

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), by technology adoption or by gaming emission tests. Using panel data covering 1998-2011, I find that the introduction of a European wide emission standard coincides with a 14% drop in emission ratings, of which 30% is explained by technology adoption and 70% by gaming. I estimate a structural model to find that the regulation missed its emission target and was not welfare improving. Abatement with sales-mixing would have reduced emissions, but at high costs. The political environment in Europe shaped the design and weak enforcement of the regulation and explains firms choices for abatement by technology adoption and gaming.

Keywords: environmental regulation, compliance, carbon emissions, automobiles, fuel economy
JEL: Q5, L5

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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. One of the major policy tools used to achieve this goal is the emission standard. A regulation that sets mandatory limits on average emission rates (or fuel economy) across the fleet. Emission standards are used across the globe in China, the European Union, Japan, the United States of America and other countries. These policies are simple to prescribe and do not explicitly tax consumers or producers. This paper studies the introduction of the emission standard in the EU and tries to estimate the welfare effects of the EU policy.

The EU regulation aimed to reduce CO₂ emissions from passenger cars by 18%. The policy was announced in 2007 and became fully binding from 2015, after a phase-in period that started in 2012. The regulation targets CO₂ emissions which is equivalent to targeting fuel consumption or fuel efficiency.¹ The EU standard is interesting to study for three reasons. First, it is a very demanding standard with a target of 130g CO₂/km. For comparison, the US standard required only 36 miles per gallon (mpg) in 2016, while the EU standard requires about 42 mpg. Second, before the standard the EU had no regulation on CO₂ emissions. The introduction of the standard thus allows us to study how market equilibrium changes with the introduction of a stringent emission standard. Third, the EU standard is attribute-based: the target for each firm depends on average vehicle weight. This means that firms producing heavier vehicles face a less stringent target. Several other countries introduced an attribute based standard.² Understanding the effects of the EU standard is thus helpful to guide the design of this type of regulation in the future and in other markets across the world.

The task of evaluating the welfare impact of emission standards is not an easy one. Firms can choose between different abatement strategies to comply with a standard and these strategies will have different effects on market equilibrium. A first strategy is sales-mixing: shifting relative prices of vehicles with different CO₂ emissions. A second strategy is downsizing: releasing smaller but more fuel efficient vehicles. A third strategy is technology adoption: improving fuel efficiency of the vehicle fleet. A fourth strategy is gaming: improving fuel efficiency as measured in official ratings without improving actual fuel efficiency on the road. These strategies will change prices, product attributes, product sets and market outcomes in different ways. Firms will choose the abatement strategy that has the lowest cost, taking into account the strategy chosen by competing firms. Also the design of the policy will matter for the costs of different abatement strategy. In order to evaluate the EU standard this paper presents a model that accounts for firms' abatement

¹CO₂ cannot be filtered during the combustion process. Fuel consumption translates proportionally into grams of CO₂ per km, with a different CO₂ content per liter for diesel and gasoline. Fuel consumption (liters per kilometer) and CO₂ emissions per kilometer are the inverse of fuel economy (miles per gallon).

²The 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.

strategy and the design of the policy.

In a first step I explain the trend in sales weighted CO₂ emission between 1998 and 2011 in the EU market. [Knittel \(2011\)](#) shows that vehicles evolve over time in terms of how much attributes are offered relative to fuel economy. He finds that there is a constant improvement in the amount of attributes and fuel economy offered and interprets this as technological progress. I follow his approach and estimate technological improvements in the trade-off that firms face between emissions and other vehicle characteristics. I find that emissions reduce 14% after the regulatory announcement. This reduction is fully explained by increases in the fuel efficiency of vehicles, while attributes remain constant. The results show that technological progress is twice as fast after the regulatory announcement, in line with findings of [Klier and Linn \(2016\)](#). Firms thus respond to emission standards by increasing the speed of technology adoption. I do not find evidence of changes in other attributes or in the product set offered by firms. However, in [Reynaert and Sallee \(2019\)](#) we studied fuel efficiency of thousands of vehicles on the road to find that there is significant gaming in the market. Emission ratings improve on paper, but these improvements do not translate to the road. Using the estimates of on-road fuel efficiency of [Reynaert and Sallee \(2019\)](#), I find that only 30% of the increased technology adoption is measurable on the road, so that 70% can be attributed to gaming.

The observed decrease in emission ratings is so strong that almost all of the firms reach the emission target before it becomes partly binding in 2012. However, looking at market outcomes before and after the policy is not sufficient to find the welfare effects of the policy. The effect of the regulation cannot be separated from changes in local regulation and taxes. Many EU member states change vehicle taxation after 2007, clearly contributing to the downward trend in emissions.³ There is also an 8 year gap between policy announcement and implementation so that demand, costs and market fundamentals potentially change. Therefore, I resort to a structural model to simulate the impact of the emission standard. The model allows me to single out the impact of the policy, and it also allows me to study how the impact changes when we change the design of the policy. I assume that the product set of firms and the product attributes are fixed, in line with the decomposition in emission trends. I then model heterogeneous consumers making discrete choices between vehicles. The firms have three strategic choices: price setting, technology adoption and gaming. The model allows me to clearly point out how equilibrium changes with each of the strategic choices. In order to simulate the model I need estimates of the primitives: preferences and price elasticities, marginal costs, changes in costs from technology adoption and changes in costs from gaming.

For the estimation of these primitives I rely on the rich panel data from before the policy announcement. This has the advantage that firms decisions are not affected by the policy. I estimate consumer tastes and price elasticities following the framework of [Berry, Levinsohn, and Pakes \(1995\)](#). I allow for heterogeneous tastes of consumers for several characteristics, including

³See for example the French bonus malus discussed in [Durrmeyer \(2018\)](#) and a Swedish rebate discussed in [Huse and Lucinda \(2014\)](#)

fuel costs. I extend the model to allow for multiple endogenous characteristics including prices, fuel economy, horsepower and weight. I instrument these characteristics with a combination of sums of characteristics, globalization and production platform instruments. The globalization instruments capture how different exposure to international markets impact engine design choices. Given the estimated demand I invert the first order conditions of the profit function with respect to prices to find vehicle marginal costs. Because I use pre-policy data this is straightforward. I also invert first order conditions with respect to fuel consumption to find the marginal benefits and marginal costs firms face in deciding how much fuel consumption (and thus emissions) to offer. This will be a crucial input to model technology adoption: the regulation will increase the marginal benefit of lowering fuel consumption as vehicles with lower emissions help the firm attaining the regulatory target. However, in doing so firms will face increases in the marginal cost of offering lower fuel consumption. I need a functional form assumption to predict cost changes from decreases in fuel consumption. I rely on two approaches. First, I use the observed relation in the data between fuel consumption and estimated marginal cost. Second, I use engineering reports submitted with the policy proposal that give detailed predictions of marginal cost increases. Finally, I need an estimate for the costs of gaming. These costs consist of expected litigation and the cost of emission test falsification. These costs are very difficult to estimate and I therefore choose to use estimated levels of gaming in the simulation, rather than solving for optimal levels. The estimated model with multiple endogenous characteristics and multiple strategic decisions on continuous variables is similar to recent contributions of [Fan \(2013\)](#) and [Crawford, Shcherbakov, and Shum \(2019\)](#).

Given the estimated primitives I introduce the EU policy in the model and simulate how it impacts market equilibrium. The simulations reveal that technology adoption in combination with gaming is indeed the equilibrium abatement strategy of firms. The increases in costs from technology adoption beyond the willingness to pay for fuel consumption make that the regulation decreases consumer surplus and profits. Because of the gaming, the reductions in CO_2 emission are a mere 5% instead of the 18% target. The sum of these emission savings and consumer and profit losses is clearly negative so that the regulation reduces welfare. However, when I consider two additional welfare effects: reductions in other externalities and corrections in consumer undervaluation, I find the emission standard to have a very small positive impact. The simulation also reveals that sales mixing in response to the target would have had starkly different welfare effects: total sales and emissions then strongly decrease at a very high costs for consumers. Why did firms choose for the combination of technology adoption and gaming in response to the EU standard?

I find that the attribute based design of the regulation, that lets the emission target vary with vehicle weight, makes sales mix abatement much more costly for firms. If the regulation would have a flat design, firms would have opted for a mixture of technology adoption and sales mixing. This would have led to CO_2 emission reductions of 11%, much closer to the 18% target. Why then was the attribute design introduced? Newspaper articles at the time cite representatives of different car producing countries. The French and Italian governments were in favor of the flat regulation while Germany lobbied heavily for a steep attribute design. The simulations confirm

that the positions of the governments are in line with their firms. The attribute basing redistributes the incidence of the regulation between French, Italian and German producers. Also the gaming is a product of the political environment. A recent evaluation by the European Parliament ([Gieseke and Gerbandy \(2017\)](#)) has placed responsibility for enforcement failures with car producing member states. The countries failed to detect and respond to gaming timely, so that the policy missed its target. Together, the political deal about attribute basing and the enforcement failures, show the importance of the political environment in which emission standards are introduced.

The paper makes several contributions. First, I find that the EU emission standard induces technology adoption and gaming by firms. The equilibrium effects of both abatement strategies are not studied in detail in the previous literature. 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 not focused on the welfare effects from gaming. Second, by estimating a structural model of demand and supply I show that the incidence and welfare effects of the regulation vary drastically between different abatement strategies. Third, my model allows me to study how the design of the regulation affects the abatement choice. Together, these three contributions show that it is crucial to take the supply responses carefully into account when evaluating and designing emission standards. Finally, this is the first paper providing a detailed study of the EU regulation and its impacts on market outcomes.

The framework in this paper builds on existing work of [Knittel \(2011\)](#), [Jacobsen \(2013\)](#) and [Reynaert and Sallee \(2019\)](#). The emission decomposition follows the estimation in [Knittel \(2011\)](#), but I find that the speed of technology adoption changes when the policy is announced. [Jacobsen \(2013\)](#) incorporates heterogeneous responses from both consumers and producers in a structural model. In an extension [Jacobsen \(2013\)](#) also considers technology adoption using the framework of [Austin and Dinan \(2005\)](#). My analysis contributes by fully considering technology adoption in the economic model. This shows the importance of the starting slope of the technology cost curve and how technology adoption lowers shadow costs endogenously. While [Jacobsen \(2013\)](#) finds that technology adoption limits the welfare losses of standards, I show that technology adoption could lead to welfare losses or gains depending on the cost effectiveness of technology relative to consumers willingness to pay for fuel consumption.⁴ In [Reynaert and Sallee \(2019\)](#) we estimate the amount of gaming in the EU market. I use the on road fuel efficiency estimates of our work to see how much of the faster technology take up translates to the road. I also use the framework we built to estimate the effects of gaming on consumer surplus. The effects of gaming crucially depend on consumer awareness and cost avoidance of gaming and we calibrate several scenarios varying these parameters. Here, the interaction between choice and gaming is embedded in the full equilibrium model interacting with other abatement strategies and I focus on overall welfare rather than narrow

⁴Other notable differences are the demand model where I estimate price elasticities on the engine level (more than 400 products per market) rather than broad category level (including 12 products) and I allow for endogenous characteristics. The model of [Jacobsen \(2013\)](#) is richer in other dimensions as it incorporates effects on the second hand market as well as changes in vehicle miles traveled as modeled in [Bento, Goulder, Jacobsen, and von Haefen \(2009\)](#)

consumer welfare.

This paper contributes to a literature that studies policies targeting vehicle emissions, see [Anderson and Sallee \(2016\)](#) for an overview. [Holland, Hughes, and Knittel \(2009\)](#) show that none of the welfare effects of emission standards are theoretically determined. A regulation might decrease or increase emissions from new vehicles, depending on the distribution of price elasticities of products below and above the emission target. This shows the importance of estimating a model allowing for rich substitution patterns. However, the welfare effects of standards become even more uncertain when we consider the variety of different abatement strategies. The empirical literature on emission standards has focused on the US CAFE standard. [Goldberg \(1998\)](#) was the first to consider the effect of standards on price setting and the composition of the vehicle fleet. [Anderson and Sallee \(2011\)](#) use a loophole in the regulation to show that the standard is hardly binding in recent years. [Jacobsen \(2013\)](#) finds that the US CAFE standard imposes a large shadow cost on domestic US firms. Both [Klier and Linn \(2012\)](#) and [Whitefoot, Fowlie, and Skerlos \(2017\)](#) extend the analysis by considering endogenous product characteristics in the model, allowing firms to change characteristics of vehicles. Both of these papers assume that the level of technology is fixed and consider re-optimization of product offerings on a fixed trade-off function between emissions and attributes. I allow the trade-off relation to change but impose that improvements must reduce fuel consumption, in line with the empirical evidence in Europe. The economic effects of attribute-based regulations are discussed in [Ito and Sallee \(2018\)](#) who focus on distortions in the market for the attribute. [Whitefoot and Skerlos \(2012\)](#) compute weight distortions for the footprint based CAFE standard. The analysis here is complementary as I study different effects of attribute-basing: the cost of different abatement strategies and the political economy behind the attribute basing.

This paper focuses on the direct welfare effects of the EU emission standard. Recent work has considered additional margins of the policy. [Jacobsen and van Benthem \(2015\)](#) study the effect of emission standards on vehicle scrap rates. [Durrmeyer and Samano \(2018\)](#) compare a standard with a rebate policy that explicitly subsidizes and taxes emission above and below the target. [Bento, Gillingham, and Roth \(2017\)](#) focus on the effect of fuel standard on dispersion in weight and its effect on accidents.⁵

The paper is structured as follows. Section 2 describes the policy and the available data. Section 3 decomposes the changes in emissions in the EU automobile market between 2007 and 2011. Section 4 presents emission standards in a model of supply and demand and discusses the possible effects of the different abatement strategies. Section 5 presents estimation results. Section 6 presents the results of policy simulations and Section 7 concludes.

