Cars or Trucks? The Impact of Discrete Attribute Basing in Fuel Economy Regulations*

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Abstract

Attribute basing is a common regulatory strategy in environmental regulations: in an effort to reduce the externality-generating dimension of a product, regulations impose standards whose stringency is based on a secondary attribute. This study provides empirical evidence of the welfare consequences of attribute basing in the context of U.S. Corporate Average Fuel Economy (CAFE) standards. Throughout the history of CAFE, the policy stringency has been based on a discrete attribute: the classification of vehicles as either passenger cars or light trucks, with the latter being subject to a less stringent target. This differential treatment of cars and trucks has perverse implications as it potentially distorts the fleet composition and increases the tailpipe emissions and accident-related externalities due to a larger market share of light trucks. By estimating a structural model of vehicle demand and supply incorporating CAFE credit trading, this study simulates a counterfactual scenario by removing the standard split and finds that attribute basing results in a 4.9% increase in the sales of light trucks and a corresponding social welfare loss that translates into $2.83 billion in 2014. Attribute basing also leads to welfare redistribution among automakers: the U.S. domestic firms benefit from the attribute basing with a profit increase of 1.8% at the expense of Asian and European automakers with a profit loss of 1.5% and 4.0% respectively.

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1 Introduction

Many public policies feature policy differentiation by providing differentiated incentives or imposing unequal compliance burdens across different subjects, mainly for equity, efficiency or political reasons. For example, in the United States, the earned income tax credit (EITC) only applies to households with annual income below certain thresholds and the exact credit amount depends on the recipient’s income and number of children. The property tax, imposed by local governments on real estate, bases the tax amount on the market value and usage of the property, and properties owned by governments, non-profit organizations, senior citizens and veterans are often completely or partially exempt from property taxes. Since policy differentiation can be easily integrated into a existing policy system, it serves as a popular tool for policy makers to redistribute compliance burden or deliberately alter certain behaviors to achieve specific goals.

In the realm of environmental regulations, policy differentiation figures prominently and is often conducted in the form of attribute basing. Attribute-based regulations (ABRs) aim to regulate product offerings or firm behaviors by basing the standard or the stringency of the regulation on one attribute of the product or the firm. Examples include the energy efficiency standards for home appliances in the U.S. and fuel economy regulations across the world, whose stringency is based on either vehicle weight or footprint. The often-cited vintage-differentiated regulations (VDRs) and spatial-differentiated regulations (SDRs) are also special cases of attribute basing with the regulation stringency being based on a temporal attribute (dates of entry) or a spatial attribute (geographical locations) of the subject (Stavins 2005; Becker and Henderson 2000). One common feature of ABRs are that they often target one attribute of a product that is directly related to the externalities that the policies intend to reduce (emissions), while basing the regulation stringency on a secondary attribute that is not the intended target (vehicle weight), primarily for the purpose of equalizing the marginal costs of regulatory compliance across different sources. However, the

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1 In 2017, the maximum credit for families with one child is $3,400, while the maximum credit for three or more children is $6,318. Similar programs include the public housing program that provides rental housing only for low-income families, managed by the U.S. Department of Housing and Urban Development (HUD).

2 In the U.S., the energy efficiency standard for refrigerators depend on the attributes such as manual or automatic defrosting and whether having an automatic icemaker, and the standard for air conditioners depend on their cooling capacity and whether they have reverse cycles.

3 The fuel economy standards in Europe, China, and Japan are based on vehicle weight with heavier vehicles subject to a lower MPG target. Since 2012, the Corporate Average Fuel Economy (CAFE) standards in the U.S. have become footprint-based and footprint is defined as the wheelbase multiplied by track, in square feet, which approximately measures the size of the rectangle defined by the four wheels. Vehicles with a larger footprint are subject to a less stringent target.
difference in the regulatory stringency based on the secondary attribute creates an incentive for market participants to manipulate the attribute in order to receive favorable policy treatment, resulting in social welfare loss due to distortion in the choice of the secondary attribute (Ito and Sallee 2016).

This study aims to empirically investigate the welfare implication of ABRs in the context of U.S. Corporate Average Fuel Economy (CAFE) standards by focusing on the attribute basing on a discrete characteristic.\footnote{As opposed to attribute basing on a continuous variable such as vehicle size or weight.} Whether the vehicle is categorized as a passenger car or a light truck.\footnote{Passenger cars mainly include sedans, hatchbacks, convertibles and wagons that are primarily for transporting no more than 10 individuals. Light trucks are truck-based vehicles with maximum gross vehicle weight rating (GVWR) less than 8,500 lbs. Light trucks include minivans/vans, SUVs and Pickup trucks. Starting model year 2012, 2-wheel-drive SUVs with GVWR less than 6,000 lbs are classified as passenger cars instead of light trucks.} Before the introduction of the footprint-based standards in 2012, the fuel economy regulation in the U.S. has always been attribute-based since its initial implementation in 1975. Under CAFE, vehicles are classified as either passenger cars or light trucks. Light trucks have been subject to a lower fuel economy standard, with about 6-8 lower in mpg (Figure 1). On May 7, 2010, the Environmental Protection Agency (EPA) and the National Highway Traffic Safety Administration (NHTSA) jointly developed a coordinated national program, which established greenhouse gas emission (GHG) standards and CAFE standards that allow manufacturers to build a single national fleet to meet requirements of both programs for model years 2012 through 2016. The joint rule sets additional attribute-based standards where the exact target for a vehicle depends on its footprint. Larger vehicles are subject to less stringent emission or fuel economy targets, and light trucks are still assigned a separate set of footprint-based standards which are less stringent than those for passenger cars. For example, in the GHG standards for Model Year (MY) 2016, light trucks are allowed to emit 30.3-71 more grams of CO_2 per mile than passenger cars of the same footprint (Figure 2). Since automakers adjust vehicle prices in the short run to make the sales-weighted average fuel economy compliant with the regulation, the fuel economy standards work as a revenue-neutral “feebate” that taxes inefficient vehicles and subsidizes efficient vehicles. By being subject to a less aggressive standard, the vehicles that are classified as light trucks are therefore being subsidized relative to passenger cars.

The rationale behind this standard split between cars and trucks dates back to the 1970s when CAFE was initially designed. At that time, light trucks were mostly comprised of pickup trucks and mainly used for small commercial and farming purposes. Policy makers did not want to impose a larger compliance burden to those buyers. However, the majority of
light trucks sold on the market are used for personal transport nowadays, not for agriculture or small businesses. The fleet composition has evolved dramatically to meet the growing demand for light trucks. With the increasing market share of SUVs, which are classified as light trucks under CAFE, the market share of light trucks has increased from about 20% in the 1970s to almost 60% in 2016 (Figure 3). Since consumers might choose between several vehicle models which fall into both the car and truck category, switching between vehicle segments is more likely to happen than 40 years ago. Although the primary goal of CAFE is to increase the fleet fuel economy to address the externalities associated with gasoline consumption, the differential treatment of cars versus trucks could distort consumer vehicle choice by encouraging more buyers to purchase light trucks, exacerbating the emission and accident externalties associated with light trucks, and impeding the progress of raising the average fleet fuel economy (Figure 3). ABRs are often justified by efficiency benefits of reducing the disparity of compliance burden across different sources. However, two new provisions under the joint program after MY 2012 muted the efficiency benefits of separating the standards between cars and trucks. First, the joint program implements footprint-based standard by setting less stringent targets for larger vehicles, which takes account of the compliance cost differences due to technological constraints. Second, the joint program features credit trading between truck and car fleets within firms and across firms, which should make the marginal cost of reducing one unit of emissions equal across vehicles. The provision of credit-trading thus eliminates the benefit of attribute basing in improving the program’s cost-effectiveness and the addition of ABR to a credit trading system will only create a welfare distortion without any benefit (Ito and Sallee 2016).

Quantifying the policy impact of discrete attribute basing in CAFE is important for the following reasons. First, the standard split between passenger cars and light trucks fails to make consumers internalize the external cost of fuel consumption, running counter to the policy goal of CAFE in achieving the socially optimal level of fuel economy. According

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6 According to U.S. Vehicle Inventory and Use Survey, the percentage of trucks (including medium- and heavy-duty trucks) used for personal transport increased from 65.7% in 1987 to 76.7% in 2002 and the percentage used for agriculture and retail business decreased from 8.5% to 2.6% and 5.6% to 2.7% respectively. Medium- and heavy-duty trucks (with gross weight weight rating over 14,000 lbs) are mainly used for business and construction with only 0.9% used for personal transport, and they are subject to a different set of standards under the joint rule of EPA and NHTSA. The vehicle use survey was discontinued by U.S. Census Bureau in 2002. The updated percentage of light trucks used for personal transport nowadays should be much higher.

7 The regulatory agents might have realized the potential impact of car-truck classification on the fleet composition, and starting MY 2011, NHTSA has reclassified many small, 2-wheel drive, sport utility (SUVs) from the truck category to the car category. Small SUVs (less than 6,000 GVWR pounds) are now grouped with cars if with 2WD and grouped with trucks if with 4WD.
to U.S. Energy Information Administration, about 143.37 billion gallons of gasoline were consumed in the U.S. in 2016, setting the highest amount on record. Increasing the fuel efficiency of the vehicle fleet is a critical step in strengthening energy security and alleviating environmental damage associated with gasoline consumption. Not only does CAFE fail to discourage consumers from adopting light trucks which are less fuel efficient, the discrete attribute basing might induce additional buyers to switch from passenger cars to light trucks. Such switching can impede the progress of raising the fleet fuel economy and exacerbate the problem of local air pollution, GHG emissions and energy security, the very externalities the CAFE regulation is designed to alleviate.

Second, the implicit subsidy for light trucks created by the standard split could make households choose vehicles with a fuel economy level that is even lower than the private optimal level. Between 2012 and 2014, U.S. households on average spent $2,090- $ 2,756 (3.7%-5.4% of total household expenditure) annually on gasoline (BLS 2015). Fuel consumption on average contributes to 29%-32.6% of the total owning cost of vehicles and the ratio increases as household income decreases (BLS 2014). For lower-income households, the fuel consumption could be the largest component of the vehicle owning cost when gasoline prices were as high as in 2012. Therefore, mis-optimization in vehicle fuel economy could lead to a significant welfare loss, especially for lower-income households. Choosing inefficient vehicles would leave consumers subject to a greater financial burden when gasoline price increases, due to both the increased operational cost and the decreased resell value. EPA and NHTSA estimate that consumers would save more than $3,000 over the lifetime of a MY 2016 vehicle from CAFE (EPA 2010), but the fuel cost savings could be undermined if some consumers are induced by CAFE to choose larger vehicles which are less fuel efficient.

Third, attribute basing could further result in additional welfare loss if the distorted secondary attribute is associated with another externality that the regulation does not intend to target. Although light trucks are likely to better protect their occupants, driving light trucks creates externalities by imposing greater danger to other road users (Gayer 2004, White 2004, Parry et al. 2007, Anderson 2008), and an increase in the market share of light trucks could exacerbate the accident-related externalities. Li (2012) estimate that the accident externality imposed by a light truck amounts to be $2,444 in 2006. Anderson and Auffhammer (2014) show that due to the structural difference, light trucks significantly raise

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8Light trucks are generally taller with higher center of mass and are more likely to hit the upper bodies of the occupants in a truck and car collision. When light trucks strike pedestrians, bicyclists and motorcyclists, they are also more likely to hit the upper bodies of the victims, resulting in greater injury. The stiffer and heavier body structures of light trucks make trucks transfer more force to the victims in collisions.
the probability of a fatality in a struck vehicle, in addition to the effect of their already higher weight, and conclude that the removal of the split in CAFE standards between cars and trucks would improve welfare. Jacobsen (2013b) estimates the rates of fatality for collisions between different vehicle classes and his policy simulation shows that a unified CAFE standard encourages switching away from light trucks into cars, which improves overall safety substantially.

Fourth, attribute basing alters the incidence of compliance across agents and could be justified on distributional grounds (Ito and Sallee 2016). Although the motive for the attribute basing in fuel economy regulations can be disputed, the attribute-based standards could constitute a form of disguised protectionism (Levinson 2017). The U.S. automakers produce a disproportionately large share of light trucks (about 70% in 2016). Allowing light trucks to receive a more lenient target reduces the compliance burden of domestic producers. However, the benefits of welfare redistribution is achieved at the cost of sacrificing social welfare from the distortion in the secondary attribute, which needs to be carefully evaluated if implementing attribute basing.

Motivated by the above considerations, this study evaluates the welfare loss of CAFE standards from attribute basing on a discrete characteristic, the car-truck classification. I utilize individual transaction data and vehicle sales data of MY 2012-2014, which covers the first three years following the implementation of the compliance trading provision of CAFE. I estimate a vehicle market equilibrium model with consumer vehicle demand using a random coefficient discrete choice model in the spirit of Berry et al. (1995) and a stylized automaker supply model assuming that multi-product firms engage in price competition by maximizing profits from both product and regulatory credit sales. With the estimated parameters, counterfactual exercises are then conducted to simulate the prices and sales under a uniform standard to evaluate the welfare impact of attribute basing on consumer surplus, the distribution of firm profits, and environmental and accident externalities. The simulation results show that the removal of the standard split between cars and trucks could increase the sales of passenger cars by 8.0% and decrease the sales of light trucks by 4.9%. Although the uniform standard results in a larger consumer welfare loss by making consumer’s choice deviate more from their private optimal choice, the deviation is nevertheless efficient by getting closer to the social optimum and the uniform standard improves the social welfare amounting to $2.83 billion from the decrease in environmental and accident-related externalities. Surprisingly, with a more stringent target, the automobile industry as a whole actually experiences a profit increase from the increased market size as fuel-efficient passenger cars become more affordable. In addition, eliminating the standard split leads to welfare redistribution among
firms, suggesting that domestic firms benefit from a profit increase of 1.8% at the expense of Asian and European firms suffering from a profit loss of 1.5% and 4.0% respectively.

