# Abatement Strategies and the Cost of Environmental Regulation: Emission Standards on the European Car Market.

Job Market Paper

Mathias Reynaert*

January 2015

**Abstract**

Emission standards are one of the major policy tools to reduce greenhouse gas emissions from transportation. The welfare effects from this type of regulation depend on how firms choose to abate emissions: by changing relative prices, by downsizing their fleet or by adopting technology. This paper studies the response of firms to a new emission standard in the European car market using panel data covering 1998-2011. The data show that firms choose to comply with the regulation by adopting new technology. To evaluate the welfare effects of the regulation I estimate a structural model using data from before the policy announcement and explicitly test the ability of the model to explain the observed responses. I find that, because the abatement is done by technology adoption, consumer welfare increases and overall welfare effects depend on market failures in the technology market. The design of the regulation matters to induce technology adoption.

*University of Leuven, University of Antwerp and Ph.D. fellow of the Research Foundation Flanders (FWO) Email: Mathias.Reynaert@kuleuven.be. I would like to thank Bruno De Borger, Jim Sallee and Frank Verboven for their support and councel. This paper also benefited from helpful comments at various stages from Jan Bouckaert, Kenneth Gillingham, Laura Grigolon, Ali Hortaçsu, Thomas Peeters, Stef Proost, Jesse Shapiro, Andreas Steinmayr, Chad Syverson, Jo Van Biesebroeck, Arvid Viaene and several audiences at the University of Chicago, University of Leuven and McMaster University. Funding for this project was generously provided by the Flemish Research Foundation Flanders (FWO).

# 1 Introduction

Transportation accounts for 20% of global greenhouse gas emissions and policy makers are taking up the challenge to reduce the use of polluting petroleum liquids. The major policy tool used to control emissions in transportation are regulations that set mandatory limits on average emission rates (or fuel economy) across the fleet. These policies are simple to prescribe but difficult to evaluate because their welfare impact depends on the way in which firms choose to comply, that is whether firms choose to change prices, downsize their fleet or adopt new technologies. The European Union (EU) recently began rolling out its first greenhouse gas emission regulation regime.

The EU emission standard limits sales weighted $CO_2$ emissions across the fleet to 130 g/km. The regulation was announced in 2007 and is fully binding by 2015, after a phase-in period that started in 2012. The regulation places a simple cap on the average emissions of new vehicle sales and does not allow firms to trade excess emissions. The regulation aims to reduce $CO_2$ emissions from passenger cars by 18%. The EU standard is significantly more demanding than similar regulations in Australia, Canada, China and the US. The EU standard translates into about 42 miles per gallon (mpg)[1] for gasoline engines, whereas the Corporate Average Fuel Efficiency (CAFE) standard in the US requires only 36 mpg in 2016. In recent years most governments have decided on, or are discussing a further tightening of emission standards.[2] The observed response to the EU standards can thus be regarded as an important signal for future responses in other markets across the world.

This paper evaluates the EU emission standard using panel data covering 1998-2011 for seven European countries. The paper makes several contributions. First, this paper uses an approach new to the literature that studies the CAFE standards in the US. I observe a strong policy shock: the announcement of one of the most stringent standards in the world, and find that the EU emission standard induces technology adoption by firms, an abatement strategy not considered in the existing literature. Second, I estimate a structural model of demand and supply to show that the incidence and the welfare effects of the regulation are very different under technology adoption than under other possible abatement strategies previously considered in the literature. Third, the paper gives an example of how to validate

[1] Note that miles per gallon is the inverse of liters per 100 km, the unit to denote fuel efficiency in the EU. Liters per 100 km translates proportionally into grams of $CO_2$ per km, with a different $CO_2$ content per liter for diesel and gasoline.

[2] The International Council on Clean Transportation (2014) compares different regulations between countries. The EU has the goal of decreasing emissions to 95g/km by 2021, the US has communicated a goal of 103 g/km by 2025, Japan 105g/km by 2020 and China 117g/km by 2020.

structural models before simulating different counterfactual outcomes. Fourth, to the best of my knowledge, this is the first paper providing a detailed evaluation of the EU regulation. Fifth, I study the impact of the attribute-based design of the regulation, so that the emission target varies with vehicle weight, and find that this is important to induce abatement by technology adoption. My analysis proceeds in several steps.

In a first step I explain the sources of the observed 14% reduction in sales weighted $CO_2$ emission between 2007 and 2011. A first strategy to abate emissions is changing the sales mix. By shifting relative prices of vehicles with different fuel efficiency firms lower the average emission of their existing fleet. I call this sales mix abatement. A second strategy is abatement through the release of smaller but more fuel efficient vehicles, I call this downsizing. A last abatement strategy of firms is the introduction of new technology that makes engines more fuel efficient. Following the approach of Knittel (2011), I estimate technological improvements in the trade-off that firms face between fuel efficiency and other engine characteristics. I find that the 14% reduction in emissions between 2007 and 2011 is fully explained by increases in the adoption of technology. The reduction cannot be explained by downsizing of the vehicle fleet neither by sales-mixing. The increase in fuel efficiency from technology is so strong that almost all of the firms reach the target of the regulation before it becomes partly binding in 2012. This allows me to evaluate the policy without data that covers the actual binding stage of the program. The response to the regulation between announcement and full implementation reveals the abatement strategy chosen by the firms. These findings are in contrast with the literature that studies the effects of the CAFE regulation in the US. This literature mostly treats changes in the level of technology as a possible longer run effect of the regulation and has focused on the effects from changes in relative prices and more recently, changes in other product characteristics.

Goldberg (1998) was the first to consider the effect of standards on price setting and the composition of the vehicle fleet. Jacobsen (2013) builds on this analysis by incorporating heterogenous responses from both consumers and producers. He finds that the CAFE standard imposes a large shadow cost on the domestic US firms. A one mile per gallon increase in the CAFE standard is predicted to reduce the sum of consumer surplus and profits by at least \$20 billion per year. This result is somewhat in contrast with Anderson and Sallee (2011) who, using a loophole in the regulation, show that the standard is hardly binding in recent years and imposes a very low shadow cost on producers. Both Klier and Linn (2012) and Whitefoot, Fowlie and Skerlos (2013) extend the analysis by considering endogenous product characteristics in the model. Both papers estimate a model that allows car makers to respond in the short run by adapting the sales mix through prices and in the medium run through adapting the type of products they offer. This softens the welfare effects of the regulation in the long run as firms have a greater flexibility on how to react to the standard. Still, Klier and Linn (2012) report yearly welfare losses in the order of $13 billion of a one mile per gallon increase in the standard. This literature simulates the effects of a tightening in the CAFE standards while the EU regulation provides me a unique and strong policy shock: the announcement and implementation of a very strict and binding emission standard. The response to this policy shock reveals that technology adoption is the primary abatement strategy to the EU regulation and previous literature did not take this into account. The incidence of the regulation under technology adoption and the overall welfare effects are an empirical question. The effect on consumer surplus is uncertain as buyers trade-off lower fuel costs with higher prices. The effect on profits is uncertain as demand, marginal cost and competing products change.

In the second step I therefore estimate and explicitly validate a structural model that will allow me to simulate the welfare effects from technology adoption and to compare the effects with those of other abatement strategies. The model allows for heterogenous tastes of consumers for several characteristics, including fuel costs. I follow the methodology proposed by Berry, Levinsohn and Pakes (1995), denoted as BLP. Marginal costs are estimated through the first order conditions assuming an oligopoly Nash-Bertrand game on the supply side. I instrument for prices using cost data on the location of production.

Before calculating welfare effects from policy simulations it is important to assess the ability of the structural model to predict counterfactual outcomes. In recent years there have been questions regarding the validity of structural estimation in general, see for example Angrist and Pischke (2010), and of the BLP model in particular, see for example Knittel and Metaxoglou (2014). I try to address these concerns in two ways. First, I estimate the model using recent methodological advances, such as approximate optimal instruments, see Reynaert and Verboven (2014), and I carefully check the properties of the obtained minimum. Second, the long time frame of the data (1998-2011) allows me to estimate the demand and cost functions using only data from before the regulation (1998-2007). I then proceed by testing how well the model is able to explain prices and quantities out of the estimation sample in 2011 (the last year of my data). Due to the large difference in fuel efficiency between 2007 and 2011 consumers face a different choice set in 2011 and this creates an opportunity to test the ability of the model to explain prices and quantities in the new choice set. I find that the model is able to replicate sales weighted characteristics and prices reasonably well, showing that consumer tastes are accurately identified.

Only after testing the ability of the estimated model to predict the observed response to the policy I proceed to evaluate the impact of different policy simulations. This is similar to the approach taken by Todd and Wolpin (2006) and Kaboski and Townsend (2011). Also in the industrial organization literature several market shocks such as mergers (Weinberg and Hosken (2013)), sudden tax increases (Rojas (2008)), and the introduction of new products (Hausman and Leonard (2002)) have been used to test commonly used estimation methods and underlying assumptions.

In a third step I use the estimated model to simulate the incidence and total welfare effects of the regulation under different abatement strategies. I find that if firms respond by adding new technology consumer surplus increases by a total of $10 billion per year relative to consumer surplus from the existing 2007 market. This is in sharp contrast with the decrease in consumer surplus of $26 billion per year if the firms would have responded with sales-mixing. The incidence of the regulation thus shifts completely to firms that have to make fixed costs to adopt the new technology. The reduction in greenhouse gas emissions under technology adoption is limited: a decrease of 6%.

Emission savings are partly countered by an increase in total sales relative to the no policy sales in 2007. Total sales increase because of a rebound effect on the extensive margin: consumers decide to buy more vehicles. The increase in sales also increases other externalities, such as accident risk and congestion. Overall, I estimate an upper bound on the welfare effects of the regulation of a €240 million loss per year. This excludes the fixed cost of increased R&D to develop the necessary technology on which I have no data. If firms had responded by shifting the relative prices of their products to adapt their sales mix the overall effect would be a yearly loss of more than €20 billion per year.

In a final and fourth step, I look at the attribute-based design of the regulation. This design, that lets the emission target vary with average weight of each producer, makes sales-mix abatement much more costly for firms and thus increases the likelihood that firms will increase their pace of technology adoption. In general, the difference in welfare effects between sales-mix abatement and technology adoption shows that policy makers should design the regulation such that the latter strategy is chosen. Attribute-based regulation might be one of the tools to achieve that. As Ito and Sallee (2014) point out attribute-basing of a regulation has several potential other economic effects such as distortions in the market for the attribute and redistribution of compliance costs between firms. Throughout the paper I will come back to these issues which reveal interesting insights about the political economy in the design of the EU regulation.

Since the regulation induces investment in technology its effect on social welfare depends on possible market failures in the technology market. A first source of market failures in technology adoption could be investment inefficiencies of the consumer. If consumers don't value future fuel cost savings to the full extent, firms will not be able to increase sales after investments in fuel efficiency. However, Grigolon, Reynaert and Verboven (2014) find that, using similar data, consumer investment inefficiencies in the EU are not large.[3] In the structural model I also find that consumers do respond to changes in fuel economy to such an extent that this channel cannot explain why firms hardly invest in fuel efficiency up until 2007. A second channel might be market failures in technology adoption related to fuel efficiency. See Jaffe, Newell and Stavins (2005) who discuss knowledge and adoption externalities and incomplete information as market failures. These failures result in a socially suboptimal equilibrium with none or too little investments.[4] Emission standards might be one of the instruments to move the whole industry out of this equilibrium. Testing the hypothesis of a suboptimal equilibrium in fuel efficiency investment would require data on the fixed costs of R&D related to fuel efficiency and a dynamic model of technology investment. Recent work, such as Hashmi and Van Biesebroeck (2012) and Aghion, Dechezleprêtre, Hemous, Martin and Van Reenen (2012) , has looked at R&D patterns in the automobile industry through patents. In sum, a possible explanation for the effectiveness of the regulation may stem from underinvestment in R&D by firms. However, detailed data on R&D expenses and fixed costs are typically not easily observable and a full analysis is out of scope for this paper.

Though the range and the detail of the data that I use in this paper are extensive, I am not able to cover all possible effects of the regulation. In the literature there has been considerable attention for the rebound effect. If consumers buy more fuel efficient vehicles, the cost per kilometer of driving the vehicle goes down and the demand for vehicle miles might increase. This further erodes the savings in greenhouse gas emissions as total vehicle miles increase. Gillingham (2012) for example uses detailed micro-level data from California to look at the interaction between the vehicle choice and the amount of driving. The data also limit my focus to new vehicle sales. Jacobsen and van Benthem (2013) study the effect of emission standards on vehicle scrappage rates. They find that efficiency standards increase vehicle lifetime. This further erodes predicted emission savings by 13-16%. The effect, also known as the Gruenspecht effect, is a consequence of changes in relative prices between new and second-hand vehicles. When firms respond to the policy with sales-mixing new polluting vehicles become more expensive, which increases demand for older polluting

[3] Allcott and Wozny (2012) find similar moderate undervaluation of future fuel savings for US consumers.

[4] It is perhaps striking that the industry itself agreed to step into a nonbinding agreement in 1998 but failed to reach the targets. The voluntary agreement aimed to bring each producer's sales weighted emissions down to 140 g $CO_2$/km by 2008. The agreement is considered a failure (only the small car makers Fiat, PSA and Renault came close to the goal) and we see strong reductions in emissions only taking place after 2007.

vehicles. My results might potentially reverse the predictions by Jacobsen and van Benthem (2013) as new vehicles become more attractive in comparison to the existing fleet, potentially decreasing vehicle lifetime through a faster replacement rate. Further interesting research opportunities thus exist on how the effects of emission standards differ with alternative abatement strategies.

The paper is structured as follows. Section 2 describes the policy and the available data in more detail. Section 3 presents emission standards in a model of supply and demand and discusses the effects of the different abatement strategies. Section 4 explains the changes in the automobile market between 2007 and 2011 and shows the technological improvements in fuel efficiency. Section 5 presents estimation results and tests the out of sample performance of the model. Section 6 presents the results of policy simulations and Section 7 concludes.

# 2 Background on the EU emission standard and data

## 2.1 The EU emission standard

The European regulation on emission standards for new passenger cars, Regulation (EC) No. 443/2009 , sets a mandatory fleet average of 130 grams $CO_2$ per kilometer. The target is set for each producer's fleet of new vehicle sales in a calendar year and trading of excess emissions between producers is not allowed. The standard is an example of an attribute-based regulation (ABR). An attribute-based regulation specifies a target that is correlated with another characteristic of the product. Panel I in Figure 1 plots both a flat and an attribute-based target as a function of characteristic $X$. Products in B and C are under the ABR and contribute to reduce sales weighted emissions, for the flat standard products in C and D contribute to compliance. For the EU regulation the emission target varies with weight. The emissions of each vehicle are adjusted by the distance in weight $w_j$ from a shifting point $w_0$ (the pivotal weight point). The shifting point $w_0$ is a mass of 1370 kg and the difference in weight from that point is multiplied by $a = 0.046$. For example, a vehicle weighing 1370 kg, a standard hatchback, has a target of exactly 130 g $CO_2$/km, the target for an SUV weighting 1650 kg is 143 g/km, while a compact car of 1250 kg has a target of 124 g/km. The exact target for each producer is the following sales weighted average:

$$\frac{\sum_{j \epsilon fleet} q_j(e_j - a(w_j - w_0))}{\sum_{j \epsilon fleet} q_j} \leq 130 \tag{1}$$

in which $q_j$ are sales in the EU in a given calendar year, $a$ is the slope of the target function, $w_j - w_0$ is the distance from the pivotal weight point and the sum is over all vehicles $j$ a producer sold.[5]

The regulation was proposed by the European Commission in 2007 and became a European law in 2009. Deters (2010) gives an overview of the full legislative process and the political background. The regulation will be fully binding in 2015 after a phase-in period of several years starting in 2012. In 2012, 65% of manufacturer's sales had to comply with the emission standard. This rose to 75% in 2013, 80% in 2014 and the standard is fully binding from 2015 onwards.

