Associations among Household Characteristics, Vehicle Characteristics and Emissions Failures: An Application of Targeted Marketing Data

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Abstract

Many U.S. cities use vehicle emissions testing programs to improve air quality by identifying gross polluting vehicles and requiring their owners to make emissions-related repairs. All vehicles that meet certain criteria must pass an emissions test as part of the vehicle registration process. States use different criteria to determine which vehicles must be tested; however, the equity impacts associated with various screening criteria are unknown. This is due to difficulties researchers have faced in linking vehicle and household characteristics. We investigate the relative influence of vehicle and household characteristics on emissions failures in Atlanta, Georgia, by linking its emissions testing database to a targeted marketing database; the latter contains information about vehicle owners. We use count and hurdle models to predict vehicle emissions failures. Our model finds a relationship between sociodemographic characteristics and emissions failures after controlling for vehicle characteristics; that is, given two identical vehicles, the one owned by a low-income or minority household is more likely to fail emissions. We use our model to investigate the impacts of different emissions testing policies by income and ethnic groups.

Keywords: vehicle emissions modeling, hurdle model, targeted marketing data

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Research Highlights

- We model emissions failures using vehicle and household characteristics.
- Failures are highly correlated with low-income and minority households.
- Vehicle attributes are correlated with both initial and subsequent failures.
- Vehicle age-based testing policies disproportionately benefit wealthier households.
- Cash-for-Clunkers programs have a high cost per avoided emissions failure.

1. Introduction

Urban air pollution, one of today's major environmental problems, is largely due to transportation-related emissions. In 2010, highway vehicles and non-road mobile sources were responsible for about 57% of the carbon monoxide (CO), 55% of the nitrogen oxide (NOx), 33% of the volatile organic compounds (VOCs), and 27% of the particulate matter (PM) emissions in the U.S. (Office of Air Quality Planning and Standards, 2012) The transportation sector is the second largest producer of greenhouse gases (GHG) in the U.S. after the industrial sector: in 2003, the transportation sector accounted for 27% of total GHG emissions (Office of Transportation and Air Quality, 2006).

As a result of the 1990 Federal Clean Air Act, the Georgia's Clean Air Force (GCAF) Program, also known as the Georgia Vehicle Inspection and Maintenance (I/M) Program, was created in 1996. The main purpose of this program is to identify high-polluting vehicles and require their owners to repair these vehicles so they meet minimum emissions standards. The program requires all gasoline-powered cars and light-duty trucks (except the three most recent model years and model years older than 25 years) that are registered in the thirteen non-attainment metropolitan Atlanta counties to undergo an annual emissions test.

However, I/M programs have been criticized since their inception (Washburn et al., 2001). Several authors have raised concerns about the accuracy and reliability of I/M test results, noting that real-world driving conditions are different from those used at I/M facilities (Calvert et al., 1993; LeBlanc et al., 1993). Therefore, it is possible that some vehicles that pass emissions tests are in reality gross polluters. A related concern is that emissions have been shown to vary substantially across multiple tests (Bishop et al., 1996). This can lead to a large number of false positive or false negative results and encourage individuals to try to "game" the emissions testing system and avoid repairing high-polluting vehicles by having these vehicles tested multiple times until they (finally) record a "pass."

Despite criticism about the reliability and accuracy of I/M programs, states are still inclined to maintain these programs. This is because states that have non-attainment areas may face fines or penalties from the U.S. Environmental Protection Agency (EPA) if they do not demonstrate that they are making efforts to address their air quality issues (Washburn et al., 2001). Nationwide, more than half of the states have emission testing policies that are based on vehicle characteristics and, in some cases, include economic hardship waivers for repairs for low-income households and/or seniors. Within Georgia, the GCAF program was able to identify and repair about two million heavy polluting vehicles between 1996 and 2011 (Georgia's Clean Air Force, 2012), which enabled the state to demonstrate that it was actively working towards achieving the Clean Air Act goals.

A second criticism of I/M programs relates to their cost-effectiveness, as every vehicle that meets certain criteria has to indiscriminately undergo inspection. According to a report by the National Academies (Committee on Vehicle Emission Inspection and Maintenance Programs, Board of Environmental Studies and Toxicology, 2001), about 50% of carbon monoxide and hydrocarbon emissions come from 10% of the vehicles. A number of studies based on statistical analysis of data from I/M emissions tests have shown that vehicle characteristics are associated with I/M failures (Beydoun and Guldmann, 2006; Choo et al., 2007; Washburn et al., 2001) According to these studies, factors such as model year, number of engine cylinders, odometer reading, vehicle manufacturer, fuel type, and presence of on-board modern emissions control systems can be used in predictive models to help identify potential high-emitting vehicles. However, although "vehicle characteristics are the most influencing factors affecting hydrocarbon and carbon monoxide emissions [...], the second most influencing construct is the driver/rider demographics" (Chiou and Chen, 2010). A few studies that have examined associations between socioeconomic criteria and vehicle emissions include one by Chiou and Chen (2010) based on 748 observations that directly linked disaggregate household-level socioeconomic criteria with vehicle emissions, and one by Singer and Harley (2000) that used a fuel-based approach to estimate vehicle emissions and linked emissions to income levels computed from census data resolved at the zip code level.

Our paper jointly considers the impact of vehicle characteristics and household demographics on emissions failures by linking a targeted marketing database that contains household characteristics to the 2010 Atlanta I/M emissions test database maintained by the Georgia Department of Motor Vehicles. After merging these databases, we have more than 250,000 records of households in the Atlanta area; this represents a substantially larger sample of disaggregate vehicle and household characteristics than samples used in prior studies.

