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

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Abstract

Emission standards are one of the major policy tools to reduce greenhouse gas emissions from transportation. The welfare effects from this type of regulation depend on how firms choose to abate emissions: by sales-mixing (changing prices), by downsizing (releasing smaller cars) or by technology adoption. Using panel data covering 1998-2011 I find that a new emission standard in the European car market induces technology adoption. I estimate and validate a structural model to find that welfare effects with technology adoption are very different from welfare effects with sales-mixing or downsizing. The design of the regulation matters to induce technology adoption.

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1 Introduction

Transportation accounts for 20% of global greenhouse gas emissions and policy makers are taking up the challenge to reduce the use of polluting petroleum liquids. The major policy tool used to control emissions in transportation are regulations that set mandatory limits on average emission rates (or fuel economy) across the fleet. These policies are simple to prescribe but difficult to evaluate because their welfare impact depends on which strategies firms use to abate emissions. A first strategy is sales-mixing: shifting relative prices of vehicles with different CO_2 emissions. A second strategy is downsizing: releasing smaller but more fuel efficient vehicles. A third strategy is adopting new technology. This paper studies the roll out of the first European emission regulation regime to find that the emission standard induces technology adoption and to show that welfare effects with technology adoption are very different from welfare effects with sales-mixing or downsizing.

This is the first paper providing a detailed study of the EU regulation using a rich panel data set on 7 countries for the period 1998-2011. The EU emission standard requires automakers to limit average CO_2 emissions across their yearly new vehicle sales. The regulation aimed to reduce CO_2 emissions from passenger cars by 18% and was announced in 2007 and is fully binding from 2015, after a phase-in period that started in 2012. The regulation targets CO_2 emissions which is equivalent to targeting fuel consumption or fuel efficiency.[1] The EU standard is thus very similar to the Corporate Average Fuel Efficiency (CAFE) standard in the US. However, the EU standard is significantly more demanding with a target of 130g CO_2/km. This translates into about 42 miles per gallon (mpg) for gasoline engines, whereas the US standard requires only 36 mpg in 2016. The EU regulation is also particular because the standard is attribute-based: the target for each firm depends on average vehicle weight. This means that firms producing heavier (lighter) vehicles face a less (more) stringent target. In recent years most governments have decided on, or are discussing a further tightening of emission standards and an introduction of attribute-basing.[2] The observed response to the EU standard can thus be regarded as an important signal for future responses to this type of regulation in other markets across the world.

The paper makes three contributions. First, I find that the EU emission standard induces

[1] CO_2 cannot be filtered during the combustion process. Fuel consumption translates proportionally into grams of CO_2 per km, with a different CO_2 content per liter for diesel and gasoline. Fuel consumption (liters per kilometer) and CO_2 emissions per kilometer are the inverse of fuel economy (miles per gallon).

[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 US and Japan have also introduced attribute-basing in their regulations.

technology adoption by firms, an abatement strategy not fully considered in the previous literature. Second, by estimating a structural model of demand and supply I show that the incidence and welfare effects of the regulation are very different with technology adoption than with sales-mixing or downsizing. Third, I study the impact of the attribute-based design of the regulation and find that it increases the costs of abating by sales-mixing. The attribute-basing is thus important to induce abatement by technology adoption as firms will choose the abatement strategy with the lowest cost. The analysis proceeds in four steps.

In a first step I explain the trend in sales weighted CO_2 emission between 1998 and 2011. Following the approach of Knittel (2011), I estimate technological improvements in the trade-off that firms face between emissions and other vehicle characteristics. I find that the 14% reduction in emissions after the regulatory announcement is fully explained by increases in technology adoption. The decrease in emissions from technology adoption is so strong that almost all of the firms reach the emission target before it becomes partly binding in 2012.[3] The literature studying the CAFE standard in the US treats changes in the level of technology as a possible longer run effect of emission standards and has focused on the welfare effects from sales-mixing and downsizing.

In a second step I estimate and validate a structural model that allows me to simulate the welfare effects from technology adoption and sales-mixing. Holland, Hughes and Knittel (2009) show that none of the welfare effects of emission standards are theoretically determined. Emissions from new vehicles might decrease or increase because of the regulation depending on price elasticities of products below and above the target. To recover price elasticities, I follow the framework of Berry, Levinsohn and Pakes (1995) that allows for heterogenous tastes of consumers for several characteristics, including fuel costs. Marginal costs are backed out from the first order conditions assuming an oligopoly Nash-Bertrand game on the supply side. I estimate the model using recent methodological advances, as described in Reynaert and Verboven (2014). Exploiting the long time frame of the panel I test the ability of the model to explain prices and quantities out of the estimation sample. I find that the model is able to replicate sales weighted characteristics and prices reasonably well.

In a third step I use the estimated model to simulate the welfare effects of the regulation under different abatement strategies. I find that if firms respond by technology adoption, marginal costs and prices increase. However, overall consumer surplus increases by €8.8

[3] The effect of the regulation cannot be seperated from other market changes which explains why the response is so strong and early. Changes in local regulation and taxes in EU member states after 2007 clearly contribute to the downward trend in emisisons.

billion because consumers gain from lower fuel consumption. The indirect utility from new vehicles is thus higher and total sales increase. Because of this extensive margin effect emissions decrease only moderately (by 6%) and other externalities from traffic, such as accident risk and congestion increase starkly. The cost of the regulation fully falls on producers who have to make fixed costs for technology adoption. Overall, I estimate that the regulation improves welfare with at most €5.8 billion before fixed costs are subtracted. This is in sharp contrast with the effects under sales-mixing: total sales, consumer surplus and variable profits strongly decrease. Despite larger gains from externality savings the regulation decreases welfare by €17 billion.

In a fourth step, I look at the attribute-based design of the regulation. This design, that makes the emission target vary with average weight, makes sales-mix abatement much more costly for firms and thus increases the likelihood that firms will abate by technology adoption. In general, the difference in welfare effects between sales-mix abatement and technology adoption shows that policy makers should design the regulation such that the latter strategy is chosen. Additionaly, I show that the attribute-basing causes a redistribution of compliance costs between firms which matches reported lobbying efforts during the design of the regulation.

This paper contributes to a literature that studies the impact of emission standards. 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. 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. 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 sales-mixing prices and in the medium run with downsizing. This softens profit losses as firms have greater flexibility on how to react to the standard. The analysis presented here confirms that in the EU sales-mixing would reduce welfare drastically but adds the insight that technology adoption should be considered as a short-term response with very different welfare effects. The economic effects of attribute-based regulations are previously discussed in Ito and Sallee (2014) who focus on distortions in the market for the attribute. The analysis here is complementary as I study different effects of attribute-basing: the marginal cost of different abatement strategies, redistribution of compliance costs between firms and lobbying by firms.

Technology adoption increased both variable profits and consumer surplus which raises the question why firms did not adopt the technology before 2007. The answer might be a combination of significant fixed costs and market failures in the technology market. The estimation results, in line with recent research[4], rule out severe investment inefficiencies on the side of the consumer. Jaffe, Newell and Stavins (2005) discuss knowledge and adoption externalities and incomplete information as market failures. When fixed costs are important, these failures combined might result in a socially suboptimal equilibrium with none or too little investments.[5] Testing this hypothesis and getting more insight in the technology adoption of firms is important to further understand how regulations and technology adoption interact.[6]

Despite the rich and long panel on the EU car market the data limits the analysis in at least two important ways. First, I only focus on new vehicle sales as second hand sales across different countries are unavailable. Jacobsen and van Benthem (2015) study the effect of emission standards on vehicle scrappage rates. They find that emission standards with sales-mixing increase vehicle lifetime because of changes in relative prices between new and second-hand vehicles. Technology adoption might reverse this as new vehicles become more attractive in comparison to the existing fleet, potentially decreasing vehicle lifetimes. A second limitation of the data is that emission measures are official numbers from standardized tests while recently Volkswagen admitted cheating on these tests. Errors in the emission numbers will change the results presented here in two ways. First, the estimated technology adoption will contain both false improvements as well as actual improvements. Second, the welfare effects from technology adoption will change because emission savings and consumer gains are not attained with false improvements. In the analysis I will carefully discuss this issue and the impact on the results in more detail. The finding that attribute-basing induces technology adoption carries over to cheating, which can be regarded as technology adoption specific to the testing procedure. In current work (joint with James Sallee) we are quantifying the degree and the economic effects of cheating.

The paper is structured as follows. Section 2 presents emission standards in a model of

[4] Grigolon, Reynaert and Verboven (2014) find that, using similar data, consumer investment inefficiencies in the EU are not large. Allcott and Wozny (2014); Busse, Knittel and Zettelmeyer (2013) and Sallee, West and Fan (2015) find at most moderate undervaluation of future fuel savings for US consumers.

[5] 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.

[6] Recent work, such as Hashmi and Van Biesebroeck (2012) and Aghion, Dechezleprêtre, Hemous, Martin and Van Reenen (2015) , has looked at R&D patterns in the automobile industry through patents.

supply and demand and discusses the possible effects of the different abatement strategies. Section 3 describes the policy and the available data. Section 4 explains the changes in the automobile market between 2007 and 2011 and shows the technology adoption. Section 5 presents estimation results and the out of sample test. Section 6 presents the results of policy simulations and Section 7 concludes.