The findings from this study are policy relevant and particularly timely since the EPA and NHTSA are having a mid-term review of the fuel economy standards and need to determine before April 1, 2018 whether the standards for Model Years 2022-2025, established in 2012, should be revised. Since the implementation of EPA-NHTSA joint rule, the gasoline price has decreased from $3.68 in 2012 to $2.25 in 2016, and the market share of light trucks among light-duty vehicles has increased from 50% to 60% at the same time. By providing the estimate of policy-induced sales of light trucks, the study helps policy makers revisit the differential treatment of cars and trucks in CAFE and re-evaluate its consequences on the fleet composition. Given the ubiquity of attribute basing in fuel economy regulations across the world including emerging automobile markets such as China and India, this study also provides guidance for those markets to re-evaluate the consequences of implementing attribute basing when using fuel economy regulations to alleviate environmental externalities.

In addition to its policy relevance, this paper makes the following three contributions to the literature. First, this paper adds to the literature on attribute basing. Although ABRs are ubiquitous in economic policies, there is limited economic literature examining the impact of ABR. Ito and Sallee (2016) provides the first analysis of the welfare consequences of ABR by providing a theoretical framework that identifies the key parameters that determine the distortionary cost and potential benefit of attribute basing. They show that ABR would only result in welfare loss if compliance trading is allowed, which has already equalized marginal compliance costs. They also empirically identify the distortion due to ABR through bunching analysis in Japanese automobile market and they use the estimated loss function as a sufficient statistic to compare the welfare impact of ABR relative to a more efficient policy. Kellogg (2017) provides a theoretical framework to evaluate the welfare loss of a fixed fuel economy standard under gasoline price violatility. He shows that although attribute-based standard builds flexibility into the regulation, the distortion in attribute caused by ABR still outweighs the flexibility benefit, extending the theoretical findings from Ito and Sallee (2016) to the case of gasoline price uncertainty. By focusing on the data period after the provision of CAFE compliance trading that eliminates efficiency gain from ABR in equalizing compliance costs, I am able to directly quantify the welfare loss of ABR due to the distortion in the secondary attribute. Unlike using a loss function to approximate the welfare as in Ito and Sallee (2016), which requires assumption of perfect competition or at least no policy impact on firm markups, this study directly models consumer vehicle choice and firm profit maximization with market power and compliance trading, and conducts counterfactual
simulations to directly and separately quantify the policy impact on consumer surplus, firm profits and externalities.

Second, it contributes to the substantial literature about CAFE standards, which mainly focuses on the efficiency of CAFE in terms of reducing gasoline consumption, such as Goldberg (1998); Kleit (2004); Austin and Dinan (2005); Jacobsen (2013a). Those studies consistently find gasoline tax could achieve the same policy goal at a much lower cost. Some studies examine the distributional impacts of CAFE and find CAFE is regressive as low-income households suffer more welfare losses than high-income households: Jacobsen (2013a); Davis and Knittel (2016); Levinson (2016). Other studies examine the safety impacts of fuel economy standards, including Crandall and Graham (1989); Jacobsen (2013b); Bento et al. (2017). Those studies find CAFE affects vehicle mix and vehicle weight distribution, leading to different safety implications. Few recent studies investigate the attribute-based CAFE standards by focusing on the footprint-based standards. Whitefoot and Skerlos (2012) models automaker’s vehicle dimension choice and finds the footprint-based standard creates an incentive for firms to increase vehicle size, undermining gains in fuel economy, with the incentive being larger for light trucks. Leard et al. (2016) use a reduced-form approach to look at the effect of recent gasoline price decreases on the stringency of fuel economy requirement and find the effect is relatively small as the gasoline price mostly makes consumers switch within the same footprint. Levinson (2017) point out that the change from a uniform standard to the new footprint-based standard constitutes a form of disguised protectionism, by imposing costs on imported cars equivalent to a tariff because larger cars are disproportionately assembled domestically. All of these recent studies examine the impact of the newly introduced footprint-based standards and none of them directly quantify the total welfare consequences. My study focuses on attribute basing on the discrete attribute, the car-truck classification, which has been in place since the introduction of CAFE but whose welfare impact has not been empirically evaluated.

Third, this study will contribute to the understanding of notched policies and vintage- or spatial-differentiated policies. Notches in policies essentially provide different marginal incentives among different decision makers depending on their proximity to a notch, resulting in bunching on the policy-favorable side of a notch (Sallee 2012; Slemrod 2010). Vintage-differentiated regulations, which are common in environmental policies, assign standards for regulated units based on the units’ dates of entry, with later entrants or newer sources facing more stringent regulation, potentially retarding the environmental progress by providing incentives for extending the lives of aging facilities and equipment (Stavins 2005). Similar to VDRs, spatial-differentiated regulations vary regulation stringency based on locations,
resulting in firm reallocation to less-regulated areas (Becker and Henderson 2000). By providing empirical evidence of welfare loss from attribute basing in the context of fuel economy regulations, the findings of this paper suggest policy makers should fully assess the welfare consequences when designing regulations that intend to limit some behaviors or product dimensions but implement unequal standards or policy incentives to do so.

The rest of this paper is organized as follows. Section 2 briefly describes the policy background of CAFE and the data sets. Section 3 uses a theoretical model with graphic illustration to demonstrate the potential welfare consequences of the discrete attribute basing. Section 4 sets up a market equilibrium model of vehicle demand and supply and discusses the estimation strategy. Section 5 presents the estimation results from the structural model. Section 6 conducts policy simulations to evaluate the welfare consequences of the attribute basing. Section 7 concludes.

2 Policy Background and Data

In this section, I first present the policy background about CAFE and its new changes since 2012. Next I present the data used in the empirical analysis.

2.1 Policy Background

CAFE standards were first enacted in 1975, following the 1973-74 Arab Oil Embargo. The Department of Transportation, through the NHTSA had the responsibility for setting and enforcing fuel economy standards since then. The CAFE standards in a given model year define the minimum level of average fuel economy that each manufacturer’s fleet is required to attain, and passenger car fleet and light truck fleet have always been subject to separate standards. The fuel economy standard for passenger cars stayed at 27.5 mpg from 1990 to 2010 and the requirement for light trucks has increased gradually from 20.7 mpg in 2004 to 23.5 mpg in 2010 (Figure 1). In 2007, The U.S. Supreme Court determined that the EPA possesses the authority under the Clean Air Act to regulate GHG emissions from motor vehicles. On May 7, 2010, EPA and NHTSA finalized a joint rule establishing standards for CAFE and emissions of GHGs, which apply to passenger cars, light-duty trucks, and medium-duty passenger vehicles for model years 2012 through 2016. Subsequently, on October 15, 2012, EPA and NHTSA issued standards for GHG emissions and fuel economy of light-duty vehicles for model years 2017-2025. The harmonized program allows manufacturers to build a single national fleet to meet requirements of both programs. The stringency of the regulation increases over years and the standards require a combined fleet-wide fuel economy
of 48.7-49.7 mpg under NHTSA’s CAFE program and a fleet-wide average emission of 163 grams/mile under EPA’s GHG program in MY 2025.\(^9\)

The joint rule sets attribute-based standard where the exact target for a vehicle depends on its footprint and vehicles with larger footprints are subject to less stringent targets. The regulatory agents believe that this design encourages the increasing of fuel economy for all vehicle sizes and discourages automakers from downsizing vehicles, creating a more equitable framework, avoiding imposing disproportionate compliance obligations for most U.S. automakers who produce larger vehicles. In addition to attribute basing on footprint, this new joint program still features differential treatment between passenger cars and light trucks as light trucks are assigned a separate set of footprint-based standards that are less stringent than those for passenger cars (Figure 2). Since automakers need to price in the additional cost in complying with the fuel economy regulations, the separate standards between cars and trucks potentially distorts the relative prices of passenger cars and light trucks and subsequently distorts consumer’s vehicle choices.

The joint program implemented starting 2012 features great flexibility including credit banking and borrowing, and the newly-added provisions including credit transfer between the car and truck fleets and credit trading across firms. A manufacturer’s car and truck fleet that achieves a fleet-average CO\(_2\) or fuel economy level better than the standard can generate credits. For example, GHG credits are owned for grams of CO\(_2\) saved beyond the standard over the lifetime of the vehicles exceeding the standard and are recorded in metric tons of CO\(_2\). Additional credits are awarded to vehicles that adopt specific alternative-fuel technologies.\(^10\)

There is great heterogeneity in terms of firms’ model offerings and the fuel efficiency technologies, therefore firms bear heterogenous compliance cost under a fuel economy regulation. Figure 4 plots the average fleet emission and the required GHG standard relative to the sales-weighted average footprint for each automaker’s newly sold vehicles in MY 2014, separately for passenger car and light truck fleets. The length of the red dashed lines reflect the relative stringency of the standard based on each automaker’s product profile. The green dashed lines represent the credit surplus if the automaker’s emissions were lower than the

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\(^9\)NHTSA sets CAFE standards only five years at a time and the 2022-2025 standards are non-final standards that were proposed to help manufacturers better plan for future products and to be harmonized with the GHG program. The EPA and NHTSA are having a midterm review of whether the 2022-2025 standards should be revised. For the GHG program, part of the improvement is expected to be made through reduction in air conditioning leakage.

\(^10\)For MY 2012-2016, GHG program allows electric vehicles and fuel cell vehicles to use a zero grams/mile compliance value and plug-in hybrid electric vehicles could use zero grams/mile for the use of grid electricity.
standard. As indicated by the figure, domestic “Big Three” (General Motors, Ford, and Fiat-Chrysler) and some German firms produce relatively large vehicles while Asian firms tend to specialize in vehicles of smaller sizes. Among domestic firms, Fiat-Chrysler faces a relatively stringent regulation for both of its passenger car and light trucks fleets, while GM and Ford face a similar compliance burden in the light truck fleet but maintain a relatively fuel-efficient passenger car fleet. Due to the technology difference, automakers face unequal compliance cost for each unit of fuel economy improvement per vehicle. Jacobsen (2013a) estimates that the additional cost to attain the standard per MPG ranges from $52 to $438 per car across manufacturers for MYs 1997-2001. However, with a credit trading provision, the automakers who have a relatively fuel-inefficient truck fleet but a fuel-efficient car fleet can transfer the credits they own from their car fleet to make up for the deficits of their truck fleets. The automakers who have an overall fuel-inefficient vehicle fleets can purchase credits from firms who produce fuel-efficient vehicles that overcomply with the regulation. A competitive credit trading will equalize the marginal cost of reducing one unit of emissions across vehicles and allows the policy goal of reducing gasoline consumption and emissions to be achieved at the lowest cost.

The credit trading provision makes the U.S. CAFE standard an ideal context to investigate the welfare loss due to attribute basing since the an efficient credit trading eliminates the efficiency benefit of ABR in reducing the disparity of marginal compliance burdens and the addition of attribute basing will only result in a welfare loss (Ito and Sallee 2016). To empirically quantify the welfare loss, I maintain the credit trading feature in a counterfactual analysis where the standard split between passenger cars and light trucks is removed, and resolve a new market equilibrium under the new policy scenario. Since credit trading equalizes the marginal compliance cost for each vehicle, the observed credit price also helps identifying the marginal cost for each vehicle, which solves the identification problem that marginal costs and Lagrangian multipliers cannot be separately identified in the first order condition of a constrained profit maximization problem (Jacobsen 2013a).

The credit banking and borrowing provision allows automakers to bank credits from overcompliance in one year to use for compliance in future model years. The banked credits could be carried up to five years to offset future shortfalls and back in time for up to three years to cover previous deficits, which helps automakers smooth economic shocks (fluctuation of fuel prices) to marginal compliance cost across years. The empirical section of this study assumes away this banking and borrowing feature when modeling vehicle supply as it involves modeling automakers’ dynamic decisions, which is beyond the scope of the paper. The implication of this abstraction will be discussed in detail in the empirical section.
2.2 Data

The primary data for the demand estimation is the individual transaction data from the household-level survey data of the Maritz Research U.S. New Vehicle Customer Study\textsuperscript{11}, which is a monthly survey of households that purchased or leased new vehicles. For each individual transaction, I observe the make, model, trim, model year, fuel type, transaction year-month and transaction price. The data also provides detailed demographic characteristics of the households who purchased each vehicle including income, family size, education level, zipcode, and valuable information on the alternative vehicle models they considered while making the purchase decisions. Since including the alternative vehicle choice greatly helps identifying consumer heterogeneity parameters, I only select the transactions that list at least one alternative vehicle choice, which is the model that consumers most seriously considered\textsuperscript{12}. In order to define a tractable choice set for each model year, I limit my analysis of the groups of consumers who report an alternative vehicle choice that is from the new vehicle choice offered in each market year. Therefore, all the consumers included in the demand estimation are assumed to choose their purchased choice and alternative choice from a single new vehicle choice set that is defined for each market year. The sample period covers MY 2012-14, the first three model-years after the implementation 2012 CAFE standards and each model year is defined as September of the previous calendar year to August of the current calendar year. For example, MY 2012 is defined as September 2011-August 2012. For computational purposes, I randomly draw a sample of 9,075 transactions from the cleaned sample after removing observations with missing observed consumer attributes or information on the purchased and seriously considered models, and end up having 2,784, 3,032, and 3,259 transactions for MY 2012-14 respectively. Table 1 summarizes the demographic information for the households who made those purchase transactions. The average household income for the survey respondents in the sample is $122,260, which is close to the average household income of $117,795 for married couples in the U.S.\textsuperscript{13}. The average household size is 2.62 and 59% of the heads of household have earned a college degree. 63% of the respondents are from an urban or suburban areas with an average commuting of 25.54 minutes and average gasoline price of $3.48 during the survey time. About 50% of the sampled households selected a light truck and the average price of the vehicles that the sampled

\textsuperscript{11}The data was accessed through the secure server of Resources for the Future and was not removed from the server.

