gasoline prices over the years are kept at the 2006 level
2. CAFE standards over the years are kept at the 2006 level
3. Both gasoline price and CAFE standards over the years are kept at the 2006 level

When estimating the model, the compliance costs are assumed to be same across fleets. In counterfactual scenarios, it is impossible to impose such constraints, because with any market changes firms, due to differences in cost and product structure, will response differently, moving the cost margins in different directions and magnitudes. Therefore, in all the simulations, I allow the compliance costs to vary across fleets such that firms maintain the original compliance status, unless it is impossible to do so (e.g. maximum mpg is less than the standard) or it is profitable to become unconstrained, not accounting for the fixed cost of non-compliance (which is not estimated in the model).

The counterfactual equilibrium is calculated using a nested iteration algorithm that sequentially solves for the equilibrium prices, the compliance costs that satisfy the compliance status, and the equilibrium choices of fuel-saving-technology adoption.

1. Outer-iteration: pick a vector of FST level $\{e_{jt}\}$
   (a) Middle-iteration: given $\{e_{jt}\}$, pick a vector of compliance cost $\{\lambda_{jt}\}$
      i. Inner-iteration: given $\{e_{jt}, \lambda_{jt}\}$ pick a vector of prices $\{p_{jt}\}$
         A. Check if $\{p_{jt}\}$ solve the first-stage FOC, up a tolerance of 1e-8
         B. If it is, go to the middle-iteration
         C. Else pick a new price vector and continue with the inner iteration
      ii. Check if the compliance constraints are all satisfied
      iii. Pick a new vector of compliance cost by tightening all the constraints that are satisfied and loosening all the constraints that are violated
      iv. If the new vector are close enough to the old vector (up to a tolerance of 1e-6), go to the outer-iteration, else continue with the middle-iteration
   (b) Check if the second-stage FOCs are satisfied, up to a tolerance of 1e-4
   (c) If it is, stop, else pick a new vector of $\{e_{jt}\}$, update the fuel-efficiency and FST costs accordingly and continue the outer-iteration

The counterfactual average fuel economy (in miles per gallon) for passenger cars and for light-duty trucks is plotted in Figure 7, 8, 9 (for cars), 10, 11 and 12 (for trucks). Two types of averages are considered: raw averages and sales-weighted averages. Raw averages are considered to separate the effect of demand from the firms choice of fuel efficiency. Thus, the raw average will reflect more of the firms adoption of fuel-tech, while the sales-weighted average will capture both the adoption by firms and the demand from consumers for fuel-efficient vehicles.

Cars Figure 7 demonstrates the effects of changing fuel prices from the corresponding level to the 2006 level on the average fuel economy of cars. The raw average of fuel economy does not change much under counterfactual fuel prices, suggesting that fuel-price changes do not significantly affect the firms choice of fuel efficiency for passengers. The sales-weighted average fuel economy decreases slightly under 2006 fuel prices (which were mostly lower than the fuel prices in other years), indicating that consumers switch to less fuel-efficient cars when fuel cost decreases.

Figure 8 demonstrates the effect of changing CAFE standards to 2006 levels on the overall car fuel efficiency. The raw average decreases slightly, especially after 2011 (the year the car standards started to rise), indicating that standards influenced firms adoption of fuel-tech for cars. The change in the sales-weighted fuel economy is more pronounced, even when fuel cost does not change, suggesting that consumers switch fuel-efficiency class when firms adjust their fleets to meet standards.

Figure 9 shows the effects of changing both fuel prices and CAFE standards to the 2006 levels. The effects on both the raw average and sales-weighted average fuel economy seem to reflect the combined effects of the individual changes.

Trucks Figure 10 shows the effect of fuel prices on truck fuel economy. Changing prices does not seem to change the average fuel efficiency firms set for their fleet, or the average fuel efficiency consumers choose for their vehicles. However, when the standards change, as shown in Figure 11, the fuel efficiency of trucks undergoes a big change, in both the raw average and the sales-weighted averages. Thus, for trucks, fuel prices have minimal impact while CAFE standards have a big impact both on how firms adopt fuel-tech for their vehicles and on how consumers choose fuel-efficient vehicles. This is related to the results discussed above regarding the marginal fuel technological cost of trucks. The options to improve the fuel-efficiency for trucks seem to have been exhausted, and so trucks have a higher marginal cost of improving their fuel efficiency further. A small decrease in standards would relieve firms of a large amount of fuel-tech costs that they incur to make their trucks comply with regulations, and this cost-saving will be passed down to consumers and induce even more change in the sales-weighted fuel economy.

5 Conclusion

In this paper, a structural model of oligopolistic competition in the U.S. automobile industry that allows for endogenous adoption of fuel-saving technologies is developed and fitted to aggregate market data. The counterfactual results show that changes in fuel-economy regulation mostly explain the automakers' adoption of fuel-saving technologies, while consumers' adoption of those technologies depends significantly on fuel prices. There is also a notable difference between light-duty trucks and passenger cars, namely that the fuel efficiency of light trucks is more influenced by regulations than by fuel prices, relative to passenger cars. These results highlight the challenges to the industry to meet the fuel-efficiency target in the near future, when the fuel prices are expected to drop substantially. It is also suggested that regulators may need to focus more on passenger cars, for which there is still much room for improvement due to relatively low cost of improving the marginal fuel efficiency of a large proportion of passenger-car models.

