Online Appendix: Who Benefits When Firms Game Corrective Policies? - Mathias Reynaert and James M. Sallee

Sample selection process

Self-reported odometer readings are sometimes missing or clearly incorrect. We eliminate unreliable data through a data selection process detailed here.

Our data selection process first eliminates a number of drivers (accounts) that have unreliable information or too few observations. With the accounts that remain, we then consider several ways to account for mismeasurement in odometer readings for individual transactions. Specifically, we first limit the sample to gasoline- or diesel-fueled vehicles, which eliminates 6.7 million transactions. Second, we drop vehicles that use the wrong type of fuel for their engine in more than 1% of the visits, e.g., putting diesel fuel in a vehicle that is labeled as gasoline in our data. Inconsistencies might be in the data because drivers use their card for a different vehicle, or these observations might be mistakes in the assignment of vehicle type. This drops 7.5 million transactions. Third, we pose some minimum requirements on the driving patterns of the drivers that produce the transactions. We drop drivers that never report an increase of more than 150km in their odometer reading (2.5 million transactions).[40] We drop car models with fewer than 10 drivers, and drivers with fewer than 10 fuel station visits (1.3 million transactions). We drop drivers that did not report driving more than 5,000km in total or reported driving more than 500,000km in total (11.3 million). Having isolated a set of drivers (accounts) with ample data, within those accounts we drop individual transactions in two steps. First, we drop transactions where the odometer difference is lower than 100km or higher than 3000km (7.6 million). Second, we drop transactions that result in a fuel consumption that is outside 1.25 times the interquartile range of estimated fuel consumption for each car model in the data (5.1 million). This results in the final dataset of 24 million observations.

The EU emission standard and member state taxes

The discussion in this section is based on Reynaert (2017). The European regulation on emission standards for new passenger cars, Regulation (EC) No. 443/2009, sets a mandatory fleet average of κ =130 grams CO_2 per kilometer. Denoting the sales of each product j by q_j and the emissions of each product by e_j, the target for a firm is as follows:

$$\frac{\sum_{j \epsilon fleet} q_j(e_j - f(w_j))}{\sum_{j \epsilon fleet} q_j} \quad \leq \quad 130.$$

[40]Note that the range of a combustion engine is easily more than 800km.

The attribute basing $f(w_{jm}) = a(w_j - w_0)$ adjusts the emissions of each vehicle by the distance in the vehicle weight w_j from a shifting point w_0 (the pivotal weight point). The shifting point w_0 is a mass of 1370 kg and the difference in weight from that point is multiplied by $a = 0.046$. The target is set for each producer's fleet of new vehicles sold in a calendar year and the trading of excess emissions between producers is not allowed. Manufacturers can obtain lower average emissions by gathering super credits. These credits are given for vehicles that emit less than 50 g/km. There are also separate standards for small manufacturers making less than 30,000 vehicles per year. Both of these exceptions count for a very small share of the total market. There is no banking system for excess emissions over time.

When producers exceed the standard they have to pay premiums for excess emissions. The premium is €5 per unit sold for the first excess g/km and increases to €95 per unit above 134 g/km. A manufacturer obtaining a sales weighted emission of 146 g/km, the average in 2007, would face a significant penalty of €1,280 per vehicle (against an average sales price of €22,250). The regulation was proposed by the European Commission in 2007 and became a European law in 2009. In 2012, 65% of manufacturer's sales had to comply with the emission standard. This rose to 75% in 2013 and 80% in 2014, and the standard was fully binding from 2015 onward. Every firm succeeded in reaching the full target by 2014.

On top of the EU wide emission standard, all European member states have fiscal policies in the vehicle market. The national policies are a combination of value added tax, registration taxes, annual taxes, fuel taxes, road taxes and emission zones. These taxes differ substantially between member states and there are also changes over time. A full discription of these taxes is out of scope, we recommend ACEA tax reports as a source for more information on these tax systems (the mere description of these taxes takes several pages per country). Using the ACEA data source, Gerlagh et al. (2018) show that several countries have increased the extent to which these taxes are base on CO_2 emissions. Several examples are a bonus malus system in France announced in 2008, Spain included CO_2 emissions in a complicated formula that determines registration taxes in 2008, Germany changed the formula of annual taxes in 2009, and the Netherlands changed tax formulas in 2010.

Empirical Bayes Correction of on-road ratings

We start by decomposing the total variance in the sample $Var(r_{nij}) = \sigma_r^2$ into three components: variance in performance of vehicles σ_j^2, drivers σ_i^2, and pump visits σ_n^2. We estimate the variance between pump visits of the same driver as:

$$\sigma_n^2 = \frac{1}{N-I}\sum_{n}^{N}(r_{nij} - \overline{r}_{ij})^2,$$

in which $\overline{r}_{ij}$ is the mean fuel consumption of driver i, N is the total number of observations and I is the total number of drivers. Next, we estimate the covariance between drivers of the same vehicles as:

$$\sigma_j^2 = cov(\overline{r}_{ij}, \overline{r}_{kj}).$$

The estimated covariance is obtained as a weighted average of covariances between randomly sorted pairs (i, k) of drivers of the same car. We weigh each pair of drivers (i, k) by the sum of their visits. Finally, we obtain σ_i^2 as the remaining variance: $\sigma_i^2 = \sigma_r^2 - \sigma_n^2 - \sigma_j^2$. The precision of the estimated gap for each driver is then defined as:

$$h_i = 1/(\sigma_i^2 + \sigma_n^2/n_i),$$

so that drivers with a high number of visits have a higher precision. We obtain precision weighted means per car as the weighted average of $\overline{r}_{ij}$ with h_i as weights. Second we shrink these precision weighted means with an estimate of their reliability:

$$\psi_j = \sigma_j^2/(\sigma_j^2 + 1/\sum_i h_{ji}),$$

where the reliability is defined as the signal σ_j over the total variance. We use the per vehicle shrunken on-road estimates $\widehat{r}_j$ to construct an alternative estimate of the gap defined in (2) and to inform us about the distribution of the gap between vehicles.

Table F.3 describes the variation in the on-road fuel consumption (σ_d^2) across release years, as well as its decomposition across three components: variation across refueling transactions for the same driver (σ_n^2), variation across drivers of the same vehicle (σ_i^2) and variation across vehicles (σ_j^2). We decompose the variation separately for each release year and describe the mean and standard deviation across release years in the table.

More than 25% of the variance is attributable to within driver variance. This variance is due to driving conditions, stockpiling effects and errors in odometer reporting. We find that the variance across drivers of the same car σ_i^2 is 0.21. This is an economically large number; it means that the on-road fuel consumption is estimated to be 0.28 liter/100km higher at the third quartile than at the first quartile of drivers in the same car.[41] A policy that would shift a driver from the third quartile of the fuel consumption gap to the first quartile would decrease fuel consumption by 3%. These numbers are interesting from a policy perspective as they give an indication of the extent to which fuel consumption and emis-

[41]If we assume that conditional on car j, r has a normal distribution, the interquartile distance is $1.349 * \sigma_i^2$.

sions can be reduced by teaching and incentivizing drivers to drive a vehicle more efficiently.[42] The remaining part of the variance σ_j^2 is the co-variance between drivers of the same car and can be seen as the information available to estimate the car specific component of on-road fuel consumption. We estimate this to be 1.35, which is more than 60% of the total variance. Table F.3 also shows that the variance components are relatively stable over time; each component has a low standard deviation across release years. There is variation in the size of the fuel consumption gap between cars and between drivers, but this variation is stable over time. Given this variance decomposition we turn next to the estimates of the distribution of r_j and d_j for each release year. Table F.4 reports the unweighted mean estimate of r_j and $\widehat{r}_j$, obtained with the empirical Bayes correction. The mean value of both r_j and $\widehat{r}_j$ are decreasing over the release years. In all years the corrected means are lower than the raw means, because on average vehicles with high r_j have less precise underlying data, but overall shrinkage and precision weighting has small effects. The resulting gap $\widehat{d}_j$ is estimated to be an imprecise 10% up until 2006. From 2007 onwards we see a significant increase in the performance gap, consistent with the previous estimates.