\textsuperscript{12}The survey asks the respondents to ranks three alternative vehicle choices, but the majority of the respondents (87%) only report one alternative vehicle choice. Therefore, I only include one alternative vehicle choice as consumer 2\textsuperscript{nd} choice when modeling demand.

\textsuperscript{13}Data source: IRS Statistics of Income, 2014.
households purchased is $29,706. The average MPG of the purchased vehicles is 25.77.

The individual transaction data is then merged with Wards data which provides detailed information on each vehicle model for each corresponding model year, including horsepower, size, curb weight, wheelbase, and fuel economy. The data set is further complemented by aggregate vehicle sales data, which provides market-level information of vehicle demand, obtained from registration data complied by IHS Automotive. The IHS data record the quarterly number of registrations for each car model, broken down by fuel type, which are aggregated to model year level to construct the market share for each vehicle model in each model year. All of the above data sets are matched at a model-fuel-type level, for example, Toyota Prius-hybrid. The total number of vehicle models that are defined in the choice set are 418, 441, and 459 respectively for MYs 2012-2014. To alleviate the concern that consumers who purchase some certain vehicle models could be over-drawn or under-drawn due to sampling issue, each individual transaction is re-weighted in the estimation with the weight defined as the ratio of the actual market share of the model that the consumer purchased to the within-sample market share of that model. The average of those sampling weights is 0.99 with a standard deviation of 0.084, indicating that in general, the sample is relatively representative of the new vehicle market.

3 Theoretical Background

Before introducing the empirical model to quantify the welfare impact of the discrete attribute basing in CAFE, this section provides a theoretic model to illustrate the welfare impact of attribute basing on a discrete characteristic, which distills intuition for the empirical analysis. Ito and Sallee (2016) uses a theoretical framework to demonstrate the welfare impact of ABR on a continuous variable: vehicle weight. The model presented here extends their main finding to attribute basing on a discrete variable. Due to the discrete choice nature, following the setup in Holland et al. (2016), I assume a discrete choice transportation model, in which consumers in the market choose between a passenger car and a light truck. The assumptions in Ito and Sallee (2016) and Holland et al. (2016) are maintained and the implications of the assumptions are discussed in details in those work. Most of the assumptions are made for model simplicity and tractability to help providing analytical results and main implications.

Assume that consumers obtain utility from a composite consumption good $x$ with price being normalized to one and buying a passenger car with the emission level $e_c$ and a light truck with the emission level $e_t$. The present discounted benefit of the two choices are denoted
as $F_c(e_c)$ and $F_t(e_t)$ respectively. Consumers have exogenous income $I$, which they allocate on the vehicle and the numeraire good $x$. The supply side is assumed as perfectly competitive and consumers pay the car or the truck with prices equal to their respective marginal costs of production $C_c(e_c)$ and $C_t(e_t)$, and the cost function is assumed to be decreasing in its argument (higher emission, lower cost). Both cars and trucks consume fuel and there is an externality associated with fuel burning with the external cost being $\delta$ for each unit of emission level. When consumers make purchase decisions, they do not take account of the external cost from emissions. Suppose a regulator wants to reduce emissions and implements an emission standard for vehicles but base the standard on the vehicle class such that cars are allowed to emit $k$ units and trucks are subject to a lenient target with $k + \sigma$ units of emissions. The mandate allows compliance trading between the car and truck fleets, and there will be a fine with an amount of $t$ dollars per unit of excess emission on either the car or truck fleet if any of them fails to comply with the mandate or have a credit balance deficit. This mandate acts as a constraint for consumers and the indirect utility of buying a passenger car and buying a light truck, after substituting the budget constraint, are defined respectively as the following:

$$V_c = \max_{e_c} F_c(e_c) - C_c(e_c) + I, \quad \text{s.t. } e_c \leq k$$

$$V_t = \max_{e_t} F_t(e_t) - C_t(e_t) + I, \quad \text{s.t. } e_t \leq k + \sigma$$

The Lagrangeans of the above maximization problems are thus defined as the following with a single Lagrangean multiplier when compliance trading equalizes the shadow cost of the regulation:

$$\mathcal{L}_c = \max_{e_c} F_c(e_c) - C_c(e_c) + I + \lambda(k - e_c)$$

$$\mathcal{L}_t = \max_{e_t} F_t(e_t) - C_t(e_t) + I + \lambda(k + \sigma - e_t)$$

Following Holland et al. (2016) and the literature of discrete choice, assuming that the choice between passenger cars and light trucks is influence by the i.i.d. random tastes drawn from the extreme value distribution with zero expected value and standard deviation that is proportional to a parameter $\mu$, the utility of cars and trucks is then defined as:
\[ U_c = V_c + \varepsilon_c, \]
\[ U_t = V_t + \varepsilon_t \]

Given the assumption of the distribution of the random taste, the probability of consumers choosing a light truck is:

\[ s = \frac{\exp(V_t/\mu)}{\exp(V_c/\mu) + \exp(V_t/\mu)} \]

and the expected utility from vehicle purchase for a consumer is:

\[ E[\max(U_c, U_t)] = \mu \ln(\exp(V_c/\mu) + (\exp(V_t/\mu)) \]

The regulator maximizes the welfare \( W \), which is the expected utility from vehicle purchase and expected revenue from noncompliance payments less the expected external cost from vehicle emissions, by choosing the policy parameters \( k, \sigma \) and \( t \):

\[ \max_{k,\sigma,t} W = \mu \ln(\exp(V_c/\mu) + (\exp(V_t/\mu)) + t[(1 - s)(e_c - k) + s(e_t - k - \sigma)] - \delta[(1 - s)e_c + se_t] \]

Proposition 1 shows that the optimal policy does not involve a standard split between cars and trucks (proofs in the appendix).

**Proposition 1**: Where there is compliance trading and the only regulatory goal is to target the emission externality with no distributional considerations, the optimal policy should have a uniform standard such that:

\[ \sigma^* = 0. \]

The proofs of Proposition 1 shows that with an optimal policy, the regulatory agent sets the standard at \( k \) such that the compliance credit price equals to the marginal cost
of emission, and the fine payment will also be set equal to the price of the trading credit, therefore \( t = \lambda = \delta \). If the fine payment is set less than the trading price, automakers would just pay the fine without increasing the fuel economy. Ito and Sallee (2016) shows that when ABR is based on a continuous variable such that the ABR standard function takes the form that \( k_j = k + \sigma(a) \) where \( a \) denotes the vehicle weight or size, the optimal attribute slope is zero: \( \sigma'(a) = 0 \). Proposition 1 coincides with their finding and extends their finding to the context of attribute basing on a discrete variable and concludes that the optimal standard split is zero. The intuition is simple, with a compliance trading which equalizes the marginal compliance cost between cars and trucks, there should not be any difference in the regulation stringency if the regulation aims to reduce emissions and the marginal damage from an additional unit of emission is equal between cars and trucks. If, however, the regulatory agent employs attribute basing by treating cars and trucks separately, there will simply be distortion in the fleet composition: a larger share of light trucks. If light trucks are associated with an additional externality that the policy does not intend to target, additional welfare loss would occur. The distortion is demonstrated via the aid of graphic illustration in Figure 5.

A policy intervention would cause deviation of consumer’s choice away from their private optima. Suppose the private optimal choice (which is the average across consumers) without any fuel economy regulation is at \((s^0, e^0)\), where \( s_0 \) is the market share of light trucks and \( e^0 \) is the average fleet emission level. Suppose the fuel economy regulation moves consumer’s vehicle choice to \((s^1, e^1)\) and denote the choice deviation as \( \Delta s = s^1 - s^0 \), and \( \Delta e = e^1 - e^0 \), and define the consumer welfare loss from this choice deviation as \( L(s^1 - s^0, e^1 - e^0) = U(s^1, e^1) - U(s^0, e^0) \). This welfare loss could be considered as a policy compliance cost, which should be evaluated against the environmental benefits of each policy less other distortionary cost if any. Following Ito and Sallee (2016), assume the loss function takes the following quadratic form for the easiness of graphic illustration:

\[
L(\Delta s, \Delta e) = \alpha(\Delta s)^2 + \beta(\Delta e)^2 + \gamma \Delta s \Delta e
\]

Panel (a) of Figure 5 depicts the impact of a uniform emission standard which is set at the level \( k \), and there is no standard difference between passenger cars and trucks. Therefore, the standard is a constant line whose slope does not change with the market share of trucks. The original optimal choice by consumers is at \((s_0, e_0)\), which has a higher emission level than the standard. If the standard is set higher than the original emission level such that \( k > e_0 \), the standard is not binding and consumer choice would stay at the original point. With a binding standard such that \( k < e_0 \), the choice moves to the new point \((s_1, e_1)\), where
the lowest level set of the loss function, which has the ellipse shape due to the quadratic function form assumption, is tangent to the regulation line. Bundles on the same ellipse (level set) experience the same utility loss due to choice deviation and the further away from the private optimal point, the larger the utility loss. The compliance cost is measured by the length of the vector and the compliance direction is reflected by the direction of the vector (lower \( e \) and lower \( s \)). The average emission level is now at \( k \) and the market share of light trucks is at \( s \), which is lower than the private optimum. This decrease in the share of light trucks (\( \Delta s \)) is an efficient change, rather than a distortion. With a fuel economy regulation that helps internalizing the externalities of gasoline consumption, consumers would choose more fuel-efficient vehicles than in a private optimum, resulting in a decrease in the share of light trucks.

Panel (b) demonstrates the impact of an ABR based on the car-truck classification. Suppose cars are subject to a higher standard \( k_1 \) and trucks received a less aggressive target at \( k_2 \) (\( k_2 > k_1 \)). Suppose the regulator still wants to achieve the original policy goal as in the uniform policy at \((s_1, e_1)\) and \( k_1 \) and \( k_2 \) are set such that \( s_1 \times k_1 + (1-s_1) \times k_2 = k \), which means when the market share of light trucks is at the level of the optimal compliance choice under the uniform standard \( (s_1) \), the sales-weighted standard is equal to the uniform standard. The fleet average standard now depends on the fleet composition. Due to the less-stringent standard of light trucks, the fleet-average standard is become less stringent (with higher emission allowance) when the market share of light trucks increases. The new compliance choice moves to \((s_2, e_2)\), with a higher share of light trucks and higher fleet emission level than under a uniform standard. The attribute basing results in a smaller consumer welfare loss compared with the uniform standard since the length of the compliance vector is smaller than in the uniform standard. However, the discrete attribute basing distorts the choice of trucks, resulting in more trucks sales (from \( s^1 \) to \( s^2 \)). With a steeper slope of the standard (with a larger difference between \( k_1 \) and \( k_2 \)), the distortion in the share of light trucks is much larger. The reduced emissions by the attribute-based standard is also lower than the uniform standard due to higher emissions from trucks (\( \Delta e^2 < \Delta e^1 \)).

The qualitative findings from the graphic illustration suggest that attribute basing not only runs counter to the policy goal of achieving a more efficient fleet, but also creates additional distortion in the secondary attribute. To quantify the welfare loss from the discrete attribute basing, we need to compare ABR with a uniform standard by taking account of the consumer welfare loss due to deviation from the private optima, the environmental benefits brought by each policy, and additional externalities due to distortion if any. Therefore, an empirical analysis which models both consumer vehicle choice and automaker vehicle supply
is needed and is presented in the following sections.

4 Empirical Model and Estimation

The empirical section aims to estimate a structural model of the automobile market so that counterfactual analysis could be carried out to quantify the welfare impact of discrete attribute basing under CAFE by comparing the market outcomes with a uniform standard that removes the standard split.

By taking advantage of the individual transaction data from Maritz, I first estimate consumer demand for new cars taking into account of both observed and unobserved consumer heterogeneity in the spirit of (Berry et al. 1995, 2004; Petrin 2002; Train and Winston 2007). With the demand estimates, marginal costs are backed out assuming optimal pricing under Bertrand-Nash competition where automakers adjust prices to maximize profits from both vehicle and regulatory credit sales, taking product choices as given. This section presents the demand and supply models as well as estimation strategies.

4.1 Vehicle Demand Model

I define a market as the aggregated market of all the MSAs for each model year from 2012 to 2014. Within each market, households purchase one model \( j \) within the inside goods or choose the outside good, which is defined as not purchasing a new vehicle. I model vehicle purchase decision statically assuming that consumers behave myopically and make their purchase decisions based on the current price and product attributes. Due to the durable nature of vehicles, consumers might delay their purchase expecting for price drop or quality improvement in future (Gowrisankaran and Rysman 2012). However, unlike the markets of cellphones, computers, and digital cameras where the technology is evolving rapidly, the automobile industry is relatively mature and no technological breakthrough happened within my sample period and the vehicle price and gasoline price were also stable between MY 12-14. Thus, the benefits of delaying a purchase may not be high and assuming a static vehicle demand model may be reasonable.

