The Abatement Cost Function for Motor Vehicle Pollution Emissions: Evidence from Canada

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Abstract

Mandatory inspection and maintenance programs require on-road vehicles to be tested regularly and repaired if they are not in compliance with air emission regulations. The purpose of this paper is to estimate the abatement cost function for a representative inspection and maintenance program. We do this by constructing a model of the statistical process that leads to non-compliance, parameterizing the model, and then by simulating the total abatement cost function. Our model predicts that the marginal abatement cost for a major representative program is so high that even a small reduction in the abatement target leads to substantial social cost savings. In addition, even for quite high levels of the abatement target, the optimal minimum testing age is substantially higher and the frequency of testing is much lower than is common in many jurisdictions.

Keywords: Abatement Cost Function, Vehicle Inspection and Maintenance, Mobile Source of Air Pollution

1. INTRODUCTION

Motor vehicle emissions remain one of the largest sources of urban air pollution despite the fact that vehicle emission standards have been tightened substantially in recent decades. Largely, this is due to the increased number of vehicles in use. However, it is also due to the fact that, historically, there have been no mechanisms in place to ensure that vehicles continue to meet emission standards after the point of sale. In an effort to address this problem, many jurisdictions in North America and Europe in recent years have introduced emission standards for in-use motor vehicles that are enforced with inspection and maintenance programs.[1]

Inspection and maintenance programs require vehicles to be tested at regular intervals to determine whether they are in compliance with emission standards. Vehicles that fail must be repaired. These efforts have led to reductions in vehicle emissions of carbon monoxide, hydro carbons and nitrogen oxides, especially in urban areas. For example, the province of Ontario reports that in the first 33 months after the program's inception in 1999, over 4 million vehicle

[1] For example, 34 US jurisdictions, Ontario and British Columbia have programs. In addition to the Inspection and Maintenance programs, some jurisdictions have a road-side drive-by pre-screening program (Colorado for example) or remote sensing program (California for example) in place. The minimum testing age in North America varies from no specific exemption for the newest vehicles implemented in Oregon, Virginia and Pennsylvania, US, to exemption of the newest 7 model years in British Columbia, Canada, the newest 6 model years in California, US and the newest 5 model years in Washington and Arizona, US and Ontario, Canada. British Columbia and Ontario have recently increased their minimum testing age to 7 and 5 from 4 and 3, respectively.

inspections were conducted and the subsequent repairs of non-compliant vehicles led to reductions estimated to exceed 15% of total emissions from the stock of in-use vehicles [5].[2]

Vehicle inspection and repair programs are, of course, not costless. In many jurisdictions, cars are tested every two years at a cost of about $30 per test and a couple of hours of the owner's time; yet, fewer than 10% of vehicles on average fail the emissions test. With such a low proportion of the vehicle fleet being subjected to any emissions-reducing repairs, but with almost all vehicles in the fleet being subjected to testing, it is natural to question the cost effectiveness of such a pollution abatement program. It is also natural to question the level of the marginal cost of abatement and to ask whether such programs have set abatement targets that are too high or too low. To the best of our knowledge, there exist no published studies that address these issues despite the fact that most large urban centres in North America have by now adopted a policy of mandatory vehicle inspection and repair.

One of the objectives of this paper is to estimate the abatement cost of a vehicle inspection program that is representative of typical programs in North America. We do this with data from the program that has been in use in the urban areas in and surrounding Toronto Canada since 1999. However, we dig deeper than this and address the problem of estimating the abatement cost function itself. To do this, we develop a model of the statistical process that leads to non-compliance as vehicles age. We parameterize the model using data from the Toronto program. This approach allows us to not only address the question of the cost effectiveness of the current policy but to also estimate the "optimal" ages at which vehicles should be tested to meet a given abatement target. In addition, we are able to obtain some insight into the question of the optimal

[2] "Ontario's Drive Clean: A Summary of the First Three Years of Light-Duty Vehicle Data (1999-2001)." August, 2002.

level of abatement. Our results suggest that the current policy is not cost minimizing in the sense that the same level of abatement could be achieved at a lower social cost by modifying the ages at which tests are required. Moreover, our model suggests that the marginal abatement cost at current levels of abatement is so high that even a modest reduction of the abatement target leads to substantial cost savings.

The remainder of the paper is organized as follows. In Section 2, we develop the theoretical model. In Section 3, we parameterize the model using data from the vehicle inspection program in Toronto and use it in Section 4 to estimate the abatement cost function and conduct our policy analysis. Conclusions are drawn in Section 5. A technical appendix appears at the end of the paper.

2. The Model

Assume the stock of in-use vehicles consists of T age cohorts. An emission standard, $\bar{e}_a$, a=1,2,…,T exists for each age cohort. We say that a vehicle is in compliance if, when tested, it meets the emission standards and is out of compliance otherwise. Typically, vehicles begin their service lives in compliance. Over time, however, emission control devices may fail or improper maintenance or engine deterioration may cause a vehicle to go out of compliance. Let t be the age at which a vehicle goes out of compliance and assume that the probability of this happening is given by the discrete Weibull probability function (Nakagawa and Osaki [4]):

$$\Pr(t = a) = f_a = p^{(a-1)^{\pi}} - p^{a^{\pi}}, \quad 0 < p < 1,\ a = 1, 2, \ldots, T \tag{1}$$

where $0<p<1$ (*i.e.* the scale parameter) is the probability of being in compliance at the beginning of the first period and $\pi \geq 0$ is the so-called shape parameter.

