Environmental Regulation and Product Attributes: The Case of European Passenger Vehicle Greenhouse Gas Emissions Standards

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Abstract

Many energy consuming consumer durable goods, such as home appliances and vehicles, are subject to energy efficiency or greenhouse gas standards. We show, in theory and in practice, that because of demand and supply linkages across product attributes, such standards can affect consumer welfare via a broader range of attributes than the literature has considered. We demonstrate these effects as part of the first retrospective analysis of European passenger vehicle standards for carbon dioxide. The standards have substantially reduced fuel consumption and emissions, but changes in other attributes undermine at least 25 percent of the welfare gains of the standards.

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1 Introduction

Many consumer durable products, such as home appliances and passenger vehicles, are subject to energy efficiency standards and environmental regulation. Such regulations introduce a shadow cost on energy consumption or emissions, which incentivizes firms to improve energy efficiency or discount energy efficient versions of their products (e.g., Goldberg 1998; Jacobsen 2013; Durrmeyer and Samano 2018). In the absence of other market failures, the regulations are less efficient than emissions taxes, but if consumers systematically undervalue energy cost savings when choosing a product, standards may be more efficient than taxes by correcting that market failure (Allcott and Greenstone 2012; Leard et al. 2017). An extensive literature has examined whether consumers undervalue energy cost savings, finding mixed results (e.g., Busse et al. 2013; Houde 2018; Leard et al. 2017)

The literature has recognized that standards may affect attributes other than the regulated one. For many products, consumers value not just the regulated attribute, such as a refrigerator's energy efficiency, but also unregulated attributes, such as storage space. A few studies have considered an unregulated attribute that is related technologically to the regulated attribute. For example, a manufacturer can modify a vehicle's power train to trade off performance for fuel economy and emissions. Consequently, tightening fuel economy or emissions standards causes manufacturers to reduce performance to reduce fuel consumption and emissions (Knittel 2011; Klier and Linn 2015; Reynaert 2019)

In this paper, we consider the welfare consequences of regulating one of multiple attributes in a differentiated product market. We show theoretically that standards can affect virtually any other attribute via demand and supply linkages. Because an unregulated market can under or over provide these attributes, not just the regulated one, the welfare consequences of standards depends on the full set of attribute changes. We consider the application of Europe's recently tightened carbon dioxide emissions standards for passenger vehicles. Although the standards have affected vehicle performance (i.e., acceleration) only modestly, they have substantially reduced residual vehicle quality, which we define as the combined willingness to pay (WTP) for all other attributes

(Houde and Spurlock 2015). The combined attribute changes offset at least 25 percent of the total fuel cost and greenhouse gas benefits, which is roughly double the magnitude of rebound and scrappage inefficiencies of passenger vehicle standards documented in the literature (Jacobsen and Van Benthem 2015).

The first part of this paper provides a general framework for environmental regulation of differentiated product markets. We consider a firm that sells a differentiated product and chooses the price and attributes of the product to maximize profits.

The firm chooses three types of attributes. The first is the attribute that is directly regulated, such as a new vehicle's fuel economy or an air conditioner's energy efficiency. The second type includes attributes that are linked technologically to the regulated attribute, as in the fuel economy—performance example above. The third type includes any other attribute, such as those the firm chooses jointly with the regulated attribute when designing the product. While the literature on fuel economy regulation has considered the first and second types (e.g., Klier and Linn 2015; Reynaert 2019), we are not aware of analysis of the third type—either for passenger vehicles or for any other product.

We derive two theoretical results from a stylized model. First, regulation of a particular product attribute may affect any other attribute either positively or negatively, depending on the structure of demand and attribute choice. For example, on the demand side of the market, a regulation that reduces a vehicle's fuel costs could increase consumer demand for cargo space if the lower fuel costs cause the consumer to take extended vacations. On the supply side, design constraints may cause the firm to trade off attributes for one another. For example, if a firm has a fixed research and development budget, regulating lower emissions could cause the firm to invest more research and development in reducing emissions and less in improving other attributes.[1]

Second, standards could increase or decrease private welfare, dependnig on whether the unregulated market over- or underprovides all attributes. Intuitively, in the absence

[1] Porter and Van der Linde (1995) and the ensuing "Porter Hypothesis" literature suggest that tighter regulation could induce innovation that either reduces the direct costs of meeting the regulation or reduces the cost of improving product attributes that are not directly related. The mechanism we discuss in this paper is distinct, because it arises from demand and cost relationships among attributes.

of regulation, if consumer demand for one attribute (such as energy efficiency) is positively correlated with demand for a second attribute (such as exterior styling), the firm may choose low levels of both attributes to help segment the market. Regulating one attribute reduces the incentive to offer a low level of the other attribute. That is, the unregulated market could underprovide attributes, in which case regulation could raise consumer welfare.

In the empirical part of the paper, we test whether Europe's carbon dioxide emissions standards for passenger vehicles have affected product attributes. European road transportation accounts for about 20 percent of Europe's carbon dioxide emissions, and Europe's carbon dioxide emissions standards are the primary policy aiming to reduce these emissions. In Europe,, about 15 million new vehicles are sold annually, and these vehicles represent roughly one-quarter of all the vehicles sold globally that are subject to fuel economy or greenhouse gas standards. Legally binding standards were finalized in 2009 and began to apply in 2012. Although manufacturers have achieved the standards partly by designing vehicles to meet the test cycles rather than reducing on-road emissions (Reynaert and Sallee 2019), the standards have substantially reduced on-road emissions (Tietge et al. 2017).

We examine three margins along which manufacturers may respond to the standards: adjusting the relative prices of vehicles to shift customers to obtain vehicles with lower emissions; trading off emissions for performance or weight; and adjusting other attributes. We use highly disaggregated data for the European market covering the years 2005 through 2017. The data include the eight countries with the largest markets in Europe, which collectively account for about 90 percent of all sales in Europe. Observations are by country, year and vehicle, where a vehicle is a unique model (nameplate), trim, body type, engine and transmission configuration, fuel type and drive type—such as the BMW 320 four-door sedan with a four-cylinder diesel-powered engine, an eight-speed automatic transmission, and rear-wheel drive.

Because the theory suggests that regulation can affect virtually any attribute, we devise a two-stage empirical strategy that allows us to estimate the effects of the standards on any attribute. First, we estimate consumer demand for vehicle attributes. As in the theoretical model, we distinguish three types of attributes: (a) fuel economy, which is directly affected by the regulation (because fuel economy is inversely related to greenhouse gas emissions); (b) horsepower and weight, which are related technologically to fuel economy; and (c) other attributes of the vehicle. The previous literature has considered attributes in categories (a) and (b), but not (c). We use the term *residual quality* to characterize the combined WTP for all attributes of the vehicle in (c), such as safety, reliability, and cargo space. Quality is a residual in that it excludes WTP for attributes in the first two categories. Importantly, quality includes any attribute that may be affected indirectly by the regulation via the design process.

We estimate WTP for each attribute and quality with a nested logit model that uses a vehicle's market segment and country of origin to define the nests. The estimation accounts for endogeneity of vehicle prices and within-nest market shares by using instruments based on the physical size and engine size of other vehicles in the market. We estimate own-price elasticities of demand and consumer WTP for fuel economy and horsepower that are broadly consistent with the European vehicle demand literature (for example, Grigolon et al. 2017; Reynaert 2019). Having estimated the demand parameters, we recover quality as a residual.

In the second stage, we test whether the European carbon dioxide standards have affected quality, horsepower, weight, and price. We identify the effects of the standards on vehicle quality and other attributes using a shift-share (i.e., Bartik) approach. We define three time periods to match the timing of the regulations: 2005—8 (no standards); 2009—11 (standards proposed but not enacted); and 2012—7 (standards enacted). We interact the overall shift in regulatory pressure over time with cross-sectional variation in the pressure that the standards apply to each firm (Klier and Linn 2016); the theoretical analysis motivates the functional form.

We find that the standards reduced quality and have had small effects on performance, weight, and vehicle prices. Whereas Klier and Linn (2016) show that the standards reduced slightly horsepower and weight in the beginning of the second period (2007 through 2010), this effect appears not to have been persistent.

We quantify the welfare implications of the quality changes by comparing them with the fuel cost savings and carbon dioxide emissions benefits of tightening the standards. For a hypothetical 1 percent tightening of the standards, the attribute changes offset at least 25 percent of the fuel cost and carbon dioxide benefits of the standards.[2]

Our paper contributes to the existing literature in several ways. First, we generalize the treatment of differentiated product regulation. Fischer (2010) shows that fuel economy regulation can improve private consumer welfare if a subset of consumers undervalue fuel economy. We show that product attribute regulation can affect a large set of other attributes that are linked to the regulated attribute via demand or supply channels, generalizing Houde and Spurlock (2015). Whereas Buchanan (1969) and Fowlie et al. (2016) analyze the implications of output distortions for introducing a carbon price to an imperfectly competitive market with a homogeneous product (such as cement), we consider the implications of market failures in attribute choices.

Second, we conduct the first retrospective analysis of the European passenger vehicle standards. Klier and Linn (2016) use data through 2010 and Reynaert (2019) uses data through 2011, which is just prior to the period in which the standards take effect. Moreover, whereas those papers consider performance and vehicle price changes, we provide the first evidence on the effect of passenger vehicle fuel economy and greenhouse gas standards on vehicle quality. We show that although the European standards appear not to have affected horsepower, weight, or vehicle prices, the standards have substantially reduced quality. Reynaert (2019) anticipates that the benefits of the standards would be lower than the costs, and our analysis confirms the low benefits of the standards.

Third, we contribute to the literature on attribute-based fuel economy and greenhouse gas standards. The European standards, like most others, depend on a vehicle attribute; the European standards depend on a vehicle's weight. Ito and Sallee (2018) show that attribute-based standards may affect the attribute on which the standard is based. We

[2]Mock et al. (2014), Tietge et al. (2015), and Reynaert and Sallee (2019) conclude that vehicle manufacturers have designed vehicles to perform well on the tests used to assess compliance with the standards. Such gaming is distinct from outright cheating, such as what occurred in the Volkswagen emissions scandal. Because of this gaming, on-road fuel consumption and emissions reductions have been roughly half as large as the reductions in tested fuel consumption and emissions. For that reason, we consider the percent change reported in the text to be a lower bound of the share of fuel cost and greenhouse gas benefits offset by attribute changes. Responding to the apparent gaming, Europe has recently adopted a new testing procedure.

highlight the possibility that standards may affect attributes other than the attribute on which the standard is based. Although Ito and Sallee (2018) find that Japan's weight-based standards distorted vehicle weight, we do not find evidence that the European standards have affected weight. The difference may arise from the fact that the European standards are linear in weight and the Japanese standards vary discretely with weight.

Finally, we analyze new vehicle markets, and Brucal and Roberts (2019) and Houde and Spurlock (2015) analyze home appliance markets. An important difference between our analysis and theirs is that whereas they identify the effects from time series variation in the standards, we combine time series variation in aggregate standards with cross-sectional variation in the stringency of the standards. This allows us to control for potentially confounding factors that may be correlated with the adoption of the standards.

2 Regulating Emissions from Differentiated Product Markets

We consider a market in which firms sell differentiated products to consumers. We begin with a case in which the product attribute is exogenous, and subsequently we endogenize the attribute. We represent the standard as a shadow price that a regulator imposes on the endogenous attribute, and conduct comparative statics of a non-marginal change in the shadow price. With an endogenous regulated attribute, increasing the stringency of regulation could cause the firm to increase or decrease other attributes.

2.1 Case 1: Exogenous regulated attribute

The market contains J products and M consumers who choose the product j that maximizes utility (for simplicity we abstract from the decision to forgo purchasing any product). Each consumer, i, has utility that is linear in the price of the product j, p_j, and other attributes of the product. The consumer values three attributes: m_j, x_j, and z_j. The attribute m_j may be subject to regulation, such as if the attribute is the vehicle's fuel economy. For the moment, all three attributes are exogenous. The utility function is given by

$$U_{ij} = \alpha p_j + m_j \beta^m + x_j \beta^x + z_j \beta^z + \varepsilon_{ij}. \tag{1}$$

The parameter $\alpha < 0$ is the disutility of forgone income, the parameters β are the utility from the corresponding product attributes, and ε_{ij} is a household-specific utility shock. Making a distributional assumption for ε_{ij} (for example, extreme value) and integrating over the error term yields a function for the product's market share

$$s_j = s(p_j, m_j, x_j, z_j; \alpha, \beta). \tag{2}$$

The market share depends on the product's price and attributes as well as the preference parameters.

The market includes $n > 1$ firms, and for simplicity we focus on a single firm that produces one type of product, j. The attribute m_j is exogenous and the firm maximizes profits by choosing the product's price,

$$\max_{p_j} (p_j - c_j) s_j M - \nu F(m_j) s_j M, \tag{3}$$

where c_j is the exogenous marginal cost of producing the product. For each unit of the product that the firm sells, a regulation introduces a cost on the product attribute $\nu F(m_j)$. The regulation function $F(m_j)$ characterizes the form of regulation. For energy efficiency and greenhouse gas standards, $F(m_j)$ is typically decreasing in m_j. For example, if m_j is the vehicle's fuel economy (miles per gallon) and the regulator imposes a fuel consumption rate tax, $F(m_j) = 1/m_j$ and ν is the tax rate; a lower fuel economy implies a higher tax. Note that for emissions rate or fuel economy standards, $F(m_j)$ is negative if the vehicle's fuel economy or emissions rate exceeds the standards.

