Abatement Strategies and the Cost of Environmental Regulation: Emission Standards on the European Automobile Market
Job Market Paper

Mathias Reynaert*

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Abstract

Emission standards are one of the major policy tools to reduce green house gas emissions from transportation. The welfare effects from this type of regulation are difficult to evaluate as they depend on how firms choose to comply. 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 new regulation by heavily investing in new technology rather than adjusting the sales mix of their existing fleet. On average, vehicles are about 14% more CO_2 efficient in 2011 than in 2007. To evaluate the welfare effects of this response I estimate a structural model using data from before the policy announcement and explicitly test how well the model is able to predict prices and sales after the large increase in fuel efficiency. I find that, because the abatement is done by technology adoption, the regulation is beneficial to both consumers and firms, but has only moderate effects on the reduction of greenhouse gas emissions because of increases in total sales. If firms had reacted by shifting relative prices of products with different fuel efficiency the regulation would have resulted in large losses to consumer surplus and profits but higher savings in emissions.

*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 Boeckaert, Kenneth Gillingham, Laura Grigolon, Ali Hortaçsu, Thomas Peeters, 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 green house 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 they choose to adopt new technologies or choose to change prices. The European Union (EU) recently began rolling out its first green house gas emission regulation regime. This paper evaluates that program using an approach new to the literature.

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 EU standard is significantly more demanding than similar regulations in Australia, Canada, China and the US. The current EU regulation translates into a standard of about 42 miles per gallon (mpg)[1] for gasoline engines, whereas the US standard requires only 35 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. To the best of my knowledge, this is the first paper providing a detailed evaluation of the EU regulation.

I study the response of firms to the new emission standard using panel data covering 1998-2011 for seven European countries. The data show that firms choose to comply with the new regulation by heavily investing in new technology rather than adjusting the sales-mix of their existing fleet. On average, vehicles are about 14% more CO_2 efficient in 2011 than in 2007. To evaluate the welfare effects of this response I estimate a structural model using data from before the policy announcement and explicitly test how well the model is able to predict prices and sales after the large increase in fuel efficiency. 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 source of emission abatement could be changes in the sales mix. By shifting relative prices of vehicles with different fuel efficiency firms lower the average emission of their fleet. I call this sales mix abatement. A second source could be abatement through the introduction of new technology that makes engines more fuel efficient. Following the approach of Knittel (2011), I estimate the trade-off firms face between fuel efficiency and other engine characteristics. Controlling for other characteristics, changes over time in fuel efficiency identify technology adoption. This shows that the 14% reduction in emissions is fully explained by an increase in the adoption of technology for existing vehicle models. The reduction can not be explained by consumers substituting to more fuel efficient products neither by relative price changes between products with different fuel efficiency. 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

[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.

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 Corporate Average Fuel Efficiency (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 standards 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. The findings in this paper are very different and add new insights to this literature and the evaluation of rule based environmental policy in general. The main difference is that instead of simulating the effects of a potential increase in the standard I observe a strong policy shock: the announcement and implementation of a very strict and binding emission standard.

In a second step I estimate and explicitly validate a structural model of supply and demand of the automobile market. 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 asses 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 careful checking of 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). The large difference in fuel efficiency between 2007 and 2011 will shift market shares and this creates a unique opportunity to test the performance of the demand model out of sample. I find that the model is able to successfully replicate sales weighted characteristics and prices 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 as 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 the predictive power of commonly used estimation methods and underlying assumptions.

In a third step I use the estimated model to answer several questions. What is the welfare impact of the regulation and the observed technology adoption by firms? Would the welfare effects have been different if firms had responded by changing relative prices? I find that if firms respond by adding new technology to vehicles variable profits and consumer surplus increase by a total of $15 billion per year. The reduction in green house gas emissions is limited, a decrease of 7%, because of an increase in total sales. This increase in total sales also increases other externalities, such as accident risk and congestion. Overall, I estimate that the regulation has a net beneficial effect of €5 billion per year. This gain does not include 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 variable profits and consumer surplus decrease by €25 billion per year. The savings in externalities do not balance this high cost and the overall effect would be a yearly loss of €20 billion per year.

This raises the question why the regulation was necessary to push the industry towards more technology investment in fuel efficiency? A first answer 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 can not explain why firms hardly invest in fuel efficiency up until 2007. A second channel might be that spillover and fixed R&D costs of increasing fuel efficiency are high. This might cause each firm to delay its investments hoping that another firm invests and resulting in a socially suboptimal equilibrium with none or too little investments.[4] The regulation might succeed in moving 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.

In a final step, the paper tries to answer whether the choice of firms for technology or sales-mix abatement depends on the design of the regulation? The EU emission standard is an attribute-based regulation, a specific feature that draws attention in relation to this question. Attribute-based regulations specify a target in terms of the externality (emissions in this case) that is correlated with a characteristic of the product (weight in this case). Producers of heavier cars, having a mass higher than 1370 kilograms, face a higher emission target and thus need less fuel efficiency on average. This part of the paper is complementary to the analysis of attribute-based regulation by Ito and Sallee (2014). They are the first to provide an overview of the possible economic effects of attribute-basing. The EU regulation serves as an interesting empirical example to their

[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.