The probability that a vehicle "survives", or remains in compliance, at least until age a can be characterized by the survival function which is given by:

$$\Pr(t \geq a) = S_a = p^{a^{\pi}} \tag{2}$$

Conversely, the complementary failure probability is $\Pr(t < a) = F_a = 1 - S_a = 1 - p^{a^{\pi}}$. Finally, the probability that a vehicle will go out of compliance while it is at age a conditional on being in compliance up to age a-1, is the hazard rate which is defined as:

$$h_a = \frac{f_a}{S_{a-1}} = 1 - p^{a^{\pi} - (a-1)^{\pi}} \tag{3}$$

The shape parameter π determines whether the hazard rate is constant, rising or falling with vehicle age. The special case $\pi = 1$ generates the geometric distribution, the discrete-time counterpart of the exponential distribution with constant hazard rate. The hazard rate is monotone increasing (decreasing) with the vehicle's age if $\pi > 1$ ($0 < \pi < 1$). The failure rate is an increasing function of age even when the hazard rate is constant; however, the failure rate data that we discuss later indicates that a rising hazard rate is more realistic in this application.

An important complication we must address is that the survival (or conversely the failure) distribution will be quite different in the steady-state - after an inspection and maintenance program has been introduced - than it is initially. There are two reasons for this. First, expression (2) represents the probability that a vehicle in any age cohort, a, will be in compliance when testing is first conducted. However, this will change after all vehicles initially found to be out of compliance are repaired and brought back into compliance. From this point on, the survival probability for a vehicle of age a will depend on whether or not it has ever been "repaired" to return it to compliance and how long it has been since the repair. Second, the hazard rate for "repaired" vehicles may differ from the hazard rate for never-repaired vehicles.

Lack of data on the failure history of repaired vehicles forces us to ignore the second reason; as a result, we assume that the hazard rate for repaired vehicles is identical to that for never-repaired vehicles. However, we show in Appendix A.1 that this assumption is unlikely to have significant consequences. We are still left with the problem that the survival probability depends on whether or not and how long ago a repair was made.

To deal with this complication, it is useful to introduce indicator variables $x_a \in [0, 1]$ (for a=1, 2… T), which determine the proportion of the a-*th* age cohort to be selected for testing. If $x_a = 0$, the cohort is not selected and if $x_a = 1$, the entire cohort is selected. If $0 < x_a < 1$, only part of the cohort is included in testing but for now it is easiest to imagine that either the entire cohort or none of the cohort is tested. The steady-state failure probabilities can now be written in recursive form as follows:

$$\begin{aligned} &F_1 = h_1 \\ &F_a = h_a + (1 - h_a)(1 - x_{a-1})F_{a-1} \qquad a = 2, 3, ..., T \end{aligned} \tag{4}$$

In the special case of $x_a = 0$ for all a (no cohorts are ever tested), this expression collapses to expression (2). In the special case $x_a = 1$ for all a (vehicles are tested every year and repaired if necessary) it collapses to the hazard function in expression (3). In practice, the x vector is a mixture of 0s and 1s. For example, in the application we study, $x_a = 0$ if a is even and $x_a = 1$ if a is odd and $x_a = 0$ for $a = 1, 2$ and for $a \geq 21$.

When a failed vehicle is repaired at age a, the amount of pollution abated per kilometre is given by q_a. The expected abatement per kilometre i periods into the future for a vehicle repaired at age a is equal to q_a multiplied by the probability of "survival" or non-failure for i periods after the repair. Expected lifetime abatement for a vehicle repaired at age a is this multiplied by annual kilometres driven and then summed over the remaining life of the vehicle. Thus, expected lifetime abatement for a vehicle repaired at age a is given by:

$$Q_a = q_a \sum_{i=a}^{T} K_i S_i \qquad \text{where } S_i = p^{i^{\pi} - (a)^{\pi}} \tag{5}$$

and where K_i and S_i are the average annual kilometres driven and the likelihood of remaining in compliance at age i, respectively.

The total expected abatement, A_a, of including the a-*th* age cohort in the testing program is then given by:

$$A_a = N_a Q_a F_a \tag{6}$$

where N_a is the number of vehicles in the age cohort and F_a is the failure probability as defined in expression 4.

The expected cost, C_a, of including the a-*th* age cohort in the testing program is given by:

$$C_a = N_a \left(c + rF_a\right) \tag{7}$$

where c is the social cost of testing a vehicle (direct cost plus the opportunity cost of the owner's time) and r is the social cost of repairing a vehicle if it fails the test (with probability F_a).

We restrict our analysis to the steady-state level of abatement and its associated abatement cost. The steady state occurs when every vehicle in the eligible population has been tested at least once, where the eligible population includes all vehicles at or above the minimum testing age. For example, if the testing program requires vehicles in odd-numbered age cohorts to be tested then the entire population is eligible and the steady state is reached after two periods. If the testing program requires only vehicles of age i to be tested then the eligible population is all vehicles of age $a \geq i$ and the steady state is reached after T – i + 1 periods.[3]

The total cost and the amount of pollution abatement that can be achieved with an inspection and maintenance program depends on how many and which age cohorts are included in the

[3] By ignoring the transition to the steady state, we explicitly eliminate any consideration of the intertemporal elements of the problem. However, we believe these are insignificant in practice because the steady state is reached very rapidly - within two years - for most inspection programs in operation.

program. The problem is to choose the age cohorts that minimize the steady-state total expected cost of abatement subject to the constraint of achieving a given expected abatement target.