When producers exceed the standard they have to pay premiums for excess emissions. The premium is €5 per unit sold for the first excess g/km and increases to €95 per unit above 134 g/km. A manufacturer obtaining a sales weighted emission of 146 g/km, the average in 2007 when the regulation was announced, would face a significant penalty of €1280 per vehicle (the average price of a vehicle in the sample is €22,250).[6]

The specifics of the regulation were heavily debated during the drafting of the law. Several newspaper reports discuss lobbying efforts by EU member states, firms and environmental groups.[7] France and Italy were strongly in favor of a flat standard, while Germany wanted an upward sloping target function in either weight or footprint (the rectangular area in between the wheels of the vehicle). The German firms BMW, Daimler and Volkswagen on average make heavier vehicles than Fiat (Italian), Renault and PSA (French). The production of each of these firms mostly takes place within the boundaries of the home country and the car sector is an important source for employment.

It is instructive to compare the EU policy with the US CAFE standard since this policy has been the subject of several studies. The CAFE standard came into place in 1978 and after a gradual phase-in has been constant at 27.5 mpg since 1990 (this corresponds to 198 g $CO_2$/km). From 2009 onwards CAFE standards are tightened towards 36 mpg in 2016 (this corresponds to 152 g $CO_2$/km). Contrary to the EU standard, light trucks (SUV's) face a different less demanding target than passenger cars. Also, firms are allowed to trade

[5] Manufacturers can also obtain lower average emissions by gathering super credits. These credits are given for vehicles that emit less than 50g/km. There are also seperate standards for small manufacturers making less than 30 000 vehicles per year. Both of these exceptions are ignored in the analysis since they count for a very small share of the total market.

[6] Contrary to the CAFE standards in the US there is no banking system for excess emissions over time. The penalties in the EU are lower for low excess emissions but increase to higher levels than the penalties for breaking the US CAFE standards.

[7] See for example "EU unveils tough emissions curbs for cars" - Financial Times, February 7 2007 and "France battles Germany over car emissions" - Financial Times, November 15 2007.

excess emissions over time and with other firms. This makes the CAFE standard a cap and trade regulation while the EU standard is a simple cap per firm. From 2012 onwards the CAFE standard also has an attribute-based part: the target varies with footprint. This is described in more detail by Ito and Sallee (2014), who also give a detailed overview of the fuel economy standard used in Japan. Japan is the only country in the world that has a similar target as the EU in terms of emissions, but the Japanese market is unusual in the sense that micro-cars (Kei cars) have a large market share.

## 2.2 Data

The main data set is obtained from a market research firm (JATO dynamics) and contains a rich panel of the European car market. The data include sales and product characteristics for each passenger car sold during 1998-2011 in seven European countries: Belgium, France, Germany, Italy, Great Britain, The Netherlands and Spain. These markets represent around 90% of the total EU market.

Characteristics and sales are given for several engine variants of a car model. A model is defined as a brand/model/body type combination (e.g., Volkswagen Golf Hatchback). The engine variants differ in fuel type (gasoline or diesel) and engine performance. Accounting for fuel type is important in the EU market as diesel variants have a considerable market share (56% in 2011) and the $CO_2$ emissions of diesel variants are lower; a diesel engine emits about 20% less $C0_2$.[8]

Sales are defined as new vehicle registrations in each of the countries. Prices are suggested retail prices (including registration taxes and VAT as obtained from the European Automobile Association). The product characteristics included in the analysis are measures of fuel efficiency (liters per 100 km and $CO_2$ emissions per km), vehicle size (footprint which is defined as length by width, weight and height) and engine performance (horsepower and displacement).[9]

The data on sales are supplemented with production data for each model. This data comes from PriceWaterhouseCoopers (PWC) and contains the country and plant of production for each model. I match this data with a producer price index and a unit labor cost measure obtained from the OECD. Finally, data on fuel prices (from DataStream),

[8] The combustion process and different energy content of the fuel make diesel engines more efficient per kilometer.

[9] $CO_2$ emmisions and fuel consumption are obtained from the New European Driving Cycle (NEDC). This is a standardized driving cycle to assess the emission levels of car engines. The cycle simulates both urban and extra-urban driving patterns and excludes the use of auxiliary features like air conditioning. Real world emissions thus differentiate from these test values. I will come back to this point below.

GDP/capita and number of households in each country (from Eurostat) are used to construct fuel costs for consumers, real prices and the number of potential buyers in each year.

Throughout the paper, the full dataset is partitioned over time and markets in several ways. To reduce the size of the data and complexity of the analysis, I leave out firms, brands and models with very low sales. The analysis will focus on the largest producers and their best selling brands on the EU market. The included firms are BMW, Daimler, Fiat, Ford, General Motors, PSA, Renault and Volkswagen. I treat the largest Asian car makers as one decision maker. This includes the firms Honda, Hyundai, Mitsubishi, Nissan, Suzuki and Toyota. Jointly, the Asian firms are the 6th largest seller on the market and sell about the same amount of vehicles as Fiat (the 7th largest producer). The list of included brands and a detailed description of the model selection and data manipulations can be found in the appendix. In total I keep 40,239 market/year/model/engine variants in 98 year/countries, or about 400 model engine variants per market. The final data contains 80% of total reported sales in the sample.

In Section 4, I collapse the data towards a unique model engine variant in each year and leave out the variation over markets. This data is used to make statements on the evolution of the supply of engine characteristics over time and contains 12,659 unique observations. To estimate the structural model I will rely only on data prior to the policy announcement and use the years 1998-2007. This exploits 30,000 year/market/model-engine observations. I will use the last year of data (2011) to test the validity of the structural model. Finally, the data from year 2007 will be used as the benchmark for the simulations in Section 6.

## 2.3 Summary Statistics

Figure 2 plots sales weighted characteristics over time from 1998 to 2011 for both the EU (Panel I) and the US (Panel II). Each characteristic is indexed in 1998. The most remarkable trend in the EU is the evolution of sales weighted $CO_2$ emissions. The level of emissions is constant up until 2002, slightly declines about 6% until 2007, and then plunges by 14% in the last four years of the sample. This shift coincides exactly with the announcement of the fuel efficiency standard by the European Commission. Historically, the 14% drop is a large improvement in efficiency over a short period of time. Klier and Linn (2012) show that the most severe tightening of the US CAFE standards sparked an increase of 42% in fuel efficiency over an 8 year period (1975-1982). The US increase in fuel efficiency was associated with a drop of more than 20% in horsepower and weight during the same period.[10] This is different in the EU, where horsepower and weight decrease somewhat between 2007 and 2009, but increase again to higher levels in 2011. Figure 2 clearly shows that engine power and weight of passenger cars have been growing consistently over the sample period. By 2011, consumers choose a vehicle that on average is 23% more powerful and 13% heavier than in 1998.

This increasing trend in vehicle size and performance is also apparent in the US market. Panel II shows that horsepower increased by 34% and weight by 10%. Knittel (2011) also documents these stark increases in characteristics of vehicles. Strikingly, the $CO_2$ emissions show a very different pattern in the US than in the EU. Until 2007 there is a very moderate decline in emissions of about 3%. Between 2007 and 2009 emissions of newly produced vehicles decline by 7% but then remain constant at 90% of the 1998 level. In the EU, emissions further decrease in 2010 and 2011 and by the end of the sample are at 80% of the 1998 level.

Figure 3 plots each producer's distance from the emission standard in 2007 and 2011. Each firm needs to move below the dotted line which presents the emission standard. The target function is up-sloping in weight because of the attribute-basing as explained above. In 2007, each of the firms is far above the line and needs to decrease emissions in order to comply. For firms in 2007 there are three options to reach the standard: reduce emissions, increase weight or combine both. The Asian firms, BMW, Daimler and Ford decrease weight and reduce emissions. Volkswagen reduces emissions keeping weight constant. Fiat, GM, PSA and Renault all increase average weight slightly while decreasing emissions strongly. A strong downward trend in emissions towards the standard is observed for all firms. The decrease in emissions is so strong that most of the firms comply with the efficiency standard four years before it is fully binding.

Table 1 quantifies this downward trend by showing the change in sales weighted vehicle characteristics between 2007 and 2011. $CO_2$ emissions decrease by 14% while there is moderate growth in other sales weighted characteristics. Additionally, the table reports stark decreases in fuel consumption for all size classes. Emissions decrease most in the luxury class (20%) and in SUVs (25%). The lowest decrease is observed for subcompact cars (12%) and compact vans (12%).

[10] The EPA keeps track of the evolution of quantity weighted characteristics for the US market. See: http://www.epa.gov/otaq/fetrends.htm

# 3 Model

This section introduces the emission standard in a structural model of supply and demand. I start by specifying a demand system for differentiated products following Berry, Levinsohn and Pakes (1995). Next, I model the regulation through the introduction of a shadow cost in the profit function. Last, I discuss the different abatement strategies of firms and how these strategies affect quantities, costs and prices.

## 3.1 Demand, Profit and Marginal Cost

**Demand** There are $M$ geographic markets, indexed by $m = 1, \ldots, M$, each market is observed $t$ times. I suppress the subscript $t$. In each market $m$ there are $A_m$ potential consumers. Consumers are assumed to purchase only in the market where they are located. Each consumer $i$ chooses one alternative $j$, which is either the outside good, $j = 0$, or one of the $J$ differentiated products, $j = 1, \ldots, J$. Consumer $i$'s conditional indirect utility for the outside good is $u_{i0m} = \varepsilon_{i0m}$, and for products $j = 1, \ldots, J$ it is:

$$u_{ijm} = x_{jm}\beta_i^x - \beta_i^e g_{jm} e_{jm} - \alpha_i p_{jm} + \xi_{jm} + \varepsilon_{ijm}, \tag{2}$$

where $x_{jm}$ is a vector of observed product characteristics, $g_{jm}e_{jm}$ are fuel costs (fuel prices $g_{jm}$ times fuel consumption $e_{jm}$), $p_{jm}$ is the vehicle price and $\xi_{jm}$ is an unobserved characteristic of vehicle $j$ in market $m$, unobserved by the researcher but observed by consumers and firms. The parameter vector $(\beta_i^e, \beta_i^x)$ consists of random coefficients, capturing individual-specific valuations for fuel costs and vehicle characteristics, $\alpha_i$ is the marginal utility of income or price valuation and $\varepsilon_{ijm}$ is a remaining individual-specific valuation for product $j$ (assumed to be i.i.d. type I extreme value). The random coefficient for characteristic $k$ is given by $\beta_i^k = \beta^k + \sigma^k \nu_i^k$, where $\nu_i^k$ is a random variable with zero mean and unit variance, so that $\beta^k$ represents the mean valuation for characteristic $k$ and $\sigma^k$ is its standard deviation across consumers. Indirect utility can be decomposed into the sum of three terms: a mean utility term $\delta_{jm} \equiv x_{jm}\beta^x - \beta^e g_{jm} e_{jm} - \alpha p_{jm} + \xi_{jm}$ common to all consumers; an individual-specific utility term $\mu_{jm}(\nu_i) \equiv \sum_k x_{jm}^k \sigma^k \nu_i^k$; and an individual error term $\varepsilon_{ijt}$ specific to each product $j$. If $\sigma^k = 0$ for all $k$, I obtain the standard logit model that does not account for any consumer heterogeneity. Notice that the coefficient on emissions $\beta_i^e$ measures the response of consumers to shifts in fuel costs.[11] The mean parameter $\beta^e$

[11] There is a growing literature that tries to identify to what extent consumers take into account future savings in fuel costs, see for example Allcott and Wozny (2012) and Grigolon, Reynaert and Verboven (2014).

captures how much consumers care about fuel costs and thus emissions on average. I do not separately allow consumers to care about the "green glow" of their vehicles, $\beta^e$ captures the private willingness to pay for fuel efficiency. The taste parameter for fuel costs varies across individuals. Reasons for individual heterogeneity in the taste for future fuel costs could be heterogeneity in discounting, in the expectation of future costs or simply in mileage across individuals.

Each consumer $i$ in market $m$ chooses the alternative $j = 0, \dots, J$ that maximizes her utility. The predicted market share of vehicle $j$ in market $m$ is the probability that product $j$ yields the highest utility across all available products (including the outside good 0). This is given by the logit choice probabilities, integrated over the individual-specific valuations for the continuous characteristics:

$$s_{jm}(\delta_m, \sigma) = \int \frac{\exp\left(\delta_{jm} + \mu_{jm}(\nu)\right)}{1 + \sum_{l=1}^{J} \exp\left(\delta_{lm} + \mu_{lm}(\nu)\right)} dP_\nu(\nu), \tag{3}$$

where $\delta_m$ is the $J \times 1$ mean utility vector in market $m$ (dependent on the mean valuation parameters $\beta^e, \beta^x$ and $\alpha$), and $\sigma$ is the vector of standard deviations around the mean valuations. To complete the demand side, I set the observed market share $s_{jm} = q_{jm}/A_m$ equal to the predicted market share (3). In vector notation, the demand side in market $m$ can then be described by the market share system:

$$s_m = s_m(\delta_m, \sigma). \tag{4}$$

**Profits** Firms maximize profits by setting prices in all countries $m$ for all of their products $j$ in their fleet $\mathcal{F}_f$ . Price setting is assumed to happen independently in each market. Total profit per year $t$ is the sum of profits from each country $m$. I suppress the subscript $t$. The emission standard is a constraint on the sales in all countries $m$ in a given year $t$ as set out in (1):

$$\max_p \sum_m \left[\pi_{fm}(\mathbf{p}, \mathbf{e})\right] \tag{5}$$

$$s.t. \ \frac{\sum_m \sum_{j \epsilon \mathcal{F}_f} q_{jm}(e_{jm} - f(w_{jm}))}{\sum_m \sum_{j \epsilon \mathcal{F}_f} q_{jm}} \leq \sigma,$$

in which $\sigma$ is the level of the standard and $f(w_j)$ is the attribute-basing on weight $w_j$. The constraint can be written as an implicit tax for vehicles that are less efficient than the required target and a subsidy for vehicles that are more efficient. This closely follows Goldberg (1998) and Jacobsen (2013) and is equivalent to writing the Lagrangian of the problem. Profits of firm $f$ in year $t$ are then given by:

$$\pi_f = \sum_m \sum_{j \in \mathcal{F}_f} \left\{ \left[ p_{jm} - c_{jm}(e_{jm}) - \lambda_f L_{jm} \right] s_{jm}(\mathbf{p}, \mathbf{e}) A_m \right\}, \tag{6}$$

$$L_{jm} = \left[ e_{jm} - f(w_{jm}) - \sigma \right] \tag{7}$$

in which $c_{jm}$ are marginal costs for product $j$ in market $m$, $L_{jm}$ is the individual contribution of each vehicle to the standard and $\lambda_f$ is the shadow cost of the regulation. The individual contribution $L_{jm}$ of each product is expressed as the distance between vehicle $j$'s emissions (or fuel consumption) and the target emission $\sigma$. Because of the attribute-basing $L_{jm}$ is a function of weight $w_j$ through $f(w_j)$ which defines the slope of the target function. For a flat standard (not attribute-based) $f(w_j) = 0$. The per vehicle shadow cost $\lambda_f$ gives the cost of deviating one unit from the standard. If the standard is non-binding $\lambda_f = 0$ and (6) reduces to a standard multiproduct profit function. If the regulation is binding, $\lambda_f > 0$ and equals the shadow cost of compliance. The shadow cost $\lambda_f$ is firm specific because trading of excess emission between firms is not allowed. Each firm has to comply with the standard by adjusting their own vehicle fleet, no matter how high the costs are compared to other firms. The shadow cost takes the same value for each vehicle in the fleet $\mathcal{F}_f$ of the firm. In equilibrium, firms will equalize shadow costs over their vehicles to be cost efficient.

To identify $\lambda_f$ Anderson and Sallee (2011) exploit loopholes in the CAFE standard, while Jacobsen (2013) exploits the first order conditions of constrained firms. Both approaches exploit a panel where compliance with the CAFE standards is observed over several years. In my analysis all of the data is from the period before the regulation such that $\lambda_f = 0$. I do observe firms' responses and their abatement choices in the run up to the regulation but I never observe a period where $\lambda_f > 0$. Instead of estimating $\lambda_f$ I will exploit the structural model and solve for values of $\lambda_f$ in simulations such that the regulation is exactly binding for all firms. This means that in the simulations all firms have to meet the standard exactly. I do not allow firms to pay fines or to do more than the standard requires. This is a simplification compared to the framework of Jacobsen (2013) in which firms are allowed to deviate from the standard. My goal however is not to estimate $\lambda_f$ (which would be impossible) but to evaluate the welfare effects of different abatement strategies. I will further discuss the role of $\lambda_f$ in the simulations below.