insights and to the reason why regulators choose this type of design. A first reason for the existence of attribute-basing Ito and Sallee (2014) point out is abatement cost equalization between firms in the absence of trading. For the EU, I find that the attribute-based target function diminishes variation in the abatement costs between firms only to a very limited extent. The target function, as specified, is not a replacement for a cap and trade system that would equalize abatement costs among firms. A second possible reason for attribute-basing is distributional concerns of the policy-maker towards different producers. Both anecdotal evidence as well as the outcome of the simulations point out that this was an important concern in the EU. Countries heavily lobbied for the target function that benefited their local producers most. French and Italian firms make lighter vehicles and thus favored a flat (not attribute-based) target. German firms produce heavier cars, benefiting most from an attribute-based target. The simulations confirm these distributional concerns. Third, I find that the cost of responding to the regulation by sales-mixing doubles when going from a flat emission target to an attribute-based emission target. The higher cost of sales-mix abatement makes technology adoption much more likely to occur, and this might be one of the reasons why we see such a strong technology adoption in response to the EU standard. Finally, Ito and Sallee (2014) discuss the distortions of attribute-based targets in terms of the supply of the characteristic with which the target correlates. For example, Ito and Sallee (2014) show that Japanese cars on average gain 100 kg because of a step-wise emission weight target in the Japanese market. Also, Whitefoot, Fowlie and Skerlos (2013) predict that the announced change in the CAFE standard, correlating the target with footprint, will have considerable effects on the size of vehicles. Contrary to these examples, I do not find this to be a primary effect in the EU market. On average weight does not increase, and detailed engine level data show that vehicles do not move closer to the standard through weight increases.

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 relative changes in prices between new and second-hand vehicles. When firms respond to the policy with sales-mixing new polluting vehicles become more expensive, increasing demand for older polluting 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.

In general, the results show that if governments opt to implement an emission standard, it is vital in terms of welfare that the policy induces technological change. The level of the standard must be reachable in the decided time-frame given expected technological improvements. I also show that the design of the policy matters. An attribute-based standard which causes the emission target to vary with another characteristic of the vehicle results in considerably higher incentives to invest in technology.

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 as described in Ito and Sallee (2014). An attribute-based regulation specifies a target that is correlated with another characteristic of the product. In this case, the emission target varies with weight. The emissions of each vehicles 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 weighting 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 raised 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

[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

were strongly in favor of a flat standard, while Germany wanted a strongly upward sloping target function in either weight or footprint. 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 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", the rectangular area in between the wheels of the vehicle. 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 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). 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 as obtained from the OECD. Finally, data on fuel prices (from DataStream), GDP/capita and number of households in each country (from Eurostat) are used to construct fuel costs for consumers, real prices and a scale for the outside good (not buying a new car).

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.

Germany over car emissions" - Financial Times, November 15 2007.

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

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 1 plots sales weighted characteristics over time from 1998 to 2011. Each characteristic is indexed in 1998. The most remarkable trend in Figure 1 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.[9] This is different in the EU, where horsepower, weight and size decrease somewhat between 2007 and 2009, but increase again to higher levels in 2011. Figure 1 clearly shows that engine power, weight and footprint of passenger cars has been growing consistently over the sample period. By 2011, consumers choose a vehicle that on average is 23% more powerful, 13% heavier and has a 8% larger footprint than in 1998. This increasing trend in vehicle size and performance is also documented by Knittel (2011) for the US market.

Figure 2 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.

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

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 efficiency 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%).

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 geographical 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:

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

where $g_{jm}e_{jm}$ are fuel costs (fuel prices g_{jm} times fuel consumption e_{jm}), x_{jm} is a vector of observed product characteristics, p_{jm} is the vehicle price and ξ_{jm} is an unobserved characteristic of vehicle j in market m, unobserved by the researcher but observed by consumers and firms. The parameter vector (β_i^e, β_i^x) consists of random coefficients, capturing individual-specific valuations for fuel costs and vehicle characteristics, α_i is the marginal utility of income or price valuation and ε_{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 ν_i^k is a random variable with zero mean and unit variance, so that β^k represents the mean valuation for characteristic k and σ^k is its standard deviation across consumers. Indirect utility can be decomposed into the sum of three terms: a mean utility term $\delta_{jm} \equiv \beta^e g_{jm} e_{jm} + x_{jm} \beta^x - \alpha p_{jm} + \xi_{jm}$ 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 ε_{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 β_i^e measures the response of consumers to shifts in fuel costs.[10] The mean parameter β^e 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, β^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.

[10] 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).

Each consumer i in market m chooses the alternative $j = 0, \ldots, J$ 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 δ_m is the $J \times 1$ mean utility vector in market m (dependent on the mean valuation parameters β^e, β^x and α), and σ 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 σ 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:

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

in which c_{jm} are marginal costs for product j in market m, L is the individual contribution of each vehicle to the standard and λ_f is the shadow cost of the regulation. The individual contribution L of each product is expressed as the distance between vehicle j's emissions (or fuel consumption) and the target emission σ. Because of the attribute-basing L is a function of weight w_j through $f(w_j)$. Note that $f(w_j)$ defines the slope of the target function. For a flat standard (not attribute-based) $f(w_j) = 0$. The per vehicle shadow cost λ_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 λ_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 also 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 λ_f Anderson and Sallee (2011) exploit loopholes in the CAFE standard, while Jacobsen (2013) exploits the first order conditions of constrained firms. To simplify the analysis, I will solve the model for values of λ_f such that the regulation is exactly binding for all firms. In the simulations, all firms just comply with the standard. I don't allow firms to pay fines or to do more than the standard requires. This replicates closely the response as observed in the market so far.

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

$$\log(c_{jm}) = \gamma^e e_j + z_{jm}\gamma^z + \omega_{jm}, \tag{7}$$

in which z_{jm} is a $1 \times L$ vector of observed product characteristics, market controls and cost shifters, ω_{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, exploiting the fact that in the majority of the data $\lambda_f = 0$ and thus firms are not constrained by the regulation. I will discuss this in more detail below.