The first-order condition for the product price is

$$\frac{\partial s_j}{\partial p_j}(p_j - c_j - \nu F)M + s_j M = 0. \tag{4}$$

Equation (4) is a variation of the standard monopoly markup equation. The greater the price sensitivity of demand (that is, $\frac{\partial s}{\partial p}$), the lower the equilibrium price. The regulation distorts the optimal price. For example, a fuel consumption tax raises the equilibrium price inversely with the vehicle's fuel economy.

2.2 Case 2: Endogenous attributes with technological trade-off

In this subsection, the attributes m_j and x_j are endogenous. The vehicle is endowed with levels of m_j and x_j, denoted by m_{j0} and x_{j0}. The variable x_j is an attribute that is linked technologically to the regulated attribute. For example, considering the market for refrigerators, a manufacturer can improve energy efficiency (m_j) by adding insulation, which may decrease storage space (x_j). In that case, there is a technological relationship between energy efficiency and storage space.

The firm makes decisions in two stages. First, the firm can design the vehicle and choose levels of m_j and x_j that differ from the endowment. Specifically, there is a trade-off between the two attributes, and if the firm selects a level of m_j that is greater than m_{j0}, the firm must reduce x_j below x_{j0}. We characterize this relationship by expressing the attributes x_j as a function of m_j: $x_j - x_{j0} = x(m_j - m_{j0})$, where $\frac{\partial x_j}{\partial m_j} < 0$. Importantly, trading off these attributes does not affect marginal costs.[3]

The first-order condition for m_j is

$$[\frac{\partial s_j}{\partial m_j} + \frac{\partial s_j}{\partial x_j}\frac{\partial x_j}{\partial m_j}](p_j - c_j - \nu F)M - \nu F' s_j M = 0. \tag{5}$$

F' is the derivative of the regulation function with respect to the product attribute. The

[3] Alternatively, we could endogenize marginal costs as in Klier and Linn (2012). Specifically, the marginal costs can increase with the level of technology (for example, the energy efficiency of a vehicle), where a higher level of technology allows the firm to increase one attribute without affecting the other attributes; consumers do not directly value the technology, but only the attribute improvements that a higher level of technology enables. Having chosen the technology, the firm can then trade off attributes without affecting marginal costs as in the main text. The conclusions are not affected by endogenizing marginal costs in this way.

firm chooses the price in the second stage, and the price first-order condition is the same as in equation (4).

To interpret equation (5), it is useful to begin by assuming that there is no regulation ($\nu = 0$). Combining equations (4) and (5) yields

$$\frac{W^m}{W^x} = -\frac{\partial x_j}{\partial m_j}, \tag{6}$$

where $W^m = -\frac{\partial s_j}{\partial m_j} / \frac{\partial s_j}{\partial p_j}$ is the marginal WTP for m_j and similarly for W^x. Equation (6) shows that the firm equates the ratio of marginal WTP with the technological tradeoff between the two attributes. If consumers have declining marginal WTP for both attributes, an increase in the marginal WTP for one attribute causes the firm to decease the other attribute.

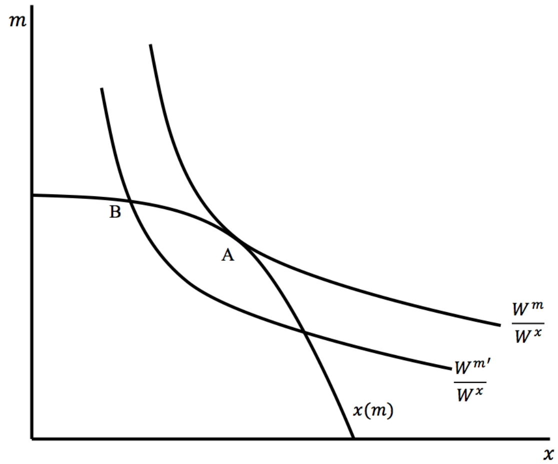
If there is regulation and $\nu > 0$, the first-order conditions can be combined to yield

$$W^m + W^x \frac{\partial x_j}{\partial m_j} = \nu F'. \tag{7}$$

As noted above, F' is typically negative, as would be the case for an emissions tax. If $\nu > 0$, the right-hand side of the equation is negative, which causes the firm to trade off x_j for m_j. This result is intuitive, as more stringent regulation causes the shadow cost (ν) to increase. The firm responds by increasing the regulated attribute at the expense of the unregulated attribute.

Figure 1 provides the intuition for equations (6) and (7). The curve labeled $x(m)$ represents the technological tradoeff between the regulated attribute (x) and the unregulated attribute (m). The curve is analogous to a production possibilities frontier, in that it describes the maximum level of x for any level of m, given the endowments of the two attributes. The curve $\frac{W^m}{W^x}$ is the ratio of the WTP for the two attributes (we assume that WTP for each attribute is decreasing in the corresponding attribute). Point A shows that without regulation the firm chooses levels of the two attributes such that the technology and WTP curves are tangent to one another. The regulation causes the firm to choose a point along the frontier such that the WTP ratio is steeper than the tradeoff; the firm substitutes the unregulated for the regulated attribute and chooses point B.

Figure 1: Firm's Profit Maximization



Note: The vertical axis represents the attribute m_j that is subject to regulation, and the horizontal axis represents the attribute x_j that is linked technologically to the regulated attribute. The curve $x(m)$ represents the technological tradeoff function: $x_j - x_{j0} = x(m_j - m_{j0})$. The curve $\frac{W^m}{W^x}$ is the ratio of the marginal WTP for the two attributes. The point A shows the firm's profit maximization without regulation (equation 6). Point B shows the firm's profit maximization under regulation (equation 7).

2.3 Case 3: Endogenous attributes with design trade-off

In this subsection we endogenize the choices of z_j and m_{j0}. The attribute z_j is not related technologically to m_j and x_j. For example, z_j may represent a vehicle's cabin space.

In cases 1 and 2, m_{j0} was exogenous and choosing $m_j > m_{j0}$ required the firm to reduce the level of x_j. In case 3, the firm chooses product attributes and price in three stages. In the design stage, the firm chooses z_j and m_{j0} and incurs a cost $D(m_{0j}, z_j)$,where the cost is increasing in both arguments. In the second stage, the firm chooses m_j and x_j, and in the third stage, the firm chooses the price. For simplicity, both x_{j0} and c_j remain exogenous (the conclusions are unaffected by endogenizing these parameters).

The firm's profit maximization problem becomes:

$$\underset{p_j, m_j, x_j, m_{j0}, z_j}{max} (p_j - c_j)s_j M - \nu F(m_j)s_j M. \tag{8}$$

As in case 2, $x_j - x_{j0} = x(m_j - m_{j0})$. In addition, we assume that there is a maximum cost that the firm can incur during the design stage, $\overline{D}$. This maximum cost captures capital market or time constraints that the firm faces, such as the need to update a refrigerator during a regular product cycle. Provided that this constraint binds, the equation $D(m_{0j}, z_j) = \overline{D}$ implicitly defines m_{j0} as a function of z_j. Given this relationship, we write $m_{j0} = D(z_j; \overline{D})$.

The first-order condition for price is the same as equation (4), and the first-order condition for m_j is the same as equation (5). The first-order condition for z_j is

$$[\frac{\partial s_j}{\partial z_j} + \frac{\partial s_j}{\partial x_j}\frac{\partial x_j}{\partial m_{j0}}\frac{\partial m_{j0}}{\partial z_j}](p_j - c_j - \nu F)M = 0. \tag{9}$$

Setting $\nu = 0$ and combining equation (9) with equation (4) yields

$$W^z + W^x \frac{\partial x_j}{\partial m_{j0}}\frac{\partial m_{j0}}{\partial z_j} = 0, \tag{10}$$

where W^z is the marginal WTP for attribute z. This equation has a similar structure to equation (6), and it shows that the choices of the unregulated attributes are related to one another according to the two trade-off functions, x and D.

Equations (7) and (10) imply that increasing ν affects both unregulated attributes. To see why, suppose for the moment that increasing ν causes the firm to trade off x_j for m_j, while leaving z_j unchanged. In that case, lower x_j would raise W^x, and equation (10) would no longer hold with equality. Consequently, marginally increasing ν also affects z_j. Thus, regulating one attribute affects not only other attributes that are linked technologically to that attribute, but also attributes that are chosen jointly with the regulated attribute during product design.

In the cases considered so far, increasing ν causes the firm to reduce x_j and z_j, but this need not hold generally. For example, suppose W^x depends not only on x_j but also on z_j, such that increasing z_j raises W^x. In particular, redesigning a vehicle's exterior to have a sporty look (z_j) could increase a consumer's marginal WTP for horsepower (x_j). Under these assumptions, increasing ν could cause the firm to increase z_j and reduce the extent to which the firm trades off x_j for m_j. Therefore, whether increasing ν causes z_j to increase or decrease depends on the magnitudes of the derivatives in equations (7) and (10) as well as the cross partial derivatives of the marginal WTP for each attribute with respect to the other attributes.

We briefly discuss the intuition for the result that increasing ν can cause the firm to increase other attributes, potentially increasing consumer welfare. Suppose consumer WTP for m_j is positively correlated with WTP for z_j. If there is no product regulation, depending on competition and attribute choices of other firms, the firm may find it optimal to offer low levels of m_j and z_j, relative to the levels of attributes chosen by other firms. For example, for home appliances, consumer preferences for energy efficiency (m_j) may be positively correlated with preferences for overall product quality (z_j). In such a situation, the firm may offer a low-quality product that also has low energy efficiency because doing so helps the firm segment the market and attract the consumers with low demand for the two attributes.

Starting from this equilibrium, hypothetically regulating m_j has a similar effect on the firm's attribute choices as if consumer demand for m_j were to increase. This can be seen by comparing equations (6) and (7), which show that $\nu > 0$ has the same effect on attribute choices as an increase in demand for m_j. Essentially, the regulation reduces the positive correlation between m_j and z_j, reducing the firm's incentive to offer a low level of z_j.

The model shows that the regulation affects product attributes that are not directly targeted. Moreover, regulation could either increase or decrease other attributes, depending on the structures of demand and costs. Above, we noted some simplifications, such as the fact that costs are exogenous and that the firm sells only one product. Relaxing these assumptions would not change the conclusion that regulation can affect unregulated attributes in either direction.

3 Background and Data

The conclusions from Section 2 motivate an empirical analysis of whether regulating one product attribute can affect a broad set of other attributes. The remainder of the paper focuses on the European carbon dioxide emissions standards, and this section describes the policy context and the data.

3.1 Policy context

In Europe, passenger cars contribute the majority of transportation emissions, and Europe's carbon dioxide emissions standards are the central policy aiming to reduce those emissions. Traditionally, European countries have taxed fuels more heavily than have other countries (Parry and Small 2005). In 1995, the European Parliament and the Council formulated an objective of reaching an average emissions rate of 120 grams of carbon dioxide per kilometer (g CO_2/km) by 2010 (European Commission 1995; a gasoline-powered vehicle that emits 120 g CO_2/km achieves about 45 miles per gallon). However, the emissions target was voluntary, and by the mid-2000s, it was apparent that the actual emissions rate would far exceed the target (European Council 2009).

Therefore, in 2007, the Commission proposed a legislative framework mandating passenger vehicle emissions reductions. For each vehicle, the carbon dioxide emissions target E_j depends on the vehicle's weight w_j:

$$E_j = \begin{cases} 130 + 0.0457 \cdot (w_j - 1372), & \text{year} \in [2012, 2015] \\ 130 + 0.0457 \cdot (w_j - 1392.4), & \text{year} \geq 2016 \end{cases}$$

A manufacturer's emissions target is the sales-weighted average of the vehicle-specific targets. Therefore, a manufacturer selling heavy vehicles has a higher target than does a manufacturer selling light vehicles. The framework included a phase-in period that began in 2012, and by 2015 each manufacturer had to attain an average carbon dioxide emissions rate for new passenger cars of 130 g CO_2/km (European Council 2009).[4] Manufacturers could comply individually or jointly. The European standards do not allow compliance

[4]Between 2012 and 2014, the standards were phased in by including a subset of the manufacturer's sales when computing its sales-weighted emissions rate: 65 percent in 2012, 75 percent in 2013, and 80 percent in 2014. Between 2012 and 2015, cars with emissions rates less than 50 g CO_2/km (which are mainly electric vehicles) earned more than 1 credit: 3.5 in 2012 and 2013, 2.5 in 2014, and 1.5 in 2015. In certain situations, the target for vehicles capable of using fuel with high ethanol content was different from that reported in the text.

credit trading across firms. The framework also set a target of 95 g CO_2/km to be met by 2020, which has since been delayed.

Since 2012, a manufacturer whose sales-weighted average emissions rate exceeds its target must pay fines that increase with the degree of the manufacturer's noncompliance. When the manufacturer exceeds its target by no more than 1 g CO_2/km, the fine is 5 euros per g CO_2/km per car. The fine increases to 15 euros from 1 to 2 g CO_2/km, to 25 euros from 2 to 3 g CO_2/km, and to 95 euros above 3 g CO_2/km.