2 Model

This section introduces an emission standard in a structural model of supply and demand. First I discuss the framework with demand, marginal costs and profits with the constraint from the regulation. In this framework I compare the effects of each abatement strategy and I argue that there are no clear theoretical predictions for the welfare effects.[7] Lastly, I compare the impact of an attribute-based and flat regulation.

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

$$u_{ijm} = x_{jm}\beta_i^x - \beta_i^e g_{jm}e_{jm} - \alpha_i p_{jm} + \xi_{jm} + \varepsilon_{ijm}, \quad (1)$$

where x_{jm} is a vector of observed product characteristics, $g_{jm}e_{jm}$ are fuel costs (fuel prices g_{jm} times fuel consumption e_{jm}), p_{jm} is the vehicle price and 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

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

consumers. Notice that the coefficient β_i^e measures the response of consumers to shifts in fuel costs.[8]

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:

$$s_{jm}(\delta_m, \sigma) = \int \frac{\exp\left(\delta_{jm} + \mu_{jm}(\nu)\right)}{1 + \sum_{l=1}^{J} \exp\left(\delta_{lm} + \mu_{lm}(\nu)\right)} dP_\nu(\nu), \tag{2}$$

where δ_m is the $J \times 1$ mean utility vector in market m (containing the mean valuation parameters β^e, β^x and α), and μ_{jm} is the individual specific utility (containing the vector of standard deviations σ). To complete the demand side, I set the observed market share $s_{jm} = q_{jm}/A_m$ equal to the predicted market share (2). In vector notation, the demand side in market m can then be described by the market share system: $s_m = s_m(\delta_m, \sigma)$.

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

$$\log(c_{jm}) = \gamma^e e_{jm} + z_{jm}\gamma^z + \omega_{jm}, \tag{3}$$

in which z_{jm} is a $1 \times L$ vector of observed product characteristics, market controls and cost shifters and ω_{jm} is unobserved. Emissions enter marginal cost as all else equal it is more expensive to produce engines with lower fuel consumption. This is confirmed in the estimation ($\gamma^e < 0$) and in several other engineering studies, see for example Whitefoot, Fowlie and Skerlos (2013). Marginal costs c_{jm} are not observed but will be backed out from the first order conditions of the profit maximization.

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. The emission standard is a

[8] The specification does not allow the mean consumers to care about emissions seperately from fuel costs (a 'green glow' effect). These preferences might be captured by the standard deviation in tastes for fuel costs as green consumers will care more about fuel costs than others. A more flexible specification including a taste for emissions/fuel consumption gives very similar results.

constraint on total sales over all countries in a given year t:

$$\max_{p} \sum_{m} [\pi_{fm}(\mathbf{p}, \mathbf{e})] \;\; s.t. \;\; \frac{\sum_m \sum_{j \epsilon \mathcal{F}_f} q_{jm}(e_{jm} - f(w_{jm}))}{\sum_m \sum_{j \epsilon \mathcal{F}_f} q_{jm}} \leq \sigma, \tag{4}$$

in which σ is the level of the standard and $f(w_{jm})$ is the attribute-basing on weight w_j. For a flat standard $f(w_j) = 0$, when $f(w_j) \neq 0$ vehicles with different weight will get reductions or penalties on their emissions.[9] I follow Goldberg (1998) and Jacobsen (2013) and rewrite the Lagrangian of the problem. Profits of firm f in year t are then given by:

$$\pi_f = \sum_{m} \sum_{j \in \mathcal{F}_f} \left\{ [p_{jm} - c_{jm}(e_{jm}) - \lambda_f L_{jm}] \, s_{jm}(\mathbf{p}, \mathbf{e}) A_m \right\}, \tag{5}$$

$$L_{jm} = [e_{jm} - f(w_{jm}) - \sigma] \tag{6}$$

in which λ_f is the shadow cost of the regulation and L_{jm} is the distance of each product from the target. When $L_{jm} < 0$ (> 0) an additional sale of vehicle j will bring the average sales weighted emissions closer to (further away) from the target. The per vehicle shadow cost λ_f gives the cost of deviating one unit from the standard. If the standard is binding $\lambda_f > 0$. If the standard is non-binding $\lambda_f = 0$ and (5) reduces to a standard multiproduct profit function. The shadow cost λ_f is firm specific because trading of excess emission between firms is not allowed. The shadow cost takes the same value for each vehicle in the fleet $\mathcal{F}_f$ because firms equalize shadow costs over their vehicles to be cost efficient.

Next, I discuss how equilibrium outcomes change when we move from a market without a standard (or a nonbinding standard), $\lambda_f = 0$ to a market with a binding standard, $\lambda_f > 0$. The changes in the market will depend on the abatement strategy of firms: sales mixing, downsizing or technology adoption.

Abatement by sales-mixing A first mechanism to abate emissions is to change relative prices of high and low emission vehicles. Figure 1 shows firms can decrease prices of vehicles in B and C ($L_{jm} < 0$) and increase prices of vehicles in A and D ($L_{jm} > 0$) to shift market shares towards vehicles that comply with the attribute-based regulation. The set of products available to each producer is assumed to be fixed and the set is bounded by the production possibility frontier given the current level of technology τ. I assume a pure Nash equilibrium

[9] Here I specify the attribute-basing as a simple additive penalty or reduction but one could design a regulation where the target is any function $g(e_{jm}, w_{jm})$ of emissions and the attribute.

in prices exists and write the first-order conditions of (5) with respect to prices as:

$$\left\{ s_j(\mathbf{p},\mathbf{e}) + \sum_{k\in\mathcal{F}_f} \frac{\partial s_k(\mathbf{p},\mathbf{e})}{\partial p_j} \{p_k - c_k - \lambda_f L_k)\} \right\} = 0 \tag{7}$$

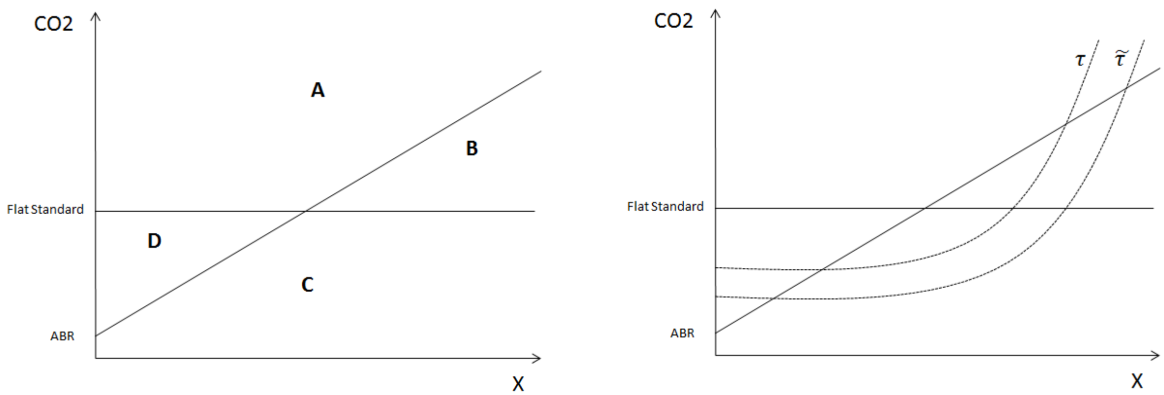
I denote the Nash equilibrium as $\mathbf{p} = \mathbf{p}^*(\mathbf{e})$. When introducing an emission standard the shadow cost becomes positive $\lambda_f > 0$. The FOC's show that prices will be higher for vehicles that are more polluting than the target ($L_{jm} > 0$). Prices will be lower for a fuel efficient vehicle that helps to comply with the standard ($L_{jm} < 0$). The regulation thus implicitly taxes vehicles with $L_{jm} > 0$ and implicitly subsidizes vehicles with $L_{jm} < 0$. The change in relative prices of products will shift sales towards vehicles with lower fuel consumption resulting in a different sales-mix.

The incidence and effectiveness of this abatement strategy largely depends on the responsiveness of consumers to these price changes. Holland, Hughes and Knittel (2009) show that when the price elasticities of the subsidized products differ from those of the taxed products total sales, as well as total emissions, might increase or decrease. Before knowing the price elasticities of the full set of products we cannot make statements on the effect of the regulation on total sales, emissions or consumer surplus. The effects on profits will depend on consumers responses to the price changes and also on the share of the fleet that is under the target. Firms with a fleet that is better adapted to the standard might increase profits as their prices will need less distortion compared to other firms. The empirical model will allow me to identify own and cross price elasticities for all products to simulate the shifts in sales when we introduce a binding regulation.

Abatement by downsizing In the medium run firms can abate emissions by designing new vehicles with $L_{jm} < 0$ and by phasing out vehicles with $L_{jm} > 0$. In Figure 1 firms abate by downsizing if they design new vehicles in B and C given the current level of technology τ and stop offering vehicles in A and D. The share of vehicles that have $L_{jm} > 0$ increases and this mitigates the need of changing relative pricing as more vehicles comply with the standard. For consumers, the effects of downsizing will be similar to those of sales-mixing. Some products with $L_{jm} < 0$ that were priced infinitely high are now implicitly subsidized and made available while the prices of some products with $L_{jm} > 0$ increase to infinity. Depending on the price elasticities of consumers the regulation can again have any effect on emissions, sales and consumer surplus.