**Marginal costs** Marginal costs are assumed to be log-linear:

$$\log(c_{jm}) = \gamma^e e_{jm} + z_{jm}\gamma^z + \omega_{jm}, \tag{8}$$

in which $z_{jm}$ is a $1 \times L$ vector of observed product characteristics, market controls and cost shifters, $\omega_{jm}$ is the unobserved part of marginal costs. Emissions enter marginal cost as all else equal it is more expensive to produce efficient engines. This is confirmed in the estimation ($\gamma^e < 0$) and in several other engineering studies, see for example Whitefoot, Fowlie and Skerlos (2013). Note that marginal costs are not directly observed in the data. Marginal costs will be derived through the first order conditions of the profit function. Marginal cost parameters $\gamma^e$ and $\gamma^z$ will be estimated using data only from before the policy announcement again exploiting the fact that in the majority of the data $\lambda_f = 0$ and the regulation has not been announced yet.

## 3.2 Abatement Strategies

The literature that empirically evaluates the effects from fuel economy standards has focused on two possible abatement strategies of producers: sales mixing and downsizing. The response to the EU standard reveals a third possible strategy: technology adoption. Below, I will show that technology adoption is fully responsible for the observed increase in fuel efficiency in the EU. Here, I compare the possible effects of each abatement strategy in detail as well as the empirical challenges to evaluate the incidence of the regulation under each strategy.[12]

**Abatement by sales-mixing** A first mechanism to abate emissions, as modeled by Goldberg (1998) and Jacobsen (2013), is to change relative prices of high and low emission vehicles. As shown in Figure 1, firms can decrease prices of vehicles in B and C ($L_{jm} < 0$) and increase prices of vehicles in A and D ($L_{jm} > 0$) to shift market shares towards vehicles that comply with the ABR. In order to comply with the flat regulation the firm can decrease prices of vehicles in C and D ($L'_{jm} < 0$) and increase prices of vehicles in A and B ($L'_{jm} > 0$). The set of products available to each producer is assumed to be constant and that set is bounded by the production possibility frontier given the current level of technology $\tau$. Since the product set is assumed to be fixed the only option that firms have is to change prices. Each firm

[12]The abatement strategies discussed do not need to happen mutually exclusive. Firms will choose their abatement strategies such that the marginal abatement costs of each strategy is equal. When firms abate by choosing only one strategy the marginal cost of that strategy must be lower than that of the other strategies.

sets prices of all its products to maximize profits as given in (6). I assume a pure Nash equilibrium in prices exists and write the first-order conditions of (6) with respect to prices as:

$$\left\{ s_j(\mathbf{p}, \mathbf{e}) + \sum_{k \in \mathcal{F}_f} \frac{\partial s_k(\mathbf{p}, \mathbf{e})}{\partial p_j} \{p_k - c_k - \lambda_f L_k)\} \right\} = 0 \tag{9}$$

I denote the Nash equilibrium as $\mathbf{p} = \mathbf{p}^*(\mathbf{e})$. If $\lambda_f = 0$ the first order conditions reduce to the well known first order conditions of a Nash Bertrand game in prices for a multi-product firm. When $\lambda_f > 0$ the efficiency standard is binding. The relative prices of products with different emissions will change as firms take into account the contribution of each vehicle to attain the standard. If a vehicle is more polluting than the target, $L_{jm} > 0$ and the firm will perceive this vehicle as having a higher cost and increase its price. The opposite is true for a fuel efficient vehicle that helps to comply with the standard. The change in relative prices of products will shift sales towards more fuel efficient vehicles resulting in a different sales-mix.

The incidence and effectiveness of this abatement strategy largely depends on the responsiveness of consumers to price changes and their tastes for characteristics that correlate with fuel efficiency. Prices of some products will increase while others will decrease. Jacobsen (2013) shows that the sales-mix response will be very costly for consumers and firms because of the strong tastes for powerful and large vehicles. My simulations confirm these findings. The effects on firms' profits will depend largely on the share of the fleet that is under the target. Firms with a fleet that is better adapted to the standard might increase profits. Their prices will need less distortion compared to other firms and so they might steal sales. The empirical model will allow me to identify own and cross price elasticities for all products and to simulate the shifts in sales from the regulation by solving for the Nash equilibrium through the first order conditions.

**Abatement by technology adoption** Firms can improve fuel efficiency of existing vehicles by adapting engines, the combustion process or features that only affect fuel efficiency.[13] The effects on equilibrium of technology adoption are very different than those of sales-mix abatement or downsizing. Consider a technology shift over time from $\tau$ to $\widetilde{\tau}$ that shifts

[13] Knittel (2011) gives several examples of specific technologies that are implemented. The International Energy Agency reported a possible 40% improvement in fuel efficiency from available technologies in 2005. These include low rolling resistance of tires, reduced driveline friction, combustion improvements, thermal management, variable valve actuation and lift, auxiliary systems improvement, thermodynamic cycle improvements and dual clutch transmission. See http://www.iea.org/publications/freepublications/publication/technology-roadmap-fuel-economy-of-road-vehicles.html.

emissions such that $e_{jm1}(\tau) > e_{jm2}(\widetilde{\tau})$ for each vehicle. In Figure 1 this shift is shown in Panel II and increases the range of possible vehicles under the target lines for both the flat standard and the ABR. A shift in emissions through technology adoption will have various effects on the equilibrium outcome. A first effect is a change in marginal costs as defined in (8) as it is more expensive to make fuel efficient vehicles. A second effect is that technology adoption leads to a reduction in the marginal cost of the regulation: $\lambda_f$ shrinks when set of vehicles under the target line ($L_{jm} < 0$) increases. This means that by increasing technology firms require less and less changes in relative prices in order to comply. Eventually, for strong shifts in $\tau$, the firm can choose its preferred price scheme once $\lambda_f = 0$. A third effect of technology improvement is changes in demand as consumers face a choice set with new product characteristics. The savings in fuel expenses might lead consumers to buy more cars or more expensive vehicles containing more of other characteristics depending on their tastes. A fourth and final effect is that firms will reach a new Nash equilibrium in prices, from $\mathbf{p}^*(\mathbf{e}(\boldsymbol{\tau_1}))$ to $\mathbf{p}^*(\mathbf{e}(\boldsymbol{\tau_2}))$. There are two sources of upward pressure on prices. Increases in marginal costs and limited pass-through of decreases in fuel costs to consumers. The degree to which prices change depends largely on the elasticity of consumers with respect to fuel costs and prices and the degree of competition in the market. I will assume that both the fixed cost of developing the technology as well as the adoption of the technology (changing production lines) are considered to be sunk costs and thus will not impact the equilibrium prices.

The total effect of technology adoption is an empirical question. On the one hand, profits might increase because of higher demand for vehicles. On the other hand, profits might decrease because of rising costs. The effect on consumer surplus is also uncertain as buyers trade-off lower fuel costs with higher prices. The empirical model will allow me to simulate and validate the increases in prices, changes in quantities and the effects on consumer surplus and firm profits from technology adoption.

**Abatement by downsizing** Both Klier and Linn (2012) and Whitefoot, Fowlie and Skerlos (2013) show that in the medium run firms can abate emissions by changing the characteristics of their vehicle fleet. Typically vehicles with less horsepower and weight will have lower emissions and therefore designing more fuel efficient cars requires downsizing if the level of technology remains fixed. When choosing to downsize firms thus extend their vehicle fleet $\mathcal{F}_f$ with newly designed products that have more fuel efficiency but less of other characteristics. In Figure 1 firms abate by downsizing if they design new vehicles in B and C given the current level of technology $\tau$ in order to comply with the ABR (for the flat standard vehicles in C and D are designed).[14] The set of vehicles that have $L_{jm} > 0$ increases and this mitigates the need of changing relative pricing as more vehicles comply with the standard. Both Klier and Linn (2012) and Whitefoot et al. (2013) simulate that this strategy would be used to a considerable amount if the CAFE standards were to be tightened. Downsizing the fleet would have to be combined with sales-mixing but might be responsible for up to 80% of the abatement. Klier and Linn (2012) compare the welfare effects of a one mile per gallon increase in the CAFE standard attained by full sales mixing with the effects of firms combining downsizing and sales mixing. They find that compliance costs for firms decrease by about 40% from $9 billion per year to $5.6 billion per year. The incidence of the regulation on consumers remains similar as they still end up buying smaller vehicles while consumers have a strong taste for horsepower, weight and other characteristics. In fact, consumer losses from the regulation increase in their simulations.

Empirically modeling downsizing is challenging for three reasons. First, one needs a realistic model of how firms choose product designs that are technically possible. Klier and Linn (2012) exploit observed relations between product characteristics and Whitefoot et al. (2013) use an engineering model. Second, the model needs to allow firms to make strategic decisions on both prices and product characteristics, which complicates solving the Nash equilibrium. Third, one needs to account for the fact that these design decisions will be correlated with unobservables such that instruments are needed to identify consumer tastes for endogenous characteristics.[15] A full model of endogenous product choices is out of the scope of this paper. The available data do not reveal significant downsizing by firms and thus not allow me to validate a model that endogenizes product characteristics. This would require panel data in which we observe firms that are constrained by the regulation over a longer period. I focus instead on firms initial move towards the EU regulation which is characterized by technology adoption.

**Flat and attribute-based standards** In the analysis I consider two designs of the regulation $L_{jm}$. First, I exactly replicate the EU policy. This results in a per vehicle burden of

[14] The incentive to literally downsize in terms of weight clearly diminishes when the ABR slope increases. Whitefoot and Skerlos (2012) discuss the possible increases in footprint because of attribute-basing in the US regulation.

[15] Also Fan (2013) endogenized product characteristics to explain the effects of mergers on the quality of newspapers. Her work provides a clear discussion of the type of variation and equilibrium assumptions that are needed to endogenize the choice of product characteristics. I experimented with several sources of variation in this dataset (such as the different degree of globalization and the specific production set up (as in Klier and Linn (2012)) but no source of variation provided strong enough instruments to reliably estimate this kind of model.

$L_{jm} = [e_{jm} - f(w_{jm}) - \sigma]$, in which $\sigma$=130g $CO_2$/km and $f(w_{jm}) = a(w_{jm} - w_0)$ as specified in (1) and plotted in Figure 3. Second, I specify a flat standard so that in equilibrium the same sales weighted emission are attained. For the flat standard $L'_{jm} = [e_{jm} - \sigma']$ and there is no correlation between the target of the standard and weight $f(w_{jm}) = 0$. The target function is a horizontal line at $\sigma'$ in this case and all firms need to reach exactly the same level of $CO_2$ emissions.

Both the shadow costs and the level of technology needed to comply with the regulation will differ between the flat standard and the attribute-based standard as a different set of vehicles has $L_{jm} < 0$ than $L'_{jm} < 0$. This can be seen clearly in Figure 1: vehicles in B and C have $L_{jm} < 0$ and comply with the ABR, while vehicles in C and D have $L'_{jm} < 0$ and comply with the flat regulation. Depending on the average weight of each firm $\lambda_f$ will thus be different than $\lambda'_f$. The attribute-based regulation shifts the distribution of costs between firms as well as the costs related to the different abatement strategies. In further research it would be interesting to compare the incentives towards downsizing and technology adoption that come from the ABR.

The attribute-based regulation might have other economic consequences. Ito and Sallee (2014) point out that attribute-based standards create a distortion in the demand and supply of the attribute itself. If heavier cars help with attaining the target, weight is indirectly subsidized and producers will choose to add more weight to their vehicles. This creates distortions, which might be significant if weight is associated with other external costs. See for example the analysis by Anderson and Auffhammer (2014) who relate weight to accident risk. In this exercise I will keep weight, and other characteristics, constant to focus on the primary effect of the regulation: the significant increase in efficiency. Ito and Sallee (2014) also show that attribute-basing might increase the cost efficiency of the regulation by equalizing abatement costs. If producers of heavier vehicles find it more difficult to abate emissions a slope in the target function can equalize the marginal cost of compliance across firms. In this sense attribute-basing can be a replacement for emission trading between firms which would fully equalize abatement costs. In the case of emission trading producers of heavy vehicles would be willing to pay producers of lighter vehicles to do more of the abatement. In the simulations I will discuss the possible effects of attribute-basing in detail.

# 4 Market Response to the EU Emission Standard

In this section I decompose the observed 14% decrease in emissions. How much of this drop is attributable to sales-mixing, technology adoption or downsizing? To answer this question I will estimate isocost functions in emissions and other vehicle characteristics using a reduced form equation. The results will reveal that the drop in emissions between 2007 and 2011 is fully attributable to technology adoption. In the next sections I will then use this result to estimate and validate a structural model in order to compare the welfare effects of technology adoption with those of sales-mixing.

I explain the causes for the decrease in sales weighted emissions between 2007 and 2011 following the approach of Knittel (2011) and estimate the technological progress in fuel efficiency and the trade-off between product characteristics $x_{jt}$ and emissions $e_{jt}$. The estimated relations between $x_{jt}$ and $e_{jt}$ are depicted as production possibility frontiers in Figure 1 Panel II. I use the estimated relations to decompose the observed gains in efficiency into a part due to changes in relative prices, a part due to downsizing and a part due to technological advances. Intuitively, sales mixing and downsizing would reveal changes in sales weighted emission without shifts in the production possibility frontier. It is important to note that this exercise will use a different dimension of the data than the structural model. In this section I collapse the dataset to each version of a vehicle that I observe and leave out all variation over markets (I am not interested in explaining prices and quantities at this stage). Notation in this section therefore is a vehicle $j$ observed in the data at some time $t$ (the market $m$ is redundant here).

**Estimation of trade-off and technology parameters** Following Knittel (2011), Klier and Linn (2012) and Klier and Linn (2013) I estimate the following regression:

$$\log(e_{jt}) = \tau_t + \eta \log(x_{jt}) + \epsilon_{jt}, \tag{10}$$

in which the technology parameter $\tau_t$ is a time fixed effect, the trade-off parameters $\eta$ denote how emissions $e_{jt}$ change due to a 1% change in a characteristic $x_{jt}$ and $\epsilon_{jt}$ is an error term. The technology parameter captures shifts over time in the trade-off between emissions and characteristic and captures engine improvements such as better thermal management and improved valve timing. Graphically $\tau_t$ captures shifts in the production possibility frontier (as shown in Figure 1) and $\eta$ gives the slope of the frontier. The trade-off parameters $\eta$ are assumed to be constant over time, such that technology $\tau_t$ can be seen as input neutral (it enters multiplicative in levels). I assume $\epsilon_{jt}$ to be i.i.d. and estimate (10) by ordinary least squares. I will discuss several concerns regarding identification below.

Table 2 presents the trade-off parameters $\eta$ from estimating (10). Model 1 is the baseline specification, close to that of Knittel (2011), and includes trade-off parameters for horsepower, weight, footprint and height. For Model 1 I find that a 10% increase in horsepower causes a 1.8% increase in emissions. A 10% increase in weight and height increases emissions by 6.6% and 4.1%, while increasing the footprint reduces emissions by 1.6% (not precisely estimated). A diesel engine is about 20% more efficient than a gasoline engine which coincides with engineering numbers. These numbers have the same sign and a similar magnitude as those reported by Knittel (2011) and are almost identical to Klier and Linn (2013) who use similar European data. Before presenting the technology parameters, I estimate six other specifications that address a number of issues. Model 2 includes diesel by characteristics interactions and thus allows a different functional form for diesel engines (instead of only a different dummy). Model 3 and Model 4 address possible biases related to technology expenditures. If unobserved expenditures on technology are correlated with characteristics on the right hand side of (10) this would bias the estimated parameters. Expenditures on technology are likely reflected in marginal costs so to control for expenditures, I add prices and marginal costs as explanatory variables.[16] If biases from unobserved expenditure would be substantial I would expect parameters to change between Model 1 and Model 3 or 4, which they do not. Model 5 estimates (10) with frequency weights for sales. If firms would increase technology only in specific groups of low or high selling vehicles the parameters in Model 1 will be biased. Again, the trade-off parameters are similar between Model 5 and Model 1. Model 6 allows the trade-off parameters to change over time (the functional form changes year by year), and Model 7 allows for a firm specific trend in technology. These last two models should result in different predictions for the technology parameters if the technology is not input neutral or is different between firms.