3.2 Abatement Strategies

The literature that empirically evaluates the effects from fuel economy standards has focused on two possible abatement strategies of producers. First, as is modelled by Goldberg (1998) and Jacobsen (2013) producers can change the relative prices of products with different fuel efficiency in order to shift their sales mix towards more fuel efficient vehicles. Vehicles that do not contribute to attain the standard ($L > 0$) are priced higher, while vehicles with emissions lower than the target ($L < 0$) are priced lower. This is considered to be the short run response towards an increase in the standard. Second, both Klier and Linn (2012) and Whitefoot, Fowlie and Skerlos (2013) have argued that in the medium run firms can also abate emissions by changing the characteristics of their vehicle fleet. Firms can extend their vehicle fleet $\mathcal{F}_f$ with newly designed products that have more fuel efficiency but less of other characteristics. This mitigates the need of changing relative pricing as more vehicles comply with the standard. Their approach is methodologically challenging for two 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 allow firms to make strategic decisions on both prices and product characteristics which requires strong assumptions and instruments.[11]

Instead, I will focus on a simpler and more tractable channel of product design without adding additional structure to the model. I will focus on the effects of changes in the technology related to fuel efficiency. Firms can improve fuel efficiency of existing vehicles by adapting engines, the combustion process or features

[11] 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 endoginize 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.

that only affect fuel efficiency[12]. Below, I will show that this channel is fully responsible for the observed increase in fuel efficiency. Here, I present the effects of improvements in the overall level of available fuel efficiency (abatement by technology adoption) and will compare these effects with those from changes in relative prices (sales-mix abatement).

Sales mix abatement Each firm sets prices of all its products to maximize profits, taking as given the prices of other firms. I assume a pure Nash equilibrium in prices exists and write the first-order conditions of (6) with respect to prices as:

$$\left\{ s_j(\mathbf{p},\mathbf{e}) + \sum_{k\in\mathcal{F}_f} \frac{\partial s_k(\mathbf{p},\mathbf{e})}{\partial p_j} \left\{ p_k - c_k - \lambda_f L(\sigma, e_k, f(w_k)) \right\} \right\} = 0 \tag{8}$$

I denote the Nash equilibrium as $\mathbf{p} = \mathbf{p}^*(\mathbf{e})$. If $\lambda_f = 0$ the first order conditions are reduced 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, $L > 0$ 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 effectiveness of this abatement strategy depends on the responsiveness of consumers to price changes. The effect on overall firm profits will be negative because firms face an additional constraint on their choices and are not able to choose their first best pricing scheme. Firms that have 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 effects on consumers surplus depend on the relative tastes for different characteristics. 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.

Abatement by technology adoption The effects on equilibrium of technology adoption are very different than those of sales-mix abatement. Consider a technology shift over time τ_1 to τ_2 that shifts emissions such that $e_{jm1}(\tau_1) > e_{jm2}(\tau_2)$ for each vehicle. The shift in emissions will have various effects on the equilibrium outcome. A first effect is a change in marginal costs as defined in (7) as it is more expensive to make fuel efficient vehicles. A second effect is that increasing fuel efficiency leads to a reduction in the distortive effect of the regulation $\lambda_f L$ on the first order conditions. The more fuel efficient vehicles become, the more they contribute to the regulation ($L < 0$). This means that by increasing technology firms require less and less changes in relative prices to comply. Eventually, 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

[12] 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 tyres , 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.

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 internalization of the decreasing in fuel costs for 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.

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. This ambiguity in the total effect of the abatement strategy is in sharp contrast with the effects of sales-mixing where firms and consumers lose both as they are forced into selling/buying other cars than they would have sold/bought without the regulation.

Flat and attribute-based standards In the analysis I consider two designs of the regulation L. First, I replicate the current EU policy which specifies a lower standard for heavier cars. This results in a per vehicle burden of $L = [1 - (\sigma - f(w_j))/e_{jt}]$, in which σ=130g CO_2/km and $f(w_j) = a(w_0 - w_j)$ as specified in (1) and graphed in Figure 2. Second, I specify a flat standard (not attribute-based) so that in equilibrium the same sales weighted emission are attained. For the flat standard $L^{'} = \left[1 - \sigma^{'}/e_{jt}\right]$ and there is no correlation between the level of the standard and weight $f(w_j) = 0$. 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 that is needed to comply with the regulation will differ between the flat standard and the attribute-based standard as a different set of vehicles has $L < 0$ than $L^{'} < 0$. Depending on the average weight of each firm λ_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.

Apart from different costs of abatement strategies and distributional effects between firms, 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 the slope in the target function runs parallel to the cost of compliance, the attribute-based regulation might resemble a cap and trade regulation. If emission reduction is costlier for heavier vehicles the attribute function reduces the regulatory burden on these vehicles and increases the burden for lighter vehicles. This could mimic what would happen under a standard with compliance trading: producers of heavy vehicles would be willing to pay producers of lighter vehicles to do more of the abatement. I will come back to this point below.

4 Market Response to the EU Emission Standard

In this section I explain the causes for the decrease in sales weighted emissions between 2007 and 2011. I will follow 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}. Next, I use the estimated relations to decompose the observed gains in efficiency into a part due to changes in characteristics and a part due to changes in the level of technology. The goal of the exercise is to estimate whether, and to which extend, the observed decline in sales weighted emissions is attributable to changes in vehicle characteristics or technology.