2 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 $\sigma = 130$ grams CO₂ per

⁵These margins play a role in the current policy debate in the US as discussed in [Bento, Gillingham, Jacobsen, Knittel, Leard, Linn, McConnell, Rapson, Sallee, van Benthem, and Whitefoot \(2018\)](#)

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.⁶ Figure 1 plots the target and the distance from the target for each producer in 2007 and 2011. 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 $a = 0.046$.⁷ 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 €1,280 per vehicle (against an average sales price of €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 onward.

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.⁸ 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 CO₂/km). From 2009 onward CAFE standards are tightened towards 36 mpg in 2016 (this corresponds to 152 g CO₂/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.⁹ From 2012 onward the CAFE standard also has an attribute-based part: the target varies with footprint.

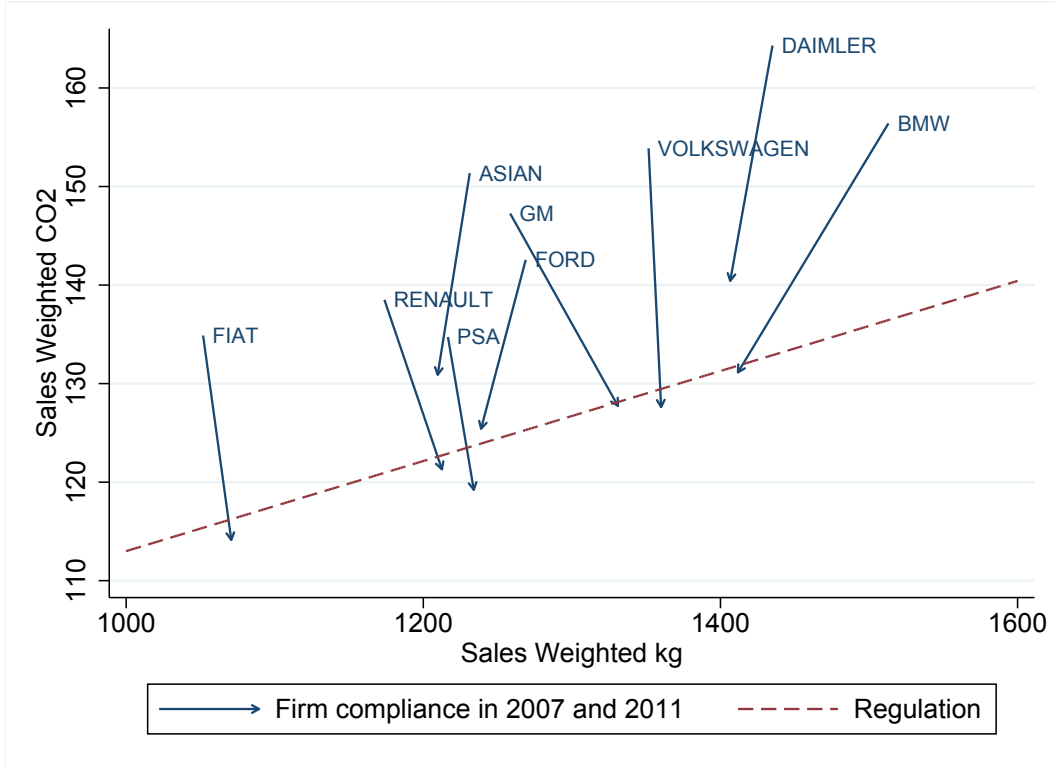
⁶Manufacturers can obtain lower average emissions by gathering super credits. These credits are given for vehicles that emit less than 50g/km. There are also separate standards for small manufacturers making less than 30 000 vehicles per year. Both of these exceptions are ignored in the analysis since they count for a very small share of the total market.

⁷The average SUV in the data weighs 1650kg, the average compact car weighs 1250kg. The SUV's emissions will be scaled down while the compact car's emissions will be scaled up.

⁸See 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.

⁹Contrary 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.

Figure 1: Compliance of Firms in 2007 and 2011



The starting point of each arrow gives the sales weighted CO₂ 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.

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.¹⁰ 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 CO₂ per kilometer.¹¹

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 give information on vehicle size (footprint defined as length by width, weight and height) and engine performance (horsepower and displacement). The data also contains information on fuel consumption (liters per 100 km and CO₂ emissions per km). These numbers are official consumption ratings obtained from the New European Driving

¹⁰These markets represent around 90% of the total EU market.

¹¹The combustion process and different energy content of the fuel make diesel engines more efficient per kilometer. Diesel cars emit less CO₂ per kilometer, but more other pollutants such as NOX.

Cycle (NEDC), a standardized driving cycle to assess the emission levels of car engines. The cycle simulates both urban and extra-urban driving patterns and excludes the use of auxiliary features like air conditioning. Real world emissions thus differentiate from these test values. In [Reynaert and Sallee \(2019\)](#) we develop a measure of on-road emissions and we show that reductions on the official CO₂ ratings do not fully translate into on-road savings. I will use this measure of on-road emissions in the analysis in order to disentangle technology adoption from gaming.¹² This information is available for a much more limited sample of vehicles. The data on sales and emissions are supplemented with production data from PriceWaterhouseCoopers (PWC) that 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.¹³ The list of excluded 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 3, 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 14,444 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. The data from year 2007 will be used as the benchmark for the simulations in Section 6.

Summary Statistics Figure 1 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.

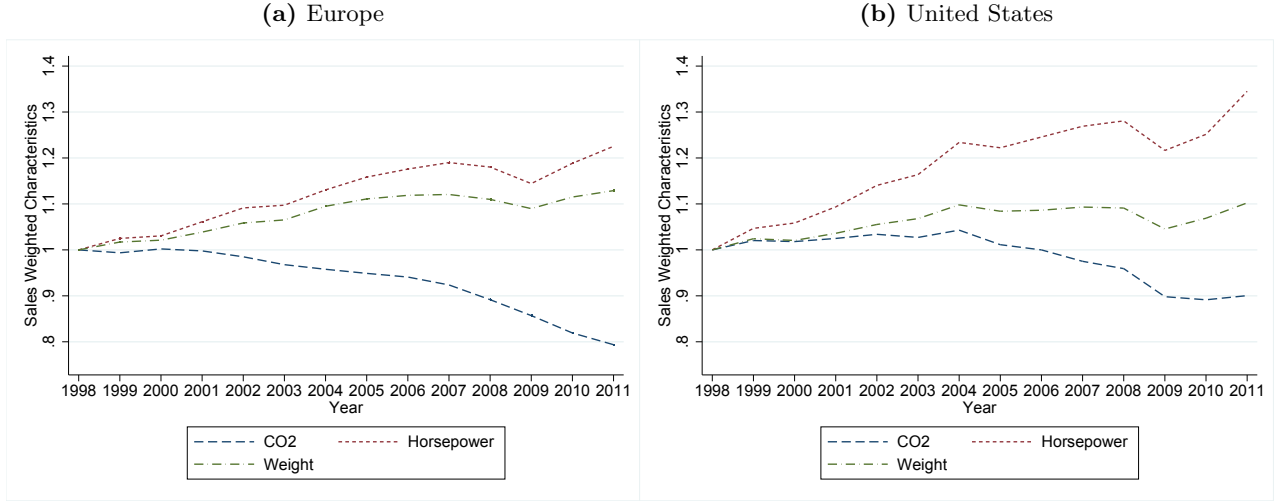
¹²In [Reynaert and Sallee \(2019\)](#) we construct on-road emissions from a panel of 12,000 drivers visiting fuel station 22 million times. We observe odometer readings and fuel purchases so that we can construct fuel consumption on the road. We compare the trend in actual fuel consumption with the official ratings.

¹³I combine the fleet of the Asian car makers because most of these firms do not have a very broad product set. This makes finding a price equilibrium with sales-mixing impossible in my algorithms. Alternatively, I could choose to only keep Toyota and Nissan, by far the largest Asian firms in the EU, but combining all Asian firms allows me to include more products.

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.

Figure 2: Sales Weighted Characteristics over Time

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>).

Fiat, GM, PSA and Renault all increase average weight slightly while decreasing emissions strongly. A strong downward trend in emissions towards the standard is observed for all firms. The decrease in emissions is so strong that most of the firms comply with the emission standard four years before it is fully binding.¹⁴ Table 1 shows the change in sales weighted vehicle characteristics between 2007 and 2011. CO₂ emissions decrease by 14% while there is moderate growth for other characteristics.

Figure 2 plots sales weighted characteristics over time from 1998 to 2011 for both the EU (Panel a) and the US (Panel b). Each characteristic is indexed in 1998. The most remarkable trend in the EU is the evolution of sales weighted CO₂ 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 CO₂ 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

¹⁴This shows that the emission standard is probably not the only mechanism driving driving down sales weighted emissions. Below I comment on complementary explanations.

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.

3 Market response to the EU emission standard

In this section I decompose the decrease of carbon emissions in the EU vehicle market. The goal of the decomposition is to measure the extent to which different abatement strategies can explain the drop in emissions. In order to do this, I estimate the trade-off relation between emissions and other vehicle characteristics. The shifts over time in the relation between characteristics and emissions supplied by car makers are decomposed into changes in technology and changes in the composition of the vehicle fleet. I also investigate to what extent the technological change translates to the road by separating gaming from actual technology.

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

$$\log(e_{jt}) = \tau_t + \eta \log(x_{jt}) + \epsilon_{jt}, \quad (1)$$

in which the technology parameter τ_t is a time fixed effect, the trade-off parameters η denote how emissions e_{jt} change with a 1% change in characteristic x_{jt} and ϵ_{jt} is an error term.¹⁵ The technology parameter captures shifts over time in the trade-off between emissions and characteristics. When the trade-off parameters η are constant over time, technology τ_t can be seen as input neutral as it enters multiplicative in levels.¹⁶ I include vehicle model fixed effects such that the identifying variation comes from different engine options within the same model. I assume the remaining unobservable ϵ_{jt} to be i.i.d.. The unobserved error comes from variation in unobserved attributes of engine versions within a model name, such as torque or the valve mechanism. These unobserved engine attributes might be correlated with explanatory variables, so that η cannot be interpreted as a causal relation between the characteristics and emissions. The goal of estimating (1) is to see changes in emissions over time while controlling for the correlation between emissions and other characteristics.

Estimation of (1) is useful because it reveals the abatement strategies that firms resort to without relying on a structural model. In Figure 2, I showed how emissions starkly decreased after the regulatory announcement. If firms choose for sales-mixing or downsizing, then the part of emissions that is explained by characteristics x_{jt} should decrease over time. Both with sales

¹⁵Knittel (2011) assumes that marginal cost is additively separable in elements related to emissions and other cost elements not related to emissions. Then this estimation can be interpreted as an estimate of the level set or iso-marginal cost relation between emissions and its determinants.

¹⁶The main specification will have constant η , but I also show robustness when η changes over time. I estimate 1 using a wide range of robustness checks specified below and reported in Appendix Table A1.

mixing and down sizing firms would sell more small and low performing cars. In contrast, when firms choose to implement technology we should see shifts in the technology parameters τ_t over time. As discussed above, there is large concern that firms have gamed the test. This is a concern when estimating (1) as the left hand side variable is the official emission rating obtained from the regulator. To test the extent to which emissions on the road change, I also estimate (1) using a measure of on-road emissions as the left hand side variable. The on-road emissions are taken from our work in [Reynaert and Sallee \(2019\)](#). This allows me to test if technological improvements revealed in official data translate to on-road measures. I now present estimates of the trade-off parameters in Table 2 and of the technology parameters in Table 3. Next, I discuss robustness of estimating (1), reported in appendix Table A1. Finally, I show the decomposition of emissions over time in Table 4.

Table 2 presents the trade-off parameters η from estimating (1). 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 is associated with a 1.8% increase in emissions. Weight is associated with higher emissions, while a 10% increase in the footprint reduces emissions by 2.9%. A diesel engine is about 20% more efficient than a gasoline engine which coincides with engineering numbers and is very robust across specifications. These numbers have the same sign and a similar magnitude as those reported by [Knittel \(2011\)](#) and also [Klier and Linn \(2016\)](#) who use similar European data. Model 2 allows for a firm specific trend in technology. The trade-off parameters are robust to introducing firm specific trends. Next, I start introducing on road measures of emissions. These measures are available for a much smaller set of vehicles so that the sample shrinks from 14 444 observations to 3 766 observations. Therefore, Model 3 replicates Model 1 with the smaller sample. The trade-off parameters shrink somewhat, but are fairly robust. Model 4 changes the dependent variable so that the relation between on road emissions and characteristics is estimated. Model 5 introduces firm specific trends. Trade-off parameters shrink further when looking at on-road emissions. However, it becomes harder to interpret these coefficients as a technical trade off that firms face. On road emissions vary not only because of physical reasons but also because consumers with different driving patterns select into different types of vehicles. For example, the diesel coefficient now deviates from engineering estimates and is 0.16 instead of 0.2. Typically, long distance drivers choose diesels because of higher fuel efficiency. If long distance drivers obtain lower fuel economy than short distance drives, this explains the deviation from the engineering estimate. Below, the trade off parameters will be used to compute the part in emissions that correlates with characteristics. First, I zoom in on the time fixed effects.