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Chapter 1: Tables

Chapter 1: Figures

Table 1: Examples of fuel-saving technologies, taken from EPA (2015)

TABLE 7.11 Summary of the Committee's Findings on the Costs and Impacts of Technologies for Reducing Light-Duty Vehicle Fuel Consumption

Fuel Consumption Technology	Description and Approximate Manufacturing Cost	Impact on Fuel Consumption (%)	Comments
Mass reduction (assume 3,600-pound vehicle)	1% (36 lb); $46-$55	0.25	Material substitution
	5% (180 lb); $270-$324	3-3.5[a]	Material substitution
	10% (360 lb); $648-$778	6-7[a]	Aggressive material substitution
	20% (720 lb); $1,600+	11-13[a]	Redesigned body with aluminum and composite-intensive structures
Transmission	Five-speed automatic transmissions; $133	2-3	Can also improve vehicle performance
	Six-speed automatic transmissions; $133-$215	3-5	Can also improve vehicle performance
	Seven-speed automatic transmissions; $170-$300	5-7	Can also improve vehicle performance
	Eight-speed automatic transmissions; $425	6-8	Can also improve vehicle performance
	Dual-clutch automated (DCT) manual transmissions (6/7 speed); $300 (dry clutch), –$14-$400 (wet clutch <350 N-m)	6-9	DCTs have replaced original automated manual transmissions
	Continuously variable transmissions; $150 (<2.8 L), $263 (>2.8 L)	1-7	Possible engine noise; not applicable to large engines
Aerodynamics	5 to 10% reduction in C_d (coefficient of drag); $40-$50	1-2	Wheel well and underbody covers, body shape, mirrors, etc.; bigger impact on highway drive cycle
Rolling resistance	Low-rolling-resistance tires; approximately $10 apiece ($30-$40)	1-2[b]	Stopping distance and durability can be compromised with inferior materials; optimal materials drive up costs
	Tire-inflation monitor; becoming standard equipment	0.7	Depends on monitor settings and driver behavior
	Low-drag brakes; becoming standard equipment	1	Most cars equipped already today
Electrical accessories	HVAC—variable stroke, increased efficiency (humidity control, paint, glass, etc.); $70-$90	3-4	Current FTP does not capture benefit (benefits reduced to 0.5-1.5% within Table 9.1)
	Electric and electric-hydraulic power steering; $70-$120	1-5	Electric for small cars, electric-hydraulic for bigger cars—benefits for the FTP are smaller (1-3%).

[a]With resized power train.
[b]Three percent may be feasible with resized power train.

Table 2: Summary statistics

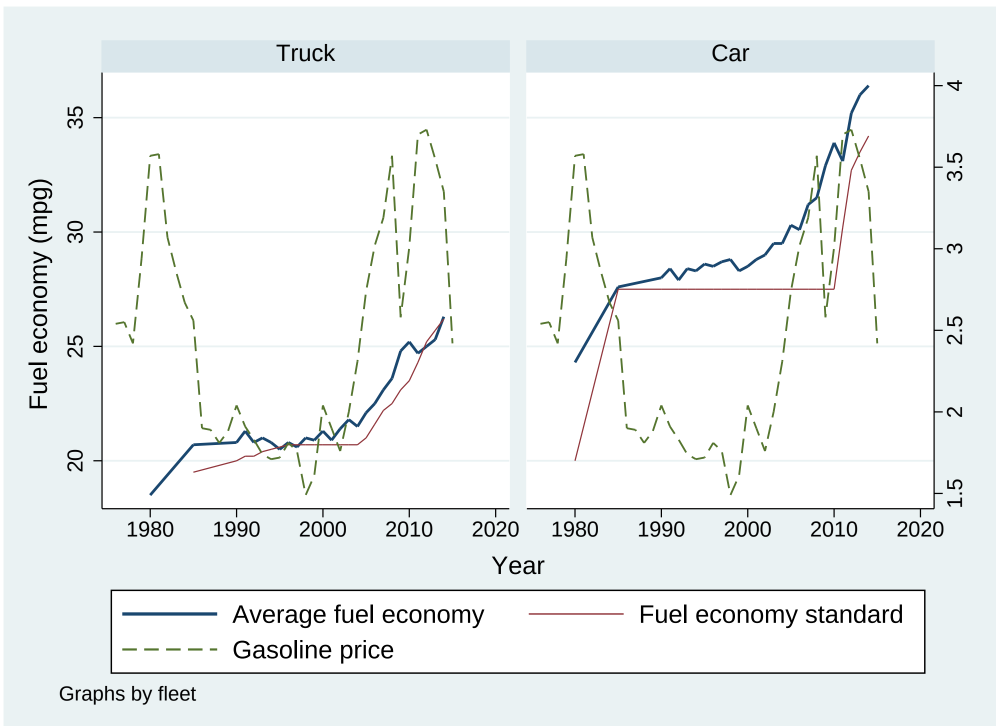
	Truck		Car		All	
Price ('000 $)	29.6	[7.77]	23.89	[11.03]	26.58	[10.04]
Household income ('000 $)	56.83	[1.61]	56.85	[1.59]	56.84	[1.60]
Price/HH income	0.52	[0.14)	0.42	[0.19]	0.47	[0.18]
Gasoline price ($)	2.84	[0.29]	2.83	[0.29]	2.84	[0.29]
Fuel efficiency (miles/gal)	26.95	[3.26]	36.64	[5.99]	32.07	[5.95]
Fuel consumption (gal/100 miles)	3.82	[0.89]	2.84	[0.76]	3.3	[1.08]
Fuel cost ($/mile)	0.13	[0.03]	0.09	[0.03]	0.11	[0.04]
Horsepower ('00 hp)	2.59	[0.59]	2	[0.67]	2.28	[0.70]
Weight ('000 lb)	4.56	[0.83]	3.26	[0.45]	3.87	[0.92]
Hp/Weight ('0 hp/lb)	0.57	[0.07]	0.6	[0.13]	0.58	[0.11]
Space ('0000 ft2)	1.54	[0.23]	1.3	[0.12]	1.41	[0.22]
Torque (lbft)	270.13	[72.25]	194.93	[67.86]	230.37	[79.39]
Car (dummy)	0	[0.00]	1	[0.00]	0.53	[0.50]