Household \( i \)'s utility from purchasing vehicle model \( j \) is defined as:

\[
 u_{ij} = \sum_{k=1}^{K} x_{jk} \beta_k - \alpha_1 \ln p_j + \xi_j + \alpha_2 \frac{\ln p_j}{Y_i} + \sum_{kr} x_{jk} z_{ir} \beta_{kr}^o + \sum_{k} x_{jk} v_{ik} \beta_k^u + \epsilon_{ij} \tag{1}
\]
where $\delta_j$ is the mean utility of vehicle model $j$ which is constant across consumers in the same market. The $x_{jk}$ stands for the $k_{th}$ vehicle attribute for model $j$, and I include horsepower, weight, size, gallons per mile as the observed vehicle attributes. The price $p_j$ is the average transaction price observed from the survey data, which is constant for a same model in all locations. The logarithm of price is employed to make the price effect decrease as the price of a vehicle model increases. The second component $\mu_{ij}$ captures heterogeneous utility driven by both observed and unobserved consumer characteristics. $Y_i$ is household $i$’s income in the corresponding year and $1/Y_i$ captures how a household’s income influences their price sensitivity. One would expect $\alpha_2$ to be negative as higher income households would be less sensitive to a price increase due to the diminishing marginal utility of money. $z_{ir}$ denotes consumer $i$’s other demographic variables including family size, whether living in an urban area, the average gasoline price in the area, which are interacted with certain vehicle attributes to capture variation in consumer preference due to observed heterogeneity. The unobserved consumer taste $v_{ik}$ is assumed to have a standard normal distribution. The coefficient $\beta_k^u$ can be interpreted as the standard deviation in the unobserved preference for the vehicle attribute $k$ conditional on the consumer’s observed attributes. Let $\theta_1 =$ \{$\beta_{kr}^o, \beta_k^u$\}, denoting the “nonlinear” parameters, and it is understood that the vector $\delta =$ \{$\delta_1, ..., \delta_j$\} is estimated conditional on a given $\theta_1$. The last component $\epsilon_{ij}$ is the idiosyncratic preference of household $i$ for vehicle model $j$ and it is assumed to have an i.i.d. Type 1 extreme value distribution. The Maritz data includes vehicle models that consumers seriously considered other than the purchased model, which allows for a ranking of both the first and second vehicle choice. Thus, the joint probability of household $i$ choosing $j$ and seriously considering $h$ as an alternative choice when the outside option and $j$ are removed is:

$$P_{ijh} = \int \frac{\exp[\delta_j(\theta_1) + \mu_{ij}(\theta_1)]}{1 + \sum_g \exp[\delta_g(\theta_1) + \mu_{ig}(\theta_1)] \cdot \sum_{g \neq j} \exp[\delta_g(\theta_1) + \mu_{ig}(\theta_1)]} f(v) dv \quad (2)$$

Instead of constructing moments exploiting the exogeneity assumption that unobserved product attributes are uncorrelated with observed attributes, I estimate the demand function using maximum likelihood as in \cite{Train and Winston 2007; Langer 2012; Goolsbee and Petrin 2004; Whitefoot et al. 2013; Murry and Zhou 2017}. Let $ln R_i = ln P_{ijh}$, denoting the individual log-likelihood of household $i$ choosing the observed purchased model $j$ and considering the observed alternative choice $h$. The log-likelihood function of the entire sample
for a single market is therefore:

\[ \ln L = \sum_{i=1}^{N} \ln R_i \]  

(3)

The nonlinear parameters \( \theta_1 \) are estimated via maximum likelihood by maximizing the likelihood function above. To reduce the dimensionality of the coefficient space, I do not directly maximize the likelihood over the entire space of \((\theta_1, \delta)\) but back out the mean utility \( \delta \) conditional on \( \theta_1 \) using market share inversion as in Berry (1994). Define the probability of observing household \( i \) choosing model \( j \) as:

\[ P_{ij} = \int \frac{\exp[\delta_j(\theta_1) + \mu_{ij}(\theta_1)]}{1 + \sum_g \exp[\delta_g(\theta_1) + \mu_{ig}(\theta_1)]} f(v) dv \]

The market demand is then the sum of individual consumers’ demand and the predicted market share is obtained by calculating \( P_{ij} \) with parameters \( \theta_1 \) and \( \delta \) and averaging over the \( N \) consumers in the survey sample. The mean utility fixed effects \( \delta \) are solved by matching the observed market shares from the aggregate sales data to those predicted by the model:

\[ S_j = \frac{\hat{S}_j(\theta_1, \delta(\theta_1, S))}{N} = \sum_n P_{ij}(\theta_1, \delta)/N \]

(4)

I estimate \( \delta \) by contraction mapping following Berry et al. (1995) and \( \delta \) is calculated for each trial value of \( \hat{\theta}_1 \) in the numerical search for the maximum of the log-likelihood function:

\[ \delta_j^t(\hat{\theta}_1) = \delta_j^{t-1}(\hat{\theta}_1) + \ln(S_j) - \ln(\hat{S}_j(\hat{\theta}_1, \delta_j^{t-1}(\hat{\theta}_1))) \]

(5)

After estimating \( \hat{\theta}_1 \) and \( \hat{\delta}(\hat{\theta}_1) \), the “linear” parameters \( \theta_2 = \{\alpha_1, \bar{\beta}_k\} \) are estimated using IV-GMM given the following specification:

\[ \delta_j = -\alpha_1 \ln p_j + \sum_{k=1}^{K} x_{jk} \bar{\beta}_k + \xi_j \]
where \( \xi_j \) denotes the unobserved vehicle attributes of model \( j \). To control for the correlation of price with the unobserved product attributes, following [Train and Winston (2007)](#), I use BLP-style instruments \( Z_j \) that measures the sum of distance and squared distance in attribute space between own product and other products in the same firm and from other firms. \( \theta_2 \) is estimated using GMM solving the following minimization problem:

\[
\min_{\theta_2} G_J(\theta_2)^\prime W G_J(\theta_2)
\]

where \( J \) is the total number of models, \( W \) is the weighting matrix and \( G_J(\theta_2) \) is the sample analog of the moment condition defined as:

\[
G_J(\theta_2) = \frac{1}{J} \sum_j \hat{\xi}_j Z_j
\]

## 4.2 Vehicle Supply

Vehicle manufacturers could meet tighter CAFE standards by adopting fuel-saving innovations, by lowering the relative price of fuel-efficient vehicles and reducing weight or adjusting other vehicle attributes. In this study, I only allow firms to adjust sales mix by changing prices to maximize the profit from both vehicle sales and regulatory credit sales holding the models introduced and vehicle characteristics constant. This “mix-shifting” strategy is a common practice that automakers adopt in complying with the fuel economy regulation. [Jacobsen (2013a)](#) tests the assumption of “mix-shifting” by exploiting time-series variation in the stringency of CAFE at the firm level and his findings strongly support this firm behavior: fuel-inefficient vehicles are priced higher and fuel-efficient vehicles are priced lower when the standard is more binding. Although there is evidence that automakers could redesign a vehicle model to make it classified as a light truck to take advantage of the preferential treatment of light trucks[14] this paper only focuses on the short-run impact of the standard split within a specific model year, and transforming a passenger car to a light truck involves significant vehicle redesign such as significantly increasing GVWR (weight), squeezing in a third row of seats or converting 2WD to 4WD which takes a much longer production phase

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[14] Examples include Subaru’s 2004 Outback four-door sedan, Chrysler’s PT Cruiser, and Lexus NX 300h, which all retain certain dimensions of a car but were classified as light trucks. The practice helped the automakers improve their light truck average fuel economy.
Besides, the number of light truck models introduced was quite stable during MY 2012-14, which my data period covers. Therefore, only allowing automakers to adjust price is a reasonable assumption for the scope of this paper and endogenizing automaker’s decision in vehicle attributes is relevant for investigating the long run impact of the discrete attribute basing on the automobile industry.

The vehicle supply follows Berry et al. (1995) with the modification of adding the revenue from regulatory credit sales from the GHG program. Since the national program is harmonized to allow automakers to build one single vehicle fleet that satisfies both CAFE and GHG standard requirements, only GHG credits sales, whose credit prices are observed, are modeled for simplicity. An automaker \( f \) is assumed to face a profit-maximization problem that maximizes the profit from both vehicle sales and sales from regulatory credits, which is defined as follows,

\[
\max_{p_j, q_j \in J_f} \pi^f = \sum_{j \in J_f} [p_j q_j(P) - v_{c_j}(q_j)] + \lambda \sum_{j \in J_f} (t_j - e_j) VMT_j \cdot q_j(P), \tag{7}
\]

where \( J_f \) is the set of all the vehicle models produced by firm \( f \). \( v_{c_j} \) is the total variable cost of producing model \( j \), \( p_j \) is the price and \( q_j \) is the sales for product \( j \). \( P \) is the vector of prices of all the vehicle models in the market. \( e_j \) is the CO\(_2\) emission for vehicle model \( j \) and \( t_j \) is the emission target for model \( j \) depending on \( j \)'s footprint \( a_j \) and whether it is classified as a car \( C \) or a light truck \( T \). Corresponding parameters \( \mu_c \) and \( \gamma_c \) or \( \mu_t \) and \( \gamma_t \) are plugged into the equation of \( t_j \) to obtain the emission targets for each vehicle model. \( VMT_j \) is the total miles traveled over the life cycle of model \( j \). EPA assumes that the lifetime \( VMT_j \) is 195,264 miles for cars and 225,865 miles for trucks. \( \lambda \) denotes the equilibrium credit trading price. Since the new joint rule starting in 2012 allows credit

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\(^{15}\)According to NHTSA (2010), even increasing the footprint requires platform changes, which usually occurs once every 5 years.

\(^{16}\)The credit trading prices are not observed for the CAFE program. The vehicle supply modeling here assumes that the two programs are equivalent. However, there are some differences between CAFE and GHG programs, which are summarized in Leard and McConnell (2017). If the two programs are not fully harmonized, prices observed in the credit trading market of one program will not reflect the marginal costs of compliance for the two programs.
trading between car and truck fleets within the same firm and also across firms, there is only one equilibrium price for each unit of credit. The second summation in Equation (7) denotes the total credit sales, which is positive if firms generate revenue from producing excess credits and is negative if firms loss revenue from buying credits from other firms to make up for credit shortage. The model here assumes away credit banking and borrowing, and automakers are required to use the credits generated within the current model year to comply with the regulation and are required to offset a negative balance by purchasing credits from other firms. Under the current joint program, automakers are allowed to bank credits for up to five years and carry back credits to offset previous deficits up to three years. The flexibility intends to help automakers harmonize compliance burden from year-to-year fluctuations of market shocks including changing fuel prices. For example, if a gasoline price drop makes consumers choose more vehicles that are less fuel-efficient, using banked credits to make up for credit shortage or carrying deficits and borrowing future credits could reduce firm’s compliance burden in that affected year. Therefore, assuming away the feature of credit banking and borrowing increases firms’ compliance cost and would potentially overestimate the policy impact. However, my data period MY 2012-14 witnessed a relatively stable gasoline price (around $3.5 per gallon in average) and the gasoline price plummeted starting October 2014, which is right after MY 2014 that is defined till August 2014. As long as the demand is stable and there is no market shock that significantly affects firms’ compliance strategies across years, the static period-by-period should coincide with the dynamic solutions that incorporates credit banking and borrowing (Jacobsen 2013a). 

The first-order condition of the firm profit defined in Equation (7) with respect to model j’s price $p_j$ is:

$$q_j(P) + \left( \sum_{r \in J_f} p_r - \sum_{r \in J_f} mc_r - \lambda \sum_{r \in J_f} (e_r - t_r)VMT_r \right) \frac{\partial q_r}{\partial p_j} = 0, \quad \forall j$$

The above systems of equations can be written in a matrix form as follows,

$$Q(P) + \Delta[P - MC - \lambda(E - T)VMT] = 0$$

$$P = -\Delta^{-1}Q(P) + MC + \lambda(E - T)VMT$$  \hspace{1cm} (8)
where $\Delta$ is a $J$ by $J$ matrix where $J$ is complete set of all vehicle models in a model year and the element of $\Delta$ are:

$$\Delta_{jk} = \begin{cases} \frac{\partial q_j}{\partial p_k} & \text{if products } j \text{ and } k \text{ are produced by same firm} \\ 0 & \text{otherwise} \end{cases}$$

and the elasticity element in the $\Delta$ matrix can be estimated as:

$$\frac{\partial q_j}{\partial p_j} = M \cdot \sum_{i=1}^{N} \frac{\partial s_{ij}}{\partial p_j} = M \cdot \frac{\sum_{i=1}^{N} -\alpha_is_{ij}(1-s_{ij})}{N}$$

$$\frac{\partial q_j}{\partial p_k} = M \cdot \sum_{i=1}^{N} \alpha_is_{ij}s_{ik}$$

where $M$ denotes the market size. With the $\Delta$ matrix estimated and $\lambda$ obtained from the credit trading market, I can back out marginal cost for each model $j$. Without $\lambda$, marginal cost and the credit price cannot be separately identified. For the trading credit values, I use the GHG credit price estimated in Leard and McConnell (2017), which are 36, 63, and 42 $/Mg$ respectively for MY 2012-2014.\footnote{Leard and McConnell (2017) calculate the GHG credit price from the revenue of GHG credit sales by Tesla, and the settlement between Hyundai and Kia and EPA and US Department of Justice concerning the two automakers’ violation of the Clean Air Act.}

\[ MC = P + \Delta^{-1}Q(P) - \lambda(E - T)VMT \]  

(9)

This first-order condition differs from a profit maximization problem without credit trading by having an extra term interacted with the credit price. If there is no credit trading, the credit price will be zero and the first-order condition will be the same as in a Bertrand price competition case for oligopolies. With a positive credit price, there will be an additional cost for the vehicles whose emissions are above the required level and an additional revenue from selling the vehicles whose emissions are below the required level. Therefore, with credit trading, the fuel economy regulation works as a revenue-neutral tax system by taxing fuel-inefficient vehicles and subsidizing fuel-efficient vehicles. Under the original CAFE system before 2012, there were three types of firms as summarized in Jacobsen (2013a): (i) firms with fleet fuel economy exceeding the standard and therefore the constraint is not binding...
(ii) firms that violate the standard and pay the associated fines and face a non-constraint less-penalty profit maximizing problem and (iii) firms that are constrained by CAFE. Under the joint program starting MY 2012, the credit-trading system encourages firms who produce vehicles that overcomply with the regulation, those who were originally not constrained by the regulation, to continue increasing fuel efficiency to generate revenue from selling credits. Under the GHG program, intentionally paying fines in lieu of meeting the standard is also no longer allowed (NHTSA 2010). Therefore, all the three types of firms under the original CAFE program have the incentives to continue increasing fuel economy to generate credits under the new joint program and all the firms’ behaviors could be modeled as a multi-product profit maximization problem with credit trading represented by the single first-order condition above (Eq. (8)).

4.3 Identification

This subsection discusses the identification of the demand model. The preference parameters are identified primarily through variation in the market shares corresponding to variation in the choice set across markets, variation in the observed vehicle attributes across models, and variation in observed consumer demographic attributes.