Firms will choose for downsizing especially when they have a low share of vehicles with

Figure 1: Emission Standards and Abatement Strategies



Flat and Attribute-based Regulation   Production Possibility Frontier

Panel I plots the target function for a flat and attribute-based regulation. Panel II adds a production possibility frontier for different technology levels τ and $\widetilde{\tau}$. The area above the production possibility frontier defines possible products.

$L_{jm} < 0$. To make this new products available, firms will have to pay fixed costs. This makes it challenging to empirically model downsizing. First, one needs a realistic model of how firms choose product designs that are technically possible. Klier and Linn (2012) exploit observed relations between product characteristics and Whitefoot et al. (2013) use an engineering model. Second, the model needs to allow firms to make strategic decisions on both prices and product characteristics, which complicates solving the Nash equilibrium. Third, one needs to account for the fact that these design decisions will be correlated with unobservables such that instruments are needed to identify consumer tastes for endogenous characteristics. Both Klier and Linn (2012) and Whitefoot et al. (2013) simulate that this strategy would be used to a considerable amount if the CAFE standards were to be tightened. Klier and Linn (2012) find that compliance costs for firms decrease by about 40% per year while consumer loss is similar to a full sales-mix scenario. Because of the empirical challenges and similarity in welfare effects between downsizing and sales-mixing I will focus on a comparison between sales-mixing and technology adoption in this paper.

Abatement by technology adoption Firms can reduce emissions of existing vehicles by adapting engines, the combustion process or features that only affect the fuel consumption.[10]

[10]Knittel (2011) gives several examples of specific technologies that are implemented. The International Energy Agency reported a possible 40% improvement in fuel efficiency from available technologies in 2005. These include low rolling resistance of tires, reduced drive-

Consider a technology shift over time from τ to $\widetilde{\tau}$, shown in Panel II of Figure 1. This shifty will decrease the emissions each vehicle as $e_{jm1}(\tau) > e_{jm2}(\widetilde{\tau})$. When emissions decrease the value of L_{jm} shrinks such that more vehicles will contribute to compliance (these vehicle shift from A and D into B and C). As a larger part of the fleet helps with compliance firms require less and less changes in relative prices in order to reach the target. Increases in τ lead to reductions in the shadow cost of the regulation λ_f. Eventually, for strong shifts in τ, the firm can choose its preferred price scheme once $\lambda_f = 0$.

The welfare effects of this strategy are once again undetermined. This time there are two offsetting effects for consumers. There is upward pressure on prices as marginal costs defined in (3) increase. These higher prices will reduce consumer surplus. But vehicles come with lower fuel consumption, decreasing the cost of operating a vehicle. This increases consumer surplus. The sum of purchase price and operating costs might thus increase or decrease. The changes in marginal costs and the degree of pass through will determine the overall effect. Given the shift in technology firms will reach a new Nash equilibrium in prices, from $\mathbf{p}^*(\mathbf{e}(\boldsymbol{\tau}))$ to $\mathbf{p}^*(\mathbf{e}(\widetilde{\boldsymbol{\tau}}))$. I assume the fixed cost of developing and adopting the technology to be sunk and thus not to impact the equilibrium prices. Firms however have to make these fixed costs in order to increase the technology. The effects on total profits depend on the changes in demand, the new price equilibrium and the amount of fixed costs.

Flat and attribute-based standards In the counterfactual I will consider two designs of the regulation. First, I exactly replicate the EU policy resulting in the upsloping attribute-based regulation (ABR) depicted in Figure 1. Second, I specify a flat standard so that in equilibrium the same sales weighted emission are attained. For the flat standard $L'_{jm} = [e_{jm} - \sigma']$ and $f(w_{jm}) = 0$. The target function is a horizontal line at σ' and all firms need to reach exactly the same level of CO_2 emissions.

Both the shadow costs, amount of downsizing and the level of technology needed to comply with the regulation will differ between the flat standard and the attribute-based standard as a different set of vehicles has $L_{jm} < 0$ than $L'_{jm} < 0$. This can be seen clearly in Figure 1: vehicles in B and C have $L_{jm} < 0$ and comply with the ABR, while vehicles in C and D have $L'_{jm} < 0$ and comply with the flat regulation. I will discuss three possible consequences of the attribute-basing.

First, the ABR might shift the costs of the different abatement strategies, making it more

line 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.

costly to choose for sales-mixing, downsizing or technology adoption. Decreasing the prices or designing vehicles in zone D in Figure 1 is possible for the flat standard but not for the ABR. Given the current level of technology τ the ABR severely limits the possibilities from sales-mixing and downsizing and makes these strategies potentially much more costly. Second, the amount of effort required from firms with different average vehicle weight changes with the slope of the ABR. Third, the ABR might increase the cost efficiency of the regulation by equalizing abatement costs. If producers of heavier vehicles find it more difficult to abate emissions a slope in the target function can equalize the marginal cost of compliance across firms. In this sense attribute-basing can be a replacement for emission trading between firms which would fully equalize abatement costs.

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.[11] In this exercise I keep weight, and other characteristics, fixed and assume there are no distortions in the attribute itself. I will compare the welfare effects of a flat standard with that of an ABR and will look to which degree marginal abatement costs of the different strategies change, to which degree firm profits change and to which degree I find evidence of cost equalization.

3 The EU emission standard and data

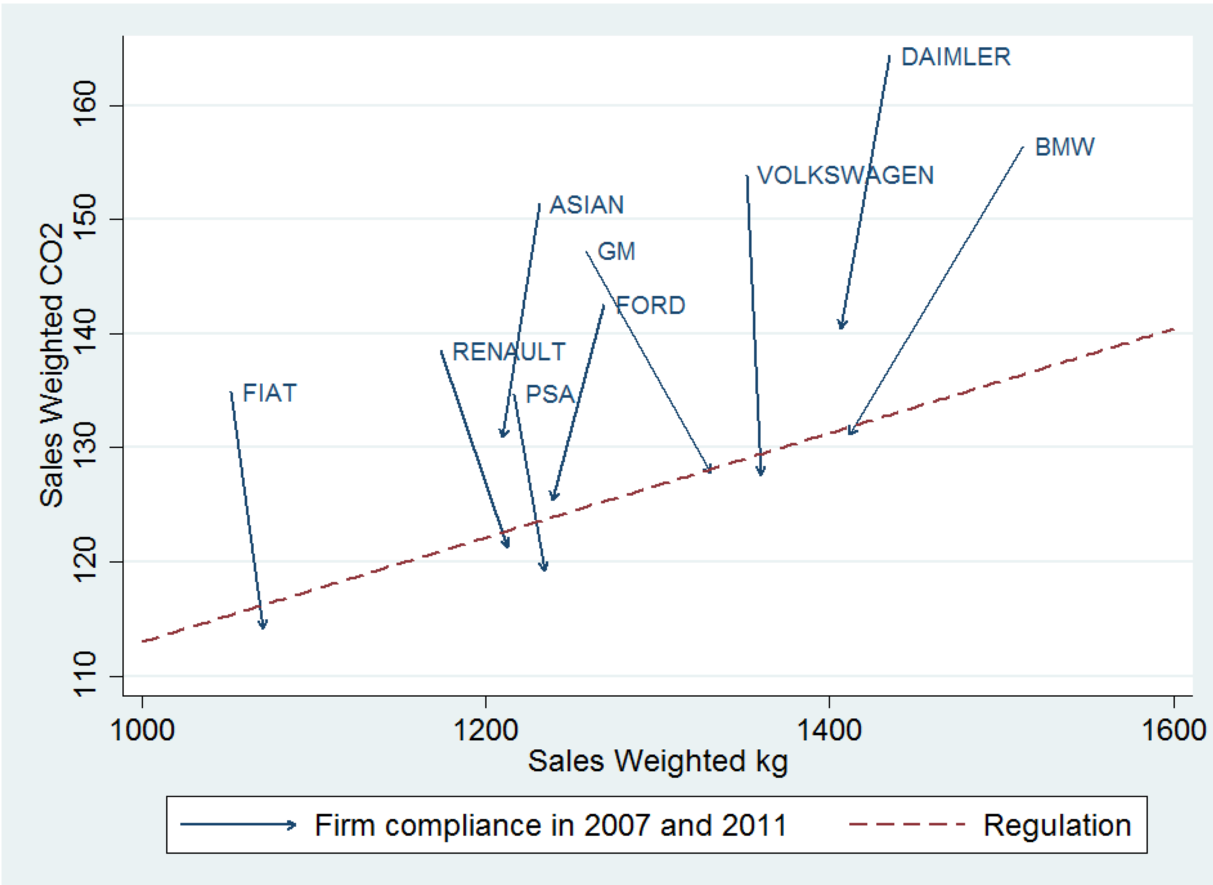
The EU emission standard The European regulation on emission standards for new passenger cars, Regulation (EC) No. 443/2009, sets a mandatory fleet average σ =130 grams CO_2 per kilometer. The target is set for each producer's fleet of new vehicles sold in a calendar year and trading of excess emissions between producers is not allowed.[12] The standard and firm distance from the regulation in 2007 and 2011 are plotted in Figure 2. The attribute basing $f(w_{jm}) = a(w_j - w_0)$ adjusts emissions of each vehicle 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 $a = 0.046$.[13]

[11] 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.