Table 3: Estimation Results

	Utility/Mean			Utility/std		
	estimate	se	t-stat	estimate	se	t-stat
price/income	-45.04	9.86	-4.57	1.47	0.16	9.20
dpm/income	-23.86	6.14	-3.89	-0.60	0.14	-4.18
hp/weight	2.77	0.70	3.97	2.26	0.40	5.64
weight	-0.46	0.15	-2.95	-0.35	0.07	-4.65
size	3.81	0.39	9.71	-0.44	0.22	-2.02
const	1.22	0.46	2.67	-14.00	0.79	-17.74
suv	-1.13	0.24	-4.65			
truck	-2.85	0.44	-6.44			
van	-3.49	0.56	-6.19			
minivan	-1.23	0.21	-5.88			

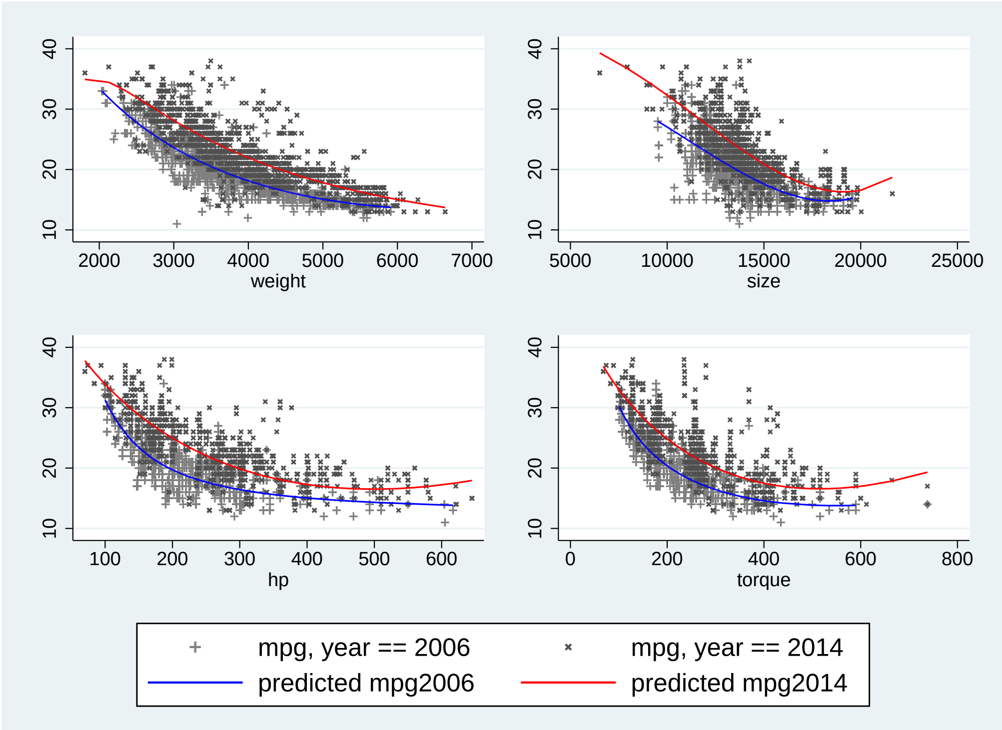
	Marginal Cost			Fuel-efficiency Frontier		
	estimate	se	t-stat	estimate	se	t-stat
log(hpwt)	1.21	0.16	7.78	-0.22	0.02	-8.88
log(weight)	2.10	0.42	5.01	-0.57	0.05	-12.27
log(size)	-1.67	0.19	-8.69	0.20	0.04	4.79
log(torque)	0.64	0.11	5.90	-0.28	0.03	-9.14
const	1.81	0.42	4.34	0.03	0.11	0.27
suv	0.02	0.04	0.41	-0.09	0.01	-13.29
truck	0.02	0.06	0.30	-0.14	0.01	-13.22
van	0.00	0.12	-0.03	-0.29	0.02	-12.92
minivan	0.12	0.06	1.92	-0.09	0.01	-7.58
trend	-0.05	0.01	-3.30			
year 2007				0.01	0.01	1.17
year 2008				0.08	0.01	7.67
year 2009				0.06	0.01	6.75
year 2010				0.09	0.01	9.37
year 2011				0.11	0.01	12.50
year 2012				0.13	0.01	13.96
year 2013				0.18	0.01	19.01
year 2014				0.18	0.01	19.11
control function				-0.03	0.01	-3.09
c_e				0.15	0.02	9.04
c_e^2				-0.02	0.00	-6.90
c_e^3				0.00	0.00	5.69

