THE DRIVERS BEHIND DIFFERENCES BETWEEN OFFICIAL AND ACTUAL VEHICLE EFFICIENCY AND CO_2 EMISSIONS

Abstract

Literature explaining the gap between official and actual vehicle efficiency and CO_2 emissions focuses on descriptive analysis to calculate this gap without examining causality. In this paper, we explore this discrepancy in detail by drawing on a database from Emissions Analytics Ltd. that provides on-road emissions measurement on more than 650 vehicles in the period 2010-2017. The data reveal concerning results: firstly, the gap in data relates both to hybrid vehicles (that are supposedly 'more fuel-efficient') and to the biggest selling vehicles (medium-sized cars). Secondly, the average deviation rate increased prior to 2015, but decreased following 'Dieselgate'. The Volkswagen scandal threw light on the discretionary behaviour of manufacturers on this question and highlighted how weak the official tests are: and this in turn points to a regulatory and compliance problem. In other words, the interpretation of the results suggests that after several years of adaptation to the protocol and the corresponding test (but no translated in real consumption), manufacturers have taken measures to reduce the divergence in real terms after the scandal.

Keywords: Emissions; Air pollution; Vehicle Efficiency; Dieselgate
JEL Classification: K32; O13; O33; Q53

1. Introduction

The differences between CO_2 emission and consumption[1] data from official test results and actual 'on the road' figures are well-established and, considering the weight from cars of total European Union emissions of CO_2 (European Commision fixed this percentage around 12%), this is not an insignificant issue. Moreover, this is not only a problem in Europe. In the US, as indicated by Green *et al.* 2015, "differences between consumers' experiences with fuel economy and label values have been a source of discussion and dissatisfaction with the official government ratings since shortly after they were first introduced in 1975 (McNutt et al., 1978)".[2] Other references for the U.S. that show differences (ranging from 10% to 20%) between test cycle and on-road fuel economy are McNutt et al. (1982), Schneider et al. (1982), Rykowski et al. (2005), Huo et al. (2011, 2012), and Greene et al. (2015).

The International Council on Clean Transportation (ICCT) annually publish a report comparing real world and official figures on fuel consumption and CO_2 emissions for passenger cars in Europe (the first study was Mock et al. 2013, and the last one is Tietge *et al.*, 2017b). This database includes nearly 1.1 million vehicles from eight countries and 14 data sources. The conclusion is unambiguous: the divergence between type-approval and real-world emission value has been increasing over time, from approximately 9% in 2001 to 42% in 2016 (although they found in the last report the first sign of slowdown in the growth of the gap).

The explanation of the gap, according to the literature, seems to be the type-approval process based on the New European Driving Cycle (NEDC), that includes measurements of CO2 emissions and fuel consumption of vehicles under controlled laboratory conditions. In Europe, the certification on pollutant emissions has been based on the NEDC and the respective test protocol,[3] which consist, for all Euro 3 and later light-duty

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[1] We use both terms 'Fuel consumption' and 'CO_2 emissions' interchangeably in this paper. As pointed out by Fontaras *et al.* (2017a), the former is indirectly derived from the measurement of the latter, hydrocarbons (HC) and carbon monoxide (CO) emissions measured during the certification tests (by taking into account the carbon mass balance in the exhaust gas). Moreover, Euro 5 and 6 have low tailpipe CO and HC emission levels, contributing to approximately 1% of the fuel consumption. In short, during vehicle's operations, CO_2 emissions can be considered to be proportional to the fuel consumed. We also empirically assess these results in section 3 of this paper.

[2] Actually, the US Environmental Protection Agency (EPA) provides "test cycle" and "label" values, i.e., two sets of fuel economy estimates.

[3] Regulation No 83 of the Economic Commission for Europe of the United Nations (UN/ECE)

vehicles, in a cold-start driving cycle used for emission type-approval (Euro 3 is the European Emission Standard regulated by Directive 98/69/EC of the European Parliament and of the Council of 13 October 1998 relating to measures to be taken against air pollution by emissions from motor vehicles and amending Council Directive 70/220/EEC).

The Worldwide Harmonized Light Vehicle Test Procedure (WLTP) and the corresponding Worldwide Harmonized Light Vehicle Test Cycle (WLTC) have both been progressively introduced since September 2017 in order to address divergences with the NEDC results (although European Commission targets with WLTP references will be established in 2020). The European Union was the first to introduce the test procedure, followed by other countries as Japan (2018) and will be implemented also by China, India, South Korea. The US will be expected to evaluate the possible benefits before deciding whether to adopt it or not (Fontaras *et al.* 2017a).

Lower fuel consumption and CO_2 emissions under the former certification procedure can be attributed to a series of factors such as the actual driving profile of the NEDC which is of low transience, the narrow boundary conditions of the certification test (e.g. a temperature range of 20 – 30 deg. C.; restricted use of auxiliaries; lower vehicle mass than during actual driving), generating a systematic underreporting and biased recording of CO_2 emissions compared to real world ones (Fontaras *et al.* 2017b). The comparison reveals the greater accuracy of the WLTP data with real-world data; but the gap does not disappear. The same authors carry out a recent comparison between the two tests and real-world conditions.

Divergences vary by segment, manufacturer, fuel, transmission, and similar. The 'flexibilities' permitted by the NEDC can be exploited to obtain favorable results and this seems to be the main reason for the divergences (Stewart *et al.*, 2015; Kühlwein, 2016; Tietge *et al.*, 2017a). Taking into account the fact that CO_2 effects are not the same in the laboratory as in real-world driving conditions, because of vehicle technologies or use, Fontaras *et al.* (2017a) define 'flexibilities' as "specific provision or interpretation of the certification procedure or an absence of such a provision or clear interpretation that, if applied, results in the measurement of lower CO_2 emission values (they also summarize the factors relating to the flexibility: use of inertia classes, short test cycle, non-realistic vehicle preconditioning…)".

Despite the improvement of emission and consumption figures for whole European Union,[4] the actual improvement caused by fuel-saving technologies has not been clearly established because the evidence seems to point to improvements in test-oriented optimization and practices.

Although some consequences could be covered by reports (for example ICCT reports), these divergences have important consequences for policies, and there are several reasons to strive to achieve more accuracy (also collected by ICCT reports). Firstly, and most evidently, is for society as a whole because of climate change and the need to reduce fossil fuel dependence. But there are also a number of effects for each sector, e.g., passengers might be misled because the divergences between official and actual figures of consumption or because environmental targets do not match.

Moreover, it is important to note that there are implications for manufacturers and goverments (Tietge *et al.*, 2017a): for the former, if manufacturers report more accurate CO_2 values they face possible penalties; and for the last, most of EU member states base vehicle taxation schemes on type-approval CO_2 emission values. Finally, there are industry effects, such as a slowdown in innovation because it seems to be unnecessary given the small potential reduction (Fontaras *et al.* 2017a).