The technology parameters $\tau_t$ are derived from the time fixed effects in each regression and plotted in Table 3 for Model 1-Model 6, results for each of the firms from model 7 are in the appendix.[17] Technology improves over time between 1998 and 2007 by an average

[16] Marginal costs are unobserved so I use the predicted marginal costs from the structural model.

[17] The time dummies capture shifts in how vehicle characteristics (horsepower, weight, size and height) translate into emissions. Two concerns are that apart from technological improvements these shifts could capture shifts in other unobserved characteristics or changes in how the value of emissions is obtained. To test wether other unobserved characteristics have changed I ran the regression (not reported) on parts of the data for which I additionaly observe cylinder and acceleration. Controling for this does not change the results. The emission values in the data are official measures stemming from the New European Driving Cycle, a standardized test that did not change during the sample period. One valid concern is that firms over

pace of between 0.7% and 1.6% over the different specifications. After 2007 the estimates reveal a significant increase in the pace of technology improvement with a yearly average increase of more than 4% for all models. The firm specific technology paths reveal similar increases in technological effort after 2007 for each firm. These findings provide strong suggestive evidence that firms speed up the adoption of technology in the period after the policy announcement in order to comply with the regulation. The move towards the policy target in Figure 3 is so clear that the policy announcement seems to be the primary candidate to explain the speed-up in technology adoption after 2007. Klier and Linn (2013) estimate the technology path for both the US and the EU and try to establish a causal impact of the policy, they find that tighter standards indeed lead to more technology adoption.

**Decomposition of the changes in fuel efficiency** The estimated relation (10) can be used to reveal the compliance strategy of firms between 2007 and 2011 and this is shown in Table 4. I define emissions $\overline{e}_{jt}$ to have constant technology $\tau_t = \tau_{2007}$. This means that any changes in the sales weighted values of $\overline{e}_{jt}$ are caused by either changes in vehicle characteristics or changes in the market shares of more fuel efficient vehicles. Sales-mixing changes the sales weighted values of $\overline{e}_{jt}$ for existing vehicle models that are released before the policy announcement (prior to 2007). Downsizing would reveal itself by values of $\overline{e}_{jt}$ that are on average smaller for vehicles released after the policy announcement. An example of a newly released model is the "Citroen DS3 Hatchback", released in 2009. Note that I do not treat new engine versions as new models as these directly capture the new technology. Next, I predict emissions, $\widehat{e}_{jt}$, using both the trade-off parameters and the technology estimates. This corresponds to the fitted values of regression (10). The trend in $\widehat{e}_{jt}$ gives the sum of sales-mix abatement, downsizing and technology adoption. I re-scale each of the predicted emissions with the attribute-based target function, such that the numbers can be read as actual distances from the regulation.[18]

The results in Table 4 reveal several interesting trends. Between 1998 and 2007 sales weighted emissions without technology increased slightly from 151 to 154 (an increase of 2%). Technology improvements were fully responsible for the observed moderate decline in emissions between 1998 and 2007. After 2007, the sales weighted emissions without technology $\overline{e}_{jt}$ keep increasing gradually from 154 to 155. There is thus no evidence of significant changes that could be attributable to either sales-mixing or downsizing. On the

time are getting better at taking the test, such that real-world emissions deviate more from tested emissions. This might cause the reported technology estimates to be overstated.

[18]The results without this correction lead to exactly the same conclusions.

contrary sales weighted emission $\overline{e}_{jt}$ increase slightly between 2007 and 2011. When I split up the sales weighted emissions into vehicle models released after and prior to 2007 the results show that the sales weighted emission of vehicles released prior to 2007 remain constant (154 in 2007 and 154 in 2011). This means that market shares of vehicles with different emissions have remained constant and relative prices have not changed. New vehicles, on average, surprisingly have higher sales weighted emissions than the existing vehicle fleet. There is thus no evidence of downsizing: vehicle models released after the policy announcement are on average more polluting than existing vehicle models. The difference between existing vehicles and vehicles released after the policy decreases over time however. This shows that the policy might also influence the growth rate of characteristics over the longer term. However, the observed decline in emissions is thus not in any sense attributable to changes in the sales mix or to the release of new downsized fuel efficient vehicles.

The sales weighted emissions with technology $\widehat{e}_{jt}$ are decreasing rapidly after 2007 and this shows that technology adoption is fully responsible for the observed drop in emissions. Strikingly, the decrease in sales weighted emissions of older vehicles due to technology is as strong as the decrease in newly released vehicles. This shows that the engine improvements are installed widely across the fleet. The degree of technology adoption is that high between 2007-2011 that firms, once the regulation is binding, will not have to change relative prices or downsize their vehicles. Because of the increase in technology adoption most firms already comply with the emission standard in 2011 as is shown in Figure 3. This finding is in contrast with the US literature discussing the compliance strategies to the CAFE standard. In the case of the European emission standard abatement by technology adoption is not a possible long term response but is observed immediately after the policy announcement and in such amounts that other abatement strategies are not needed for further compliance. Below, I will try to explain why this abatement strategy is chosen and why this matters in order to evaluate the welfare effects of the regulation.

# 5 Estimation

In this section I estimate a structural model of demand and supply of the automobile market as set out in Section 3. The model allows me to make statements on the welfare effects of the regulation, as well as to compare the effects of technology adoption with those of alternative abatement strategies. The structural model will rely on heavy functional form assumptions. In order to test the validity of those assumptions, I will explicitly test the ability of the model to predict prices and market shares after the policy announcement. This 'out of sample' testing is important as it will show to what extent the model is able to explain the observed changes before making welfare statements from simulated changes. In this section I make use of the full panel structure of my data and include variation over countries and time.

## 5.1 Estimation of demand and marginal cost function (using data from before policy announcement)

I have a panel of 70 markets, to estimate the taste and marginal cost parameters as defined in Section 3. The sample is restricted to markets that are observed before the policy announcement and contains the data for 7 countries in the period 1998-2007. This allows me to estimate a model in which firms choose prices to maximize unconstrained profits as given in (6) with $\lambda = 0$. The vector of parameters $\theta$ to be estimated consists of the taste parameters $\beta_i^e, \beta_i^x$ and $\alpha_i$ and the cost parameters $\gamma^e$ and $\gamma^x$. I estimate both a mean and a standard deviation of the taste for fuel consumption, horsepower, weight, footprint and a dummy for foreign perceived cars (e.g. a BMW in France). I specify $\alpha_i$ to be proportional to income $y_{mt}$ in market $mt$, so $\alpha_i = \alpha / y_{mt}$. A set of controls is added for which I only estimate the mean taste. These include height, brand fixed effects, market fixed effects, diesel by market interactions, body type dummies, size class dummies, a dummy for 3 doors, months on market dummies (for vehicles introduced within a calendar year), and a time trend. The remaining unexplained variation in market shares is $\xi_{jmt}$. Marginal costs are explained by the same set of variables, except that fuel efficiency enters instead of fuel consumption, the diesel market interactions are dropped (as these capture tax differences for consumers), a full set of year dummies is added and labor costs and a production in the country of sales dummy are added. This captures transportation and distribution costs. The remaining part of marginal costs $\omega_{jmt}$ is unobserved.

The parameters are obtained by minimizing the GMM criterion:

$$\min_{\theta} \rho\,(\theta)'\, g(z)' A \rho\,(\theta)'\, g(z)' \tag{11}$$

in which $\rho_{jmt} = (\xi_{jmt}, \omega_{jmt})$ the matrix of demand and supply unobservables stacked over all markets, $g(z)$ is the matrix of instruments and $A$ is a weighting matrix. I follow the estimation algorithm described in Berry, Levinsohn and Pakes (1995) and Nevo (2001). I take into account recent cautionary warnings and improvements and carefully check the properties of the obtained minimum.[19] For simplicity, I estimate the demand and supply separately and do not exploit cross equation restrictions on the price parameter. I instrument for prices using the production data that gives me the location and plant of production for every vehicle. I add sums of characteristics per size class for each vehicle as additional price instruments. A third group of instruments identifies the nonlinear parameters through approximations of the optimal instruments following the approach described in Reynaert and Verboven (2014). I estimate marginal costs under the assumption of perfect and imperfect competition. Perfect competition serves as a benchmark since price equals marginal costs estimation is an ols of prices on cost shifters. With the assumption of imperfect competition, marginal costs are the solution of the system of first order conditions as given in (9). As a benchmark I also present the results from a simpler logit model, ignoring all individual heterogeneity.

Table 5 presents the estimated parameters and standard errors. The demand parameters for both the logit and RC logit show that consumers dislike higher prices, higher fuel costs and foreign cars. Consumers have positive tastes for weight and footprint. In the RC logit, the standard deviation for both fuel costs and horsepower is estimated to be significant. On average consumers dislike fuel costs but some consumers find this more important than others. Grigolon, Reynaert and Verboven (2014) discuss this heterogeneity, related to differences in mileage among consumers, in more detail. The taste heterogeneity for horsepower is very strong and it causes the mean parameter to shift sign between the logit and RC logit specification. Other standard deviations on weight, footprint and foreign are found to be small or imprecisely estimated.

The marginal cost estimates under perfect competition in Table 5 are identical for both the logit and RC logit, it is simply a linear regression of prices on cost shifters. These estimates are useful though as they show that both cost instruments obtained from the production data are significant and have the expected sign. Increases in labor cost increase marginal costs and production in the local market decreases costs. All marginal cost regressions show that increasing the fuel efficiency of the vehicle is costly. A one unit decrease in the liters per 100km increases cost with 2.5% to 8.7% over the different specifications. All

[19] More specifically I do the following: (i) I use a nested-fixed point (NFP) algorithm, BLP's contaction mapping with a very thight convergence criterion (1e-12) to solve for $\xi_{jmt}$, (ii) I re-estimate the model with 10 different starting values for the non linear parameters, (iii) I check first and second order conditions at the obtained minimum, (iv) I use the Interior/Direct algorithm in Knitro. I use a NFP because Mathematical Programming under Equilibrium Constraints proved to be slower in this application once I parralized the computation of the contraction mapping. As is shown in Reynaert and Verboven (2014) both estimation algorithms should give the same results.

characteristics also have the expected sign. Adding horsepower, weight, footprint or height, makes vehicles more costly.

I conclude this section by emphasizing that emissions enter the model through two channels. First, all else equal, consumers dislike vehicles that have higher emissions because they are more costly. There is considerable and significant variation in the degree consumers dislike fuel costs. Second, building vehicles that are more efficient and have lower $CO_2$ emissions is costly for manufacturers. Both of these parameters will be of importance in the simulations.

## 5.2 Out of sample performance of the structural model

Before proceeding to the simulations and welfare results it is important to assess the ability of the structural model to predict counterfactual outcomes. In recent years there have been questions regarding the reliability and usefulness of structural estimation in general. Angrist and Pischke (2010) for example state that many of the new industrial organization studies forecast counterfactual outcomes without showing that the simulations deliver accurate predictions. The RC logit demand model in particular has been criticized by Knittel and Metaxoglou (2014). They show that results might change significantly depending on the optimization algorithm used.

As I observe the abatement strategy chosen by the firms in response to the policy, I will test the ability of the estimated model to predict the observed market outcomes after the technology adoption. This exercise provides a test of the predictive power of the structural estimates and thereby tries to address the recent critiques. This is different from most of the literature as it requires both before and after policy intervention data, though there are some important papers that do a similar exercise. For example, Todd and Wolpin (2006) and Kaboski and Townsend (2011) evaluate the impact of different policies after first testing the ability of the estimated model to predict the observed response to the policy. Also, in the industrial organization literature several market shocks such as mergers (Weinberg and Hosken (2013)), stark sudden tax increases (Rojas (2008)), and the introduction of new products (Hausman and Leonard (2002)) have been used to test the predictive power of commonly used estimation methods.

In Section 5.1. I estimated demand and marginal cost parameters using 10 years of data from 1998-2007 before the policy announcement. Because of the technology adoption, consumers face a different choice set in 2011 than in 2007, with vehicles being on average 14% more fuel efficient. Firms will also face a different pricing decision as marginal costs have changed and competing products have different fuel efficiency. This large shift in one of the characteristics of the vehicles provides me with the opportunity to test the fit of the estimated model to the new choice set. If taste and cost parameters remain constant over time and are estimated precisely a correctly specified model should be able to explain observed sales and prices of vehicles with a significantly higher fuel efficiency in 2011.

The procedure for the out of sample test is straightforward. First, I make the assumption that both the supply $\omega_{jmt}$ and demand error $\xi_{jmt}$ in equation (8) and (3) are at their expected level ($E(\omega_{jm2011}) = E(\xi_{jm2011}) = 0$). Intuitively this means that I only rely on predictive power from the observables and ignore all information about the unobservable.[20] Second, I predict the marginal costs $\widehat{c}_{jt}$ for each vehicle on sale in 2011 using the estimated parameters from Table 5. I estimated marginal cost parameters using only data from 1998-2007, so this is a first out of sample prediction. Given the predicted marginal costs $\widehat{c}_{jm2011}$ I solve for prices. Under the assumption of perfect competition this is done by setting $\widehat{p}_{jm2011} = \widehat{c}_{jm2011}$. When assuming imperfect competition I solve the system of nonlinear equations given by the first order conditions (9). Because the regulation is still not binding in 2011 and firms do not change their sales mix I solve for the unconstrained price equilibrium and set the shadow cost of the regulation $\lambda = 0$. Given prices $\widehat{p}_{jm2011}$ and marginal costs $\widehat{c}_{jm2011}$ I solve for quantities by integrating over each of the simulated logit probabilities. Table 6 summarizes the sales weighted characteristics over all countries in 2007 and 2011 for each of the four estimated models. I focus on sales weighted characteristics instead of individual vehicle sales and prices for two reasons. First, from a policy perspective I am not interested in which specific cars get sold the most but in the overall emission level of the vehicle fleet. Second, the data is very disaggregated on a version level (similar vehicles with almost the same characteristics but very different sales). This means I expect large variability in the demand unobservable. I come back to this point below.

The first panel of Table 6 gives the results for the within sample fit of the model. Prices and quantities are predicted by setting $\omega_{jm2007} = \xi_{jm2007} = 0$. This shows the cost of setting the unobservables equal to zero without changes in characteristics out of the sample. All predicted sales weighted characteristics are within a 5% error margin of the observed sales weighted characteristics. All four of the models generate similar predictions though the RC logit is closer to all the observed characteristics except for the percentage of diesel vehicles sold.

The second panel of Table 6 gives the results for the out of sample fit. The model is able

[20] Sampling $k$ times from the distributions $\widehat{\omega}_{jmt}$, $\widehat{\xi}_{jmt}$ and averaging over the $k$ simulations takes into account the estimated distribution of the error terms but made almost no difference in practice.

to predict most of the decrease in sales weighted characteristics. CO2 emissions are predicted to be 130 g/km from the logit and 129 g/km from the RC logit estimates, while observed emissions decreased from 147 g/km to 126 g/km. This means sales weighted emissions differ by only 2.3% from observed emissions, while there was an actual drop of 14%. Also weight, footprint and the share of diesel are very close to the observed 2011 levels. The prediction of both the sales weighted level of horsepower and prices has an error margin of 6.2% and 7.2%. The error is not attributable to a bias in predicted prices (the actual bias is almost zero for predicted prices), but it comes from the estimation of the market shares of more expensive higher horsepower vehicles. In general though, these numbers show that the out of sample fit is good and that the model is able to predict market quantities of interest despite a large change in one of the characteristics. When we compare the four different estimation models it is again the RC logit model with imperfect competition that is closest to the observed values. This will be the preferred model I will use throughout the simulations.

To end this section I give a few cautionary remarks and thoughts for further research. First, the out of sample test provides a validation of the demand model but not of the assumptions regarding price competition. I find that both the cost functions under perfect and imperfect competition are able to predict prices accurately after the product characteristics change. However, this does not provide any information as to what extent the divide between markups and costs is realistic. There is no large structural break in the data that gives me the necessary variation in markups and prices to test several competitive models against each other (see Rojas (2008)).