The problem then is to choose x_a for a =1, 2… T so as to

$$\underset{x_a}{Minimize} \quad C\left(\overline{A}\right) = \left\{ \sum_{a=1}^{T} C_a x_a \,\middle|\, \sum_{a=1}^{T} A_a x_a \geq \overline{A} \right\} \tag{8}$$

subject to $0 \leq x_a \leq 1$ and where A_a, C_a, and F_a are defined above.[4]

Analytical solutions to this problem turn out to be extremely difficult to obtain because the failure distribution is endogenous. Therefore, the strategy we adopt is to first present a heuristic characterization of the solution and then turn to the empirical analysis in the next section. To keep things as simple as possible here, we assume each age cohort has the same number of vehicles, normalized to one.

Intuition would suggest that the cost minimizing solution should have the following two properties. First, it should be optimal to target the oldest age cohorts because they have the highest failure probabilities and therefore are the biggest polluters. Second, the cost-minimizing solution should involve testing the lower-cost cohorts before testing higher-cost cohorts. It turns out that neither of these is correct in general. We attempt to explain these in turn.

Although old cars are more likely to fail the emission standard and therefore are the biggest polluters, repairs yield abatement for a small number of years (the remaining life). Conversely, younger cars have a lower failure probability but they also have a longer remaining life. Therefore, conditional on a failure occurring, a repair to a young car yields higher expected

[4] In principle, we could treat the control variable as distance driven rather than age of vehicle. In other words, the model would determine the thresholds, denominated in accumulated kilometres driven, at which vehicles must be tested. This would allow for greater fine-tuning than we can achieve by denominating the thresholds in terms of years of age. However, because the only available data are denominated by vehicle age (i.e. failure rates and pollution abatement), we can only implement a model denominated in terms of vehicle age.

lifetime abatement. As a result, it is very unlikely to be optimal to target the oldest cohorts first. Consider the following example.

Suppose there are only 3 age cohorts and define the expected cost per unit of abatement for each cohort as

$$c_a(x_1, x_2) = \frac{c + rFa(x_1, x_2)}{Q_a F_a(x_1, x_2)}; \quad a = 1,2,3$$

where the notation explicitly recognizes that the failure probabilities, as defined in (4), are endogenous. Specifically, the failure probability for cohort a is lower (and therefore unit abatement cost is higher) if the cohort was already tested at a younger age. Note that

$$\frac{\partial c_a}{\partial x_i} \begin{Bmatrix} = 0 & \text{if } i \geq a \\ > 0 & \text{if i} < \text{a} \end{Bmatrix}$$

Before proceeding, note that the cost-minimizing solution will have at most one cohort i such that $0 < x_i < 1$. All other cohorts $j \neq i$ will have either $x_j = 0$ or $x_j = 1$. Intuitively, either the entire cohort will be tested or none of it will be tested. The possible exception is the marginal (highest cost) cohort, of which only the portion needed to exactly meet the abatement target will be tested. This result follows from the fact that c_a is independent of x_a (so unit abatement cost is linear within a cohort) and that the inter-cohort externality on cost is positive.[5]

In the absence of any testing ($x_a = 0$ for all a), F_a rises monotonically with age starting from a value close to zero. However, expected lifetime abatement resulting from a repair at age a, Q_a, falls monotonically with age. As a result, expected lifetime abatement resulting from a test at age a, $F_a Q_a$, typically has an inverted u-shape before any testing begins. The implication of this is that expected unit cost typically is u-shaped as a function of age. Consequently, it is the

[5] Thus, if for any target abatement level the *ith* cohort has the lowest unit abatement cost when $0 < x_i < 1$, it must still have the lowest unit abatement cost when x_i is increased. Therefore it will continue to be chosen as the target abatement level is increased until $x_i = 1$. Similarly, if the jth cohort has a higher unit abatement cost than the *ith* it will not be chosen (i.e. $x_j = 0$) as long as $x_i < 1$.

middle-aged cohorts that have the lowest unit abatement costs and, as a result, it is typically (but not always, as we show next) optimal to target them before the oldest cohorts.

Continue with this example and assume expected unit cost to be u-shaped initially. Specifically, assume that

$$c_2(0,0) < c_3(0,0) < c_1(0,0)$$

Cohort 2 has the lowest unit cost of abatement so intuition would suggest it should be optimal to always test that cohort if there is any testing at all. As mentioned earlier, this is not necessarily correct.

Consider Figure 1. On the vertical axis are marked the initial unit costs for each of the three age cohorts and on the horizontal axis is the target level of abatement. A_2 is the maximum achievable abatement level from cohort 2 (achieved when $x_2 = 1$ and $x_1 = 0$). For target levels of abatement up to A_2, the solution is clearly to test only that fraction of cohort 2 that is needed to meet the target. The unit cost of abatement is constant over this range and equal to $c_2(0,0)$. Therefore, the unit cost of abatement function is the horizontal line segment *ab* for abatement levels up to A_2.