Therefore, the objective of this paper is to analyze which variables affect this gap. In particular, by drawing on on-road data from Emissions Analytics Ltd., this study seeks to establish, for example, whether the gap is uniform or whether there are differences across brands or types. It is clear that manufacturers take advantage of the 'flexibility', but is this response uniformly distributed? Are some manufacturers "cleverer" than others? Are there certain types of cars that show a greater gap, for example, or a certain fuel?

As far as we know, this is the first time that such a multivariate analysis has been undertaken in order to define which factors underpin the differences between on-road and official CO_2 emissions. The relevant literature has only partially addressed this issue, as we illustrate in section 2 (the papers that have employed multivariate analysis have missed some important variables). Section 3 explains the data and provides some descriptive statistics. The multivariate analysis and discussion of results are included in section 4. Finally, section 5, details our main conclusions that provide responses to the questions

[4] The European Environment Agency, EEA, confirmed in 2013 the achievement of specific objectives, with an average EU emissions of all manufacturers equal to 123.4 g CO_2, for example, being below the 2015 target of 130 gCO_2 (EEA, 2014a). In 2017, the provisional figure was 118.5 gCO_2 (https://ec.europa.eu/clima/policies/transport/vehicles/cars_en#tab-0-0).

mentioned in the previous paragraph: the divergence between official and on-road CO_2 emissions is not random and the results point to the central role of the manufacturer.

2. Literature review

There are a number of academic studies that compare reported data and real-world figures for CO_2 emissions and consumption. However, most focus on test accuracy in a descriptive and/or engineering way (experimental analysis). Table 1 reviews the evolution of this gap between the laboratory and the real-world, and the main characteristics related to this study, in order to compare them.

However, there are a number of papers not included in Table 1 that are more related to this work, which use multivariate analysis in order to explain the causality of the gap. First, Tietge *et al* (2017a) validates and refines a regression model developed by Mellios *et al.*, (2011) and Ntziachristos *et al.* (2014) for the estimation of real-world fuel consumption, which is employed in policy-relevant applications. On the one hand, this regression model is employed to estimate real-world fuel consumption of new European passenger cars for the European Environment Agency (EEAb, 2014). On the other hand, it is employed to estimate real-world CO2 emissions of passenger cars using the COPERT model (Tietge *et al.* 2017a). However, there are similar regression models (for example, see Greene et al., 2015 or Ligterink *et al.*, 2016). COPERT is a software tool used world-wide to calculate air pollutant and greenhouse gas emissions from road transport (http://emisia.com/products/copert). It is used by several EU states for inventories and in policy relevant studies (EEA, 2016; Kioutsioukis *et al.*, 2010 and EEA, 2011).

Table 1: Evolution of the gap between real world and type-approval vehicle CO_2 emissions, and the main characteristics

Reference	Real world - Certification value CO_2 shortfall	Observations and period	Covariates considered	Estimation method
ECMT (2005)[5]	12%	-	-	Descriptive
Zallinger *et al.* (2009)	19%	n.a.	n.a.	n.a.
Weiss *et al.* (2011)	21%	12 (2004-2010)	fuel; route characteristics; vehicle type; ambient conditions	Descriptive
Mellios *et al.* (2011)	25%	68 (2005-2008)	mass; rated power (engine capacity)[6]	Regression
Fontaras and Dilara (2012)	22.5%	2000-2010	fuel type	data + vehicle dynamics model + stochastic techniques
Ligterink *et al.* (2013)	30%	9 (2010-2013)	vehicle type; route characteristics	Descriptive
Mock *et al.* (2014)	38%	>500,000 (2001-2013)	it depends on the source (segment, manufacturer, fuel, transmission type,…)	Descriptive
Ligterink and Eijk (2014)	44%	>250,000 (excluding plug-ins) (2004-2014)	fuel type	Descriptive
Tietge *et al.* (2015)	40%	≈500,000 (2001-2014)	it depends on the source (segment, manufacturer, fuel, transmission type,…)	Descriptive
Tietge *et al.* (2016)	42%	≈1,000,000 (2001-2015)	it depends on the source (segment, manufacturer, fuel, transmission type,…)	Descriptive
Tietge *et al.* (2017b)	42%	≈1,100,000 (2001-2015)	it depends on the source (segment, manufacturer, fuel, transmission type,…)	Descriptive

Source: Updated from Fontaras *et al.* (2017a) and own elaboration. We have extracted specific data from the aforementioned papers and reported information that is relevant to this research, in order to compare studies.

Mellios *et al.* (2011) sought to explain type-approval fuel consumption through characteristic variables (i.e. mass, engine capacity, rated power, and power to mass ratio), using a database of only 68 cars in the period 2005-2008 and various model specifications. However, the main objective of Mellios *et al.* (2011) is different to that of present work, because of the variable involved (i.e. the gap; not the type-approval figures). Ntziachristos

[5] This study analyzed the literature and determined that the major factors affecting shortfall included: low ambient temperatures; short trips; driving behaviors; highway; speed; and use of the air conditioner (other factors such as topography or road conditions have less impact). Next, this research analyzed effects on fuel economy, alternative driving cycles and shortfall data. Finally the report focused on technologies to improve the fuel economy of gasoline and diesel vehicles, and concluded by identifying technology and policies to promote technologies that improve fuel economy.

[6] Variables used in the regression model.

et al. (2014), using a database of 924 passenger cars (hybrid cars are not included) from Europe, also explain real figures versus type-approval in-use fuel consumption, by controlling for engine capacity and mass and power with various model specifications. They find a gap of 11% and 16% (for petrol and diesel, respectively).

As noted above, Tietge *et al* (2017a) drew on these two papers and used a least square model with three parameters (type-approval fuel consumption value, engine capacity, and vehicle mass), to refine the model of Ntziachristos *et al.* (2014). They employed a database of 130,000 vehicles (gasoline and diesel), and added two more factors: temporal trend (through year dummy variables) and company vehicles. These two aspects allowed them to capture the increasing gap over time, and the greater gap because of company cars (i.e. "vehicles owned by legal persons").

Greene *et al.* (2015) analysed the American market. They collected data from the joint DOE/EPA website during 1984-2015,[7] where customers had uploaded data from their own vehicles (75,000 observations). The objective is to evaluate the effectiveness of the government's estimates through the estimation of the data upload from drivers through test figures and some variables (including manufacturer, temporal trend and vehicle type). Because of this, as Mellios *et al.* (2011), they do not estimate the gap, but an approximation of it because the dependent variable is not the gap itself. Specifically, their results showed a gap of 15%, 7%-10% and 22%-27% for gasoline, diesel and gasoline-electric hybrid from test cycle figures.

Ligterink *et al.* (2016) published an extensive engineering report for the European Commission that analyzed the factors which could explain the divergences through different regression models from several data sources (they use data from 2000 to 2015). Specifically, they identify the factors that affect the actual emissions data, and they also make the official emissions an independent variable (in addition to some of the vehicles' physical variables). Furthermore they analyzed the trend of the data (actually they analyze the trend of the gap) with a regression where they explain the evolution of the gap using only years as independent variables, and they observe a growing trend until 2014. Finally, they analyze similar regression models by drawing on different databases (e.g. LeasePlan data or Spritmonitor.de) using the same idea and variables. They conclude that there are four key factors: different ambient conditions and vehicle usage and weight; excluded

[7] www.fueleconomy.gov

factors from the type-approval test; optimized testing within the test bandwidth; and NEDC test specific vehicle technology.