The objective of this paper is to understand how household demographics, vehicle characteristics, and interactions among demographics and vehicle characteristics are associated with emissions failures. This objective is consistent with prior studies published in Transportation Research Part A that have examined one or more aspects of emissions modeling (Beck et al., 2013; Bureau and Glachant, 2008; Poudenx, 2008; Rogan et al., 2011, e.g.,) Hurdle models are used to examine whether a vehicle passes or fails its emissions test and, if it fails its emissions test, how many repeat tests are conducted before the vehicle passes. We use our estimated model to evaluate three potential emission testing policies for Georgia: (1) exempting vehicles less than five years old from testing; (2) providing vehicle maintenance subsidies to low-income households; and, (3) offering rebates for trading in an older vehicle and purchasing a newer, more fuel-efficient vehicle.

The paper is organized into several sections. Section 2 provides an overview of the data. Sections 3, 4, and 5 discuss the modeling methodology, results, and validation, respectively. Section 6 uses the results of our models to evaluate impacts of different emissions testing and vehicle replacement policies. The paper concludes with a summary of the main findings and directions for future research.

2. Data

Our analysis database was compiled from three different sources: (1) the 2010 Georgia's Clean Air Force Inspection/Maintenance (GCAF I/M) emissions test results for vehicles in the 13 non-attainment counties in the metro Atlanta area; (2) the vehicle registration database maintained by the Georgia Department of Motor Vehicles (DMV); and, (3) the targeted marketing (TM) records of a consumer credit reporting agency. Although the two first data sources are commonly employed for transportation modeling, the use of TM records is only recently developing (Kressner and Garrow, 2012).

2.1. Georgia's Clean Air Force Inspection/Maintenance Database

In Georgia, every gasoline-fueled car and light-duty truck with a gross vehicle weight rating of 8,500 pounds or less registered in one of the 13 non-attainment metro Atlanta counties has to pass an annual emissions test in order to obtain or maintain registration (Georgia's Clean Air Force, 2012; Office of Transportation and Air Quality, 2006). The three most recent model year vehicles are exempt from emissions testing, as are vehicles that are 25 years or older. Emissions test results for 2010 were used for our analysis; thus model years 1986-2007 are represented in the database. Diesel-fueled and exclusively alternatively-fueled vehicles, motorcycles, and recreational vehicles (motor homes) are exempted from testing. The I/M database keeps a record of each vehicle's emissions test result (pass/fail). In case of a failure at the test, the vehicle can be retested for free during the next 30 calendar days at the original testing location. Thus, the number of emissions tests per vehicle is also recorded in the database. The I/M database does not contain information on the types or cost of repairs necessary to successfully pass a subsequent test.

The I/M database was used to calculate the dependent variable, defined as the number of emissions failures a vehicle experienced in 2010. As shown in Table 1, 93.9% of vehicles passed their first emissions tests (i.e. had zero failures). Of the remaining vehicles that failed at least one emissions test, the majority were able to pass their second test.

Table 1: Number of emissions failures per vehicle.

Number of failed tests	Frequency	Percent
0	459,589	93.9
1	26,236	5.4
2	2,905	0.6
3	533	0.1
4	145	0.0
5	46	0.0
6	19	0.0
7	7	0.0
8	4	0.0
9	0	0.0
10	1	0.0

Table 2: Descriptive statistics for vehicles.

Continuous variables	Mean	Minimum	Maximum	Std. Dev
Number of cylinders	5.87	1	12	1.45
Vehicle age (years)	8.43	3	24	4.16

Categorical variables	Level	Frequency	Percent
Fuel type	Hybrid	1,450	0.3%
	Gasoline	488,035	99.7%
Make	Asian	209,509	42.8%
	European and North American	279,979	57.2%

2.2. Georgia Department of Motor Vehicle Database

Credit reporting companies are legally not permitted to disclose information about vehicles associated with a household due to the Shelby Amendment to the Drivers Privacy Protection Act that went into effect in 2000. Hence, vehicle variables used in this study are obtained from the DMV database. The database provides information on vehicle make, model year, engine cylinders and fuel type. Only vehicles that were required to pass emissions tests in 2010 are included in the analysis. Descriptive statistics for vehicle characteristics that are included as covariates in our model are found in Table 2. As only gasoline-fueled vehicles need to take the emissions test, the fuel type variable is defined as a binary variable taking a value of one if the vehicle is a gasoline-fueled hybrid vehicle, and a value of zero if the vehicle has an ordinary gasoline-fueled internal combustion engine.

2.3. Targeted Marketing Database

Credit reporting companies assemble financial and demographic information at the household level in order to assess every adult's creditworthiness. Parts of these large datasets are then made commercially available. The level of detail attained by TM datasets has increased dramatically with the explosion of electronic financial transactions, but there are some fields traditionally used in urban planning studies that are currently not well populated in the TM database and thus were excluded from our analysis. For example, adults' occupations and education levels are included in the TM database but are missing for the majority of observations (91% and 85%, respectively). The number of children in a household was also not used in our analysis because the TM database coded the number of children in a way that makes the interpretation of the variable ambiguous: a household with a zero in the number of children variable can either have actually no children or simply not have provided the information. An analysis against Census data (US Census Bureau, 2010) revealed that although 38% of households in the Atlanta metropolitan statistical area have children, only 27% of the households in our analysis database do.[1]

The TM dataset provides information for up to four adults per household. The covariates from the TM dataset that are included in our models include ethnicity, income, gender, and householder age. Descriptive statistics for these household characteristics are reported in Table 3. Ethnicity is recorded in the TM database at the household level and refers to the household's cultural origins (e.g., did ancestors emigrate from a Western European country?). Ethnicity was classified into three categories: Western European, African-American, and Hispanic. Income is also given at the household level and is reported in ranges, with the lowest income category below \$15,000 and the highest above \$250,000 annually. In the model, the median value of each category is used to represent income (e.g. for households in the \$100,000 to \$125,000 range, the income variable has a value of \$112,500). Gender and age in two-year ranges are provided for adults 18 years and older. For modeling purposes, we used age and gender for the (self-reported) head of household only.