If the target abatement level rises above A_2, an additional cohort must be added. If the third cohort is added, the cost per unit of abatement from the third cohort is $c_3(0,1)$ which is very high because of the dependence of cohort 3's failure probability on x_2. The overall average cost of abatement becomes a weighted average of $c_2(0,0)$ and $c_3(0,1)$ and therefore rises linearly as a function of the target level of abatement as the weight on $c_3(0,1)$ grows.[6] Thus, the unit cost of abatement function given this strategy is the line *abc*.

Consider the alternative of not testing the second cohort at all but instead testing the first and third cohorts. What does the unit cost function for this alternative look like? If the sufficient

[6] To keep the argument as simple as possible, we assume that the combination of cohorts 2 and 3 is cheaper than 2 and 1.

conditions given in the appendix are satisfied, it looks like the function given by the line *def* which intersects the line *abc* at the abatement level A'. The implication is that for target abatement levels above A', it is cheaper to test the first and third cohorts than to test the second and third. Consequently, the cost-minimizing solution excludes the lowest-cost cohort.

The explanation for this result lies in the dependence of the failure probabilities on the history of testing. When cohort 2 is tested, it exerts a strong externality on cohort 3 because only one year elapses between tests. When cohort 1 is tested, it exerts a weaker externality on cohort 3 because two years elapse between tests. As a result, the unit cost of abatement from cohort 3 is lower when cohort 1 is tested than when cohort 2 is tested. The reduction of the externality costs from testing cohort 1 instead of 2 may more than compensate for the higher direct cost of testing cohort 1 rather than cohort 2. When this is the case, it is cheaper to exclude the lowest-cost cohort from the abatement program.[7]

In summary, we have illustrated that corner solutions (x_i = 0 or 1) will be the norm, that middle-aged cohorts will be the most attractive cohorts to single out for testing, and that it will not always be optimal to test what appear to be the lowest-cost cohorts. Next, we turn to the problem of parameterizing the model so that numerical solutions can be obtained. Solving the minimization problem for a given target level of abatement generates one point on the abatement cost function. We repeat the minimization problem many times for many different target abatement levels to generate many points on the abatement cost function.

3. EMPIRICAL APPLICATION

[7] Once we take the externalities into account, cohort 2's status as the lowest-cost cohort clearly becomes blurred depending on whether x_3 = 0 or 1.

We use data from the Drive Clean Program, a large inspection and maintenance program in operation in Toronto, Canada and surrounding areas. The program is similar in structure to most inspection and maintenance programs in use in urban areas throughout the United States and the one other program in Canada.[8] This, combined with the fact that vehicle emission control technologies and standards are very similar between Canada and the United States means that our results should be applicable to many jurisdictions.

The inspection and maintenance program in the Toronto area was introduced in 1999. All light-duty vehicles (*i.e.* less than 4,500 kg) three years of age and up to 20 years of age are

[8] As mentioned earlier, at least 34 US jurisdictions have programs. The one other Canadian program is in the lower mainland of British Columbia. Ontario Drive Clean is a revenue-neutral program, funded entirely out of fees paid by vehicle owners for emissions tests (www.driveclean.com). The maximum test fee has increased from $30 to $35 since October 1, 2002. The government receives one-third of test fees which must cover all the administration costs. Drive Clean facilities retain the remainder of the fee as well as all of the fees for retests. The maximum retest fee has also risen from $15 to $17.50. The repair cost is confined to Repair Cost Limit (RCL). The RCL sets a maximum of $450 which must be spent on emissions system repairs if a vehicle fails its initial test (for the first two years of the program, the RCL was $200. The RCL is currently under revision that can increase its amount to $600). This means that if repairs are estimated to cost more than RCL (including cost of Drive Clean diagnostic), the vehicle will only require repairs that can be done up to the amount of the RCL. Furthermore, if there is a single problem that cannot be corrected within the RCL, the vehicle will qualify for the conditional pass without any repairs being made.

required to undergo an emissions test every two years in order to renew vehicle registration. Any vehicle for which ownership is transferred is also required to undergo an emissions test.

The emissions inspection consists of dynamometer testing. A treadmill-like machine allows a computer to analyze exhaust emissions under simulated driving conditions and then the average emissions readings by computer are compared to standards for the vehicle's year, make and model. The regulation also specifies provisions and conditions for a Repair Cost Limit (RCL) for Light-Duty vehicles in non-compliance with prescribed standards. If the estimated cost of repairs required to return the vehicle to compliance exceed the Repair Cost Limit, this provision allows the owner to spend a smaller amount and still qualify for vehicle registration. This provision can be invoked only once per vehicle.[9]

Empirical implementation of our model requires estimates for a number of parameters. Our data are taken from Ontario's Drive Clean: A Summary of the First Three Years of Light-Duty Vehicle Data (1999-2001) [5], EPA MOBILE 6: Fleet Characterization Data for MOBILE 6 [2], the Evaluation of Ontario Drive Clean Program by Eastern Research Group, Inc [1], and Canadian Vehicle Survey for 2000-2005 by Statistics Canada [3].