Proofs

PROPOSITION 1: *In the absence of policy ($\lambda = 0$), buyer surplus falls with the level of gaming. Specifically:*

$$\frac{dBS}{dg} \approx -\underbrace{\rho(1-\alpha)\beta D}_{\textit{price effect}} + \underbrace{(1-\alpha)^2\beta^2 D' g}_{\textit{choice distortion}} \leq 0.$$

We derive this by starting with the definition of buyer surplus as the integral under the inverse demand curve. Because the true attribute of the good x is unaffected by gaming, we can analyze buyer surplus using the true demand curve. The standard portion of buyer surplus is the integral from the final price, denoted p^* up to infinity. Denote by $\tilde{p}$ the upfront purchase price that would induce a sophisticated consumer to purchase the amount of the good that is in fact purchased at price p^* by the consumer with perception $(1-\alpha)$. The choice distortion can be written as the difference between the revenue generate between p^* and $\tilde{p}$ and the consumer value generated between those points.

[42]Significant variation across drivers of identical cars is consistent with results reported in Ashley Langer and Shaun McRae (2014), who analyze extremely detailed driving data from a few dozen drivers of an identical car, the Honda Accord. In contrast, our data come from a large sample and cover many models.

$$BS = \underbrace{\int_{p^*}^{\infty} D(z+\beta x)dz}_{\text{BS of correct quantity}} + \underbrace{\int_{\tilde{p}}^{p^*} D(z+\beta x)dz}_{\text{Value of excess quantity}} - \underbrace{\int_{\tilde{p}}^{p^*} D(\tilde{p}+\beta x)dz}_{\text{Cost of excess quantity}} . \tag{D.1}$$

Differentiation of equation D.5, in which p^* and $\tilde{p}$ are endogenously determined by g, yields the result. Note that the inside of the third integral is a constant with respect to the variable of integration, so it can be pulled out of the integral, leaving only the constant 1 inside. Specifically:

$$\begin{aligned}\frac{dBS}{dg} &= -D(p^*+\beta x)\frac{dp^*}{dg} + \left\{D(p^*+\beta x)\frac{dp^*}{dg} - D(\tilde{p}+\beta x)\frac{d\tilde{p}}{dg}\right\} \\ &\quad - \left\{(p^*-\tilde{p})D'(\tilde{p}+\beta x)\frac{d\tilde{p}}{dg} + D(\tilde{p}+\beta x)\left(\frac{dp^*}{dg} - \frac{d\tilde{p}}{dg}\right)\right\}.\end{aligned} \tag{D.2}$$

Using the pass through coefficient ρ, a change in g scales to a change in tax by $(1-\alpha)\beta$, so $dp^*/dg = \rho(1-\alpha)\beta$. This simplifies the first term to yield the result.

For the second term in D.2, note that $\tilde{p} = p^* - (1-\alpha)\beta g$ by definition. Then, substitute a first-order Taylor approximation to write demand at $\tilde{p}$ as a function of demand at p^* and $D' \times (\tilde{p} - p^*)$:

$$\begin{aligned}&D(p^*+\beta x)\frac{dp^*}{dg} - D(\tilde{p}+\beta x)\frac{d\tilde{p}}{dg} \\ =&D(p^*+\beta x)\frac{dp^*}{dg} - D(p^*+\beta x-(1-\alpha)\beta g)\frac{d\tilde{p}}{dg} \\ \approx&\left\{D(p^*+\beta x-(1-\alpha)\beta g) + D'(p^*+\beta x-(1-\alpha)\beta g)(1-\alpha)\beta\right\}\frac{dp^*}{dg} - D(p^*+\beta x-(1-\alpha)\beta g)\frac{d\tilde{p}}{dg} \\ =&D(p^*+\beta x-(1-\alpha)\beta g)\left(\frac{dp^*}{dg} - \frac{d\tilde{p}}{dg}\right) + D'(p^*+\beta x-(1-\alpha)\beta g)(1-\alpha)\beta\frac{dp^*}{dg}\end{aligned} \tag{D.3}$$

Now consider the third term in D.2. After substituting $\tilde{p} = p^* - (1-\alpha)\beta g$, we see that the term that multiplies the difference in derivatives will cancel in the third term of D.2 and the second-term, defined using D.3. This means that D.2 can be written:

$$\begin{aligned}\frac{dBS}{dg} &= -D(p^*+\beta x)\rho(1-\alpha)\beta + D'(p^*+\beta x-(1-\alpha)\beta g)(1-\alpha)\beta\frac{dp^*}{dg} \\ &\quad - \left\{(p^*-\tilde{p})D'(\tilde{p}+\beta x)\frac{d\tilde{p}}{dg}\right\}.\end{aligned} \tag{D.4}$$

Substitute $p^* - \tilde{p} = (1-\alpha)\beta g$ and $d\tilde{p}/dg = (\rho - 1)(1-\alpha)\beta$, which follows from differentiating the definition of $\tilde{p}$ and using the pass through result for p^*. Then, simplification yields the final result:

$$\begin{aligned}
\frac{dBS}{dg} &= -D(p^* + \beta x)\rho(1-\alpha)\beta + D'(p^* + \beta x - (1-\alpha)\beta g)(1-\alpha)\beta\rho(1-\alpha)\beta \\
&- \left\{(1-\alpha)\beta g D'(\tilde{p} + \beta x)(\rho - 1)(1-\alpha)\beta\right\} \\
&= -D(p^* + \beta x)\rho(1-\alpha)\beta + D'(p^* + \beta x - (1-\alpha)\beta g)(1-\alpha)^2\beta^2\rho \\
&- (1-\alpha)^2\beta^2 g D'(\tilde{p} + \beta x)(\rho - 1) \\
&= -D(p^* + \beta x)\rho(1-\alpha)\beta + (1-\alpha)^2\beta^2 g D'(\tilde{p} + \beta x).
\end{aligned}$$

Note that, with the local linear demand assumption, the derivative of D evaluated at either $\tilde{p}$ or p^* is the same. ■

PROPOSITION 2: *In the presence of a binding standard ($\lambda > 0$), a change in gaming affects buyer surplus as follows:*

$$\frac{dBS}{dg} \approx \underbrace{(-\rho(c' - \alpha\beta) - \beta)D}_{\textit{price effect}} + \underbrace{(1-\alpha)^2\beta^2 D' g}_{\textit{choice distortion}}.$$

Proposition 2 is derived in a similar way to Proposition 1, but we define surplus using integrals over the demand function starting with full prices f. (This same could have been done in the prior proof, yielding the same result.) Recall that $f = p + \beta x$ and $\tilde{f} = p + \beta x - (1-\alpha)\beta g$.