Because each manufacturer must meet the standard and manufacturers cannot trade compliance credits with one another, the shadow cost of the regulation may vary across manufacturers, ν_m. Therefore, the regulation function from the previous section is given by $F(m_j) = \nu_m(k_f/m_j - E_j)$, where k_f is the carbon content of the fuel (which varies by fuel type). The regulation creates an implicit tax on a vehicle if $k_f/m_j > E_j$, and it creates an implicit subsidy otherwise.

3.2 Data

The main data were obtained from IHS Markit. For the eight EU countries with the largest car markets in Europe (Austria, Belgium, France, Germany, Italy, the Netherlands, Spain, and the United Kingdom), the data include registrations by month and vehicle from 2005 through 2017. A vehicle is defined as a unique model, submodel, version, trim, market segment, number of doors, body type, fuel type (diesel, gasoline, hybrid, plug-in hybrid, or electric), and drive type (front-, rear-, or all-wheel). For each vehicle, the data also include the vehicle's length, height, width, gross vehicle weight, size, fuel consumption rate, carbon dioxide emissions rate, engine horsepower, number of engine cylinders, engine size (that is, displacement), and number of transmission speeds, as well as the retail price.[5] The data are similar to those used in Klier and Linn (2015), except that our data extend through 2017, whereas theirs ended in 2010.

We construct a categorical variable labeled *origin* that takes one of three values:

[5]There is far less negotiation between consumers and car dealers in Europe than in the United States. Most of the literature on European new car markets uses retail prices rather than transaction prices (e.g., Reynaert 2019).

whether the car is produced by a domestic manufacturer, a foreign European or US manufacturer, or an Asian manufacturer. We calculate the vehicle purchase tax, ownership tax, and fuel tax using the annual European Automobile Manufacturers Association (ACEA) Tax Guide. We also construct the vehicle's per-kilometer fuel price by multiplying the fuel consumption rate (liters of fuel per kilometer) by the fuel price (2005 euros per liter). Monthly prices for gasoline (petrol) and diesel fuel are obtained from the Weekly Oil Bulletin and are converted to 2005 euros using consumer price indexes from Eurostat.

We drop vehicles with weight greater than 3,500 kilograms because they are not subject to the carbon dioxide emissions rate standards for passenger cars, and we drop vehicles with prices exceeding 59,537 euros, which is the 99th percentile of the price distribution. In the final data set, a unique observation is a vehicle by country by year. The data set contains 341,725 observations and 68,089 unique vehicles.

Table 1: Summary Statistics

Variable	Period 1 2005—8	Period 2 2009—11	Period 3 2012—17
Annual registrations of each vehicle in each country	336.15	295.08	212.28
	(1099.48)	(1044.79)	(687.06)
Price (1,000 2005 euros)	25.78	25.94	26.46
	(11.19)	(11.70)	(11.53)
Tax (1,000 2005 euros)	3.88	3.30	3.14
	(5.25)	(4.69)	(4.83)
Engine horsepower	139.36	143.64	144.90
	(54.03)	(59.08)	(60.57)
Gross vehicle weight (metric tons)	1.86	1.87	1.88
	(0.27)	(0.29)	(0.29)
Size (cubic meters, m^3)	11.26	11.33	11.36
	(1.43)	(1.47)	(1.41)
Fuel cost (2005 euros/100 km)	8.31	7.21	6.10
	(2.46)	(2.06)	(1.92)
Fuel consumption rate (liters/100 km)	7.02	6.26	5.15
	(1.71)	(1.51)	(1.23)
CO_2 emissions rate (g CO_2/km)	174.42	154.32	125.60
	(37.91)	(33.76)	(27.16)
Number of engine cylinders	4.34	4.25	4.01
	(0.84)	(0.80)	(0.71)
Number of observations	101,389	74,709	165,627

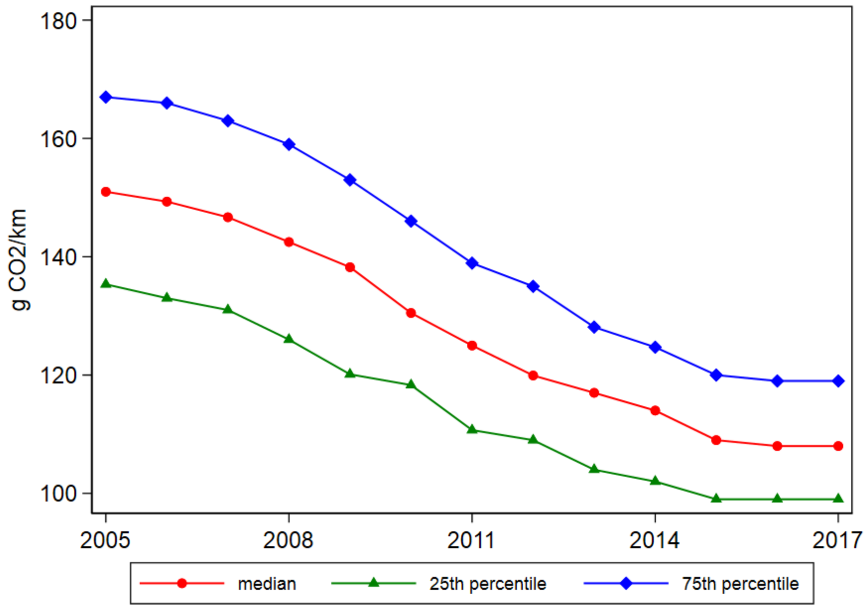
Notes: The table reports means of the attributes for the time periods indicated in the row headings, with standard deviations in parentheses. See text for details on data construction.

Table 1 provides summary statistics by time period. The table defines three policy regimes that are used in the empirical analysis below. During the first period (2005—8), the standards were voluntary and there were no fines for noncompliance. During the second period (2009—11), manufacturers knew that mandatory standards would be imposed starting in 2012. During the third period (2012—17), the standards were phased in and firms were assessed fines for noncompliance.

The average price is stable across the periods, and the average tax decreases substantially. The average fuel consumption rate, fuel costs, and carbon dioxide emissions rate decrease across the three periods, which is consistent with the fact that the carbon dioxide standards tightened during the sample.

Figure 2 shows the median carbon dioxide emissions rate as well as the 25th and 75th percentiles of the emissions rate across vehicles. By the end of the sample, the average emissions rate was far below the target of 130 g CO_2/km, which likely is explained by manufacturers' efforts to comply with the target of 95 g CO_2/km by the early 2020s.

Figure 2: CO_2 Emissions Trend



Note: The figure shows the median, 25th percentile, and 75th percentile of CO_2 emissions rate by year, weighted by registrations.

Table 2 motivates the nested logit structure that we adopt in the next section. France and Germany have the largest markets in Europe, and the table shows the market shares in France and Germany of the top three French and German brands. The table indicates a strong home bias, such that the French brands have substantially higher market shares in France than they do in Germany, and vice versa for the German brands.

Table 2: Home Bias in Vehicle Market Shares

Brand	Origin	Market share in France	Market share in Germany
Citroen	France	0.13	0.02
Renault	France	0.21	0.04
Peugeot	France	0.20	0.03
Volkswagen	Germany	0.08	0.20
Audi	Germany	0.04	0.10
BMW	Germany	0.03	0.09

4 Estimating Consumer Preferences and Vehicle Quality

In this section, we implement a method similar to that of Houde and Spurlock (2015) to estimate consumer preferences and vehicle quality. The first two subsections describe the demand model and empirical strategy, and the third subsection reports the estimation results.

4.1 Demand model

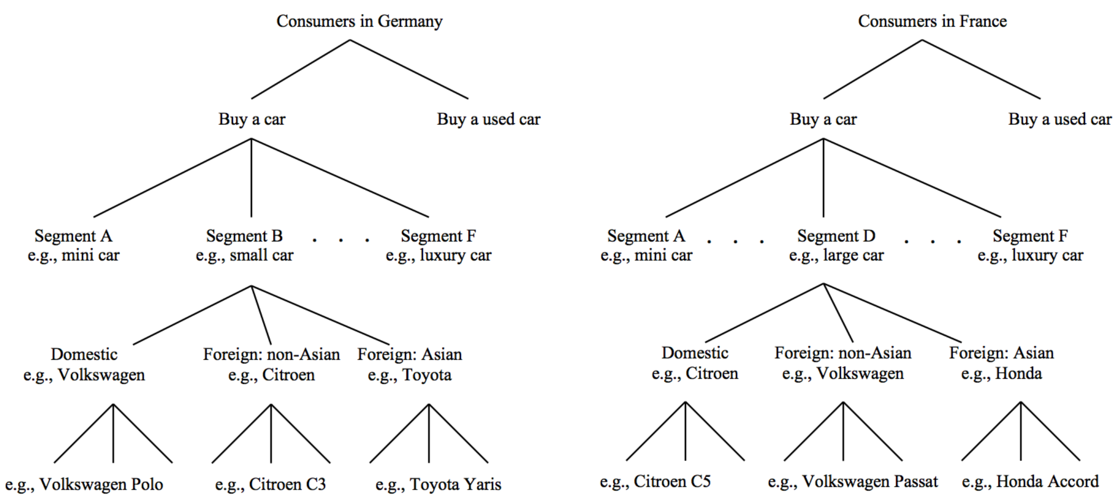
A market corresponds to a country c and year y, and each country has M_{cy} consumers who are considering purchasing a vehicle. Each consumer can choose a new or a used vehicle, where $j = 0$ indicates a used vehicle and $j = \{1, \ldots, J\}$ indexes the new vehicles. As is customary in the vehicle choice literature (e.g., Berry et al. 1995), consumer i's utility is linear in vehicle attributes and an idiosyncratic preference shock:

$$U_{ijcy} = \alpha p_{jcy} + X_{jcy}\beta + \xi_{jcy} + \varepsilon_{ijcy} \tag{11}$$

The retail price of the vehicle is p_{jcy}, and X_{jcy} includes the vehicle's tax, fuel costs, log of the ratio of horsepower and weight, log weight, and log size (the product of width, length, and height). We include the vehicle's price and tax separately in the utility function to allow for the possibility that consumers respond differently to taxes than prices, because of salience or other factors (Cerruti et al. 2019). Fuel costs are the price of fuel per 100 km of travel, as constructed for Table 1, and fuel costs are proportional to the present discounted value of fuel costs over the vehicle's lifetime assuming that the current price equals the expected future real price. This measure of fuel costs is commonly used and is consistent with existing evidence of consumer fuel price expectations (Anderson et al. 2013). The log of the ratio of horsepower and weight is included because it is directly related to the vehicle's acceleration (Leard et al. 2017). We define ξ_{jcy} as the vehicle's quality; the variable represents the mean utility across all consumers of the vehicle arising from all attributes except price and the attributes in X_{jcy}. For example, ξ_{jcy} includes cabin comfort and cargo space. Finally, ε_{ijcy} is the household's preference shock.

We use a nested logit structure to capture preference heterogeneity across consumers. Figure 3 illustrates the structure. First, the consumer decides whether to purchase a new or used vehicle. If the consumer decides to purchase a new vehicle, the consumer then chooses a market segment, where segments are denoted A through F and correspond roughly to vehicle size (for example, A indicates mini cars and B indicates small cars). Having chosen a segment, the consumer chooses an origin (domestic, other European or US, or Asian) and a specific vehicle. We differentiate between foreign and domestic cars to capture the home bias indicated in Table 2. The nesting structure implies that $\varepsilon_{ijcy} = \eta_{ig(j)cy} + (1 - \sigma_g)\nu_{ijcy}$, where $\eta_{ig(j)cy}$ represents consumer i's specific taste for group $g(j)$, and ν_{ijcy} is an independently and identically distributed variable with Type 1 extreme value distribution.

Figure 3: Nested Logit Structure of Vehicle Choice



The probability of choosing vehicle j, P_j, is

$$P_j = P_{j|so} \cdot P_{o|s} \cdot P_s, \tag{12}$$

where $P_{j|so}$ is the probability of choosing vehicle j conditional on choosing segment s and origin o, $P_{o|s}$ is the probability of choosing origin o conditional on choosing segment s, and P_s is the probability of choosing segment s. The nesting structure and assumptions on the error term yield

$$P_{m_l|j_{l-1}} = \frac{exp(\frac{\lambda_{m_l} IV_{m_l}}{\lambda_{j_{l-1}}})}{\sum_{k\in\Theta_{j_{l-1}}} exp(\frac{IV_{k_l}\lambda_{k_l}}{\lambda_{j_{l-1}}})} \tag{13}$$

$$IV_{m_l} = log[\sum_{p\in\Theta_{m_l}} exp(\frac{\delta_{p_{l+1}}}{\lambda_{m_l}})], \tag{14}$$

where the subscript l represents a particular level in the choice tree, the subscript $l-1$ represents the choice level above, and subscript $l+1$ refers to the choice level below (McFadden 1981; Goldberg 1995). The subscript m_l represents a specific alternative m at the choice level l. $P_{m_l|j_{l-1}}$ is the probability that a consumer chooses alternative m at the choice level l conditional on the consumer having chosen j at the higher choice level $l-1$. The inclusive value IV_{m_l} measures the expected utility of the choice subset given the choice m on level l. The dissimilarity coefficients are λ_{m_l} and $\lambda_{j_{l-1}}$, which measure the dissimilarity of consumer utility for choices belonging to the same nest. Consistency of equation (13) with random utility maximization requires that $\lambda_{m_l}, \lambda_{j_{l-1}} \in [0,1]$. Moreover, vehicles belonging to the same nest at level l are more similar on average to vehicles belonging to the nest at level $l-1$. For example, segment A (mini) cars sold by French brands in France are more similar to one another than are all segment A cars sold in France. This assumption implies that $0 < \lambda_{m_l} < \lambda_{j_{l-1}} < 1$. When λ approaches 1, the distribution of ε_{ij} approaches an independently and identically distributed extreme value distribution, and the nested logit model degenerates to a multinomial logit model.