Following Knittel (2011), Klier and Linn (2012) and Klier and Linn (2013) I estimate the following regression:

$$\log(e_{jt}) = \tau_t + \eta \log(x_{jt}) + \epsilon_{jt}, \tag{9}$$

in which the technology parameter τ_t is a time fixed effect, the trade-off parameters η denote how emissions e_{jt} change due to a 1% change in a characteristic x_{jt} and ϵ_{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. The trade-off parameters η are assumed to be constant over time, such that technology τ_t can be seen as input neutral (it enters multiplicative in levels). I assume ϵ_{jt} to be i.i.d. and estimate (9) by ordinary least squares. I will discuss several concerns regarding identification below. Once parameters are estimated I predict the level of emissions of each vehicle keeping technology constant $\overline{e}_{jt}$ ($\tau_t = \tau_{2007}$) and letting technology change over time $\widehat{e}_{jt}$ ($\tau_t = \tau_t$). The difference in the sales weighted trend between $\overline{e}_{jt}$ and $\widehat{e}_{jt}$ decomposes the downward trend in sales weighted emissions into a part attributable to shifts in characteristics ($\overline{e}_{jt}$) and a part attributable to technology ($\widehat{e}_{jt}$).

Table 2 presents the trade-off parameters η from estimating (9). The data are collapsed such that there is a single observation for each vehicle sold in a given year (vehicles that are sold in different countries appear only once). 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 for 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 (9) this would bias the estimated parameters. Expenditures on technology are likely reflected in marginal costs and in so order to control for expenditures, I add prices and marginal costs as explanatory variables.[13] 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 (9) 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

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

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 τ_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. Technology improves over time between 1998 and 2007 by an average 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. Though this provides strong evidence that firms speed up the adoption of technology in response to the regulation, this is by no means causal evidence. Other causes might be changes in the expectations of future gasoline prices or changes in the environment relating to the development of technology. The change in the trend of innovation and the move towards the policy target in Figure 2 are so clear that the policy announcement at least seems to be one of the primary reasons for the speed-up. 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 lead to more technology adoption.

The estimated relation (9) can be used to reveal the compliance strategy of firms between 2007 and 2011. How much of the decline in sales weighted emissions is attributable to changes in the sales-mix? How much is due to new efficient vehicle releases? And how much is due to the increase in technology adoption? First, I define emissions with constant technology level $\overline{e}_{jt}$ using the trade-off parameters and keeping the technology level constant at $\tau_t = \tau_{2007}$. If firms react by sales-mixing we expect the sales weighted average of $\overline{e}_{jt}$ to decrease over time as sales shift towards more fuel efficient vehicles. This decrease could stem from two sources: changes in relative prices and releases of new vehicle models. Therefore, I split the sales weighted average into a part for vehicle models released before and 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. Note that this correspond to the fitted values of regression (9). The trend in $\widehat{e}_{jt}$ gives the sum of sales-mix abatement and technology abatement. 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.[14]

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 9% drop in emissions between 1998 and 2007 from 169 to 154. After 2007, the sales weighted emissions without technology $\overline{e}_{jt}$ keep increasing gradually from 154 to 155. There is thus no evidence at all of changes in the sales-mix, on the contrary sales weighted emission with constant technology increase slightly between 2007 and 2011. When we split up the sales weighted emissions into vehicle models released after and prior to 2007 we see that new vehicles, on average, have higher sales weighted emissions. This shows that introducing newly more fuel efficient vehicles is not the strategy responsible for any of the observed decreases in emissions, on the contrary new vehicles are on average more polluting without technology. The sales weighted emissions with technology $\widehat{e}_{jt}$ are decreasing rapidly after 2007 and technology adoption is fully responsible for the observed drop in emissions. Strikingly, the decrease in sales weighted

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

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 surprising feature of this findings is not that firms do not adapt their sales-mix between 2007-2011. The regulation is only binding from 2012 onwards, so firms have no incentive to change relative prices before that year. What is surprising about the findings, is the degree and speed of the technology adoption abatement strategy. The increase in technology adoption is so strong that most firms already comply with the emission standard in 2011 as is shown in Figure 2. This finding is in contrast with the literature discussing the compliance strategies to the CAFE standard. In the case of the European emission standard abatement by technology adoption is thus not a possible long term response but the sole and immediate abatement strategy that firms choose. Below, I will try to answer why this abatement strategy is chosen and why this matters for the welfare effects of the regulation.

5 Estimation

In this section I estimate the structural model of demand and supply as set out in Section 3. The model will be used to answer what the welfare effects of the strong increase in technology adoption are, and whether the regulation design is related to which abatement strategy firms choose. Before proceeding, I discuss estimation and validation of the model.

5.1 Estimation of demand and marginal cost function (using data from 1998-2007)

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 θ to be estimated consists of the taste parameters β_i^e, β_i^x and α_i and the cost parameters γ^e and γ^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 α_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 ξ_{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 ω_{jmt} is unobserved.

The parameters are obtained by minimizing the GMM criterion:

$$\min_{\theta} \rho\left(\theta\right)' g(z)' A \rho\left(\theta\right)' g(z)' \tag{10}$$

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 et al. (1995) and Nevo (2001). I take into account recent cautionary warnings and improvements and carefully check the properties of the obtained minimum.[15] For simplicity, I estimate the demand and supply separately, i.e. I don't 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 (8). 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 other characteristics 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 asses the ability of the structural model to predict counterfactual outcomes. In recent years there have been questions regarding the reliability

[15] More specifically I do the following: (i) I use a nested-fixed point (NFP) algorithm, BLP's contaction mapping with a very thigh convergence criterion (1e-12) to solve for ξ_{jmt}, (ii) I re-estimate the model with 10 different starting values for the non linear parameters, (iii) I carefully 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.

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 6.2 I estimated demand and marginal cost parameters using 10 years of data from 1998-2007. As discussed in Section 5 firms respond starkly to the policy between 2007 and 2011 by adding new technology to their vehicles. This means that 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 fit 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 in 2011.