(D.5)

$$BS = \underbrace{\int_{f^*}^{\infty} D(z)dz}_{\text{BS of correct quantity}} + \underbrace{\int_{\tilde{f}}^{f^*} D(z)dz}_{\text{Value of excess quantity}} - \underbrace{\int_{\tilde{f}}^{f^*} D(\tilde{f})dz}_{\text{Cost of excess quantity}}.$$

Differentiating, using the same Taylor approximation as above to simplify, yields:

$$\frac{dBS}{dg} \approx -D(f^*)\frac{df^*}{dg} + D'(f^*)(f^* - \tilde{f})\left(\frac{df^*}{dg} - \frac{d\tilde{f}}{dg}\right).$$

Substitute the pass through result described in the text: $df^*/dg = \rho(c'(x) + \alpha\beta) + \beta)$. Substitute the definition of $\tilde{f}$, which shows that $f^* - \tilde{f} = (1-\alpha)\beta g$. And substitute $\frac{df^*}{dg} - \frac{d\tilde{f}}{dg} = (1-\alpha)\beta$:

$$\frac{dBS}{dg} \approx -D(f^*)(\rho(c'(x)+\alpha\beta)+\beta) + D'(f^*)\left\{(1-\alpha)\beta g\right\}\left\{(1-\alpha)\beta\right\}$$

$$= -D(f^*)(\rho(c'(x)+\alpha\beta)+\beta) + D'(f^*)(1-\alpha)^2\beta^2 g. \tag{D.6}$$

This yields the result. ■

Estimation Details

We estimate the parameters θ using the following GMM objective:

$$\min_{\theta} \xi_j Z'\omega Z\xi_j$$

in which Z is a matrix of instruments and ω is a weighting matrix.

We use a panel containing sales, prices and characteristics for all new vehicle sales in seven European countries between 1998 and 2007.[43] We only use data from before 2008 to estimate demand, so that our estimates come from a period in which the performance gap was stable. We thus assume variation in x_j is informative about actual fuel cost differences. The vector Δ_j contains information on horsepower, weight, footprint (a measure of vehicle size), height and a dummy specifying if the car is of a foreign brand (e.g., Fiat in France). Additionally, we include fuel type by market dummies, dummies for the number of months a vehicle was on sale in a country-year, country fixed effects, a linear time trend, body type fixed effects, vehicle class fixed effects and brand fixed effects. We divide prices by income per capita in each country-year, so that price sensitivity varies with income in the market. We need instruments for price and for the standard deviations of the random coefficients. We instrument for prices using both cost shifters and sums of characteristics instruments, which follows Berry, Levinsohn and Pakes (1995). The sums of characteristics instruments are the sum of fuel costs, horsepower, weight, footprint and height across all other products in the market and across all other products within the same firm in the market. We also include the number of competing products and the number of products in the same firm. The cost shifters are the log of labor costs in the country of production and a dummy specifying if the vehicle is sold in the country of production. For the standard deviations, we use approximately optimal instruments that are constructed using a two-step procedure as described in Mathias Reynaert and Frank Verboven (2014). We estimate considerable heterogeneity in the taste for horsepower, weight and footprint. Vehicles perceived as foreign are less attractive for consumers. Cars with four doors are preferred over cars with two doors.

[43]The seven countries are: Belgium, France, Germany, Great Britain, Italy, Netherlands and Spain.

Additional Tables

Table F.1— Summary statistics

	Mean	St. Dev.
Car Characteristics		
Fuel Consumption (L/100km)	6.65	1.73
Vehicle Weight in kg	1,354	245
Diesel Engines	0.46	0.50
Drivers per car	107	219
Driver Characteristics		
Pump visits	134	80
Total liters purchased	6,015	3,666
Total distance (km)	111,726	53,942
Pump Visit Characteristics		
Liters per visit	45.3	10.8
Odometer increase per visit	671	192

The table gives summary statistics for the 2,696 vehicles, 266,616 drivers and 23,989,576 pump visits in the sample.

Table F.2— Summary statistics: Netherlands and Travelcard

	Mean	St. Dev.	Mean	St. Dev.
	TravelCard		**Netherlands**	
Price (euro)	31,672	13,367	40,767	29,676
Fuel Consumption (L/100km)	6.74	1.60	7.89	2.46
Vehicle Weight in kg	1,344	230	1,409	308
Diesel Engines	0.45	0.50	0.36	0.48

Summary statistics for the TravelCard sample and the full dutch market between 1998 and 2011.

Table F.3—Variance decomposition

	σ_d^2	σ_i^2	σ_j^2	σ_n^2
Mean	2.11	0.21	1.35	0.56
Standard deviation	0.57	0.03	0.45	0.11
Variance decomposition (%)	100	10.36	62.34	27.30
Standard deviation		2.54	6.76	4.40

σ_d^2 is the total variance in r_{nij}, σ_i^2 is the variation attributable to differences across individuals driving the same vehicle, σ_j^2 is the covariance between drivers in the same vehicle, σ_n^2 is the variation across refueling visits of the same driver in the same vehicle. The variance decomposition is performed separately for each release year, and the mean and standard deviation across years are reported in table.

Table F.4—Estimated vehicle gaps by release year, with and without empirical Bayes correction

Release	Unweighted r_j	$\widehat{r}_j$	Shrinkage	$\widehat{d}_j$	TS $\widehat{d}_j$
1998	7.91	7.87	0.99	7.85	
	(1.41)	(1.39)	(0.00)	(7.82)	
1999	7.90	7.88	0.99	8.70	1.16
	(1.49)	(1.46)	(0.01)	(6.90)	(1.29)
2000	7.96	7.94	0.99	8.60	-0.17
	(1.44)	(1.43)	(0.01)	(7.36)	(0.88)
2001	7.73	7.72	0.99	11.15	2.10
	(1.44)	(1.41)	(0.00)	(7.12)	(0.98)
2002	7.63	7.60	0.99	11.02	1.86
	(1.58)	(1.57)	(0.00)	(9.17)	(1.58)
2003	7.83	7.80	0.99	11.01	3.21
	(1.61)	(1.56)	(0.00)	(9.18)	(1.47)
2004	8.31	8.29	0.99	9.52	2.90
	(1.68)	(1.64)	(0.00)	(9.58)	(1.47)
2005	7.87	7.82	0.99	12.56	6.37
	(1.71)	(1.59)	(0.01)	(9.14)	(1.57)
2006	8.10	8.06	0.99	12.55	11.57
	(1.57)	(1.53)	(0.00)	(8.17)	(4.99)
2007	7.71	7.68	0.99	17.66	10.04
	(1.37)	(1.34)	(0.00)	(9.67)	(1.48)
2008	7.46	7.45	0.99	17.57	12.14
	(1.36)	(1.34)	(0.00)	(9.00)	(1.28)
2009	7.24	7.21	0.99	22.34	21.73
	(1.30)	(1.28)	(0.00)	(10.07)	(2.01)
2010	7.15	7.13	0.99	26.38	27.24
	(1.33)	(1.32)	(0.00)	(10.68)	(2.23)
2011	6.92	6.90	0.99	29.74	27.16
	(1.24)	(1.21)	(0.01)	(10.29)	(1.35)
2012	6.64	6.62	0.99	37.46	38.92
	(1.08)	(1.06)	(0.01)	(11.05)	(2.84)
2013	6.23	6.23	0.99	44.23	45.72
	(0.92)	(0.89)	(0.01)	(11.34)	(1.79)
2014	6.18	6.15	0.98	52.90	48.68
	(1.20)	(1.13)	(0.02)	(12.04)	(2.46)

Table reports mean and standard deviations for the distribution of estimated on-road consumption r_j, Bayes corrected on-road consumption $\widehat{r}_j$, shrinkage factor and Bayes corrected efficiency gap $\widehat{d}_j$ by release year. The final column gives the efficiency gap estimated from a two stage procedure. The first step regresses the gap on driver by vehicle fixed effects with time controls, the second step regresses the driver by vehicle effects on release year.