In sum, academic literature and a number of non-academic documents using various databases and approaches have been used to analyze the comparison between reported data and real-world figures for CO_2 emissions and consumption, but most have not employed a multivariate analysis in order to jointly control for the drivers of the gap. As we show in Table 1, the most frequent analysis has been descriptive. Moreover, the papers that have employed multivariate analysis have missed some variables that could be relevant in the explanation. For example, Mellios *et al.* (2011), Ntziachristos *et al.* (2014) or Ligterink *et al.* (2016), do not include manufacturer or vehicle type. None of the papers reviewed include hybrid vehicles in their studies. Furthermore, Dieselgate[8] has not been considered. With this paper, we try to complete and complement this previous work in order to explain the gap between real world and type-approval figures.

3. Data

As mentioned above, our database was built by drawing on real-world data from Emissions Analytics Ltd. (hereafter, EA).[9] The main aim of this company is "to gather emissions data representative of the vehicle's performance in a wide range of normal driving conditions in one long-form test using a Portable Emissions Measurement System (PEMS)". Its results are obtained by driving cars, in the default state from the manufacturer, on real highways in real-world conditions.[10]

Following EA's methodology, the database contains four groups of variables:

1. *Real and official vehicle's consumption and CO_2 emissions*: information about official consumption and CO_2 emissions of vehicles was provided by manufacturers. On-road consumption and emissions data were obtained from Emissions Analytics. Our interest is to calculate the deviation from official data and, for this reason, our

[8] The Volkswagen emissions scandal was also called "emissionsgate" or "dieselgate". It began in September 2015, when the United States Environmental Protection Agency (EPA) issued a notice of violation of the Clean Air Act to German automaker Volkswagen Group. The EPA found that VW had intentionally programmed diesel engines in order to control their emissions during laboratory tests. An important implication was the decrease in market share.

[9] The data we have is a mixture of vehicles tested in the United Kingdom and Germany. All of them are European Union homologated vehicles and they are sold at all EU. For further information, see: http://emissionsanalytics.com/

[10] For more information about the technical approach, visit: https://drive.google.com/file/d/0B0-iHSV9dj9hVldLR1BnMDZiUjA/view?usp=sharing

endogenous variable will be the average deviation rate (ADR) between these two figures, namely:

$$ADR = \frac{\text{Real consumption or emission-Official consumption or emission}}{\text{Official consumption or emission}} \quad [1]$$

2. *Vehicle characteristics*: the literature review (see, for example, Fontaras *et al.,* 2017a or Tietge *et al.*, 2017a,b) found the main vehicle factors affecting car efficiency. Specifically, Fontaras *et al.*, (2017a) categorize factors that affect fuel consumption and CO_2 emissions into three groups: factors related to vehicle characteristics and systems, factors related to environmental and traffic conditions, and factors related to the vehicle driver. The only group with information available is the first of these three. But it is the latter two groups that comprise the major reason why the gap between real world and type-approval figures may exist. Ntziachristos *et al.* (2014) and Tietge *et al.* (2017a) suggest that type-approval fuel consumption value, engine capacity and vehicle mass accounts for a large portion of the variance in real world fuel consumption (coefficients of determination greater than 0.85). For this reason, we consider vehicle characteristics as being the main drivers of consumption and emissions. In this sense, the database contains detailed information about the number of doors, seats, gears, wheel drives (2 or 4-wheel drive), fuel (petrol, diesel or hybrid), transmission (automatic or manual) and engine capacity (engine CC).[11]

3. *Brands and model characteristics*: as far as we know, previous papers have not taken into account the effects on endogenous variable by brand or vehicle type in regressions. In a descriptive way, some studies have sought to highlight differences between brands and segments (see for example Greene *et al.*, 2015 or Tietge *et al.,* 2017b). We take into account not only the brand, but also the type of car (bodystyle)[12] and segment[13] in our regressions.

4. *Trends*: finally, two variables are included in order to test whether the average rate of deviation changes over time: a year variable (2010-2017) and a 'Dieselgate' variable.

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[11] We also have information about horse power and cylinders for each vehicle; but they show high correlation (>0.8) with the size of the engine. In order to avoid multicollinearity problems, only engine CC was used.

[12] The options for this variable are: convertible, coupe, coupe-convertible, estate, hatchback, MPV, SUV, Saloon, Saloon-long wheelbase and targa.

[13] In this case, the options are: Executive Car (E), Large Car (D), Luxury Car (F), Mini Car (A), Multipurpose Car (M), Small Car (B), Sport Utility Offroad Vehicle (J) and Sports Coupe (S).

The latter takes value 1 following the announcement of the investigation into VW car emissions. This has been included in order to test 'changes in trend' following this announcement. If ADR depends only on a car's characteristics, this variable should not be statistically significant.

Descriptive statistics of 655 vehicles on the database are included in Table 2. Plug-in hybrid electric vehicles are not included in our database. The main point to highlight is that the average rate described in equation [1] (i.e., ADR) reaches values around 38%.

Table 2: Descriptive statistics

Main covariates	Obs.	Average	S.D.	Min	Max
Average rate on-road vs official. Consumption (from eq. [1])	655	0.36	0.13	0.02	0.85
Average rate on-road vs official. CO_2 Emissions (from eq. [1])	655	0.38	0.13	0.03	0.88
Number of doors	655	4.50	0.90	2	6
Number of seats	655	4.97	0.72	2	7
Engine capacity in cubic centimeters	655	1868.03	635.30	875	6592
Number of gears	655	6.14	1.32	1	9

Source: Own elaboration from Emissions Analytics data.