2.4. Assumptions Used to Merge Databases

The I/M, DMV, and TM databases were merged using vehicle identification numbers (VIN) and home addresses. Home addresses were standardized prior to merging the databases, however approximately 1.5% of the observations in our sample had to be excluded as these addresses omitted apartment numbers. During the merge process, this resulted in a large number of vehicles being associated with multi-unit buildings.

[1] The TM company recently updated the methodology they use to populate fields related to children. Thus, more reliable data for the presence of children in the household will be available for future studies.

Table 3: Descriptive statistics for vehicles.

Continuous variables	Mean	Minimum	Maximum	Std. Dev
Income (kUSD)	75.02	10	250	44.9
Number of adults	1.77	1	5	0.78
Number of vehicles	2.12	1	5	1.02
Age of head of household	50.1	18	99	13.7

Categorical variables	Level	Frequency	Percent
Gender of head of household	Male	175,448	63.4%
	Female	101.167	36.6%
Ethnicity	Western European	221,742	80.2%
	African-American	45,134	16.3%
	Hispanic	9,739	3.5%

Although it was not possible to determine exactly which addresses represented unique households (versus a multi-unit building), we assumed those addresses with five or fewer vehicles represented unique households.

Our analysis database contains 276,615 households, which represent 14.3% of the total households in the region (US Census Bureau, 2010). Collectively, these households own 489,485 vehicles that were tested for emissions in 2010. Our analysis database only includes households that own at least one vehicle that is required to undergo emissions testing. Approximately 6% of the households in our original dataset were excluded from the analysis, as they only owned vehicles that did not have to be tested in 2010.

3. Methodology

The source data we conduct our analysis from contains the result of every emissions test performed on a given vehicle in the calendar year 2010. Various models can be used to predict emissions failures. The simplest approach consists of constructing a binary response model that predicts whether a vehicle will pass or fail its first emissions test. However, information is lost in this formulation because all vehicles that do not pass their emissions tests are labeled as failing, regardless of the number of failures they experience. If we assume that subsequent failures are indicative of more substantial emissions concerns, modeling higher numbers of failures is important for policy analysis. A logit model can be used to represent multiple failure outcomes, but is limited because information about the inherent ordering of failure outcomes is not incorporated. Information about ordered outcomes can be incorporated using count models.

Two of the most common count models include the Poisson regression model and the negative binomial regression model (see Greene (2008) for an overview of these models). In the Poisson regression model, the probability that the response variable Y_i takes on a specific value y_i is given as:

$$P(Y_i = y_i|x_i) = \frac{e^{-\lambda(x_i)}\lambda(x_i)^{y_i}}{y_i!}, y_i = 0, 1, \ldots; i = 0, 1, \ldots, N \tag{1}$$

where x_i is a vector of covariates and N is the number of observations. The conditional means are given by $\lambda(x_i) = \mathrm{E}[y_i|x_i] = exp(x_i'\beta)$ where β is the vector of parameters estimated from the data. In the Poisson regression model, the conditional means are equal to the conditional variances. However, if the count data are dispersed — meaning the conditional variances differ from the conditional means — then the Poisson regression estimates will be biased. Potential dispersion can be accommodated with the negative binomial regression model by introducing heterogeneity in the conditional mean. Formally, $E[y_i|x_i, \epsilon_i] = exp(x_i'\beta + \epsilon_i) = \lambda(x_i)u_i$ where ϵ_i is an independent random variable and u_i is gamma distributed with mean one and variance α. The conditional means for the Poisson regression and negative binomial regression models are the same, but the conditional variances differ. The conditional variances for the negative binomial regression model are given as:

$$\mathrm{Var}[y_i|x_i] = \lambda(x_i) + \alpha\lambda(x_i)^2 \tag{2}$$

where the dispersion parameter α along with the βs are estimated from the data. Note that if $\alpha = 0$ the variance is equal to the Poisson regression variance, or $\lambda(x_i)$. A value of $\alpha > 0$ implies that the data is overdispersed and a value of $\alpha < 0$ implies the data is underdispersed. The negative binomial regression model thus provides a convenient way to test if the data is dispersed (and if the simpler Poisson regression model is appropriate).

