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The development of a prescreening model to identify failed and gross polluting vehicles

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Abstract

The California State Bureau of Automotive Repair uses a high-emitter profile model to direct, or screen a fraction of the vehicle fleet in for inspection and maintenance testing at test-only facilities. Reviews by the California Inspection/Maintenance Review Committee showed the high-emitter profile to be inefficient and in need of improvement. In this study, using in-use vehicle emissions data from California's statewide smog check program, we specified a new multinomial logit model designed to improve the screening efficiency for targeting potential failed and gross polluting vehicles. Modeling results show that factors such as odometer reading, model year, vehicle make, as well as the presence of emissions control systems are significant factors in predicting the likelihood that a screened vehicle will test as a failed or a gross polluting vehicle. Comparisons indicate that the new multinomial logit model specification can predict various inspection/maintenance test outcomes more accurately than the existing high-emitter profile model.

Keywords: Gross polluting vehicles; High-emitter profile; Inspection and maintenance; Multinomial logit model

1. Introduction

The California Bureau of Automotive Repair administers the state's smog check program. The Smog Check program is designed to reduce hydrocarbons (HC) and oxides of nitrogen (NO_x) in automobiles and light duty trucks emission by ensuring that vehicle fleets are well maintained and high-emitting vehicles are identified for repair. The program is considered an important component toward reducing ozone and is credited with removing a combined 337 tons per day of HC and NO_x pollutants from California's air in 2005 (California Inspection and Maintenance Review Committee, 2006).

In 1996, Radian International (now Eastern Research Group Inc.) developed a high-emitter profile (HEP) model for the California Bureau of Automotive Repair (BAR). The HEP model was developed as part of the California Pilot Inspection and Maintenance (I/M) Program and designed to help BAR more efficiently

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identify, or screen for those vehicles most likely to be fail vehicle smog tests (Klausmeier et al., 1997).[1] A later comparison by the California I/M Pilot Project Review Committee of the failure rates between vehicles directed to I/M testing showed that the HEP directed vehicles had only a slightly better than random chance of correctly identifying those vehicles likely to fail the smog test (26%); randomly directed vehicles had a 22% failure rate (California Inspection and Maintenance Review Committee, 2000). This comparison suggested that the HEP efficiency rate was much lower than estimated in a pilot test where it was claimed that the HEP identified 72% of vehicle smog check failures versus 27% among randomly selected vehicles (Klausmeier et al., 1997; Klausmeier and Kishan, 1998). Subsequent reviews (e.g., California Inspection and Maintenance Review Committee, 2000, 2006) have continued to indicate the need for improvement in HEP performance and improvement in the smog check program efficiency including the implementation of vehicle model-specific emissions failure cutpoints.

The Radian HEP model is a logistic regression model with variables that include vehicle type, model year, engine (size) displacement, and whether there is an oxidation catalyst, three-way catalyst, EGR and/or air injection systems (Bureau of Automotive Repair, 1998). Many of these variables have been identified in the literature as being correlated with high-emitting vehicles. For example, vehicle characteristics, such as vehicle age (or model year), engine size, number of engine cylinders, odometer reading, and use of oxygenated fuels, have been associated with higher emissions or higher failure rates (Wayne and Horie, 1983; Kahn, 1996; Washburn et al., 2001; Bin, 2003). Other technology-based relationships that have been explored include those between the failure rates and repairs of specific emissions control system components, such as the catalyst, oxygen sensor, or exhaust gas recirculation (EGR) system, and higher emissions (Lawson et al., 1996; Heirigs et al., 1996; Wenzel and Ross, 1998). Some studies have also correlated specific manufacturers (e.g. Chevrolet, Ford, Nissan) with higher emissions (Wayne and Horie, 1983), or associated groups of manufacturers (e.g. domestic versus foreign) with higher emissions or higher failure rates (Washburn et al., 2001). However, even the distinction between foreign and domestic may not be sufficiently refined enough (Wenzel and Ross, 1997); emissions of a given manufacturer's vehicles can also vary substantially by model or engine family (Wenzel and Ross, 1998).

The HEP logit model remains the intellectual property of Eastern Research Group. Consequently, not many details are available with regard to model specification (Klausmeier et al., 1997). However, the California I/M Pilot Project Review noted that the original HEP model was not based on the rich data and large sample sizes that are currently available. As a result, it along with a subsequent National Research Council I/M program review both recommended development of a new HEP with contemporary data (California Inspection and Maintenance Review Committee, 2000; National Resource Council, 2001).