The mean utility component \( \delta \) represents the average consumer utility for each vehicle model and is backed out by matching the observed market shares with the model prediction. If there is no consumer heterogeneity, all variation in market shares would be driven by variation in the observed vehicle attributes. The linear parameters \( \bar{\beta} \) and \( \alpha_1 \) in the mean utility are identified though variation in market shares corresponding to the variation in price and other observed vehicle attributes (such as vehicle size). Due to the potential correlation between unobserved vehicle attributes \( \xi_j \) with price \( p_j \) as automakers observe \( \xi_j \) when choosing prices, instruments that capture the extend of price competition are used to correct for potential endogeneity. More specifically, following Train and Winston (2007) and Langer (2012), I use BLP-style instruments as the sum of the difference in attribute space between the vehicle and all others sold by the same firm and all others sold by other firms, and also the sum of the squared differences. Those distance instruments measure the competition pressure that automakers face when pricing each model, which provides exogenous variation in price that aids the identification of consumer average price sensitivity.

The consumer heterogeneity component includes both the observed heterogeneity portion that could be explained by observed consumer attributes and the unobserved heterogeneity portion that are related to unobserved consumer tastes. Consumers have heterogenous pref-
ference and therefore different vehicle models would attract consumers with different tastes. The parameters $\beta_{kr}$, which are associated with observed consumer attributes, are identified with the aid of demographic information observed for different households who purchased different vehicle models. For example, if we observe households with a larger family size disproportionately purchased larger and heavier vehicles, we would expect a positive coefficient for the interaction between family size and vehicle weight. Variation in the transaction prices of the purchased vehicles across different income groups helps identifying the parameter $\alpha_2$. If higher income groups tend to be less price sensitive to vehicle prices and disproportionately buy more expensive vehicle models, we would expect a negative sign for $\alpha_2$, which captures the impact of income on consumers’ price sensitivity.

The unobserved consumer heterogeneity parameters $\beta^u_k$ governs the substitution pattern and are identified by the substitution patterns observed from both the macro and micro-level data. At the macro data level, variation in the market shares corresponding to variation in the choice set (available vehicle models) helps identifying $\beta^u_k$. For example, if we observe a consumer purchases model A in market 1 and another consumer with similar observed consumer attributes in market 2 purchases model B when model A exits or becomes more expensive, the proximity in vehicle attributes between model A and B helps the identification of $\beta^u_k$. At the micro data level, the alternative choices that consumers considered when making purchase decisions provides valuable information in estimating consumer’s substitution pattern between vehicles, which greatly assists the identification of $\beta^u_k$. The alternative vehicle choices are the choices that consumers make in a choice set where both the purchased choice and the outside option are removed. By observing each consumer’s alternative choice in a hypothetical choice set that varies across consumers is similar to observing consumer’s substitution with actual variation in choice sets. Since different consumers buy different vehicle models, the number of the hypothetical choice sets created by the alternative choice data equals to the number of purchased vehicle choices, which provides variation in choice sets that are much richer than that provided by macro-level data, which often relies on observing multiple markets or multiple model years. More specifically, the closeness in the vehicle attributes between the purchased vehicle choice and the alternative vehicle choice facilitates identifying the parameters $\beta^u_k$. For example, if consumers’ purchased vehicles and their seriously considered alternative choices are often within a certain fuel economy range, we would expect a statistically significant coefficient for the unobserved heterogeneity parameter associated with MPG. Since my data covers only 3 markets (MY12-14) which is relatively small compared to previous applications of random coefficient discrete choice models that relies on observing a large number of markets, most of the identification of the
unobserved heterogeneity parameters comes from the alternative choice information. [Berry et al. (2004)] note that having micro-level 2nd choice data greatly helps the estimation of random coefficients when they only have observations for one model year and [Train and Winston (2007)] also mention that including alternative choice data significantly improves the precision of the random coefficient estimates.

5 Estimation Results

5.1 Demand parameters

Table 2 reports the estimation results of the demand model. The mean utility $\delta$ represents the average preference consumers have for each vehicle model and are estimated via matching the model predicted market share to the observed market share. The mean preference coefficients for price and each observed vehicle attribute are recovered from GMM-IV estimation with the instruments correcting for the endogeneity of price. Both OLS and IV results are reported in Table 2 Panel (a) and reflect the preferences for vehicle attributes that are generally expected. In average, consumers have a negative preference for price and the price coefficient in the IV specification is more negative, suggesting OLS underestimates the price sensitivity. Consumers have a positive preference for acceleration, measure by horsepower/weight. Without interacting with gasoline price, the coefficient for gallons/mile is positive, suggesting average consumers do not like fuel-efficient cars but prefer cars that are more powerful. Consumers in general prefer cars that are heavier and dislike alternative fuel vehicles including hybrid and plug-in electric vehicles. Conditional on other vehicle attributes, consumers dislike vans and pickups but favors SUVs relative to passenger cars, which coincides with the evidence that the SUV segment experiences the largest sales increase among all vehicle categories in recent years. The positive signs for MY 13 and MY 14 dummies suggest that consumers prefer MY 13 and MY 14 vehicles to MY 12 models, controlling for other vehicle attributes.

Turning to the consumer heterogeneity parameters, with the aid from the individual transaction data, the interaction terms of consumer demographics with vehicle attributes are estimated precisely with intuitive signs. The coefficient of log(price) divided by income captures the extent to which a consumer’s price sensitivity varies with income. The negative sign of the estimate suggests that households with lower income react more negatively to a vehicle’s price than households with higher income. The elasticities implied from the price preference will be further discussed below. Compared with households who live in suburban...
and rural areas, households who live in urban areas are less likely to adopt pickups, probably due to less towing utility and limited parking space, but are more interested in alternative fuel vehicles (AFVs) due to both more frequent city driving needs and better refueling infrastructure provided in urban areas. Households of a larger family size prefer larger vehicles that are heavier. The interaction of gasoline price with gallons/mile, which measures the operating cost per mile of the vehicle, has a negative sign, suggesting that consumers have a negative preference for the fuel cost.

Three random coefficients are included, which represent unobserved consumer heterogeneous preference for gallons/mile, horsepower/weight, and light trucks. As indicated by the estimation results, data on consumers’ alternative vehicle choices greatly helps precisely identifying those parameters. Based on the standard normal distribution of the random taste \( v_{ik} \), the coefficient \( \beta^u_k \) can be interpreted as the standard deviation in the unobserved preference for the vehicle attribute \( k \). To reduce simulation noise and bias, following Train and Winston (2007), I use 150 Halton draws in the simulation of the integral over the unobserved consumer taste \( v \). All of the three coefficients are statistically significant, indicating that consumers have heterogeneous preference for those vehicle attributes conditional on the observed consumer characteristics. Those precisely estimated random coefficient parameters help breaking down the I.I.A. problem experienced in traditional logit models and play a critical role in governing the substitution patterns.

### 5.2 Elasticities and Profit Margins

The demand system implies sensible elasticities and markups. All implied own-price elasticities are greater than one, ranging from -7.75 to -3.5 with an average being -5.51 and standard deviation being 0.37. The sales-weighted average elasticity among all the 1,318 products in three model years is -5.55. The magnitude of the own-price elasticities are close to those obtained in Berry et al. (1995), Petrin (2002), Beresteanu and Li (2011) and Li (2012). Figure 6 plots the own-price elasticities against price and demonstrates that more expensive models tend to have less elastic demand. With the elasticity estimates, the price-cost margins are recovered. The average implied price-cost margin is 19.0% (sales-weighted average being 19.1%) of the transaction price, which is close to 24% in Berry et al. (1995), 16.7% in Petrin (2002), 17.7% in Beresteanu and Li (2011) and 18.13% in Li (2012). Figure 7 plots the estimated profit-cost margins against transaction prices, which demonstrates a pattern that more expensive models have a larger profit margin as they usually target consumers.

\footnote{Halton draws are a type of low-discrepancy sequence. The demand results are similar when the number of Halton draws are increased to 200.}
who have a higher income and thus are less sensitive to prices. Alternatively, products with more elastic demand tend to have lower price-cost margins than products with less elastic demand. For example, the price-cost margins for 2014 Chevrolet Spark and Porsche 911 are 16% and 22% respectively.

With the estimated implied profit-cost margins and the credit trading component, marginal costs are backed out from transaction prices using the first order condition in Equation (9), which will be used for counterfactual simulations.

6 Policy Simulations

To quantify the welfare impact of the discrete attribute basing in CAFE standards, I set passenger cars and light trucks subject to a uniform standard using a single footprint-based standard formula and simulate counterfactual market outcomes and compare the social welfare with the observed scenario.

6.1 Simulation Method

I run a counterfactual simulation where light trucks and passenger cars are subject to a uniform footprint-based standard. The footprint-based feature is still preserved, since it encourages automakers to improve fuel economy of all sizes and helps preserving the size distribution of the entire fleet by reducing the incentives for automakers to downsize the vehicles, alleviating the safety concern. Keeping the footprint-based standards instead of having one single target for all vehicles also makes the alternative policy less aggressive. The alternative policy essentially removes the differential treatment between cars and trucks with the same footprint. Since my paper focuses on the impact of attribute basing on the car-truck classification, maintaining the footprint-based feature helps me isolate the impact of the standard split between cars and trucks.

The uniform standard would use the sales-weighted average parameters for the footprint-based emission standard formula:

\[
t_j = \mu + \gamma a_j, \quad \forall j
\]

\[
\mu = (1 - s)\mu_c + s\mu_t, \quad \gamma = (1 - s)\gamma_c + s\gamma_t
\]

where \(s\) denotes the market share of light trucks. Figure 8 depicts the uniform footprint-based standards for MY 2014: light trucks are subject to more stringent targets and pas-
senger cars are subject to less stringent targets. Throughout the counterfactual exercise, I assume that automakers do not change vehicle attributes other than price, and therefore the estimated results reflect the short-run impact of the discrete attribute basing under CAFE. To compare the policy impacts on consumer surplus, I compare the welfare losses of the two policies in making consumers’ choices deviate from their private optima. More specifically, I estimate the monetary transfer that is need to make consumers indifferent between the choice with policy and the choice without policy for both of counterfactual and observed policy scenarios, which measures the policy compliance cost borne by consumers.

Since automakers are subject to a different standard in the counterfactual scenario, the new equilibrium regulatory credit price along with the new equilibrium vehicle prices and sales need to be resolved. The simulations are carried out through the following steps:

1. Plug the initial credit price and the initial vehicle price vector \( p \), but the counterfactual emission target into the first order condition, as defined in Equation (8).

2. Update the price vector such that the difference between the left-hand side and the right-hand side are within a certain threshold.

3. Calculate the credits generated by each firm conditioning on the new equilibrium sales. Sum across all firms to obtain the total credits for the market. If there is excess demand (supply) for credits in the equilibrium, increase (decrease) the credit price and repeat from step (1) to find a new equilibrium.

4. If there is again excess demand (supply), further increase (decrease) the credit price and repeat the above steps until the newly searched credit price clears the credit trading market.

6.2 Impacts on market outcomes

Under the uniform standard, the more efficient passenger car models are subject to a lower standard than before and thus receive more subsidy, while the less efficient trucks are subject to a more stringent target and thus receive a higher implicit tax. Due to the larger share of light trucks, the automaker industry is facing a more stringent regulation in general. The original credit price is too low to clear the credit trading market, inducing excess credit demand. Not surprisingly, the simulated new credit price increases to $133.1, reflecting an increase in the stringency and marginal compliance burden of the regulation. With changes in the credit price and emission targets from removing the attribute basing, automakers
need to re-adjust the sales mix by increasing the sales of the vehicles which could generate more credits while balancing between the revenue from vehicles sales and credit sales. The magnitude of vehicle price and sales changes depend on the own and cross price elasticities. Table 3 shows the price and market share impacts of the uniform standard on different vehicle segments.

In average, the price of passenger cars decreases by $471 with the largest price reduction from battery electric vehicles (BEVs) such as Tesla Model S, Nissan LEAF, Ford Focus Electric, which would have a price reduction over $13,000. With a higher regulatory credit price, automakers rely more on BEV models to generate credits since they are the models which have the least tailpipe emissions and they are treated having zero emissions under the current regulation. The implicit subsidy under CAFE is close to the price difference between EVs and their gasoline counterparts. Having a uniform standard would make BEV models more affordable and encourage more consumers to adopt this new technology. With a higher credit price, automakers are also reducing the sales of car models which are least fuel-efficient by increasing their prices. The car models that experience the highest price hikes are Dodge Viper, Audi R8, Mercedes-Benz C63, which are all luxury sporty cars with the lowest fuel efficiency.

Without the favorable treatment for the light truck category, the prices for light trucks would increase by $2,766.2 in average. More specifically, SUVs would have an average price increase of $2,215.9, with the least price increases from SUV models that are fairly fuel efficient such as Lexus RX350, Lexus RX450 Hybrid, and Subaru XV Crosstrek Hybrid, and the largest price increases from the models which are the least fuel efficient: Mercedes-Benz G63, Lexus Lx570 and Mercedes-Benz GL63. Similar patterns are observed for the van segment. The average price increase of vans is $2,988.7 with GMC Savana Passenger Van, Ford E-150 and Ford E-350 Passenger Vans experiencing the largest price increase over $7,000. The prices for pickups would go up by $4,317.2 in average, higher than both the SUV and Van segments due to a higher emission level in general. The pickup models that are hurt most under the uniform standard are: RAM Pickup 3500 and RAM Pickup 2500. Figure 9 panel (a) and (b) plot the relationship between the price change under the uniform standard and fuel economy level for the passenger car and light truck segments respectively. As expected, the sign and magnitude of the price changes are highly correlated with the fuel economy levels. In general, passenger cars with higher fuel efficiency experience a larger price decrease and light trucks with lower fuel efficiency experience a larger price increase.