	Compliance cost		
	estimate	se	t-stat
compliance cost	0.23	0.13	1.84



Notes: This figure plots gasoline prices (USD/gal), CAFE standards (miles per gallon) and the harmonic average fuel economy of new light-duty vehicles sold in the US (in miles per gallon) from 1980 to 2014 (the gaosoline prices series covers some extra years). The number are reported separately for passenger cars (right panel) and light-duty trucks (left panel). Source: NHTSA

Figure 1: Gasoline prices, average fuel economy, CAFE standards



Scatter plots between fuel economy (in miles per gallon) and weight (top left panel), size (top right panel), horse power(bottom left panel) and torque (bottom right panel) in 2006 (light gray + dots) and 2014 (black X dots). The solid lines plots the best fitted curves for each scatter plots. Each dot is a vehicle model at trim level in each year (e.g. Toyota Camry SE 4dr Sedan). Source: edmunds.com

Figure 2: Fuel economy and vehicle characteristics

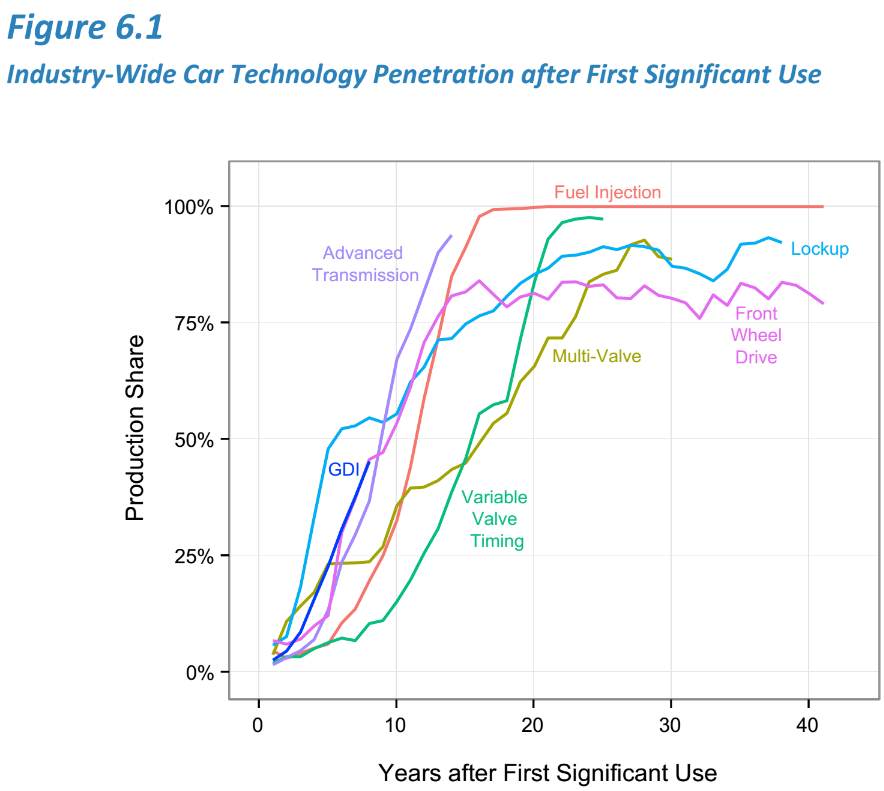
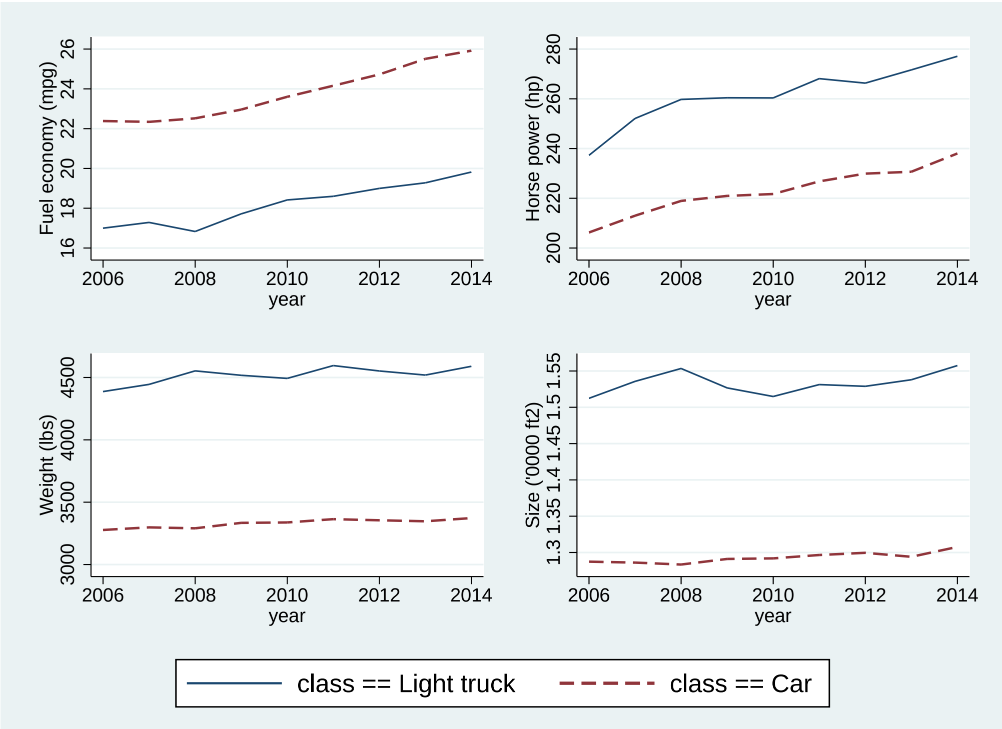
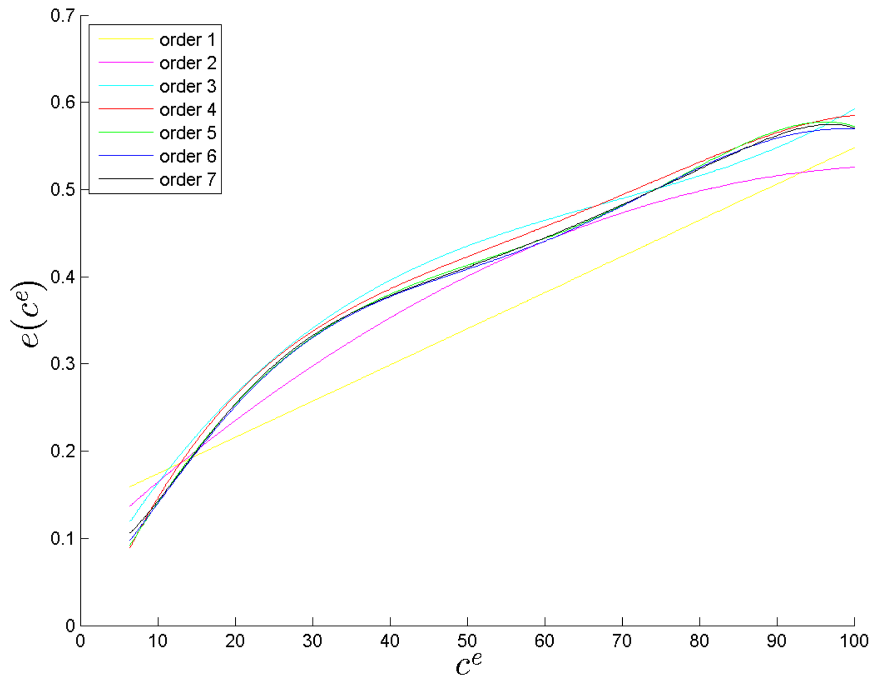


Figure 3: Adoption rate of different fuel-saving technologies, taken from EPA (2015)



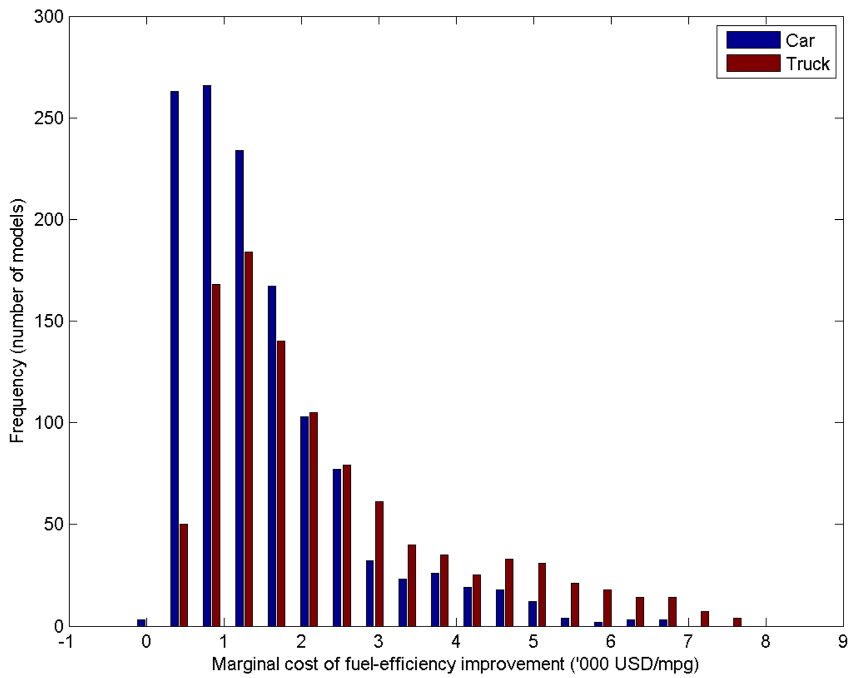
Notes: fuel economy on top left panel, horse power top right, weight bottom left, size bottom right; dahsed lines are for passenger cars and solid lines are for light-duty trucks. This is raw average (not weighted by sales) of all model at trim level. Source: edmunds.com