[12] Manufacturers can 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.

[13] The emissions of an average SUV of 1650kg will count for less in the sales weighted sum and the emissions of a compact car of 1250 kg will count for more.

Figure 2: Compliance of Firms in 2007 and 2011



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.

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, would face a significant penalty of €1280 per vehicle (the average price of a vehicle in the sample is €22,250). 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. In 2012, 65% of manufacturer's sales had to comply with the emission standard. This rose to 75% in 2013, 80% in 2014 and the standard is fully binding from 2015 onwards.

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.[14] France and Italy were strongly in favor of a flat standard, while Germany wanted an upward sloping target function in either weight or footprint (the rectangular area in between the wheels of the vehicle). The German firms BMW, Daimler and Volkswagen on average make heavier vehicles than Fiat (Italian), Renault and PSA (French). The production of each of these firms mostly takes place within the boundaries of the home country and the car sector is an important source for employment.

It is instructive to compare the EU policy with the US CAFE standard since this policy has been the subject of several studies. The CAFE standard came into place in 1978 and after a gradual phase-in has been constant at 27.5 mpg since 1990 (this corresponds to 198 g CO_2/km). From 2009 onwards CAFE standards are tightened towards 36 mpg in 2016 (this corresponds to 152 g CO_2/km). Contrary to the EU standard, light trucks (SUV's) face a different less demanding target than passenger cars. Also, firms are allowed to trade excess emissions over time and with other firms.[15] From 2012 onwards the CAFE standard also has an attribute-based part: the target varies with footprint.

Data The main data set is obtained from a market research firm (JATO dynamics) and contains 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.[16] Characteristics and sales are given for several engine variants of a car model. A model is defined as a brand/model/body type combination (e.g., Volkswagen Golf Hatchback). The engine variants differ in fuel type (gasoline or diesel) and engine performance. Accounting for fuel type is important in the EU market as diesel variants have a considerable market share (56% in 2011) and the emissions of diesel variants are lower; a diesel engine emits about 20% less $C0_2$ per kilometer.[17]

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 consumption (liters per 100 km and CO_2 emissions per km)[18], vehicle size (footprint

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

[15] Contrary to the CAFE standards in the US there is also 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.

[16] These markets represent around 90% of the total EU market.

[17] The combustion process and different energy content of the fuel make diesel engines more efficient per kilometer. Diesel cars emit less CO_2 per kilometer, but more other pollutants such as NOX.

[18] CO_2 emmisions and fuel consumption are obtained from the New European Driving Cycle (NEDC). This is a standardized driving cycle to assess the emission levels of car engines. The cycle simulates both

defined as length by width, weight and height) and engine performance (horsepower and displacement). The data on sales are supplemented with production data from PriceWaterhouseCoopers (PWC) and contain the country and plant of production for each model. I match this with a producer price index and a unit labor cost measure 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 the number of potential buyers in each year.

To reduce the size of the data and complexity of the analysis, I leave out firms, brands and models with very low sales. The analysis will focus on the largest producers and their best selling brands on the EU market. The included firms are BMW, Daimler, Fiat, Ford, General Motors, PSA, Renault and Volkswagen. I treat the largest Asian car makers as one decision maker. This includes the firms Honda, Hyundai, Mitsubishi, Nissan, Suzuki and Toyota. 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.

Throughout the paper, the full dataset is partitioned over time and markets in several ways. 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.

Summary Statistics 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 attribute-based emission standard. In 2007 each firm is far above the target and has 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

urban and extra-urban driving patterns and excludes the use of auxiliary features like air conditioning. Real world emissions thus differentiate from these test values. I will come back to this point below.

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%

The Table presents sales weighted vehicle characteristics in the EU in 2007 and 2011.

firms comply with the emission standard four years before it is fully binding.[19] Table 1 shows 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. The decrease in emissions is observed in all car size classes and is largest among SUV's (-25%) and smallest among subcompact cars (-12%).

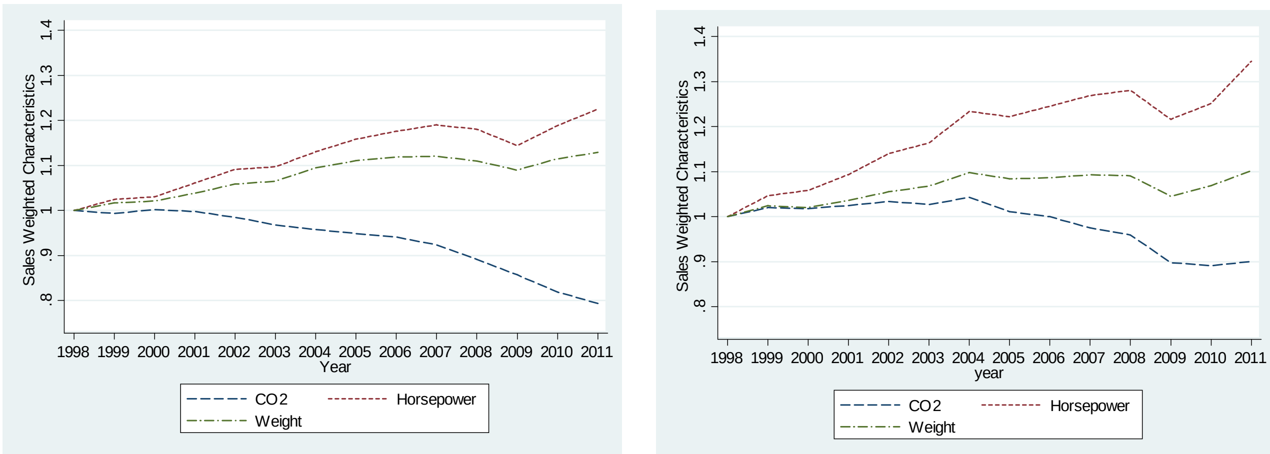
Figure 3 plots sales weighted characteristics over time from 1998 to 2011 for both the EU (Panel I) and the US (Panel II). Each characteristic is indexed in 1998. The most remarkable trend in the EU is the evolution of sales weighted CO_2 emissions. The level of emissions is constant up until 2002, slightly declines about 6% until 2007, and then plunges by 14% in the last four years of the sample. This shift coincides exactly with the announcement of the fuel efficiency standard by the European Commission. The CO_2 emissions show a very different pattern in the US than in the EU. Until 2007 there is a very moderate decline in emissions of about 3%. Between 2007 and 2009 emissions of newly produced vehicles decline by 7% but then remain constant at 90% of the 1998 level. In the EU, emissions further decrease in 2010 and 2011 and by the end of the sample are at 80% of the 1998 level. In both the EU and the US weight and horsepower grow consistently over time. By 2011, European consumers choose a vehicle that on average is 23% more powerful and 13% heavier than in 1998. Knittel (2011) already documented these stark increases in characteristics of vehicles for the US.

4 Market response to the EU emission standard

In this section I decompose the observed decrease in emissions. How much of this drop is attributable to sales-mixing, downsizing or technology adoption? To answer this question I

[19] This shows that the emisison standard is probably not the only mechanism driving driving down sales weighted emissions. Below I comment on complementary explanations.

Figure 3: Sales Weighted Characteristics over Time



Europe

United States

The figure shows the evolution of quantity weighted characteristics from 1998 until 2011, indexed at 1998. The EU trends represent the evolution of sales weighted characteristics as observed in the data. The US trends represent the evolution of production weighted characteristics as reported by the EPA (http://www.epa.gov/otaq/fetrends.htm).

estimate isocost functions in emissions and other vehicle characteristics using a reduced form equation. First I describe estimation of trade-off and technology parameters, then I use the estimated relation to decompose the downward trend in emissions.

Estimation of trade-off and technology parameters Following Knittel (2011) I estimate the following regression:

$$\log(e_{jt}) = \tau_t + \eta \log(x_{jt}) + \epsilon_{jt}, \tag{8}$$

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. Graphically τ_t captures shifts in the production possibility frontier (as shown in Figure 1) and η gives the slope of the frontier. 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 (8) by ordinary least squares.

Table 2 presents the trade-off parameters η from estimating (8). 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. Model 2 includes diesel by characteristics interactions and thus allows a different functional form for diesel engines (instead of only a different dummy). Model 3 and Model 4 address possible biases related to technology expenditures. If unobserved expenditures on technology are correlated with characteristics on the right hand side of (8) this would bias the estimated parameters. Expenditures on technology are likely reflected in marginal costs so I add prices and marginal costs as controls.[20] 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 (8) with frequency weights for sales. If firms would increase technology only in specific groups of low or high selling vehicles the parameters in Model 1 will be biased. Again, the trade-off parameters are similar between Model 5 and Model 1. Model 6 allows the trade-off parameters to change over time (the functional form changes year by year), and Model 7 allows for a firm specific trend in technology. These last two models should result in different predictions for the technology parameters if the technology is not input neutral or is different between firms.