Additional challenges arise when zero counts dominate; for example, in our data a large percentage of vehicles pass their emissions test at the first attempt. This leads to a skewed distribution that is often referred to as a zero-inflated distribution. Several methods can be used to handle such situations, including a hurdle model (Cragg, 1971; Mullahy, 1986). As described by Rose et al. (2006), the hurdle model is effectively a two-stage model. In the first stage, a density distribution f_1 is used to predict the probability of a zero outcome. In the second stage, a different density distribution f_2 with a truncated-at-zero density is used to predict the number of events above zero.

$$P(y = 0) = f_1(0) = p, n = 0 \tag{3}$$

$$P(y = n) = (1 - p)\frac{f_2(n)}{1 - f_2(0)}, n > 0 \tag{4}$$

In principle, any discrete density distributions could be used to construct a hurdle model. A common hurdle model uses a binary logit model for f_1, and a Poisson model for f_2,

$$P(Y_i = y_i) = \begin{cases} p_i & \text{for } y_i = 0 \\ (1-p_i)\frac{e^{-\lambda(x_{2i})}\lambda(x_{2i})^{y_i}}{(1-\lambda(x_{2i}))y_i!} & \text{for } y_i > 0 \end{cases} \tag{5}$$

where $p_i = e^{x'_{1i}\beta_1}/(1 - e^{x'_{1i}\beta_1})$, the well-known binary logit probability equation and $\lambda(x_{2i}) = \mathrm{E}\left[y_i|x_{2i}\right] = e^{x'_{2i}\beta_2}$, the conditional mean of the Poisson density function.

Conceptually, the hurdle model is a modified count model that allows the underlying data generation processes for zeros and positive counts to differ. Note that the parameters β_1 and covariates x_1 used to model the zero outcome may differ from the parameters β_2 and covariates used to model the positive outcomes x_2. This is an important feature of the hurdle model, as it allows us to examine how the relative influence of vehicle and demographic characteristics differs for the zero-event outcome (representing whether a vehicle passes or fails) and the positive-event outcomes (representing the number of emissions failures). Various software packages can estimate hurdle models, including the PSCL package for R that we used in our study (Zeileis et al., 2008).

The models presented to this point assume independence across observations. However, the unit of observation for our study represents a vehicle that was tested for emissions in 2010. Thus, a household that owns multiple vehicles that needed to be tested in 2010 will appear multiple times in our dataset. To account for correlation within households, we use a hurdle model with random effects (also called a mixed hurdle model) as described by Min and Agresti (2005). Correlation is incorporated by defining $z_(ih) = 1$ if vehicle i belongs to household h and zero otherwise, $h = 1, 2, \ldots, H$ where H is the number of households. The arguments to the density functions in Equation 5 become

$$x'_{1ih}\beta_1 + \gamma_{1i}z_{1ih} \tag{6}$$

$$x'_{2ih}\beta_2 + \gamma_{2i}z_{2ih} \tag{7}$$

where γ_{1i} and γ_{2i} are assumed to be distributed jointly normal:

$$\gamma_i = \begin{pmatrix} \gamma_{1i} \\ \gamma_{2i} \end{pmatrix} = MVN\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} s_1 & s_{12} \\ s_{12} & s_2 \end{bmatrix} \right) \tag{8}$$

with means of zero, variances s_1, s_2, and covariance s_{12}. The β_1 and β_2 parameter vectors as well as the s_1, s_2, and s_{12} parameters are estimated from the data using maximum likelihood. Various software packages can be used to estimate hurdle models with random effects, including the NLMIXED procedure for SAS that we used in our study. In particular, we modified the SAS code provided by Min and Agresti (2005).

4. Results

As part of the modeling process, we estimated parameters for Poisson and negative binomial count models, Poisson and negative binomial hurdle models, and mixed hurdle models. Collectively, these models allowed us to investigate how the interpretation is influenced by: (1) using separate models to predict initial failure probabilities and, conditional on a failure, the expected number of failures; and, (2) incorporating correlation across observations due to the same household appearing more than once in the dataset.

A selection of models is presented in Table 4.[2] The results presented in this section were determined using an iterative modeling approach. As part of this modeling process, more than a dozen utility functions were investigated. These included logarithmic transformations to the vehicle age, income, and the age of the head of household; only income and vehicle age benefited from applying this transformation. We also explored an array of interaction terms between vehicle and household characteristics. Interaction terms allow the impact of vehicle characteristics to vary with household characteristics; for example, negative coefficients associated with vehicle age and household income indicate that emissions failure rates decrease as either vehicle age or household income increases. However, a positive coefficient associated with the interaction between vehicle age and household income means that these rates decrease at a decreasing rate as vehicle age and household income rise together.

Of the variables shown in Table 4, several are not included in the final model specification due to the fact they were not significant and/or resulted in parameter estimates with the incorrect signs. However, when both a main effect and interaction effect are included in the model, the main effect is always estimated and reported, even if just the interaction effect is significant.

Model 1 is a negative binomial count model, where the significance of the α parameter indicates that the data is overdispersed and that a Poisson model would not be inappropriate. The negative binomial hurdle model presented as Model 2, on the other hand, reveals that the problem of overdispersion cannot be confirmed when modeling the zero counts with a separate process; though the overdispersion parameter

[2] Results from an array of models used to develop functional form and covariate specification are available from the authors upon request.

has a very large estimated value, its standard error is insufficiently small to reject that the parameter is not zero. The mixed hurdle specification in Model 3 therefore uses a Poisson distribution for the positive counts. The estimated coefficients across all three models exhibit similar behavior, but the model likelihoods are sufficiently different to reject that the models fit the data equally well. Further, the significance of the correlation parameters s_1 and s_2 allows us to reject the null hypothesis of zero within-household correlation, and identify the mixed hurdle model as the most appropriate empirical framework.