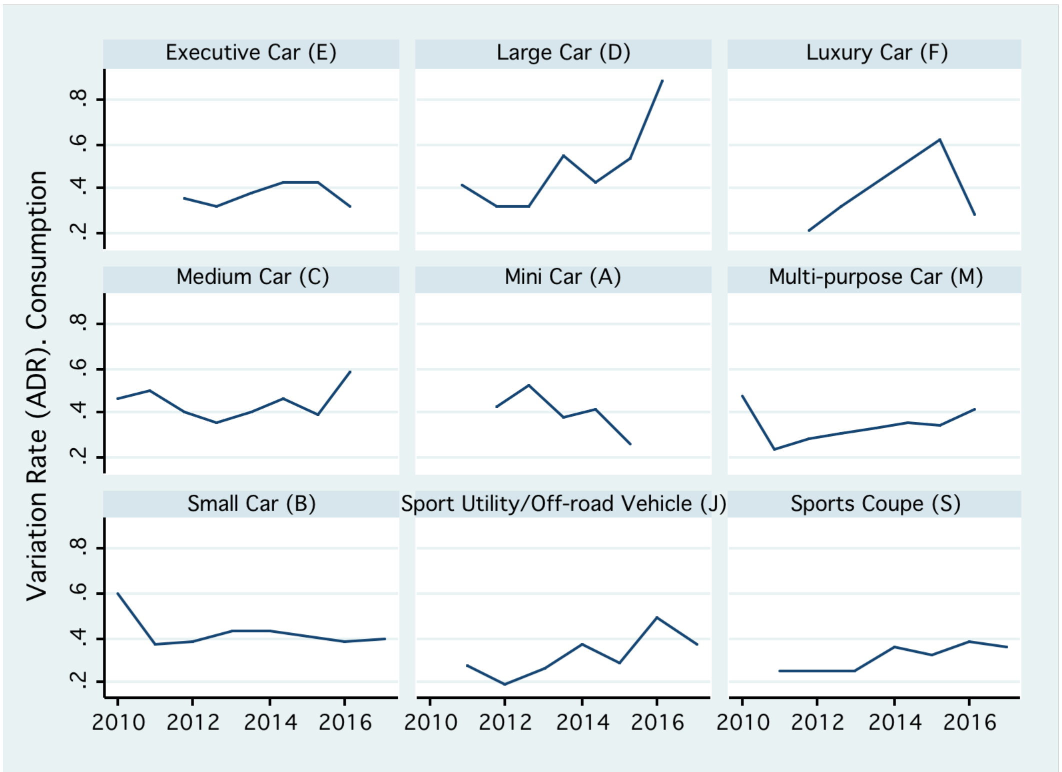
Figures 3 and 4 show the average deviation rate by brand, and Table 4 (see Annex) incorporates both the number of vehicles included in our sample by brand (within brackets, next to the name of the brand) and the average and standard deviation of ADR.

[Insert Figures 3 and 4 and Table 3 here]

It is important to highlight the fact that the ADR around 0.35 is the modal value (0.36 and 0.38 is the average value, respectively, as Table 2 details), although some differences exist by brand. For example, we note the highest values are from DS (0.56) or Alfa Romeo (0.55). On the right-hand side, Rolls Royce (0.19), Porsche (0.21) and Subaru (0.22) represent the lowest deviation from official data supplied by manufacturers.[14]

Figures 1 and 2 (see annex for the later) show the evolution of the ADR over the analyzed period (2010-2017), in function of each car type.

Figure 1: Variation Rate On-road vs. Official, by segment vehicle. Consumption



Source: Own elaboration from Emissions Analytics

Despite previous descriptive outcomes, a multivariate analysis is needed in order to estimate the drivers of the relative contribution to the deviation rate. We now turn to section 4, which details the empirical strategy and results.

[14] There is a positive and high correlation between data on ADR CO_2 emissions and consumption; specifically 0.99 (see footnote 1).

4. Regression model and results

Our regression model is based on a multivariate analysis by adding, in different estimations, several covariates that may affect the endogenous variable we have considered (Average Deviation Rate of vehicle's CO_2 emissions and consumption). Specifically, we estimate the following general equation [2]:

$$\begin{aligned} &ADR_{it} = \beta_0 + \beta_1 Doors + \beta_2 Seats + \beta_3 Ln(engineCC) + \beta_4 Gears + \\ &+\beta_5 Drivenwheels + \beta_6 Transmission + \sum_{j=8}^{11} \beta_j Combustible + \\ &+\sum_{j=12}^{20} \beta_j Segment + \beta_{21} \text{Registration}Year + \beta_{22} \text{Dieselgate} + \sum_{j=23}^{29} \beta_j Group_{it} + \\ &\sum_{j=30}^{67} \beta_j Brand + \sum_{j=68}^{77} \beta_j Bodystyle_{it} + \varepsilon_{it} \end{aligned} \quad [2]$$

We progressively add each group of variables, in order to test the robustness of the estimated coefficients. In fact, four models are analyzed. Firstly, vehicle characteristics, fuel, segment, body style and temporal variables (registration year and periods after Dieselgate) are examined as possible drivers. In estimation 2 we include brands as a new driver; and this is the most complete estimation we do.

Estimation 3 and 4 use a subset of the dataset. The former seeks to estimate whether there are differences among car groups (i.e., common behavior among particular brands that operate under the same scheme).[15]

The latter estimation (number 4 in Tables 4 and 5) replicates estimation 2 but we only consider the top ten brands by sales in UK.[16]

[Insert Table 4 and 5 here]

As we detail in footnote 1, the high correlation between emissions and consumption yields similar outcomes for estimations made for these two endogenous variables. For this

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[15] In our database, the groups are: VW, which includes Audi, VW, Seat, Skoda, Bentley, Bugatti, Lamborghini, and Porsche. The Toyota group is Toyota and Lexus; General Motors include Vauxhall and Chevrolet; BMW has Mini, BMW and Rolls Royce; Mercedes Benz is part of the Daimler group; and the Fiat-Chrysler Automobiles Abarth group includes Alfa Romeo, Fiat, Jeep and Maserati.

[16] Brands that had more than 88% of combined market share in 2016-17 in the UK were (in order, from highest to lowest): Ford, Vauxhall (Opel), Volkswagen, Mercedes-Benz, Audi, BMW, Nissan, Toyota, Kia, Hyundai, Peugeot, Skoda, Land Rover, Renault, Mini, Seat, Citröen, Honda and Fiat. Source: SMMT. https://www.smmt.co.uk/vehicle-data/

reason, the following results apply to both variables. In general, the overall explanatory power of all estimations shows R^2 in the range [0.3-0.43]. The coefficients estimated are very stable, regardless of the sample selected (estimations 3 and 4) and the covariates we add (estimations 1 and 2).

Regarding coefficients, estimations describe several outcomes: First, the car's characteristics related to both consumption and emissions are: engines (average effect of 18% change by 1% increase of cubic centimeters), number of driven wheels (ADRs are lower in 4x4 vehicles) and transmission (ADRs are lower in automatic vehicles).

Taking diesel cars as the reference, petrol cars have Average Deviation Rates smaller than Diesel cars (3,0% - 4,2%), but Petrol Hybrid cars have Average Deviation Rates that are higher than for Diesel cars 10,1% - 18,5%. This is consistent with the literature, which points to their greater susceptibility to specific factors, such as ambient temperature (see, for example, Fontaras *et al.* 2017b).

Moreover, there are studies that have highlighted plug-in hybrid electric vehicles (PHEV) as the worst case regarding divergence estimates, as they frequently exceed 200% of divergence (see for example Tietge *et al.*, 2017b). The principal reason is the low electric-drive share in real-world conditions, compared to official tests, where a high amount of electric driving is used (on the battery charged through the electric mains). Actually, the distance covered by electricity is around 15%-30% of total distance in real world conditions (Ligterink and Eijk, 2014). In this sense, and following Ligterink *et al.* (2016), policies encouraging the purchase of PHEVs face the challenge of ensuring that they are charged in an appropriate manner to increase electric-drive shares.