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[9] It should, however, be mentioned that the Ontario Ministry of the Environment has recently released its latest proposed changes to the Drive Clean Program (Ontario's Drive Clean Program – Recommendations for Change, Nov, 2005 [1]). The main amendments in the proposal are: 1- To increase the minimum testing age from 3 to 5 years (effective January 1, 2006) 2- To increase the maximum testing age from 20 to 21 years (will be implemented January 1, 2009) 3- Annual testing for vehicles 12 years and older (effective in 2007) 4- To increase in the Repair Cost Limit from $450 to $600 5- To implement On-Board Diagnostics (OBDII) testing for 1998 and newer light duty vehicles.

3. 1. The Failure Distribution:

The two parameters of the Weibull distribution, p and π, are estimated from the failure rates observed for each age cohort when the Drive Clean Program was first introduced in 1999. We expect that the measured failure rate for vehicles of age a is given by F_a as defined implicitly in (2), assuming that the Weibull distribution is the correct probability function. We use nonlinear least squares to fit the failure function by using the empirical data from the Drive Clean program. Table 1 shows the results from the NLS estimation and Figure 1 depicts the estimated failure rate against the empirical failure rate. As expected, the estimated value of π exceeds unity (statistically significant at the 99% confidence level) indicating a rising hazard rate. In other words, the probability of failing the emissions test, conditional on passing up to that age, rises with age.

Table 1

Parameters	Estimates	Standard Error	P-value
Log(p) =	-.550523E-02	.284719E-02	[.053]
π =	1.65936	.184823	[.000]
R-squared =	.924602		
Adjusted R-squared =	.919576		
Number of Observation =	17		

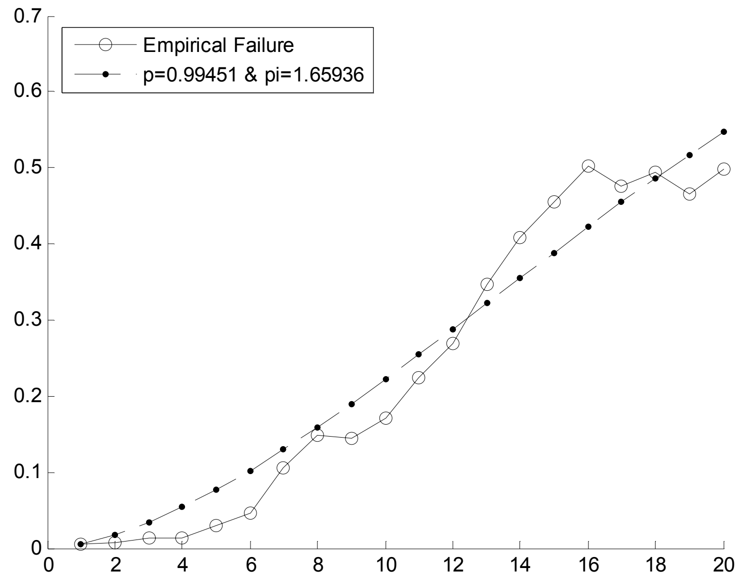

Figure 1 – Empirical failure vs. estimated failure

3. 2. Age Distribution of Vehicles

The age distribution of the vehicle fleet at any point in time reflects, among other things, past levels of general economic activity. For example, the age distribution of the fleet in the Toronto area at the time Drive Clean was introduced in 1999 shows a remarkable dip in the number of five-year old vehicles because new vehicle sales took a dramatic drop in 1994 due to macroeconomic conditions at that time. In order to make our results somewhat more representative of conditions one might expect to prevail, we used the Canadian Vehicle Survey Data for 2000-2005 by Statistics Canada [3] which provides the age distribution of Canadian vehicles for number of years. We used Ordinary Least Squares to fit a quadratic function to the empirical percentage changes calculated from these data. Equation 9 presents the resulting function we used to generate the simulated age distribution for our analyses and Figure 2 plots this distribution as well as the distributions based on the 1999 and 2001 Drive Clean data.[10]

$$N_a = N_0\left[1-\left(3.647821-1.33059a+0.187515a^2\right)\right] \tag{9}$$
$$\text{Where } N_0 = 450{,}000 \text{ and for } a = 1,\ldots,20$$

Figure 2 depicts this function versus the actual number of Drive Clean tests for phase 1 and 2 in 2001, as well as the total number of vehicles in Ontario (*i.e.* vehicles in phase 1, 2, 3 and in non Drive Clean areas) based on Canadian Vehicle Survey 2001.