In this paper, we present a new multinomial logit model utilizing recently collected in-use vehicle data. We begin by describing the California I/M smog check data and the available modeling variables. The modeling specification results are then presented followed by a comparison between the performance of the 1996 Radian HEP and the new model.

2. Data

The data were supplied by the California Bureau of Automotive Repair (BAR) and contains all I/M test results for vehicles tested in the California in October of 2002. The dataset contains 837,829 observations and 94 variables, most of which are associated with vehicle characteristics and/or generated from three sets of tests typically performed as part of the smog check program; test data are sent electronically to the state's vehicle information database (VID). The three tests performed on all vehicles include: a visual inspection of emissions control equipment, a functional test of emissions control equipment, and a set of tailpipe emissions tests to measure exhaust emissions (Bureau of Automotive Repair, 2002).

When the results from all three tests are combined into a final test result, the possible outcomes are: passed, failed, gross polluter, or aborted. If we look at the overall I/M test results for the data set, approximately 4.6%

[1] According to BAR, a gross polluter is defined as a vehicle that emits at least twice the emissions level allowed for that particular make, model, and model year (Bureau of Automotive Repair, 1998).

of all vehicles tested were labeled as gross polluters, which is a subset of the 12.4% of test failures (7.8% failed plus 4.6% gross polluters). It should be noted that it is possible that some of the aborted emissions tests (5.3%) were actually failed or gross polluter test results, but we did not make any assumptions about the nature of the aborted tests for this analysis.[2]

During a typical smog check test, all required emissions control equipment is identified in the visual inspection and must appear connected and functional. Possible outcomes of the visual inspection include: passed, failed, or tampered. Tampered failures are distinguished from normal defective failures and include cases where equipment has been disconnected, has been modified, or is missing from the vehicle. The primary emission components examined by the smog check technician include the exhaust gas recirculation (EGR) system, the positive crankcase ventilation (PCV) system, the thermostatic air cleaner (TAC), the evaporation control system (EVAP), the catalytic converter (CAT),[3] the oxygen sensor (O_2 sensor), and the air injection (AI) system. Visual inspections are also made of various wirings, lines, hoses, sensors, and switches, along with any liquid fuel leaks and a check of the integrity of the fuel cap.

The functional inspection does not provide much information but is part of the standard smog check procedure. The functional inspection includes pass/fail inspections (when applicable) of the on-board diagnostic (OBD) system, the ignition timing, the fill pipe restrictor, and the fuel cap integrity. Most tests are conducted according to specific manufacturer's functional test procedures.

Along with the visual and functional tests, one of two sets of tailpipe emissions tests is conducted. Either a pair of "loaded", acceleration simulation mode (ASM) tests or a pair of "unloaded", two-speed idle (TSI) tests are performed. In the loaded ASM tests, vehicles are placed on a dynamometer and run at first, 50% of the maximum engine load encountered on the federal test procedure (FTP) at 15 mph (known as an "ASM 5015" test), and second, at 25% of the maximum engine load encountered on the FTP at 25 mph (known as an "ASM 2525" test). Second-by-second emissions data are recorded for both tests. If a vehicle cannot be tested on a dynamometer (e.g. if it is too heavy, too big, or operates only in four-wheel drive), a pair of two-speed idle (TSI) tests is performed. In the TSI tests, emissions are measured while the vehicle at 2500 rpm and at idle (which is usually between 400 and 1250 rpm). A vehicle passes the inspection if its observed emissions are less than a specified regulated level or "cutpoint" for that vehicle type, size, and weight.

For all tests, emissions concentrations are measured directly from exhaust concentrations. Measured gases include hydrocarbons (HC), carbon monoxide (CO), carbon dioxide (CO_2), oxygen (O_2), and nitric oxide (NO). Vehicles pass or fail the tailpipe inspection based on the established emissions standards. There are a separate set of standards that a vehicle must exceed to be labeled as a failed "gross polluter". In other words, it is possible for a vehicle to fail an emissions test, yet not be labeled as a gross polluter – which is defined by BAR as being at least two times the allowable emissions level for the particular make and model of the vehicle (Bureau of Automotive Repair, 1998).

Table 1 provides a list of available input variables that were available for use in the model specification. Not all of the data available by BAR is useful in this analysis, because a large portion of the data are used by the emissions test analyzer or for test record keeping purposes (e.g. ambient air temperature, the time and date, and the vehicle identification number).