Figure 4: Average vehicle characteristics over time



Notes: This figure plots the amount of improvement on fuel efficiency (in proportion, vertical axis) against the marginal technological cost of further improving the fuel-efficiency (USD per 100% improvement). Polynomials of different order are used to fit this curve, which is indicated by different colors

Figure 5: Marginal fuel saving cost curve



Notes: this figure is based on the model's estimates for the marginal fuel technological cost, i.e. the cost of improving the fuel efficiency further by 1mpg.

Figure 6: Distribution of the marginal fuel technological cost

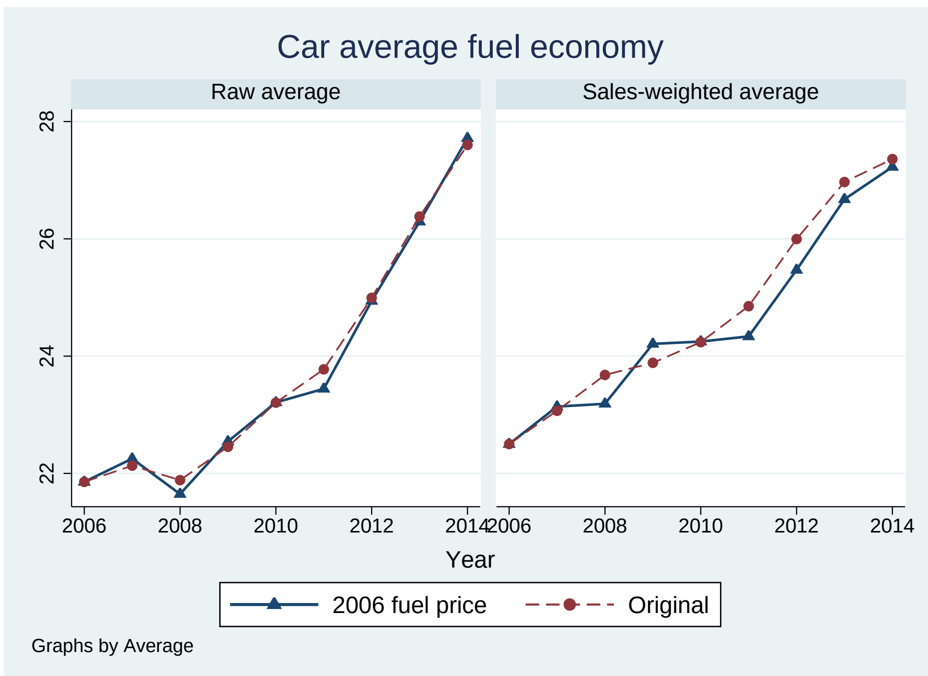


Figure 7: Counterfactual car average fuel economy if fuel prices are set at 2006 level

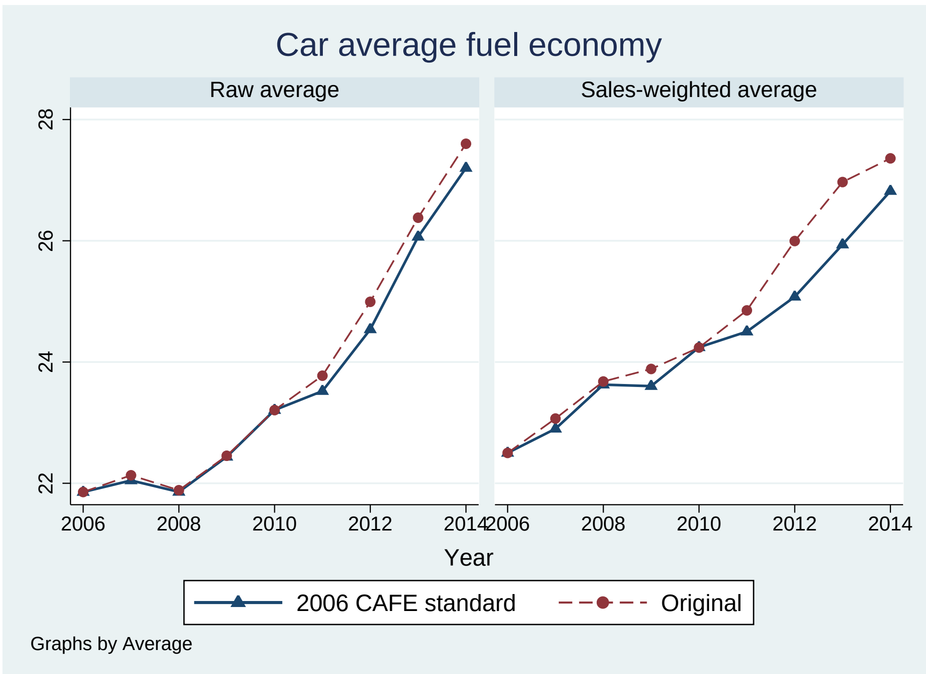


Figure 8: Counterfactual car average fuel economy if CAFE standards are set at 2006 level