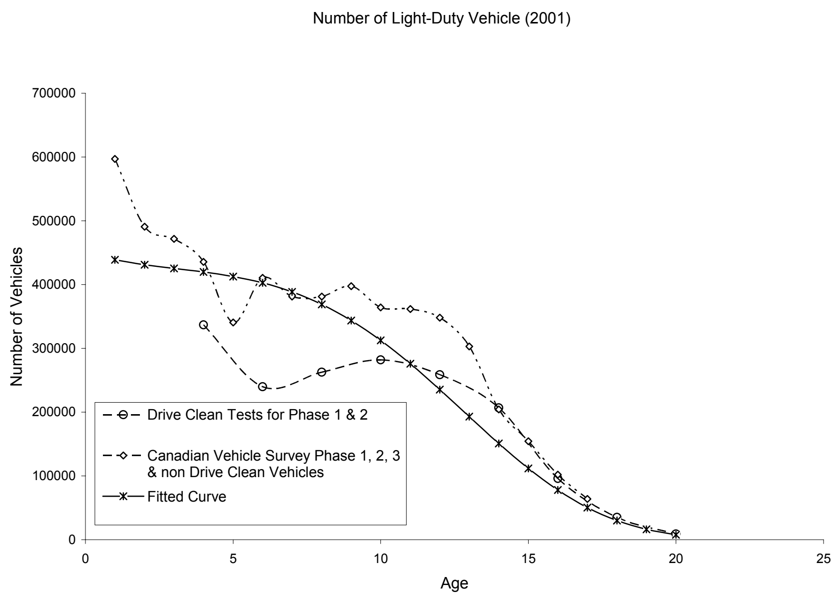

Figure 2 - $N_a = N_0\left[1-\left(3.647821-1.33059a+0.187515a^2\right)\right]$ vs. the actual number of odd vehicles in the Drive Clean Data and Canadian Vehicle Survey Data in 2001

3. 3. Abatement per Kilometre:

We calculate the emissions reduction by age cohort associated with repairs from the summary of the first three years of the Drive Clean data [5]. Since vehicles are actually required to comply

[10] Refer to appendix A.2. for further discussion of the age distribution.

with emissions standards for each of three types of pollutants: nitrogen oxides (NO_x), volatile organic compounds (VOC_s) and carbon monoxide (CO), the empirical results contain estimates of abatement per kilometre for each of the three pollutants for each age cohort. For our numerical analyses, we fit a quadratic function to the observed average abatement per kilometre. For example, in the case of CO, the estimated function relating abatement per kilometre to age is given by Equation 10.

$$\begin{aligned} q_a = {} & 0.31625 + 0.872308a - 0.01829a^2 \\ & (0.849) \quad (0.186) \quad\quad (0.009) \end{aligned} \tag{10}$$

where standard errors are shown in parentheses. The fitted equation shows abatement per kilometre rising with age at a decreasing rate. A similar relation was found for HC. However, for NO_x, the abatement data show the peculiar phenomenon of first decreasing with age and then eventually rising beginning at about age 12. Details are provided in Appendix A.3.

We have concerns about assuming that abatement per kilometre is either rising or falling with age. In a steady-state, where technology is constant, one should expect abatement per kilometre that is achievable to be independent of age. That is, while the age at which the technology fails is a random variable, the level of pollution emissions it controls and therefore the achievable abatement by repairing it should be the same regardless of age. Because we want our results to be representative of what might occur in a steady-state scenario and to be less influenced by what may be idiosyncratic results (for example, we have only 2 years of data on which to base the estimation of Equation 10), we consider an additional scenario in which abatement per kilometre is assumed to be constant across age cohorts. Therefore, in the second scenario, we assume a constant level of abatement per kilometre for each pollutant equal to the average observed over all cohorts.

3. 4. The Average Annual Kilometres Driven:

The "Technical Summary of the First Three Years of Light-Duty Vehicles (1999-2001)" [5] assumes discrete reductions in the average annual kilometre driven by vehicle age. For example, in 2001, the average annual kilometres driven for vehicles up to seven years of age is assumed to be 22,000. For vehicles between 8 and 13 years of age, it drops to 17,000 and then falls to 12000 for vehicles between 14 and 20 years old. However, average annual kilometres driven is more likely to decrease gradually by vehicle age. In fact, this is the approach adopted by U.S. EPA MOBILE 6 [2] for their evaluation of vehicle emissions. We used U.S. EPA MOBILE 6 [2] estimations as our average annual kilometre driven (even though Statistics Canada [3] estimates that light-duty vehicles were driven an average of 16,000 kilometres whereas the EPA estimates for US light-duty vehicles were 19,300 kilometres, adjustment for the discrepancies will result in a poor fit for the Drive Clean Data and therefore we used the EPA MOBILE 6 [2] estimations). Figure 3 depicts the average annual kilometres driven from the Technical Summary of the First Three Years of Light-Duty Vehicles [5] and the estimation from U.S. EPA MOBILE 6 [2] (Fleet Characterization Data for Mobile6, 2001).