Vehicle characteristics help predict both whether a vehicle fails emissions and, if it fails, the expected number of failures. The initial failure probabilities and the expected number of failures are both lower for newer vehicles and vehicles with a larger number of cylinders. Vehicles manufactured in Asia are less likely to fail an initial emissions test, but do not have significantly fewer subsequent failures . Hybrid vehicles are much less likely to fail an initial emissions test than are gasoline vehicles, although, conditional on failure, the expected numbers of failures for hybrid and gasoline vehicles are similar.

Demographic characteristics also help predict both whether a vehicle fails emissions and, if it fails, the expected number of failures. The initial failure probabilities and the number of expected failures are lower for higher-income households and households that have heads who are older. Gender is associated with the initial failure probabilities, but not with the expected number of failures. Households of African American and Hispanic descent are more likely to own vehicles that fail their first emissions test. Conditional on failure, Hispanic households are more likely to experience multiple failures . The positive interaction between income and vehicle age shows that higher-income owners of older cars are more likely to fail multiple times than lower-income owners of older cars. To more clearly visualize the interactions among vehicle and demographic characteristics, Figure 1 shows the effects of income, age, and vehicle manufacturer by household ethnicity. It is interesting to note that Hispanic owners of older vehicles are more similar to African-American households.

In summary, model results show that emissions failures are influenced by both vehicle and demographic characteristics. The hurdle model provides a richer interpretation of how these characteristics influence initial emissions failures and, conditional on failure, the expected number of failures.

5. Validation

To validate our model, we estimated a hurdle model with a Poisson distribution on a random sample of 391,588 vehicles, representing 80% of the data. The coefficients from the model that used 80% of the data closely match the coefficients from the model reported in Table 4 that used 100% of the data. The model that used 80% of the data was applied to predict the failure probability distribution of the 391,588 vehicles in the

Table 4: Estimation results

	Model 1 Negative Binomial		Model 2 Hurdle NB		Model 3 Hurdle Poisson (Mixed)	
Binomial Model	β	t-stat	β	t-stat	β	t-stat
Vehicle Characteristics						
Number of cylinders			−0.071	−15.5	−0.072	−15.5
log(Vehicle age)			−0.172	−0.82	−0.173	−0.82
Asian Make			−0.344	−24.8	−0.374	−24.7
Hybrid			−1.338	−4.61	−1.338	−4.60
Household Characteristics						
log(Income)			−0.339	−8.0	−0.344	−8.04
Ethnicity (ref. = W. European)						
African-American			0.340	21.7	0.342	21.4
Hispanic			−0.142	−1.00	−0.143	−0.99
Male head of household			−0.038	−2.93	−0.038	−2.88
Age of head of household			−0.014	−29.9	−0.014	−29.6
Interacted Characteristics						
log(Vehicle age) × log(Income)			0.079	4.17	0.080	4.15
log(Vehicle age) × Hispanic			0.184	2.91	0.184	2.87
Other Parameters						
Intercept			0.740	1.59	0.739	1.57
Count Model	β	t-stat	β	t-stat	β	t-stat
Vehicle Characteristics						
Number of cylinders	−0.074	−16.0	−0.043	−3.13	−0.041	−3.61
log(Vehicle age)	−0.120	−0.57	−0.442	−0.77	−0.524	−0.84
Asian Make	−0.327	−23.7				
Hybrid	−1.232	−4.52				
Household Characteristics						
log(Income)	−0.347	−8.16	−0.424	−4.31	−0.477	−3.60
Ethnicity (ref = W. European)						
Hispanic	−0.169	−1.19	0.269	3.78		
African-American	0.321	20.43				
Male head of household	−0.041	−3.17				
Age of head of household	−0.014	−29.5	−0.005	3.78	−0.006	−4.35
Interacted Characteristics						
log(Vehicle age) × log(Income)	0.080	4.18	0.114	2.04	0.115	2.02
log(Vehicle age) × Hispanic	0.021	3.24				
Other Parameters						
Intercept	0.776	1.66	−9.417	−0.31	2.134	1.48
α (dispersion)	2.86	47.8	1.12×10^5	−0.38		
s_1					0.374	5.68
s_2					0.984	42.1
s_{12}					0.596	2.58
$\log(\mathcal{L})$	−122,885		−122,770		−122,737	
AIC	245,796		245,580		245,515	
N	489,485		489,485		489,485	

Note: Positive parameters indicate higher emission failure probabilities or a higher number of expected failures.