The technology parameters τ_t are derived from the time fixed effects in each regression and plotted in Table 3 for Model 1-Model 6, and results for 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. These findings provide strong suggestive evidence that firms speed up the adoption of technology in the period after the policy announcement in order to comply with the regulation.

A potential problem with these estimated technology residuals is that the estimated emission decreases might not translate into on-road fuel savings for consumers. The data are official measures stemming from the New European Driving Cycle. The concern is that firms over time are getting better at taking the test without improving actual on-road emissions.

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

Table 2: Trade-off Estimates between Emissions and Characteristics

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
ln(Hp)	0.18***	0.26***	0.16***	0.20***	0.13***	0.05	0.17***
	(0.02)	(0.05)	(0.03)	(0.03)	(0.02)	(0.05)	(0.02)
ln(Weight)	0.66***	0.54***	0.63***	0.70***	0.63***	0.81***	0.80***
	(0.09)	(0.08)	(0.09)	(0.09)	(0.08)	(0.11)	(0.08)
ln(Footprint)	-0.16*	-0.14*	-0.16*	-0.15	-0.11	-0.16*	-0.29***
	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)	(0.07)	(0.08)
ln(Height)	0.41***	0.30**	0.43***	0.40***	0.31**	0.42***	0.29**
	(0.11)	(0.10)	(0.12)	(0.12)	(0.11)	(0.11)	(0.09)
Diesel	-0.20***	-0.83***	-0.21***	-0.20***	-0.21***	-0.20***	-0.21***
	(0.01)	(0.20)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Price			0.03				
			(0.03)				
Marginal Cost				-0.02			
				(0.02)			
Year F.E.?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Diesel×Char.?		Yes					
Year×Char.?						Yes	
Year×Firm?							Yes
Observations	12,659	12,659	12,659	12,659	132×10^6	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 (8). Robust standard errors are reported between brackets and clustered per firm, *** p<0.01, ** p<0.05, *p<0.10. Model 1 is estimated with ols and includes only year fixed effects, Model 2 includes diesel by characteristic interactions, Model 3 includes price as an explanatory variable, Model 4 includes marginal costs (as estimated from the structural model), Model 5 is a weighted least square using sales as frequency weights, Model 6 interacts the time trend with characteristics and Model 7 allows for a different time trend for each model.

Table 3: Technological Progress Estimates

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

The table gives the estimated yearly change of technology in the CO_2 production function as derived from the year fixed effects in (8). Each of the estimated models corresponds to Table 2, firm specific technology paths for Model 7 are given in the appendix. The shaded area are years after the policy announcement.

This could have a large impact on the consumer surplus and externality changes of the regulation discussed below.

Decomposition of the changes in fuel efficiency The estimated relation (8) can be used to reveal the compliance strategy of firms between 2007 and 2011. First, I predict emissions, $\widehat{e}_{jt}$, as the fitted values of regression (8).[21] Second, I predict $\overline{e}_{jt}$ using (8) but fixing the technology at the 2007 level ($\tau_t = \tau_{2007}$). The prediction $\overline{e}_{jt}$ will thus only depend on characteristics x_{jt} and not on the time fixed effects. If firms choose for sales-mixing or downsizing the average sales weighted values of $\overline{e}_{jt}$ will decrease over time as these abatement strategies result in either changes in vehicle characteristics or changes in the market shares of more fuel efficient vehicles. The trend in average sales weighted values $\widehat{e}_{jt}$ gives the sum of sales-mix abatement, downsizing and technology adoption.

[21] 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.

The results in Table 4 show that between 1998 and 2007 sales weighted emissions without technology increased slightly from 151 to 154 (an increase of 2%). Technology improvements were fully responsible for the observed moderate decline in emissions between 1998 and 2007. After 2007, the sales weighted emissions without technology $\overline{e}_{jt}$ keep increasing gradually from 154 to 155. There is thus no evidence of significant changes that could be attributable to either sales-mixing or downsizing. When I split up the average sales weighted emissions into vehicle models released after and prior to 2007 the results show that the emissions $\overline{e}_{jt}$ of vehicles released prior to 2007 remain constant.[22] Vehicle models released after the policy announcement are on average more polluting than existing vehicle models. The difference between existing vehicles and vehicles released after the policy decreases over time however. The observed decline in emissions is thus not in any sense attributable to changes in the sales mix or to the release of new downsized fuel efficient vehicles.

The sales weighted emissions with technology $\widehat{e}_{jt}$ are decreasing rapidly after 2007 and this shows that technology adoption is fully responsible for the observed drop in emissions. Strikingly, the decrease in sales weighted emissions of older vehicles due to technology is as strong as the decrease in newly released vehicles and the engine improvements are installed widely across the fleet.[23]

In sum, this is strong suggestive evidence that technology adoption is the preferred abatement strategy. The observed response is so strong that most firms already comply with the emission standard in 2011 as shown in Figure 2, four years before the regulation is fully binding. Four other explanations for the increase in technology adoption come to mind: changes in fuel prices, changes in preferences, the economic crisis and local regulation by EU member states. Fuel prices do not show a strong increasing pattern after or before 2007. Changes in preferences or an aggregate demand shock from the crisis would cause consumers to choose less expensive vehicles revealing changes in $\overline{e}_{jt}$, but it is unclear how these shocks would clarify increases in technology. Individual member states do increase emission based taxation and regulation during the same period.[24] This combination of new regulations, together with the standard, can explain why the response is so strong and why compliance is attained so early.

[22] 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.

[23] When I zoom in on vehicle models I find (not reported) that the likelihood of releasing an engine version with lower than existing emissions is significantly much higher after 2007.

[24] Examples are the bonus/malus system in France and low emission zones in Germany as well as various scrapping schemes.

Table 4: Decomposing the Decrease in Emissions

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

The table reports observed and predicted levels of average 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.

5 Estimation of Demand and Marginal Cost

In this section I estimate the model as set out in Section 2. I explicitly test the ability of the model to predict prices and market shares out of sample after the large changes in technology. In this section I make use of the full panel structure of the data and include variation over countries and time.

Estimation I have a panel of 70 markets, to estimate the taste and marginal cost parameters as defined in Section 2. 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 (5) 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 consumption enters instead of fuel costs, 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:

$$\min_{\theta} \rho(\theta)' \, g(z)' A \rho(\theta)' \, g(z)' \tag{9}$$

in which $\rho_{jmt} = (\xi_{jmt}, \omega_{jmt})$ the matrix of demand and supply unobservables stacked over all markets, $g(z)$ is the matrix of instruments and A is a weighting matrix. I follow the estimation algorithm described in Berry, Levinsohn and Pakes (1995) and Nevo (2001). I take into account recent cautionary warnings and improvements and carefully check the properties of the obtained minimum.[25] For simplicity, I estimate the demand and supply

[25] More specifically I do the following: (i) I use a nested-fixed point (NFP) algorithm, BLP's contaction mapping with a very thight convergence criterion (1e-12) to solve for ξ_{jmt}, (ii) I re-estimate the model with

separately and do not exploit cross equation restrictions on the price parameter. I instrument for prices using the production data that gives me the location and plant of production for every vehicle. I add sums of characteristics per size class for each vehicle as additional price instruments. A third group of instruments identifies the nonlinear parameters through approximations of the optimal instruments following the approach described in Reynaert and Verboven (2014). I estimate marginal costs under the assumption of perfect and imperfect competition. Perfect competition serves as a benchmark since price equals marginal costs estimation is an ols of prices on cost shifters. With the assumption of imperfect competition, marginal costs are the solution of the system of first order conditions as given in (7). 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 magnitude of consumers willingness to pay for fuel savings is similar to that found in our previous work.[26] 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 characteristics also have the expected sign. Adding horsepower, weight, footprint or height,

10 different starting values for the non linear parameters, (iii) I check first and second order conditions at the obtained minimum, (iv) I use the Interior/Direct algorithm in Knitro. I use a NFP because Mathematical Programming under Equilibrium Constraints proved to be slower in this application once I parralized the computation of the contraction mapping. As is shown in Reynaert and Verboven (2014) both estimation algorithms should give the same results.

[26] Table 9 will show that consumers are responsive to changes in fuel consumption.

Table 5: Estimation Results

Demand Estimation

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

Marginal Cost Estimation

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

The Table reports estimated parameters for the demand and marginal cost equations. 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). Both the demand and marginal cost equation include market fixed effects, body type dummies, size class dummies, a dummy for 3 doors, months on market dummies (for vehicles introduced within a calendar year). The demand includes brand fixed effects, fueltype by market dummies and a time trend while year dummies are included in marginal costs.

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.

Out of sample performance Before proceeding to the simulations and welfare results I assess the ability of the structural model to predict outcomes. I test the ability of the estimated model to predict prices and quantities after the observed technology adoption. Because of the technology adoption, consumers face a different choice set in 2011 than in 2007, with vehicles being on average 14% more fuel efficient. This large shift in one of the characteristics of the vehicles provides me with the opportunity to test the fit of the estimated model to the new choice set. If taste and cost parameters remain constant over time and are estimated precisely, a correctly specified model should be able to explain observed sales and prices in 2011. The procedure for the out of sample test is as follows: 1. Set both the supply ω_{jmt} and demand error ξ_{jmt} in equation (3) and (2) are at their expected level $(E(\omega_{jm2011}) = E(\xi_{jm2011}) = 0)$;[27] 2. Predict the marginal costs $\widehat{c}_{jm2011}$ for each vehicle on sale in 2011 using the estimated parameters from Table 5; 3. Solve for prices and quantities under the assumption of perfect or imperfect competition.