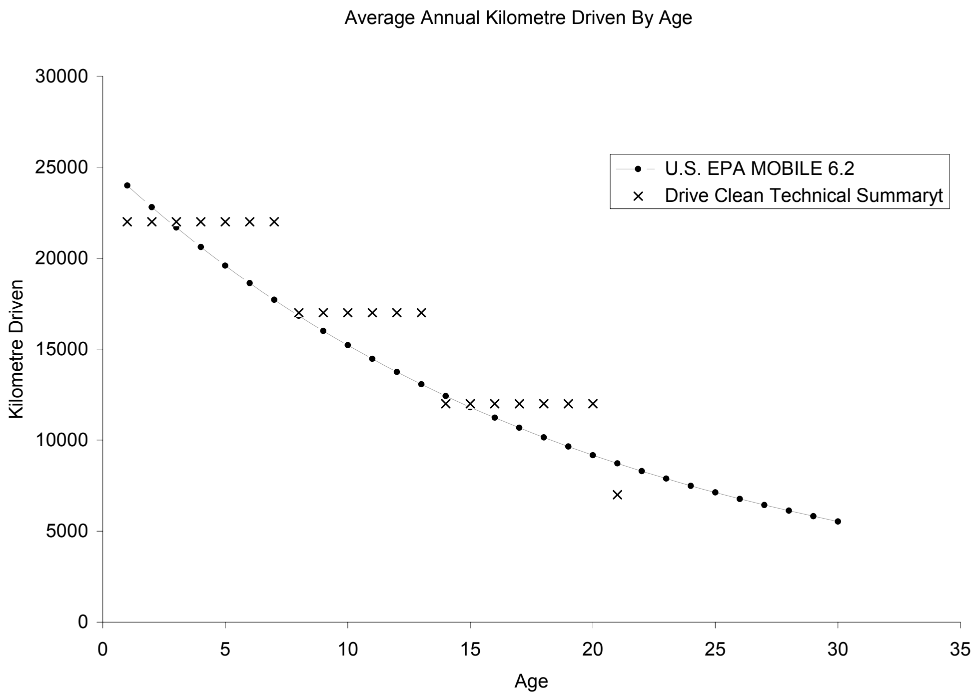

Figure 3 – Average annual kilometres driven

3. 5. Cost Data:

We assume the social cost of an inspection to be \$50. This is comprised of the \$30 direct cost of the test and an assumed additional cost of \$20 for the opportunity cost of the test time, fuel and other expenses related to travelling to and from and waiting for the test. We assume an average repair cost of \$150 which is the third quartile between 0 and the Repair Cost Limit of \$200 that was in effect for most of our sample period. Finally, we truncate the number of age cohorts at 20 for computational convenience. According to the summary of the first three years of the Drive Clean DATA, this captures more than 98% of the stock of vehicles.[11]

4. The Estimated Abatement Cost Function

[11] See Appendix A.4.for further discussion.

A problem that confronts all studies of motor vehicle emissions is how to aggregate the three gases that are controlled: HC, CO and NO_X. While it is not uncommon for the three to be summed together to form a composite pollutant, we are not aware of any scientific basis for doing this. Moreover, an index based on simple summation is dominated by CO which accounts for more than 80% by weight of such an index. In the absence of a sound method for aggregating the three gases, we present instead an abatement cost function for CO only. In doing this, we are implicitly attributing all of the abatement effort and cost towards CO reduction. This assumption does not affect our qualitative results because it turns out that the shape of the abatement cost curve is remarkably similar regardless of which pollutant we use or for any kind of aggregation of the three gases (provided the composite pollutant is an increasing function of each of the individual pollutants). It does of course affect the level of abatement costs that we estimate. Effectively, we have a classic example of joint production (in which the products are abatement of different pollutants) and the inherent problem of attributing cost among the joint products. A good direction for future research is to obtain sufficient data on abatement of the three gases to determine the empirical relationship among them as a way around the cost assignment problem. This is beyond the scope of this paper, however, and we here maintain the simpler solution of attributing all of the cost to a single pollutant.

We estimate the abatement cost function by repeatedly solving the constrained cost minimization problem at different abatement target levels using MATLAB. We construct the abatement cost function for two types of scenarios for abatement. In the first, the abatement per kilometre is assumed to rise with age as in Equation 10. In the second, we assume abatement of CO per kilometre is constant across age cohorts at 8.5 grams per kilometre, the observed average across age cohorts.

Figure 4 shows the abatement cost curves for these scenarios. The panel on the left corresponds to the assumption of abatement rising with age; the panel on the right corresponds to the assumption of constant abatement. The first striking result is how steeply both curves begin to rise at high levels of abatement indicating that marginal abatement cost becomes quite high at high levels of abatement regardless of which scenario we assume. Interestingly, it turns out that the current level of abatement achieved under the Drive Clean Program (approximately 84,260 and 127,092 tonnes per year under the first and second scenarios, respectively) are located in the very steep region of the curves.[12] More importantly, we can see from Figure 4 that the current policy can be depicted by a point lying above the abatement cost curve, for each scenario, indicating that the abatement levels are not achieved at least cost. Instead, our model predicts that the same abatement levels could be achieved at a lower cost than the estimated actual cost of $142.5 million per year (the least-cost solutions are $81 and $131 million per year under the first and second scenarios, respectively).[13] The savings are realized by increasing the minimum testing age (in the first scenario) and eliminating the requirement that vehicles be tested when they change ownership (in both scenarios) and reducing the maximum testing age from 20 to 19 in the first scenario and to 18 in the second scenario. Finally, the optimal testing interval

[12] The existing policy dictates which age cohorts must be tested. The corresponding abatement achieved by testing these cohorts is then estimated by the model and this of course will depend on the assumed abatement per kilometre by age cohort.

[13] Both abatement cost and level of abatement are estimated to be higher under the second scenario. However, unit abatement costs are roughly the same in both scenarios. For example, the least-cost solution for the current policy's abatement level is about $960 per tonne of CO in Scenario 1 and $1030 per tonne in Scenario 2.

remains at two years in the first scenario and for vehicles under 12 years of age in the second scenario but is reduced to one year for vehicles age 13 to 18. Essentially, these policy changes produced by our model can be viewed as a way of more effectively targeting the more likely prospects for pollution abatement. However, given that the level of abatement achieved under the current policy exceeds 90% of the theoretical maximum attainable abatement, there is not much leeway for changing the policy.