The technology parameters τ_t are derived from the time fixed effects in each regression and plotted in Table 3 for Model 1 to 5. Note that Model 2 and 5 report the average of firm specific trends. The bottom panel of the table presents the difference in the mean of τ_t for 1999-2007 and for 2008-2011, corresponding to the pre- and post-policy announcement period. Model 1-3 all explain official emission ratings and I find that technology improves significantly faster in the

later years of the sample. All estimates show that the technology shifts τ_t are more than 2% higher after 2007 than in the years before. The difference is statistically significant. After 2007, the estimates thus reveal a significant increase in the pace of technology improvement. The firm specific trends are reported in Table Appendix A2. The change in trends is there for all firms but the magnitude differs. BMW and Renault have the lowest difference in technology growth (0.9% and 0.8%), while Volkswagen has the highest difference (5.4%). In the official emission measures we find evidence of rapid changes in technology adoption, but these emission reductions might not translate to the road. Indeed, once we explain the shifts in on-road emissions in Model 4 and 5 we find that the technology growth does not increase as rapid in the post-policy period. Between 2008-2011, the mean technology change shrinks from 3.9% in Model 2 to a mere 1.5% in Model 5. Still, Model 4 and 5 reveal higher average technology growth in later years relative to prior years, but the difference shrinks from 2.4% to 0.7%. Firm specific values, reported in Table Appendix A2, show similar patterns except for BMW and Renault. Overall, this reveals that firms do engage in technology adoption after the policy announcement but that a large part of the technology is aimed at reducing official emission ratings rather than on-road emissions. The estimates show that 70% of the additional reduction in official emissions comes from gaming, while 30% comes from actual technology improvement. This 30/70 ratio will be used in the structural model below.¹⁷

To show robustness for the estimation of trade off parameters and trends in technology I replicate the estimation of 1 in several robustness exercises. Table Appendix A1 shows estimates and differences in technology take up for Model 6 that changes the functional form from Cob Douglas to Translog so that higher order terms in x_{jt} are included. Model 7 keeps only the first appearance of each vehicle, Model 8 allows trade off parameters to change over time, Model 9 weighs observations by sales, Model 10 includes marginal costs as estimated in the structural model as a control and Model 11 interacts characteristics with fuel type. All specifications are ran on the full sample with official ratings as the dependent variable. All specifications estimate that emissions decrease between 2.1% and 3.3% more rapidly after the policy announcement. The baseline in Model 1 is 2.3%.

Decomposition of the changes in emissions The estimated relation (1) can be used to decompose the decline in emissions over time. The decomposition is done as follows: I predict emissions, \hat{e}_{jt} , as the fitted values of regression (1) with Model 2. I also predict \bar{e}_{jt} using (1) but fixing the technology level at $\tau_t = \tau_{2007}$.¹⁸ The evolution in sales weighted values of \bar{e}_{jt} only changes when the composition of characteristics x_{jt} changes over time, while \hat{e}_{jt} changes both because of underlying

¹⁷I use the market level estimate of gaming rather than the firm level in the structural model for two reasons. First, the firm level estimates are not statistically precise and introducing firm heterogeneity in gaming will create large differences in welfare outcomes between firms. The preciseness of the estimates in Model 4 and 5 is overstated in the standard errors as the left hand side are estimates of on-road performance and I did not adjust standard errors for this (bootstrapping is computationally impossible because it would require multiple estimations over 22 million observations. The second reason is that in Reynaert and Sallee (2019) we analyze data up until 2015 rather than 2011. Over this longer period all firms game in large and similar amounts.

¹⁸I 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. Not doing this re-scaling has no impact on the results.

Table 2: Trade-off Estimates between Emissions and Characteristics

	Model 1		Model 2		Model 3		Model 4		Model 5	
	Official Ratings				On Road Ratings					
	Coef.	St.E.	Coef.	St.E.	Coef.	St.E.	Coef.	St.E.	Coef.	St.E.
ln(Hp)	0.18	0.02	0.18	0.02	0.13	0.02	0.12	0.02	0.12	0.02
ln(Weight)	0.62	0.04	0.64	0.05	0.55	0.06	0.29	0.04	0.29	0.04
ln(Footprint)	-0.29	0.09	-0.33	0.10	-0.34	0.08	-0.08	0.07	-0.13	0.06
ln(Height)	-0.02	0.12	-0.00	0.12	0.00	0.12	0.06	0.08	0.04	0.08
Diesel	-0.20	0.01	-0.20	0.01	-0.21	0.02	-0.16	0.01	-0.16	0.01
Year F.E.?	Yes				Yes		Yes			
YearXFirm?			Yes						Yes	
Car Name F.E.?	Yes		Yes		Yes		Yes		Yes	
Observations	14,444		14,444		3,766		3,766		3,766	
R ²	0,85		0,86		0,78		0,88		0,88	

This table gives the trade-off parameters η between characteristics and emissions from equation (1). Robust standard errors clustered per firm are reported between brackets. In Model 1, 2 and 3 official $\ln(CO_2)$ ratings is the dependent variable, in Model 4 and 5 on road measures are the dependent. Model 1 includes year fixed effects, Model 2 introduces year by firm fixed effects, Model 3 limits the sample to data for which on-road estimates are available but the dependent is still the official rating, Model 4 has on-road $\ln(CO_2)$ estimates as the dependent variable and has year fixed effects, Model 5 has year by firm fixed effects.

Table 3: Technological Progress Estimates

	Model 1		Model 2		Model 3		Model 4		Model 5	
	Official Ratings				On Road Ratings					
	Coef.	St.E.	Coef.	St.E.	Coef.	St.E.	Coef.	St.E.	Coef.	St.E.
1999	-0.5	0.8	-1.4	0.1	-1.7	1.4	-0.9	0.5	-1.2	0.1
2000	1.9	0.6	2.4	0.1	1.7	0.9	-1.5	0.2	-1.5	0.1
2001	-1.5	0.4	-2.2	0.2	-1.4	0.9	-1.2	0.2	-1.7	0.1
2002	-1.3	0.4	-1.5	0.2	-1.5	0.6	-0.9	0.3	-0.8	0.1
2003	-1.5	0.3	-1.9	0.2	-0.8	0.3	-0.5	0.2	-0.5	0.1
2004	-1.8	0.5	-2.1	0.2	-1.4	0.7	-0.7	0.3	-0.9	0.2
2005	-1.5	0.3	-1.9	0.2	-0.9	0.2	-0.2	0.2	-0.1	0.1
2006	-1.3	0.3	-1.7	0.1	-1.1	0.5	-0.4	0.2	-0.4	0.1
2007	-1.4	0.6	-2.2	0.1	-0.9	0.9	-0.2	0.5	-0.5	0.1
2008	-2.7	0.4	-3.1	0.1	-2.2	0.8	-0.9	0.4	-0.9	0.0
2009	-3.0	0.6	-3.6	0.1	-3.2	1.0	-1.4	0.5	-1.4	0.1
2010	-4.3	0.7	-4.7	0.1	-5.5	1.6	-2.5	0.5	-1.8	0.0
2011	-3.3	0.4	-4.5	0.1	-3.2	1.1	-1.3	0.6	-1.9	0.1
Difference in Technology Growth 2011-2007 and 2007-1998										
Difference	2.3	0.5	2.42	0.07	2.6	0.9	0.8	0.3	0.65	0.08

The table gives the estimated yearly percentage change in emission rates due to technological improvements. Percentages are obtained from differencing the year fixed effects in (1), standard errors are computed with the Delta method. Each of the estimated models correspond to Table 2. The shaded area are years after the policy announcement. The last rows give the difference in average technology growth between 2011-2007 and 2007-1998. For Model 2 and Model 5 the average across firm specific trends are reported, firm level estimates are reported in Appendix Table A2.

characteristics and technology.

The results in Table 4 show that between 1998 and 2007 sales weighted emissions without technology \bar{e}_{jt} declined slightly from 156 to 152. Technology improvements are responsible for the remaining moderate decline in emissions between 1998 and 2007. After 2007, the sales weighted emissions without technology \bar{e}_{jt} stay constant. There is thus no evidence of significant changes that could be attributable to either sales-mixing or downsizing as these would change the part of emissions that correlates with attributes. When I split up the average sales weighted emissions into vehicle models released after and prior to 2007 the results show that the emissions \bar{e}_{jt} of vehicles released prior to 2007 remain constant.¹⁹ 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 attributable to changes in the sales mix or to the release of new downsized fuel efficient vehicles. Though, I cannot rule out that the vehicles would have grown without the policy.

The sales weighted emissions with technology \hat{e}_{jt} are decreasing rapidly after 2007 and this shows that technology adoption is fully responsible for the observed drop in official emission ratings. 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.²⁰

There are two concerns regarding the results presented so far. First, the Great Recession and EU debt crisis coincide with the policy announcement and cover the post policy announcement period. In general, economic downturn would lead consumers to spend less on durables and thereby would add to the likelihood of finding evidence for shifts in the composition in the fleet towards smaller vehicles. The fact that we do not see this is thus strengthening the argument that firms respond with technology adoption. Technology adoption itself could be affected by the crisis, the direction of that effect is unclear. A second concern is that the observed response is so strong that most firms already comply with the emission standard in 2011, four years before the regulation is fully binding. Individual member states do increase emission based taxation and regulation in response to the EU wide policy.²¹ This combination of new local taxation, together with the standard, can explain why the response is so strong and why compliance is attained early. It would be very interesting to study the interaction between national regulation and the EU wide standard but this is out of scope of the current project. In the remaining analysis, I will therefore model firm behavior in response to a standard to single out the effects of the EU emission standard.

In sum, I presented evidence that the observed decline in emissions is attributable to changes in the official CO_2 ratings while the sales mix and characteristics of the fleet are unaffected. Estimates show that the decline is for 70% explained by gaming and for 30% by actual technology adaption.

¹⁹ An example of a newly released model is the "Citroen DS3 Hatchback", released in 2009.

²⁰ 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 higher in the years after 2007.

²¹ 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 \leq)		New Models (> 2007)	
		No Tech.	Tech.	No Tech.	Tech.	No Tech.	Tech.
	True	\bar{e}_{jt}	\hat{e}_{jt}	\bar{e}_{jt}	\hat{e}_{jt}	\bar{e}_{jt}	\hat{e}_{jt}
1998	169	156	172	156	172		
1999	168	156	170	156	170		
2000	169	155	171	155	171		
2001	167	154	169	154	169		
2002	164	154	166	154	166		
2003	161	153	162	153	162		
2004	158	152	159	152	159		
2005	156	152	157	152	157		
2006	154	152	155	152	155		
2007	151	152	152	152	152		
2008	147	152	147	151	147	157	152
2009	142	152	143	152	142	160	150
2010	135	152	136	152	136	154	137
2011	130	152	130	152	130	154	132

The table reports observed and predicted levels of average sales weighted CO₂ 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 and Table 3 Model 2. The columns \bar{e}_{jt} contain sales weighted predicted emissions keeping technology constant at $\tau_t = \tau_{2007}$. The columns \hat{e}_{jt} contain sales weighted predicted values for emissions with estimated τ_t .

These findings form the basis for developing an economic model in which firms can respond to emission standard with technology adoption or gaming, keeping the other characteristics of their fleet unaffected.

4 Model

This section introduces an emission standard in a structural model of consumer demand and firm behavior. After describing the model, I discuss how different abatement strategies affect market outcomes. I argue that there are no clear theoretical predictions for the welfare effects of emission standards and discuss what I need to estimate. Finally, I discuss how the design choices of the regulator regarding attribute basing and enforcement affect firm abatement choice.²²

Demand There are M geographical markets, indexed by $m = 1, \dots, M$, each market is observed $t = 1, \dots, T$ times.²³ I suppress the subscript t . In each market m there are A_m potential consumers.

²²The 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.

²³I observe prices and quantities at the country level. Therefore, the geographical market will correspond to a country in the empirical analysis.

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, $j = 1, \dots, J$. Consumer i 's conditional indirect utility for the outside good is $u_{i0m} = \varepsilon_{i0m}$, and for products $j = 1, \dots, J$ it is:

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

where x_{jm} is a vector of observed product characteristics, $g_{jm}e_{jm}$ are fuel costs (fuel prices g_{jm} times fuel consumption e_{jm}), p_{jm} is the vehicle price and 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 draw from a standard normal distribution, so that β^k represents the mean valuation for characteristic k and σ^k the standard deviation across consumers.

Notice that the coefficient β_i^e measures consumers valuation of fuel costs. Consumers use vehicles for several years and thus care about expected fuel costs over the vehicle lifetime. I follow the literature on fuel cost valuation (see for example [Allcott and Wozny \(2014\)](#) and [Grigolon, Reynaert, and Verboven \(2018\)](#)) and make the assumption that consumers expect fuel prices to follow a random walk. This is consistent with survey evidence as shown by [Anderson, Kellogg, and Sallee \(2013\)](#). The fuel price at the time of purchase times the vehicle fuel consumption then captures expected cost per kilometer of travel in each year of usage. The parameter β_i^e estimates the mean and heterogeneity in value for fuel costs scaled by mileage and a capitalization factor.^{24,25}

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

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

where δ_m , the mean utility, collects all terms in (2) that do not vary across individuals, and μ_{jm} is the term that captures the individual idiosyncratic deviations from the mean utility: $\mu_{jm} = \sum_k \sigma^k \nu_i^k x_{jm}^k$. To complete the demand side, I set the observed market share $s_{jm} = q_{jm}/A_m$ equal to the predicted market share (3). In vector notation, the demand side in market m can then be described by the

²⁴Total expected fuel costs can be written as $E[\sum_{s=1}^S (1+r)^{-s} m_i g_s e_j]$ in which $s=1$ is the time of purchase, S is the time of scrappage, r is the interest rate and m is mileage. Using the random walk assumption for g , we can write expected fuel costs as $\rho m_i g_1 e_j$, with ρ being the capitalization coefficient. See [Grigolon, Reynaert, and Verboven \(2018\)](#) for a detailed discussion. In the utility specification in (2) β_i^e absorbs ρm_i .

²⁵The specification does not allow consumers to separately care about emissions (a 'green glow' effect). These preferences might be captured by the standard deviation in tastes for fuel costs as green consumers will value fuel costs more than others.

market share system: $\mathbf{s}_m = \mathbf{s}_m(\delta_m, \sigma)$.

Firm Behavior To study firms' responses to the emission standard I model a game in which firms have three choices: price setting, technology adoption and gaming. I assume that the vehicle fleet of firms is given exogenously. Each firm sells hundreds of differentiated products and I do not model the decision which vehicles firms choose to offer. I also assume that at the time of decision, firms have perfect information on all observable and unobservable characteristics. Given their vehicle fleet, firms have the option to change prices and fuel consumption of each of the products. Fuel consumption can be changed by adding technology or by gaming the test that determines the level of fuel consumption. When firms face a regulation, choices will be altered in order to comply. The regulation is binding across total sales from all EU markets. The goal of this section is to understand how firms will change decisions on pricing and fuel consumption levels when facing a binding regulation.