Table F.5—: Regression of performance gap on controls

	(1) Base	(2) Control	(3) Gas.	(4) Dies.	(5) MY	(6) Age1	(7) Age2	(8) Age3	(9) Loc.	(10) FY
Release:										
1999	1.996	0.526	-0.103	-0.749	0.524		0.798	0.691	0.523	
	(1.454)	(0.881)	(1.042)	(1.146)	(0.880)		(0.886)	(0.878)	(0.871)	
2000	0.319	0.745	1.216	0.582	0.745		0.875	0.898	0.727	
	(0.884)	(0.724)	(1.001)	(1.137)	(0.724)		(0.700)	(0.705)	(0.716)	
2001	2.329	-0.179	1.367	-2.423	-0.178		-0.0845	-0.0199	-0.163	
	(0.976)	(0.949)	(0.869)	(1.183)	(0.949)		(0.886)	(0.904)	(0.941)	
2002	1.766	1.271	2.150	-0.152	1.278		1.161	1.532	1.279	
	(1.561)	(1.067)	(1.060)	(1.552)	(1.066)		(1.039)	(1.044)	(1.061)	
2003	2.463	1.307	1.661	-0.498	1.313		1.032	1.410	1.304	
	(1.319)	(0.801)	(1.048)	(1.144)	(0.801)		(0.787)	(0.782)	(0.793)	
2004	3.300	2.566	2.256	1.221	2.570		2.279	2.570	2.506	
	(1.408)	(0.783)	(0.940)	(1.233)	(0.782)		(0.763)	(0.763)	(0.778)	
2005	4.709	4.200	6.193	1.942	4.201		3.565	3.863	4.189	2.497
	(1.432)	(0.966)	(1.531)	(1.254)	(0.966)		(0.923)	(0.928)	(0.956)	(2.391)
2006	10.59	3.842	5.559	2.758	3.834	0.284	3.308	3.395	3.808	5.803
	(5.085)	(1.085)	(1.236)	(1.482)	(1.085)	(1.029)	(1.151)	(1.077)	(1.075)	(1.733)
2007	7.381	8.460	8.619	8.057	8.444	4.404	7.643	7.985	8.392	2.790
	(1.385)	(1.036)	(1.344)	(1.347)	(1.035)	(1.071)	(0.999)	(0.998)	(1.030)	(2.087)
2008	9.533	8.857	9.230	8.292	8.833	4.271	7.536	7.983	8.796	12.60
	(1.370)	(1.003)	(1.060)	(1.476)	(1.002)	(1.080)	(0.988)	(0.984)	(0.992)	(2.474)
2009	18.50	13.74	10.37	16.22	13.72	8.715	11.97	12.38	13.66	15.66
	(2.238)	(1.411)	(1.098)	(2.444)	(1.409)	(1.717)	(1.337)	(1.316)	(1.397)	(2.207)
2010	22.57	17.93	15.54	19.60	17.91	12.47	15.52	15.99	17.82	19.85

Table F.5—: Regression of performance gap on controls

	(1) Base	(2) Control	(3) Gas.	(4) Dies.	(5) MY	(6) Age1	(7) Age2	(8) Age3	(9) Loc.	(10) FY
	(2.100)	(1.442)	(1.312)	(1.815)	(1.442)	(1.544)	(1.383)	(1.384)	(1.427)	(2.078)
2011	23.43	18.34	15.82	20.41	18.33	12.34	15.47	16.10	18.27	23.28
	(1.570)	(1.128)	(1.425)	(1.428)	(1.129)	(1.386)	(1.111)	(1.130)	(1.116)	(2.095)
2012	35.16	28.62	19.72	35.46	28.65	22.09	24.80	25.61	28.60	36.96
	(2.948)	(2.086)	(1.601)	(2.095)	(2.085)	(2.311)	(2.022)	(2.068)	(2.057)	(4.378)
2013	41.24	35.86	31.80	39.04	35.93	28.87	30.82	31.69	35.84	43.16
	(1.887)	(1.655)	(2.233)	(1.987)	(1.651)	(1.955)	(1.624)	(1.683)	(1.632)	(2.482)
2014	42.68	40.72	32.26	48.83	40.71	33.68	35.96	35.48	40.54	41.50
	(2.466)	(3.501)	(3.982)	(2.309)	(3.495)	(3.660)	(3.155)	(3.450)	(3.470)	(2.521)
Year:										
2005		0.121	0.537	-0.165						
		(0.133)	(0.135)	(0.180)						
2006		0.560	1.608	-0.107						
		(0.222)	(0.259)	(0.293)						
2007		0.710	1.681	0.0657						
		(0.285)	(0.348)	(0.378)						
2008		1.068	1.984	0.390						
		(0.330)	(0.398)	(0.448)						
2009		1.378	2.000	0.661						
		(0.377)	(0.467)	(0.520)						
2010		1.966	2.823	0.831						
		(0.422)	(0.526)	(0.588)						
2011		2.363	2.899	1.209						
		(0.489)	(0.609)	(0.693)						

Table F.5—: Regression of performance gap on controls

	(1) Base	(2) Control	(3) Gas.	(4) Dies.	(5) MY	(6) Age1	(7) Age2	(8) Age3	(9) Loc.	(10) FY
2012		3.330	3.251	2.436						
		(0.601)	(0.674)	(0.870)						
2013		3.919	3.423	3.115						
		(0.689)	(0.729)	(1.017)						
2014		3.139	2.240	2.464						
		(0.762)	(0.800)	(1.125)						
2015		4.743	3.555	3.842						
		(0.817)	(0.870)	(1.202)						
Month:										
2		-0.914	-0.812	-1.001						
		(0.0205)	(0.0308)	(0.0267)						
3		-2.049	-2.155	-1.988						
		(0.0616)	(0.123)	(0.0554)						
4		-3.605	-4.170	-3.219						
		(0.106)	(0.210)	(0.0723)						
5		-4.197	-5.303	-3.429						
		(0.138)	(0.253)	(0.0984)						
6		-4.479	-5.567	-3.738						
		(0.157)	(0.299)	(0.107)						
7		-3.841	-5.135	-2.949						
		(0.164)	(0.302)	(0.112)						
8		-4.292	-5.650	-3.348						
		(0.161)	(0.293)	(0.104)						
9		-4.923	-5.834	-4.318						

Table F.5—: Regression of performance gap on controls

	(1) Base	(2) Control	(3) Gas.	(4) Dies.	(5) MY	(6) Age1	(7) Age2	(8) Age3	(9) Loc.	(10) FY
		(0.155)	(0.297)	(0.121)						
10		-4.129	-4.566	-3.889						
		(0.115)	(0.224)	(0.105)						
11		-2.400	-2.338	-2.537						
		(0.0751)	(0.146)	(0.0795)						
12		0.120	0.360	-0.191						
		(0.0425)	(0.0489)	(0.0532)						
Diesel		2.083			2.089	2.085	3.273	2.449	2.182	
		(0.336)			(0.336)	(0.341)	(0.329)	(0.327)	(0.334)	
DistPerY		-1.48e-05	-3.98e-05	-5.30e-06	-1.47e-05	-1.54e-05	-6.47e-06	-4.87e-05	-1.21e-05	
		(4.40e-06)	(5.52e-06)	(5.67e-06)	(4.39e-06)	(4.41e-06)	(4.53e-06)	(3.23e-06)	(4.33e-06)	
DistPerY^2		2.09e-10	4.05e-10	1.29e-10	2.06e-10	2.06e-10	-0	2.78e-10	1.91e-10	
		(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	
DistPerY^3		-0	-0	-0	-0	-0	0	-0	-0	
		(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	
Age:										
1						0.599		-1.871		
						(0.380)		(0.114)		
2						-0.210		-3.366		
						(0.458)		(0.204)		
3						-0.885		-4.627		
						(0.545)		(0.308)		
4						-1.532		-5.876		
						(0.640)		(0.422)		