Combining equations (12) and (13) yields the market-level equation

$$logS_{jcy} - logS_{0cy} = \alpha p_{jcy} + X_{jcy}\beta + \sigma_{so} logS_{j|so,cy} + \sigma_s logS_{o|s,cy} + \xi_{jcy}, \tag{15}$$

where S_{jcy} and S_{0cy} are market shares for vehicle j and the outside option (used car). The similarity parameters are $\sigma_{so} = 1 - \lambda_{so}$ and $\sigma_s = 1 - \lambda_s$.

4.2 Strategy for estimating preference parameters and quality

Equation (15) is the basis for estimating preference parameters and vehicle quality. We decompose the error term in the equation into five components: $\xi_{jcy} = \delta_{mb(j)} + \delta_j^f + \delta_{sy} + \delta_{cy} + \mu_{jcy}$. The first component includes a fixed effect for each model and body type, such as the hatchback version of the Volkswagen Golf, as distinct from the station wagon version of the Golf. The second component includes fixed effects for each fuel type (gasoline, diesel, gasoline hybrid, plug-in hybrid, and electric), which allows preferences to vary across fuel types for reasons such as durability and refueling convenience. The third component includes fixed effects for each segment by year, controlling for segment-level demand or supply shocks, such as the increase in consumer demand for larger vehicles over the sample. The fourth component includes a fixed effect for each market, which includes the average utility from the outside option. The final term is a mean zero error term.

This decomposition of the error term in equation (15) yields the estimation equation

$$logS_{jcy} - logS_{0cy} = \alpha p_{jcy} + X_{jcy}\beta + \sigma_{so} logS_{j|so,cy} + \sigma_s logS_{o|s,cy} + \delta_{mb(j)} + \delta_j^f + \delta_{sy} + \delta_{cy} + \mu_{jcy}. \tag{16}$$

Estimating equation (16) by ordinary least squares (OLS) would yield biased parameter estimates because the vehicle's price and the within-nest shares are likely to be correlated with μ_{jcy}. Following Berry et al. (1995) we use the sum of attributes of other vehicles in the market to instrument for price and market shares. The intuition supporting the relevance of the instruments is that the profit-maximizing price of vehicle j depends on attributes of other competing vehicles in the market, and that an increase in the number of competing vehicles reduces the firm's price. A similar intuition applies to the endogenous market shares, because the equilibrium market share is likely to be correlated with attributes of other vehicles. The relevance of the instruments arises from the firm's profit-maximizing price choices.

The exclusion restriction is satisfied if attributes of competing vehicles are uncorrelated with μ_{jcy}. Vehicle manufacturers typically make major redesigns of vehicles at regular intervals, during which they may make substantial changes to the vehicle's power train, architecture, and components. In between redesigns, manufacturers make more modest changes, such as modifying the power train to adjust fuel economy or horsepower. Consequently, μ_{jcy} is particularly likely to be correlated with attributes of other vehicles that vary between redesigns. The correlation between μ_{jcy} and other vehicles' attributes may be weaker for attributes that are typically changed only during redesigns. Based on this reasoning, we use as instruments the physical dimensions (length, width, and height) of other vehicles, as well as the number of engine cylinders, because these attributes change infrequently during major redesigns; Leard et al. 2019 use similar instruments.

After estimating the preference parameters in equation (16), we recover the vehicle's residual quality as $\widehat{\xi}_{jcy} - \widehat{\delta}_{cy} = \widehat{\delta}_{mb(j)} + \widehat{\delta}_j^f + \widehat{\delta}_{sy} + \widehat{\mu}_{jcy}$. We exclude the country-year fixed effects from quality because they include the mean utility from the outside option. We normalize quality by the disutility of the vehicle price, $\widehat{Q}_{jcy} = -(\widehat{\xi}_{jcy} - \widehat{\delta}_{cy})/\widehat{\alpha}$, to express quality in 2005 euros. Note that the instruments are necessary to obtain consistent estimates of the preference parameters, but not the fixed effects components of quality.

4.3 Results

4.3.1 Preference parameters

Columns 1 and 2 of Table 3 report estimates of a multinomial logit model to compare with column 3, which is the preferred nested logit model. Parameters are estimated by OLS in column 1 and by IV in columns 2 and 3, using attributes of other vehicles as instruments. Standard errors are clustered by model and trim to allow for correlation within trims. All regressions include fixed effects for model by body type, country by year, fuel type and segment by year. The appendix reports the first-stage estimates for the IV models. The Sanderson-Windmeijer multivariate F-test of the excluded variables reduces concerns about weak instruments bias and rejects the null assumption that the model is underidentified.

Table 3: Estimated Preference Parameters

	(1)	(2)	(3)
	Multinomial logit	Multinomial logit	Nested logit
Estimated by	OLS	IV	IV
Price (1,000 2005 euros)	-0.035	-0.288	-0.088
	(0.003)	(0.049)	(0.016)
Log within segment-origin share			0.773
			(0.018)
Log share of origin in segment			0.497
			(0.029)
Tax (1,000 2005 euros)	-0.064	0.033	-0.006
	(0.003)	(0.018)	(0.006)
Fuel cost (2005 euros/100 km)	-0.339	-0.275	-0.063
	(0.011)	(0.016)	(0.008)
Log horsepower/weight (hp/kg)	-0.013	2.603	0.900
	(0.078)	(0.515)	(0.158)
Log weight (tonnes)	-0.543	4.871	1.735
	(0.269)	(1.063)	(0.321)
Log size (m^3)	8.223	8.270	1.963
	(0.378)	(0.409)	(0.196)
First-stage summary			
F-test of excluded instruments for price		20.05	16.55
F-test of excluded instruments for within-origin share			50.58
F-test of excluded instruments for share of origin in segment			58.37
Number of observations	341,725	341,725	341,659
Number of unique vehicles			68,089
Number of unique vehicle models			429

Notes: The table reports coefficient estimates with standard errors in parentheses, clustered by model and trim. All regressions include country—year fixed effects, model—body type fixed effects, fuel type fixed effects, and segment—year fixed effects. Column 1 is estimated by ordinary least squares, and columns 2 and 3 are estimated by instrumental variables, using width, length, height, and number of engine cylinders as instruments (see text). We use the Sanderson-Windmeijer multivariate F-test of excluded instruments to account for clustering of the standard errors.

The price coefficient is negative and statistically significant at the 1 percent level for all three demand models. The magnitude of the price coefficient is larger using IV than OLS, which is consistent with expectations because the IV strategy corrects for the positive correlation between price and the error term. Table 4 shows that the OLS estimates yield implausibly small own-price elasticities.[6] The preferred IV estimates in column 3 yield own-price elasticities that typically lie between -5.8 and -8.9, which is consistent with the fact that the price sensitivity parameter is identified by variation across highly disaggregated vehicles. The estimates are somewhat larger than other estimates that use similarly disaggregated European data (e.g., Grigolon et al. 2017).

Table 4: Estimated Own-Price Elasticities

	Multinomial logit OLS	Multinomial logit IV	Nested logit IV
Median	-0.68	-5.58	-7.41
Mean	-0.67	-5.55	-7.37
Standard deviation.	0.08	0.64	0.87
5th percentile	-0.81	-6.68	-8.90
95th percentile	-0.53	-4.36	-5.80

Notes: Own-price elasticities are calculated using equation (17). The elasticities are weighted by registrations.

Coefficients on the within-group shares represent the similarity parameters for vehicles within the same group. Both estimates are significant at the 1 percent level and lie between 0 and 1. The similarity parameter for the share of origin within segment is less than the within-origin share, which is consistent with the assumed nesting structure.

The tax coefficient in Table 3 is negative (as expected), but it is not statistically significant. The lack of significance may reflect the strong correlation between taxes and prices after including model—body type fixed effects. The estimated own-price elasticities are similar if we add the tax to the price, as in Grigolon et al. (2017).

In column 3, the estimates of the fuel cost and log of the ratio of horsepower and weight coefficients are statistically significant, and they have the expected signs. The coefficient on weight is positive and statistically significant. The coefficient reflects consumer preferences for performance, safety, and components such as speakers, all of which

[6] The elasticity of choice probability for vehicle j with respect to attribute $X^{(n)}$ is

$$\frac{\partial P_j/P_j}{\partial X_j^{(n)}/X_j^{(n)}} = [\frac{1-P_{j|so}}{\lambda_{so}} + \frac{(1-P_{o|s})P_{j|so}}{\lambda_s} + (1-P_s)P_{o|s}P_{j|so}]\beta^{(n)}X_j^{(n)}, \tag{17}$$

where λ_s is the dissimilarity of alternatives belonging to the same segment but having different origins, and λ_{so} is the dissimilarity of alternatives belonging to the same segment and having the same origin. The elasticity increases with the preference coefficient and decreases with the dissimilarity parameters.

are correlated with weight. Finally, the vehicle size coefficient is statistically significant and positive, as expected.

Table 5 provides an economic interpretation of the coefficients on fuel costs, performance, weight, and size. For comparability with the literature, the top panel reports the mean willingness to pay for 1 percent changes in the indicated attributes. The three columns correspond to the three demand models reported in Table 3. On average, consumers are willing to pay 46 euros for a 1 percent reduction in fuel cost savings and about 102 euros for a 1 percent increase in performance. These estimates are similar to those reported in Leard et al. (2017) for the US market.

Table 5: Willingness to Pay and Valuation Ratio

	(1)	(2)	(3)
Willingness to pay for 1 percent change (2005 euros)			
Fuel cost decrease	617	61	46
Horsepower/weight increase	-4	90	102
Weight increase	-155	169	197
Size increase	2,349	287	223
Valuation ratio			
15 years, r = 0.06	6.63	0.65	0.49
15 years, r = 0.03	5.55	0.55	0.41
10 years, r = 0.06	8.74	0.86	0.65

Notes: Each column reports results using preference parameter estimates from the corresponding column in Table 3. Valuation ratio is the willingness to pay for a 1 percent reduction in fuel costs divided by the present discounted value of the fuel cost savings. These calculations assume that each vehicle is driven 14,700 kilometers each year and that the future real price of fuel equals the average real price of fuel in the estimation sample. The calculations use the vehicle lifetime and real discount rate indicated in the row heading.

The bottom panel of Table 5 provides a second interpretation of the willingness to pay for fuel cost savings. We define the valuation ratio as the willingness to pay for a 1 percent reduction in fuel cost savings divided by the present discounted value of a 1 percent reduction in fuel cost savings. A valuation ratio of 1 implies full valuation, where consumers pay 1 euro for 1 euro of present discounted fuel cost savings; a ratio less than 1 implies undervaluation. Making this calculation requires assumptions on future fuel costs, kilometers traveled, and the real discount rate. The first row shows the valuation ratio under the same assumptions as in Grigolon et al. (2017). Our estimated valuation ratio, 0.49, is smaller than their estimate of 0.91, which they estimated using data prior to the carbon dioxide standards.

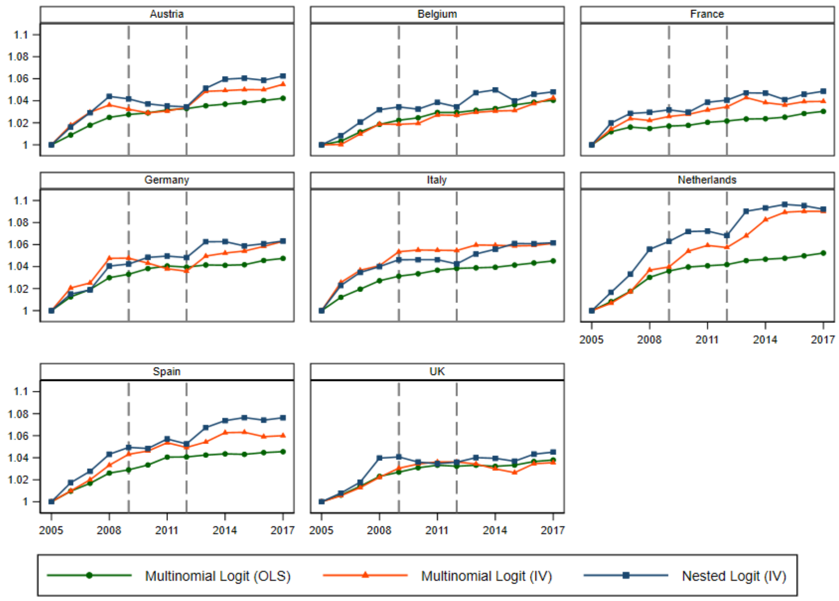
The fuel cost coefficient in the utility function and the valuation ratio are identified by variation in fuel costs across vehicles and over time in the estimation sample. Some of the variation arises from the adoption of fuel-saving technologies, such as high-speed transmissions and stop-start ignition. Therefore, the parameter estimates and valuation ratios reflect any consumer utility or disutility from the underlying technologies, which could explain the low valuation ratio that we estimate.