Table 6 summarizes the sales weighted characteristics over all countries in 2007 and 2011 for each of the four estimated models.[28] The first panel of Table 6 gives the results for the within sample fit of the model by setting $\omega_{jm2007} = \xi_{jm2007} = 0$. This shows the cost of setting the unobservables equal to zero without changes in characteristics out of the sample. All predicted sales weighted characteristics are within a 5% error margin of the observed sales weighted characteristics.

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 emissions. CO2 emissions are predicted to be 130 g/km from the logit and 129 g/km from the RC logit estimates, while observed

[27] 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.

[28] 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) making it very hard to predict sales of versions that are very similar.

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.

emissions decreased from 147 g/km to 126 g/km. This means sales weighted emissions differ by only 2.3% from observed emissions, while there was an actual drop of 14%. Also weight, footprint and the share of diesel are very close to the observed 2011 levels. The prediction of both the sales weighted level of horsepower and prices has an error margin of 6.2% and 7.2%. These errors are considerable but one has to take into account that this is a demanding test for the model as the value of all dummy variables is unchanged while the market changes considerably in these four years. An example is the entry of lower end SUV's while the SUV category dummy stays the same. In general, these numbers show that the out of sample fit is reasonably well and that the model is able to predict market quantities of interest despite a large change in one of the characteristics. When we compare the four different estimation models it is again the RC logit model with imperfect competition that is closest to the observed values. This will be the preferred model I will use throughout the simulations. Note however that the differences between the several models are very limited and probably statistically insignificant.[29]

6 Welfare effects

In this section I use the structural model to compare the welfare effects of abatement by sales-mixing with abatement by technology adoption. I will start this section by presenting the set-up of the simulations. Next, I will show how the impact of the regulation differs with the chosen abatement strategy. Finally, I will compare the effects of an attribute regulation with those of a flat regulation.

Simulation set-up I run four different policy simulations. In the first two, I simulate a policy exactly equal to the EU emission standard and let firms respond by either sales-mixing or technology adoption. In the last two simulations, I let firms comply to a flat standard instead of the attribute based regulation (ABR). The flat standard is set at a target such that the sales weighted CO_2 emissions are equal to those obtained from the ABR.

For the simulations with sales mixing I jointly solve for the firm specific shadow cost λ_f, and the price equilibrium such that each firm exactly complies with the standard. For the simulations with technology adoption I jointly solve for the firm specific technology τ_f,

[29] Currently, I don't give confidence intervals on the predictions and the counterfactual because of computation time, simulation results will be available upon request. In the appendix I further discuss some of the findings related to testing the performance of the model and I perform a Chi-square diagnostic test. This test assigns predicted and observed sales to different groups. The test rejects the null hypothesis that predicted distributions equal observed distribution in 4/5 group divisions.

and the price equilibrium such that each firm exactly complies with the standard.[30] The technological improvement does not vary across vehicles and should be seen as fleet wide % improvements in the firms' fleet. This is a simplification and avoids modeling the decision of when to implement the technology. Solving for the shadow costs, technology shocks and resulting prices in each of the scenarios is done by following a step-wise algorithm. This algorithm is described in the appendix. In all simulations I use the estimated coefficients from the RC Logit model with imperfect competition from Table 5. Note that the regulation is binding over the sum of geographical markets. I therefore solve for the responses in each of the countries, aggregate the responses and then evaluate the solution.

For each simulation I use the vehicle set of the year 2007 with a technology improvement of 6.4% for all vehicles. This mimics the market in 2011 when emissions would have decreased by 1.4% per year, the estimated trend before the regulation from Table 3. The market equilibrium for this hypothetical product set is the reference point of comparison for each simulation. All welfare changes in the simulations give the total vehicle lifetime changes for one year of new vehicle sales. I assume a vehicle lifetime of 15 years, a yearly mileage of 14000km and a discount rate of 6% to capitalize the yearly gains/losses in externalities.[31] The amount consumers drive is assumed to be constant, ignoring possible rebound effects on the intensive margin. I value a ton of CO_2 at €28.[32] Parry, Walls and Harrington (2007) give an estimate for 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.[33]

Welfare Effects The first panel of Table 7 shows the effect on market size of abatement to the ABR. Market size increases with technology adoption (+5%) and decreases with sales-mixing (-10%). With technology adoption, more consumers buy a vehicle because the savings from fuel consumption outweigh the losses from price increases. The 5% increase in sales is thus a rebound effect on the extensive margin: despite increases in fuel efficiency of

[30] It is important to note that I exactly solve for the level of technology or the shadow cost such that the regulation is just binding. Each of the firms' sales weighted emissions will end exactly on the policy lines as plotted in Figure 1. In reality, this does not need to be the case as firms may deviate from the standard and pay fines or firms may obtain emission levels lower than the target.

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

[32] This number comes from the Interagency Working Group on the Social Cost of Carbon.

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

10%, total CO_2 emissions reduce by only 6%.[34] With sales-mixing the subsidized part of the market gains less sales than the taxed part loses. Therefore, the reduction in emissions is much larger (-20%) with sales-mixing and close to the policy goal of an 18% reduction.

The second panel of Table 7 shows that market shares of different size classes do not change significantly with technology adoption. This finding is in stark contrast with substitution patterns from sales-mixing. In this case subcompact vehicles and compact vehicles reach a combined share of 72% (up from 62%). All other classes lose market share.

The final panel in Table 7 gives the changes in consumer surplus, profits, and externalities. Consumer surplus from new vehicles increases by €10 billion per year under technology adoption. Consumers are benefiting from lower fuel consumption and this outweighs the decreases in utility from higher prices. With sales-mix abatement consumer surplus decreases by more than €20 billion. The price changes push consumers out of the market or towards vehicles from which they get less utility. These findings are important in the sense that the incidence of the regulation shifts with the different abatement strategies. This is very different than the conclusion that is drawn in the previous literature that stressed the cost of the regulation for consumers from looking at sales-mixing and downsizing. The finding that technology causes increases in consumer surplus might partly explain why this type of regulation is a popular option for policy makers compared to fuel taxes.

The conclusions on firm profits are less clear. Variable profits increase by €4 billion under technology adoption and decrease starkly, by €10 billion, under sales-mixing. The sum of changes in variable profits hides interesting patterns between the different firms on which I comment below. There are two reasons why we can't draw final conclusions for firm profits. First, I do not endogenize the size of the firm responses, I simply require them to meet the target. It might be optimal for firms to either pay fines, or to do more than the regulation requires (in fact this is what we observe between 2012 and 2015 for a number of firms). The profit changes can thus not be interpreted as a steady state for the car market. Second, the total effect of the regulation on firms is unclear because I lack information on the fixed costs of technology adoption. Technology adoption requires adaptation of production lines as well as investments in R&D, both of which are unobserved. However, from the simulations it is clear that technology adoption leads to increases in variable profits that are potentially

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

Table 7: Simulation Outcomes

	Technology Adoption	Sales Mixing
	Market Size	
Total Sales	+5%	-10%
Total CO_2 Emissions	-6%	-20%
	Market Structure (Δ% points)	
Subcompact	+1	+7
Compact	-1	+3
Intermediate	0	-1
Standard	-1	-1
Luxury	-1	-1
Van	0	-3
SUV	0	-4
Sports	0	-1
	Welfare Effects (Δ in billion €'s)	
Δ Consumer Surplus	+8.81	-26.61
Δ Variable Profits	+4.39	-9.90
Δ Fixed Costs	?	0
Δ CO_2 Savings	+0.31	+1.07
Δ Other Externalities	-7.67	+17.60
Δ Total:	]...,5.84]	-17.84

The table gives aggregated effects over all markets and firms for each policy simulation. The table reports the change in market size, change in welfare in billion € over the total expected lifetime of the vehicle and the changes in market structure. 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.

offset by increases in fixed costs. Sales-mixing leads to stark decreases in variable profits.

The gains from the reduction in CO_2 emissions are small in comparison to other magnitudes, smaller than 10% of gains or losses in consumer surplus or variable profits in all simulations. With technology adoption a moderate €350 million is gained per year while sales-mix abatement leads to gains of about €1 billion attributable to lower emissions. Because of the effects on the size of the market and thus total yearly vehicle miles, the regulation will change other external costs from traffic such as accident risk, local pollution and congestion. I find that with technology adoption the increase in these externalities easily offsets all gains from emissions. Because the external effects from traffic apart from CO_2 emissions are estimated to be much higher a regulation that does not decrease traffic will increase the amount of total external costs. With sales-mix abatement the amount of vehicles on the road decreases and this reduce externalities by more than €10 billion.