Table F.5—: Regression of performance gap on controls

	(1) Base	(2) Control	(3) Gas.	(4) Dies.	(5) MY	(6) Age1	(7) Age2	(8) Age3	(9) Loc.	(10) FY
5						-1.932		-7.277		
						(0.737)		(0.523)		
6						-2.272		-8.915		
						(0.788)		(0.638)		
7						-2.599		-10.60		
						(0.860)		(0.774)		
8						-3.127		-12.55		
						(0.944)		(0.930)		
9						-3.734		-12.92		
						(1.034)		(1.213)		
10						-4.628		-14.77		
						(1.147)		(1.447)		
11						-5.327		-18.40		
						(1.242)		(2.009)		
12						-5.852				
						(1.366)				
13						-5.803				
						(1.542)				
14						-5.579				
						(1.718)				
15						-4.740				
						(1.893)				
16						-3.471				
						(2.068)				

Table F.5—: Regression of performance gap on controls

	(1) Base	(2) Control	(3) Gas.	(4) Dies.	(5) MY	(6) Age1	(7) Age2	(8) Age3	(9) Loc.	(10) FY
17						-3.851				
						(2.272)				
Odom.							-4.24e-05			
							(2.11e-06)			
Const.	11.69	13.52	16.15	15.02						10.28
	(0.660)	(0.654)	(0.658)	(0.887)						(1.385)
Model F.E.	-	569	569	569	569	569	569	596	596	-
MonthYear F.E.	-	-	-	-	135	135	135	135	135	-
Location F.E.	-	-	-	-	-	-	-	-	19954	-
Observations	23,989,576	23,989,576	10,173,983	13,815,593	23,989,576	23,989,576	23,989,576	23,989,576	23,751,895	779,761
R-squared	0.281	0.400	0.361	0.459	0.401	0.401	0.409	0.405	0.413	0.469

Table reports coefficients of regressions of performance gap on controls. (1) includes only release year fixed effects (2) controls for year, month, fuel type, distance traveled per year and model fixed effects (absorbed), (3) equals (2) but limits the sample to gasoline engines, (4) equals (2) but limits the sample to diesel engines, (5) includes month by year fixed effects and model fixed effects (both absorbed), (6) equals (5) but includes age dummies, (7) equals (5) but includes odometer reading, (8) equals (5) but includes alternative age dummies, (9) equals (5) but adds fuel station fixed effects and (10) limits the sample to first year of driving.

Table F.6—: Regression of performance gap in levels on controls

	(1) Base	(2) Control	(3) Gas.	(4) Dies.	(5) MY	(6) Age1	(7) Age2	(8) Age3	(9) Loc.	(10) FY
Release:										
1999	0.0813	0.0627	-0.00764	-0.0143		0.0626	0.0776	0.0709	0.0626	
	(0.0724)	(0.0468)	(0.0608)	(0.0509)		(0.0468)	(0.0472)	(0.0469)	(0.0463)	
2000	0.0305	0.0649	0.0821	0.0486	0.0649		0.0720	0.0725	0.0637	
	(0.0495)	(0.0391)	(0.0591)	(0.0573)	(0.0391)		(0.0378)	(0.0382)	(0.0386)	
2001	0.118	0.0252	0.109	-0.0945	0.0252		0.0304	0.0330	0.0261	
	(0.0512)	(0.0446)	(0.0517)	(0.0491)	(0.0446)		(0.0419)	(0.0429)	(0.0442)	
2002	0.0241	0.0725	0.123	-0.0458	0.0730		0.0666	0.0855	0.0730	
	(0.0721)	(0.0504)	(0.0641)	(0.0660)	(0.0503)		(0.0487)	(0.0493)	(0.0499)	
2003	0.137	0.0692	0.0937	-0.0139	0.0696		0.0542	0.0744	0.0690	
	(0.0769)	(0.0412)	(0.0577)	(0.0570)	(0.0411)		(0.0408)	(0.0405)	(0.0407)	
2004	0.191	0.149	0.177	0.0746	0.149		0.133	0.149	0.145	
	(0.0603)	(0.0390)	(0.0533)	(0.0531)	(0.0390)		(0.0380)	(0.0383)	(0.0386)	
2005	0.214	0.238	0.365	0.0951	0.238		0.203	0.221	0.237	0.0286
	(0.0713)	(0.0494)	(0.0843)	(0.0579)	(0.0494)		(0.0466)	(0.0473)	(0.0488)	(0.135)
2006	0.514	0.231	0.326	0.179	0.230	0.0281	0.202	0.209	0.228	0.376
	(0.165)	(0.0569)	(0.0688)	(0.0837)	(0.0569)	(0.0533)	(0.0642)	(0.0568)	(0.0563)	(0.128)
2007	0.400	0.413	0.495	0.345	0.413	0.184	0.369	0.390	0.409	0.0848
	(0.0776)	(0.0493)	(0.0680)	(0.0583)	(0.0493)	(0.0520)	(0.0478)	(0.0478)	(0.0489)	(0.142)
2008	0.458	0.429	0.507	0.366	0.428	0.171	0.357	0.386	0.425	0.535
	(0.0629)	(0.0474)	(0.0578)	(0.0672)	(0.0474)	(0.0518)	(0.0469)	(0.0468)	(0.0468)	(0.132)
2009	0.715	0.556	0.505	0.597	0.555	0.274	0.459	0.489	0.551	0.587
	(0.0600)	(0.0526)	(0.0535)	(0.0823)	(0.0525)	(0.0630)	(0.0500)	(0.0494)	(0.0519)	(0.123)

Table F.6—: Regression of performance gap in levels on controls

	(1) Base	(2) Control	(3) Gas.	(4) Dies.	(5) MY	(6) Age1	(7) Age2	(8) Age3	(9) Loc.	(10) FY
2010	0.800	0.700	0.746	0.708	0.699	0.393	0.568	0.604	0.693	0.768
	(0.0549)	(0.0472)	(0.0707)	(0.0577)	(0.0472)	(0.0622)	(0.0453)	(0.0455)	(0.0466)	(0.119)
2011	0.912	0.762	0.769	0.782	0.762	0.422	0.605	0.653	0.758	0.887
	(0.0543)	(0.0489)	(0.0764)	(0.0585)	(0.0490)	(0.0663)	(0.0481)	(0.0483)	(0.0483)	(0.116)
2012	1.153	0.977	0.843	1.093	0.979	0.604	0.767	0.829	0.975	1.220
	(0.0585)	(0.0584)	(0.0703)	(0.0695)	(0.0583)	(0.0783)	(0.0579)	(0.0582)	(0.0573)	(0.119)
2013	1.241	1.142	1.215	1.173	1.145	0.739	0.865	0.935	1.140	1.266
	(0.0459)	(0.0518)	(0.0868)	(0.0639)	(0.0517)	(0.0786)	(0.0528)	(0.0532)	(0.0509)	(0.111)
2014	1.319	1.251	1.220	1.413	1.251	0.835	0.991	0.991	1.242	1.259
	(0.0542)	(0.0892)	(0.134)	(0.0685)	(0.0891)	(0.110)	(0.0760)	(0.0883)	(0.0887)	(0.114)
Year:										
2005		0.00828	0.0314	-0.0126						
		(0.00750)	(0.00895)	(0.00927)						
2006		0.0388	0.109	-0.0142						
		(0.0130)	(0.0167)	(0.0153)						
2007		0.0451	0.115	-0.00926						
		(0.0165)	(0.0221)	(0.0199)						
2008		0.0622	0.134	0.00328						
		(0.0190)	(0.0253)	(0.0237)						
2009		0.0708	0.128	0.0128						
		(0.0213)	(0.0290)	(0.0278)						
2010		0.0981	0.170	0.0165						
		(0.0232)	(0.0321)	(0.0309)						