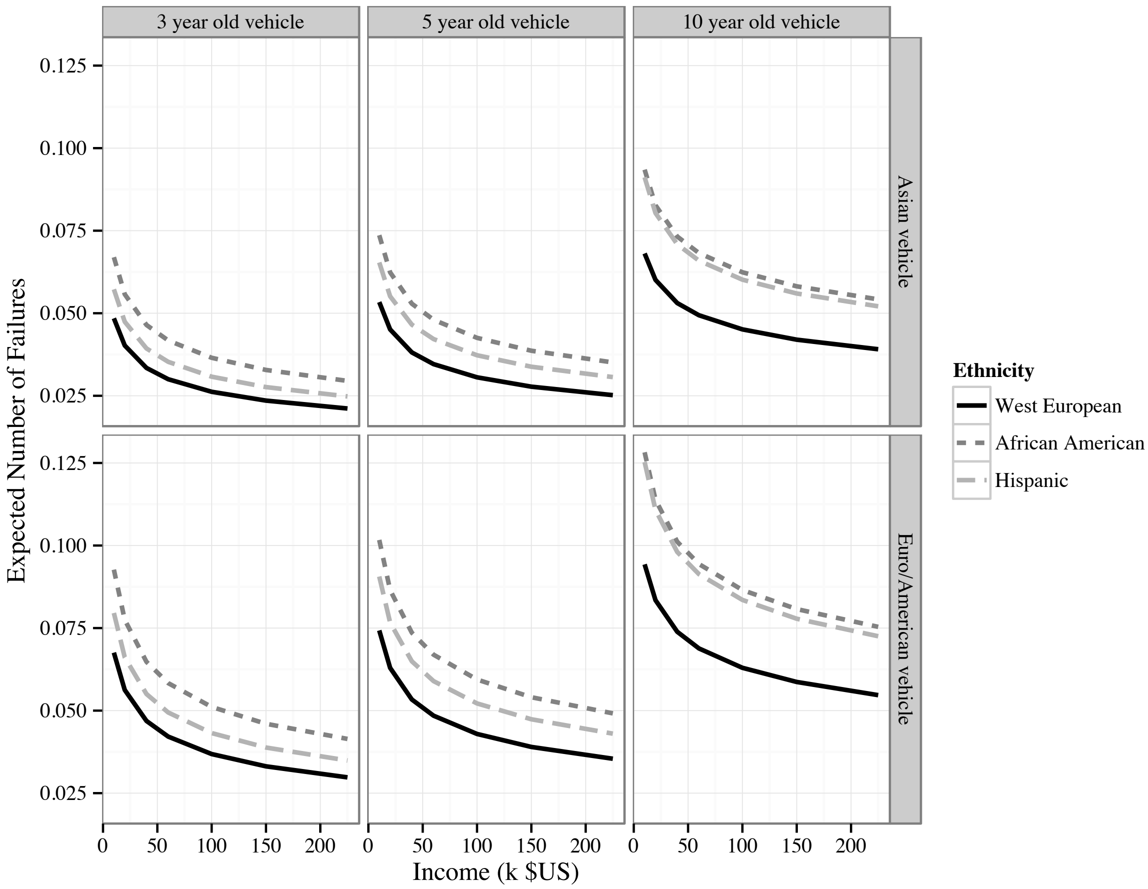

Figure 1: Expected number of failures by income, vehicle age, and ethnicity.

Table 5: Distribution of the number of failed tests for validation sample.

Predicted # of failed tests	80% Estimation	20% Holdout	Difference
0	0.9388	0.9388	4.52E-05
1	0.0525	0.0524	3.40E-05
2	0.0078	0.0078	9.64E-06
3	0.0009	0.0009	1.45E-06
4	0.0001	0.0001	1.54E-07
5	6.68E-06	6.67E-06	1.20E-08
6	4.84E-07	4.84E-07	6.27E-10
7	3.19E-08	3.19E-08	5.85E-12
8	1.92E-09	1.93E-09	3.31E-12
9	1.08E-10	1.08E-10	4.98E-13
10	5.62E-12	5.67E-12	4.92E-14

estimation dataset as well as the 97,897 vehicles in the holdout sample. These distributions are compared in Table 5. As shown, the predicted failure distribution in the two datasets is virtually indistinguishable.

6. Policy Analysis

We can use our analysis database and the findings from our models to investigate the impacts of various emissions testing policies across different income and ethnic groups. Based on a review of emissions testing policies in different states, we use our database and our estimated model to evaluate three potential policies for Georgia. As our dataset may be seen as representative of the Atlanta vehicle fleet, we can apply either the dataset or the estimated model to evaluate these policies with the expectation that our results could be extrapolated to the full population. The first proposed policy extends the current testing exemption for vehicles less than three years old to vehicles less than five years old; we apply our demographic database to determine the equity of this proposal. The second policy provides maintenance subsidies to low-income households in an effort to proactively avert a failed test; we apply our model to predict the potential success of this proposal. The third policy proactively removes potentially failing vehicles from the road through a repeat of the 2009 “Cash-for-Clunkers” rebate program; we predict the potential effects of this program by applying our model in a simulation. The impacts of these policy changes are measured in terms of changes in consumer surpluses experienced by different income groups and the potential for failing to identify gross-polluting vehicles. As shown in Figure 1, we expect these policies to have different impacts across ethnic and income groups, since emissions failure rates are a function of both vehicle and sociodemographic characteristics.

Table 6: Evaluation of exempting vehicles less than five years old from testing.

Newly exempted vehicles per household	Low Income	Low to Middle Income	Middle to High Income	High Income
W. European	0.262	0.326	0.610	0.273
African-American	0.244	0.286	0.468	0.175
Hispanic	0.244	0.320	0.605	0.252
Sample Mean = 0.331				
Percent of failures among new exemptions				
W. European	3.1%	2.8%	2.4%	2.2%
African-American	4.7%	4.6%	3.9%	4.1%
Hispanic	3.3%	3.4%	2.7%	1.7%
Sample Mean = 2.9%				

6.1. Extended Exemptions to Vehicles Newer than Five Years

Exempting vehicles that are three and four years old from testing reduces the number of vehicles in our database that need to be tested by 91,549 vehicles, or 18.7% of the vehicles that currently require testing. Given an average testing fee of $20, vehicle owners in the 13-county metro area would collectively save about $1.8 million annually. These savings in testing fees come at a cost, however, in that 2,645 gross-polluting vehicles would have been "missed" in 2010 and allowed to continue to operate without necessary emissions repairs. Whether the external costs to society of these vehicles outweighs the private surplus is beyond the scope of this study, but the equitable distribution of the surplus can be assessed directly using our analysis database. Table 6 shows the average number of exempted vehicles per household distributed by ethnicity and income quartiles, and therefore the distribution of households which benefit from the new policy. Table 6 also shows the percentage of newly exempted vehicles that failed their initial emissions test.