The procedure for the out of sample test is straightforward. First, I make the assumption that both the supply ω_{jmt} and demand error ξ_{jmt} in equation (7) and (3) are at their expected level ($E(\omega_{jm2011}) = E(\xi_{jm2011}) = 0$).[16] Second, I estimate the marginal costs $\widehat{c}_{jt}$ for each vehicle on sale in 2011 using the estimated parameters from Table 5. Given the estimated 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 (8). Because the regulation is still not binding in 2011 and firms do not change their sales-mix I set $\lambda = 0$ and simulate prices as if firms do not alter them in response to the policy. 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 for examples). 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

[16] 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.

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 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. There 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 perfect 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 fur further research. First, the out of sample test provides a validation of the demand model but not so much of the assumptions regarding price competition. I find that both the cost functions under perfect and imperfect competition are able to predict prices accurate 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 is partly attributable to entry of new and cheap SUVs on the market between 2007 and 2011. In 2007, an SUV was a very luxurious car, while in 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 imprecisely 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. After presenting the set up for the simulations, I present the market share for different size classes and changes in consumer surplus, profits and externalities. I end the section with a discussion on the specific effects of the attribute-based regulation by comparing it to a flat standard.

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 also 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 let the emissions of all vehicles decrease by 6.4%, which corresponds to the estimated trend in technology from Table 3 for four years. This is an approximation of what the car fleet would have looked like in 2011 without a policy intervention. In Figure 3, I plot each of the vehicles in an emission/weight diagram. The diagonal line is the target function for the attribute-based standard (heavier cars are allowed to emit more CO_2) 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. Sales-mixing abatement requires each firm to sell enough vehicles that are under the policy target in order to bring the total sales weighted emissions on or below the target line. Technology adoption decreases the emissions of each of the points in Figure 3, Panel I until the target is reached. The outcome from technology adoption towards the attribute-based standard is depicted in Figure 3, Panel II. Figure 3, Panel III presents 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.[17] In the technology abatement scenario the unknown is the level of technology, while in the sales mix scenarios this is the shadow cost λ_f. Solving for the necessary technology, shadow costs 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 after abatement. With the attribute-base standard, technology adoption causes very moderate shifts in the importance of

[17] 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 3. In reality, this does not need to be the case as firms may deviate from the standard and choose to pay fines.

each size class. vans (from 16% to 18%) and subcompacts (from 39% to 42%) gain some market share. Compacts, intermediate and standard vehicles all lose some market share. This finding is in stark contrast with substitution from sales-mix abatement. In this case subcompact vehicles and compact vehicles have a combined share of 72% (up from 61%). All other classes lose market share. The difference between technology adoption and sales-mix abatement is even more pronounced under the flat standard. The flat standard does not differentiate between size classes. The combined share of subcompacts and compacts now raises to 78%. In sum, this shows that adding technology to new vehicles does not change the size distribution of the car fleet. If 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.

Welfare effects Table 8 reports aggregate welfare effects over all included countries and firms for each policy simulation. The table starts by giving the percentage changes in total CO_2 emissions and total sales.[18] CO_2 emissions decrease by 7% with technology adoption and by 18% with sales-mix abatement. Total sales increase by 11% under technology adoption and decrease 3% with sales-mix abatement. Technology adoption results in modest effects on total emissions because more consumers decide to buy a vehicle and they do not substitute to smaller vehicles. We see a similar pattern for the flat standard in terms of emissions but now total sales increase for both abatement strategies. This is somewhat surprising but is related to the fact that almost all subcompact cars decrease in price to change the sales-mix. The increase in their sales makes up for the loss of sales of less fuel efficient cars.

Next, Table 8 gives the changes in consumer surplus, variable profits, CO_2 emissions and other externalities such as noise and accident risk. These numbers should be interpreted as total vehicle lifetime changes from yearly sales. Changes in emissions and other externalities are discounted sums over the expected vehicle lifetime. I assume a yearly mileage of 14000 km/year, a vehicle lifetime of 15 years and a discount rate of 6% to capitalize the yearly gains/losses in externalities.[19] The amount consumers drive is assumed to be constant, ignoring possible rebound effects. Because consumers face lower costs due to the gains in efficiency, demand for vehicle miles might go up, see Gillingham, Kotchen, Rapson and Wagner (2013) for an overview. I also do not take into account any fixed costs related to technology adoption and development.

Consumer surplus (net of the externality effect) increases by €15 billion per year under technology adoption. The slight increases in prices do not make up for the decreases in fuel costs over the vehicle lifetime and this makes consumers better off. If firms had chosen for sales-mix abatement consumer surplus would have decreased by €16 billion because consumers are forced by high prices to substitute to smaller cars. The changes in consumer surplus are similar for the flat standard, but the decrease in surplus due to sales-mixing is smaller.

For variable profits we see the same opposite pattern for the two abatement strategies. Technology adoption increases profits (mainly due to new vehicle sales) while sales-mix abatement is very costly for firms. Note that the total decrease in profits from sales-mix abatement is twice as large for the attribute-based standard than for the flat standard. The sum of total profits hides interesting patterns between the different firms on which I comment below.

The gains from the reduction in CO_2 emissions are small in comparison to the other reported effects.

[18] Total emissions is the sum over all new vehicles of the grams of CO_2 per km of each vehicle multiplied by the average yearly mileage.