Total profit per year t is the sum of profits from each country m :

$$\max_{p, \tau, g} \left(\sum_m [\pi_{fm}(p, \tau, g)] - FC(\tau, g) \right) \text{ s.t. } \frac{\sum_m \sum_{j \in F_f} q_{jm} ((1 - \tau_j - g_j) e_j - f(w_j))}{\sum_m \sum_{j \in F_f} q_{jm}} \leq \sigma, \quad (4)$$

in which π are variable profits, FC are fixed costs, 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.²⁶ I model technology adoption and gaming as percentage reductions in fuel consumption so that $0 \geq \tau \leq 1$, $0 \geq g \leq 1$ and $0 \geq \tau + g \leq 1$. I follow [Goldberg \(1998\)](#) and [Jacobsen \(2013\)](#) and write the Lagrangian of the problem. Variable profits of firm f in year t are then given by:

$$\pi_f = \sum_m \sum_{j \in F_f} [(p_{jm} - c_{jm} - \lambda_f L_j) s_{jm} A_m], \quad (5)$$

$$L_j = (1 - \tau_j - g_j) e_j - f(w_j) - \sigma \quad (6)$$

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 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 F_f because, in equilibrium, firms will equalize shadow costs over their fleet to be cost efficient.

The optimal solution of the profit maximization problem is described by three first order conditions. I introduce the following matrices in order to write the first order conditions concisely:

²⁶Here 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.

Φ denotes a $J \times J$ ownership matrix with each element (i, j) equal to one if i and j are owned by the same firm and zero otherwise, Δ_k denotes the $J \times J$ matrix of first order derivatives of market shares with respect to $k = p, e$ or g . The J first order conditions with respect to prices, technology and gaming can be written as:

$$\frac{\partial \mathcal{L}}{\partial p} = 0 = \mathbf{q} + \Phi \circ \Delta_p(\mathbf{p} - \mathbf{c} - \lambda \mathbf{L}) \quad (7)$$

$$\frac{\partial \mathcal{L}}{\partial \tau} = 0 = (-\mathbf{c}'_\tau + \lambda \mathbf{e})\mathbf{q} + \Phi \circ \Delta_\tau(\mathbf{p} - \mathbf{c} - \lambda \mathbf{L}) - FC'_\tau \quad (8)$$

$$\frac{\partial \mathcal{L}}{\partial g} = 0 = \lambda \mathbf{e}\mathbf{q} + \Phi \circ \Delta_g(\mathbf{p} - \mathbf{c} - \lambda \mathbf{L}) - FC'_g \quad (9)$$

The FOC with respect to prices shows the standard trade off between increases in mark up (first term) and losses from reduced sales (second term) when increasing price. The FOC with respect to technology adoption shows that firms will trade-off marginal cost increases \mathbf{c}'_τ and fixed costs of adoption with slacking the regulatory constraint and the benefits of increased market share (we expect $\Delta_\tau > 0$). The FOC with respect to gaming is very similar but gaming will induce fixed cost changes and no marginal cost changes.

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, technology adoption or gaming. I will discuss the effect of each strategy in turn, keeping the other strategies fixed.

Abatement by sales-mixing A first mechanism to abate emissions is to change relative prices of high and low emission vehicles. Firms can decrease prices of vehicles with emissions below the target ($L_j < 0$) while increasing prices of vehicles with emissions above the target ($L_j > 0$). The FOC with respect to prices (7), shows that the shadow cost of the regulation, λ_f , determines to what extent prices will be distorted from a no-policy equilibrium:

$$\mathbf{p} = \mathbf{c} + \lambda \mathbf{L} - (\Phi \circ \Delta_p)^{-1} \mathbf{q} \quad (10)$$

The regulation implicitly increases costs and taxes vehicles with $L_j > 0$, while it is an implicit subsidy for vehicles with $L_j < 0$. This change in relative prices of products will shift sales towards vehicles with lower fuel consumption resulting in a different sales-mix, explaining the name of this strategy.

The incidence and effectiveness of this abatement strategy largely depends on the responsiveness of consumers to these price changes as captured in Δ_p . [Holland, Hughes, and Knittel \(2009\)](#) show that when the price elasticities of subsidized products differ from those of taxed products, total sales and emissions might increase or decrease. Without knowledge of own and cross price elasticities we cannot make statements about the effect of the regulation on sales, emissions or consumer surplus. The effects on profits will depend on consumers responses to price changes but also depend on the

position of the fleet relative to the target. Firms with a fleet that is better adapted to the standard might increase profits as their prices will need less distortion than the prices of competitors. The empirical model will allow me to identify own and cross price elasticities for all products and to simulate the shifts in sales when we introduce a binding regulation.

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.²⁷ From (8) we see that the regulation gives incentives to the firms to adopt more technology. The first term, $(-c'_\tau + \lambda e)q$ specifies that increases in fuel efficiency change the marginal cost of each unit sold, but the technology also makes the regulation slacker, resulting in a marginal benefit of λ . Without a regulation, $\lambda = 0$ and the marginal benefits of technology adoption would thus be lower. The second term captures the change in sales from technology, $\Phi \circ \Delta_\tau$, times profits per unit, $(p - c - \lambda L)$. Finally, implementing technology can increase fixed costs captured by FC'_τ .

It is important to stress that each unit of technology adoption lowers L . The fleet of the firm shifts closer to the regulatory target and as such the regulatory constraint becomes slacker. This reduces the shadow cost of the regulation λ_f as firms need less distortions from the the preferred price schedule in order to comply. When determining to what extent firms adopt technology or sales mixing in equilibrium, the shadow cost λ and the amount of technology will be determined endogenously.

The welfare effects of this strategy are again undetermined theoretically. This time there are two offsetting effects for consumers. There is upward pressure on prices as marginal costs increase with c'_τ . This reduces consumer surplus. But offsetting this, firms offer vehicles with lower fuel consumption, decreasing the cost of operating a vehicle. The sum of purchase price and operating costs might thus increase or decrease. Even though the resulting vehicle fleet will have lower emissions it is not clear emissions will decrease: if consumers benefit from technology they might purchase more vehicles. The changes in marginal costs and the degree of pass through will determine the overall effect. Given that vehicles have different fuel consumption, equilibrium pricing will also adjust, creating another welfare change for consumers. For firms, technology adoption will be a preferred abatement strategy if the shadow cost of changing prices is high and marginal cost and fixed cost changes of technology adoption are low.

Abatement by gaming I define gaming as efforts of the firm that decrease official emission ratings but not actual on-road emissions. Gaming helps with compliance in a very similar way as technology adoption. Each unit of gaming will reduce L and thereby the shadow cost of the regulation λ_f until firms can price without regulatory constraints. The benefits and costs of gaming

²⁷Knittel (2011) gives several examples of specific technologies that are implemented. The International Energy Agency reported a possible 40% improvement in fuel efficiency from available technologies in 2005. These include low rolling resistance of tires, reduced driveline friction, combustion improvements, thermal management, variable valve actuation and lift, auxiliary systems improvement, thermodynamic cycle improvements and dual clutch transmission. See <http://www.iea.org/publications/freepublications/publication/technology-roadmap-fuel-economy-of-road-vehicles.html>.

are very different though. In [Reynaert and Sallee \(2019\)](#) we empirically study the extent of gaming and discuss the effects of gaming on buyer welfare in detail, here I summarize what is needed to understand firms choices and welfare implications.

The costs of gaming are very different than those of technology adoption. As summarized in media reports following the Volkswagen crisis, gaming is essentially a fixed cost that does not affect the marginal costs of production. The New European Driving Cycle (NEDC) is the procedure to determine CO_2 emissions and fuel consumption.²⁸ The procedure takes a single vehicle (the golden vehicle) and optimizes that vehicle for the test. Tape, non-resistant tires and software, referred to as defeat devices, make the engine run in a program specialized for the test. Note that none of these features impacts how the consumers experience vehicles on the road, nor do they impact the marginal cost of production. The fixed costs of gaming are the costs of installing the defeat devices and more importantly, the potential legal costs and consumer blow-back when gaming is uncovered. When deciding to game firms will trade off these costs against the benefits of cheap compliance. I will not model the reputation costs explicitly but since firms have opted to game the regulation it reveals that firms did not expect these reputation costs to be larger than the costs of other compliance mechanisms.

Note, that the second term in FOC (9) accounts for market share changes of gaming. Gaming will not affect the on road experience of consumers and will not reduce actual fuel consumption. However, when purchasing a vehicle consumers might be fooled by the advertised fuel consumption and believe it to be the truth. The official ratings were designed to be used in advertising and window-shield stickers to inform consumers about fuel costs and pollution. As such gaming will have demand effects that distort consumer choice. In the results I will discuss what happens when consumers are fooled or when they are fully aware of the gaming. The effects for consumer welfare will critically depend on this consumer sophistication. If consumers do not see through gaming, the information in the official ratings becomes a noisy signal of fuel costs and might therefore distort consumer choices. This choice distortion reduces consumer surplus, and might also lead to higher prices. Firms with market power will increase prices if the perceived fuel costs reduce. But gaming might also have positive effects for consumers as it allows firms to avoid costly compliance and high pricing. If technology adoption or sales-mixing is very costly consumers might actually prefer firms to game, benefiting from avoiding the cost increases or price distortions. The effects on emissions from gaming can be pervasive. First, each reduction in fuel consumption that is obtained with gaming does not reduce actual emissions. Second, consumers will respond to the decreases in perceived fuel costs by substituting to higher performance cars. Because cars look cheaper on paper overall sales might increase. Both of these effects potentially increase emissions relative to honest compliance.

²⁸The NEDC is also used to determine compliance with Euronorms that regulate local pollutants such as NO_x , CO and PM. The Volkswagen scandal was about NO_x emissions in diesel vehicles. The fallout of the scandal made clear that the majority of EU car makers is not in compliance with Euronorms, see the ICCT reports.

Abatement by downsizing I assume the fleet of each firm to be given. Previous work, see for example [Klier and Linn \(2012\)](#) and [Whitefoot, Fowlie, and Skerlos \(2017\)](#), has tried to relax this assumption by modeling not only improvements in fuel consumption but by allowing firms to re-optimize a larger set of attributes. This strategy is coined downsizing as firms reduce the size and power of vehicles to lower fuel consumption. [Klier and Linn \(2012\)](#) find that compliance costs decrease by about 40% per year when firms down size instead of sales mix. Consumer loss is similar. [Whitefoot, Fowlie, and Skerlos \(2017\)](#) use an interesting engineering model. In this paper I will not discuss downsizing for two reasons. First, as I showed in [Section 3](#), I find no evidence of downsizing in the EU. Second, a model that would allow strategic choices over several characteristics for the rich engine version level data that I use is out of the scope of this paper.

Design of emission standards One of the key contributions of this paper is to show how political choices about the design features of emission standards interact with firms abatement choices. In the counterfactual I will consider two design choices of the regulation. First, I study the EU’s choice to have a policy that is attribute-based and therefore up-sloping as depicted in [Figure 1](#). Second, I study the implications of weak enforcement of the regulation.

It is instructive to compare the attribute based regulation with a flat tax. For a 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 sales weighted emissions. Each firm will have a different set of vehicles with $L_{jm} < 0$ and $L'_{jm} < 0$. The upsloping ABR in the EU, makes that sales of many small lightweight vehicles do not help with compliance while they would have helped with compliance under a flat standard. As such, the attribute basing reduces the number of products that have $L_{jm} < 0$. It follows that sales mixing becomes much costlier because firms have less products to which they can shift sales. Reducing fuel consumption by technology adoption or gaming helps to increase the number of products that have emissions underneath the target. In the empirical section I will show that the ABR increases stringency for French and Italian firms but reduces stringency for German firms. This matches lobbying efforts by the governments described at the time of negotiations. I will also show that sales mixing became so expensive for firms such that they had to resort to lowering fuel consumption.

The attribute-based regulation might have other economic consequences. [Ito and Sallee \(2018\)](#) 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.²⁹ In this exercise I keep weight fixed and assume there are no distortions in the attribute itself. The reason is that I do not observe any changes in weight consistent with this distortion and that endogenizing additional characteristics is computationally costly.

The EU’s political structure has also led to weak enforcement of the policy. In the empirical section I will discuss how failures in delegation of enforcement have led to the gaming crisis in

²⁹This creates distortions, which might be significant if weight is associated with other external costs. See for example the analysis by [Anderson and Auffhammer \(2014\)](#) relating weight to accident risk.

the EU market. Theoretically, enforcement is captured by the fixed cost of gaming $FC(g)$. When enforcement would be strict and legal punishment for gaming high, the fixed costs of gaming would increase. This would mean that gaming as an abatement strategy becomes less attractive so that firms would resort to sales mixing or technology adoption. In the empirical section I will discuss what would have happened if firms had not gamed the EU regulation.

5 Estimation

In this section I describe the estimation. I use a panel of 7 countries over 10 years to estimate taste and cost parameters. The sample is restricted to 1998-2007, the years before the policy announcement. This allows me to estimate a model in which firms maximize unconstrained profits as given in (5) with $\lambda = 0$. I first discuss demand estimation that allows for endogeneity of both prices and engine characteristics. Next, I discuss the supply side and estimation of costs. I also discuss functional form assumptions needed to make a projection of marginal costs out of sample in order to model technological improvements. With the estimates of consumers preferences, marginal costs and the functional form assumption we can simulate the impact of the emission standard in the next section.