Table F.6—: Regression of performance gap in levels on controls

	(1) Base	(2) Control	(3) Gas.	(4) Dies.	(5) MY	(6) Age1	(7) Age2	(8) Age3	(9) Loc.	(10) FY
2011		0.105	0.160	0.0203						
		(0.0254)	(0.0360)	(0.0341)						
2012		0.132	0.160	0.0527						
		(0.0283)	(0.0393)	(0.0379)						
2013		0.145	0.156	0.0667						
		(0.0310)	(0.0423)	(0.0419)						
2014		0.0948	0.0804	0.0288						
		(0.0336)	(0.0458)	(0.0455)						
2015		0.127	0.105	0.0541						
		(0.0357)	(0.0489)	(0.0484)						
Month:										
2		-0.0526	-0.0534	-0.0526						
		(0.00110)	(0.00175)	(0.00139)						
3		-0.114	-0.133	-0.101						
		(0.00225)	(0.00392)	(0.00166)						
4		-0.208	-0.265	-0.168						
		(0.00401)	(0.00569)	(0.00246)						
5		-0.245	-0.337	-0.178						
		(0.00553)	(0.00648)	(0.00361)						
6		-0.259	-0.350	-0.195						
		(0.00617)	(0.00830)	(0.00412)						
7		-0.224	-0.321	-0.153						
		(0.00674)	(0.00892)	(0.00480)						

Table F.6—: Regression of performance gap in levels on controls

	(1) Base	(2) Control	(3) Gas.	(4) Dies.	(5) MY	(6) Age1	(7) Age2	(8) Age3	(9) Loc.	(10) FY
8		-0.252	-0.358	-0.175						
		(0.00662)	(0.00803)	(0.00438)						
9		-0.282	-0.366	-0.224						
		(0.00577)	(0.00800)	(0.00411)						
10		-0.237	-0.288	-0.202						
		(0.00408)	(0.00599)	(0.00358)						
11		-0.137	-0.145	-0.133						
		(0.00266)	(0.00486)	(0.00281)						
12		0.00161	0.0203	-0.0175						
		(0.00204)	(0.00298)	(0.00231)						
Diesel		-0.206			-0.206	-0.203	-0.141	-0.188	-0.199	
		(0.0167)			(0.0167)	(0.0172)	(0.0159)	(0.0161)	(0.0165)	
DistPerY		-1.57e-06	-3.26e-06	-6.16e-07	-1.56e-06	-1.59e-06	-1.12e-06	-3.21e-06	-1.35e-06	
		(2.13e-07)	(3.49e-07)	(2.55e-07)	(2.13e-07)	(2.14e-07)	(2.20e-07)	(1.85e-07)	(2.05e-07)	
DistPerY^2		0	0	0	0	0	0	0	0	
		(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	
DistPerY^3		-0	-0	-0	-0	-0	-0	-0	-0	
		(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	
Age:										
1						0.0115		-0.0970		
						(0.0205)		(0.00487)		
2						-0.0330		-0.172		
						(0.0251)		(0.00852)		

Table F.6—: Regression of performance gap in levels on controls

	(1) Base	(2) Control	(3) Gas.	(4) Dies.	(5) MY	(6) Age1	(7) Age2	(8) Age3	(9) Loc.	(10) FY
3						-0.0740		-0.232		
						(0.0297)		(0.0122)		
4						-0.111		-0.291		
						(0.0346)		(0.0165)		
5						-0.130		-0.359		
						(0.0399)		(0.0213)		
6						-0.151		-0.446		
						(0.0431)		(0.0290)		
7						-0.167		-0.526		
						(0.0465)		(0.0397)		
8						-0.188		-0.638		
						(0.0501)		(0.0463)		
9						-0.216		-0.651		
						(0.0541)		(0.0645)		
10						-0.262		-0.770		
						(0.0596)		(0.0904)		
11						-0.295		-0.940		
						(0.0645)		(0.136)		
12						-0.325				
						(0.0703)				
13						-0.331				
						(0.0784)				
14						-0.328				

Table F.6—: Regression of performance gap in levels on controls

	(1) Base	(2) Control	(3) Gas.	(4) Dies.	(5) MY	(6) Age1	(7) Age2	(8) Age3	(9) Loc.	(10) FY
						(0.0862)				
15						-0.299				
						(0.0928)				
16						-0.262				
						(0.100)				
17						-0.264				
						(0.107)				
Odom.							-2.32e-06			
							(1.15e-07)			
Const.	0.723	1.014	1.062	0.838						0.722
	(0.0356)	(0.0326)	(0.0390)	(0.0407)						(0.105)
Model F.E.	-	569	569	569	569	569	569	596	596	-
MY F.E.	-	-	-	-	135	135	135	135	135	-
Location F.E.	-	-	-	-	-	-	-	-	19954	-
Observations	23,989,576	23,989,576	10,173,983	13,815,593	23,989,576	23,989,576	23,989,576	23,989,576	23,751,895	779,761
R-squared	0.117	0.211	0.182	0.259	0.212	0.212	0.220	0.215	0.225	0.191

Table reports coefficients of regressions equavalent to those reported in Table F.5 but the dependent variable is the level gap not %-gap. (1) includes only release year fixed effects (2) controls for year, month, fuel type, distance traveled per year and model fixed effects (absorbed), (3) equals (2) but limits the sample to gasoline engines, (4) equals (2) but limits the sample to diesel engines, (5) includes month by year fixed effects and model fixed effects (both absorbed), (6) equals (5) but includes age dummies, (7) equals (5) but includes odometer reading, (8) equals (5) but includes alternative age dummies, (9) equals (5) but adds fuel station fixed effects and (10) limits the sample to first year of driving.

TABLE F.7—ESTIMATION RESULTS

	Mean Taste		St. Dev.	
	Coeff.	St. Error	Coeff.	St. Error
Price/Inc.	-6.51	(0.45)		
Fuel Cost	-0.53	(0.01)	0.05	(0.03)
Horsepower	1.48	(0.21)	1.78	(0.10)
Weight	0.22	(0.21)	4.32	(0.16)
Footprint	0.88	(0.05)	0.58	(0.04)
Foreign	-0.92	(0.03)	0.02	(0.16)
Height	0.02	(0.02)		
Doors	0.50	(0.11)		

The table shows estimated taste parameters from a random coefficient logit estimation on the the car market for seven EU countries using data from 1998 to 2007. Taste distributions are assumed to be normal, and mean and standard deviations are estimated for selected characteristics. Additional controls are fuel type by market dummies, months for sale if less than 12, country fixed effects, linear time trend, body type fixed effects, vehicle class fixed effects and brand fixed effects. Model is estimated using a two-step GMM using approximate optimal instruments with sum of characteristics and cost shifter instruments for prices.

TABLE F.8—DIVERSION RATIOS

	Own Price Elast.	Outside Good	FC Q1	FC Q2	FC Q3	FC Q4
Fuel Cons Q1	-4.47	0.45	0.15	0.21	0.12	0.08
Fuel Cons Q2	-4.78	0.41	0.15	0.22	0.13	0.09
Fuel Cons Q3	-5.30	0.37	0.16	0.23	0.13	0.10
Fuel Cons Q4	-7.36	0.29	0.17	0.26	0.16	0.13

The table shows the average own price elasticity in each of the fuel consumption quartiles in the vehicles included in the counterfactual (Netherlands, year 2007). Column II gives the average diversion ratio to the outside good, while Column III-VI give diversion ratios from the row fuel consumption quartile to the column fuel consumption quartile. The diversion ratio is defined as $(\partial s_k/\partial p_j)/\mid \partial s_j/\partial p_j \mid$ so that Column II-VI sum up to 1.