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

I value a ton of CO_2 at €28.[20] The total gains from reduced emissions are smaller than 10% of gains or losses in consumer surplus or variable profits in all simulations. With technology adoption a moderate €380 million is gained per year while sales mix-abatement leads to gains of almost €1 billion. In total 2.6 million tons of CO_2 would be saved under sales-mix abatement and the attribute-based standard. This saving would cost €25 billion in consumer and producer surplus which leads to a cost of € 9615 per ton, which 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 is 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. I find that with technology adoption the changes in these externalities easily offset all gains from emissions reductions. Other external costs increase by more than €17 billion from technology adoption. Sales-mix abatement under the attribute standard is the only simulation that results in less total sales and so results in €4.3 billion decrease in other external costs.

To conclude, I find that technology adoption has beneficial effects on both consumer surplus and variable profits and reduces emissions by 7%. However, increases in other external costs due to the increase in overall demand for vehicles largely offset the three other gains. Yet, the regulation has an overall positive welfare effect of about €5 billion per year. This is before taking into account any fixed costs related to the technology adoption. If firms would have responded with sales-mix abatement, the regulation is costly and would reduce welfare by about €20 billion per year. There is not much difference in the overall effect between the attribute-based and the flat standard.

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. Note that Table 8 already revealed that the sum of variable profits lost due to sales-mixing was almost doubled when going from the flat target to the upward sloping target.

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 for 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 τ_f needed are largest for Daimler, Volkswagen and the Asian firms who all need to bring their CO_2 emission down by more than 20% in order to comply. Note that these are indeed the firms with the largest distance from the regulation in Figure 2. 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 19% (up from 13%) and Fiat by 8% (down

[20] 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.

from 14%). This matches the expectation as BMW can't exploit the reduction on their heavy cars and Fiat does not have to increase efficiency of their lighter vehicles. The large increases in efficiency result in more variable profits for all of the firms, except for BMW. Volkswagen and the Asian firms gain most. In sum, the distributional effects from technology abatement over firms are almost equal between the flat and the attribute-based standard.

The results of the sales-mix abatement in Table 9 show some interesting patterns. Under the attribute standard there are three firms, BMW, Ford and PSA, that 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 3). These three firms thus face the lowest shadow costs and need to distort their prices significantly less than all the other firms. BMW, Ford and PSA increase profits by about €1 billion while all the other firms lose between € 1.5 billion and € 4.4 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 average compliance cost changes and the distribution of compliance cost changes. I discuss these two differences in detail.

The change in the average compliance costs is potentially very important as it makes technology adoption more likely than sales-mix abatement. The results show that λ_f is considerably higher than $\lambda_f^{'}$ for most of the firms (except for BMW). The mean shadow cost of sales mixing goes up from 1.37 to 2.39 which means that the strategy of sales mixing on average becomes twice as costly (which matches the difference in total profits). The incentives to invest in technology thus increase significantly because of the slope in the target function. This might be one of the reasons why we have seen such a clear choice for technology adoption in the EU. 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 firms the profit losses for most firms from sales-mix abatement are so large that I would expect them to react by increasing efficiency.

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 in general 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.

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. The 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 0.33 to 0.31.

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. 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, using similar data, 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 can not explain why firms hardly invested in fuel efficiency up until 2007.

A second channel might be high R&D costs and possible spillover effects. This might cause each firm to delay investments until another firm invests in fuel efficiency. The result being a socially suboptimal equilibrium with no or too little investments. The regulation gives clear and binding efficiency targets for the whole industry and thus might succeed in moving the industry out of the suboptimal equilibrium. It is perhaps striking that the industry itself agreed to step into a nonbinding agreement in 1998, but failed to reach the targets.[21] 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 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.

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 different vehicles in the years after the regulation. I find that, because of the large improvement in technology adoption, the

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

regulation has a positive effect on overall welfare. Both consumers and producers gain from lower fuel costs and increased sales. These results are net of the fixed costs incurred by firms, which I do not observe. 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 overall vehicle sales increase. A back of the envelope calculation shows that because of the increase in the number of vehicles, other external costs such as accident risk and increased congestion offset most of the gains in emission reduction, consumer surplus and variable profits. 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 green house gas emissions (up to 18%). 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. 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.