Several variables were excluded from the model including fuel type, body type, and transmission type. Washburn et al. (2001) suggested that the use of alternative fuels may be associated with failing a tailpipe test, but vehicles from the California smog check program were overwhelmingly gasoline (99.9% of the sample). There was no theoretical justification for including vehicle body type or transmission type because they have no influence on the vehicle emissions that cannot be explained by engine variables, such as engine size or and number of cylinders.

It is also important to note that many of the variables in Table 1 may be influenced directly or indirectly by other variables (e.g. correlations). For technician qualifications or test facility type, the percentage of failed and gross polluters identified was lower on average when the test performed by a basic area technician (6.4%) than an advance emissions specialist (12.4%), which is in line with the overall average (12.4%). We also

[2] Aborted tests are tests that were started but never completed. Records are kept for all tests, even those that were canceled for any reason after the test was started.

[3] No distinction is made between oxidation catalysts and three-way catalysts in this dataset.

Table 1
List of input variables descriptions

	Variable type
Vehicle characteristics	
Model year: 1966–2004[a]	Continuous
Vehicle make	Categorical
Vehicle model	Categorical
Odometer reading	Continuous
Gross vehicle weight	Continuous
Vehicle test weight	Continuous
Engine size (Displacement in liters)	Continuous
Number of cylinders: 2, 4, 6, 8, 12, 16	Categorical
Vehicle type: passenger car, truck, motorhome	Categorical
Body type: sedan, pickup, SUV, wagon, van, minivan, other	Categorical
Transmission type: automatic or manual	Categorical
Fuel type: gasoline, liquid propane gas, methanol, etc.	Categorical
Emission control equipment	
PCV system visual/functional inspection result	Categorical
Catalytic converter visual/functional inspection result	Categorical
Thermostatic air cleaner visual/functional inspection result	Categorical
Carburetor visual/functional inspection result	Categorical
Fuel injection system visual/functional inspection result	Categorical
Air injection system visual/functional inspection result	Categorical
Exhaust gas recirculation visual/functional inspection result	Categorical
Ignition spark control visual/functional inspection result	Categorical
Fuel evaporative control visual/functional inspection result	Categorical
Oxygen sensor visual/functional inspection result	Categorical
Other information	
Inspection reason: biennial, change of ownership, HEP, etc.	Categorical
Required emissions test type: ASM or TSI	Binary
"Plate issuing state"	Categorical
Emissions inspection system (EIS) type	Categorical
Test facility type: test-only, test-and-repair, etc.	Categorical
Technician qualifications: specialist, basic, intern, etc.	Categorical

[a] It should be noted that pre-1974 model year vehicles are exempt from I/M testing, and vehicles less than four-years old (1999–2002 model year vehicles) are exempt from I/M testing unless there is a change in ownership. Our 2002 dataset contains 17 observations of pre-1974 model year vehicles.

found that "test and repair" facilities had a lower rate of failed and gross polluter vehicle identification (9.2%) than "test-only" facilities (16.5%), with higher than average identification rates. Despite the summary statistics, the different test facilities and technician qualifications were not considered particularly useful model variables because they were likely to be biased. Vehicles that have already been identified as a gross polluter must, by state law, be sent to test-only facilities where only advanced emissions technicians are permitted to perform the test (Bureau of Automotive Repair, 1998). As a result, they were more likely to be gross polluters when retested at test-only facilities by advanced emissions technicians.

Vehicle model years represented in the data ranged from 1966 to 2004 (Fig. 1). Caveats with respect to vehicle age are that: (1) new vehicles are granted a four-year exemption from the biennial I/M test in the State of California (unless there is a change of ownership in that four-year period), (2) pre-1974 vehicles are exempt from I/M testing in California, and (3) there are spikes in the data in 1998, 1996, and 1994 for each biennial inspection required for each model year prior to 2002, excluding those vehicles who qualify for the four-year exemption. Disproportionate numbers of failed vehicles and gross polluters of pre-1991 model year vehicles are observed, relative to the overall sample. For instance, 1982 model year vehicles account for only about 1% of the vehicles tested in the sample but about 16% of the identified failed vehicles and about 12% of the identified gross polluters. Fig. 2 shows a trend of decreasing emissions. It indicates that older vehicles produce higher emissions, and the more likely it is to be a failed vehicle or a gross polluter. It is important to point