Demand Estimation The vector of parameters θ to be estimated consists of the taste parameters β_i^e, β_i^x and α_i . I estimate both a mean and a standard deviation of the taste for fuel consumption, horsepower, 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 $\alpha_i = \alpha/y_{mt}$.³⁰ A set of controls is added for which I only estimate the mean taste. These include weight, footprint, height, a dummy for 3 or 5 doors, market fixed effects, diesel by market interactions, months on market dummies (for vehicles introduced within a calendar year), and a market specific time trend.³¹ Finally, I add fixed effects on the vehicle model level so that all identifying variation for the taste parameters comes from different engine versions within the same vehicle model. The remaining unexplained variation in market shares is ξ_{jmt} . The parameters are obtained by minimizing the GMM criterion:

$$\min_{\theta} \xi(\theta)' g(z)' A \xi(\theta)' g(z)' \quad (11)$$

in which ξ is a vector of demand unobservables stacked over all markets, $g(z)$ is the matrix of instruments and A is a weighting matrix. I use the two step efficient GMM estimator so that the second step A is the estimate of the optimal weighting matrix. I follow the estimation algorithm described

³⁰ Assume utility is Cob Douglas in income and characteristics of the good, as in [Berry, Levinsohn, and Pakes \(1995\)](#). The logarithm of indirect utility can be written as $u_{ij} = \alpha \log(y_i - p_j) + u(x, g, \xi, \epsilon, \theta)$, where the first part is utility from income and the second part utility from consumption of the good. Assuming that $p_j < y_i$ we can write $\log(y_i - p_j) \approx \log(y_i) - p_j/y_i$ and substitute $\alpha_i = \alpha/y_{mt}$ in (2).

³¹ I introduce random coefficients on 3 variables that capture important margins on which I expect consumer heterogeneity to matter. Height, weight and footprint do not have a random coefficient because the identification of multiple random coefficients proved impossible with multiple endogenous characteristics. The remaining variables try to control for market or time level shifts and seem less fit to be candidates to model individual heterogeneity.

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.³²

A common exclusion restriction in the literature is $E[\xi|x] = 0$, so that any function of observed characteristics is a valid candidate to form the unconditional moments. This means that we allow for correlation between prices and ξ but assume that all vehicle characteristic choices of firms are independent of ξ . The counterfactual considers strategic choices in response to a regulation. However, even before the regulation firms will design products in order to maximize profits. The concern when estimating demand is that firms know more about consumer tastes than the econometrician when the product is designed. This potentially introduces omitted variable bias through correlation of the demand unobservable ξ and product characteristics, despite the rich set of fixed effects. In order to account for this I introduce additional instrumental variables. The identification assumption is $E[\xi|z^k] = 0$ so that demand unobservables are mean independent from instruments z . There are three sets of parameters for which we need to construct moments: the taste parameter for price, the taste parameters for endogenous characteristics and the nonlinear parameters. First, I will consider instruments z^1 for the model with price endogeneity. Second, I will consider instruments z^2 for the more general case with endogenous characteristics.

Instruments The instrument set z^1 contains all characteristics and demand shifters except price as included instruments. The excluded instruments are sums of other products characteristics (both the sum across all competing firms products and the sum across products of the same firm). These are valid instruments for prices only when characteristics are chosen mean independent of the demand unobservable. Using the location where each vehicle is produced, I include the logarithm of local labor costs in the country of production as a cost shifter.

For instrument set z^2 I follow recent work by [Whitefoot, Fowlie, and Skerlos \(2017\)](#) who use engineering procedures to distinguish between fixed vehicle characteristics and more mutable characteristics. In the first engineering step, dimensions of the vehicle (footprint and height) are set. In following steps engines are fitted in the design. I therefore assume that footprint and height are exogenous and remain in the set of included instruments. Fuel costs, horsepower and weight are allowed to be endogenous so that we need excluded instrument for four variables: the three mutable characteristics and prices.

Because the mutable characteristics are potentially correlated with ξ , their sums (across own or other firm products) are not valid instruments anymore. I therefore form additional instruments that aim to capture variation in engine design decisions of firms. Using global production data, I exploit changes in the exposure of each vehicle model to non EU markets over time. I compute the

³²More specifically I do the following: (i) I use a nested-fixed point (NFP) algorithm, BLP’s contraction mapping with a tight convergence criterion (1e-12) to solve for ξ_{jmt} . I use a NFP because Mathematical Programming under Equilibrium Constraints proved to be slower in this application once I parallelized the computation of the contraction mapping, (ii) I re-estimate the model with 25 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 of Knitro, (v) I compute the integral over individual market shares using sparse grids, see [Heiss and Winschel \(2008\)](#), (vi) I estimate variances of the random coefficients rather than standard deviations, see [Ketzer \(Forthcoming\)](#).

share of each vehicle model that is produced in Africa, Asia, Eastern Europe, North America and South America. These production shares evolve within a model over time as some models become popular in the US (e.g. the BMW X5) or in China (e.g. the AUDI A8). A vehicle designed for the EU and US market will be different than a model designed for the EU and China. I assume that these differences in exposure to other markets impact the design choice but are orthogonal to the EU unobserved demand ξ_{jmt} .³³ In the production data I also observe a size variable, scaled from 1 to 10, for each vehicle produced. Using these observations, I compute a weighted sum of size for each model and brand. The weights are the regional production shares and the size is the production weighted average size of all vehicles produced in a region. Just like the sums of characteristics instruments, this captures the degree of competition in product space for each vehicle from other vehicles across all the regions where the vehicle is produced. Next, I follow [Klier and Linn \(2012\)](#) and include the average footprint and height of vehicles in different classes that are produced on the same production platform. For example, the AUDI A5 in the luxury class is produced on the same platform, named MLB, as the AUDI Q5, an SUV. The average attributes of the Q5 are used as an instrument for the A5, and vice versa. The idea behind the instrument is that vehicles produced on the same platform will share both fixed and mutable characteristics.³⁴ Finally, fuel costs are the interaction of fuel prices times fuel consumption. Fuel prices are exogenous so I interact them with the projection of fuel consumption on all instruments.

In order to estimate the variances of the random coefficients, I compute approximate optimal instruments to identify the nonlinear parameters following the approach described in [Berry, Levinsohn, and Pakes \(1999\)](#) and [Reynaert and Verboven \(2014\)](#). To approximate the infeasible optimal IV's, I perform a two stage approach, first estimating the nonlinear model with a guess for the nonlinear parameters in the first step of the GMM and then updating the approximation at the first stage estimates.³⁵ This procedure generates a number of additional instruments that is equal to the number of standard deviations of random coefficients to estimate but these instruments are nonlinear functions of the previously described included and excluded instruments. [Appendix 7](#) gives a detailed overview of all the instrumental variables.

Costs Marginal costs c_{jm} are not directly observed but are obtained from the first order conditions of the firms' profit maximization. Using equation (7), the demand estimates and the fact that $\lambda = 0$ in the estimation sample, I compute c_{jm} . Similarly, we can use equation (8) to back out product level estimates of c' . These estimates give pre-policy estimates of the slope of the marginal cost with respect to reductions in fuel consumption. Information on c' is useful because the slope of c' in the final year reveals the cost changes that firms are willing to incur to provide current levels of fuel

³³Note that because of the vehicle fixed effects, the identifying variation of the IV's comes from the different trends in globalization within different models.

³⁴Notice that [Klier and Linn \(2012\)](#) include all characteristics of different class vehicles on the same platform. This means that the exclusion restriction related to characteristics is specific to vehicle classes. I allow the exclusion restriction to be more general and include only footprint and height in the computation of this instrument.

³⁵The guess for the nonlinear parameters is the Logit taste parameter divided by 10. I compute the approximated optimal IV at $\xi = 0$ and use projections of the endogenous variables on included and excluded instruments in the computation, see [Reynaert and Verboven \(2014\)](#)

consumption in their products. Further improvements would be more costly, but those would not be made because the benefit from the improvements is smaller than the costs. If the supply model is correctly specified, any cost function for further reductions in emissions must start at $c'_{\tau=0}$, else it is at odds with the revealed choices of firms and consumers. I will therefore use the estimated c' as the intercept for the cost slope in the simulations.³⁶

We also need an estimate for values of $c'_{\tau>0}$ when the regulation requires fuel consumption reductions above what we observe. I will use two approaches for this problem. The first approach is to rely on cost estimates by engineers. The EU Commission has relied on several studies to support the design of the EU emission standard, see [TNO \(2011\)](#). These documents describe several existing technologies to reduce emissions, at zero development cost. The policy report only includes improvements that should be readily available for the car makers at no fixed costs. The studies specify convex cost functions for percentage reductions in emissions. I will use these functions in the main results and I will refer to them as the engineering cost curve. However, I shift the intercept in the engineering cost function from zero to the point where the slope of the engineering function equals $c'_{\tau=0}$.³⁷

The second approach is to rely on historical marginal costs in the data to get information on how costs change with fuel consumption. Under the assumption that marginal costs are log-linear we have:

$$\log(c_{jm}) = \gamma^e e_{jm} + d_{jm} \gamma^d + \omega_{jm}, \quad (12)$$

in which d_{jm} is a $1 \times L$ vector of observed product characteristics, market controls and cost shifters and ω_{jm} is unobserved. Fuel consumption enter marginal cost as all else equal it is likely to be more expensive to produce engines with lower fuel consumption. The estimated parameter on emissions informs us how marginal costs change with changes in e_{jm} . The functional form allows us to make predictions on the costs of further reductions in fuel consumption that are not observed in the sample. In the counterfactuals, I will show how the results change when we rely on the estimated cost function rather than the engineering cost function.

Estimation Results Table 5 reports estimated parameters and standard errors for the demand model. The table presents four specifications. The first two specification assume exogenous characteristics and use instrument set z^1 in both a logit and a RC Logit. The last two specifications allow for endogenous characteristics and use instrument set z^2 . The first stage results are reported in Appendix Table A3. When prices are the sole endogenous variable, the excluded IV's are strong and have an F statistic of 67. The labor cost instrument has the expected positive sign. With multiple endogenous variables the instruments are weaker with F stats that account for the multiple

³⁶The counterfactual results will also consider a case where we start from another intercept below the estimated one. As I will discuss below there might be reasons, such as market failures in technology adoption, to think that the actual slope is smaller than the estimated $c'_{\tau=0}$.

³⁷The engineering estimates specify a polynomial function for the cost of emission reduction, I use that function and compute its derivative at each point. See Table 79 in the report [TNO \(2011\)](#). I use separate cost functions for diesel and gasoline and the coefficients for medium sized vehicles (the reported cost functions only differ between size categories for very large reductions in emissions of more than 40%).

endogenous variables being between 5.7 and 21.2.

The demand parameters for the model with endogenous prices shows that consumers dislike higher prices, higher fuel costs and cars perceived as foreign (BMW in France). Consumers prefer vehicles that are more powerful, heavier and larger. In the RC logit, the standard deviation on horsepower and weight show that there is considerable variation in the taste for horsepower and weight. The estimates change considerably when I allow for multiple endogenous characteristics. The price coefficient decreases from -6.7 to -8.1, while the fuel cost parameter increases from -2.6 to -1.2. This will matter for the welfare simulations: when consumers care less about fuel costs relative to price they will derive lower utility from technologies that drive up costs to decrease fuel costs. The remaining coefficients have larger standard errors than in the model with less endogeneity, and several mean tastes switch sign in the RC Logit model. The standard deviations show considerable heterogeneity in the taste for fuel costs, horsepower and foreign vehicles in this case.

The second panel of Table 5 gives results from a regression of marginal costs on product characteristics. I show results under perfect competition (a regression of prices on characteristics) and imperfect competition for both the RC Logit models. These results show that cost shifters have the expected sign: increases in labor cost increase marginal costs and larger more powerful cars are also costlier. 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 2.8% to 4.7% in the two specifications.

Finally, I use the model to compute the cost slope that rationalizes fuel consumption choices of firms before the policy. Also here, there is an important difference when I allow for more endogenous variables. When consumers care less about fuel costs it becomes less interesting for firms to provide fuel consumption reduction. As the marginal benefit of fuel consumption reductions decreases, so does the implied marginal cost slope in (8). Indeed, the model with endogenous characteristics implies a pre-policy intercept of the cost slope that is five times less steep than what the price endogeneity model implies. The level of cost increases caused by the policy will be lower when the initial intercept is lower, so that it is more likely that the emission standard will increase welfare.

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 to which consumers dislike fuel costs. Second, producing vehicles with lower emissions and fuel costs is costly for manufacturers. The first channel matters for all compliance strategies, the second channel matters to evaluate the cost changes from technology adoption.

6 Welfare effects

In this section I use the estimated model to compare the welfare effects of emission standards with various compliance strategies. I start by describing the solution methods and computation of welfare. After that, I describe the welfare impact of the EU emission standard, the role of the

Table 5: Estimation Results

Demand Estimates								
	Price Endog. (z^1)				Charact. Endog. (z^2)			
	Logit		RC Logit		Logit		RC Logit	
	Est.	St. Err.	Est.	St. Err.	Est.	St. Err.	Est.	St. Err.
Price/Inc.	-6,709	0,365	-6,476	0,325	-8,074	0,569	-8,452	0,694
Fuel Cost	-2,649	0,120	-2,842	0,127	-1,291	0,192	-1,036	0,269
Horsepower	2,889	0,227	1,232	0,152	3,868	0,673	-1,546	0,760
Weight	0,666	0,181	1,248	0,156	-6,130	2,143	1,530	1,300
Base	0,580	0,056	0,526	0,051	1,499	0,229	0,878	0,179
Height	0,183	0,041	0,215	0,037	0,477	0,091	0,291	0,060
Foreign	-0,848	0,023	-1,218	0,043	-0,698	0,042	-0,973	0,060
Standard Deviations								
Fuel Cost			0,000	0,033			1,196	0,484
Horsepower			1,604	0,272			2,878	2,445
Foreign			1,276	0,192			0,897	0,185
Marginal Cost Estimates								
	Perf.Comp.		Imp.Comp.		Imp.Comp.			
Fuel Cost	-0,028	0,001	-0,047	0,001	-0,041	0,001		
Horsepower	0,629	0,005	0,692	0,006	0,627	0,004		
Weight	0,664	0,009	0,670	0,011	0,600	0,008		
Base	0,092	0,002	0,026	0,003	0,021	0,002		
Height	-0,005	0,001	0,051	0,001	0,035	0,001		
Log Labor Cost	0,229	0,010	0,081	0,012	0,111	0,009		

The Table reports estimated parameters for the demand and marginal cost equations. The first two columns in the Demand Estimates are the Logit and RC Logit for the model with endogenous prices and instrument set z^1 . The last two columns are the Logit and RC Logit for the model with endogenous prices and characteristics and instrument set z^2 . The additional controls in all the demand specifications are: market fixed effects, a dummy for 3 doors, months on market dummies (for vehicles introduced within a calendar year), fuel type by market dummies, a time trend and 331 vehicle model fixed effects. Marginal Costs slope estimates are reported for perfect competition in the first column (regression of price on characteristics). Column two and three give marginal cost estimates under the assumption a Nash Bertrand game in prices (imperfect competition) for both the RC Logit Models. Note that standard errors are not corrected for the uncertainty in the marginal cost levels.

attribute basing, the role of enforcement and the importance of the cost assumptions. These results show the main contribution of the paper: the abatement strategy of firms matters for welfare and is determined by the design of emission standards.