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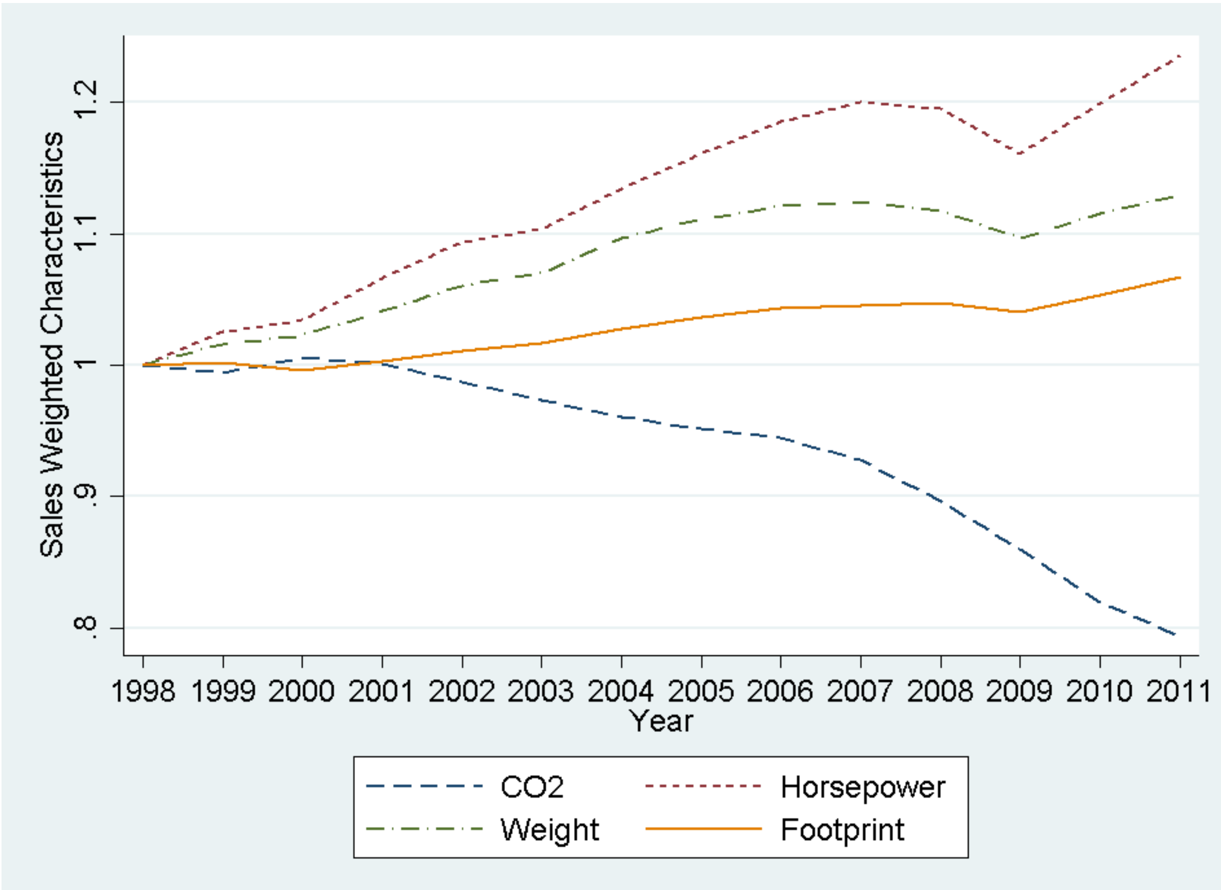
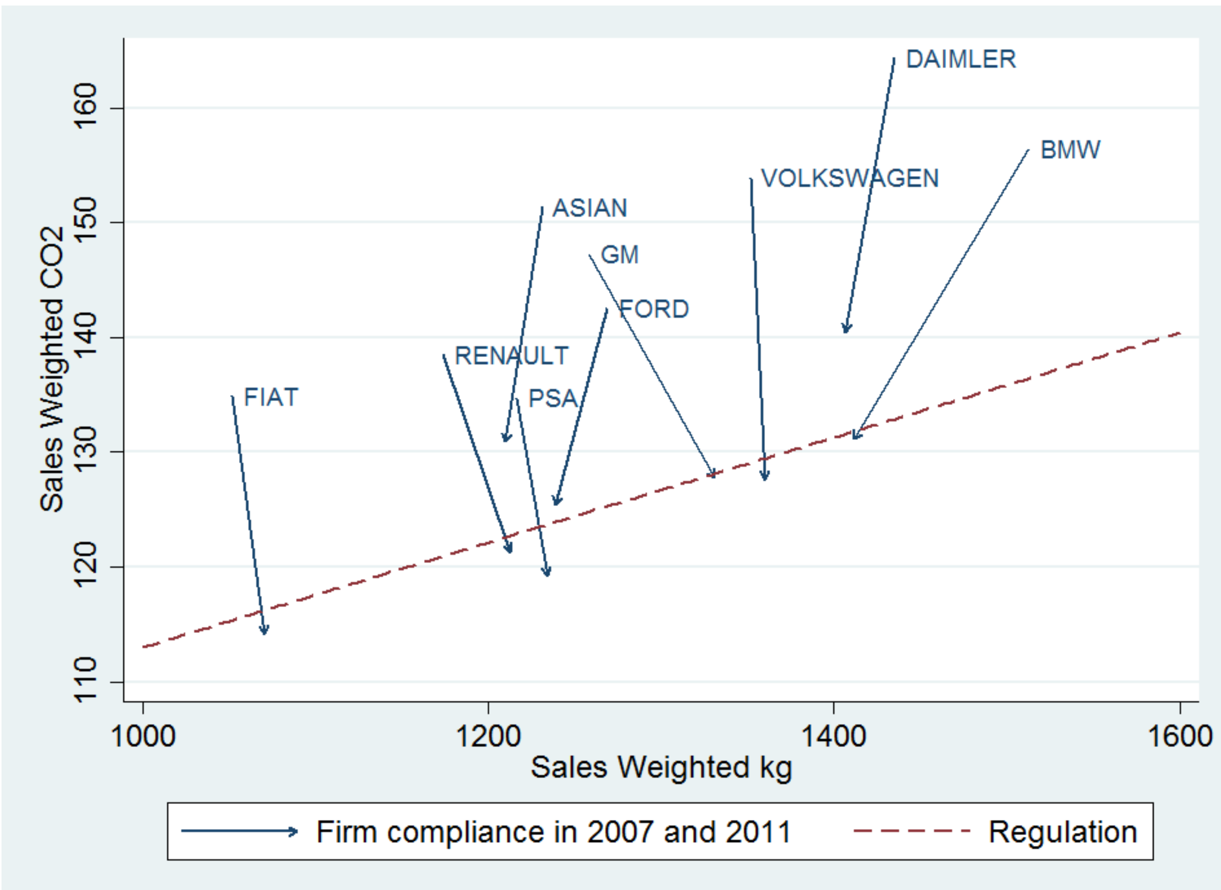
8 Figures and Tables