4.3.2 Quality

After estimating the preference parameters, we compute the quality in euros as described at the end of Section 4.2. Figure 4 plots the unweighted mean quality by country and year, for each of the three demand models estimated in Table 3. For each country, quality may vary over time because of within-vehicle changes in quality as well as entry and exit of vehicles. The vertical dashed lines indicate the three regimes of the standards.

Overall, quality increases over time. There are a few instances, typically around the time of the 2008—9 economic recession, when quality decreased, which appears to have been due to the exit of some high-end vehicles. The figure indicates that for most countries, quality increased more quickly during the first period (before the standards took effect) than in the second and third periods (after the standards were announced and as they were phased in). This pattern provides suggestive evidence that the standards caused quality to increase less quickly than in the first period. Of course, other factors may have contributed to the slowing quality growth, such as the economic recession; the empirical analysis in the next section aims to disentangle the effects of the carbon dioxide standards from other factors.

Figure 4: Mean Quality by Country and Year (2005 = 1)



Notes: The figure plots the estimated model-weighted quality index by country and year, using estimates from the indicated demand model (see Table 3). The quality is divided by the negative of price coefficient and normalized to equal one in 2005. Vertical dashed lines indicate the cutoffs for the three policy periods.

Table 6 shows that estimated residual quality varies with observed vehicle attributes that are not included in the demand model. In this figure and for the remainder of the paper we normalize estimated quality by the negative of the vehicle price coefficient (α), and quality is measured in 2005 euros. Vehicles belonging to the E and F segments (large medium and large cars) have about 10 percent higher quality than do smaller cars. Similarly, vehicles with engines in the highest quartile of engine size have quality about 10 percent higher than vehicles with smaller engines. Because quality includes vehicle attributes that are not shown in the table, we do not interpret the correlations among quality and observed attributes as causal relationships. Instead, we interpret the table as showing strong correlations among quality, vehicle size, and engine size.

Table 6: Mean Quality by Vehicle Attribute

Segment	Mean	Drive type	Mean	Number of engine cylinders	Mean	Engine size	Mean
A/B	103	All	114	$\leq$4	103	Lowest quartile	103
C	104	Front	103	5/6	113	Second quartile	104
D	104	Rear	108	$\geq$7	151	Third quartile	104
E/F	114					Highest quartile	114

Notes: The table reports the sales-weighted mean quality by the indicated attribute. Quality is divided by the negative of price coefficient and is measured in thousands of 2005 euros.

4.3.3 Alternative demand specifications

Because residual quality is derived from the demand model, we report a number of alternative demand model specifications in the appendix. Appendix Table 11 shows the main parameter estimates using alternative nesting structures. The two subsequent tables show that the estimated own-price elasticities and WTP are similar for the other nesting assumptions.

In Appendix Table 14 we return to the preferred nesting structure from Table 3. Column 1 repeats the estimates from that model, and columns 2 through 4 include additional fixed effects for model trim and time, which account for potential unobserved factors at the trim level. The estimated own-price elasticities and WTP vary somewhat across these specifications.

The nested logit model, as with other discrete choice models derived from a linear utility model with an additive error term, can yield biased estimates of own-price elasticities because of implicit assumptions on the cross-vehicle variation of unobserved product attributes (Ackerberg and Rysman 2005; Berry and Pakes 2007). One approach to address this problem is to control for the number of products in the same segment and to control for the similarity of observed attributes across products. Column 5 follows Houde and Spurlock (2015) and adds these two variables to the preferred model.

In our baseline demand estimation, we drop luxury cars whose prices are above the 99th percentile of the price distribution. To check the effect of dropping luxury cars, instead of dropping those luxury cars, we generate a dummy variable for them and include it in the demand estimation (see column 6 of Appendix Table 14). The price coefficient is smaller than the baseline, which implies less elastic demand and a higher valuation ratio.

To address the possibility that demand shocks affect the WTP for fuel costs or weight, we reestimate the consumer demand model and allow the preference parameters to vary across time periods (see column 7). The average of the preference coefficients is similar to our baseline estimates.

Appendix Figure 6 plots the quality index by year for different demand estimations. The quality index estimated by the alternative models has similar patterns to the preferred estimation. Because the estimated preference parameters vary across the demand specifications reported in the appendix, in robustness analysis below we report results using quality estimated from the alternative specifications.

5 Estimating the Effects of the Standards on Quality and Other Attributes

The first subsection describes the empirical strategy for estimating the effects of the carbon dioxide standards on vehicle quality, horsepower, weight, and vehicle price. The second subsection reports the point estimates, discussing statistical significance and potential sources of bias.

5.1 Empirical strategy

The objective is to estimate the effects of the standards on equilibrium quality and observed attribute choices. Motivated by the model in Section 2 and following Klier and Linn (2015), we construct a measure of stringency that is analogous to a shift-share or Bartik-style estimation (Bartik 1991). Equations (7) and (10) show that the standards affect vehicle attribute choices in proportion to the shadow cost of the regulation, ν, which varies across firms. We assume that the shadow cost is proportional to the amount the firm has to reduce the average emissions of its fleet, and we define stringency $Stringency_f$ as

$$Stringency_f = ln(e_f) - ln(E_f), \tag{18}$$

where e_f is the registration-weigthed average emissions rate of the firm's vehicles, and E_f is the registration-weighted emissions rate target. We use the emissions rate, weight, and registrations of vehicles during the first year of the sample to compute $Stringency_f$. Therefore, $Stringency_f$ does not vary over time, and it measures the amount that the firm has to reduce emissions during the sample.

Because of the timing of the regulation, we expect $Stringency_f$ to affect attributes by different amounts in the three periods: (1) 2005—8, pre-standard period; (2) 2009—11, announcement period; and (3) 2012—17. Therefore, we interact the variable with fixed effects for the three time periods. The estimation equation is

$$Y_{jct} = \gamma_1 + \gamma_2 Stringency_f * I_t^{(2)} + \gamma_3 Stringency_f * I_t^{(3)} + \delta_j + \delta_{sy} + \delta_{cy} + \varepsilon_{jcy}, \tag{19}$$

where Y_{jct} is the dependent variable (quality, $ln(horsepower/weight)$, log weight, or log price); $I_t^{(l)}$ is an indicator for period l; δ_j, δ_{sy} and δ_{cy} are vehicle, segment by year and country by year fixed effects; ε_{jcy} is an error term; and γ are coefficients to be estimated. The dependent variable $ln(horsepower/weight)$ is a proxy for performance, because it is proportional to acceleration (Leard et al. 2017). Because the equation includes vehicle and country-year fixed effects, we omit the main effects of $Stringency_f$ and time period fixed effects. The dependent variables for quality, $ln(horsepower/weight)$, and log weight are normalized by $-\alpha$, and we interpret the variables as the WTP for quality, horsepower, and weight. Note that we use a vehicle-level measure of stringency for the regressions that include price as a dependent variable. This is because according to equation (4), the regulation affects prices in proportion to the difference between the vehicle's emissions rate and its target, rather than the firm's average emissions rate and target.

The key coefficients γ_2 and γ_3 are identified by cross-sectional stringency variation interacting with the temporal variation in the (unobserved) shadow cost of the standards. For example, γ_2 would be negative if vehicles sold by firms with high stringency experience larger quality decreases between the first and second periods compared with vehicles sold by firms with low stringency. We test whether the coefficients γ_2 or γ_3 are statistically significant from zero, which we interpret as the market-wide average effect of the standards on the dependent variables during the corresponding periods. That is, by defining stringency as a proxy for the shadow cost of the standards and interacting the variable with time period fixed effects, we estimate the average effects of the standards on the dependent variables, despite the fact that the shadow costs of the standards are unobserved.

We estimate equation (19) by OLS. The vehicle fixed effects control for the cross-sectional correlation between stringency and the dependent variable, and the country by year fixed effects control for country-level demand or supply shocks to the dependent variable. We also include the segment by year fixed effects to control for segment-level demand or supply shocks. For example, the vehicle fixed effects control for the possibility that high-quality vehicles typically are heavier or have higher carbon dioxide emissions rates.

Because carbon dioxide emissions rates are strongly correlated with fuel consumption rates, it might seem that demand for fuel cost savings would be correlated with $Stringency_j$, which would bias the estimates. However, this is not a significant concern because quality is a residual estimated from the demand model, which purges the variable of consumer WTP for fuel cost savings.

A more serious concern is that the causal interpretation relies on a parallel trends assumption: in the absence of the standards, temporal variation of the dependent variables would not be correlated with $Stringency_f$. A violation of this assumption amounts to an omitted variable that is correlated cross-sectionally with stringency and that varies over time. In the robustness analysis below, we modify equation (19) to address several types of omitted variables bias.

5.2 Results

Table 7 reports the estimates of equation (19). The dependent variables are quality, $ln(horsepower/weight)$, log weight, and log price. In columns 1 through 3, the coefficients on the stringency variables are the change in WTP (in thousands of 2005 euros) for the dependent variable caused by a 1 percent change in stringency during the relevant period. All regressions include fixed effects for vehicle, segment by year, and country by year. Standard errors are bootstrapped to account for the fact that the stringency variable is computed after estimating equation (16).

Table 7: Effects of the Standards on Quality, Performance, Weight, and Price

	(1)	(2)	(3)	(4)
Dependent Variable	Quality	Log (Horsepower/Weight)	Log Weight	Log Price
Stringency Variable	firm-level	firm-level	firm-level	vehicle-level
Period 2 x Stringency	-5.227	1.87	-0.086	-0.009
	(1.747)	(0.450)	(0.291)	(0.012)
Period 3 x Stringency	-2.672	0.194	0.413	-0.021
	(2.332)	(0.711)	(0.416)	(0.013)
Joint F—test	5.186	16.932	1.999	5.465
P Value	0.006	0.000	0.136	0.004
Number of Observations	339,065	345,033	345,033	348,320
Adjusted R-squared	0.825	0.967	0.986	0.992

Notes: Each regression is weighted by registrations and includes vehicle fixed effects, country fixed effects, year fixed effects, country by year fixed effects and segment by year fixed effects. All columns use the firm-level stringency variable except for column 4, which uses the vehicle-level stringency variable. Standard errors are in parentheses, bootstrapped using 1,000 replications and clustered by model and trim. The dependent variable in columns 1 through 3 is normalized by $-\alpha$, and the variables are measured in thousands of 2005 euros.

Column 1 shows that the standards reduced quality in periods 2 and 3. According to the estimates, a 1 percent increase in stringency in period 2 reduced quality by 52 euros, which is statistically significant at the 1 percent level. The stringency coefficient for period 3 is negative but it is not statistically significant, which may reflect the fact that emissions decreased sharply in period 2 but were flat in period 3 (see Figure 2)

The standards slightly increased performance in period 2 and did not affect weight. In contrast, Klier and Linn (2015) find that the standards slightly reduced horsepower and weight at the end of the 2000s. Our results suggest that although the standards initially reduced horsepower and weight, this effect appears not to have persisted into the enforcement period. The fact that performance did not decrease in period 2 is consistent with the consumer preference estimates reported in the previous section. Recall that manufacturers can trade off horsepower for fuel economy, but doing so reduces consumer WTP for the vehicle if the consumers value the horsepower more highly than the fuel economy. The estimate preferences suggest that such a trade-off would substantially reduce WTP for the vehicle, and by more than the quality reduction reported in Table 7.

Column 4 shows that the standards did not affect vehicle prices. This likely reflects two opposing forces that roughly cancel one another. On the one hand, an increase in stringency causes the firm to adopt fuel-saving technology that reduces emissions, which raises production costs and vehicle prices. On the other hand, the lower quality reported in column 1 indicates a decline in demand, which reduces the price.[7]

Next, we assess the robustness of the estimates of equation (19). Because Table 7 shows that the standards affected quality primarily, henceforth we report results using only quality as the dependent variable; the appendix includes results for the other dependent variables. For convenience, column 1 of Table 8 repeats the baseline estimate from Table 7.

[7]Another possibility is that an increase in stringency causes manufacturers to reduce prices to encourage consumers to purchase vehicles with lower stringency. Reynaert (2019) finds that manufacturers did not pursue this strategy before 2012.

Table 8: Robustness Results for Quality

	Dependent variable is quality					
	(1)	(2)	(3)	(4)	(5)	(6)
Specification	Baseline	Include quality trends	Include horsepower trends	Include fuel consumption trends	Median regression	Include dummy for luxury cars
Period 2 x Stringency	-5.227	-5.376	-5.419	-6.126	-2.861	-10.833
	(1.747)	(1.725)	(1.788)	(1.735)	(0.007)	(3.564)
Period 3 x Stringency	-2.672	-2.647	-2.929	-2.454	-0.653	-4.953
	(2.332)	(2.379)	(2.502)	(2.301)	(0.012)	(4.734)
Joint F—test	5.186	5.764	5.419	7.587	162109.240	5.538
P value	0.006	0.003	0.004	0.001	0.000	0.004
N	339,065	339,065	339,065	339,065	339,065	353,725

Notes: Standard errors are in parentheses, bootstrapped using 1,000 replications and clustered by model and trim. All regressions use the firm-level stringency, and include vehicle fixed effects, segment by year fixed effects and country by year fixed effects. All regressions are weighted by registrations. Column 1 repeats column 1 from the previous table. Columns 2 through 4 include the change in the variable indicated in the row heading between 2005 and 2008, interacted with year fixed effects. Column 5 uses the median regressions. Columns 6 includes the dummy variable for luxury cars, which equals to one if the car has a price above the 99th percentile.