ADDITIONAL FIGURES

Table F.9—Diversion Ratios specification IV Table 2

	Own Price Elast.	Outside Good	FC Q1	FC Q2	FC Q3	FC Q4
Fuel Cons Q1	-4.24	0.03	0.28	0.38	0.20	0.11
Fuel Cons Q2	-4.55	0.02	0.27	0.37	0.20	0.14
Fuel Cons Q3	-5.04	0.01	0.25	0.37	0.22	0.15
Fuel Cons Q4	-7.01	0.00	0.21	0.35	0.23	0.20

The table shows the average own price elasticity in each of the fuel consumption quartiles in the vehicles included in the counterfactual (Netherlands, year 2007) when the demand is estimated with a low 10% outside good share. Column II gives the average diversion ratio to the outside good, while Column III-VI give diversion ratios from the row fuel consumption quartile to the column fuel consumption quartile. The diversion ratio is defined as $(\partial s_k/\partial p_j)/\mid \partial s_j/\partial p_j \mid$ so that Column II-VI sum up to 1.

Table F.10—Consumer surplus changes from gaming under alternative policies

	Policy Target		
	3%	5%	10%
	Attribute-Based Standard		
Total	33.19	208.27	608.74
Choice Distortion	-17.77	-16.72	-13.47
Price Effect	50.96	224.99	622.22
	Flat Standard		
Total	3.92	107.93	398.69
Choice Distortion	-17.58	-16.93	-15.01
Price Effect	21.50	124.86	413.70
	Fuel Tax		
Total	-24.59	-24.94	-25.80
Choice Distortion	-17.42	-17.66	-18.23
Price Effect	-7.16	-7.29	-7.57

This Table presents consumer surplus changes when there is industry wide 5% gaming and policies with varying stringency: in Column (1) the target is a 3% reduction in emissions, Column (2) a 5% reduction (as in the previous Tables) and Column (3) a 10% reduction. The first panel shows the consumer surplus changes when firms game and there is an attribute-based standard, the second panel shows the effect of gaming when there is a flat standard, the third panel shows the effect of gaming when the policy is a fuel tax rather than a standard.

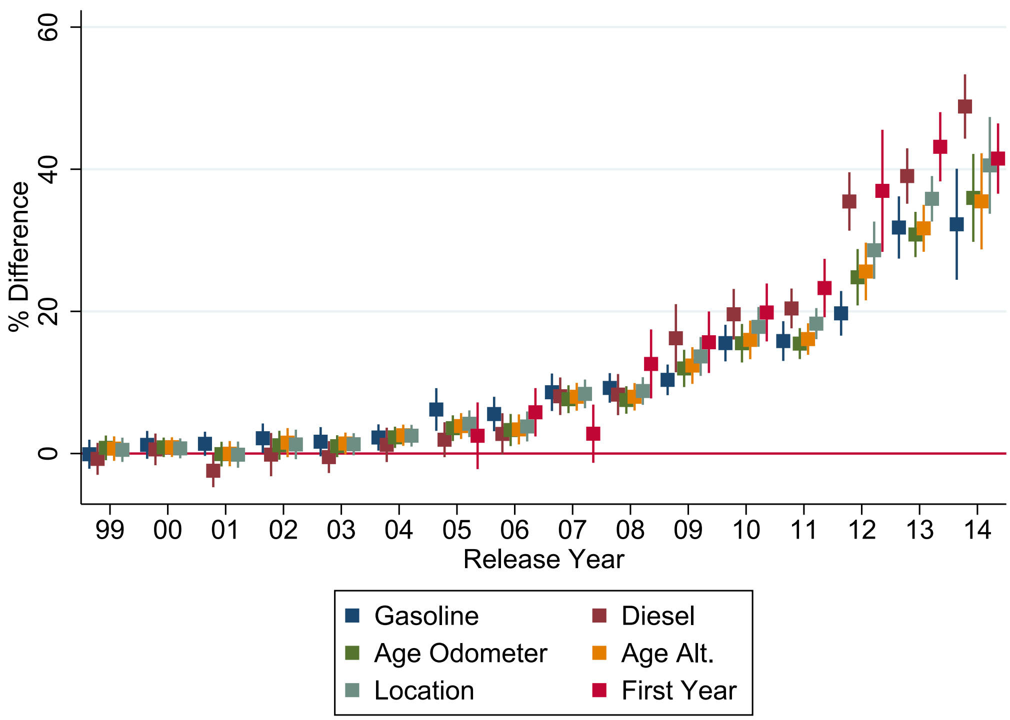

Figure G.1. Release year coefficients from fixed effect regressions

Note: Figure plots coefficients from a regression of the performance gap (d_{nij}) on release year fixed effects. Coefficients correspond to regressions (3),(4),(7),(8),(9) and (10) and from Table F.5.

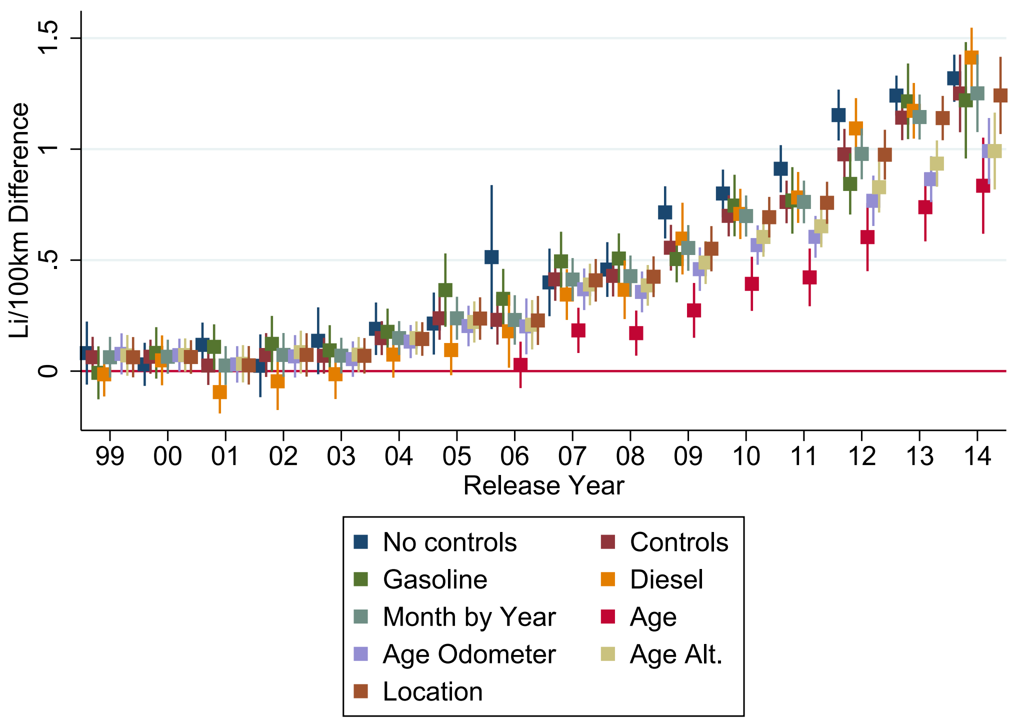

Figure G.2. Release year coefficients from fixed effect regressions

Note: Figure plots coefficients from a regression of the performance gap in li/100km, on release year fixed effects. Coefficients correspond to regressions from Table F.6.