Simulation set-up The goal of the welfare simulation is to find the welfare effects of the introduction of the EU emission standard, to test robustness to the economic assumptions and to compare its effects with alternative policy designs. The counterfactual is computed by solving the system of first order conditions (7), (8) and (9) for a binding regulation with a target to reduce sales weighted emissions to 130g/km. The goal of the counterfactual is to simulate the optimal changes in prices, technology and gaming in response to the emission standard. To do so I take the vehicle fleet of each firm in 2007 as given and improve emissions by 6%. This adjusts for the fact that there would have been reductions in emissions even without the regulation. All vehicles and characteristics of this fleet are fixed in the simulation except price, technology τ , and gaming g . Furthermore, in line with the engineering documents I assume that there are no fixed costs to develop or adopt the technology. All cars would have gone through a redesign cycle in the eight years between policy announcement and implementation. I will comment on fixed costs of gaming below. Finally, I solve for the equilibrium so that each firm exactly complies. In reality, this does not need to be the case as firms may not comply with the standard and pay fines.³⁸ Note that no firm has incentives to over comply as it would involve distorting optimal choices further from the pre-policy equilibrium, as such the counterfactual singles out the effect of the policy.

Solving for the system of equations (7), (8) and (9) and the policy target is computationally infeasible. Solving the full system would require a solution for j unknown prices, τ 's and g 's in each country, as well as a level of λ for each firm. I proceed by making a couple of additional assumptions. First, the first order conditions for gaming (9) are satisfied only when the fixed cost of gaming is positive. This cost is very difficult to pin down as it depends on future legal fees, brand reputation and hidden efforts. Therefore, I will use the reduced form results from estimating the trade off relationship to fix the level of gaming. Given the estimates derived in Section 3, I assume that each percentage improvement in fuel consumption consists for 70% of gaming and for 30% of actual technology. This means that I solve (7) and (8) with respect to prices and technology while imposing that each 0.3 units of τ imply 0.7 units of g . When discussing the role of gaming and enforcement we vary this ratio so that either each unit of technology has no gaming with it, or technology is full gaming. I further reduce the number of variables to solve for by assuming that technology is implemented fleet wide for each firm. This reduces the number of equations in (8) from j to the number of firms.

Given these simplifications I run the following algorithm. Step 1 is to choose a value for the firm level technology τ and shadow cost λ . Given these values I compute the changes in marginal costs from technology and the product price distortion implied by the shadow cost λL for each product.

³⁸In equilibrium this will end up to not be a constraint on the solution as all firms prefer compliance over paying fines in the main scenario. Except in the case where I restrict firms to sales mixing, the fines will matter and change the outcome. I discuss this in Appendix 7.

Step 2 solves for the Nash equilibrium in prices given the values chosen in Step 1. This step thus solves for (7). Step 3 evaluates how far we are from satisfying (8) and the regulatory target given the guess from Step 1 and the prices from Step 2. I then update the guess, and redo Step 1-3 until we are sufficiently close to (8) and the policy target. This final iteration gives the solution for τ and λ , the implied prices and the implied amount of gaming. To update the guess between Step 3 and Step 1 I use the least square nonlinear equation solver provided by Knitro with bounds on the parameters. The parameter space is bounded because the shadow costs must be positive and the technology improvements must be between 0 and 1.

Given the solution vectors of τ , λ and prices I compute changes in outcomes between the initial equilibrium and the new equilibrium. All welfare changes give the total vehicle lifetime changes for one year of new vehicle sales. The direct effects of the regulation will be changes in consumer welfare, profits and gains from correcting externalities. Consumer surplus is calculated using the log sum formula of [Small and Rosen \(1981\)](#). There is an additional step to account for gaming. When consumers are fooled by gaming, it creates a difference between decision and experience utility. To compute consumer surplus for non-sophisticated consumers I compute the size of the choice distortion created by the differences in decision and experience utility. Consumer surplus partly comes from reduced fuel expenses. 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 change. Changes in profits are obtained from prices, marginal costs and quantities. Note that emission standards do not result in monetary transfers from firms to the government when every firm complies. Appendix 7 show when firms would opt not to comply and pay fines. To compute changes in emissions, 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.³⁹ Mileage is assumed to be constant, ignoring possible rebound effects on the intensive margin. I value a ton of CO₂ at €28.⁴⁰

Finally, I compute two additional welfare effects of the policy that were not explicit targets of the policy maker. The regulation will change the number of vehicles sold, so that the size of the market changes. [Parry, Walls, and Harrington \(2007\)](#) give an estimate for the total external cost from driving for the US market. They report an externality of €12 cent per kilometer. This number is probably not directly applicable to the EU market but at least gives a sense of the relative importance of emissions and other externalities.⁴¹ I will report gains from shrinking the size of the vehicle market using this €12 cent per kilometer number. Note that this is very optimistic as the emission standard only targets sales of new vehicles, not when they drive or how much they drive. When the new vehicle fleet shrinks it is very uncertain congestion will decrease as existing vehicles might fill the gap. A second additional welfare effect is related to behavioral biases of consumers. It has been argued that emission standards are a more effective tool to reduce pollution

³⁹Yearly mileage and vehicle lifetime are chosen to match statistics reported by Eurostat.

⁴⁰This number comes from the Inter-agency Working Group on the Social Cost of Carbon.

⁴¹This number is probably an upper bound for the EU since taxes on fuel and driving are on average higher than in the US.

if consumers undervalue future fuel savings. Using the same data and similar methodology, in Grigolon, Reynaert, and Verboven (2018) we find that consumer undervaluation of fuel costs in the EU is at most modest.⁴² For the model with endogenous characteristics I find that consumers value fuel costs less and purchase prices more. At these estimates using the annual mileage and interest rate of 6%, I find that consumers only value a 1 euro reduction in future fuel costs at 0.42 cents. The emission standard will result in consumers purchasing vehicles with lower fuel costs and I include the future gains consumers get from this. To do this, I change consumers experience utility from vehicles so that their valuation of net present fuel costs is equal to their valuation of price. The change in consumer surplus is paternalistic in the sense that I take a stance on what consumer valuation should be, see Allcott (2016).

I will now discuss the welfare effects of the EU emission standard, the role of attribute basing and enforcement, and the importance of the assumptions about costs.

Welfare Effects Table 6 Column I shows the central welfare estimates for the EU emission standard. The simulation assumes that 70% of emission reductions are due to gaming, the standard is the actual attribute based regulation, consumers are sophisticated so that choices do not respond to gaming and technology increases marginal costs through the engineering cost function that starts at the estimated level of \hat{c}' . Column I solves for the optimal firm strategy so that firms can employ both sales mixing and technology (and the gaming that comes mechanically with it). Column II restricts firms abatement strategy to technology adoption and Column III restricts it to sales-mixing.

Column I and II are almost equivalent, showing that firms choose to abate almost fully by technology adoption and gaming.⁴³ In the baseline estimate of Column I we see that the emission standard reduces sales by 1% and emissions by 4.9%. The standard did not change the share of small vehicles (defined as vehicle class compact and subcompact). If firms would have responded by sales mixing, Column III, we would have seen stark decreases in sales and emissions and a stark increase in the market share for small vehicles. This illustrates already that the abatement strategy chosen by firms is crucial for the market outcomes of the standard.

The second panel of Table 6 shows the welfare effects of the regulation. I find that the EU standard decreased both consumer surplus and profits by 2.6 billion and 0.6 billion euros. These losses are incurred because the firms are forced to take up technology beyond the marginal benefit. In turn, this increases prices for consumers above their willingness to pay for fuel consumption. The CO_2 reduction of 5% is much lower than the policy target because of the gaming. Total emission savings are worth only 0.3 billion, much less than the private losses. Dividing private losses by tons of CO_2 I find an implied value of the government for a ton of CO_2 of €2633. This is much higher than the current estimated levels of social cost of carbon. There are other policies available

⁴²Also recent work in the US has found limited to no undervaluation for fuel costs. See Busse, Knittel, and Zettelmeyer (2013), Allcott and Wozny (2014) and Sallee, West, and Fan (2016)

⁴³The percentage improvements in technology in both scenarios are almost equal with differences of 0.1% points while the shadow costs are very close to zero. On the margin, a very small amount of sales mixing will always be efficient.

such as a gasoline tax, or more general an economy wide carbon tax, that would reduce carbon at a much lower cost. Note that the effects on consumer surplus and profits would have been much more negative with sales mixing, so that the regulation would have been worse for welfare.

However, the policy has two indirect potential benefits that I report in final panel of Table 6. First, if the fleet of vehicles on the road becomes smaller that reduces other externalities from traffic. Given the assumption of 12 cents per km the 1% reduction in traffic increases welfare with 2.2 billion. This is a large number, and as explained above most likely an absolute upper bound.⁴⁴ Second, correcting undervaluation reduces the consumer surplus losses significantly with 1.5 billion. Because consumers undervalue fuel consumption in the RC Logit II model, reduced future fuel expenses of the new choices will benefit consumers in the future more than they value today. Both these indirect welfare effects need to be added in full to find positive welfare effects.

The regulation was introduced with the goal of reducing CO_2 emissions. The regulation failed meeting its target because most reductions in CO_2 happened only on paper and not on the road. Yet, the regulation reduced private welfare by substantial amount relative to the emission gains. Other savings, either in other externalities or from correcting undervaluation are both needed to find positive welfare effects from the regulation. Why did firms choose for abatement with technology and gaming? I continue to discuss the role of attribute basing and the enforcement.

Attribute Basing In the baseline result we find that firms choose to abate almost exclusively by lowering emission rates. The reason for this choice is the attribute basing of the regulation. Table 6 Column IV gives the welfare effects of compliance to a flat regulation. This scenario would have led to more sales mixing and more emission savings. The share of small cars increases with 9% points. Why does a flat standard allow for more sales mixing? The slope in the target has the effect that many low weight products are above the target rather than below. This is illustrated for Fiat in Figure 3. The figure plots all products in the fleet, scaled by sales, in the emission-weight space. This shows that many products in the lower left of the figure are below the red flat target but above the green sloped target. For all these products the policy is an implicit subsidy under a flat regulation, but an implicit tax for the attribute based regulation. This makes sales mixing much more costly because the firm has much less products to which it can shift sales.

Why was the EU emission standard attribute based? Deters (2010) describes the legislation 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."* While Romano Prodi, Italian Prime Minister, stated: *"A steeper value curve would lead to a significant distortion of competition and an illegitimate hardship for the producers of small cars"*. Both these statements contrast nicely with Angela Merkel, Chancellor of Germany: *"The proposed value curve is already a reduction duty far above average for larger cars"*. A steeper target function (the Germans proposed a slope $a = 0.06$ instead of 0.04) would have

⁴⁴Less sales of new cars increases lifetime of existing old and dirtier cars (see Jacobsen and van Benthem (2015), efficient vehicles might be driven more, congestion does not necessarily reduce with less vehicles and effects of local pollution depends heavily on where vehicles drive.

Table 6: Simulation Outcomes

	I	II	III	IV	V	VI	VII
	Opt.	Tech	Sales Mix	Flat	Foiled	Enforce	Engin.
Solve For:	λ, τ	τ	λ	λ, τ	λ, τ	λ, τ	λ, τ
Gaming:	70%	70%	-	70%	70%	0%	0%
Consumer Soph.:	Yes	Yes	Yes	Yes	No	-	-
Market Size							
Total Sales (%)	-1,08	-1,30	-7,34	-0,98	-0,12	-1,73	0,20
Emissions (%)	-4,85	-4,31	-19,16	-11,71	-3,81	-12,60	-5,47
Share small (%-p.)	0,00	0,00	0,13	0,09	0,00	0,01	0,03
Direct Welfare Effects (Δ in billion €'s)							
Consumer Surplus	-2,57	-2,51	-19,10	-7,62	-2,62	-4,45	-2,68
Profits	-0,60	-0,65	-2,58	-0,96	-0,13	-0,95	-0,19
CO2 Value	0,34	0,30	1,32	0,81	0,26	0,87	0,38
Total	-2,83	-2,86	-20,36	-7,76	-2,49	-4,53	-2,49
Implied Value CO ₂	2633,89	2962,79	4564,40	2952,01	2911,62	1730,62	2113,26
Indirect Welfare Effects (Δ in billion €'s)							
Other Ext.	2,19	2,65	14,94	2,00	0,24	3,52	-0,41
Undervaluation	1,52	1,28	6,75	3,62	1,19	3,89	1,92
Total:	0,88	1,07	1,33	-2,14	-1,07	2,87	-0,98

The table gives aggregated effects over all countries and firms for each policy simulation. Column I solves for the optimal abatement strategy given baseline assumptions: engineering cost function starts at \tilde{c}' , each emission reduction is 30% technology and 70% gaming and consumers are sophisticated (gaming does not affect choice). Column II only allows for abatement by technology and gaming. Column III only allows for abatement by sales mixing, Column IV solves for optimal abatement to a flat standard with a target of 130g of CO₂/km, Column V allows gaming to change consumer choice, Column VI enforces the police so that there is no gaming, Column VII starts from the intercept of the engineering cost function rather than at the point \tilde{c}' . See the text for assumptions behind the welfare calculations.