While PHEVs are not directly considered in this paper, the broader point is that hybrid petrol and plug-in hybrid electric vehicles stand to gain market share. If the divergence is high for these types of vehicle, the implications for consumers are correspondingly a concern.

Turning to the various segments, 'Luxury' and 'Executive' show on-road data that is closer to official figures, compared to the Medium Car (C) segment (the reference). This result implies a second relevant outcome: some of the biggest selling cars[17] are those with higher ADRs.

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[17] See for example the page 16 of "European vehicle market statistics pocketbook 2017-18" by The International Council of Clean Transportation.

Time variables (Registration Year and Dieselgate) are also very relevant and they show another outcome of these estimations. Both variables show opposite results: while ADR increases over time (a positive coefficient of around 1.5 percentage points by year), they clearly decrease after Dieselgate (a negative coefficient of around 4 percentage points by year).[18] The latter is one more justification for the gaps: if there were no technical or legal changes at this time, why does the ADR decrease after this shock? Only discretionary behaviour by brands can explain it.

We have to bear in mind that Dieselgate relates to NO_X emissions, which could have led to manufacturers focusing less on optimizing CO_2 after this external shock, and less optimization may mean greater gaps. In other words, if this hypothesis is true, manufacturers have been more focused on NO_X in recent years, and some of the strategies they have employed have increased the gap, and even caused increased real-world fuel consumption. In this case, a new estimation of estimation 1 to 4 of the equation [2] - but using on-road emissions as endogenous - would conclude that the coefficient of binary variable Dieselgate would be positive. However, this outcome does not emerge and, in fact, this estimated parameter shows statistical significance and is negative (i.e., on-road emissions decrease after Dieselgate).

On the other hand, if manufacturers focus on NO_X, they could have greater levels of CO_2 (and thus consumption) because they have not continued taking advantage of possible "flexibilities" in tests as we have stated in section 1.[19] This situation will decreased the gap if on-road emissions decrease and official emissions are more stable. We repeated previously cited estimations, this time using official emissions as an endogenous variable, and no change was found after Dieselgate.

In the analyses developed by Groups (estimation 3), all have higher values of average deviation rates rate than the Toyota group (the reference). Finally, considering the effect of Brands in our estimations (estimations 2 and 4), a few brands have different values from VW (the reference brand).

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[18] In order to make a simple robustness check, we applied estimations 3 of Tables 4 and 5, but considering two fake periods. Concretely we move the date of Dieselgate one year after and one before. These two estimations include no statistical significance of Dieselgate covariate (and Registration variable is still statistical significance). They support our main results.

[19] NO_X and CO_2 are largely decoupled thanks to after-treatment systems

5. Conclusions

Differences between test figures and actual figures are real, and the relevant literature has confirmed this especially for the past two decades. Several papers have studied this gap, comparing test results with on-road figures and drivers' reports, comparing old and new tests, and so on. However, this issue needed a causal analysis in order to determine factors that can explain this gap.

In this paper, we used a database from Emissions Analytics, a company that runs comparable tests of real-world car fuel and consumption and CO_2 emissions. More than 650 observations from 2010 to 2017 comprise the database. By using regression analysis, we have sought to analyze this gap, by simultaneously taking into account car characteristics, brands, segments, model characteristics and time trends. The results have allowed us to establish some conclusions.

As mentioned above, the gap exists and it is around 36-38%; but this is an average of descriptive data. A causal analysis has allowed us to explain the drivers of this gap. Thanks to this analysis, firstly we found that the average deviation rate between official and real CO_2 emissions increased over this period (2011-2015), but it decreased after Dieselgate. The latter is an interesting reflection on manufacturer behaviour because, as far as we know, there were no technical or other changes that can explain this outcome.

Secondly, the petrol hybrid group shows higher rates of deviation than the other segments. We must remember that cars in the hybrid sector are often sold to a highly conscientious population who may be more concerned about the gap between on-road and official results. Thirdly, the segment that is probably one of the biggest-selling (that of the medium-sized car) displays higher gaps than that of the Luxury and Executive segments.

All these outcomes support some of the previous results found in the literature and highlight others that have been less studied, giving us information about causal analysis on this issue. The change to WLTP and the corresponding test cycle may improve the situation, but we have to be cautious due to the behaviour of manufacturers that could take advantage (again) of possible "weaknesses" in the test protocol.

Finally, we have to remember that these differences have specific consequences for policies, as well as other factors (such as climate change, the misleading of consumers and motorists, taxation policy where based on consumptions or emissions and rates of innovation). Accordingly there are many important reasons to strive to achieve greater accuracy.