Next, the fact that sales of high priced and high horsepower vehicles are estimated too high might have two reasons. First, if measured fuel efficiency gains from the test cycle do not fully translate into reduced fuel costs, the model will overpredict the obtained fuel savings and the shares of high price and performance vehicles. Second, between 2007 and 2011 the price of SUVs dropped by 20% as less luxurious models with similar observables entered the market. This shows the inherently static features of the estimation method as the mean quality of an SUV is not assumed to change over time. Despite these dynamic changes in the market, and the entrance of new and redesigned models the static model actually provides a surprisingly good fit over a four year period of changes.

Another remark is related to the role of the outside good and the total size of the car market. The model is not able to predict the decrease in total sales in the European market observed between 2007 and 2011. I use (in line with previous research) the number of households as a scale for the total possible market. The number of households between 2007 and 2011 did not change while the total number of sales decreased by 20% because of the

2008 crisis. The model is thus not able to predict large macro-economic trends. This is relevant for the counterfactual analysis as all simulations are made under the assumption that there will be no changes in the overall demand for vehicles except for those related to the policy intervention.

A last point of caution is related to the models' ability to predict individual sales and prices of vehicles. Prices are estimated precisely while market shares are estimated less precisely. The variance of the demand error is much higher than that of the supply error. In other words, observables are sufficient to make precise predictions of prices but not of quantities. This is partly due to the very disaggregated level of the data with many vehicles similar in observables except sales. The model is able to capture the taste for characteristics precisely and thus correctly estimates the total share of similar vehicles but not their individual share. This issue raises concerns when one is interested in predicting the effects of smaller market interventions (such as the introduction of a new vehicle for example). For this project it is sufficient to see that the model is able to predict changes in aggregate outcomes in fuel efficiency and other characteristics.

# 6 Welfare effects of alternative abatement strategies

In this section I use the structural model to compare the welfare effects of sales-mix abatement and abatement by technology adoption. Previous literature has already shown that the burden of the regulation falls heavily on both consumers and firms when relative prices change in order to abate emissions or when firms choose to downsize. The impact of the regulation when firms respond with technology adoption has not been studied and is an empirical question as consumers will trade-off higher prices against lower fuel costs. I will start this section by presenting the set-up of the simulation. Second, I will show how the aggregate sales and the distribution of sales changes in response to a standard. This will establish intuition on the effects of standards on the composition of sales. Third, I will show how the impact of the regulation differs with the chosen abatement strategy. Fourth, I will look at the distributional effects of the standard between the major European car producers and how these effects relate to the design of the regulation. Finally, I will discuss why the regulation might solve a market failure in technology adoption by firms.

**Simulation set-up** I will run four different policy simulations. In the first two scenarios I simulate a policy exactly equal to the EU emission standard and let firms respond either by sales-mix abatement or by technology adoption (the observed response). In the last two scenarios, I consider the effects of a flat standard with both abatement strategies. All the policy simulations will be identical in the final obtained sales weighted $CO_2$ emissions. I use the observed vehicle characteristics from the year 2007 and the estimated coefficients of the RC Logit model with imperfect competition from Table 5. I decrease the emissions of all vehicles by 6.4%, which corresponds to the estimated trend in technology from Table 3 for four years. All other product characteristics remain at their 2007 levels and I do not account for new vehicle entries. This is an approximation of what the car fleet would have looked like in 2011 without a policy intervention. In Figure 4, I plot each of the vehicles in an emission/weight diagram. The diagonal line is the target function for the attribute-based standard while the horizontal line is the target with a flat standard. All dots underneath the policy lines contribute to the standard, this is a different set for the horizontal target than for the up-sloping target. The vehicle fleet after technology adoption towards the attribute-based standard is depicted in Figure 4, Panel II. Figure 4, Panel III depicts the vehicle fleet after technology adoption towards the flat target function.

In each of the simulations I have to solve for a set of unknowns that will equate each of the firms' emissions with the standards.[21] Under abatement by sales mixing the unknown is the shadow cost $\lambda_f$, while under technology adoption I have to solve for the level of fuel efficiency required for each firm to attain the standard. Solving for the necessary shadow costs, technology and resulting prices and quantities in each of the scenarios is done by following a step-wise algorithm. This algorithm is described in the appendix. Note that the regulation is binding over the sum of geographical markets. I therefore have to solve for the responses in each of the countries, aggregate the responses and then evaluate the solution.

**Effects on market structure** In Table 7 I show the market shares of different size classes, changes in total sales and changes in total emissions after abatement. Technology adoption causes almost no shifts in the importance of each size class. This finding is in stark contrast with substitution patterns from sales-mix abatement. In this case subcompact vehicles and compact vehicles have a combined share of 72% (up from 62%). All other classes lose market share. The difference between technology adoption and sales-mix abatement is even more pronounced under the flat standard as the target function does not vary between size classes. The combined share of subcompacts and compacts now rises to 78%. In sum, this shows that adding technology to new vehicles does not change the size distribution of the car fleet. If

[21] It is important to note that I exactly solve for the level of technology or the shadow cost such that the regulation is just binding. Each of the firms' sales weighted emissions will end exactly on the policy lines as plotted in Figure 4. In reality, this does not need to be the case as firms may deviate from the standard and pay fines or firms may obtain emission levels lower than the target.

firms abate with sales-mixing we see large substitution towards smaller vehicles. A slope in the target function moderates this, though only to a certain extent. This finding is somewhat surprising since one of the stated reasons for the introduction of the attribute function was to keep the size distribution constant. Panel I in Figure 4 clearly shows that the attribute function is not steep enough to attain this goal: most vehicles that are under the diagonal line weigh less than 1600 kg.

Under technology adoption, total sales increase by 5%, both for the ABR and flat regulation. Technology adoption increases sales because of a rebound effect on the extensive margin. The average vehicle delivers a higher utility for consumers because it is more fuel efficient and some consumers switch from the outside good towards buying a vehicle. Because more consumers decide to buy a vehicle and there is no substitution to more fuel efficient vehicles, technology adoption results in modest effects on total $CO_2$ emissions: a decrease of 6%[22]. A large part of the efficiency gain is lost due to the rebound effect on the extensive margin.[23].

Under sales-mix abatement I find a decrease in total sales of 10% for the ABR and 6% for the flat standard. Under sales-mix abatement the product characteristics of the vehicle fleet remain constant but the relative prices change. As explained above, vehicles that are more fuel efficient than the target receive an implicit subsidy and vehicles with a lower fuel efficiency are taxed. The change in total sales depends on the own and cross price elasticities of all the products in the market as well as the changes in the prices needed to attain the standard. In this case, the subsidized part of the market gains less sales than the taxed part loses, causing a 10% (ABR) and a 6% (flat regulation) decrease in sales[24]. The decline in total sales and substitution towards more fuel efficient vehicles cause large reductions in total $CO_2$ emissions: a decrease by 20/ (ABR) and 16% (flat regulation).

**Welfare effects** Table 8 gives the changes in consumer surplus, profits, and externalities. These numbers should be interpreted as total vehicle lifetime changes from yearly sales. I

[22] Total emissions is the sum of the grams of $CO_2$ per km of each vehicle over all new vehicles multiplied by the average yearly mileage, assumed to be constant at 14 000 km/year.

[23] See Gillingham, Kotchen, Rapson and Wagner (2013) for an overview on the rebound effect. A second rebound effect that might be expected is an increase in vehicle usage, or a rebound effect on the intensive margin. A further rebound effect could come from the use of savings on vehicle expenses on other energy intensive activities. This is known as the indirect rebound effect. Lastly, a decrease in the demand for fuels might lower the price of oil causing further shocks in the economy (known as the macro-economic rebound effect).

[24] Standards and sales-mixing abatement might also lead to increases in total sales. Holland, Hughes and Knittel (2009) show that when the subsidized products are more elastic than the taxed products total sales might increase.

assume a vehicle lifetime of 15 years, a yearly mileage of 14000km and a discount rate of 6% to capitalize the yearly gains/losses in externalities.[25] The amount consumers drive is assumed to be constant, ignoring possible rebound effects on the intensive margin.

Consumer surplus from new vehicles increases by €10 billion per year under technology adoption with the ABR and €9 billion with the flat standard. The increase in prices due to higher marginal costs do not make up for the decreases in fuel costs over the vehicle lifetime and this makes consumers better off. These findings are in stark contrast with the effects on consumer surplus from sales-mix abatement. With sales-mix abatement consumer surplus would have decreased by €26 billion (ABR) and €20 billion (flat regulation) because high prices force consumers to smaller cars. The flat standard results in significantly lower consumer losses because a much larger part of the market is implicitly subsidized. Figure 4, Panel I, shows that more vehicles are under the flat target line than under the upward sloping target, such that the required substitution is less pronounced.

These findings are important in the sense that the incidence of the regulation shifts with the different abatement strategies. This is very different than the conclusion that is drawn in the literature that empirically evaluates the CAFE standard and has treated technology improvement more as a long run response, thereby stressing the cost of the regulation for consumers. The finding that the EU market fully responds with technology adoption which causes increases in consumer surplus might partly explain why this type of regulation is a popular option for policy makers compared to fuel taxes.

The conclusions with respect to the effects on firm profits are less clear. Variable profits decrease by a moderate €2 billion under technology adoption and decrease starkly, by €16 billion under sales-mixing. The sum of changes in variable profits hides interesting patterns between the different firms on which I comment below. The total effect of the regulation on firms is unclear however because I lack information on the fixed costs of technology adoption. These costs are twofold: technology adoption requires adaptation of production lines as well as investments in R&D, both of which are unobserved. Below, I discuss possible scenario's of why firms did not make these investments in fuel efficiency before the regulation.

The gains from the reduction in $CO_2$ emissions are small in comparison to the other reported effects. I value a ton of $CO_2$ at €28.[26] The total gains from reduced emissions are smaller than 10% of gains or losses in consumer surplus or variable profits in all simulations.

[25] Yearly mileage and vehicle lifetime are chosen to match statistics reported by Eurostat.

[26] This number comes from the Interagency Working Group on the Social Cost of Carbon. Even severe increases in the cost of carbon by a magnitude of 5 (or more than €100 per ton which is considered to be a high estimate in the literature) would still mean the other effects in the table would be of a larger magnitude. A ton of $CO_2$ traded for €7.75 in the EU cap and trade system at the end of 2013.

With technology adoption a moderate €350 million is gained per year while sales-mix abatement leads to gains of about €1 billion attributable to less emissions. In total 38 million tons of $CO_2$ would be saved under sales-mix abatement and the attribute-based standard. This saving would cost €43 billion in consumer and producer surplus which leads to a cost of €1131 per ton and shows that the policy would have been extremely costly had firms responded by sales-mixing.

A final effect of the regulation are changes in other external costs from traffic such as accident risk, local pollution and congestion, which are related to the total amount of vehicle miles in a year. Parry, Walls and Harrington (2007) give the total external cost from driving for the US market. The number Parry et al. (2007) compute is probably not directly applicable to the EU market but at least gives a sense of the relative importance of these effects. I take this number to be €12 cent per kilometer, at best an approximation[27]. I find that with technology adoption the increase in these externalities due to increased sales easily offsets all gains from emissions reductions. Other external costs increase by more than €7 billion from technology adoption. Sales-mix abatement results in less total sales and so results in €18 billion (ABR) and €11 billion (flat regulation) decreases in other external costs. Since external costs from congestion and accident risk are estimated to be higher than the external costs of $CO_2$ emissions a regulation that does not get the extensive margin right will increase the amount of total external costs instead of decrease. Emission standards lead to increased sales when the abatement strategy is technology adoption or when the subsidized part of the market gains more sales than the taxed part loses and thus are an inadequate instrument to decrease the total amount of external effects in the car market.

To conclude, I find that the incidence of the regulation shifts with the abatement strategy: consumer surplus increases by a significant amount under technology adoption and decreases strongly under sales-mixing. This might partly explain why this type of regulation is a popular option among policy makers. Next, the simulations show that emission standards are not an effective instrument to reduce externalities from the car market. The rebound effect on the extensive margin is considerable under technology adoption. Because other externalities related to increased traffic are typically estimated to be more costly than emissions there is no overall reduction in externalities and the regulation does not attain its goal. When firms respond with sales-mixing a decrease in traffic is possible but the savings in externalities do not outweigh the loss in consumer surplus and profits and the overall effect of the regulation is clearly negative. The sales-mix abatement scenarios can be seen as a lower bound for

[27] This number is probably an upper bound for the EU since taxes on fuel and driving are on average higher than in the US.

the total welfare effects since technology adoption is the preferred revealed strategy by firms sales-mixing must be more costly. The technology scenarios can be regarded as an absolute upper bound on the regulation, before deducting the fixed technology costs and further rebound effects[28].

**Incidence on different firms** Here I compare the design of the current attribute-based regulation with the flat standard to see whether the impact on different firms changes between the designs. In Table 9 I give the sales weighted $CO_2$ emissions per firm for both the attribute-based and the flat standard. For each of the simulations I report the level of technology or the shadow cost that was needed to force each firm onto the target function and the effects on variable yearly profits in € millions. The sales weighted $CO_2$ emissions of each firm with the up-sloping target function vary with their average weight. This is most outspoken for BMW that reaches the standard with emission of 134 g $CO_2$/km and Fiat that reaches the standard with 116 g $CO_2$/km. The total sales weighted level of emissions is 124 g $CO_2$/km and that is the required level I set for the flat standard.

With attribute-basing the technology efforts $\tau_f$ needed are largest for Daimler, Volkswagen and the Asian firms who all need to bring their $CO_2$ emission down by more than 13% in order to comply. Note that these are indeed the firms with the largest distance from the regulation in Figure 3. Technology abatement under the flat standard results in exactly the same picture except that the effort that is needed from each firm changes somewhat. BMW now needs to increase efficiency by 12% (up from 6%) and Fiat by 2% (down from 7%). This matches the expectation as BMW cannot exploit the reduction on their heavy cars and Fiat does not have to increase efficiency of their lighter vehicles. The large heterogeneity in efficiency requirements results in large shifts in variable profits. BMW and Daimler lose market share while Fiat and the Asian brands gain considerably.

The results of the sales-mix abatement in Table 9 show some interesting patterns. Under the attribute-based standard three firms, BMW, Ford and PSA, have a vehicle fleet that is best adapted to the standard (in practice: they have most vehicles underneath or close to the diagonal line in Figure 4). These three firms thus face the lowest shadow costs and need to distort their prices significantly less than all the other firms. All the other firms

[28] Another reason why the numbers from technology adoption can be seen as an upper bound is that I fully count gains in consumer surplus as welfare gains. A large part of consumer gains comes from reduced spending on fuel and about 60% of the fuel expenses are fuel taxes paid to the government. Depending on whether these taxes are efficient, and how they are redistributed, this part of the consumer gains could be seen as a transfer from the government to consumers and not as a pure welfare gain. This would also affect the consumer welfare changes from sales-mixing in a similar sense.

lose between € 500 million and € 4.7 billion. Under the flat standard the set of firms with the most adapted fleet changes to Fiat, PSA and Renault, which all face lower shadow costs and increase profits. Under sales-mixing there are two important differences between the attribute-based and the flat standard: the marginal compliance cost changes and the distribution of compliance costs changes. I discuss these two differences in detail.

The change in the marginal compliance costs is potentially very important as it makes technology adoption more likely than sales-mix abatement. In equilibrium firms will choose to use an abatement strategy as long as the marginal abatement costs are lower than that of an other strategy. Firms might as well apply a mixture of strategies. The empirical results obtained here show that $\lambda_f$ is considerably higher than $\lambda'_f$ for most of the firms (except for BMW and Ford). The mean of the marginal shadow cost of sales mixing goes up from 1.1 to 1.7 which means that the strategy of sales mixing on average becomes more costly on the margin, especially for Daimler, Fiat and the Asian firms. The incentives to invest in technology thus increase significantly because of attribute-basing. This might be one of the reasons why we have seen such a clear choice for technology adoption in response to the EU standard. The recent reform of the CAFE standard also includes a slope in the target function which makes future technology adoption in the US more likely.[29] The upward slope in the target function makes sales-mix abatement more costly but the results are not so strong to state that a slope in the target function is a necessary condition to get technology abatement. With a flat target the profit losses for most firms from sales-mix abatement are so large that at least some technology investment is expected.[30]

The changes in the distribution of compliance costs are in line with the lobbying by different countries as described above. The French (Renault and PSA) and Italian (Fiat) firms face lower shadow costs with the flat standard than with the attribute-based standard. This is in line with the strong positions the countries took when bargaining over the regulation. Still, the French and Italian firms in general face a lower regulatory burden. A steeper target function (the Germans proposed a slope $a = 0.06$ instead of 0.04) would have resulted in lower effort needed from the German firms. The policy debate in 2007, as reported in newspapers and by Deters (2010), focused mainly on this distributional issues and not on the effect of the slope on the likelihood of different abatement strategies.