Removing the standard split between cars and trucks has a significant impact on the
market structure of the automobile industry. The total sales in the car segment would increase by 8.0% and the total sales of light trucks would decrease by 4.9% with the sales in the SUV, van and pickup segments falling by 1.5%, 12.2%, and 11.9% respectively. The uniform standard hurts the van segment more since it has fewer models available than the SUV and pickup segments, making it easier for consumers to switch to other segments given a price increase. The SUV segment has the least percentage decrease in profit due to its largest sales base and the largest number of available model choices among the light truck category. With more models to choose from, consumers are more likely to switch from expensive SUV models to less-expensive SUV models instead of switching out of the segment. The sales decrease of the SUV segment is also likely to be offset by consumers switching from the van and pickup segments. The uniform standard affects the market structure by increasing the market share of cars and decreasing the market share of light trucks. The total market share of passenger cars increases from 46.6% to 49.7% and the market share of light trucks decreases from 53.4% to 50.3%. The decreasing price for some fuel-efficient car models increase the utility of owning new cars and makes some consumers switch from the outside good towards buying a new vehicle. The uniform standard increases the sales from the subsidized car segment more than the sale losses from truck segment that is being taxed more. This should not be surprising considering that small car buyers are more price sensitive than truck buyers and they are more likely to switch from choosing public transportation or used cars to purchasing new cars. With a stronger preference for new vehicles, existing light truck buyers are also less likely to switch to the outside option due to a higher price from the removal of the preferential treatment for trucks. The uniform standard also makes a more efficient vehicle fleet by increasing the sales-weighted average fuel economy from 26.1 mpg to 27.5 mpg, compared with the current standard that features the discrete attribute basing. This fuel economy change translates to a considerable vehicle-lifetime gasoline consumption saving up to 1.61 billion gallons discounted to MY 2014.

6.3 Welfare impact

This section explores the welfare impact of removing the discrete attribute basing by focusing on consequences on consumer surplus, firm profits, and externalities associated with air pollutants, emissions and accidents, which are interpreted as total vehicle lifetime changes from annual sales.
6.3.1 Consumer surplus

A policy intervention like the fuel economy regulation intends to alter consumer vehicle choice to help consumers internalize the externalities associated with their behaviors. An efficient policy is to improve the social welfare by reducing the external costs from the externality that the policy intends to target while minimizing the distortionary cost and the welfare loss in consumer surplus. Consumer surplus loss under the regulation could be thought as the compliance cost that consumers need to bear and is defined as the utility loss due to deviation from their private optimal choice. If a consumer purchases a vehicle that is being subsided (taxed) under CAFE while the consumer would have purchased the same vehicle without CAFE, this consumer experiences a welfare gain (loss), which is equal to the difference of consumer surplus of purchasing the model with and without the subsidy (tax). If, however, consumers are induced by CAFE to pick a model that deviates from their private optimal choice, they suffer a welfare loss, which is equal to the gap in the intrinsic utility between a consumer’s top choice and the policy-induced choice. For example, if a consumer chooses a vehicle model A without CAFE, while being induced to purchase a sub-optimal model B by the relative price change due to CAFE, the consumer suffers a welfare loss which is equal to the difference between the consumer surplus obtained from the private optimal choice A and that obtained from the suboptimal choice B.

To compare the welfare impact on consumer surplus between the two CAFE policies with and without attribute basing, I first simulate the equilibrium price without CAFE regulation. Following Barwick et al. (2017), I use simulations to compare the welfare loss from the fuel economy regulations with and without the discrete attribute basing. I draw 10,000 random idiosyncratic preference vectors $\epsilon_i$ from the Type 1 extreme value distribution for each consumer $i$. Conditional on each draw, I calculate the difference in the intrinsic utility between a consumers’ private optimal choice and the policy-induced choice under each CAFE scenario. Let $j^*$ denote the private optimal choice for consumer $i$ with its intrinsic utility defined as:

$$u_{ij^*}^0 = \max_{j=0,...,J} \{\delta_j^0 + \mu_{ij}^0 + \epsilon_{ij}\} \quad (10)$$

where $\delta_j^0$ and $\mu_{ij}^0$ are evaluated at the price level under the no CAFE scenario. Suppose consumer $i$ chooses vehicle model $g$ instead of $j^*$ under the CAFE policy such that:
\[ u_{ig}^1 = \max_{j=0,\ldots,J} \{ \delta_j + \mu_{ij}^1 + \epsilon_{ij} \} \]  

(11)

where \( \delta_j \) and \( \mu_{ij} \) are evaluated at the price level with CAFE. The monetized welfare loss for consumer \( i \) is defined as the difference in the intrinsic utility between the private optimal choice \( j^* \) with the choice \( g \) made under CAFE, divided by consumer \( i \)'s price sensitivity:

\[
\Delta CS_i = \frac{(u_{ij}^0 - u_{ig}^0)}{\partial u_{ij} / \partial p_j}, \quad g \neq j^* 
\]

(12)

When consumer does not change their optimal choice with the CAFE policy, the change in consumer surplus is the welfare loss (gain) from the implicit tax or subsidy he or she receives:

\[
\Delta CS_i = (-\alpha_1 (\ln P_{ij}^1 - \ln P_{j*}^0) + \frac{\alpha_2}{Y_i} (\ln P_{ij}^1 - \ln P_{j*}^0)) / \partial u_{ij} / \partial p_j, \quad g = j^* 
\]

(13)

where \( P_{ij}^0 \) and \( P_{j*}^1 \) are the prices for the optimal vehicle choice \( j^* \) under the no policy and CAFE policy scenarios respectively. The above consumer surplus change is evaluated for each \( \epsilon_i \) draw and then averaged across all draws to obtain the welfare loss (gain) for consumer \( i \). The total welfare loss due to policy is obtained by averaging the individual welfare changes and multiplied with the total market size.

A policy would result in a higher consumer welfare loss if it makes more people to choose a model that deviates from their private optimal choice. The simulation results suggest that the current CAFE with discrete attribute basing costs $0.77 billion in consumer welfare while the CAFE policy removing the standard split results in a higher welfare loss, amounting to $1.75 billion. The uniform standard leads to a higher consumer welfare loss since the magnitude of the implicit tax/subsidy is larger due to a more stringent regulation, more likely to make consumers deviate from their private optimal choice. This finding is actually consistent with the implication from the theoretical illustration that the uniform standard incurs a higher compliance cost, reflected by the longer length of the compliance vector in Figure 5. Reynaert and Sallee (2017) study the impact of firms’ gaming in carbon emission standards for automobiles and find gaming in a binding fuel economy regulation
could benefit consumers since it leads to lower prices by reducing firms’ regulatory costs.\textsuperscript{19} Analogously, the CAFE standards that feature the discrete attribute basing could reduce the compliance cost of automakers, especially the firms that produce a greater amount of light trucks, potentially benefit consumers through lower prices. However, the compliance burden measured by the loss in consumer private surplus needs to be evaluated against the social benefits from reduction in externalities that the policy intends to target. With a optimally-set policy standard, consumers would benefit more from the reduction in externalities than they loss in private surplus. Although the uniform standard leads to a larger consumer welfare loss, much of the policy-induced switching is not a distortion but an efficient change because it makes more consumers switch from the private optimal choice to the socially optimal choice by taking into consideration of the external costs of gasoline consumption. By allowing light trucks which generally emit more to receive a preferential treatment, the CAFE with attribute basing fails to make a consumer’s vehicle choice achieve the socially optimal level. The relative subsidy for light trucks could even result in deviation from private optimum which is not efficient: consumers might choose vehicle models which are neither privately optimal nor socially optimal. In contrast, the uniform standard not only eliminates the loophole of implicitly subsidizing light trucks, but also encourages a consumer’s vehicle choice towards the social optimum.

6.3.2 Firm Profits

Table 4 summarizes the impact of removing the discrete attribute basing on firms’ profits. Removing the car-truck standard split decreases the total profits of domestic firms by 1.8% while the European and Asian enjoy a 4.0% and 1.5% boost in total profits respectively. The results imply that discrete attribute basing favors domestic firms at the expensive of foreign firms, which should not come as a surprise. Domestic firms have a disproportionately large share of vehicles that are classified as light trucks (Figure 11). The discrete attribute, which essentially provides a preferential treatment for light trucks, reduces the compliance burden for domestic firms. Asian firms, on the other hand, produce relative fuel-efficient vehicles. Even though they also have a relative large production presence in SUVs and vans in recent years, their fuel economy is higher and some are above the fuel economy targets. Asian firms also did not produce pickup trucks, which are normally dominated by domestic firms.

\textsuperscript{19}Reynaert and Salle\textsuperscript{e} (2017) examine firms’ manipulation of fuel economy ratings in the case of the carbon emissions regulation for automobiles in Europe. They find the implementation of aggressive carbon policies coincided with a significant decline of the accuracy of laboratory-based carbon emission ratings. They show that even gaming causes consumers to mis-optimize which leads to a loss in consumer surplus, it could benefit consumers through lower prices as gaming allows firms to reduce their costs.
European firms are hurt by the ABR the most due to their least production of light trucks. The changes in firm profits are also in line with the lobbying efforts by different firms. Asian firms have been advocating a more uniform standard while domestic firms tend to support the attribute-based standard.

On one hand, the car-truck standard split leads to a higher relative price of passenger cars, which puts cars into a position of disadvantage. On the other hand, by offering light trucks a less-stringent target, firms with a larger share of passenger cars also lose revenues from selling excess credits to firms who produce more light trucks and run a credit shortage. Table 4 also shows the total profit of the automobile industry increases, which might be surprising at first sight. Even though removing the attribute basing increases the stringency of the regulation and makes firms bear a large compliance burden, it makes fuel-efficient passenger cars such as electric vehicles, hybrid vehicles and some fuel-efficient small and mid-sized gasoline cars more affordable, attracting consumers who were not originally planning to purchase a new vehicle to buy those cars, increasing the market size of new vehicles. The results imply that the implementation of the discrete attribute basing under CAFE deters the diffusion path of alternative fuel vehicle (AFVs) technologies. Due to the technology constraint such as the battery constraint, most of the alternative fuel vehicles are built on passenger car chassis. The ABR puts passenger cars into a disadvantage and indirectly negatively impact the growth of the market size of alternative fuel vehicles. Especially during the early deployment stage of a new technology, the car-truck standard split generates externalities in those AFV markets due to indirect network effects, and the total impact could be significantly large if taking into account of the feedback loops (Li et al. 2016). Figure 10 presents the impact of removing ABR on the profits of a selected group of automakers covering different countries of origin. The heterogenous impact on different firms reflect important heterogeneity that arises from the differences in firm’s product mix. Firms with a larger production share of fuel-efficient passenger cars are hurt by the attribute basing the most, while the firms with a larger production share of fuel-inefficient light trucks benefit more from ABR. With the removal of standard split between cars and trucks, domestic Big Three all experience a profit drop with Fiat-Chrysler suffering the largest profit decrease due

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20 As pointed in Section 6.2, small car buyers are more price sensitive than truck buyers and are more likely to switch between the outside option (public transportation and used cars) and new cars. It is expected that a uniform standard leads to a larger market size from an increasing number of new car buyers, more than offsetting the loss in the truck segment.

21 By the end of May 2017, 12 out of the 13 BEV models are passenger cars, 16 out of the 21 PHEV models are passenger cars, and the only 3 hydrogen vehicles are all passenger cars.

22 For example, a smaller number of EV sales would negatively impact the investment of charging stations, which would then further decrease the sales of EVs.
to its largest production share of light trucks (about 70%). Ford and GM also maintain a relatively fuel-efficient passenger car fleet compared with Fiat-Chrysler, as shown in Figure 4.\textsuperscript{23} With a uniform standard, the standard for passenger cars actually becomes looser while the standard for light trucks becomes more stringent. Many of the vehicles in the passenger car fleet of both Ford and GM generate abundant credits and their relative prices will be lower, attracting consumers who were originally planning to buy a light truck and who were not considering buying a new vehicle. The increase in profits from the passenger car fleet offsets part of the profit loss from the light truck segment. Fiat-Chrysler, on the other contrary, does not benefit much from the uniform standard due to their less-fuel efficient passenger car fleet, and thus the profit increase from its passenger car fleet is not able to offset much of the profit loss of their light truck fleet, leading to a larger profit loss. Tesla, which only produces EVs, benefits from the uniform standard by being able to generate more revenue from selling regulatory credits to other firms.

Among Asian firms, Toyota and Nissan experience a profit increase around 5%, while Honda suffers a profit loss about 0.6% from removing the discrete attribute basing. Even though Honda maintains a relatively fuel-efficient fleet for both passenger cars and light trucks, when the standard split is removed, the sales increase in the its passenger car fleet is not able to cover the profit loss from its light truck fleet, due to increased competition from Toyota and Nissan in the passenger car segment. Honda also has a higher production share of light trucks (40%) than Toyota (35%) and Nissan (29%) and thus suffer more compliance burden from the uniform standard (Figure 11). Among Asian firms, Honda is also considered as one of the “laggards” in electric vehicle industry with its minimum effort in investing EVs (Reichmuth and Anair\textsuperscript{[2016]}). Therefore, with a more stringent regulation, Honda is not able to rely on EVs to generate more credits as other automakers who lead the EV market. The European firms, however, all experience a profit increase due to their larger investment in passenger cars and the least production share of light trucks (about 20%). Combining Figure 10 and Figure 11 reveals a general pattern that the distributional effects of the discrete attribute basing is highly correlated with the production share of light trucks: firms with a larger light truck fleet suffer more from the removal of attribute basing.