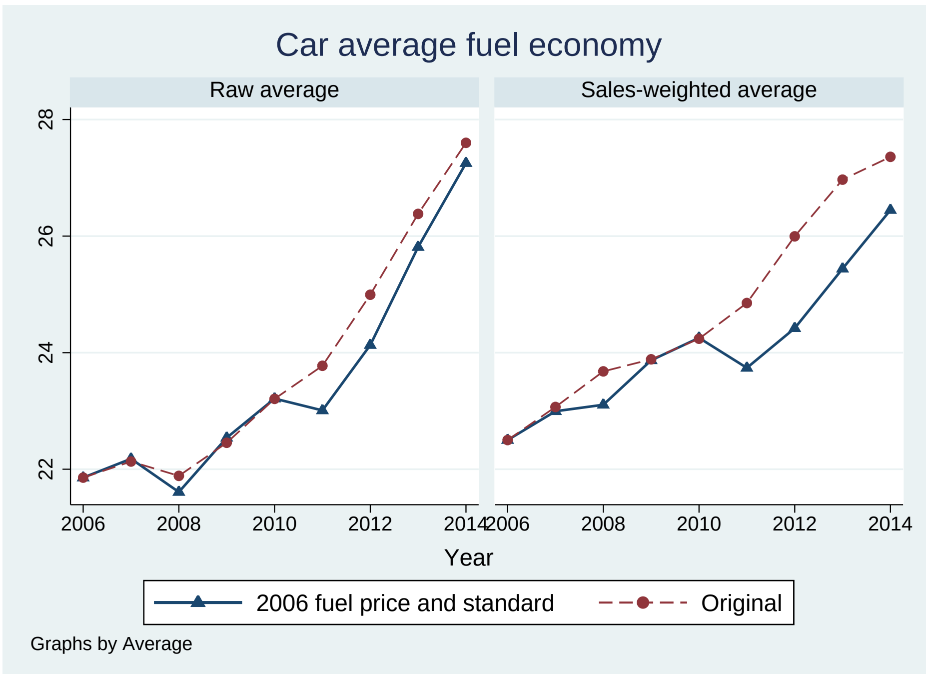


Figure 9: Counterfactual truck average fuel economy if fuel prices and CAFE standards are set at 2006 level

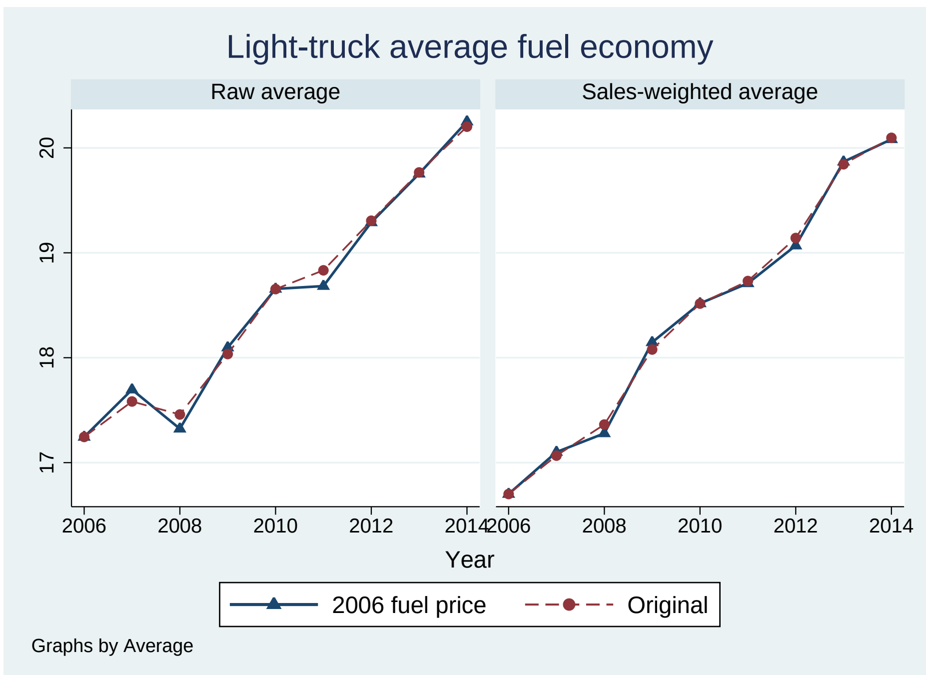


Figure 10: Counterfactual truck average fuel economy if fuel prices are set at 2006 level