Table 7: Profits and Stringency per Producing State

	ABR					Flat				
Solve for:	I		II			III			IV	
Solve for:	τ, λ		λ			τ, λ'			λ'	
	Δ Prof.	τ	λ	Δ Prof.	λ	Δ Prof.	τ	λ	Δ Prof.	λ
Asia	-212	14	0,09	-1660	1,33	-380	2	0,33	-163	0,41
France	23	4	0,04	1527	0,45	382	0	0,04	1296	0,05
Germany	-635	13	0,08	-1855	0,93	-1287	8	0,33	-3196	0,57
Italy	-84	8	0,07	-682	1,12	28	0	0,00	281	0,00
US	-44	8	0,06	86	0,85	299	3	0,21	578	0,43

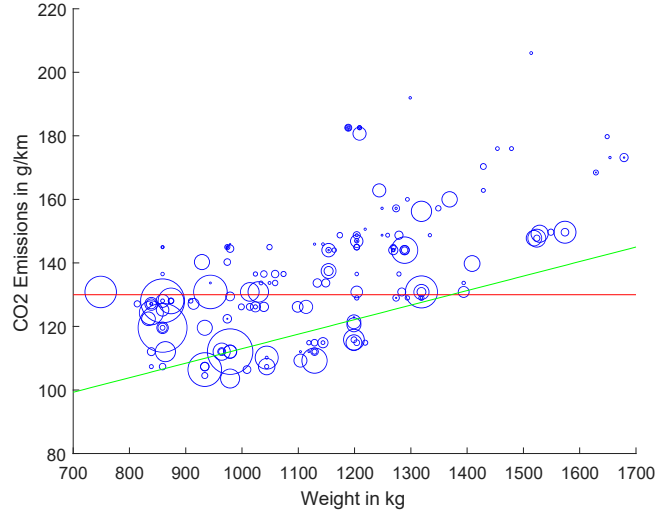
The table gives the average shadow costs and changes in profits for German, Italian, French, Asian and US firms from abatement in response to both the Attribute Based Regulation and a Flat Regulation. In all solutions there is no gaming, only actual technology adoption. Solution I solves for equilibrium abatement to the ABR, II allows only for sales mixing. Solution III solves for equilibrium abatement to the flat standard, IV allows only for sales mixing.

resulted in lower effort needed from the German firms. The attribute basing was thus the result of a political agreement between the car producing countries.

In Table 7, I compare the effects of the attribute-based and flat regulation. I compare the profits, technology and shadow costs for different firms averaged per production region: Asia, France, Germany, Italy and the US. The left panel gives changes of compliance to the ABR when firms choose optimally or when they are restricted to sales mixing, the right panel does the same for the flat target. Restricting firms to sales mixing, shows that the shadow costs of sales mixing increases with the slope of the regulation. The mean shadow costs of sales mixing triple from 0.29 to 0.94 when introducing the attribute basing. To see this, compare λ and λ' in II and IV. Fiat, the only Italian firm, would have automatically complied with a flat target, while they have the highest shadow cost under the attribute based standard. Because sales mixing to the ABR is so costly for Fiat (and also the Asian firms) it will abate mostly by technology and gaming. This has large implications for market equilibrium: because some firms start improving emission ratings (and consumers benefit from lower fuel costs), other firms face competitive pressure to follow. This equilibrium behavior explains why we see a shift from some technology and some sales mixing in III to almost exclusively technology and gaming in I.

Changes in profits in Table 7 show that French and Italian firms benefit from a flat standard, while all the compliance costs fall on the German firms. This is in line with the strong positions the countries took when bargaining over the regulation. The policy debate in 2007 focused mainly on these distributional issues and not on the effect of the slope on the likelihood of different abatement strategies. This clearly shows the importance of the political economy of the regulation. The ABR was agreed such that all firms would have similar distance from the target and thus would face similar compliance efforts. However, this design made sales mixing more expensive so that the industry needed to reduce official emission numbers in order to be able to comply with the regulation.

Figure 3: Position of the Fiat fleet relative to flat and attribute based target



The figure plots every vehicle sold by Fiat in 2007 as it appears in the base data for the counterfactual. Each blue circle is a product and the circles scale with quantity sold. The red line is the flat target at 130 grams of CO_2 per km. The green line is the attribute based target. More sales of products below the target help with compliance.

Enforcement Interestingly, it is again national interests that led to the weak enforcement of emission testing and ultimately led to gaming. In a recent report the European Parliament ([Gieseke and Gerbandy \(2017\)](#)) blamed both the European Commission and the member states for allowing firms to game emission tests. The report states that member states contravened their legal obligation to monitor and enforce defeat devices, while France, Germany and Italy had evidence that emission control systems were not focused on the use of vehicles in on-road conditions. The report states that these countries did not take steps to understand the performance gap between official and on-road emission, pointing in the direction of maladministration. The report also blames member states for under-funding testing facilities (in practice car makers paid the testing facilities themselves). Even after the Volkswagen scandal in the US most member states did not start immediate and consistent investigation nor did they adopt an effective and dissuasive penalty system. On top of that the European Commission failed to oversee the enforcement of member states. In sum, the main car producing countries were aware of the gaming but failed to enforce regulation. The overseeing European Commission in its turn failed to follow up on signals that downstream enforcement was failing.

Columns I, V and VI of Table 6 shed light on the economic consequences of the weak enforcement. The difference between Columns I and V is consumers awareness of the gaming. In I gaming does not affect consumer choice, while it does in V. When consumers are fooled by gaming they perceive cars to have lower fuel consumption, to find out this is not true while driving. This

causes a choice distortion to consumers and thus a further reduction in consumer surplus. On top of that the firms increase prices because products are perceived to be of higher quality. For the environment things are worse: there is almost no reduction in sales and emissions now. Overall, this causes the regulation to have a clear negative welfare effect (even when taking into account other externalities and undervaluation). Column VI shows what the welfare effects would have been had the standard been fully enforced. This would have increased private losses in consumer surplus and profits, but would have led to much higher CO_2 and other externality savings. Column VI is the simulation that shows most positive welfare numbers, but the EU failed to attain this. Finally, if abatement would be 100% gaming there would be no changes in the static equilibrium with sophisticated consumers. Car makers would report different emissions to the regulator but prices and fuel costs would remain the same

The evidence presented here shows that the design of the regulation is responsible for the observed outcome. First, political bargaining between France, Germany and Italy led to an attribute based standard with a steep slope. This increased the cost of sales mixing and thus increased the likelihood of compliance by gaming and technology adoption. Next, enforcement failures on the level of the member states then enabled firms to resort to gaming.

Cost function and investment inefficiencies In the main simulation we start from the economic point where marginal benefits of emission reductions equal marginal costs. The engineering reports however present a cost function that starts with a lower slope than the estimated point concurring with the economic model. If the engineers are right this means that firms leave money on the table: they do not choose to adopt available cost effective technology for which there is willingness to pay.⁴⁵ Also economists have argued that there might be market failures in the supply and adoption of technology. [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 sub-optimal equilibrium with no or too little investment and technology adoption. The regulation gives clear and binding efficiency targets for the whole industry and thus might have succeeded in moving the industry out of a sub-optimal equilibrium by inducing technology adoption. There has been very little work on empirical validation of these supply side market failures but the framework here allows to test the welfare effects of emission standards when the supply side undervalues technology.⁴⁶

By comparing Column VI and VII in [Table 6](#) we see that supply side failures in technology adoption are not necessarily bad for welfare when externalities are at play. The cheap technology makes that the regulation lets firms reduce fuel consumption for less than willingness to pay of consumers. This means that vehicles become cheaper: consumers get better characteristics for a price below their willingness to pay. As such the market size will increase rather than decrease.

⁴⁵Notice that the main results already account for the welfare effects of potential undervaluation by consumers, here I consider suboptimal technology adoption of firms.

⁴⁶Recent work, such as [Hashmi and Van Biesebeek \(2016\)](#) and [Aghion, Dechezlepretre, Hemous, Martin, and Reenen \(2016\)](#), has looked at R&D patterns in the automobile industry through patents.

The regulation now has a rebound effect on the extensive margin.⁴⁷ The cheap technology reduces consumer and profit losses but also wipes out the savings in other externalities so that surprisingly more technology adoption is not necessarily better for welfare. Note that the regulation pushes firms beyond what could be explained by market failures, a policy that would only require cost efficient technology would be less stringent. In general, I believe this scenario not to be very credible. In line with [Anderson and Sallee \(2011\)](#) we expect car makers to abate with the least costly compliance strategies. If technology is so cheap and would have costed only €190 million in variable profits, why would firms have resorted to gaming?

In Appendix Table A4 Column II I also show results with the estimated cost function specified in (12). Results are very similar to the main scenario but the estimated cost function is less convex than the engineering cost function. This reduces the consumer and profit losses. The question is to which extent historical cost increases identify future cost changes.⁴⁸

Fixed Costs The profit changes reported in Table 6 are changes in variable profits. The abatement strategies technology adoption and gaming potentially have fixed costs. We can use the static analysis of variable profits to bound fixed costs but this exercise is not very informative.⁴⁹ The fixed costs of technology adoption are related to the development of technology, implementation of technology and redesign of the vehicle. As stated above engineers state that the technology to attain the emission reduction was available at the time of the policy announcement. The policy then allows for a period of 8 years between announcement and enforcement. Vehicles typically go through faster redesign cycles, see [Blonigen, Knittel, and Soderbery \(2017\)](#), so that there would be no additional fixed cost of redesigning. The design effort would partially be concentrated on compliance, this could be more costly than the usual redesign. Gaming has obvious fixed costs: the implementation and design of defeat devices that allow gaming the emission test, the risk of facing liability for noncompliance and class actions from consumers. The same gaming devices are also used to avoid pollutant standards so it is unclear if we should attribute all of this to the emission standard.

The framework in principle allows me to compute upper bounds on fixed costs of technology adoption and gaming. I could solve for an equilibrium where a single firm is constraint to use a certain amount of gaming or technology different than its optimal strategy, while all other firms

⁴⁷See Gillingham, Kotchen, Rapson and Wagner (2013) for an overview on possible sources of rebound effects. 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.

⁴⁸Additionally, the slope of the estimated cost function with respect to fuel costs is highly dependent on the functional form. In many specifications the regression of predicted marginal costs on fuel costs results in positive sign, such that fuel economy lowers marginal costs. These issues could be due to multicollinearity as well as changes in mark ups that are correlated with fuel costs but not captured in the first order condition, see [Langer and Miller \(2013\)](#).

⁴⁹[Eizenberg \(2014\)](#) and [Wollmann \(2018\)](#) identify fixed costs from multiple products entering and exiting the product set. Here, the product set is constant and products change in continuous dimensions. In this setting we only have a single policy and a single optimal response to deviate from.

respond optimally. This gives deviations in variable profits from the optimal strategy for the deviating firm. After transforming these deviations into net present values that require a discount rate and investment horizon of the firm we would obtain upper bounds on the fixed costs.⁵⁰

7 Conclusion

This paper has evaluated the response to a recent EU wide emission standard. I find that between 2007 and 2011 sales weighted emissions from new vehicle sales have decreased by 14%. Decomposing this decrease I find that two thirds of the decrease in emission is attributable to firms gaming the emission test procedure. One third of the decrease stems from actual technology adoption. A structural model of demand and supply, allowing for endogenous abatement strategy choices revealed that the overall effect of the regulation has been negative for consumers and producers and did not save large amounts of carbon. For the regulation to be welfare improving we need to optimistically scale the reduction in the size of the new vehicle fleet with a cost of saving other externalities, such as accidents and local pollution, while this was not the goal of the regulation. The projected carbon savings did not materialize because of noncompliance and gaming on emission tests. The reason that firms chose this abatement strategies is the attribute basing and the lack of enforcement. Both of the reasons are a product of the political environment in the EU.

This exercise provides important lessons for emission standards as a policy tool. First, the compliance strategy that firms use matters for the welfare and environmental outcomes of the policy. The design of the policy has potentially large impacts on which strategies are employed. I showed that the attribute basing made sales mixing so costly that some firms had almost no choice but to decrease emission ratings of all their vehicles. Second, emission standards are designed, implemented and enforced in a world where politics matter. I find that even in a developed world setting such as the EU, this political reality matters for the outcome as both the attribute basing and lack of enforcement where to result of the political economy. Third, technology adoption is a crucial mechanism of compliance and needs to be considered when evaluating emission standards. This is very difficult because the evaluation depends on assumptions about the cost curve of technology adoption. Both consumers and firms might undervalue fuel consumption reductions. It is crucial to understand to what extent this is happening, especially on the supply side we lack evidence of market failures so that our economic models are at odds with engineering estimates.

Overall, I want to stress that emission standards are a risky and weird policy instrument when the goal is to reduce carbon emissions. Standards rely on emission tests that could be potentially gamed when compliance costs become very high. It is uncertain that emissions actually reduce because of the policy. If the engineers are right and there is cost effective technology available, then standards might increase the size of the market rather than decrease. A correct fuel tax in combination with subsidies to adopt technology would fare better as the first instrument corrects

⁵⁰I do not pursue this as it is unclear in this applications which deviations are informative about fixed costs, it would be very computationally intense to compute equilibria for deviations firm by firm, and it is unclear how to obtain statistical inference.

for the externality and the second for the supply side market failures. All EU countries have very high fuel taxes that cover more than the carbon externality. From an economic perspective it is hard to understand from an economic perspective why the EU chose this policy as a mechanism to reduce carbon emissions. Yet, the EU keeps announcing ever more stringent emission standards for the future.

The numbers derived in this paper are obtained under various assumptions and one should keep in mind the limitations of the model and the data. First, I focus only on sales of new vehicles and assume there will be no effects on prices and vehicle lifetimes in the used car market. It would be interesting to study if there are different effects from gaming, technology adoption and sales mixing on the used car market. Second, all welfare numbers are obtained ignoring possible rebound effects on driving behavior. Third, I did not include dynamics in the analysis. Important fixed costs on the firm side might have effects on market structure and rapid technology adoption might result in consumers strategically timing purchases. Even without these complications, the counterfactual outcomes show us that the welfare effects from emission standards are far from obvious and that the design of the regulation matters for which abatement strategies will be chosen.