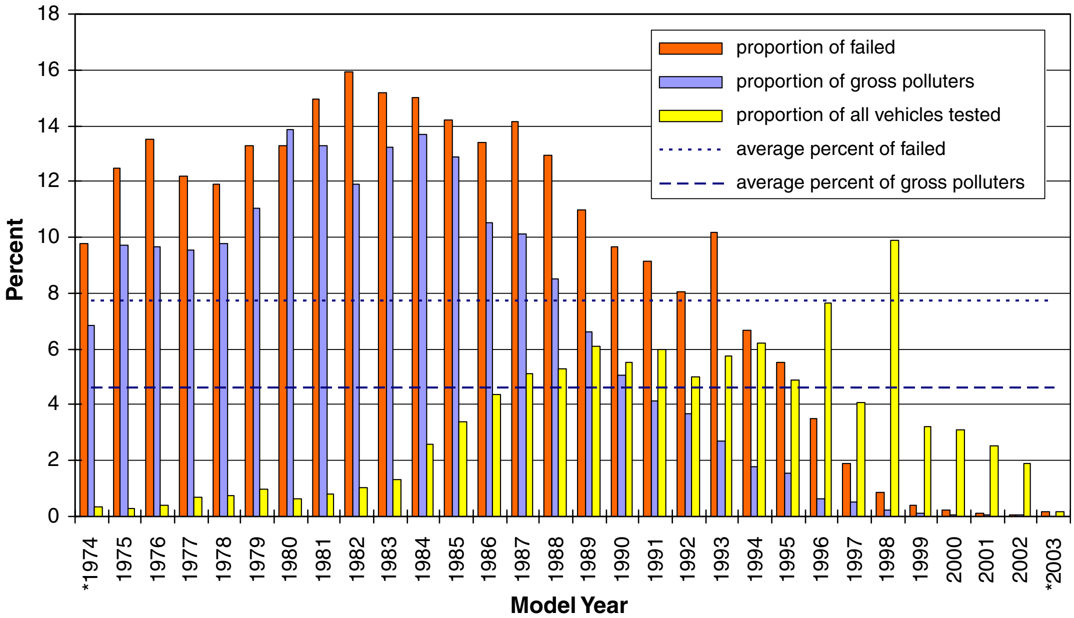

Fig. 1. Proportions of failed and gross polluting vehicles by model year. *Note*: Model year 1974 includes pre-1974 (17 vehicles) and model year 2003 also includes after 2003 (2 vehicles).

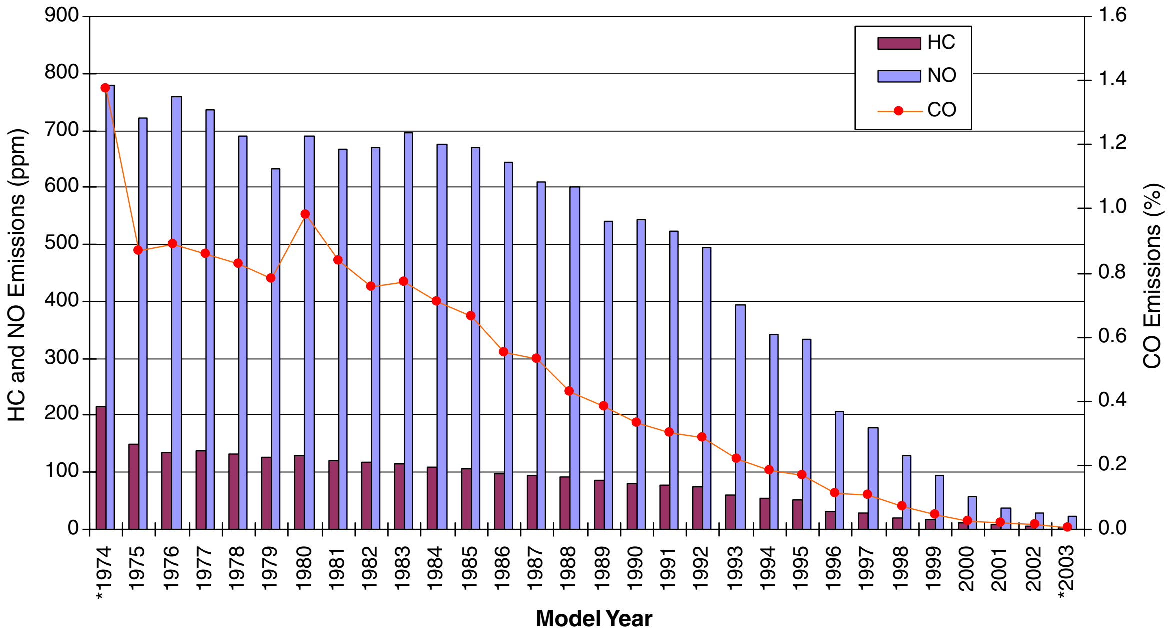

Fig. 2. Average emissions per vehicle by model year (ASM 5015 test-only). *Note*: Model year 1974 includes pre-1974 (17 vehicles) and model year 2003 also includes after 2003 (2 vehicles).

out that, because of changes in California's new vehicle emissions standards and the implementation of emission control technologies on vehicles, the distributions of failed and gross polluting vehicles by model year, shown in Fig. 1, does not necessarily correspond to the distribution of emissions by vehicle year shown in Fig. 2.