Above we noted that the main threat to identification would be an unobserved shock correlated with the stringency variable in the cross section and that varies over time. We take several approaches to modify the estimation equation and control for such omitted variables. First, we consider demand or supply shocks that occur in the first period and that persist across periods. To control for such shocks, we compute the changes in quality, horsepower, and fuel consumption rate between 2005 and 2008, and interact the changes with year fixed effects. Adding these interactions to the estimation equation controls for shocks correlated with the corresponding variables that occurred in the first period and persist into the subsequent periods. Columns 2 through 4 show that adding these variables does not affect the results.

Second, we allow for demand shocks correlated with stringency that occur during any period. Because stringency depends on the vehicle's fuel consumption rate and weight, such demand shocks could affect the WTP for fuel costs, performance, or weight. The appendix shows that allowing consumer demand for these attributes to vary over time does not affect the results. Moreover, Appendix Tables 17and 18 show that the results are similar if we compute quality from the range of demand models that were discussed in the previous section.

Third, we follow a common approach to assessing the magnitude of omitted variables bias, which is to consider whether the key independent variable (i.e., stringency) is correlated with observables, under the presumption that unobserved and omitted variables are likely to be correlated with observables. The appendix shows the results if we replace vehicle fixed effects with higher-level fixed effects, such as model-trim fixed effects. Reassuringly, the estimates are similar to the baseline, suggesting that stringency is not strongly correlated with observed vehicle attributes and reducing concerns about omitted variables bias.

We check that the results are not driven by the presence of outliers. Using a median regression in column 5 yields smaller estimates, but they remain statistically significant. Overall, quality is correlated with vehicle price, and some high-end vehicles have particularly high estimated quality. In our baseline regressions, we drop vehicles whose prices are above 99th percentile of the price distribution. Instead of dropping those vehicles, column 6 includes them and adds a dummy variable for them in the demand estimation and equation (19). Overall, the estimates vary across specifications, but we observe negative and statistically significant effects of the standards on quality in the second period.

Because of the vehicle fixed effects, the stringency coefficients are identified by within-vehicle changes in the dependent variables over time. This specification may omit quality changes caused by entry and exit of individual vehicles due to the standards. We can allow for this possibility by aggregating the data to the model level and reestimating equation (19). In this case, the stringency coefficients are identified by within-vehicle quality changes as well as model-level quality changes caused by entry and exit of vehicles belonging to a specific model. This does not include model entry and exit, but the appendix shows that such entry and exit are rare. Aggregating the data to the model-level causes the stringency coefficients to increase, especially for the third period. However, we treat these results with caution because unlike with the disaggregated results, when aggregating to the model level it is not possible to control for potential vehicle-level demand or supply shocks.

6 Welfare Analysis

We use the estimation results to quantify the consumer and social welfare effects of increasing stringency by 1 percent for each vehicle sold in the last year of our sample. We focus on consumer and social benefits, and abstract from compliance costs, which is outside the scope of the paper.

We consider a hypothetical 1 percent stringency increase for all manufacturers. We assume that manufacturers reduce emissions by reducing the fuel consumption rate of gasoline and diesel fuel vehicles. This assumption is consistent with the fact that reducing emissions rates of these vehicles, rather than introducing new plug-in vehicles, has accounted for nearly all of the emissions reductions observed through the end of the sample. Under this assumption, the higher stringency reduces fuel consumption rates and fuel costs by 1 percent.

The first row of Table 9 reports the consumer benefits of the lower fuel costs using two approaches to value the savings, which we use to bound the consumer benefits. First, we use estimated willingness to pay from the demand model. This is the appropriate welfare measure if the undervaluation reported in Table 5 arises from hidden costs, as discussed above. In that case, the undervaluation includes the disutility from the technologies, and using the estimated preference parameters accounts for these hidden costs.

Table 9: Consumer and Social Welfare Effects of a 1 Percent Stringency Increase (2005 euros per vehicle)

	Benefits from fuel cost savings and lower emissions	
Method	Fuel savings computed using preference estimates	Fuel savings computed using full value
Fuel cost savings	45.54	93.15
Social value of lower GHG emissions	7.39	
	Willingness to pay for changes in attributes and quality	
WTP for the quality change	-39.50	
WTP for the performance change	9.29	
WTP for the weight change	2.84	
Price change	2.90	
Sum	-24.47	
	Impact on vehicle weight and emissions target	
Percentage change in weight	0.16%	
Percentage change in target	0.09%	

Notes: The table reports the consumer and social welfare effects of increasing stringency by 1 percent. In the first panel, we use two methods to compute the benefits from fuel cost savings and the social value of lower emissions: the first method uses the estimated preference parameters, and the second uses the present discounted value of the fuel cost savings. The social value of the lower emissions uses the same assumptions on vehicle lifetimes and driving as those used to compute fuel cost savings, a 3 percent discount rate, and the US Environmental Protection Agency estimates of the social cost of carbon. The second part computes the willingness to pay for changes in attributes and quality due to a 1 percent increase in stringency. We use the estimates from Table 7 to compute the changes in attributes and quality. The third part computes the impact of the stringency increase on vehicle weight and the emissions target. The tighter standards increases the vehicle weight, which raises the emissions target.

The second approach is to assume that undervaluation reflects a consumer mistake, and that consumers incorrectly undervalue the fuel cost savings. In this case, consumers benefit from the full value of the fuel cost savings (see Train 2015). The second column of the table uses the value of fuel cost savings computed in Table 5, and with the same assumptions as in the first row of that table.

The second row reports the social benefits of the lower greenhouse gas emissions. The calculation uses the same assumptions on vehicle lifetimes and driving as those used for the fuel cost calculations. We use the US Environmental Protection Agency's estimates of the social cost of carbon, counting the global benefits and using a 3 percent discount rate.

The second panel reports changes in WTP for performance, weight, and quality, as well as the price change. Note that the weight and price changes are not statistically significant, but the point estimates are included in the welfare calculations. The net welfare change is -24 euros, which is 25 percent of the combined fuel cost and emissions benefits in the first panel.

These calculations assume that a 1 percent stringency increase translates to a 1 percent reduction in on-road fuel consumption and emissions. However, Mock et al. (2014), Tietge et al. (2015), and Reynaert and Sallee (2019) conclude that on-road fuel consumption reductions have been just half as large as the reductions in tested emissions rates because of gaming of the emissions tests. Accounting for this effect means that the quality reduction caused by tighter standards offsets 50 percent of the consumer and social benefits in Table 9.

7 Conclusions

In this paper, we have investigated the effects of regulating product attributes on other attributes and social welfare, focusing on the European passenger vehicle carbon dioxide emissions standards. We used a static model of a differentiated product market to derive two general results. First, regulating one product attribute may affect a wide range of other attributes. Whereas the literature on passenger vehicle fuel economy regulation has considered attributes that are technologically related to fuel economy, such as horsepower, we showed that many other attributes may be affected because of trade-offs in the product design process and demand correlations across attributes.

Second, we showed that in an imperfectly competitive market, firms can under or over provide attributes. Therefore, regulating one attribute could increase welfare by causing firms to increase other attributes. Because the consumer welfare effects of regulation depend on changes in all product attributes, estimating welfare effects of regulations requires accounting for all these changes.

The remainder of the paper focuses on European carbon dioxide emissions standards for passenger vehicles. We defined the residual quality of the vehicle as the consumer WTP for the vehicle excluding fuel costs, performance, and size. We estimated quality and willingness to pay for other attributes using a nested logit demand model, and we found that the standards have substantially reduced quality. In particular, the attribute changes offset at least 25 percent of the fuel cost and greenhouse gas benefits of the standards.

For context, there is an extensive literature on two inefficiencies of the standards: rebound and vintage differentiated regulation (e.g., Jacobsen and Van Benthem 2015). The rebound effect refers to the increase in driving caused by the fact that the standards reduce per-mile fuel costs, which undermines some of the greenhouse gas and fuel consumption benefits. Moreover, because the standards apply to new but not existing vehicles on the road, the standards are a form of vintage differentiated regulation and can delay scrappage of older and higher-emitting vehicles. The estimated welfare effects of attribute changes are roughly twice the magnitude of the rebound or scrappage effects reported in the literature. Future research could investigate the underlying sources of quality changes or consider whether standards in other countries have affected quality.

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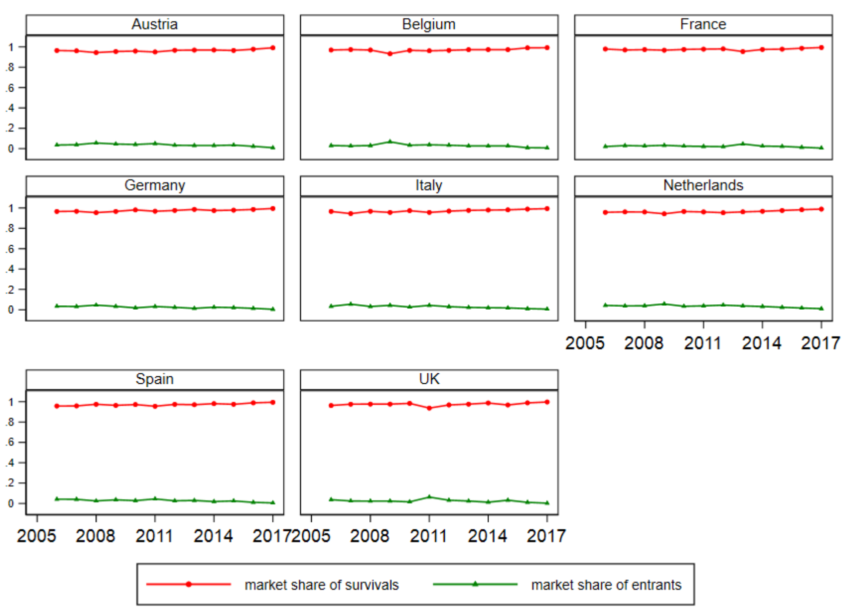
Appendix

Data construction

Our main data were obtained from IHS Markit. The data include registrations by month and vehicle, and we aggregated the data to country-year level for estimation. A vehicle is defined as a unique model, submodel, version, trim, market segment, number of doors, body type, fuel type (diesel, gasoline, hybrid, plug-in hybrid, or electric) and drive type (front-, rear-, all-wheel).

In the data, the names of models, body type, fuel type, and drive type are sometimes inconsistent across countries and years. We harmonize these variables across countries and years. Figure 5 shows the market shares of survivals and entrants after harmonizing the model names. Market shares of surviving vehicles are typically above 95 percent, and market shares of entering vehicles are typically less than 5 percent. Note that one of the demand specifications that we consider in the robustness analysis includes model by year fixed effects, which controls for changes in unobserved attributes due to entry and exit.

Figure 5: Market Shares of Surviving and Entering Models



First-stage results

Table 10: First-Stage Estimation Results for Preferred Nested Logit Model

	Price	Log share within segment-origin	Log origin share within segment
Sum length (same firm, different segments)	-2.70E-06	-3.60E-07	-8.80E-07
	(7.7e-07)	(4.1e-07)	(1.1e-07)
Sum length (different firm, same segment)	8.70E-06	6.10E-06	-3.90E-06
	(2.2e-06)	(1.4e-06)	(4.3e-07)
Sum width (same firm, different segments)	-4.30E-06	-7.10E-08	-7.00E-08
	(2.2e-06)	(1.0e-06)	(3.4e-07)
Sum width (different firm, same segment)	-4.10E-05	8.30E-06	1.30E-05
	(7.8e-06)	(5.3e-06)	(1.9e-06)
Sum height (same firm, different segments)	1.10E-05	4.50E-07	2.90E-06
	(2.2e-06)	(1.0e-06)	(3.1e-07)
Sum height (different firm, same segment)	9.60E-06	-1.90E-05	-8.40E-06
	(6.4e-06)	(4.9e-06)	(2.0e-06)
Sum engine cylinder (same firm, different segments)	1.40E-03	2.20E-04	-1.30E-05
	(2.5e-04)	(1.2e-04)	(3.5e-05)
Sum engine cylinder (different firm, same segment)	5.70E-03	-3.50E-03	1.90E-03
	(1.5e-03)	(8.5e-04)	(4.5e-04)
Sum length (same firm, different origins)	-7.90E-06	-6.00E-06	4.10E-06
	(2.2e-06)	(1.4e-06)	(4.0e-07)
Sum width (same firm, different origins)	4.40E-05	-8.40E-06	-1.20E-05
	(7.9e-06)	(5.3e-06)	(1.8e-06)
Sum height (same firm, different origins)	-1.70E-05	2.10E-05	8.30E-06
	(6.3e-06)	(4.8e-06)	(2.0e-06)
Sum length (different firms, same origin)	-1.30E-06	1.90E-06	-4.50E-07
	(5.7e-07)	(3.3e-07)	(1.6e-07)
Sum width (different firms, same origin)	-8.40E-06	3.50E-06	-8.50E-07
	(1.7e-06)	(7.6e-07)	(3.8e-07)
Sum height (different firms, same origin)	1.30E-05	-7.30E-06	3.80E-07
	(1.6e-06)	(8.1e-07)	(4.2e-07)
Sum engine cylinders (same firm, different origins)	-5.40E-03	3.10E-03	-2.50E-03
	(1.6e-03)	(8.5e-04)	(4.3e-04)
Sum engine cylinders (different firms, same origin)	5.80E-04	-1.30E-03	8.70E-04
	(2.6e-04)	(1.2e-04)	(8.7e-05)