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Appendix For Online Publication Only

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 and 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, Cadillac, 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 lose 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.

Details on Excluded Instruments

For the specification with endogenous prices the following 13 excluded instruments are used in the first stage:

- Sum of the characteristics fuel consumption, horsepower, weight, footprint, height of all other products sold by the same firm in the market (5 instruments)
- Sum of the characteristics fuel consumption, horsepower, weight, footprint, height of all other products in the market (5 instruments)
- Number of products sold by the same firm in the market (1 instrument)
- Number of products in the market (1 instrument)
- Log of labor cost in country of production of vehicle (1 instrument)

For the specification with endogenous prices, fuel costs, horsepower and weight the following 17 excluded instruments are used in the first stage:

- Sum of the characteristics footprint, height of all other products sold by the same firm in the market (2 instruments)
- Sum of the characteristics footprint, height of all other products in the market (2 instruments)
- Number of products sold by the same firm in the market (1 instrument)
- Number of products in the market (1 instrument)
- Log of labor cost in country of production of vehicle (1 instrument)
- Production share of vehicle model in Africa, Asia, East Europe, North America, South America (5 instruments)
- Weighted sum of average size of all vehicles produced in each region, weights equal production share of vehicle model (1 instrument)
- Weighted sum of average size of all vehicles produced in each region, weights equal production share of vehicle brand (1 instrument)
- Sum of the characteristics footprint, height of vehicles of different vehicle segment produced on the same platform (2 instruments)
- Fuel consumption projected on all included and excluded instruments interacted with fuel prices (1 instrument)

The role of Fines

As explained in Section 2 the fines are given by €5 per unit sold for the first excess g/km and increase to €95 per unit above 134 g/km. These are the pure monetary fines: it could be that noncompliance with the regulation brings other reputation costs. Though, when firms choose to game these reputation costs might not matter anymore.

The fines are an increasing schedule, so that minor deviations are punished lightly at €5 per vehicle sold and deviation of more than 4 grams are punished at €95 per vehicle. In between fines are €15 and €25 for gram 2 and 3 for noncompliance. I consider the smaller fines as minor punishments for unexpected changes in the fleet averages and the fine of €95 per vehicle as the punishment for actual noncompliance. This fine will matter for the abatement strategies.

In principle, the fines give an upper bound for the Lagrangian multipliers λ . If the per unit shadow cost of the regulation becomes higher than the fine a firm would prefer pay the fine above further price distortions. In practice, I find that this matters only in the scenario Flat reported in Column IV Table 6. In all other solutions the equilibrium value of λ is far below this upper-bound. The framework can accommodate fines flexibly however. As I solve the model with bounds on λ and τ , I can replace the upper-bound of λ from infinity to the level of the fine. Column III of Table A4 presents results where the firms pay fines. Only Volkswagen ends up in an equilibrium where they deviate from the emission standard and they pay 400million euro. This is a profit loss, but the profit loss flows to the state, so it is not necessarily a welfare loss. Otherwise, the equilibrium outcomes are very comparable.

The solution presented in Table A4 also bounds technology. When firms hit the upper-bound on λ , the algorithm will resort to increasing τ to attain compliance. Therefore, I use the solution of τ when there is no upper-bound on λ as an upper-bound in this algorithm. This is a bit over-restrictive as somewhat more technology will have a lower cost than the fine. The τ also has an implicit per vehicle cost that should be lower than the fine. This cost depends on the equilibrium conditions and is thus harder to solve for (I could in principle restate the variable to solve for in per vehicle technology costs rather than percentage reductions).

Additional Figures and Tables

Table A1: Robustness for Table 2 and Table 3

	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
ln(Hp)	0.43 (0.58)	0.21 (0.02)	0.08 (0.03)	0.13 (0.02)	0.22 (0.02)	0.26 (0.05)
ln(Weight)	-1.34 (2.05)	0.68 (0.06)	0.75 (0.05)	0.65 (0.03)	0.67 (0.05)	0.55 (0.03)
ln(Footprint)	0.35 (3.02)	-0.15 (0.10)	-0.28 (0.09)	-0.40 (0.10)	-0.26 (0.08)	-0.33 (0.10)
ln(Height)	-17.28 (5.90)	-0.07 (0.11)	0.01 (0.10)	0.04 (0.15)	-0.04 (0.13)	-0.06 (0.12)
Diesel	-0.20 (0.01)	-0.20 (0.01)	-0.20 (0.01)	-0.21 (0.01)	-0.20 (0.01)	-0.65 (0.15)
Year F.E.?	Yes	Yes	Yes	Yes	Yes	Yes
YearXFirm?						
Car Name F.E.?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,444	3,441	14,444	14,444	14,444	14,444
R^2	0.87	0.81	0.86	0.86	0.86	0.86
Difference in Technology Growth 2011-2007 and 2007-1998						
Difference	2.6 0.5	2.1 0.5	3.3 0.7	2.2 0.7	2.3 0.5	2.5 0.5

The table presents robustness for the findings in Table 2 and Table 3. Each Model estimates equation (1) and the Table presents the first order terms of trade off parameters and the difference in technological change between 2011-2007 and 2007-1998. Standard errors are robust and clustered per firm. Standard error for the difference is computed using the Delta method. Model 6 changes the functional form from Cob Douglas to Translog so that higher order terms in attributes are included. Model 7 keeps only the first appearance of each vehicle, Model 8 allows trade off parameters to change over time, Model 9 weighs observations by sales, Model 10 includes marginal costs as estimated in the structural model as a control, Model 11 interacts characteristics with fuel type.

Table A2: Technological Progress Estimates per Firm for Model 3 and Model 5

	BMW		Daimler		Fiat		Ford		GM		PSA		Renault		VW		Asian	
	Off.	Road	Off.	Road	Off.	Road	Off.	Road	Off.	Road	Off.	Road	Off.	Road	Off.	Road	Off.	Road
1999	0,0	-2,0	-3,9	-1,2	-4,2	1,1	-7,6	-2,3	0,0	-1,1	-1,3	-1,2	-1,2	-2,2	1,3	0,0	3,7	-1,1
2000	4,1	-1,0	3,9	-1,2	-2,7	0,0	7,6	-2,2	3,9	-2,2	1,3	-2,3	0,0	-2,1	2,6	-1,1	1,3	-1,1
2001	-3,1	-1,9	-2,6	-1,1	-2,6	-3,2	-3,8	-1,1	-1,3	-2,1	-5,2	-2,2	-2,4	-1,1	0,0	-1,1	-1,3	-1,1
2002	0,0	0,0	-1,3	-1,1	0,0	-1,1	-1,3	0,0	0,0	0,0	-2,5	-1,1	-2,4	-1,0	-1,3	-1,1	-3,7	-2,2
2003	-1,0	-0,9	-1,3	-1,1	-2,6	0,0	-2,5	0,0	-2,6	0,0	-1,3	0,0	-2,3	-1,0	-2,6	0,0	-1,2	-1,1
2004	1,0	0,0	-2,5	0,0	-1,3	-1,0	-1,2	-1,1	-3,8	0,0	-6,1	-2,2	-3,4	-2,0	0,0	-1,1	-1,2	-1,1
2005	-1,0	0,0	-3,7	-1,1	-1,3	0,0	-3,6	-1,1	-2,4	-1,0	-2,3	0,0	0,0	0,0	-1,3	0,0	-1,2	2,1
2006	-2,0	0,0	-1,2	-1,1	-3,7	0,0	-1,2	1,1	-1,2	0,0	-2,3	-1,1	-1,1	0,0	-1,3	-1,1	-2,3	-1,1
2007	-9,3	-6,4	0,0	0,0	-2,4	0,0	1,2	0,0	-1,2	1,0	-2,3	2,1	-1,1	0,0	-1,2	0,0	-1,2	-1,1
2008	-5,2	-2,6	-3,5	-1,1	-3,5	1,0	-2,3	0,0	-2,3	-2,1	-2,2	-1,1	0,0	0,0	-6,0	-2,1	-3,4	0,0
2009	-0,8	-0,8	-6,8	-2,1	-3,4	-1,0	-1,1	1,1	-3,4	0,0	-2,2	-2,1	-4,3	-1,0	-5,7	-2,1	-4,4	-4,1
2010	-1,6	-0,8	-2,2	1,1	-6,6	-3,1	-6,6	-2,2	-7,6	-3,0	-3,2	-4,1	-2,1	0,0	-7,5	-3,1	-4,2	-1,0
2011	-0,8	0,0	-7,3	-7,3	-6,2	-1,0	-7,3	-7,3	-5,1	0,0	-4,1	-1,0	-3,0	0,0	-4,1	-1,0	-3,0	0,0
Difference in Technology Growth 2011-2007 and 2007-1998																		
Difference	0,9	-0,3	3,5	1,5	2,6	0,5	3,0	1,3	3,7	0,7	0,5	1,2	0,8	-0,8	5,4	1,5	3,0	0,4

The table gives the estimated firm specific yearly change of technology in the CO₂ production function as derived from the year fixed effects in (1) for Model 3 and Model 5 in Table 2. The first column for every firm reports percentage technological change in official emission ratings, the second column in on road emission ratings. The shaded area are years after the policy announcement.

Table A3: First Stage Estimates

	(1)	(2)	(3)	(4)	(5)
	Price/Income	Price/Income	Euro per Km	Horsepower	Weight
Log Labor Costs	0.191*** (0.0252)	0.159*** (0.0269)	-0.394** (0.120)	-0.0734* (0.0316)	-0.0236* (0.0105)
Sum of own Fuel Consumption	-2.440*** (0.487)				
Sum of own Horsepower	-1.476 (2.408)				
Sum of own Weight	1.024** (0.384)				
Sum of own Footprint	3.215*** (0.750)	3.602*** (0.596)	-4.856 (2.779)	-0.967 (0.756)	-1.303*** (0.234)
Sum of own Height	1.944*** (0.497)	1.853*** (0.412)	3.418 (1.924)	0.646 (0.525)	0.561*** (0.162)
Sum of own Products	-4.659*** (0.876)	-5.330*** (0.863)	-1.473 (4.036)	-0.156 (1.101)	0.144 (0.339)
Sum of other Horsepower	-33.81*** (4.241)				
Sum of other Weight	-0.701 (0.572)				
Sum of other Footprint	9.614*** (1.522)	-2.211* (0.920)	2.147 (4.244)	0.280 (1.145)	-1.054** (0.361)
Sum of other Height	3.818*** (0.854)	2.917*** (0.831)	3.444 (3.834)	0.602 (1.035)	-0.0873 (0.326)
Sum of other Products	-8.803*** (1.480)	-2.649* (1.273)	-6.613 (5.910)	-0.973 (1.603)	0.944 (0.500)
Gasoline Price by proj. Li		-0.00975*** (0.00209)	1.013*** (0.00978)	0.00254 (0.00266)	-0.00209* (0.000822)
Production Share Africa		0.137* (0.0598)	0.247 (0.273)	-0.0252 (0.0730)	0.0895*** (0.0234)
Production Share Asia		-0.0423** (0.0160)	-0.111 (0.0650)	-0.00323 (0.0162)	0.0104 (0.00622)
Production Share East Europe		0.0453 (0.0624)	-0.700* (0.285)	-0.289*** (0.0762)	-0.0154 (0.0245)
Production Share North America		-0.270** (0.0958)	1.051* (0.438)	-0.0481 (0.118)	-0.0877* (0.0375)
Production Share South America		0.149*** (0.0442)	-0.303 (0.203)	-0.112* (0.0547)	-0.0302 (0.0173)
Brand Prod. shares by Size		-0.0345** (0.0118)	0.162*** (0.0474)	0.0495*** (0.0117)	0.0245*** (0.00458)
Model Prod. shares by Size		0.120*** (0.0326)	-0.189 (0.150)	0.0332 (0.0406)	0.0327* (0.0128)
Plant Height Other Segment		1.069 (1.953)	-15.06 (9.059)	-6.392** (2.452)	-1.424 (0.766)
Plant Footprint Other Segment		-3.810 (3.720)	26.97 (17.27)	10.98* (4.677)	2.666 (1.460)
SW F Stat	67.35	5.82	21.20	5.75	11.20
# End. Vars	1	4	4	4	4
# Excl. Instr.	13	17	17	17	17
Observations	28775	28775	28775	28775	28775

The table gives the first stage estimates for the specification with endogenous prices (1) and the specification with endogenous prices, fuel costs, horsepower and weight (2-4). The coefficients and robust standard errors for all excluded instruments are reported (the included instrument coefficients are not reported). The Sanderson-Windmeijer multivariate F test of excluded instruments is reported for every endogenous variable, this statistic equals the standard F-test of excluded variables with a single endogenous variable in (1).

Table A4: Simulation Outcomes

	I	II	III
	RC Logit I	Estimated Tech	Flat with Fines
Solve for:	λ, τ	λ, τ	λ, τ
Gaming:	70%	70%	70%
Consumer Soph.:	1	1	1
	Market Size		
Total Sales	-14,78	-0,14	-0,11
Emissions	-19,45	-5,69	-10,66
Share small	0,02	0,03	0,09
	Direct Welfare Effects (Δ in billion €'s)		
Consumer Surplus	-29,67	-3,04	-6,19
Profits	-9,50	-0,25	-0,44
CO2 Value	1,35	0,39	0,74
Total	-37,82	-2,89	-5,89
Implied Value for CO2	8109,22	2330,24	2338,86
	Indirect Welfare Effects (Δ in billion €'s)		
Other Externalities	29,66	0,28	0,22
Paternalism	-7,21	1,95	3,31
Fines:			0,44
Total:	-15,37	-0,67	-1,92

The table gives aggregated effects over all countries and firms for each policy simulation. Column I solves for the optimal abatement strategy given baseline assumptions but at parameter estimates of the RC Logit I model without endogenous characteristics. Column II is the same as Column I Table ?? but using the estimated cost function. Column III is the same as Column IV Table ?? but introducing fines as an upperbound for the Lagrangian multiplier. See the text for assumptions behind the welfare calculations.