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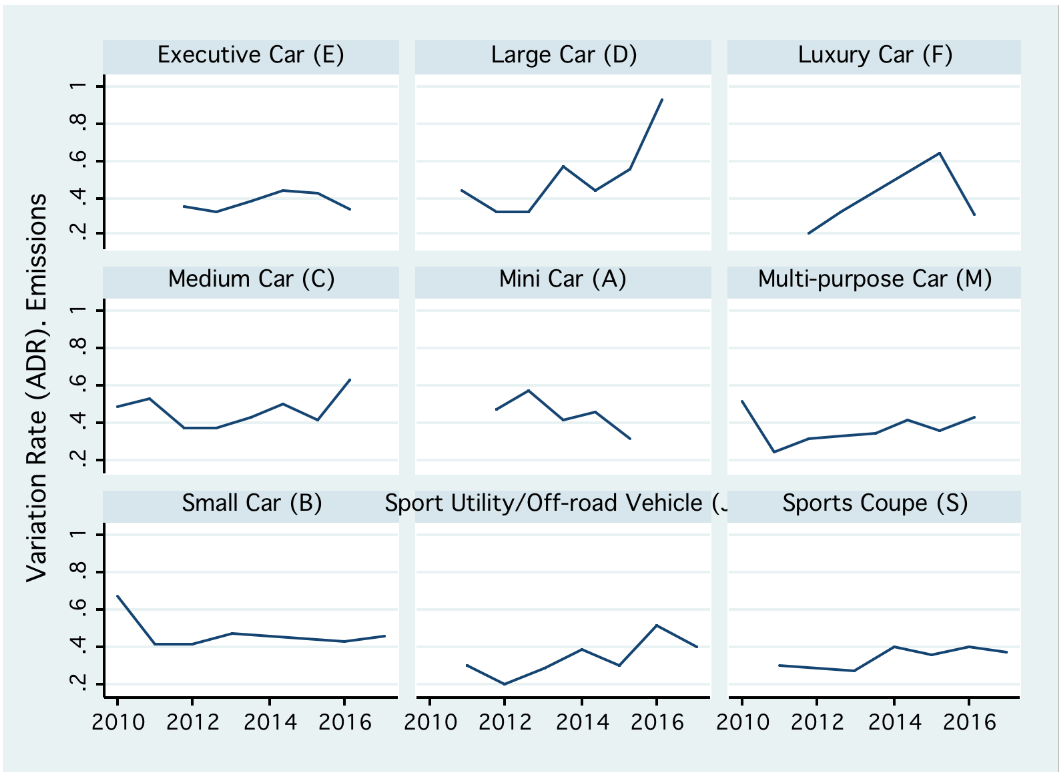
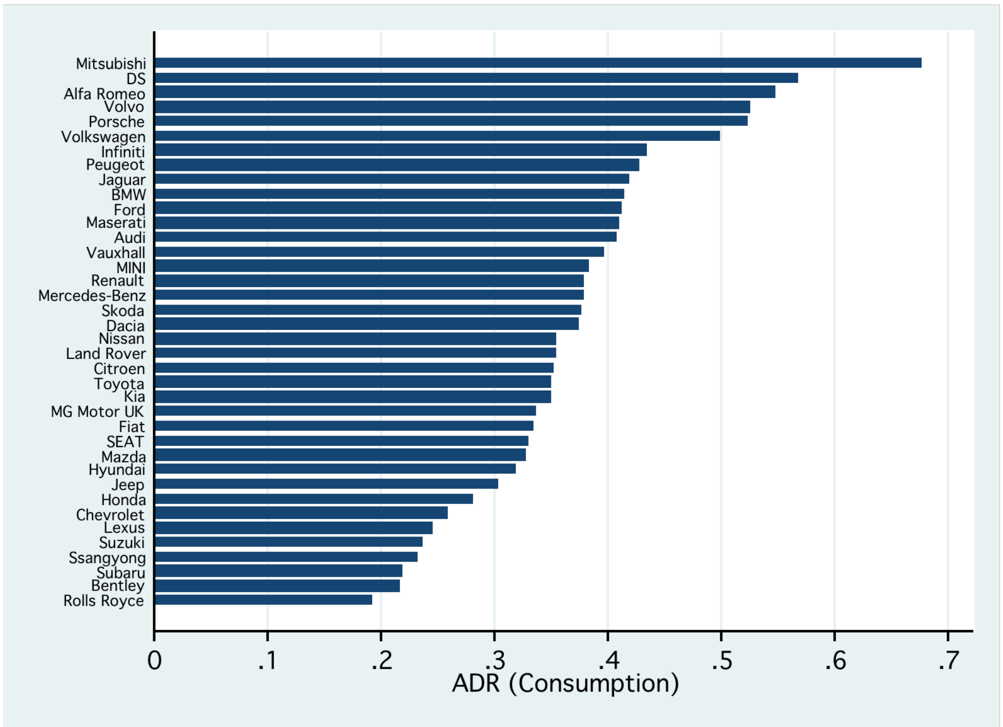
Annex

Figure 2: Variation Rate Real vs. Official, by segment vehicle. Emissions



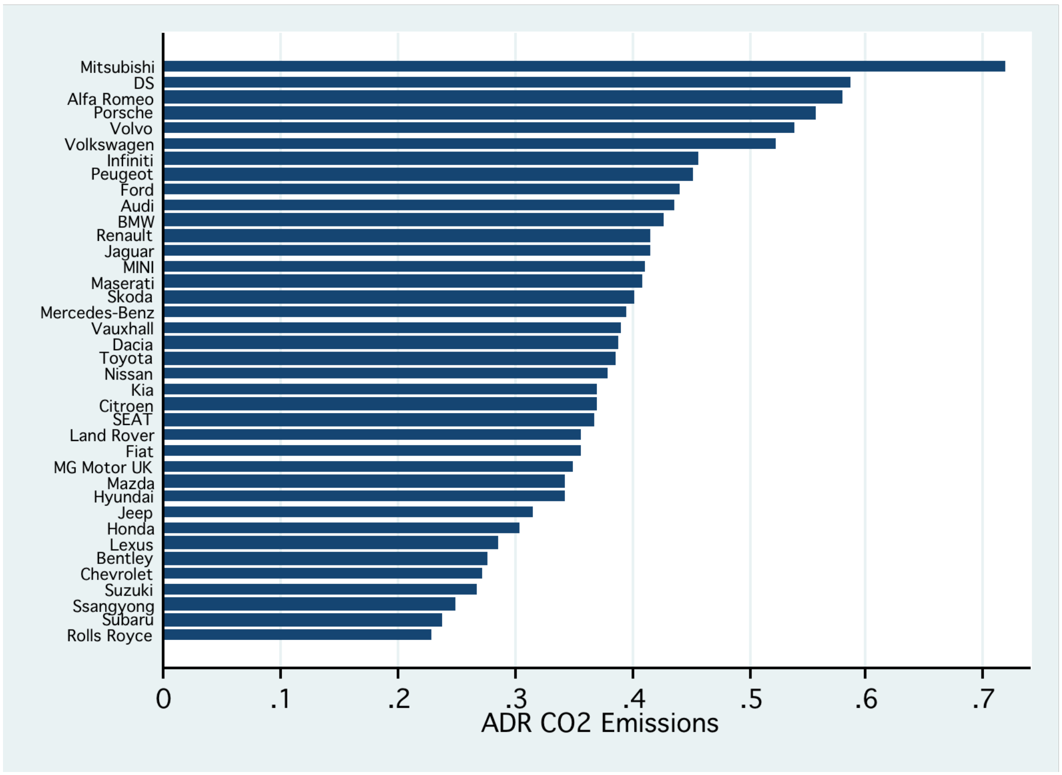
Source: Own elaboration from Emissions Analytics

Figure 3: Average Deviation Rate. Consumption



Source: Own elaboration from Emissions Analytics

Figure 4: Average Deviation Rate. CO_2 Emissions



Source: Own elaboration from Emissions Analytics

Table 3: Average Deviation Rate (ADR). On-road vs. Official. By brand

Brand	**ADR Consumption**	**ADR** CO_2 **Emissions**	**Brand**	**ADR Consumption**	**ADR** CO_2 **Emissions**
Alfa Romeo [5]	0.55 (0.25)	0.58 (0.27)	Mini [16]	0.38 (0.14)	0.41 (0.14)
Audi [50]	0.37 (0.11)	0.40 (0.11)	Maserati [1]	0.41	0.41
BMW [55]	0.35 (0.09)	0.36 (0.09)	Mazda [18]	0.33 (0.09)	0.34 (0.09)
Bentley [1]	0.21	0.27	Mercedes-Benz [43]	0.38 (0.11)	0.39 (0.11)
Chevrolet [4]	0.26 (0.10)	0.27 (0.11)	Mitsubishi [6]	0.29 (0.06)	0.31 (0.07)
Citröen [15]	0.35 (0.09)	0.37 (0.09)	Nissan [22]	0.35 (0.12)	0.38 (0.13)
DS [2]	0.56 (0.02)	0.58 (0.05)	Peugeot [19]	0.42 (0.13)	0.45 (0.14)
Dacia [2]	0.37 (0.12)	0.38 (0.12)	Porsche [10]	0.21 (0.09)	0.22 (0.10)
Fiat [9]	0.33 (0.19)	0.35 (0.22)	Renault [23]	0.38 (0.11)	0.41 (0.13)
Ford [43]	0.41 (0.14)	0.44 (0.14)	Rolls Royce [1]	0.19	0.23
Honda [13]	0.28 (0.06)	0.30 (0.07)	SEAT [25]	0.33 (0.11)	0.37 (0.13)
Hyundai [22]	0.32 (0.11)	0.34 (0.11)	Skoda [32]	0.37 (0.11)	0.40 (0.11)
Infiniti [7]	0.43 (0.12)	0.45 (0.10)	SsangYong [5]	0.23 (0.08)	0.25 (0.09)
Jaguar [14]	0.42 (0.13)	0.41 (0.13)	Subaru [5]	0.22 (0.06)	0.23 (0.07)
Jeep [4]	0.30 (0.15)	0.31 (0.17)	Suzuki [6]	0.23 (0.06)	0.27 (0.07)
Kia [19]	0.35 (0.13)	0.37 (0.13)	Toyota [23]	0.35 (0.13)	0.38 (0.15)
Land Rover [11]	0.35 (0.14)	0.35 (0.14)	Vauxhall (Opel) [31]	0.39 (0.15)	0.39 (0.13)
Lexus [7]	0.24 (0.03)	0.28 (0.03)	Volkswagen [60]	0.37 (0.13)	0.40 (0.13)
MG Motor UK [2]	0.33 (0.09)	0.35 (0.07)	Volvo [24]	0.42 (0.13)	0.43 (0.14)