Table 2
Vehicles tested by inspection reason and incidence of failed vehicles and gross polluters

Inspection reason	Failed	Gross polluter	Total tested vehicles
Change of ownership	12,930	6679	262,442
High-emitter profile	27,882	15,864	224,105
Biennial inspection	5336	2418	180,987
Initial (out of state) registration	4195	2543	91,206
1.9% Random sample	1791	1283	14,110
Other	12,725	9849	64,946
Total	64,859 (7.7%)	38,636 (4.6%)	837,796 (100.0%)

Notes: $N = 33$ (0.0%) missing cases total. Vehicles subjected to testing as either part of the 1.9% random sample or the high-emitter profile are directed to test-only stations (Bureau of Automotive Repair, 1998). California state law requires that 1.9% of emissions tests in the areas with the most severe air pollution be randomly performed at test-only facilities to evaluate the overall effectiveness of the smog check program (BAR, 2003).

Approximately 27% of those vehicles directed for I/M testing are HEP-flagged (Table 2). The two other most common reasons for I/M testing are resulting from a change of ownership (31%) and required biennial inspection (nearly 22%). About 7% of those vehicles flagged as potential gross polluters are actually gross polluters, which is comparable to the capture rate of gross polluting vehicles that were randomly selected for testing at test-only stations (9%). "Other" tests include prescreening tests (pretests) for gross polluting vehicles, so they were excluded from our model due to selectivity bias.

The presence of various emission control devices were determined from visual/function test results in the dataset. It should also be noted that the presence of many of these controls, such as catalysts, exhaust gas recirculation, oxygen sensors, positive crankcase ventilation, ignition spark controls, and fuel injection, are in most vehicles and work together to achieve a common goal (i.e. reducing CO, HC, or NO_x emissions) and were found to be correlated at the 95% confidence level as shown in Table 3.

Using composite variables is helpful for reducing multi-collinearity problems in the model specification. Exploratory factor analysis on the seven emissions control variables plus other control variables (air injection, carburetor, and thermostatic air cleaner) were unsatisfactory in producing conceptually unacceptable factors, or having component variables with counter-intuitive signs. A single-factor solution was obtained from the seven variables through principal component analysis, accounting for 66% of the total variance of the variables. Table 4 shows the component score coefficients of the factor variable. Other emissions control variables were included as independent variables in our model specification, together with the factor score variable.

If we cross tabulate the proportion of failed and gross polluters identified with various on-board emissions control devices (Table 5), we find that vehicles with carbureted fuel systems are more likely to be either failed (14.7%) or gross polluting vehicles (14.0%) compared with the overall sample average percentages (7.7% and 4.6%, respectively), while vehicles with injected fuel systems are less likely to be either failed (6.9%) or gross polluting vehicles (3.2%). This observation is consistent with a 1996 American Petroleum Institute (API) study

Table 3
Correlation coefficients among emissions control system devices

Control	PCV	EVAP	CAT	EGR	SPARK	FI	O_2
PCV	1.000	0.970[a]	0.846[a]	0.430[a]	0.749[a]	0.490[a]	0.685[a]
EVAP		1.000	0.859[a]	0.431[a]	0.741[a]	0.499[a]	0.697[a]
CAT			1.000	0.387[a]	0.658[a]	0.561[a]	0.791[a]
EGR				1.000	0.346[a]	0.088[a]	0.268[a]
SPARK					1.000	0.357[a]	0.531[a]
FI						1.000	0.688[a]
O_2							1.000

Notes: PCV = positive crankcase ventilation, EVAP = evaporative emissions controls, CAT = catalyst, EGR = exhaust gas recirculation, SPARK = ignition spark controls, FI = fuel injection, O_2 = oxygen sensor.

[a] Two parameters are statistically significant at the 95% confidence level.

Table 4
Component score coefficients of single emissions control factor

Component	PCV	EVAP	CAT	EGR	SPARK	FI	O_2
Coefficient	0.204	0.205	0.201	0.104	0.171	0.141	0.182

Notes: PCV = positive crankcase ventilation, EVAP = evaporative emissions controls, CAT = catalyst, EGR = exhaust gas recirculation, SPARK = ignition spark controls, FI = fuel injection, O_2 = oxygen sensor.