To conclude, I find that the overall effect of the regulation is clearly negative with sales-mixing and positive before fixed costs with technology adoption. The simulations show that emission standards are not an effective instrument to reduce externalities from the car market when firms respond with technology adoption. The rebound effect on the extensive margin is considerable and overall externalities increase. The technology scenario can be regarded as an upper bound on the welfare effects, before deducting the fixed technology costs and further rebound effects. When firms respond with sales-mixing total sales and externalities decrease but the savings do not outweigh the loss in consumer surplus and profits. The sales-mix abatement scenario can be seen as a lower bound for the profit losses since technology adoption is the preferred revealed strategy by firms, sales-mixing must be more costly. Lastly, the incidence of the regulation shifts with the abatement strategy: consumer surplus increases by a significant amount under technology adoption and decreases strongly under sales-mixing.

These effects are subject to some limitations. First, I fully count gains in consumer surplus as welfare gains. A large part of consumer gains comes from reduced fuel consumption and about 60% of these expenses are fuel taxes paid to the government. Depending on whether these taxes are efficient, this part of the consumer gains could be seen as a transfer from the government to consumers and not as a pure welfare gain. Second, if the fuel savings do not translate into on-road fuel savings for consumers (the firms only do better on the test), then the welfare effects will be very different. If consumers would be perfectly informed about the gap between tests and on-road there would be hardly any changes in welfare. If consumers are misled into believing that cars are more efficient while they are not, the regulation will ex-post not reduce emissions and not decrease fuel consumption. If the technology does result in on-road savings a reason why we may underestimate the welfare improvements from technology adoption could be positive externalities from spillovers into other markets.

Attribute based versus flat regulation Here I compare the effects of the attribute-based and flat regulation. The differences in welfare effects between sales-mixing and technology adoption are very similar with a flat regulation, see Table A2 in the appendix.

In Table 8 I compare the outcomes for different firms using sales-mixing towards a flat and an ABR. I focus on firm outcomes of sales-mixing because that is where slope of the regulation matters most.[35] The results allow us to look at three possible differences between the ABR and the flat regulation. First, do the compliance costs of sales-mixing change with the slope of the regulation? Second, which firms gain from a flat regulation? Third, does attribute-basing equalize the compliance costs between firms?

First, the change in the marginal compliance costs is potentially very important as firms will choose to use a strategy as long as the marginal abatement costs of the strategy is lower than that of any other strategy. The empirical results in Table 8 show that the shadow cost of doing sales-mixing increases with the slope of the regulation. The mean shadow cost $\lambda_f^{'}$ for the flat regulation is 1.06 while for the ABR the mean shadow cost λ_f is 1.75. This means that choosing the strategy of sales mixing on average becomes much more costly with attribute-basing. This is especially clear for Daimler, Fiat, Renault and the Asian firms. Because sales-mixing becomes a lot more costly, the incentives to invest in technology increase with attribute-basing. This might be one of the reasons why we have seen such a clear choice for technology adoption in response to the EU standard. The upward slope in the target function makes sales-mix abatement more costly but the results are not so strong to state that a slope in the target function is a necessary condition to get technology abatement. With a flat target the profit losses for most firms from sales-mixing are so large that at least some technology investment is expected.[36]

Second, the firms that increase profits with a flat standard are Fiat, PSA and Renault. This is in line with the strong positions the countries took when bargaining over the regu-

[35] For completeness Table A4 gives the results for technology adoption towards a flat and ABR. Profits of firms are increasing in their technology efforts. Firms only lose when they need less technology than other firms to reach the target. This illustrates again that the outcome of the simulation is not a long term equilibrium as some firms will have an incentive to do more than the regulation.

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

Table 8: Profits and Emission per firm

	Target		Sales Mixing			
	ABR	Flat		ABR		Flat
	CO_2	CO_2	λ_f	Δ Profit	$\lambda_f^{'}$	Δ Profit
BMW	134	124	0.8	1614	1.4	-350
Daimler	121	124	2.4	-1401	1.0	-655
Fiat	116	124	2.5	-1973	0.4	366
Ford	126	124	1.0	998	1.3	-20
GM	125	124	2.7	-2419	2.2	-2054
PSA	123	124	0.6	1818	0.3	1564
Renault	120	124	1.5	-352	0.6	501
VW	125	124	1.6	-4450	1.4	-5322
Asian	118	124	2.7	-3736	1.0	-756

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.

lation.[37] 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 focused mainly on this distributional issues and not on the effect of the slope on the likelihood of different abatement strategies.

Third, if the abatement costs are higher for producers of heavier vehicles, a slope in the target function might equalize abatement costs and bring the market closer to an equilibrium that would be reached when trading is allowed. This would make the regulation more cost-efficient as it mimics the outcome of a cap and trading system. 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 λ'_f with a flat target is 0.55, higher than with an up-sloping target $\lambda_f = 0.48$. The equalization of abatement costs is thus very limited and there is still large heterogeneity in the shadow costs with attribute-basing.[38] The reason for the limited equalization of compliance costs is twofold. First, the regulation is binding on the level of the firm and not on the level of a single product. Since all firms sell products

[37] Deters (2010) describes the legaslation process in detail. He gives the following quote from French president Nicolas Sarkozy clearly favoring a flat regulation: "There is no legitimate reason to give the buyer of a heavy vehicle a right to more pollution than any other buyer."

[38] When we look at the technology efforts needed in Table A4 (assuming the technology effort translates literally into costs), there is almost no equalization. The coefficient of variation for the effort goes from 0.60 to 0.54.

in the different size classes firms are already able to equalize costs between their wide range of products. Second, a simple linear function of weight is probably not a very good fit to actual differences in compliance costs between large firms.

Incentives to invest in fuel efficiency The numbers given above raise the question why the regulation was necessary to spark investment in fuel efficiency. A first reason could be low demand for fuel efficiency by consumers, a second reason could be market failures in the supply of technology and R&D or steep fixed costs of investment. In this paragraph I show that there is little evidence for investment inefficiencies of consumers such that market failures in the supply or steep costs are probably important.

If consumers do not value future fuel cost savings to the full extent, firms will not be able to increase sales after investments in fuel efficiency. Grigolon, Reynaert and Verboven (2014) find that consumer investment inefficiencies in the EU are not large. In Table 9 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. So consumers do increase demand in response to increases in fuel economy and this channel cannot explain why firms hardly invested in fuel efficiency up until 2007.

A second channel might be market failures in the supply and adoption of technology or steep fixed costs. Jaffe, Newell and Stavins (2005) point to spillovers in technology, spillovers in adoption and incomplete information about future returns of the investment as possible market failures. The result of these market failures could be a socially suboptimal equilibrium with no or too little investment and technology adoption. If fixed costs are important these market failures might matter even more. The regulation gives clear and binding efficiency targets for the whole industry and thus might have succeeded in moving the industry out of this suboptimal equilibrium and to induce technology adoption.

Table 9: 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.

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%. Decomposing this decrease I find that firms do not change their sales-mix or downsize their vehicle fleet but adopt new technology. The welfare effects of this technology adoption are very different than the effects of other abatement strategies. In sum, technology adoption increases consumer welfare and increases total sales of new vehicles while sales-mixing decreases consumer welfare and sales. The total welfare effects from technology adoption are positive before fixed costs and very negative with sales-mixing.

This shows that if governments choose for emission standards the design of the regulation should aim to induce technology adoption. I find that the attribute-based design in the EU regulation makes sales-mix abatement much more costly for firms and thus increases the likelihood that firms will increase their pace of technology adoption. However, since technology adoption decreases fuel costs significantly the rebound effect on the extensive margin has negative effects on externalities from traffic. A more optimal regulation should try to pice these externalities directly while giving incentives for technology adoption.

Finally, I would like to end with some cautionary remarks. The numbers derived in this paper are obtained under strong assumptions. Despite, testing the performance of the structural model one should keep in mind the limitations of the model and the data. First, I focus only on sales of new vehicles and assume implicitly there will be no effects on prices and vehicle lifetimes in the second hand market. I expect the effects of technology adoption on the existing vehicle fleet to be very different from those of sales-mixing. Second, all welfare numbers are obtained ignoring possible rebound effects on driving behavior. Third, I do not observe any of the fixed costs related to implementing and inventing the new technology related to fuel efficiency. Fourth, the emission data might contain errors as car makers have admitted cheating on the tests. The estimated technology parameters will contain these false improvements and are thus potentially biased. It is an open question to which degree consumers are aware of the possible cheating when purchasing a vehicle. Each of these issues could be interesting for further research but require either a different empirical approach or additional data.

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Appendix For Online Publication

Details on Data Selection

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

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

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

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

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

Technology Estimates for Individual Firms

Table A1: Technological Progress Estimates per Firm

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

The table gives the estimated firm specific yearly change of technology in the CO_2 production function as derived from the year fixed effects in (8). The estimates correspond to Model 7 in Table 2. The shaded area are years after the policy announcement.

Algorithm for Policy Simulations

The algorithm follows these steps:

1. Start with a guess for the shadow costs or technology level
2. Solve the Nash equilibrium in prices given the values in 1
3. Compute the market shares given the price equilibrium and the values in 1
4. Compute the sales weighted emission for each of the firm
5. Compute the difference between the value in 4 and the required standard

6. If the difference is smaller than 1e-6 return end, else update the guess return to step 1

The updating is done by a trust-region-dogleg algorithm of the nonlinear equation solver in matlab (fsolve). Solving for λ_f and τ_f with fixed prices is not demanding as the algorithm only needs few iterations to equal sales weighted emissions of each firm with the target. Therefore, I first solve for λ_f and τ_f keeping prices fixed and use this as the starting value for the algorithm. However, the scale of the data and the stepwise re-optimizing for prices in all the markets and λ_f or τ_f, makes that finding a solution to the algorithm takes a considerable amount of cpu-time.