The empirical findings here are consistent with Ito and Sallee\textsuperscript{[2016]} that attribute basing could achieve redistribution if policy makers want to shift welfare across producers based

\textsuperscript{23}Ford and GM are also more actively involved in the alternative fuel vehicle market. GM’s Chevrolet Volt has been one of the most popular PHEV models. Ford has introduced many popular hybrid and PHEV vehicles including Ford Fusion Hybrid, Ford C-Max Hybrid, Ford C-Max Energi, and Ford Fusion Energi. The uniform CAFE standard will benefit the two firms from the increase in sales of those AFV models. Chrysler is not an active player in either the hybrid or the EV segment.
on the secondary attribute. The CAFE regulators could use the car-truck standard split to redistribute producer surplus from foreign firms to domestic firms who produce a larger share of less fuel-efficient light trucks. However, the benefits of the distributional goals, possibly protectionism, should be evaluated against the potential welfare loss due to the distortion from the secondary attribute. When policy makers are designing the optimal standard difference, they should balance between maximizing the distributional goals (which requires an increase in the standard gap) and minimizing the welfare loss from the distortion in the secondary attribute (which requires a reduction in the standard gap).

ABR also decreases the vehicle market size by discouraging some consumers from buying new vehicles. Those consumers would then switch to the outside option by buying a used car or choosing public transportation. The implementation of ABR thus results in a redistribution of producer surplus across industries from the substitution to the outside option. Evaluating the impact of ABR across industries is beyond the scope of this paper and this study will evaluate the welfare impact within the automobile industry without taking account of the cross-industry profit redistribution.

6.3.3 Externalities

As indicated in the graphic illustration of Figure 5, the attribute basing results in a decrease in emission reduction and an increase in the market share of light trucks. Therefore, removing the car-truck standard split will reduce both the emission level and the sales of light trucks. A uniform standard will result in a market share of light trucks that is even smaller than the level in a no-regulation scenario. However, this is an efficient change rather than a distortion, reflecting that consumers internalize the externalities of gasoline consumption when choosing between a passenger car and a light truck.

Simulation results show that unifying the standards results in total reductions in vehicle lifetime gasoline consumption up to 1.61 billion gallons (or a 1.92% decrease) and CO₂ emissions up to 14.9 million metric tons over vehicle lifetime for the vehicles sold in 2014. The total external costs that could be saved from this reduction in CO₂ emissions by switching from the ABR to a uniform standard are estimated to be $0.54 billion. Through burning petroleum, vehicle use also generates certain criteria air pollutants, including volatile organic compounds (VOC), nitrogen oxides (NOₓ), fine particulate matter (PM₂.₅), and sulfur dioxide (SOₓ). The consumption of petroleum products also increases the external costs associated with dependence on oil imports. To quantify the economic value of reduction in criteria air pollutants and oil imports, I connect the changes of the fleet composition due to the uniform standards with the external costs associated with one gallon of gasoline usage using the
estimates adopted by NHTSA in evaluating the environmental benefits of CAFE standards, converted to 2014 dollars adjusting for inflation. The parameter values and sources are reported in Table 6 and the external cost savings from the removal of the discrete attribute basing are reported in Table 5. All of the numbers of externality savings reflect total vehicle lifetime changes from annual sales and are discounted to the model year 2014.\(^{24}\)

It is worthwhile noting the caveats underlying those estimates. First, the lifetime VMT is assumed to be fixed under the two CAFE scenarios. Under the uniform standard, consumers choose the fuel efficiency level higher than in the ABR, which could induce them to drive more due to the decreased cost of driving per mile for a given gasoline price, resulting in the rebound effects, which could undermine the policy gain from a more stringent CAFE. However, stricter fuel economy regulations encourage consumers to choose smaller and lower-performance vehicles, which reduces the marginal benefits of driving per mile. Thus, the rebound effects could be weakened by shrinking car size and the net response of miles could be zero or negative (Anderson and Sallee 2016; West et al. 2017). Second, the outside option is assumed not to consume any gasoline. In reality, all the other transportation methods (subway, buses, biking...) are lumped into the outside option with each consuming different levels of gasoline. Assessing the substitution with each of the alternative transportation mode in the outside option and evaluate the respective gasoline consumption change is beyond the scope of this paper. The simulation results show that removing the discrete attribute basing makes some consumers switch from the outside option to new cars, and assuming that the outside option does not consume gasoline would underestimate the gasoline savings from the uniform standard by the amount equaling to the total gasoline consumption from the outside choices.

Basing the stringency of the regulation on a secondary attribute is likely to create a undesirable byproduct if the distortion in the secondary attribute is related to an unwanted outcome or another externality that regulation does not intend to target. In addition to having a higher weight than passenger cars that impose greater risks to victims in a collision, light trucks are constructed to be taller implying a higher probability of hitting the head or the upper body of other road users. Light trucks also have stiffer frames that transfer more force to the victims, resulting in a higher probability of fatality (Gayer 2004; White 2004; Parry et al. 2007; Anderson 2008; Anderson and Auffhammer 2014). Consumers buy light trucks as a precautionary measure to protect themselves in a multi-vehicle collisions, while\(^{24}\) EPA assumes the total vehicle lifetime mileage to be 195,264 for passenger cars and 225,865 for light trucks. I assume a vehicle lifetime of 15 years for both passenger cars and light trucks and an annual mileage of 13,018 and 15,058 respectively. The annual discount rate is assumed to be 5%.
creating an externality to other road users due to a greater danger that light trucks impose to both other light trucks and passenger cars. This kind of “arms race” results in market share of light trucks larger than the socially optimal level (Li 2012). The differential treatment of passenger cars and light trucks under CAFE not only fails to correct for this externality, but exacerbates the externality by implicitly subsidizing light trucks and creating additional policy-induced distortion. By estimating consumer’s preference for reduced fatality risk in vehicle collisions, or the value of a statistical life (VSL), Li (2012) estimates that the accident externality imposed by a light truck during a 10-year discounted vehicle life time is equal to $2,444 in 2006. By updating parameters using 2014 market conditions, the accident-related externality is estimated to be $2,701 in 2014 dollars. The discrete attribute basing leads to an additional sales of 354,269 in light trucks. One back-of-the-envelop estimate implies that the increase in light trucks leads to a welfare loss of $0.96 billion. However, the uniform standard that removes the standard split between cars and trucks makes the fuel-efficient passenger cars more affordable, increasing the market size of new vehicles. Part of the external cost savings from fewer light trucks are offset by the increased automobile usage. To take account of this effect, the external cost of increased accidents from the additional cars are subtracted from the accident externality savings from the uniform standard by assuming all the consumers who switch from the outside option to new cars were not planning to buy any vehicle. The resulting net-savings in accident externalities from the uniform standard is estimated to be $0.42 billion.

This estimate provided here is relatively crude, which does not take account of the heterogeneity of the risks imposed by the vehicles within the light truck segment. A more accurate estimate would require a more detailed estimate of the additional probability of fatality that light trucks impose in a multi-vehicle collision for each of the light truck model, which currently is unavailable. The externality estimate here also does not include the externality that light trucks impose to road users other than vehicle occupants.

Figure 12 summaries the findings of the welfare consequences discussed above. Compared with the ABR, although a uniform standard results in larger loss in consumer surplus by making more consumers’ choices deviate from the private optima, the changes are rather efficient, resulting in a larger firm profit, and larger savings in external costs related to gasoline consumption and vehicle accidents, and eventually a net social welfare improvement up to $2.83 billion in MY 2014.

25The value of accident-related external cost from additional cars used for calculating accident externality savings from a uniform standard is reported in Table 6.
7 Conclusion

This paper investigates the welfare consequences of attribute basing on a discrete characteristic in the context of U.S. fuel economy regulation. Through a structural model of vehicle demand and supply, I run simulations of removing the standard split between passenger cars and light trucks and find that the discrete attribute basing raises the sales of light trucks by 4.9% and reduces the sales of passenger cars by 8.0%. The policy-induced sales increase of light trucks leads to increases of externalities associated with vehicle-lifetime pollutant emissions, carbon emissions, and oil imports amounting to $1.09 billion. Due to the structural difference of light trucks, the favorable treatment of light trucks also results in an increase in accident-related externalities equivalent to $0.42 billion. Although the uniform standard results in a larger deviation in vehicle choice away from consumer’s private optimum, much of the change is actually efficient and the uniform standard dominates the attribute basing policy by $2.83 billion in social welfare taking into account consumer surplus, firm profits and externalities. ABR redistributes producer surplus between domestic and foreign firms: the car-truck standard split increases the profits of domestic firms by 1.8% and reduces the profits of Asian and European firms by 1.5% and 4.0% respectively. However, the benefit of favoring domestic firms should be evaluated against the additional distortionary cost induced by the discrete attribute basing. Since most of alternative fuel vehicles are built on a passenger car chassis due to technology constraint, the standard split that puts passenger cars into disadvantage could potentially deter the diffusion of alternative fuel technologies and the negative impact could be multiplied due to the existence of indirect network effects. Results of this paper suggest that any political and distributional argument in favor of policy differentiation should be carefully evaluated against the significant distortions created by the difference in regulation stringency or policy incentive.

This paper has several limitations and motivates two lines of possible extensions. First, the vehicle supply framework is based on a static setup and assumes away credit banking and borrowing. Since my data sample covers MY 2012-14, a period when the fuel prices were quite stable and no significant demand shock occurred, the static solution of this study should approximate the dynamic solution when firms are allowed to carry credits backward or forward. Future work could model a firm’s dynamic decision in maximizing profits from vehicle and credit sales by incorporating the credit banking feature to investigate the impact of attribute basing on the automobile industry in a longer horizon. Second, this study assumes that automakers choose only price to maximize profit from vehicle and compliance credit sales. However, automakers in reality employ the strategy that is the least costly and
might apply a mixture of strategies to comply with the regulation. When the “sales-mix” strategy is rather expensive to adopt due to an increase in regulation stringency, automakers might seek alternative methods that result in lower compliance cost such as increasing fuel economy of existing models. Therefore, by restricting automakers to apply the “sales-mix” strategy, the results presented in this study would overestimate the policy impact from a more stringent standard. However, as long as the time horizon is short and the distribution of compliance burdens across fleets does not change, the qualitative findings in my study would remain. Further research that focuses on the long-term impact could estimate the distortionary cost of the discrete attribute basing by estimating the additional cost and resources that automakers put in designing light trucks to receive a more favorable regulatory treatment.
References


Davis, Lucas W. and Christopher R. Knittel, “Are Fuel Economy Standards Regres-


Kleit, Andrew N., “Impacts of Long-range Increases in the Fuel Economy (CAFE) Stan-


<table>
<thead>
<tr>
<th>Variables</th>
<th>2012</th>
<th></th>
<th>2013</th>
<th></th>
<th>2014</th>
<th></th>
<th>All Years</th>
<th></th>
</tr>
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<tr>
<td></td>
<td>Mean</td>
<td>Std.Dev</td>
<td>Mean</td>
<td>Std.Dev</td>
<td>Mean</td>
<td>Std.Dev</td>
<td>Mean</td>
<td>Std.Dev</td>
</tr>
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<td>Household income (1,000$)</td>
<td>121.38</td>
<td>97.71</td>
<td>122.83</td>
<td>108.31</td>
<td>122.47</td>
<td>97.78</td>
<td>122.26</td>
<td>101.39</td>
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<td>1.24</td>
<td>2.63</td>
<td>1.22</td>
<td>2.58</td>
<td>1.18</td>
<td>2.62</td>
<td>1.21</td>
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<td>0.59</td>
<td>0.49</td>
<td>0.59</td>
<td>0.49</td>
<td>0.59</td>
<td>0.49</td>
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<td>Living in an urban area</td>
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<td>0.48</td>
<td>0.61</td>
<td>0.49</td>
<td>0.63</td>
<td>0.48</td>
<td>0.63</td>
<td>0.48</td>
</tr>
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<td>Average commuting time (mins)</td>
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<td>5.96</td>
<td>25.57</td>
<td>5.83</td>
<td>25.47</td>
<td>5.88</td>
<td>25.54</td>
<td>5.89</td>
</tr>
<tr>
<td>Average gasoline price ($)</td>
<td>3.51</td>
<td>0.63</td>
<td>3.52</td>
<td>0.64</td>
<td>3.43</td>
<td>0.58</td>
<td>3.48</td>
<td>0.62</td>
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<tr>
<td>Average price of the purchased vehicle (1,000$)</td>
<td>28.89</td>
<td>12.98</td>
<td>29.66</td>
<td>13.68</td>
<td>30.44</td>
<td>13.97</td>
<td>29.71</td>
<td>13.58</td>
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<td>Purchasing a light truck</td>
<td>0.48</td>
<td>0.50</td>
<td>0.50</td>
<td>0.50</td>
<td>0.52</td>
<td>0.50</td>
<td>0.50</td>
<td>0.50</td>
</tr>
<tr>
<td>Average MPG of the purchased vehicle</td>
<td>25.09</td>
<td>7.39</td>
<td>25.83</td>
<td>8.55</td>
<td>26.30</td>
<td>9.27</td>
<td>25.77</td>
<td>8.50</td>
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<tr>
<td>Observations</td>
<td>2784</td>
<td>3032</td>
<td>3259</td>
<td>9075</td>
<td></td>
<td></td>
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Table 2: Demand Estimation Results

Panel (a): Parameters in Mean Utility

<table>
<thead>
<tr>
<th></th>
<th>(1) OLS</th>
<th></th>
<th>Coefficient</th>
<th>S.E.</th>
<th>(2) IV</th>
<th></th>
<th>Coefficient</th>
<th>S.E.</th>
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<tr>
<td>constant</td>
<td>8.1667</td>
<td>0.7080</td>
<td>6.3266</td>
<td>0.9295</td>
<td></td>
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<tr>
<td>log(price)</td>
<td>-1.2533</td>
<td>0.4987</td>
<td>-4.1081</td>
<td>1.0613</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>horsepower/weight</td>
<td>1.6455</td>
<td>0.7089</td>
<td>4.0015</td>
<td>1.0496</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>gallons/mile</td>
<td>1.6460</td>
<td>0.4862</td>
<td>1.2802</td>
<td>0.5161</td>
<td></td>
<td></td>
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<tr>
<td>weight</td>
<td>1.0295</td>
<td>0.2606</td>
<td>1.0167</td>
<td>0.2731</td>
<td></td>
<td></td>
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<tr>
<td>AFV dummy</td>
<td>-2.5336</td>
<td>1.0462</td>
<td>-3.0228</td>
<td>1.1280</td>
<td></td>
<td></td>
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<tr>
<td>van dummy</td>
<td>-0.1785</td>
<td>0.0323</td>
<td>-0.2166</td>
<td>0.0349</td>
<td></td>
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<tr>
<td>pickup dummy</td>
<td>-5.4737</td>
<td>0.5096</td>
<td>-5.3216</td>
<td>0.4880</td>
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<tr>
<td>SUV dummy</td>
<td>-0.8165</td>
<td>0.6849</td>
<td>1.4264</td>
<td>1.0017</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>model year 13 dummy</td>
<td>2.0349</td>
<td>0.1206</td>
<td>2.0104</td>
<td>0.1270</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>model year 14 dummy</td>
<td>1.5426</td>
<td>0.1031</td>
<td>1.5100</td>
<td>0.1050</td>
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<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel (b): Parameters in Heterogeneity Component