Table 5
Summary statistics of emission controls and incidence of failed and gross polluting vehicles

ECS component	Failed	Gross polluting	Total tested vehicles
Positive crankcase ventilation system	63,856	38,039	789,891
Thermostatic air cleaner	28,075	21,698	201,432
Fuel evaporative controls	63,644	37,844	787,856
Catalyst	62,507	36,613	773,538
Exhaust gas recirculation	53,763	32,049	632,325
Ignition spark controls	61,912	36,962	757,056
Carbureted	17,421	16,622	118,411
Fuel-injected	46,470	21,436	671,884
Air injection	10,058	8318	83,194
Oxygen sensor and connectors	57,777	32,557	743,556

Note: The number of missing cases varies by ECS component.

on vehicle emissions in which a clear distinction was made between carbureted and fuel-injected vehicles; carbureted vehicles tended to be older with higher mileage than fuel-injected vehicles (Heirigs et al., 1996).

3. Model estimation

Expanding the binary logit models focused on emission test failures (e.g. Bin, 2003) or gross polluters (e.g., the original HEP by Radian, 1997), a multinomial model was used to predict probabilities of three different (mutually exclusive) types of I/M test outcomes: passed, failed (non-gross polluter), and (failed) gross polluter,

$$P_n(i) = \frac{e^{\beta_i X_{in}}}{\sum_{\forall I} e^{\beta_I \mathrm{X}_{In}}}$$

where $P_n(i)$ is the probability that vehicle n has the I/M test result i, I is the set of all possible discrete I/M test outcomes (i.e., passed, failed, gross polluter), $\mathbf{X}_{in}$ is a vector of measurable characteristics (vehicle-specific characteristics, emissions test variables, etc.) that determines the I/M test outcome for vehicle n, and β_i is a vector of coefficients estimated through maximum likelihood methods. Note here that the MNL model must hold the independence from irrelevant alternatives (IIA) property that the ratio of choosing probabilities of two alternatives is never affected by any other alternative.

To estimate the model, the data were first randomly divided approximately in half; the first half ($N = 418{,}222$) was used to specify the model and the second half ($N = 419{,}607$) was used to evaluate the model specification and compare its performance results to that of the existing HEP model. The "passed" alternative was selected as the base alternative in the model. As shown in Table 6, the final model has two alternative-specific constants (ASCs) and 40 alternative-specific variables (ASVs). All explanatory variables are statistically significant at $\alpha = 0.05$. In addition, we conducted t-tests to explore whether coefficients of each of the explanatory variable were statistically significantly different between the failed and gross polluter alternatives. The tests indicate that nine of 20 pairs of explanatory variables are not statistically different at $\alpha = 0.05$. That is, the impacts of those variables on likelihoods of being a failed vehicle and a gross polluter are not significantly different.

The model goodness-of-fit statistics indicate that the inclusion of covariates improves the model fit. The likelihood ratio test statistic ($\chi^2 = 37{,}582$) shows that we can reject the null hypothesis, at $\alpha \ll 0.0001$, that

Table 6
Estimated multinomial logit model (Base alternative = passed)

Explanatory variables	Failed		Gross polluter
Constant	−4.262		−5.489
Odometer reading (in thousands of miles)	0.00382		0.00296
Engine size/displacement (in liters)	−0.0444		−0.132
Model year: before 1980 (1 = yes, 0 = no)	1.847		2.790
Model year: 1980–1985 (1 = yes, 0 = no)	2.307		3.370
Model year: 1986–1990 (1 = yes, 0 = no)	2.082		3.049
Model year: 1991–1995 (1 = yes, 0 = no)	1.672		2.063
Carbureted fuel system (1 = yes, 0 = no)	0.113		0.612
Air injection system (1 = yes, 0 = no)	−0.199[a]		−0.201[a]
Other emission control system presence factor scores (standardized values, min = −3.84, max = 0.41)	−0.507		−0.462
TSI emissions test: (1 = yes, 0 = no)	−1.115		−0.559
Make: Cadillac (1 = yes, 0 = no)	0.634[a]		0.651[a]
Make: Chevrolet (1 = yes, 0 = no)	0.312		0.149
Make: Dodge (1 = yes, 0 = no)	0.312[a]		0.350[a]
Make: Honda (1 = yes, 0 = no)	−0.147[a]		−0.173[a]
Make: Hyundai (1 = yes, 0 = no)	0.921[a]		0.825[a]
Make: Infiniti (1 = yes, 0 = no)	−0.612[a]		−0.584[a]
Make: Jaguar (1 = yes, 0 = no)	0.461[a]		0.305[a]
Make: Jeep (1 = yes, 0 = no)	0.173		0.583
Make: Lexus (1 = yes, 0 = no)	−0.601[a]		−0.953[a]
Make: Mitsubishi (1 = yes, 0 = no)	0.409[a]		0.431[a]
Log likelihood at convergence [$LL(\boldsymbol{\beta})$]		−133,863.3	
Number of observations		365,488	
McFadden ρ^2		0.123	