Further analysis of Out of Sample performance

It is important to give some further attention to some issues and limitations of performing an out of sample test of the structural model.

First, the out of sample test provides a validation of the demand model but not of the assumptions regarding price competition. I find that both the cost functions under perfect and imperfect competition are able to predict prices accurately after the product characteristics change. However, this does not provide any information as to what extent the divide between markups and costs is realistic. There is no large structural break in the data that gives me the necessary variation in markups and prices to test several competitive models against each other. A different game than Nash Bertrand pricing would change the divide between marginal costs and markups and thus the simulated effects on profits.

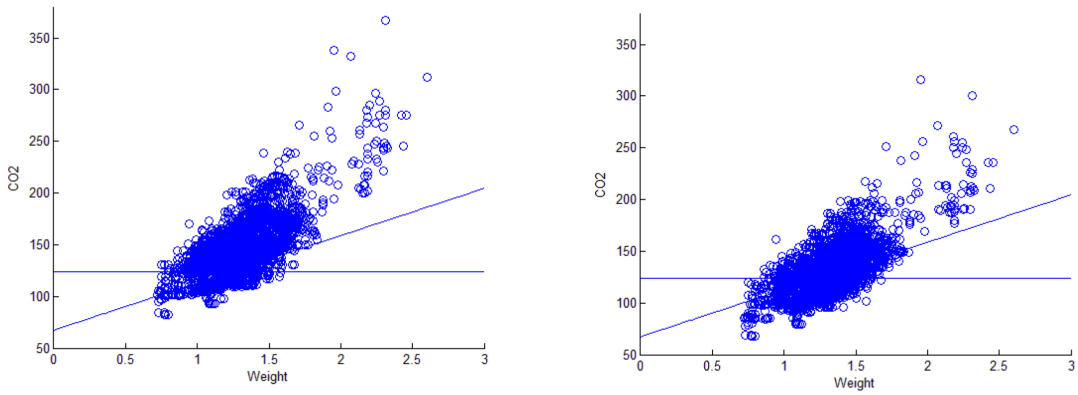
Next, the fact that sales of high priced and high horsepower vehicles are estimated too high might have at least three reasons. First, if measured fuel efficiency gains from the test cycle do not fully translate into reduced fuel costs, the model will overpredict the obtained fuel savings and the shares of high price and performance vehicles. Second, between 2007 and 2011 the price of SUVs dropped by 20% as less luxurious models with similar observables entered the market. This shows the inherently static features of the estimation method as the mean quality of an SUV is not assumed to change over time. Despite these dynamic changes in the market, and the entrance of new and redesigned models the static model actually provides a surprisingly good fit over a four year period of changes. Third, income effects are controlled for in a rather rudimentary way (prices relative to year country specific GDP). When income (or expected income) changes this might affect car choice in a more general and heterogenous way. This is also important for the next insight.

Another remark is related to the role of the outside good and the total size of the car market. The model is not able to predict the decrease in total sales in the European market observed between 2007 and 2011. I use (in line with previous research) the number of households as a scale for the total possible market. The number of households between 2007 and 2011 did not change while the total number of sales decreased by 20% because of the 2008 crisis. The model is thus not able to predict large macro-economic trends. This is relevant for the counterfactual analysis as all simulations are made under the assumption that there will be no changes in the overall demand for vehicles except for those related to the policy intervention.

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

Additional Figures and Tables

Figure 4: Policy Simulations



Start of policy simulation

Attribute 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. The second panel gives the set of vehicles after full technology adoption to the attribute-based standard (the diagonal line is binding).

Table A2: Simulation Outcomes Flat Standard

	Technology Adoption	Sales Mixing
	Market Size	
Total Sales	+5%	-6%
Total CO_2 Emissions	-6%	-16%
	Market Structure (Δ% points)	
Subcompact	0	+17
Compact	0	-1
Intermediate	0	-2
Standard	0	-2
Luxury	0	-2
Van	0	-5
SUV	0	-4
Sports	0	-1
	Welfare Effects (Δ in billion €'s)	
Δ Consumer Surplus	+8.81	-20.86
Δ Variable Profits	+4.33	-6.72
Δ Fixed Costs	?	0
Δ CO_2 Savings	+0.34	+0.87
Δ Other Externalities	-7.67	+10.88
Δ Total:	]...,5.81]	-15.84

The table is equivalent to Table 7 but gives the results of policy simulations towards a flat standard instead of the attribute based standard.

Table A3: Simulation Outcomes Flat Standard

	Technology Adoption	Sales Mixing
	Market Size	
Total Sales	+3%	-5%
Total CO_2 Emissions	-6%	-14%
	Market Structure (Δ% points)	
Subcompact	0	2
Compact	1	7
Intermediate	0	0
Standard	0	1
Luxury	0	-2
Van	0	-3
SUV	0	-4
Sports	0	-1
	Welfare Effects (Δ in billion €'s)	
Δ Consumer Surplus	+5.19	-9.96
Δ Variable Profits	+2.44	-2.87
Δ Fixed Costs	?	0
Δ CO_2 Savings	+0.28	0.70
Δ Other Externalities	-5.04	+8.08
Δ Total:	]...,2.88]	-4.06

The table is equivalent to Table 7 but gives the results of policy simulations when the model is estimated with a marginal cost function in which characteristics enter much more flexible: $\log(c_{jm}) = \gamma_1^e e_{jm} + \gamma_2^e e_{jm}^2 + \gamma_3^e e_{jm}^3 + z_{jm}\gamma_1^z + z_{jm}^2\gamma_2^z + z_{jm}^3\gamma_3^z + \omega_{jm}$.

Table A5: Chi-square Diagnostic Test

Bounds: $\leq x$	$x <$	CO_2 f	CO_2 $\widehat{f}$	Price f	Price $\widehat{f}$	Hp f	Hp $\widehat{f}$	Weight f	Weight $\widehat{f}$	Foot f	Foot $\widehat{f}$
	$\overline{x} - 1.5\sigma_x$	0.05	0.05	0.02	0.00	0.00	0.00	0.11	0.04	0.11	0.06
$\overline{x} - 1.5\sigma_x$	$\overline{x} - \sigma_x$	0.22	0.16	0.17	0.10	0.23	0.16	0.15	0.11	0.10	0.10
$\overline{x} - \sigma_x$	$\overline{x} - 0.75\sigma_x$	0.09	0.08	0.15	0.11	0.13	0.14	0.09	0.10	0.15	0.16
$\overline{x} - 0.75\sigma_x$	$\overline{x} - 0.25\sigma_x$	0.21	0.20	0.23	0.26	0.28	0.28	0.14	0.19	0.08	0.13
$\overline{x} - 0.25\sigma_x$	$\overline{x}$	0.08	0.06	0.13	0.14	0.09	0.11	0.10	0.11	0.11	0.13
$\overline{x}$	$\overline{x} + 0.25\sigma_x$	0.16	0.17	0.09	0.10	0.06	0.06	0.10	0.11	0.09	0.09
$\overline{x} + 0.25\sigma_x$	$\overline{x} + 0.5\sigma_x$	0.10	0.13	0.11	0.13	0.10	0.11	0.14	0.14	0.22	0.18
$\overline{x} + 0.5\sigma_x$	$\overline{x} + \sigma_x$	0.03	0.05	0.04	0.04	0.05	0.06	0.05	0.06	0.02	0.03
$\overline{x} + \sigma_x$	$\overline{x} + 1.5\sigma_x$	0.04	0.06	0.03	0.04	0.02	0.04	0.08	0.08	0.08	0.09
$\overline{x} + 1.5\sigma_x$		0.02	0.03	0.04	0.05	0.03	0.05	0.04	0.05	0.04	0.04
χ^2 statistic		15.85		19.88		19.18		27.79		19.71	
p-value		0.07		0.02		0.02		0.00		0.02	

This table divides characteristics x in 10 groups and assigns each observed and predicted sale to a group. The frequency of observed sales f and predicted sales $\widehat{f}$ is reported. The final lines report the χ^2 statistic and p-value of the chi-square diagnostic test. The null hypothesis that the frequency distributions are equal is rejected at a 5% confidence value for 4/5 characteristics.

Table A4: Profits and Emission per firm

	Target ABR CO_2	Target Flat CO_2	Technology Adoption τ_f	Technology Adoption ABR Δ Profit	Technology Adoption τ'_f	Technology Adoption Flat Δ Profit
BMW	135	124	5	-271	12	-81
Daimler	131	124	11	129	15	290
Fiat	114	124	8	503	2	-215
Ford	125	124	6	106	7	195
GM	124	124	9	566	10	615
PSA	122	124	3	-250	2	-338
Renault	120	124	6	256	4	50
VW	126	124	12	2178	14	2689
Asian	123	124	12	1178	12	1122

The table is equivalent to Table 8 but shows results from abatement with technology adoption. The level of technology adoption is simulated such that each firm exactly reaches the target.