The proposed policy benefits households in the mid-to-high income quartile the most and households in the highest income quartile the least. This finding is intuitive in the sense that the wealthiest households may be more likely to own or lease the newest vehicles, which are already exempt under the current policy. The total number of missed failures is relatively low at 2.9% of the newly exempt vehicles, but the distribution of missed failures is not uniform across income or ethnic groups. African-Americans of all income levels have a failure expectation above the average, and Western European and Hispanic households with incomes above the median are below the expected failure rate. Were an exemption on three and four year old vehicles to be considered, policy makers should be aware of the potential for inequity in application, though many of these same issues likely exist under the current emissions testing policy.

Our assessment examines the direct effect of exempting vehicles that are three or four years old from testing. Those that directly benefit (from not paying emissions testing fees) are predominately from households in the mid-to-high income quartile. Extending the exemption period may also result in additional negative externalities on lower income households. Other studies have shown that lower income households are exposed to higher traffic emissions at home than higher income households as their homes are more likely to be near high-volume roadways (see: Bell and Ebisu, 2012; Beckx et al., 2009; Marshall, 2008). Thus, lower income households would disproportionately bear the external costs of exempting additional vehicles, while receiving little of the direct benefits.

6.2. Maintenance Vouchers

Results from our mixed hurdle model showed that given two identical vehicles, the one owned by a low-income household was more likely to fail its emissions test. This may be due to financial challenges low-income households face in maintaining their vehicles. We can use our model to evaluate the benefits associated with providing maintenance vouchers to low-income households that enable them to obtain free or discounted oil changes and air filters. Regular oil changes and air filter replacements have been associated with improved fuel efficiency and emissions ratings (US Department of Energy, 2013), and we therefore expect that the voucher system would result in a reduction in the number of vehicles failing emissions tests (as well as a possible improvement in fuel efficiency).

We need to make several assumptions in order to evaluate a maintenance subsidy policy. We define eligibility based on two degrees of "low-income" households. The first degree classifies low-income households as those that are eligible to receive food stamps. The second degree includes households with incomes up to twice as large as those eligible to receive food stamps. To model the effects of a maintenance voucher program, we assume that households eligible to receive the subsidy would experience improvements in their initial vehicle emissions failure probabilities equivalent to households that do not receive the subsidy (after controlling for all other vehicle and demographic characteristics). That is, we assume that a vehicle owned by a household eligible for the subsidy would exhibit the failure pattern of an identical vehicle owned by an otherwise identical household with an income at the maximum (or double the maximum) income eligible to qualify for food stamps. We assume the voucher system provides \$100 per vehicle for maintenance, which is roughly the cost of two annual oil changes/air filter replacements.

The expected benefits and costs of a maintenance subsidy program are shown in Table 7. The first policy would offer 17,333 households eligible for food stamps a \$100 voucher. The cost of this program is \$1.7 million but only reduces the number of failing vehicles by 101 vehicles, i.e., the cost associated with preventing one vehicle from failing emissions is \$17,333. The second policy would offer 82,196 households a maintenance voucher. The cost of the second policy is \$8.2 million and reduces the number of failing

Table 7: Evaluation of maintenance voucher program.

Policy	Total Cost	Reduction in initial failures	Cost per prevented failure
Current (no subsidy)	$ —	0	$ —
Vouchers for HHs with incomes up to the threshold for food stamp eligibility	$1,733,300	101	$17,333
Vouchers for HHs with incomes up to twice the threshold for food stamp eligibility	$8,219,600	430	$19,124

vehicles by 430 vehicles. The cost associated with preventing one vehicle from failing emissions is higher for the second policy, at $19,124. The small decrease in failing vehicles and high cost associated with preventing one additional vehicle from failing emissions can be partially explained by the fact that households on food stamps are the lowest-income households and own fewer vehicles. It is therefore difficult to capture additional failing vehicles.

6.3. Cash-for-Clunkers

In 2009, the U.S. Congress passed the Car Allowance Rebate System (CARS) Act, more commonly known as "Cash-for-Clunkers" program. The program offered a $3,500 or $4,500 rebate to new car buyers that traded in an older vehicle, provided the vehicle met certain requirements, such as a fuel efficiency rating below 18 miles per gallon and an age of less than 25 years. To prevent the older vehicles from reentering the fleet, dealers that claimed the rebates had to destroy the engines of the traded vehicles. The program was quite popular; in less than a month, almost 700,000 old vehicles were traded in nationwide (National Highway Traffic Safety Administration, 2010). The program resulted in a 0.6-0.7 mile per gallon increase in the average fuel economy of all newly purchased vehicles (Sivak and Schoettle, 2009) in July and August of 2009. Further, a life-cycle analysis showed that the program also reduced equivalent greenhouse gas emissions by about 4.4 million metric tons (Lenski et al., 2010).

Our model can be used to estimate the expected reduction in emissions failures, were a CARS-like program to be repeated in the Atlanta region. Given we do not have fuel efficiency ratings available in our database, we determined eligibility for the program by using data about vehicle body styles that were traded as part of the initial CARS program. In particular, we defined "eligible clunkers" to include jeeps, vans, light-duty trucks and sports utility vehicles (SUVs) between 10 and 25 years old; this represents about 76% of all vehicles traded in as part of the Cash-for-Clunkers program (National Highway Traffic Safety Administration, 2010). There are 72,045 vehicles in our database that meet these criteria. We approximated

Table 8: Evaluation of cash-for-clunkers rebate program based on 100 simulations.