Notes: All coefficients are statistically significant at $\alpha = 0.05$.
[a] Coefficients of alternative-specific variables (ASVs) for both alternatives are not statistically significantly different at $\alpha = 0.05$.

all of the model parameters are collectively equal to zero. McFadden's ρ^2 statistic was calculated as 0.123, which indicates a relatively low goodness-of-fit.[4] This may be attributable to the fact that 28 of the 42 variables in the model were indicator variables defined by the vehicle manufacturer or model year. Despite the large number of observations, we were still limited by the amount of data available for each vehicle emissions test.

Consistent with Wenzel and Ross (1998), Washburn et al. (2001), Bin (2003), and Beydoun and Guldmann (2006), as odometer mileage increases, the likelihood of being identified as a failed vehicle or a gross polluter increases. To create the model year dummy variables, model years were classified into five groups based on emission control technology implementation as cited, in part, by Cadle et al. (1999) and using CARB's existing EMFAC model categorization (CARB, 2003): pre-1980 model years (oxidation catalysts or no catalytic converters); 1980–1985 model years (three-way catalysts), 1986–1990 (known to be equipped with fuel injection engines and improved engine control units), 1991–1995, and post-1995 (second-generation on-board diagnostics) as a base category. As expected, the model year variables have positive signs, meaning that older vehicles[5] are more likely to be identified as failed vehicles and gross polluters. Looking at the magnitudes of model year variables, older model years have stronger effects on gross polluters than failed vehicles. While this finding may seem to conflict with the simple notion that emission control failures are typically associated with older vehicles, it is also important to realize that older vehicles are not held to the same emissions standards as newer vehicles. Instead, this finding may suggest that a more complex relationship exists between emissions technology and vehicle age. Vehicles in the early- to mid-1980s with first generation emissions technology are more likely to be gross polluters than older vehicles without modern emissions technology but more lenient

[4] McFadden's ρ^2 is a measure of overall goodness-of-fit and is calculated as $1 - [LL(\boldsymbol{\beta})/LL(\mathbf{MS})]$, where $LL(\boldsymbol{\beta})$ is the model log likelihood at convergence and $LL(\mathbf{MS})$ is the log likelihood of the market share model (with constant terms only).
[5] The model year grouping from 1996 to 2004 was used as the base (reference) grouping.

emissions standards. Otherwise, vehicles with second-generation emissions control systems seem be related to age, as might be expected with normal deterioration of emission systems.

As expected, the presence of air injection and the composite presence measure of seven ECS components (positive crankcase ventilation, evaporative emissions controls, catalyst, exhaust gas recirculation, ignition spark controls, fuel injection, and oxygen sensor) are negatively associated with being failed vehicles and gross polluters. On the other hand, carbureted engines are strongly associated with being a failed vehicle and a gross polluter. This finding replicates those of Bin (2003) who suggested a similar conclusion with regard to emissions test failures.

Vehicles with larger engines were also found to be negatively related to being failed vehicles and gross polluters. Under constant loading applied during I/M tests, we might expect larger engines to produce more emissions and be more susceptible to being identified as either a failed vehicle or a gross polluter. It is important to remember, however, that vehicles with larger engines (all else being equal) are held to the same standards as smaller engine vehicles so that alone should not be justification for the decreased likelihood of being either a failed vehicle or a gross polluting vehicle. Instead, it is possible that vehicles with larger engines (all else being equal) may operate more frequently under lower loads, resulting in less engine work and less damage or degradation to emissions control devices. Interestingly, the negative impact of a larger engine on being a gross polluter is nearly three times that of being a failed vehicle.