[29] The improvements in fuel efficiency obained in the EU might also spill over into other markets, creating positive externalities.

[30] Additionally, the attribute-based function might potentially change the costs of compliance from downsizing as well as the direction of the downsizing. The attribute-based target clearly gives an incentive not to lower weight when choosing to downsize the fleet. Whitefoot and Skerlos (2012) simulate this possibility for the footprint based target in the CAFE standards.

Ito and Sallee (2014) point out one other possibly important effect of attribute-based regulation. If the costs of increasing fuel efficiency are higher for heavier vehicles, the slope of the target function might equalize abatement costs and bring the market closer to an equilibrium that would be reached under a cap and trade system. That might make the regulation more cost-efficient and mimic a trading system that might be infeasible for political or practical reasons. When the regulation would be a cap and trade system all firms would face exactly the same shadow costs such that $\lambda_f = \lambda$. The coefficient of variation of $\lambda_f'$ with a flat target is 0.55, higher than with an up-sloping target $\lambda_f = 0.48$. The equalization of abatement cost is thus very limited. Also, when we look at the technology efforts needed (assuming the technology effort translates literally into costs), there is almost no equalization. The coefficient of variation for the effort goes from 0.60 to 0.54. The reason for the limited increase in equalization of compliance costs is twofold. First, the regulation is binding on the level of the firm and not on the level of a single product. Since all firms sell products in the different size classes firms are already able to equalize costs between their wide range of products. Second, a simple linear function of weight is probably not a very good fit to actual differences in compliance costs between large firms.

**Incentives to invest in fuel efficiency** The numbers given above raise the question why the regulation was necessary to spark investment in fuel efficiency. In Table 10 I endow each of the firms with a 5% increase in fuel efficiency. Each column gives the effects on profits of all firms after a new Nash equilibrium is reached. The diagonal of the table gives the yearly return in variable profits from the technology investment (provided that the other firms respond only by changing prices). The table shows that each firm can increase variable profits compared to the status quo by investing in fuel efficiency. If there are private gains to be made by investing in technology, why then did firms invest such a limited amount in fuel efficiency up until 2007?

A first answer to this could be investment inefficiencies of the consumer. If consumers do not value future fuel cost savings to the full extent, firms will not be able to increase sales after investments in fuel efficiency. Grigolon, Reynaert and Verboven (2014) find that consumer investment inefficiencies in the EU are not large (consumers value future savings at more than 80%). Allcott and Wozny (2012) report a somewhat lower number for the US. As the exercise in table 10 shows, as well as the overall results, consumers do increase demand in response to increases in fuel economy and this channel cannot explain why firms hardly invested in fuel efficiency up until 2007.

A second channel might be market failures in the supply and adoption of technology.

Jaffe, Newell and Stavins (2005) discuss market failures associated with innovation and diffusion of technologies. A first market failure might be spillovers in technology, such that innovation has a positive externality. Second, there might be positive externalities related to the adoption of new technologies. A third channel might be incomplete information about future returns of the investment. In the car market this could be relevant as fuel prices and taxation vary extensively over time. The result of these market failures could be a socially suboptimal equilibrium with no or too little investment and technology adoption. The regulation gives clear and binding efficiency targets for the whole industry and thus might succeed in moving the industry out of this suboptimal equilibrium and to induce technology adoption. It is perhaps striking that the industry itself agreed to step into a nonbinding agreement in 1998, but failed to reach the targets.[31] The voluntary agreement aimed to bring each producers' sales weighted emissions down to 140 g $CO_2$/km by 2008. The agreement is considered a failure as only the small car makers Fiat, PSA and Renault came close to the goal and strong reductions in emissions only happened after 2007, when the binding regulation was announced.

Testing this hypothesis of a market failure in technology adoption would require data on the fixed costs of R&D related to fuel efficiency and a dynamic model of technology investment, which is out of scope for this paper. Recent work has looked at R&D patterns in the automobile industry. Hashmi and Van Biesebroeck (2012) estimate and solve a dynamic model to look at the relation between industry concentration and innovation exploiting variation in the number of firms through globalization. Aghion et al. (2012) present evidence, by looking at patents, that firms invest more in the development of electric and hybrid engines in periods of high fuel prices. They also find strong evidence for path dependency: firms that previously invested in green technology are more likely to continue these investments. Also, Klier and Linn (2013) look at the impact of regulation on the pace of technology improvement and find significant effects of regulation on the pace of technology adoption.

Further empirical evidence on the degree and the causes of underinvestment in technology would be useful to further evaluate the policy. Several interesting questions remain to be answered. Are emission standards a useful policy instrument to solve for technology adoption failures? What is the optimal level of the standard in that case? How do the effects of standards compare with other policy options like innovation subsidies and tax credits? To what extent should these measures be combined with more direct externality taxes? All major car markets in the world are currently subject to a system of fuel taxes, sales taxes,

[31] This agreement is known as the ACEA agreement.

targeted subsidies and emission or fuel efficiency standards. The interplay of those different taxes and regulations and the margins they address remain fertile ground for research.

# 7 Conclusion

This paper has evaluated the response to a recent emission standard that was announced for the European Union in 2007. I find that between 2007 and 2011 sales weighted emissions from new vehicle sales have decreased by more than 14%. The decrease is fully explained by firms' response to the regulation. Firms choose to abate emissions by installing new technology in engines that increases fuel efficiency for the whole vehicle fleet. Firms do not change their sales-mix, nor do they release significantly downsized vehicles in the years after the regulation. I find that, because of the large improvement in technology adoption, the regulation has a large positive effect on consumers. The incidence of the regulation thus fully falls on producers. Overall, I find that greenhouse gas emissions from new vehicle sales reduce by 7%. Despite the 14% gains in efficiency, emissions go down by only 7% because a large rebound effect on the extensive margin. A back of the envelope calculation shows that because of the increase in total sales, other external costs such as accident risk and increased congestion offset all of the gains in emission reduction. I find that the effects of the regulation would have been very different if firms had responded by changing the relative prices of products in order to get a sales-mix with better fuel efficiency. This would have resulted in large losses in consumer surplus and variable profits but more savings in greenhouse gas emissions (up to 20%). The overall welfare effects of this abatement strategy would have been in the order of negative €20 billion, making it a very costly regulation to reduce emissions.

Next, I find that the attribute-based design of the regulation, so that the emission target varies with average weight of each producer, makes sales-mix abatement much more costly for firms and thus increases the likelihood that firms will increase their pace of technology adoption. In general, the difference in welfare effect between sales-mix abatement and technology adoption show that policy makers should design the regulation such that the latter strategy is chosen. Attribute-based regulation might be one of the tools to achieve that, as well as providing a clear and long enough time path for the abatement combined with heavy fees for breaking the standard.

Finally, I would like to end with some cautionary remarks. The numbers derived in this paper are obtained under some strong assumptions. Contrary to most other work, I do specifically test the performance of the structural model to explain observed market outcomes. However, one should keep in mind the limitations of the model. First of all, the model does not allow to predict the size of the outside good (not choosing to buy a vehicle) out of sample, the model does not account for the strong decline in sales observed between 2007-2011. I do predict however, that this decline in sales might have been more severe if fuel efficiency had not increased. Second, I do focus only on sales of new vehicles and assume implicitly there will be no effects on prices and vehicle lifetimes in the second hand market. I expect the effects of technology adoption on the existing vehicle fleet to be very different from those of sales-mixing. Third, all welfare numbers are obtained ignoring possible rebound effects on driving behavior. Fourth, I do not observe any of the fixed costs related to implementing and inventing the new technology related to fuel efficiency. Each of these issues could be interesting for further research but require either a different empirical approach or additional data.

# References

**Aghion, Philippe, Antoine Dechezleprêtre, David Hemous, Ralf Martin, and John Van Reenen**, "Carbon Taxes, Path Dependency and Directed Technical Change: Evidence from the Auto Industry," NBER Working Papers 18596, National Bureau of Economic Research, Inc December 2012.

**Allcott, Hunt and Nathan Wozny**, "Gasoline Prices, Fuel Economy, and the Energy Paradox," *Review of Economics and Statistics*, 2012, *forthcoming.*

**Anderson, Michael and Maximilian Auffhammer**, "Pounds that Kill: The External Costs of Vehicle Weight," *Review of Economic Studies*, 2014, *81 (2)*, 535–571.

**Anderson, Soren T. and James M. Sallee**, "Using Loopholes to Reveal the Marginal Cost of Regulation: The Case of Fuel-Economy Standards," *American Economic Review*, 2011, *101* (4), 1375–1409.

**Angrist, Joshua D. and Jörn-Steffen Pischke**, "The Credibility Revolution in Empirical Economics: How Better Research Design Is Taking the Con out of Econometrics," *Journal of Economic Perspectives*, 2010, *24* (2), 3–30.

**Berry, Steven T., James Levinsohn, and Ariel Pakes**, "Automobile Prices in Market Equilibrium," *Econometrica*, 1995, *63* (4), 841–890.

**Deters, Henning**, "Legislating on Car Emissions. What Drives Standards in EU Environmental Policy," Technical Report 2010.

**Fan, Ying**, "Ownership Consolidation and Product Characteristics: A Study of the US Daily Newspaper Market," *American Economic Review*, 2013, *103* (5), 1598–1628.

**Gillingham, Kenneth**, "Selection on Anticipated Driving and the Consumer Response to Changing Gasoline Prices," Technical Report 2012.

_ **, Matthew Kotchen, David Rapson, and Gernot Wagner**, "The Rebound Effect is Over-played.," *Nature*, 2013, *493*, 475–476.

**Goldberg, Pinelopi Koujianou**, "The Effects of the Corporate Average Fuel Efficiency Standards in the US," *Journal of Industrial Economics*, March 1998, *46* (1), 1–33.

**Grigolon, Laura, Mathias Reynaert, and Frank Verboven**, "Consumer valuation and the effectiveness of tax policy - Evidence from the European car market," Technical Report 2014.

**Hashmi, Aamir Rafique and Johannes Van Biesebroeck**, "The relationship between market structure and innovation in industry equilibrium: a case study of the global automobile industry," *Review of Economics and Statistics*, 2012, *Forthcoming.*

**Hausman, Jerry A and Gregory K Leonard**, "The Competitive Effects of a New Product Introduction: A Case Study," *The Journal of Industrial Economics*, 2002, *50* (3), 237–263.

**Holland, Stephen P., Jonathan E. Hughes, and Christopher R. Knittel**, "Greenhouse Gas Reductions under Low Carbon Fuel Standards?," *American Economic Journal: Economic Policy*, 2009, *1* (1), 106–46.

**International Council On Clean Transportation,**, "Global passenger vehicle standards," *http://www.theicct.org/info-tools/global-passenger-vehicle-standards*, 2014.

**Ito, Koichiro and James M. Sallee**, "The Economics of Attribute-Based Regulation: Theory and Evidence from Fuel-Economy Standards," Technical Report 2014.

**Jacobsen, Mark R.**, "Evaluating US Fuel Economy Standards in a Model with Producer and Household Heterogeneity," *American Economic Journal: Economic Policy*, 2013, *5* (2), 148–87.

_ **and Arthur van Benthem**, "Vehicle Scrappage and Gasoline Policy," Technical Report 2013.

**Jaffe, Adam B., Richard G. Newell, and Robert N. Stavins**, "A tale of two market failures: Technology and environmental policy," *Ecological Economics*, 2005, *54 (2-3)*, 164–174.

**Kaboski, Joseph P. and Robert M. Townsend**, "A Structural Evaluation of a Large-Scale Quasi-Experimental Microfinance Initiative," *Econometrica*, 2011, *79* (5), 1357–1406.

**Klier, Thomas and Joshua Linn**, "New-vehicle characteristics and the cost of the Corporate Average Fuel Economy standard," *The RAND Journal of Economics*, 2012, *43* (1), 186–213.

_ **and** _ , "Technological Change, Vehicle Characteristics, and the Opportunity Costs of Fuel Economy Standards," Discussion Papers dp-13-40, Resources For the Future December 2013.

**Knittel, Christopher R.**, "Automobiles on Steroids: Product Attribute Trade-Offs and Technological Progress in the Automobile Sector," *American Economic Review*, December 2011, *101* (7), 3368–99.

**Knittel, Christopher R and Konstantinos Metaxoglou**, "Estimation of Random-Coefficient Demand Models: Two Empiricists' Perspective," *Review of Economics and Statistics*, 2014, *96* (1), 34–59.

**Nevo, Aviv**, "Measuring Market Power in the Ready-to-Eat Cereal Industry," *Econometrica*, March 2001, *69* (2), 307–42.

**Parry, Ian W. H., Margaret Walls, and Winston Harrington**, "Automobile Externalities and Policies," *Journal of Economic Literature*, 2007, *45* (2), 373–399.

**Regulation (EC) No. 443/2009,** , "Setting emission performance standards for new passenger cars as part of the Community's integrated approach to reduce CO2 emissions from light-duty vehicles," *Official Journal of the European Union*, 2009, *L 140/1.*

**Reynaert, Mathias and Frank Verboven**, "Improving the performance of random coefficients demand models: The role of optimal instruments," *Journal of Econometrics*, 2014, *179* (1), 83 – 98.

**Rojas, Christian**, "Price Competition In U.S. Brewing," *The Journal of Industrial Economics*, 2008, *56* (1), 1–31.

**Todd, Petra E. and Kenneth I. Wolpin**, "Assessing the Impact of a School Subsidy Program in Mexico: Using a Social Experiment to Validate a Dynamic Behavioral Model of Child Schooling and Fertility," *American Economic Review*, 2006, *96* (5), 1384–1417.

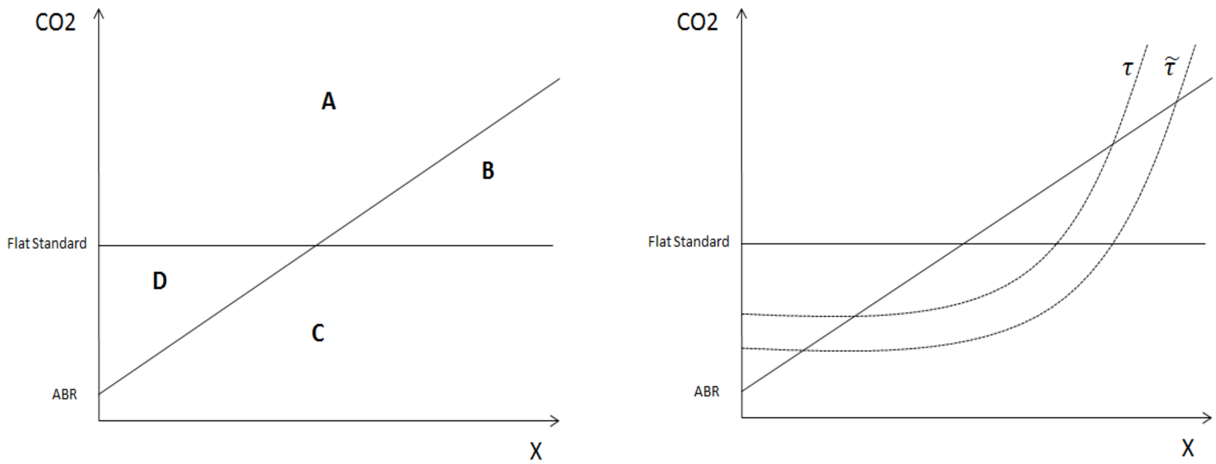
**Weinberg, Matthew C. and Daniel Hosken**, "Evidence on the Accuracy of Merger Simulations," *The Review of Economics and Statistics*, 2013, *95* (5), 1584–1600.

**Whitefoot, K. S. and S. J. Skerlos**, "Design Incentives to Increase Vehicle Size Created from the U.S. Footprint-based Fuel Economy Standards.," *Energy Policy*, 2012, *41 (1)*, 402–411.