Source: Own elaboration from Emissions Analytics. Standard deviation by brand in parenthesis. Observations by brand are closed to its commercial name.

Table 4: Estimation of Average Deviation Rate (ADR). Consumption

Covariates	Estimation (1)	Estimation (2)	Estimation (3)	Estimation (4)
Doors	0.002	0.008	0.004	0.007
	[0.009]	[0.008]	[0.012]	[0.009]
Seats	0.004	0.014	0.009	0.011
	[0.009]	[0.009]	[0.014]	[0.011]
Ln(engine cc)	**-0.178*** **	**-0.198*** **	**-0.148*** **	**-0.184*** **
	[0.024]	**[0.025]**	**[0.032]**	**[0.027]**
Gears	**0.020*** **	**0.013** **	**0.019** **	**0.013* **
	[0.006]	**[0.006]**	**[0.009]**	**[0.007]**
Driven wheels	**-0.021** **	**-0.016* **	**-0.029** **	**-0.016* **
	[0.008]	**[0.009]**	**[0.012]**	**[0.010]**
Transmission	**-0.044*** **	**-0.043*** **	**-0.043** **	**-0.044*** **
	[0.013]	**[0.013]**	**[0.019]**	**[0.015]**
Diesel Hybrid	0.045	0.022	-0.018	0.021
	[0.051]	[0.050]	[0.083]	[0.051]
Petrol	**-0.030*** **	**-0.033*** **	-0.023	**-0.042*** **
	[0.011]	**[0.011]**	[0.016]	**[0.012]**
Petrol Hybrid	**0.101** **	**0.161*** **	**0.185*** **	**0.178*** **
	[0.040]	**[0.043]**	**[0.064]**	**[0.050]**
Executive Car E	**-0.066** **	**-0.087*** **	**-0.057* **	**-0.062** **
	[0.026]	**[0.026]**	**[0.031]**	**[0.029]**
Large Car D	-0.017	-0.021	-0.026	-0.027
	[0.016]	[0.016]	[0.021]	[0.018]
Luxury Car F	-0.062	**-0.115*** **	-0.064	-0.070
	[0.038]	**[0.043]**	[0.048]	[0.064]
Mini Car A	0.007	0.043	0.045	0.046
	[0.028]	[0.029]	[0.039]	[0.030]
Multipurpose Car M	-0.016	-0.002	-0.030	-0.005
	[0.026]	[0.026]	[0.037]	[0.029]
Small Car B	0.016	0.018	0.035	0.020
	[0.015]	[0.015]	[0.022]	[0.016]
Sport Utility Offroad J	-0.030	-0.033	-0.069	-0.044
	[0.023]	[0.024]	[0.042]	[0.029]
Sports Coupe S	-0.041	-0.032	-0.038	-0.035
	[0.026]	[0.025]	[0.030]	[0.026]
Registration Year	**0.010** **	**0.014*** **	**0.016*** **	**0.011** **
	[0.004]	**[0.004]**	**[0.006]**	**[0.005]**
After Dieselgate	-0.017	**-0.035** **	**-0.047** **	**-0.041** **
	0.002	**[0.016]**	**[0.022]**	**[0.017]**
VW group			**0.099*** **	
			[0.031]	
General Motors Group			**0.086** **	
			[0.035]	
Toyota Group			**Reference group**	
BMW Group			**0.088** **	
			[0.035]	
Daimler Group			**0.090** **	
			[0.038]	
Abarth Group			**0.096** **	
			[0.041]	
AlfaRomeo		**0.133*** **		
		[0.050]		

(continuation Table 4)

Covariates	Estimation (1)	Estimation (2)	Estimation (3)	Estimation (4)
Audi		**0.044****		**0.041***
		[0.021]		**[0.022]**
BMW		0.006		0.005
		[0.021]		[0.022]
Bentley		**0.206***		
		[0.120]		
Chevrolet		-0.085		
		[0.055]		
Citroen		-0.023		-0.027
		[0.031]		[0.032]
DS		**0.149***		
		[0.077]		
Dacia		-0.019		
		[0.077]		
Fiat		**-0.083****		**-0.089****
		[0.041]		**[0.042]**
Ford		**0.045****		**0.044****
		[0.022]		**[0.022]**
Honda		**-0.099*****		**-0.098*****
		[0.033]		**[0.033]**
Hyundai		**-0.091*****		**-0.095*****
		[0.027]		**[0.028]**
Infiniti		0.041		
		[0.044]		
Jaguar		**0.091****		
		[0.037]		
Jeep		0.002		
		[0.056]		
Kia		-0.040		-0.037
		[0.028]		[0.029]
LandRover		**0.070***		**0.075***
		[0.038]		**[0.040]**
Lexus		**-0.107****		
		[0.054]		
MGMotorUK		-0.029		
		[0.076]		
MINI		0.033		0.028
		[0.032]		[0.032]
Maserati		0.135		
		[0.114]		
Mazda		-0.015		
		[0.029]		
MercedesBenz		0.015		0.013
		[0.024]		[0.025]
Mitsubishi		-0.040		
		[0.047]		
Nissan		0.031		0.033
		[0.029]		[0.030]
Peugeot		0.038		0.034
		[0.029]		[0.029]
Porsche		0.014		
		[0.042]		
Renault		-0.014		-0.016
		[0.027]		[0.027]

(continuation Table 4)