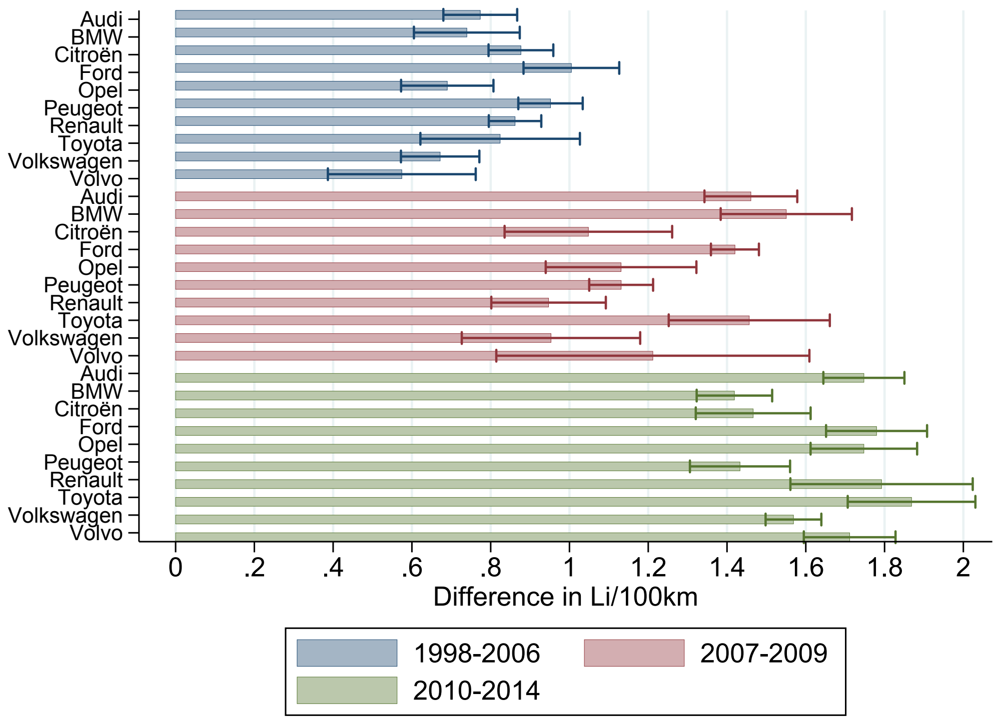

Figure G.3. Gap between on-road and official fuel consumption per firm in levels

Note: Figure shows estimated coefficients and standard errors from regressing the performance gap in levels on three sets of model release years (early, middle and late) per automaker, the data is restricted to the ten brands with most observations.

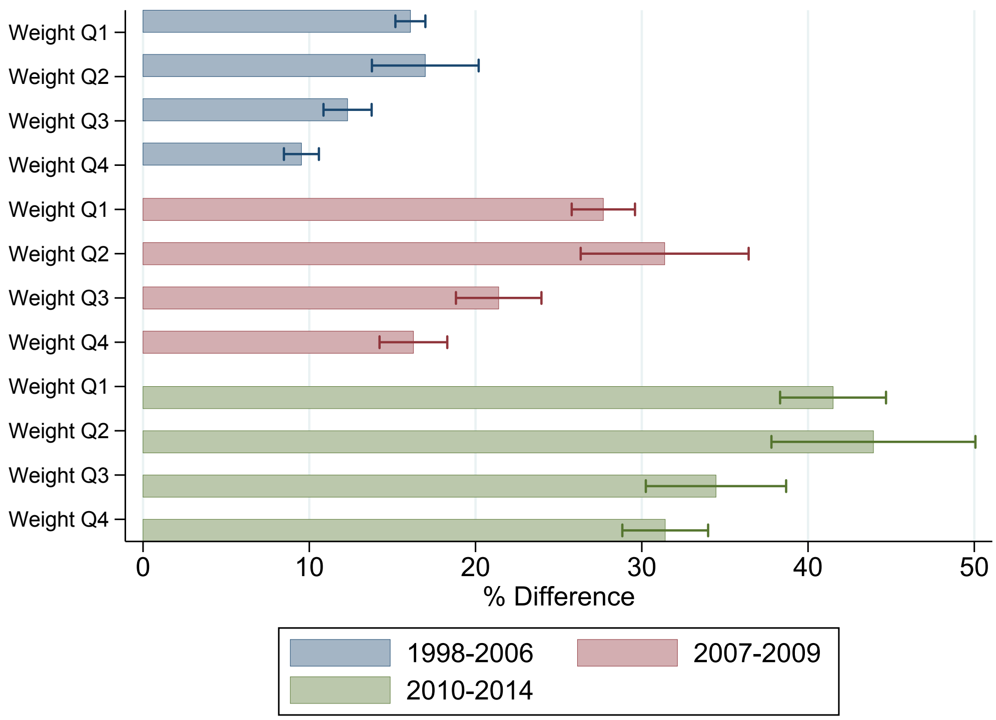

Figure G.4. Gap between on-road and official fuel consumption per weight quartile

Note: Figure shows estimated coefficients and standard errors from regressing the performance gap on three sets of model release years (early, middle and late) per weight quartile.

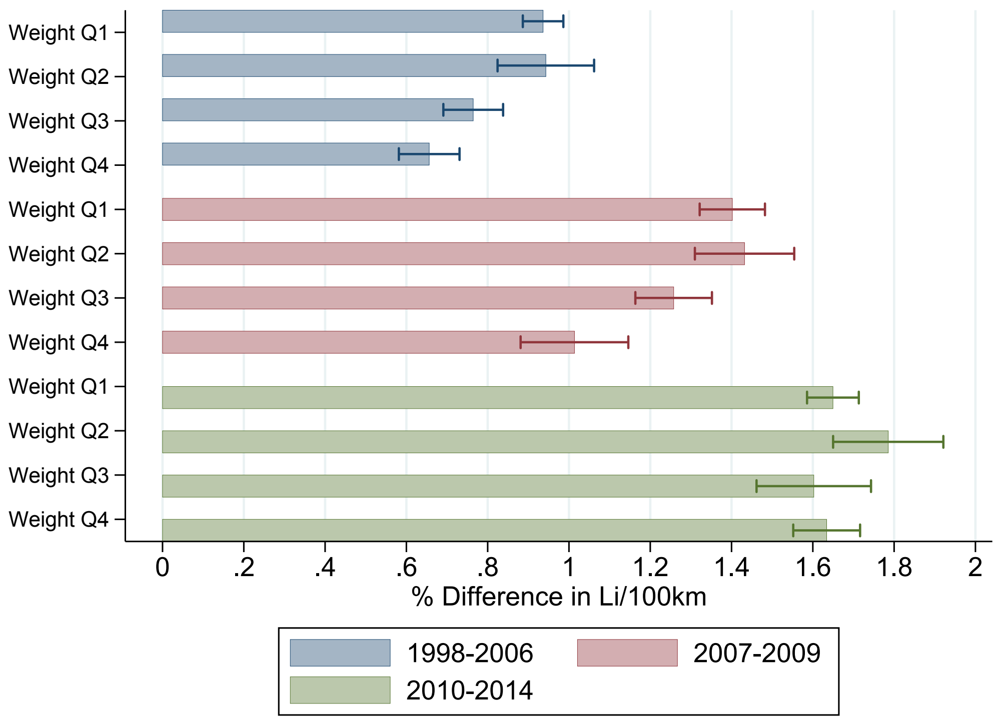

Figure G.5. Gap between on-road and official fuel consumption per weight quartile

Note: Figure shows estimated coefficients and standard errors from regressing the performance gap in levels on three sets of model release years (early, middle and late) per weight quartile.