**Whitefoot, Kate S., Meredith Fowlie, and Steven J. Skerlos**, "Compliance by design: Industry response to energy efficiency standards," Technical Report 2013.

# 8 Figures and Tables

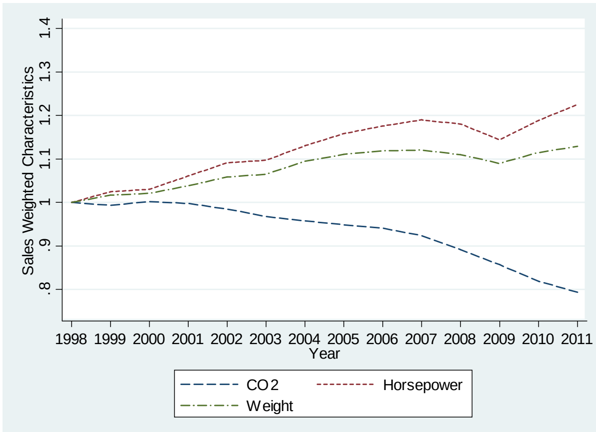
Figure 1: Emission Standards and Abatement Strategies



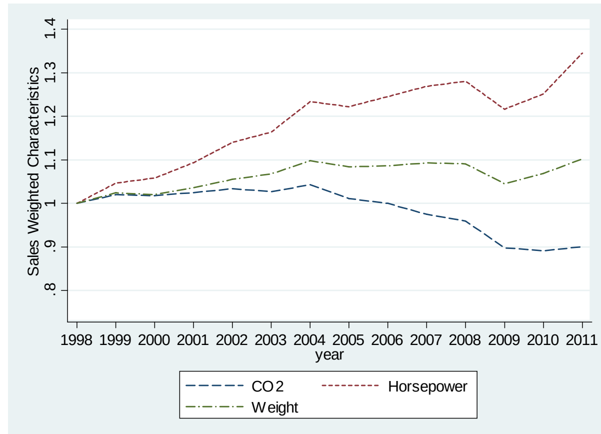

Flat and Attribute-based Regulation | Production Possibility Frontier

Panel I plots the target function for a flat and attribute-based (ABR) regulation in a plot with $CO_2$ emissions on the vertical axis and product characteristics $X$ on the horizontal axis. The flat standard has the same target for each vehicle, the ABR varies with $X$. Products on or underneath the target line contribute to compliance with the regulation. Panel II plots the same regulations and adds the production possibility frontier for different technology levels $\tau$ and $\widetilde{\tau}$. The area above the production possibility frontier gives all possible product combinations and expands as technology improves from $\tau$ to $\widetilde{\tau}$. Three possible abatement strategies are the following: 1. Sales-Mixing: increase prices of products above the target (A and B for the flat regulation, A and D for the ABR) and decrease prices of products below the target (C and D for the flat regulation, B and C for the ABR); 2. Downsizing: design and sell new products below the target, given the current production possibility frontier $\tau$ (C and D for the flat regulation, B and C for the ABR); 3. Technology Adoption: increase technology from $\tau$ to $\widetilde{\tau}$ such that the set of possible product combinations below the target increases.

Figure 2: Sales Weighted Characteristics over Time



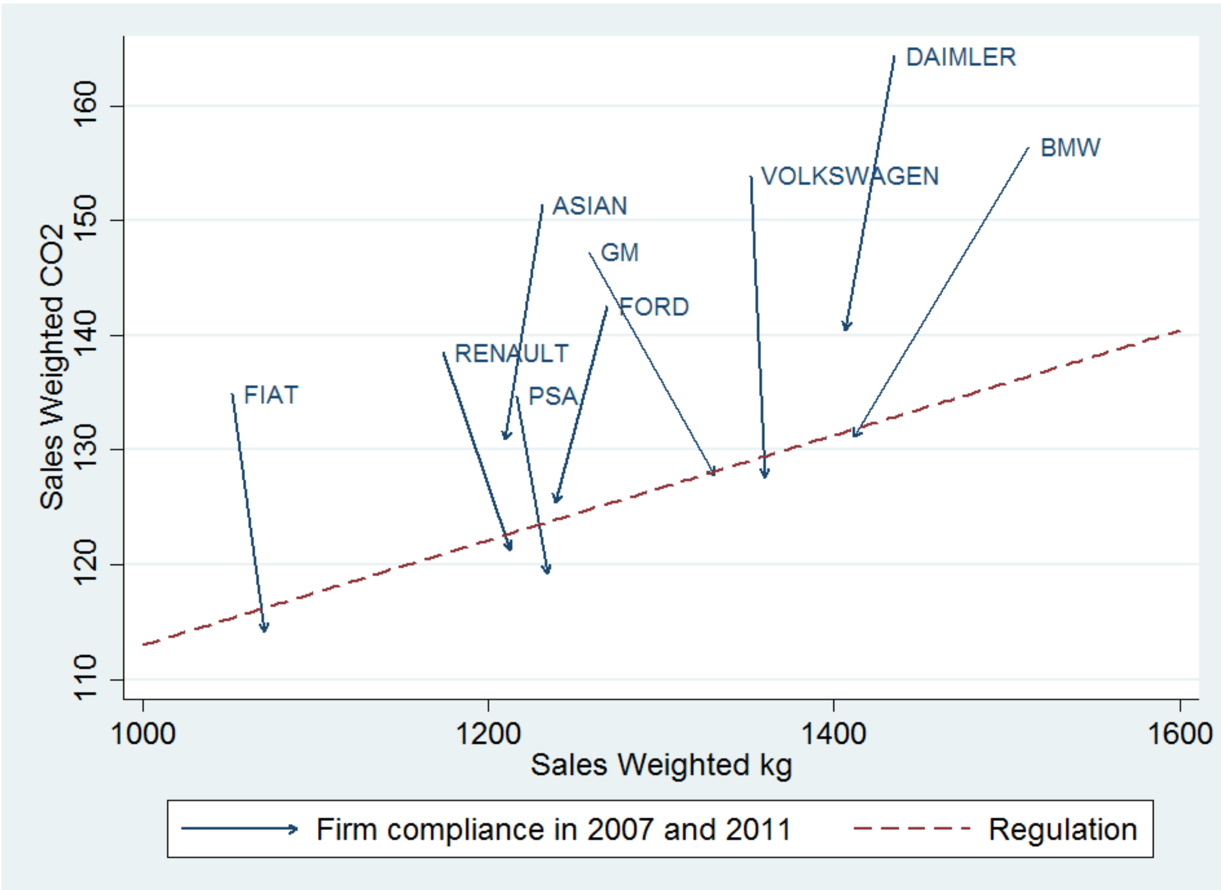

Europe




United States

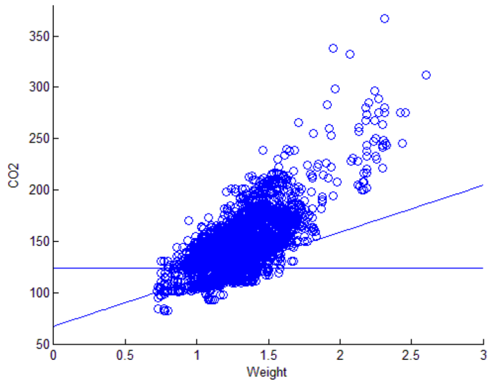
The figure shows the evolution of quantity weighted characteristics from 1998 until 2011, indexed at 1998. The EU trends represent the evolution of sales weighted characteristics as observed in the data. In the EU $CO_2$ emissions decrease by 20%, horsepower and weight increase by 22% and 13%. The US trends represent the evolution of production weighted characteristics as reported by the EPA (http://www.epa.gov/otaq/fetrends.htm). In the US $CO_2$ emissions decrease by 10%, horsepower and weight increase by 34% and 10%.

Figure 3: Compliance of Firms in 2007 and 2011

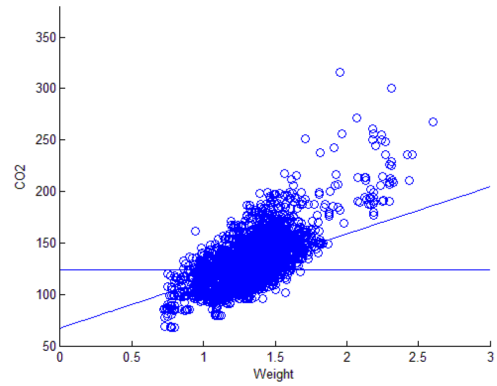



The figure shows the response of each of the firms to the regulation. The starting point of each arrow gives the sales weighted $CO_2$ and mass for each producer in 2007 as observed in the data. The end of each arrow gives the same point in 2011. The dashed diagonal line is the regulation, fully binding in 2015.

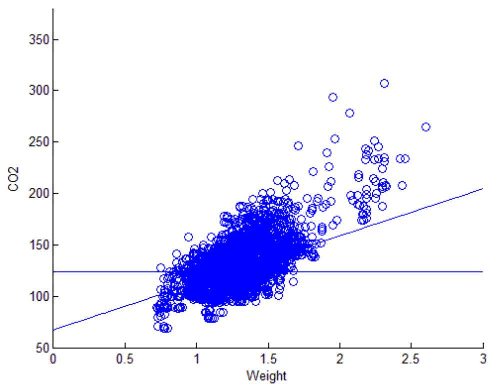
Figure 4: Policy Simulations




Start of policy simulation




Attribute standard




Flat standard

The figure shows each vehicle in a $CO_2$-weight diagram. $CO_2$ is in g/100km and weight is in 1000kg. The diagonal line represent the attribute based standard and the horizontal line is the flat standard. The first panel gives the vehicle fleet at the start of the simulation and shows all vehicles sold in 2007 with a fuel efficiency improvement of 6.4%. When firms respond with sales-mix abatement the target must be reached with this set of vehicles, such that only points under the diagonal (horizontal) line help with attaining the attribute-based (flat) standard. The second panel gives the set of vehicles after full technology adoption to the attribute-based standard (the diagonal line is binding). The third panel gives the set of vehicles after full technology adoption to the flat standard (the horizontal line is binding).

Table 1: Sales weighted vehicle characteristics in 2007 and 2011

| Characteristics | 2007 | 2011 | % Change |
|---|---|---|---|
| $CO_2$ (in g/km) | 147 | 126 | -14% |
| Horsepower (in kW) | 77 | 80 | 3% |
| Footprint (in $m^2$) | 7.2 | 7.4 | 2% |
| Weight (in kg) | 1271 | 1280 | 1% |
| Diesel | 56% | 56% | 0% |

| $CO_2$ (in g/km) per class | 2007 | 2011 | % Change |
|---|---|---|---|
| Subcompact | 130 | 115 | -12% |
| Compact | 145 | 125 | -14% |
| Intermediate | 157 | 132 | -16% |
| Standard | 159 | 136 | -15% |
| Luxury | 182 | 145 | -20% |
| Compact Van | 153 | 134 | -12% |
| SUV | 206 | 154 | -25% |
| Sports | 174 | 145 | -17% |

The upper panel of the table presents vehicle characteristics that are sales weighted over the 7 observed countries in 2007 and 2011. The lower panel gives the sales weighted $CO_2$ emissions per size class. The last column presents the percentage difference in characteristics between 2007 and 2011.

Table 2: Trade-off Estimates between CO2 Emissions Characteristics

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 |
|---|---|---|---|---|---|---|---|
| ln(Hp) | 0.18*** | 0.26*** | 0.16*** | 0.20*** | 0.13*** | 0.05 | 0.17*** |
| | (0.02) | (0.05) | (0.03) | (0.03) | (0.02) | (0.05) | (0.02) |
| ln(Weight) | 0.66*** | 0.54*** | 0.63*** | 0.70*** | 0.63*** | 0.81*** | 0.80*** |
| | (0.09) | (0.08) | (0.09) | (0.09) | (0.08) | (0.11) | (0.08) |
| ln(Footprint) | -0.16* | -0.14* | -0.16* | -0.15 | -0.11 | -0.16* | -0.29*** |
| | (0.08) | (0.07) | (0.08) | (0.08) | (0.08) | (0.07) | (0.08) |
| ln(Height) | 0.41*** | 0.30** | 0.43*** | 0.40*** | 0.31** | 0.42*** | 0.29** |
| | (0.11) | (0.10) | (0.12) | (0.12) | (0.11) | (0.11) | (0.09) |
| Diesel | -0.20*** | -0.83*** | -0.21*** | -0.20*** | -0.21*** | -0.20*** | -0.21*** |
| | (0.01) | (0.20) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Price | | | 0.03 | | | | |
| | | | (0.03) | | | | |
| Marginal Cost | | | | -0.02 | | | |
| | | | | (0.02) | | | |
| Year F.E.? | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Diesel×Char.? | | Yes | | | | | |
| Year×Char.? | | | | | | Yes | |
| Year×Firm? | | | | | | | Yes |
| Observations | 12,659 | 12,659 | 12,659 | 12,659 | $132\times10^6$ | 12,659 | 12,659 |
| $R^2$ | 0,82 | 0,83 | 0,84 | 0,83 | 0,81 | 0,83 | 0,83 |

This table gives the trade-off parameters $\eta$ between characteristics and emissions from equation (10). Robust standard errors are reported between brackets and clustered per firm, *** p<0.01, ** p<0.05, *p<0.10. Model 1 is estimated with ols and includes only year fixed effects, Model 2 includes diesel by characteristic interactions, Model 3 includes price as an explanatory variable, Model 4 includes marginal costs (as estimated from the structural model), Model 5 is a weighted least square using sales as frequency weights, Model 6 interacts the time trend with characteristics and Model 7 allows for a different time trend for each model.

Table 3: Technological Progress Estimates

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| 1999 | 2% | 1% | 1% | 2% | 2% | -1% |
| 2000 | -2% | 0% | -1% | -2% | -1% | -3% |
| 2001 | 2% | 0% | 2% | 2% | 1% | -2% |
| 2002 | 2% | 2% | 1% | 2% | 2% | -1% |
| 2003 | 2% | 2% | 2% | 2% | 2% | 3% |
| 2004 | 2% | 2% | 3% | 2% | 2% | 2% |
| 2005 | 2% | 2% | 1% | 2% | 2% | 4% |
| 2006 | 2% | 1% | 2% | 2% | 1% | 3% |
| 2007 | 2% | 2% | 2% | 2% | 2% | 1% |
| 2008 | 3% | 3% | 3% | 3% | 3% | 4% |
| 2009 | 4% | 4% | 4% | 4% | 4% | 3% |
| 2010 | 5% | 5% | 5% | 5% | 5% | 7% |
| 2011 | 5% | 5% | 5% | 5% | 4% | 2% |
| | | | Average Technology Growth | | | |
| 1998-2007 | 1.6% | 1.3% | 1.4% | 1.6% | 1.4% | 0.7% |
| 2008-2011 | 4.3% | 4.3% | 4.3% | 4.3% | 4.0% | 4.0% |

The table gives the estimated yearly change of technology in the $CO_2$ production function as derived from the year fixed effects in (10). Each of the estimated models corresponds to Table 2, firm specific technology paths for Model 7 are given in the appendix. The shaded area are years after the policy announcement.

Table 4: Decomposing the Decrease in Emissions

| | | All Vehicles | | Existing Models (2007≤) | | New Models (>2007) | |
|---|---|---|---|---|---|---|---|
| | | No Tech. | Tech. | No Tech. | Tech. | No Tech. | Tech. |
| | True | $\overline{e}_{jt}$ | $\widehat{e}_{jt}$ | $\overline{e}_{jt}$ | $\widehat{e}_{jt}$ | $\overline{e}_{jt}$ | $\widehat{e}_{jt}$ |
| 1998 | 169 | 151 | 172 | 151 | 172 | | |
| 1999 | 168 | 152 | 170 | 152 | 170 | | |
| 2000 | 169 | 151 | 172 | 151 | 172 | | |
| 2001 | 167 | 152 | 170 | 152 | 170 | | |
| 2002 | 164 | 152 | 168 | 152 | 168 | | |
| 2003 | 161 | 152 | 164 | 152 | 164 | | |
| 2004 | 158 | 153 | 161 | 153 | 161 | | |
| 2005 | 156 | 153 | 158 | 153 | 158 | | |
| 2006 | 154 | 154 | 157 | 154 | 157 | | |
| 2007 | 151 | 154 | 154 | 154 | 154 | | |
| 2008 | 147 | 153 | 148 | 153 | 148 | 161 | 156 |
| 2009 | 142 | 154 | 144 | 153 | 143 | 163 | 151 |
| 2010 | 135 | 154 | 137 | 154 | 136 | 157 | 138 |
| 2011 | 130 | 155 | 131 | 154 | 130 | 157 | 132 |

The table reports observed and predicted levels of sales weighted $CO_2$ emissions. Emissions are corrected with the attribute function $f(w_j)$ and represent the actual target values for the regulation. All predictions use the estimates from Table 2 Model 1. The columns $\overline{e}_{jt}$ contain sales weighted predicted emissions keeping technology constant at $\tau_t = \tau_{2007}$. The columns $\widehat{e}_{jt}$ contain sales weighted predicted values for emissions with estimated $\tau_t$. For each measure I report results for all vehicle models, models released not later than 2007 and models released after 2007. The shaded area are years after the policy announcement.