Table 10: *(Continued)*

	Price	Log share within segment-origin	Log origin share within segment
Tax (1,000 2005 euros)	**4.00E-01**	**-7.00E-02**	**-6.90E-03**
	(7.1e-03)	**(3.7e-03)**	**(6.8e-04)**
Fuel cost (2005 euros/100 km)	**2.60E-01**	**-3.40E-01**	**-5.80E-03**
	(1.9e-02)	**(1.1e-02)**	**(1.3e-03)**
Log horsepower (hp)	**1.00E+01**	**-4.20E-01**	**4.80E-02**
	(1.6e-01)	**(6.9e-02)**	**(7.8e-03)**
Log weight (tonnes)	**2.20E+01**	**-1.20E+00**	**-5.00E-02**
	(6.4e-01)	**(2.7e-01)**	**(4.4e-02)**
Log size (m^3)	**4.40E-01**	**7.80E+00**	**5.20E-01**
	(6.0e-01)	**(4.0e-01)**	**(9.1e-02)**
EV/PHEV	**6.50E+00**	**-4.30E-01**	**-3.50E-03**
	(6.4e-01)	**(1.9e-01)**	**(1.3e-02)**
Gas/hybrid	**-2.00E+00**	**3.30E-01**	**5.20E-03**
	(6.2e-02)	**(3.8e-02)**	**(4.1e-03)**
Constant	**3.60E+01**	**-2.40E+01**	**-1.60E+00**
	(1.5e+00)	**(9.7e-01)**	**(2.2e-01)**
First-stage summary			
F-test of excluded instruments for price		20.05	16.55
F-test of excluded instruments for within-origin share			50.58
F-test of excluded instruments for share of origin in segment			58.37
Number of observations	341,725	341,725	341,659

Notes: The table reports the first-stage estimation results for our preferred demand estimation (Column 1 in Table 3 3). The Sanderson-Windmeijer multivariate F-test of the excluded variables concerns about weak instruments bias and underidentification in the case of multiple endogenous regressors and clustered standard errors.

Demand: Alternative specifications

Table 11: Alternative Nesting Structures

	Dependent variable is log market share			
	(1)	(2)	(3)	(4)
Nests	Segment and origin	Segment	Origin	Segment by origin
Price (1,000 2005 euros)	-0.088	-0.102	-0.08	-0.147
	(0.016)	(0.019)	(0.014)	(0.025)
Log within-segment share		0.742		
		(0.023)		
Log within-origin share			0.817	
			(0.020)	
Log within segment-origin share	0.773			0.606
	(0.018)			(0.019)
Log share of origin within segment	0.497			
	(0.029)			
Tax (1,000 2005 euros)	-0.006	-0.0004	0.012	0.006
	(0.006)	(0.007)	(0.005)	(0.010)
Fuel cost (2005 euros/100 km)	-0.063	-0.068	-0.045	-0.107
	(0.008)	(0.008)	(0.006)	(0.009)
Log horsepower	0.9	1.016	0.782	1.454
	(0.158)	(0.190)	(0.146)	(0.261)
Log weight (tonnes)	1.735	1.994	1.404	2.749
	(0.321)	(0.387)	(0.293)	(0.522)
Log size (m^3)	1.963	2.07	1.955	3.54
	(0.196)	(0.235)	(0.199)	(0.235)
Number of observations	341,659	341,659	341,659	341,659

Notes: The table reports estimation results for different nesting structures. Column 1 is repeated from column 3 in Table 3. Column 2 assumes a single nest corresponding to market segments, column 3 assumes a single nest corresponding to origin, and column 4 assumes a single nest corresponding to market segment by origin. Columns 2 through 4 are otherwise identical to column 1. Standard errors are in parentheses, clustered by model and trim.

Table 12: Estimated Own-Price Elasticities: Alternative Nesting Structures

	(1) Segment and origin	(2) Segment	(3) Origin	(4) Segment by origin
Median	-7.41	-7.59	-8.42	-7.18
Mean	-7.37	-7.55	-8.37	-7.13
Standard deviation	0.87	0.88	0.97	0.84
5th percentile	-8.90	-9.11	-10.09	-8.62
95th percentile	-5.80	-5.95	-6.58	-5.61

Notes: Each column reports results using preference parameter estimates from the corresponding column in Table 11. The calculations are otherwise identical to those in Table 4.

Table 13: Willingness to Pay and Valuation Ratio: Alternative Nesting Structures

	(1) Segment and origin	(2) Segment	(3) Origin	(4) Segment by origin
Willingness to pay for 1 percent change (2005 euros)				
Fuel cost decrease	46	42	36	46
Horsepower/weight increase	102	100	98	99
Weight increase	197	195	176	187
Size increase	223	203	244	241
Valuation ratio				
15 years, r = 0.06	0.49	0.46	0.38	0.50
15 years, r = 0.03	0.41	0.38	0.32	0.42
10 years, r = 0.06	0.65	0.60	0.51	0.66

Notes: Each column reports results using preference parameter estimates from the corresponding column in Table 11. The calculations are otherwise identical to those in Table 5.

Table 14: Demand: Alternative Specifications

	Dependent variable is log market share							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price (1,000 2005 euros)	-0.088	-0.118	-0.07	-0.116	-0.093	-0.043	-0.090	-0.088
	(0.016)	(0.031)	(0.023)	(0.018)	(0.017)	(0.013)	(0.016)	(0.004)
Log within segment-origin share	0.773	0.764	0.761	0.771	0.581	0.744	0.761	0.773
	(0.018)	(0.023)	(0.019)	(0.019)	(0.029)	(0.021)	(0.019)	(0.005)
Log share of origin within segment	0.497	0.514	0.507	0.489	0.51	0.474	0.482	0.497
	(0.029)	(0.035)	(0.027)	(0.031)	(0.036)	(0.032)	(0.030)	(0.009)
Tax (1,000 2005 euros)	-0.006	-0.001	-0.017	0.004	-0.014	-0.02	-0.006	-0.006
	(0.006)	(0.011)	(0.009)	(0.007)	(0.006)	(0.005)	(0.006)	(0.001)
Fuel cost (2005 euros/100 km)	-0.063	-0.063	-0.074	-0.049	-0.119	-0.071	-0.06	-0.063
	(0.008)	(0.012)	(0.010)	(0.008)	(0.010)	(0.008)	(0.009)	(0.002)
Log horsepower/weight	0.9	0.942	0.562	1.118	0.899	0.452	0.841	0.9
	(0.158)	(0.248)	(0.197)	(0.179)	(0.172)	(0.136)	(0.165)	(0.038)
Log weight (tonnes)	1.735	2.274	1.234	2.561	1.753	0.655	1.631	1.735
	(0.321)	(0.616)	(0.453)	(0.400)	(0.338)	(0.247)	(0.357)	(0.082)
Log size (m^3)	1.963	2.238	2.039	2.21	3.53	2.214	2.126	1.963
	(0.196)	(0.271)	(0.202)	(0.222)	(0.298)	(0.218)	(0.253)	(0.061)
Log number in nest					-0.188			
					(0.029)			
Within-nest distance across attributes					-0.046			
					(0.012)			
Luxury						0.551		
						(0.162)		
Model—body type fixed effect	X		X	X	X	X	X	X
Model—body type—trim fixed effect		X						
Trim fixed effect			X					
Model—year fixed effect				X				
Segment—year fixed effect	X	X	X	X	X	X	X	X
Number of observations	341,659	339,821	341,286	341,378	341,655	356,479	341,659	341,659

Notes: All regressions include country by year fixed effects. Column 1 repeats the specification in column 3 of Table 3. Column 2 includes model by body type by trim fixed effects. Column 3 includes model by body type fixed effects and trim fixed effects. Column 4 includes model by body type and model by year fixed effects. Column 5 includes the log number of within-nest vehicles and the distance variable from Houde and Spurlock (2015). Column 6 includes a dummy variable for luxury cars. Column 7 allows the preference parameters to vary across time. And preference parameters shown in column 7 are the averages across time. Columns 2 through 8 are otherwise identical to column 1. Standard errors are in parentheses, clustered by model and trim except for column 8, which reports standard errors that are robust to heteroskedasticity.

Table 15: Estimated Own-Price Elasticities: Other Demand Models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Median	-7.41	-9.61	-5.61	-9.69	-4.27	-3.26	-7.21	-7.41
Mean	-7.37	-9.56	-5.57	-9.63	-4.25	-3.27	-7.17	-7.37
Standard deviation	0.87	1.12	0.65	1.13	0.49	0.43	0.84	0.87
5th percentile	-8.90	-11.55	-6.74	-11.64	-5.13	-4.10	-8.66	-8.90
95th percentile	-5.80	-7.52	-4.39	-7.58	-3.35	-2.58	-5.64	-5.80

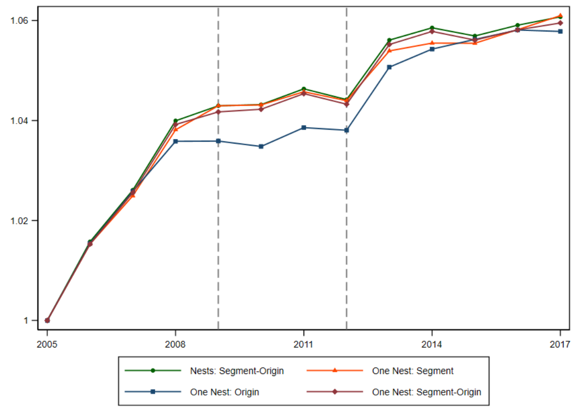
Notes: Each column reports results using preference parameter estimates from the corresponding column in Table 14. The calculations are otherwise identical to those in Table 4.

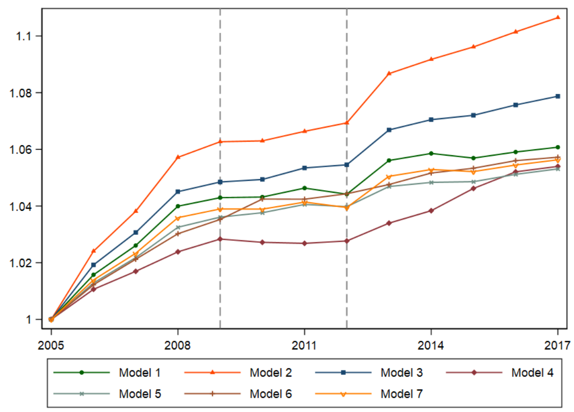
Table 16: Willingness to Pay and Valuation Ratio: Other Demand Models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Willingness to pay for 1 percent change (2005 euros)								
Fuel cost decrease	46	34	67	27	82	105	42	46
Horsepower/weight increase	102	80	80	96	97	105	93	102
Weight increase	197	193	176	221	188	152	181	197
Size increase	223	190	291	191	380	515	236	223
Valuation ratio								
15 years, r = 0.06	0.49	0.37	0.72	0.29	0.88	1.13	0.46	0.49
15 years, r = 0.03	0.41	0.31	0.61	0.24	0.73	0.95	0.38	0.41
10 years, r = 0.06	0.65	0.48	0.95	0.38	1.16	1.49	0.60	0.65

Notes: Each column reports results using preference parameter estimates from the corresponding column in Table 14. The calculations are otherwise identical to those in Table 5.

Figure 6: Quality Index: Alternative Demand Models





Notes: The figure plots the estimated quality index by year, where quality is computed similarly to Figure 4. The top panel uses estimates from Table 11, and the lower panel uses estimates from Table 14.

Quality regressions: Alternative specifications

Table 17: Robustness Results for Quality: Alternative Nesting Structures

	Dependent variable is quality			
	(1)	(2)	(3)	(4)
	Nests: Segment-Origin	One Nest: Segment	One Nest: Origin	One Nest: Segment-Origin
Period 2 x Stringency	-5.227	-4.064	-4.669	-3.744
	(1.747)	(1.545)	(1.488)	(1.490)
Period 3 x Stringency	-2.672	-2.457	-2.931	-1.214
	(2.332)	(2.024)	(2.732)	(2.113)
Joint F—Test	5.186	3.834	6.744	3.845
P Value	0.006	0.022	0.001	0.021
N	339,065	339,065	339,065	339,065

Notes: Standard errors are in parentheses, bootstrapped using 1,000 replications and clustered by model and trim. All regressions include vehicle fixed effects, segment by year fixed effects and country by year fixed effects. Each column uses the quality computed from different nesting structures. Column 1 replicates our baseline results assuming a multi-level nested logit model as in the Column 1 of Table 11 11. Column 2-4 assume a one-level nesting structure, and each column assumes the same demand model as in the corresponding column in Table 11 11.