Policy	Average failures after 3 years	95% Confidence Interval
Rebate: 1,600 clunkers are traded for new vehicles	50.6	49.7 — 51.3
Baseline: expected failures if 1,600 clunkers not traded	145.8	143.6 — 147.6
Reduction in failures	95.2	93.6 96.6
Cost per avoided failure	$58.8K	$57.8 – $59.7K

the number of eligible vehicles that would be traded by their owners in the Atlanta metropolitan area, again based on the 2009 CARS program. Car dealers in Georgia qualified for just under $69.5 million in rebates; at the minimum rebate of $3,500 per vehicle, a maximum of 19,851 vehicles could have been traded in all of Georgia during the Cash-for-Clunkers program. Given that the Atlanta metropolitan area accounts for 56% of the vehicles in Georgia (US Census Bureau, 2011) and our dataset is a 14.3% sample of Atlanta households, we estimate that a maximum of 1,600 vehicles in our database would be traded should a similar program be offered in the immediate future.

We assessed the number of emissions failure reductions associated with the Cash-for-Clunkers program by randomly sampling 1,600 out of the 72,045 eligible trade-in vehicles and replacing them with a new vehicle. The new vehicles were assumed to have four-cylinder engines and 60% of the new vehicles were assumed to be from an Asian manufacturer, the approximate percentage observed in the CARS program (National Highway Traffic Safety Administration, 2010). Because new vehicles in Georgia are not tested for emissions until they are three years old, we compared predicted emissions failure rates for the 1,600 traded vehicles three years after they were purchased to a baseline scenario in which the random sample of 1,600 clunkers were allowed to age for three additional years. To take into account the sensitivity of the sampling process, we analyzed the average results of 100 random samples. Results are summarized in Table 8.

Under the baseline scenario, an average of 146 of the 1,600 vehicles failed at least one inspection three years later. In the Cash-for-Clunkers rebate scenario, an average of 51 new vehicles failed the first inspection after three years. This implies that after three years, a CARS-like program offering $3,500 per vehicle would remove about 95 vehicles that failed emissions tests from the road in our sample of Atlanta, at a cost of approximately $59,000 per avoided failure. The analysis assumes that no clunkers would have been otherwise removed from the fleet during the three year period; this implies that our analysis understates the potential cost of the program in dollars per avoided failure. There may be many other reasons to pursue a Cash-for-Clunkers program (such as those presented at the beginning of this section), but our analysis suggests that removing emissions-failing vehicles from the fleet should not be one of them.

7. Discussion and Conclusions

Our study contributes to the literature in several key ways. To the best of our knowledge, this is the first study that has comprehensively examined the influence of vehicle and demographic characteristics on emissions failures and estimated the effects of different testing policies.

Current U.S. emissions testing policies are often viewed as inefficient as they do not discriminate between the vast majority of vehicles that are likely to pass and the relatively few vehicles that should be identified for repair. Exempting vehicles that are three and four years old from testing (versus just one or two years old) would save our sample of Atlanta consumers approximately $1.8 million annually. These private savings come at a public cost, however, as 2,645 vehicles that are failing emissions tests would be allowed to remain unrepaired. Another downside to extending exemptions is that households with middle to high incomes benefit most from this policy. Our analysis suggests that a pre-screening model, where cars more likely to fail are more likely to require testing, would exhibit similar inequity. This inequity results from the fact that our models show emissions failures are a function of household characteristics as well as vehicle characteristics.

We also considered two policy changes that more directly address the issue of high-emissions vehicles. A proactive policy that provides maintenance subsidies to low-income households in an effort to avoid an initial test failure would indeed reduce the probability of missed tests, but the cost of each avoided failure is too expensive to justify the policy. Similarly, incentivizing motorists to replace their older vehicles, which are more likely to fail an emissions test through a "Cash-for-Clunkers" rebate program would also reduce the number of failed tests. This program, however, would be even more expensive in terms of cost per avoided failure.

The results of our analysis highlight one of the key challenges that arises with emissions testing policies: it is difficult to design equitable and cost-effective emission testing policies due to inherent challenges in identifying gross polluting vehicles. Indiscriminate testing has a high aggregate economic cost, but we have shown that potential strategies to reduce these costs are inequitable, ineffective, or expensive. It is important to recognize that I/M programs are just one of the policy tools that states can use to improve air quality. Other transportation policy tools, such as reformulated fuels or congestion mitigation strategies, may be more environmentally and economically justified. These policies may be particularly relevant outside the U.S. where the adoption of new technologies differs. For example, in the U.S., all new vehicles sold since 2005 have been equipped with a catalytic converter ; worldwide, however, only 90 percent of sold vehicles have a catalytic converter (Manufacturers of Emission Controls Association, 2006). Policy instruments that focus on increasing the penetration of “new” technologies in the fleet, such as reformulated fuels and catalytic converters, may be even more effective in reducing emissions, particularly for non-U.S. countries.

A second main contribution of this study is that it is one of the first in transportation to be based on targeted marketing data. It would be interesting to use similar targeted marketing data for future studies. We expect that, similar to our study, the integration of targeted marketing data with traditional transportation datasets will lead to new behavioral insights, and potentially better decision-making.

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