Another interesting finding is that the emissions test type is a significant factor with identified failed and gross polluting vehicles. The results indicate that TSI tests are less likely to result in a failed vehicle or a gross polluter than a normal ASM test. If we were to look at the type of emissions tests administered to each vehicle, we would observe that almost 85% of all vehicles take the accelerated simulation mode (ASM) test, while only about 15% of vehicles take the two-speed idle (TSI) test. The TSI test can be conducted in lieu of an ASM test for any vehicle over 8500 lbs (gross vehicle weight) that will not fit on a dynamometer (Bureau of Automotive Repair, 2002) but it only measures HC and CO emissions and can only be done in non-urbanized "basic areas". In "enhanced areas", ASM tests for HC, CO, and NO_x must be done, with a subset being directed to test-only stations. If we cross-tabulate failed vehicles and gross polluters with the emissions test type, we see that TSI tests (3.4% and 3.5%, respectively) have lower identification rates than ASM tests (8.5% and 4.8%, respectively). The fact that the test measures fewer emissions could be one reason it identifies fewer failed and gross polluting vehicles, as well as the reason why state law mandates ASM testing.

One issue that many researchers have tried to address has been the tendency of certain manufacturers to produce a disproportionate number of failing and gross polluting vehicles. The final model indicates that Honda, Infiniti, and Lexus were less likely to be identified as having produced failed and gross polluting vehicles, while Cadillac, Chevrolet, Dodge, Hyundai, Jaguar, Jeep, and Mitsubishi were more likely to be identified as having produced failed and gross polluting vehicles. It is difficult to compare these results to previous findings because past studies often pooled vehicle manufacturers into categories (i.e., foreign versus domestic) due in part to smaller sample sizes. Nonetheless, Wayne and Horie (1983), Kahn (1996), Ross et al. (1998), Washburn et al. (2001) and Bin (2003) all found significant relationships between manufacturers and emission rates.

Additionally, two types of IIA tests, the Hausman–McFadden and nested logit (NL) structure tests (Hausman and McFadden, 1984) were conducted. The Hausman–McFadden tests could not be completed due to the singularity of the $\{V(r) - V(f)\}$ matrix. However, this is empirically common if IIA holds and thus $V(r)$ and $V(f)$ tend to be similar (Small and Hsiao, 1985). On the other hand, only one of three nested structure models, nesting failed and gross polluter alternatives, was estimated, but its inclusive value parameter was significantly greater than one (i.e. not theoretically sound). This finding suggests that the final multinomial logit model is superior to any nested logit model. The fact that all explanatory variables are alternative-specific variables is a potential solution to avoid IIA violations (Ben-Akiva and Lerman, 1985). Overall, we can conclude that the IIA property holds with the multinomial logit model.

The multinomial logit (MNL) model is validated using the remaining half of the entire dataset, which includes a variable identifying whether vehicles were flagged as potential gross polluters using the existing HEP. Using the actual test results and the flagged HEP variable we were able to compare actual I/M test results with predicted test results by both the MNL and Radian models. It should be noted that the Radian model can only predict gross polluting versus non-gross polluting vehicles, while the MNL model can predict

Table 7
Comparison of Radian model versus MNL model efficiency

		Predicted test results					
		MNL			Radian		
		GP	F	P	GP	F	P
Actual I/M test results	Gross polluter (GP)	1258	1810	11,367	7930		(6505)
	Failed (F)	1788	3016	21,264	(99,746)		(253,224)
	Passed (P)	11,340	21,316	294,246			

Notes: Number of observations = 367,405. The numbers in parentheses mean non-gross polluters, which are the sum of failed and passed vehicles. The diagonal (underlined) cells indicate correct prediction.

passing, failing, and gross polluting vehicles. Table 7 shows that the MNL model correctly predicted 81% of the I/M test results, while the Radian model correctly predicted 71%. When we compare results (Table 7), the new MNL appears to have significantly higher predictability accuracy than the existing Radian model. An important secondary advantage is that it is able to also predict three different categories of I/M test results, including pass, fail, and gross polluting vehicles.

4. Conclusion

Past evaluations of the in-use BAR high-emitter profile indicated that it was not very efficient at prescreening gross polluting vehicles. In this paper, we develop a multinomial logit model to identify factors that are significantly associated with identified failed and gross polluting vehicles, using a large sample of actual California I/M test data. The results indicate that factors such as odometer reading, model year, and vehicle make, along with the presence of modern day emission control systems, are significant factors in predicting the likelihood being labeled as a failed vehicle and a gross polluter. The new MNL model yielded a better predictability of I/M test results (passed, failed, and gross polluter) when compared to the existing HEP model. Results from this study extend the ability of regulators in California to better sample failed vehicles or gross polluters and improve the cost-effectiveness of its existing I/M program.

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