Covariates	Estimation (1)	Estimation (2)	Estimation (3)	Estimation (4)
RollsRoyce		0.159		
		[0.122]		
SEAT		-0.038		-0.041
		[0.026]		[0.026]
Skoda		-0.006		-0.007
		[0.024]		[0.024]
SsangYong		**-0.093***		
		[0.050]		
Subaru		**-0.100***		
		[0.051]		
Suzuki		**-0.172*****		
		[0.046]		
Toyota		**-0.084*****		**-0.093*****
		[0.030]		**[0.031]**
Vauxhall		0.005		0.007
		[0.024]		[0.024]
Volvo		**0.056****		
		[0.026]		
Body style	Included	Included	Included	Included
Constant	**-18.705****	**-25.662*****	**-31.667****	**-21.276****
	[8.527]	**[8.521]**	**[12.130]**	**[9.453]**
Sample	**All sample**	**All sample**	**Only Car groups**	**Only Big firms by market share**
Observations	**655**	**655**	**352**	**531**
R-squared	**0.263**	**0.387**	**0.299**	**0.310**

Note: Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Estimation of Average Deviation Rate (ADR). CO_2 Emissions

Covariates	Estimation (1)	Estimation (2)	Estimation (3)	Estimation (4)
Doors	0.011	**0.017****	0.017	**0.016***
	[0.009]	**[0.008]**	[0.011]	**[0.009]**
Seats	0.001	0.012	0.003	0.010
	[0.009]	[0.009]	[0.014]	[0.010]
Ln(engine cc)	**-0.194*****	**-0.214*****	**-0.162*****	**-0.205*****
	[0.024]	**[0.025]**	**[0.031]**	**[0.027]**
Gears	**0.020*****	**0.013****	**0.018****	**0.012***
	[0.006]	**[0.006]**	**[0.009]**	**[0.007]**
Driven wheels	**-0.021****	**-0.016***	**-0.033*****	**-0.016***
	[0.008]	**[0.008]**	**[0.011]**	**[0.010]**
Transmission	**-0.046*****	**-0.042*****	**-0.044****	**-0.044*****
	[0.013]	**[0.013]**	**[0.019]**	**[0.014]**
Diesel Hybrid	0.053	0.032	-0.014	0.029
	[0.051]	[0.050]	[0.081]	[0.051]
Petrol	0.002	-0.001	0.004	-0.010
	[0.011]	[0.011]	[0.015]	[0.012]
PetrolHybrid	**0.143*****	**0.211*****	**0.228*****	**0.225*****
	[0.040]	**[0.043]**	**[0.063]**	**[0.049]**
Executive Car E	**-0.069*****	**-0.090*****	**-0.059****	**-0.063****
	[0.026]	**[0.026]**	**[0.030]**	**[0.029]**
Large Car D	-0.018	-0.020	-0.022	-0.023
	[0.016]	[0.016]	[0.020]	[0.018]
Luxury Car F	-0.058	**-0.108****	-0.056	-0.072
	[0.038]	**[0.043]**	[0.047]	[0.063]
Mini Car A	0.004	**0.047***	0.053	**0.050***
	[0.028]	**[0.029]**	[0.038]	**[0.030]**
Multipurpose Car M	-0.014	0.006	-0.013	0.005
	[0.026]	[0.026]	[0.036]	[0.028]
Small Car B	0.019	0.024	**0.048****	**0.027***
	[0.015]	[0.015]	**[0.021]**	**[0.016]**
Sport Utility Offroad J	-0.030	-0.026	-0.061	-0.033
	[0.023]	[0.024]	[0.041]	[0.029]
SportsCoupeS	-0.039	-0.030	-0.032	-0.032
	[0.026]	[0.024]	[0.029]	[0.026]
Registration Year	**0.014*****	**0.018*****	**0.022*****	**0.016*****
	[0.004]	**[0.004]**	**[0.006]**	**[0.005]**
After Dieselgate	-0.025	**-0.044*****	**-0.059*****	**-0.050*****
	[0.016]	**[0.015]**	**[0.022]**	**[0.017]**
VW group			**0.112*****	
			[0.030]	
General Motors Group			**0.062***	
			[0.034]	
Toyota Group			**Reference group**	
BMW Group			**0.094*****	
			[0.034]	
Daimler Group			**0.105*****	
			[0.037]	
Abarth Group			**0.100****	
			[0.040]	
AlfaRomeo		**0.138*****		
		[0.049]		

(continuation Table 5)

Covariates	Estimation (1)	Estimation (2)	Estimation (3)	Estimation (4)
Audi		**0.044****		**0.041***
		[0.021]		**[0.022]**
BMW		-0.001		-0.002
		[0.021]		[0.022]
Bentley		**0.234****		
		[0.119]		
Chevrolet		**-0.100***		
		[0.055]		
Citroën		-0.029		-0.033
		[0.031]		[0.031]
DS		**0.128***		
		[0.077]		
Dacia		-0.026		
		[0.076]		
Fiat		**-0.096****		**-0.102****
		[0.041]		**[0.042]**
Ford		**0.043****		**0.044****
		[0.021]		**[0.022]**
Honda		**-0.108*****		**-0.106*****
		[0.033]		**[0.033]**
Hyundai		**-0.096*****		**-0.100*****
		[0.027]		**[0.027]**
Infiniti		0.035		
		[0.044]		
Jaguar		**0.075****		
		[0.037]		
Jeep		-0.012		
		[0.055]		
Kia		-0.044		-0.041
		[0.028]		[0.029]
LandRover		0.059		**0.065***
		[0.038]		**[0.039]**
Lexus		**-0.119****		
		[0.054]		
MGMotorUK		-0.050		
		[0.075]		
MINI		0.026		0.021
		[0.031]		[0.032]
Maserati		0.118		
		[0.113]		
Mazda		-0.029		
		[0.029]		
MercedesBenz		0.019		0.017
		[0.024]		[0.024]
Mitsubishi		-0.044		
		[0.046]		
Nissan		0.027		0.029
		[0.029]		[0.030]
Peugeot		0.031		0.027
		[0.028]		[0.029]
Porsche		0.012		
		[0.041]		
Renault		-0.005		-0.006
		[0.026]		[0.027]

(continuation Table 5)

Covariates	Estimation (1)	Estimation (2)	Estimation (3)	Estimation (4)
RollsRoyce		0.161		
		[0.121]		
SEAT		-0.030		-0.032
		[0.025]		[0.026]
Skoda		-0.010		-0.011
		[0.024]		[0.024]
SsangYong		**-0.107****		
		[0.050]		
Subaru		**-0.108****		
		[0.050]		
Suzuki		**-0.184*****		
		[0.045]		
Toyota		**-0.095*****		**-0.104*****
		[0.030]		**[0.031]**
Vauxhall		-0.037		-0.035
		[0.024]		[0.024]
Volvo		**0.055****		
		[0.026]		
Body style	Included	Included	Included	Included
Constant	**-26.241*****	**-35.082*****	**-42.544*****	**-30.926*****
	[8.516]	**[8.443]**	**[11.821]**	**[9.350]**
Sample	**All sample**	**All sample**	**Only Car groups**	**Only Big firms by market share**
Observations	**655**	**655**	**352**	**531**
R-squared	**0.300**	**0.427**	**0.352**	**0.362**

Note: Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1