<table>
<thead>
<tr>
<th>Observed Heterogeneity</th>
<th>Coefficient</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(price)/income</td>
<td>-13.2672</td>
<td>0.6879</td>
</tr>
<tr>
<td>urban*pickups</td>
<td>-0.6819</td>
<td>0.0799</td>
</tr>
<tr>
<td>urban*afv</td>
<td>0.4064</td>
<td>0.1014</td>
</tr>
<tr>
<td>family size*vehicle weight</td>
<td>0.1067</td>
<td>0.0345</td>
</tr>
<tr>
<td>gasoline price*gallons/mile</td>
<td>-0.0747</td>
<td>0.0221</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Random coefficients</th>
<th>Coefficient</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>gallons/mile</td>
<td>0.3858</td>
<td>0.0136</td>
</tr>
<tr>
<td>horsepower/weight</td>
<td>5.2485</td>
<td>0.1690</td>
</tr>
<tr>
<td>light trucks</td>
<td>2.8224</td>
<td>0.2537</td>
</tr>
</tbody>
</table>

| Own-price Elasticity   | -5.51       |

Note: the number of observations are 9075. log-likelihood at convergence: -94215.03. 150 Halton draws are used for simulating the unobserved heterogeneity. The instrument variables used to estimate the linear parameters are the difference and squared difference in characteristics with other products in the same firm and in other firms.
Table 3: Market Outcomes of a Uniform Standard

<table>
<thead>
<tr>
<th>Segment</th>
<th>No.of Models</th>
<th>Average Price($)</th>
<th>Price Change ($)</th>
<th>Sales in 2014</th>
<th>Sales Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>cars</td>
<td>260</td>
<td>29,745</td>
<td>-471.0</td>
<td>6,264,019</td>
<td>8.0%</td>
</tr>
<tr>
<td>suvs</td>
<td>147</td>
<td>36,773</td>
<td>2215.9</td>
<td>4,736,461</td>
<td>-1.5%</td>
</tr>
<tr>
<td>vans</td>
<td>14</td>
<td>27,382</td>
<td>2988.7</td>
<td>106,266</td>
<td>-12.2%</td>
</tr>
<tr>
<td>pickup trucks</td>
<td>38</td>
<td>40,622</td>
<td>4317.2</td>
<td>1,780,584</td>
<td>-11.9%</td>
</tr>
<tr>
<td>light trucks</td>
<td>199</td>
<td>38,270</td>
<td>2766.2</td>
<td>6,623,311</td>
<td>-4.9%</td>
</tr>
</tbody>
</table>

Note: the average prices reported are sales-weighted. The price changes are sales-weighted average price changes per model, summarized by segment.

Table 4: Firm Profit Impact from Removing Attribute Basing

<table>
<thead>
<tr>
<th>Firms</th>
<th>Profit Change (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Domestic</td>
<td>-1.77</td>
</tr>
<tr>
<td>European</td>
<td>4.03</td>
</tr>
<tr>
<td>Asian</td>
<td>1.53</td>
</tr>
<tr>
<td>Total</td>
<td>0.89</td>
</tr>
</tbody>
</table>
Table 5: Welfare Consequences of Removing Attribute Basing

<table>
<thead>
<tr>
<th>Welfare</th>
<th>billion $</th>
</tr>
</thead>
<tbody>
<tr>
<td>∆ Consumer surplus</td>
<td>-0.98</td>
</tr>
<tr>
<td>∆ Firm profit</td>
<td>2.30</td>
</tr>
<tr>
<td>∆ Pollutant emission externality savings</td>
<td>0.24</td>
</tr>
<tr>
<td>∆ GHG emission externality savings</td>
<td>0.54</td>
</tr>
<tr>
<td>∆ Oil imports externality savings</td>
<td>0.31</td>
</tr>
<tr>
<td>∆ Accident externality savings</td>
<td>0.42</td>
</tr>
<tr>
<td>∆ Total social welfare</td>
<td>2.83</td>
</tr>
</tbody>
</table>

Note: the external cost savings are vehicle lifetime savings discounted to year 2014. Pollutant emission externality savings include VOC, NO\(_x\), PM\(_{2.5}\) and SO\(_2\). The parameters used for external cost calculation are reported in Table 5.

Table 6: Parameters for External Cost Calculation

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discount rate</td>
<td>5%</td>
<td></td>
</tr>
<tr>
<td>Lifetime VMT for cars</td>
<td>195,264</td>
<td>EPA (2014)</td>
</tr>
<tr>
<td>Lifetime VMT for trucks</td>
<td>225,865</td>
<td>EPA (2014)</td>
</tr>
<tr>
<td>Emission rates</td>
<td>grams/gallon</td>
<td></td>
</tr>
<tr>
<td>VOC</td>
<td>24.9</td>
<td>EPA (2008)</td>
</tr>
<tr>
<td>NO(_x)</td>
<td>16.7</td>
<td>EPA (2008)</td>
</tr>
<tr>
<td>PM(_{2.5})</td>
<td>0.1</td>
<td>EPA (2008)</td>
</tr>
<tr>
<td>SO(_2)</td>
<td>0.17</td>
<td>EPA (2008)</td>
</tr>
<tr>
<td>Emission damage costs</td>
<td>$/ton (2014 value)</td>
<td></td>
</tr>
<tr>
<td>VOC</td>
<td>1,482</td>
<td>NHTSA (2010)</td>
</tr>
<tr>
<td>NO(_x)</td>
<td>6,042</td>
<td>NHTSA (2010)</td>
</tr>
<tr>
<td>PM(_{2.5})</td>
<td>330,600</td>
<td>NHTSA (2010)</td>
</tr>
<tr>
<td>CO(_2)</td>
<td>36</td>
<td>EPA (2016)</td>
</tr>
<tr>
<td>External cost of oil imports ($/gallon)</td>
<td>0.17</td>
<td>EPA (2008)</td>
</tr>
<tr>
<td>External cost of additional light truck ($/ unit)</td>
<td>2.444</td>
<td>Li (2012)</td>
</tr>
<tr>
<td>External cost of additional car ($/mile)</td>
<td>0.026</td>
<td>NHTSA (2010)</td>
</tr>
</tbody>
</table>
Figure 1: Historic CAFE standard split between passenger cars and light trucks

Data source: U.S. Department of Transportation

Figure 2: GHG emission standard split for passenger cars and light trucks in MY 2016

Figure 3: Annual market share of passenger cars and light trucks in the U.S.

Data source: data on market shares of passenger cars and light trucks are from Ward’s Automotive Reports, and data on annual average fleet fuel economy from 1980 to 2015 are obtained from U.S. Bureau of Transportation Statistics.
Figure 4: GHG emission targets and actual fleet-average emissions

Panel (a) Passenger cars

Panel (b) Light trucks

Notes: The blue squares represent the sales-weighted average emission per mile. The green dots represent the GHG emission standard targets for the corresponding footprint level.
Figure 5: Graphic illustration of discrete attribute basing

Panel (a) Uniform Standard

Panel (b) Discrete Attribute Basing

Notes: the horizontal axis represents the market share of light trucks (s), while the vertical axis represents the emission level (e). The uniform standard assigns an emission mandate at k. The policy of discrete attribute basing assigns a standard k₁ for passenger cars and k₂ for light trucks.
Figure 6: Own-price elasticity estimates

Figure 7: Estimates of price-cost margins
Figure 8: Uniform footprint-based standards for MY 2014

Notes: the uniform footprint-based standards use the sales-weighted average parameters of the passenger car and light truck fleets for the emission standard formula.
Figure 9: Price changes due to removal of attribute basing

Panel (a) Price impact on passenger cars

Panel (b) Price impact on light trucks

Notes: the figure plots the price changes due to the removal of the car and truck standard split. Fuel efficient vehicles would experience a price decrease with the largest reductions from EV models. All the light trucks experience a price increase with the largest increase from the least fuel-efficient models.
Figure 10: Firm profit changes due to removal of attribute basing

Figure 11: Production share of light trucks in MY 2014
Figure 12: Welfare changes by removing the discrete attribute basing

Notes: The figure shows the welfare impacts from removing the attribute basing. All the welfare changes are capitalized to 2014 $ and are recorded in billion $. Oil consumption externality savings include savings of external costs from air pollutant emissions, CO$_2$ emissions and oil imports.
Appendices

Proof of proposition 1

**Proposition 1:** Where there is compliance trading and the only regulatory goal is to target the emission externality with no distributional considerations, the optimal policy should have a uniform standard such that:

\[ \sigma^* = 0. \]

The regulator maximize the welfare \( W \), which is sum of the expected utility from vehicle purchase and expected revenue from noncompliance fines less the expected external cost from vehicle emissions, by choosing the policy parameters \( k, \sigma \) and \( t \):

\[
\max_{k, \sigma, t} W = \mu \ln(\exp(V_c/\mu) + (\exp(V_t/\mu)) + t((1-s)(e_c - k) + s(e_t - k - \sigma)) - \delta((1-s)e_c + se_t)
\]

To ease exposition, denote the following three terms as the expected consumer utility, the revenue from noncompliance punishment, and the externality from emissions respectively:

\[
V = \mu \ln(\exp(V_c/\mu) + (\exp(V_t/\mu)) \\
T = t((1-s)(e_c - k) + s(e_t - k - \sigma)) \\
E = \delta((1-s)e_c + se_t)
\]

First note that \( \frac{\partial V_c}{\partial \sigma} = \frac{\partial V_t}{\partial \sigma} = 0 \), \( \frac{\partial V_c}{\partial \sigma} = \frac{\partial V_t}{\partial \sigma} = \sigma \) by the envelop theorem. The optimal value for the standard difference \( \sigma^* \) could be found by setting the first order condition of \( W \) with respect to \( \sigma \) equaling to zero. The first order conditions of the three terms with respect to \( \sigma \) are:

\[
\frac{\partial V}{\partial \sigma} = \mu \frac{\frac{1}{\mu} \exp(V_c/\mu) \frac{\partial V_c}{\partial \sigma} + \frac{1}{\mu} (\exp(V_t/\mu)) \frac{\partial V_t}{\partial \sigma}}{\exp(V_c/\mu) + (\exp(V_t/\mu))} = \frac{\exp(V_t/\mu) \lambda}{(\exp(V_c/\mu) + (\exp(V_t/\mu))} = s \lambda
\]
\[
\frac{\partial T}{\partial \sigma} = t[\frac{\partial (1-s)}{\partial \sigma}(e_c - k) + (1-s)\frac{\partial (e_c - k)}{\partial \sigma} + \frac{\partial s}{\partial \sigma}(e_t - k - \sigma) + s\frac{\partial (e_t - k - \sigma)}{\partial \sigma}]
\]
\[
= t[-\frac{\partial s}{\partial \sigma}(e_c - k) + \frac{\partial s}{\partial \sigma}(e_t - k - \sigma) + s(\frac{\partial e_t}{\partial \sigma} - 1)]
\]
\[
= t\frac{\partial s}{\partial \sigma}(e_t - e_c) - t\frac{\partial s}{\partial \sigma} + ts\frac{\partial e_t}{\partial \sigma} - ts
\]

\[
\frac{\partial E}{\partial \sigma} = \delta[\frac{\partial (1-s)}{\partial \sigma}e_c + (1-s)\frac{\partial e_c}{\partial \sigma} + \frac{\partial s}{\partial \sigma}e_t + s\frac{\partial e_t}{\partial \sigma}]
\]
\[
= \delta[-\frac{\partial s}{\partial \sigma}e_c + \frac{\partial s}{\partial \sigma}e_t + s\frac{\partial e_t}{\partial \sigma}]
\]
\[
= \delta\frac{\partial s}{\partial \sigma}(e_t - e_c) + \delta s\frac{\partial e_t}{\partial \sigma}
\]

Therefore the first order condition of \(w\) with respect to \(\sigma\) is:
\[
\frac{\partial W}{\partial \sigma} = \frac{\partial V}{\partial \sigma} + \frac{\partial T}{\partial \sigma} - \frac{\partial E}{\partial \sigma}
\]
\[
= s\lambda + t\frac{\partial s}{\partial \sigma}(e_t - e_c) - t\frac{\partial s}{\partial \sigma} + ts\frac{\partial e_t}{\partial \sigma} - ts - \delta \frac{\partial s}{\partial \sigma}(e_t - e_c) - \delta s\frac{\partial e_t}{\partial \sigma}
\]

An optimal policy requires the regulator to set \(k^*\) such that the equilibrium regulatory credit price (or the marginal compliance cost) is equal to the marginal benefit of one unit of emission reduction \(\delta\): \(\lambda = \delta\). The regulator is also going to set the fine payment for one unit of noncompliance at the same price of the regulatory credit. Otherwise, no firm would comply with regulation but voluntarily pays the fine. Therefore, an optimal regulation implies that \(\lambda = t = \delta\). The above first order condition reduces to:
\[
\frac{\partial W}{\partial \sigma} = -t\frac{\partial s}{\partial \sigma}
\]

Setting the first order condition to zero and solving for \(\sigma\) gives:
\[
\sigma^* = 0.
\]