Table 5: Estimation Results

| | Demand Estimation | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Logit | | | | RC logit | | | |
| | Mean Valuation | | St. Dev. | | Mean Valuation | | St. Dev. | |
| | Param. | St.Err. | Param. | St.Err. | Param. | St.Err. | Param. | St.Err. |
| Price/Inc. | -3.894 | 0.288 | - | - | -3.690 | 0.275 | | |
| Fuel Cons. (€/km) | -0.259 | 0.010 | - | - | -0.342 | 0.028 | 0.116 | 0.049 |
| Horsepower | 1.355 | 0.191 | - | - | -0.928 | 0.249 | 2.009 | 0.191 |
| Weight | 1.620 | 0.163 | - | - | 1.941 | 0.175 | 0.169 | 0.348 |
| Footprint | 0.281 | 0.034 | - | - | 0.283 | 0.037 | 0.064 | 0.045 |
| Height | 0.015 | 0.016 | - | - | 0.004 | 0.016 | | |
| Foreign | -0.864 | 0.023 | - | - | -0.904 | 0.047 | 0.405 | 0.260 |

| | Marginal Cost Estimation | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Logit | | | | RC logit | | | |
| | Perfect Comp. | | Imp. Comp. | | Perfect Comp. | | Imp. Comp. | |
| | Param. | St.Err. | Param. | St.Err. | Param. | St.Err. | Param. | St.Err. |
| Fuel Cons. (Li/100km) | -0.037 | 0.001 | -0.025 | 0.001 | -0.037 | 0.001 | -0.087 | 0.001 |
| Horsepower | 0.574 | 0.005 | 0.439 | 0.005 | 0.574 | 0.005 | 0.973 | 0.008 |
| Weight | 0.595 | 0.009 | 0.452 | 0.009 | 0.595 | 0.009 | 0.980 | 0.016 |
| Footprint | 0.008 | 0.002 | 0.001 | 0.002 | 0.008 | 0.002 | 0.081 | 0.004 |
| Height | 0.003 | 0.001 | 0.002 | 0.001 | 0.003 | 0.001 | 0.003 | 0.002 |
| Foreign | -0.026 | 0.003 | -0.043 | 0.003 | -0.026 | 0.003 | 0.045 | 0.004 |
| Log Labor Cost Proxy | 0.169 | 0.007 | 0.083 | 0.007 | 0.169 | 0.007 | 0.417 | 0.013 |
| Production in market | -0.013 | 0.002 | -0.009 | 0.002 | -0.013 | 0.002 | -0.031 | 0.004 |

The Table reports estimated parameters for the demand and marginal cost equations. Demand is estimated with a Logit and a Random Coefficient Logit. Marginal Costs are derived and estimated using the first order conditions of the profit function under the assumption of perfect competition and a Nash Bertrand game in prices (imperfect competition).

Table 6: Out of sample fit of sales weighted characteristics

| | | Perfect Competition | | Imperfect Competition | |
|---|---|---|---|---|---|
| | Observed | Logit | RC Logit | Logit | RC Logit |
| Sales Weighted: | Within Sample Fit (2007) | | | | |
| $CO_2$ (in g/km) | 147 | 149 | 148 | 149 | 149 |
| Price/Income | 0.71 | 0.74 | 0.73 | 0.74 | 0.71 |
| Horsepower (in kW) | 78 | 81 | 79 | 81 | 80 |
| Weight (in kg) | 1271 | 1293 | 1283 | 1289 | 1285 |
| Footprint (in $m^2$) | 7.2 | 7.3 | 7.2 | 7.3 | 7.3 |
| Diesel | 56% | 54% | 53% | 54% | 52% |
| | Out of Sample Fit (2011) | | | | |
| $CO_2$ (in g/km) | 126 | 130 | 129 | 130 | 129 |
| Price/Income | 0.69 | 0.76 | 0.75 | 0.75 | 0.74 |
| Horsepower (in kW) | 80 | 87 | 85 | 87 | 85 |
| Weight (in kg) | 1280 | 1319 | 1314 | 1317 | 1307 |
| Footprint (in $m^2$) | 7.4 | 7.5 | 7.5 | 7.5 | 7.5 |
| Diesel | 56% | 57% | 56% | 57% | 56% |

This Table gives the sales weighted characteristics using predicted quantities and prices in 2007 and 2011. For each of the estimated models in Table 5 I solve for quantities and prices within and out of sample given the estimated parameters.

Table 7: Market shares per size class

| | | Technology Adoption | | Sales Mix | |
|---|---|---|---|---|---|
| | 2007 | ABR | Flat | ABR | Flat |
| | | | Market Shares | | |
| Subcompact | 41 | 42 | 41 | 48 | 58 |
| Compact | 21 | 20 | 21 | 24 | 20 |
| Inter. | 6 | 6 | 6 | 5 | 3 |
| Standard | 6 | 5 | 5 | 5 | 4 |
| Luxury | 3 | 2 | 2 | 2 | 1 |
| Van | 18 | 18 | 18 | 15 | 12 |
| SUV | 5 | 5 | 5 | 1 | 1 |
| Sports | 2 | 2 | 2 | 1 | 1 |
| | | | Aggregate Effects | | |
| Total Sales | | 5% | 5% | -10% | -6% |
| Total $CO_2$ Emissions | | -6% | -6% | -20% | -16% |

The table gives the market shares of different size classes and the effect of the regulation on total sales and emissions. The first column gives the observed market shares in 2007. The next columns give the market shares from policy simulations with technology adoption and sales-mix abatement for a an attribute-based (ABR) and a flat regulation. For each simulation I use estimated parameters from the RC logit with imperfect competition from Table 5.

Table 8: Welfare Effects

| Δ in billion €'s: | Technology Adoption ABR | Technology Adoption Flat | Sales Mixing ABR | Sales Mixing Flat |
|---|---|---|---|---|
| Consumers: | | | | |
| Δ Consumer Surplus | 9.50 | 8.81 | -26.61 | -20.86 |
| Firms: | | | | |
| Δ Variable Profits | -1.84 | -2.20 | -16.43 | -13.26 |
| Δ Fixed Costs | ? | ? | 0 | 0 |
| Externalities: | | | | |
| Δ $CO_2$ Savings | 0.35 | 0.34 | 1.07 | 0.87 |
| Δ Other Externality Savings | -8.25 | -7.67 | 17.60 | 10.88 |
| Δ Total: | ]...,-0.24] | ]...,-0.72] | -24.37 | -22.37 |

The table gives aggregated effects over all markets and firms for each policy simulation. The table reports the total change in welfare in billion € over the total expected lifetime of the vehicle. A vehicle is expected to live for 15 years and to have an annual mileage of 14 000 km per year, the discount rate is 6%. A ton of $CO_2$ is valued at €28 (this value is taken from the interagency working group on social cost of carbon). Other externalities are valued at 12cent per kilometer following Parry et al. (2007). Other externalities include local pollution, congestion, and accident risk.

Table 9: Profits and Emission per firm

| | Target ABR $CO_2$ | Target Flat $CO_2$ | Technology Adoption $\tau_f$ | Technology Adoption ABR Δ Profit | Technology Adoption $\tau'_f$ | Technology Adoption Flat Δ Profit | Sales Mixing $\lambda_f$ | Sales Mixing ABR Δ Profit | Sales Mixing $\lambda'_f$ | Sales Mixing Flat Δ Profit |
|---|---|---|---|---|---|---|---|---|---|---|
| BMW | 134 | 124 | 6 | -1240 | 12 | -1033 | 0.8 | 662 | 1.4 | -1302 |
| Daimler | 121 | 124 | 17 | -565 | 15 | -623 | 2.4 | -2313 | 1.0 | -1567 |
| Fiat | 116 | 124 | 7 | 346 | 2 | -217 | 2.5 | -1976 | 0.4 | 363 |
| Ford | 126 | 124 | 5 | -355 | 7 | -110 | 1.0 | 692 | 1.3 | -326 |
| GM | 125 | 124 | 9 | -11 | 10 | 146 | 2.7 | -2888 | 2.2 | -2522 |
| PSA | 123 | 124 | 3 | -355 | 2 | -394 | 0.6 | 1762 | 0.3 | 1508 |
| Renault | 120 | 124 | 7 | 90 | 4 | -100 | 1.5 | -502 | 0.6 | 351 |
| VW | 125 | 124 | 13 | -364 | 14 | 46 | 1.6 | -7093 | 1.4 | -7965 |
| Asian | 118 | 124 | 16 | 617 | 12 | 82 | 2.7 | -4775 | 1.0 | -1795 |

The table gives sales weighted emissions in grams of $CO_2$ per km for each firm for both the attribute-based and the flat standard. The level of technology adoption and the shadow costs $\lambda_f$ of the regulation is given such that each firm exactly reaches the target. The difference in profits between estimated 2007 profits and profits obtained in each of the simulations are in million €'s.

Table 10: Incentives to Invest in Fuel Efficiency

| | Firm increases fuel efficiency by 5% | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | BMW | Daimler | Fiat | Ford | GM | PSA | Renault | VW | Asian |
| BMW | 137 | -13 | -17 | -28 | -33 | -27 | -18 | -58 | -34 |
| Daimler | -6 | 185 | -14 | -18 | -23 | -18 | -13 | -48 | -24 |
| Fiat | -4 | -9 | 518 | -29 | -33 | -38 | -20 | -42 | -33 |
| Ford | -10 | -10 | -27 | 511 | -42 | -40 | -23 | -64 | -46 |
| GM | -11 | -12 | -27 | -39 | 577 | -40 | -24 | -68 | -46 |
| PSA | -5 | -7 | -33 | -39 | -43 | 709 | -58 | -69 | -52 |
| Renault | -2 | -4 | -17 | -21 | -23 | -50 | 442 | -39 | -29 |
| VW | -25 | -38 | -47 | -86 | -101 | -85 | -55 | 1176 | -127 |
| Asian | -9 | -11 | -30 | -46 | -51 | -54 | -34 | -85 | 670 |
| Total | 65 | 81 | 306 | 204 | 229 | 357 | 197 | 703 | 278 |

The table gives the difference in variable profits from the status quo from increasing fuel efficiency by 5%. Column 1 gives the effect of a fuel efficiency increase for BMW on all other firms after reaching a new Nash equilibrium in prices, column 2 gives the effect of an increase in Daimlers fuel efficiency on all firms variable profits, etc. Numbers are in € millions. The last row gives the sum of each column.

# Appendix

## Details on Data Selection

I focus the analysis on the largest EU firms that sell more than 50 000 vehicles in each year of the sample. These are: BMW, Daimler, Fiat, Ford, GM, PSA, Renault and Volkswagen. I consider the largest Asian manufacturers as being one firm in the model. This firm includes: Honda, Hyundai, Mazda, Mitsubishi, Nissan, Suzuki and Toyota. The following firms are not considered in the analysis: Alpina, Aston Martin, Brilliance Auto, Chana, DR Motor, Geely Group, Great Wall, Isuzu, Jensen, Jiangling, Lada, Mahindra & Mahindra, MG Rover, Morgan, Perodua, Porsche, Proton, SAIC, Santana, Spyker, Ssangyin, Subaru, Tata, TVR, Venturi and Wiesmann. Daimler and Chrysler merged during the sample period an I will treat them as one and the same firm in the whole sample.

For the included firms I focus on the most popular brands. I drop the following brands which mostly include luxurious sports cars and temporary owned brands: Abarth, Bentley, Buick, Cadillic, Corvette, Daimler, Dodge, Ferrari, Galloper, Hummer, Infiniti, Innocenti, Iveco, Jaguar, Lamborghini, Land Rover, Lincoln, Maserati, Maybach, Pontiac, Rolls-Royce and Tata.

In total the firms and brands that are not included account for 3.5% of the sales.

Additionally, to reduce the number of observations I select only the 50% most selling models which are a combination of a Brand/Model/Body indicator, e.g. "Volkswagen Golf Hatchback". Of the 50% most popular models I select the engine variants that are sold at least 20 times. Because of this selection, that is necessary to make the number of market share equations tractable, I loose another 14% of sales such that the final data set includes 81.5% of total reported sales. I lose another 3% of total reported sales due to missing values and unrealistic outliers in the characteristics.

The definition of the variable weight changes throughout the sample from curb weight before 2010 to gross vehicle weight in the years 2010 and 2011. I transform the gross vehicle weight to curb weight by matching vehicles that are identical in all characteristics between 2009 and 2010. I regress curb weight on gross vehicle weight, doors and displacement and use the predicted value of that regression to obtain curb weight in 2010 and 2011. The $R^2$ of that regression is 0.95. Curb weight is about 72% lower than gross vehicle weight. Observed and imputed curb weight are then used to compute each vehicles compliance with the regulation.

# Technology Estimates for Individual Firms

Table A1: Technological Progress Estimates per Firm

| | BMW | Daimler | Fiat | Ford | GM | PSA | Renault | VW | Asian |
|---|---|---|---|---|---|---|---|---|---|
| 1999 | 0% | 3% | 2% | 9% | 1% | 2% | 3% | 1% | -2% |
| 2000 | -3% | -3% | 2% | -8% | -3% | 0% | 1% | -1% | 0% |
| 2001 | 4% | 4% | 3% | 4% | 0% | 5% | 1% | 0% | 2% |
| 2002 | 1% | 1% | 1% | 1% | 0% | 2% | 2% | 1% | 4% |
| 2003 | 0% | 2% | 3% | 2% | 3% | 1% | 3% | 2% | 3% |
| 2004 | 0% | 2% | 1% | 3% | 4% | 7% | 3% | 1% | 1% |
| 2005 | 1% | 4% | 1% | 2% | 2% | 2% | 0% | 2% | 1% |
| 2006 | 3% | 1% | 4% | 1% | 1% | 2% | 3% | 1% | 1% |
| 2007 | 10% | 1% | 3% | 0% | 2% | 3% | 1% | 1% | 3% |
| 2008 | 6% | 3% | 3% | 2% | 2% | 2% | 0% | 4% | 3% |
| 2009 | 2% | 5% | 4% | 1% | 3% | 2% | 4% | 6% | 6% |
| 2010 | -1% | 3% | 7% | 7% | 8% | 4% | 4% | 6% | 4% |
| 2011 | 3% | 6% | 6% | 7% | 6% | 5% | 3% | 4% | 3% |
| Average Technology Growth | | | | | | | | | |
| 1998-2007 | 1.8% | 1.7% | 2.2% | 1.6% | 1.1% | 2.7% | 1.9% | 0.9% | 1.4% |
| 2008-2011 | 2.5% | 4.3% | 5.0% | 4.3% | 4.8% | 3.3% | 2.8% | 5.0% | 4.0% |

The table gives the estimated firm specific yearly change of technology in the $CO_2$ production function as derived from the year fixed effects in (10). The estimates correspond to Model 7 in Table 2. The shaded area are years after the policy announcement.

# Algorithm for Policy Simulations

The algorithm follows these steps:

1. Start with a guess for the shadow costs or technology level
2. Solve the Nash equilibrium in prices given the values in 1
3. Compute the market shares given the price equilibrium and the values in 1
4. Compute the sales weighted emission for each of the firm
5. Compute the difference between the value in 4 and the required standard
6. If the difference is smaller than 1e-6 return end, else return to step 1