Table 18: Robustness Results for Quality: Alternative Demand Specifications

	Dependent variable is quality							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Baseline	FE2	FE3	FE4	Congestion effect	Dummy for luxury cars	Time-variant preference parameters	Model—level quality
Period 2 x Stringency	-5.227	-3.484	-6.418	-3.681	-3.194	-10.833	-4.869	-6.160
	(1.747)	(1.373)	(2.195)	(1.399)	(2.210)	(3.564)	(1.730)	(3.491)
Period 3 x Stringency	-2.672	-2.045	-3.232	-2.12	0.203	-4.953	-2.967	-13.793
	(2.332)	(1.838)	(2.908)	(1.881)	(3.076)	(4.734)	(2.351)	(3.919)
Joint F—Test	5.186	3.573	5.030	3.829	1.948	5.538	4.257	8.168
P Value	0.006	0.028	0.007	0.022	0.143	0.004	0.014	0.0003
N	339,065	337,693	338,769	338,807	339,062	353,725	339,065	16,929

Notes: Standard errors are in parentheses, bootstrapped using 1,000 replications and clustered by model and trim. All regressions except the column 8 include vehicle fixed effects, segment by year fixed effects and country by year fixed effects. Column 1 replicates the baseline results in Table 77. Columns 2-7 use the quality computed from different specifications of the demand model as in the corresponding column in Table 14 14. All columns assume a multi-level nested logit model for demand. In column 2-4, the demand model includes different fixed effects. Column 5 includes the congestion effect in the demand model. Column 6 uses the full sample instead of dropping cars whose prices are above 99th percentile of the price distribution, and it includes a dummy for those luxury cars. Column 7 allows the preference parameters to vary across time. Column 8 aggregates the data to the model by country by year level, and regresses the model-level quality on the interactions of the firm-level stringency with time periods as well as country by year fixed effects and the model fixed effects.

Table 19: Robustness Results for Log (Horsepower/Weight): Other Specifications

	Dependent variable is log horsepower to weight					
	(1)	(2)	(3)	(4)	(5)	(6)
Specification	Baseline	Include quality trends	Include horsepower trends	Include fuel consumption trends	Median regression	Include dummy for luxury cars
Period 2 x Stringency	1.87	1.863	1.497	1.878	1.924	3.844
	(0.450)	(0.447)	(0.489)	(0.476)	(0.000)	(0.921)
Period 3 x Stringency	0.194	0.236	-0.267	0.554	0.902	0.457
	(0.711)	(0.706)	(0.756)	(0.802)	(0.000)	(1.449)
Joint F—test	16.932	16.738	11.168	13.867	5.69E+12	16.993
P value	0.000	0.000	0.000	0.000	0.000	0.000
N	345,033	345,033	345,033	345,033	345,033	360,270

Notes: Standard errors are in parentheses, bootstrapped using 1,000 replications and clustered by model and trim. Each column replicates the same regression as the corresponding column in table 8 except the dependent variable is log of the ratio of horsepower and weight.

Table 20: Robustness Results for Log Weight: Other Specifications

	Dependent variable is log weight					
	(1)	(2)	(3)	(4)	(5)	(6)
Specification	Baseline	Include quality trends	Include horsepower trends	Include fuel consumption trends	Median regression	Include dummy for luxury cars
Period 2 x Stringency	-0.086	-0.102	-0.059	0.079	0.097	-0.17
	(0.291)	(0.290)	(0.311)	(0.307)	(0.000)	(0.595)
Period 3 x Stringency	0.413	0.415	0.572	0.418	0.348	0.861
	(0.416)	(0.413)	(0.437)	(0.470)	(0.000)	(0.848)
Joint F—test	1.999	2.161	2.949	0.634	8.07E+6	2.056
P value	0.136	0.115	0.052	0.531	0.000	0.128
N	345,033	345,033	345,033	345,033	345,033	360,271

Notes: Standard errors are in parentheses, bootstrapped using 1,000 replications and clustered by model and trim. Each column replicates the same regression as the corresponding column in table 8 except the dependent variable is log weight.

Table 21: Robustness Results for Log Price: Other Specifications

	Dependent variable is log price					
	(1)	(2)	(3)	(4)	(5)	(6)
Specification	Baseline	Include quality trends	Include horsepower trends	Include fuel consumption trends	Median regression	Include dummy for luxury cars
Period 2 x Stringency	-0.0093	-0.0097	-0.009	-0.0088	-0.0004	-0.0094
	(0.0121)	(0.0119)	(0.0122)	(0.0123)	(0.0000)	(0.0120)
Period 3 x Stringency	-0.0207	-0.0212	-0.0206	-0.0188	-0.0086	-0.0207
	(0.0126)	(0.0124)	(0.0127)	(0.0130)	(0.0000)	(0.0124)
Joint F—test	5.465	5.540	5.558	4.029	1.75E+5	5.652
P value	0.004	0.004	0.004	0.018	0.000	0.004
N	348,320	348,320	348,320	348,320	348,320	363,635

Notes: Standard errors are in parentheses, bootstrapped using 1,000 replications and clustered by model and trim. Each column replicates the same regression as the corresponding column in table 8 except the dependent variable is log price.

Table 22: Robustness Results for Quality: Different Fixed Effects

	Dependent variable is quality								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fixed Effects	model-trim	model-trim-body type	model-trim-body type-fuel type	model-trim-body type-fuel type-segment	model-trim-body type-fuel type-segment-transtype	model-trim-bodytype-fuelcat-segment-transmission type-drive type	model-trim-bodytype-fuelcat-segment-transmission type-drive type-number of doors	model-trim-bodytype-fuelcat-segment-transmission type-drive type-number of doors-number of engine cylinders	vehicle
Period 2 x Stringency	-5.382	-5.177	-5.585	-5.506	-5.699	-5.825	-5.448	-5.128	-5.227
	(1.796)	(1.766)	(1.756)	(1.751)	(1.768)	(1.771)	(1.740)	(1.727)	(1.747)
Period 3 x Stringency	-6.902	-5.882	-5.478	-5.161	-4.836	-5.591	-4.587	-2.448	-2.672
	(2.731)	(2.713)	(2.620)	(2.633)	(2.594)	(2.622)	(2.378)	(2.293)	(2.332)
Stringency	-46.439	-38.021	-39.963	-40.027	-46.769	-46.972	-47.102	-50.421	
	(4.622)	(5.346)	(16.740)	(16.681)	(10.536)	(10.580)	(10.548)	(7.833)	
Joint F—Test	5.021	4.476	5.131	4.981	5.201	5.423	4.903	4.873	5.186
P Value	0.007	0.011	0.006	0.007	0.006	0.004	0.007	0.008	0.006
N	336,480	336,295	336,036	335,987	335,384	335,100	334,947	334,657	339,065

Notes: A vehicle is defined as a unique model, submodel, version, trim, market segment, number of doors, body type, fuel type (diesel, gasoline, hybrid, plug-in hybrid, or electric), transmission type, number of engine cylinders, number of gears, and drive type (front-, rear-, or all-wheel). Each column includes the fixed effects indicating in the header, while controlling for all other variables that are used for defining a vehicle. All regressions include the country-year fixed effects, segment-year fixed effects, and use the firm-level stringency.

Table 23: Robustness Results for Log (Horsepower/Weight): Different Fixed Effects

	Dependent variable is log (horsepower/weight)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fixed Effects	model-trim	model-trim-body type	model-trim-body type-fuel type	model-trim-body type-fuel type-segment	model-trim-body type-fuel type-segment-transtype	model-trim-bodytype-fuelcat-segment-transmission type-drive type	model-trim-bodytype-fuelcat-segment-transmission type-drive type-number of doors	model-trim-bodytype-fuelcat-segment-transmission type-drive type-number of doors-number of engine cylinders	vehicle
Period 2 x Stringency	0.921	0.916	1.524	1.533	1.421	1.397	1.391	1.52	1.87
	(0.622)	(0.629)	(0.581)	(0.584)	(0.598)	(0.606)	(0.602)	(0.658)	(0.450)
Period 3 x Stringency	-2.03	-1.848	-1.404	-1.36	-1.512	-1.411	-1.495	-1.192	0.194
	(0.973)	(1.000)	(0.929)	(0.934)	(0.993)	(0.994)	(0.948)	(1.056)	(0.711)
Stringency	8.671	8.364	-6.322	-6.319	-3.651	-3.567	-3.461	-3.108	
	(0.735)	(0.794)	(1.629)	(1.625)	(1.133)	(1.083)	(1.081)	(1.214)	
Joint F—Test	6.592	5.843	8.487	8.367	7.635	7.134	8.594	11.246	16.932
P Value	0.001	0.003	0.000	0.000	0.000	0.001	0.000	0.000	0.000
N	341,748	341,553	341,292	341,233	340,616	340,329	340,175	339,882	345,033

Notes: A vehicle is defined as a unique model, submodel, version, trim, market segment, number of doors, body type, fuel type (diesel, gasoline, hybrid, plug-in hybrid, or electric), transmission type, number of engine cylinders, number of gears, and drive type (front-, rear-, or all-wheel). Each column includes the fixed effects indicating in the header, while controlling for all other variables that are used for defining a vehicle. All regressions include the country-year fixed effects, segment-year fixed effects, and use the firm-level stringency.

Table 24: Robustness Results for Log Weight: Different Fixed Effects

	Dependent variable is log weight								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fixed Effects	model-trim	model-trim-body type	model-trim-body type-fuel type	model-trim-body type-fuel type-segment	model-trim-body type-fuel type-segment-transtype	model-trim-bodytype-fuelcat-segment-transmission type-drive type	model-trim-bodytype-fuelcat-segment-transmission type-drive type-number of doors	model-trim-bodytype-fuelcat-segment-transmission type-drive type-number of doors-number of engine cylinders	vehicle
Period 2 x Stringency	0.043	0.081	0.148	0.144	0.145	0.127	0.074	0.035	-0.086
	(0.298)	(0.306)	(0.281)	(0.282)	(0.286)	(0.286)	(0.285)	(0.288)	(0.291)
Period 3 x Stringency	1.295	1.36	1.292	1.292	1.314	1.227	0.936	0.577	0.413
	(0.448)	(0.438)	(0.415)	(0.417)	(0.424)	(0.415)	(0.390)	(0.419)	(0.416)
Stringency	-1.568	0.861	-1.134	-1.134	-0.894	-0.929	-0.929	-1.000	
	(0.131)	(0.155)	(0.174)	(0.174)	(0.187)	(0.144)	(0.156)	(0.129)	
Joint F—Test	8.0951	8.8564	8.3022	8.3092	8.6189	8.0720	6.4531	2.3125	1.9987
P Value	0.0003	0.0001	0.0002	0.0002	0.0002	0.0003	0.0016	0.0991	0.1356
N	341,748	341,553	341,292	341,233	340,616	340,329	340,175	339,882	345,033

Notes: A vehicle is defined as a unique model, submodel, version, trim, market segment, number of doors, body type, fuel type (diesel, gasoline, hybrid, plug-in hybrid, or electric), transmission type, number of engine cylinders, number of gears, and drive type (front-, rear-, or all-wheel). Each column includes the fixed effects indicating in the header, while controlling for all other variables that are used for defining a vehicle. All regressions include the country-year fixed effects, segment-year fixed effects, and use the firm-level stringency.

Table 25: Robustness Results for Log Price: Different Fixed Effects

	Dependent variable is log price								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fixed Effects	model-trim	model-trim-body type	model-trim-body type-fuel type	model-trim-body type-fuel type-segment	model-trim-body type-fuel type-segment-transtype	model-trim-bodytype-fuelcat-segment-transmission type-drive type	model-trim-bodytype-fuelcat-segment-transmission type-drive type-number of doors	model-trim-bodytype-fuelcat-segment-transmission type-drive type-number of doors-number of engine cylinders	vehicle
Period 2 x Stringency	-0.012	-0.011	-0.01	-0.01	-0.01	-0.01	-0.011	-0.009	-0.009
	(0.009)	(0.009)	(0.011)	(0.011)	(0.012)	(0.012)	(0.013)	(0.013)	(0.012)
Period 3 x Stringency	-0.02	-0.02	-0.021	-0.02	-0.02	-0.02	-0.022	-0.02	-0.021
	(0.009)	(0.009)	(0.013)	(0.013)	(0.014)	(0.014)	(0.015)	(0.014)	(0.013)
Stringency	0.02	0.018	0.017	0.016	0.015	0.014	0.016	0.031	
	(0.008)	(0.008)	(0.012)	(0.012)	(0.014)	(0.014)	(0.016)	(0.021)	
Joint F—Test	3.042	3.007	2.619	2.448	2.238	2.220	2.120	5.409	5.465
P Value	0.048	0.049	0.073	0.086	0.107	0.109	0.120	0.004	0.004
N	345,752	345,559	345,300	345,250	344,642	344,364	344,212	343,925	348,320

Notes: A vehicle is defined as a unique model, submodel, version, trim, market segment, number of doors, body type, fuel type (diesel, gasoline, hybrid, plug-in hybrid, or electric), transmission type, number of engine cylinders, number of gears, and drive type (front-, rear-, or all-wheel). Each column includes the fixed effects indicating in the header, while controlling for all other variables that are used for defining a vehicle. All regressions include the country-year fixed effects, segment-year fixed effects, and use the firm-level stringency.