Figure 1: Sales Weighted Characteristics over Time



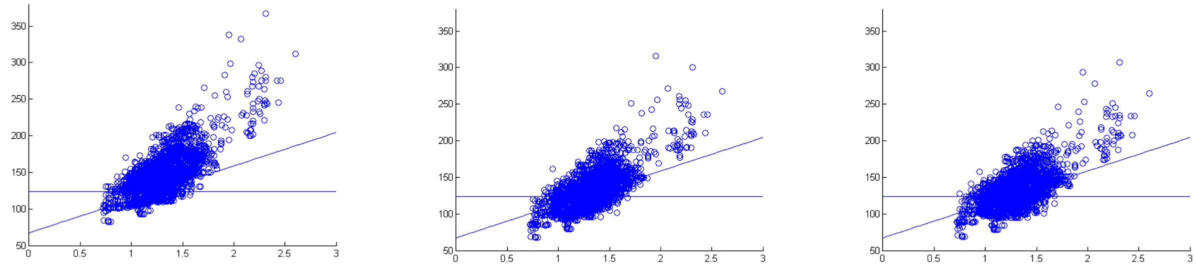
The figure shows the evolution of sales weighted characteristics over the sample period indexed at 1998. The figure shows that CO_2 emissions decrease by 20%, horsepower increases by more than 20%, weight by 13% and footprint by 8% between 1998 and 2011.

Figure 2: 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 3: 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 Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Diesel×Charact. Effects?		Yes					
Year×Charact. Effects?						Yes	
Year×Firm Effects?							Yes
Observations	12,659	12,659	12,659	12,659	132×10^6	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 η between characteristics and emissions from equation (9). 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%
2007-2011	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 (9). Each of the estimated models corresponds to Table 2, firm specific technology paths for Model 7 are given in the appendix.

Table 4: Decomposing the Decrease in Emmisions

First Model Year:	All	All	2007$\leq$	>2007	All	2007$\leq$	>2007
Year	True	$\overline{e}_{jt}$ $(\tau_t = \tau_{2007})$			$\widehat{e}_{jt}$ $(\tau_t = \tau_t)$		
1998	169	151	151		172	172	
1999	168	152	152		170	170	
2000	169	151	151		172	172	
2001	167	152	152		170	170	
2002	164	152	152		168	168	
2003	161	152	152		164	164	
2004	158	153	153		161	161	
2005	156	153	153		158	158	
2006	154	154	154		157	157	
2007	151	154	154		154	154	
2008	147	153	153	161	148	148	156
2009	142	154	153	163	144	143	151
2010	135	154	154	157	137	136	138
2011	130	155	154	157	131	130	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 τ_t. For each measure I report results for all vehicle models, models released not later than 2007 and models released after 2007.

Table 5: Estimation Results

Demand Estimation

	Logit				RC logit			
	Mean Valuation		Standard Dev.		Mean Valuation		Standard Dev.	
	Param.	St.Err.	Param.	St.Err.	Param.	St.Err.	Param.	St.Err.
Price/Inc.	-3.894	0.288	-	-	-3.690	0.275		
Fuel Consumption (€/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.		Imperfect Comp.		Perfect Comp.		Imperfect Comp.	
	Param.	St.Err.	Param.	St.Err.	Param.	St.Err.	Param.	St.Err.
Fuel Consumption (Liter/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 within sales 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

		Attribute Standard		Flat Standard	
	Observed	Tech.Ab.	Sales.Ab.	Tech.Ab.	Sales.Ab.
Subcompact	39	42	49	41	59
Compact	22	20	23	21	19
Inter.	8	6	5	6	3
Standard	6	5	5	5	4
Luxury	3	2	2	2	1
Van	16	18	14	18	12
SUV	5	5	1	5	1
Sports	2	2	1	2	1

The table gives the market shares of different size classes. The first column gives the observed market shares in 2007. In the next columns the market shares from policy simulations with an attribute-based and a flat standard, technology adoption and sales-mix abatement are given. For each simulation estimated parameters from the RC logit with imperfect competition from Table 5 are used.

Table 8: Welfare Effects

	Attribute Standard		Flat Standard	
	Tech.Ab.	Sales.Ab.	Tech.Ab.	Sales.Ab.
% Change:				
CO2 Emissions	-7%	-18%	-7%	-14%
Sales	11%	-3%	10%	2%
Δ in billion €'s:				
Δ Consumer Surplus	15.10	-15.81	14.40	-8.00
Δ Variable Profits	7.71	-10.33	7.34	-9.26
Δ CO_2 Savings	0.38	0.98	0.37	0.74
Δ Other externality Savings	-17.25	4.32	-16.66	-3.96
Δ Total:	5.94	-20.84	5.45	-20.49

The table gives aggregated effects over all markets and firms for each policy simulation. The table reports the percentage change in yearly CO_2 emissions and total yearly change. 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

	Attribute Standard					Flat Standard				
		Tech. Ab.		Sales Ab.			Tech. Ab		Sales Ab.	
	CO_2	τ_f	Profit	λ_f	Profit	CO_2	τ_f'	Profit	λ_f'	Profit
BMW	134	0,13	-400	1,15	1118	124	0,19	-193	1.77	-954
Daimler	121	0,23	384	3,03	-1590	124	0,22	314	1.18	-1177
Fiat	116	0,14	737	3,43	-1810	124	0,08	173	0.53	347
Ford	126	0,12	249	1,32	890	124	0,13	500	1.70	-206
GM	125	0,15	847	3,78	-2333	124	0,16	995	2.86	-2122
PSA	123	0,09	197	0,80	1784	124	0,08	164	0.38	1325
Renault	120	0,13	554	2,09	-308	124	0,11	368	0.86	396
VW	125	0,20	3081	2,13	-4413	124	0,21	3470	1.73	-5804
Asian	118	0,22	2060	3,84	-3664	124	0,19	1548	1.37	-1069

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 λ_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%
2007-2011	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 (9). The estimates correspond to Model 7 in Table 2.

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