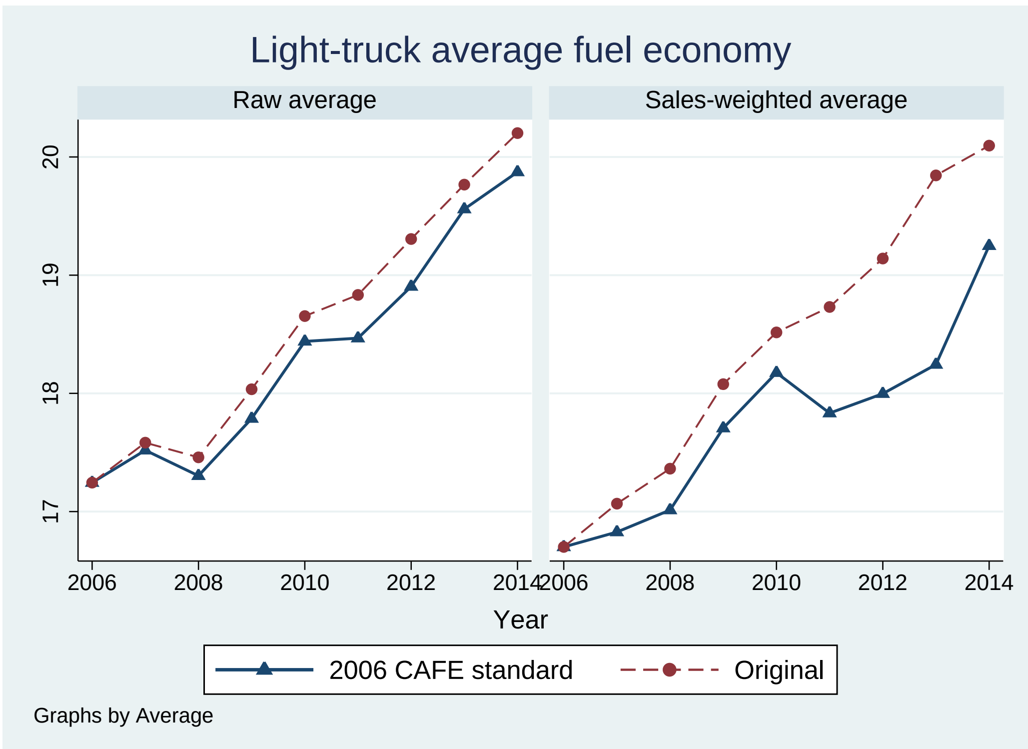


Figure 11: Counterfactual truck average fuel economy if CAFE standards are set at 2006 level

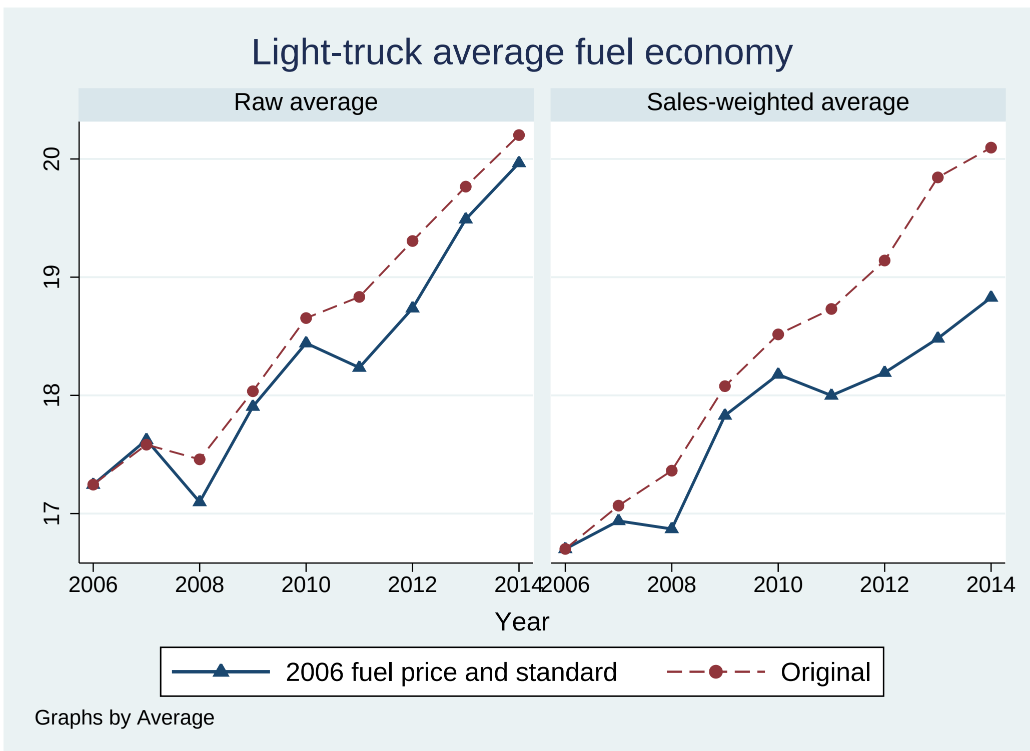


Figure 12: Counterfactual truck average fuel economy if fuel prices and CAFE standards are set at 2006 level