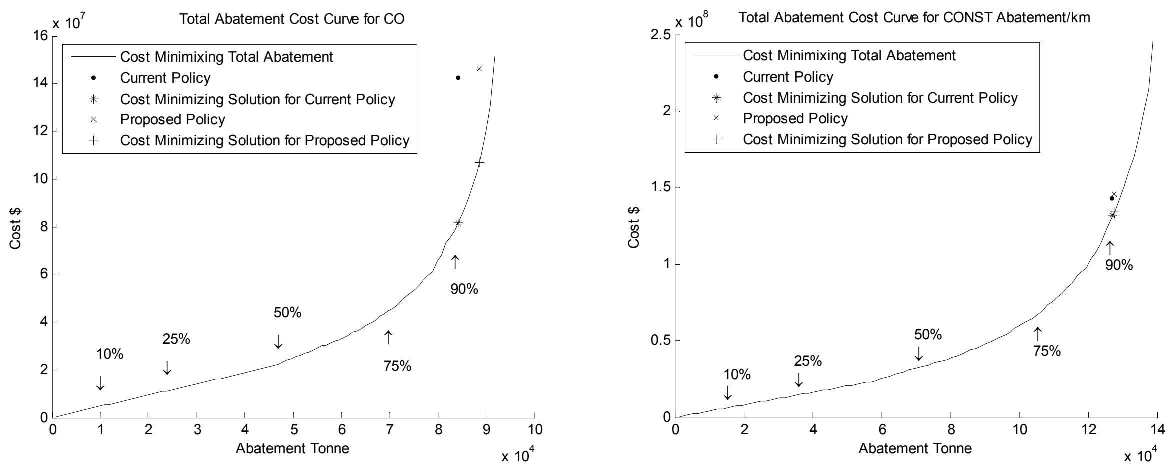

Figure 4 – Abatement Cost Curves for the first and second scenarios

Next, we evaluate the consequences of reducing the stringency of the program. Tables 2 and 3 show some selective cost minimizing solutions for different levels of abatement under the first and second scenarios, respectively. They also present the results in terms of the percentages of the theoretical maximum amount of abatement (MAA) and the maximum total cost (MTC) achieved. For example, in the first scenario, the current policy will be achieved at 91.8% of the MAA at a cost which is 94.4% of the MTC (the least-cost solution for this abatement target is 53.9% of the MTC). Under the second scenario, the current policy will be achieved at 91.5% of the MAA at a cost which is 57.9% of the MTC (the least-cost solution for this target level is 53.5% of the MTC).

Because of the steepness of the abatement cost function at high levels of abatement, even a slight reduction of the abatement target leads to substantial cost savings. For example, by marginally reducing the abatement target from 91.8% under scenario one or 91.5% under scenario two to 89% of MAA, annual total cost is reduced by about $8 and $17 million under the two respective scenarios, which represents a 10.2% or 13.4% reduction relative to the least-cost solution at the 91.5% target level (but actually a 48.7% or 20.1% saving relative to the current policy).

Reducing the abatement target to 82% of the MAA reduces annual costs to $53.5 and $84.5 million respectively which represents a 34% and 35.7% cost reduction relative to the optimized current policy with respect to the first or second scenario, respectively. At this lower level of abatement, the optimal minimum testing age rises to 8 or 5 years and the optimal interval increases to 3 years for the first scenario and to 3 years until after 11 years of age at which the optimal test interval is two years and the last cohort tested is age 17 under both scenarios.

Finally, one can infer from Table 2 that an abatement target of about 60% of MAA can be achieved by testing only two age cohorts. The least-cost solution further shows that an abatement target of about 70% of MAA can be achieved by testing three age cohorts. Also for abatement targets less than about 80% of MAA, it is not cost-effective to test vehicles younger than 6 years old or older than 17 years old.

In conclusion, the optimal solution appears to suggest that up to very high levels of abatement (*i.e.* 80 percent of MAA), it is not optimal to test vehicles that are younger than 6 years old. Furthermore, the cost minimizing solution does not require annual testing for all the age cohorts greater than 6 years.

Our investigations reveal, as one would expect, that higher inspection costs result in an increase in the starting age of testing. In general, the higher are inspection costs relative to repair costs, the higher will be the starting age of testing because it becomes relatively more costly to achieve any given level of abatement from younger vehicles (since they have lower failure probabilities).

On the other hand, higher repair costs result in a decrease in the starting age of testing. This is because when the repair costs are high, it will be inefficient to repair the oldest vehicles since they have a shorter remaining expected life time which means smaller expected life time abatement. On the other hand, it now pays to repair younger vehicles that stay on the road for a longer period of time and have larger expected life time abatement. In other words, when the repair costs are high relative to inspection costs, it becomes relatively more costly to achieve any given level of abatement from older vehicles.[14]

If the abatement for a repaired vehicle increases by age at which it is repaired, this will result in an increase in the starting age of testing. In this case, repairing older vehicles results in more instantaneous abatement and hence it would be more advantageous to spend resources for testing/repairing older vehicles.

[14] In our model, the average repair cost for each age cohort is set equal. However, in reality, the average repair costs for younger vehicles can be higher than the average repair costs for older vehicles. In addition, some jurisdictions require higher Repair Cost Limits for younger vehicles. For example, the Repair Cost Limits under the AirCare program in British Columbia are as follows: $300 for 1980 and older, $400 for 1981-1987,$500 for 1988-1991, $600 for 1992-1998, and no limit for 1999 and newer vehicles.

If older vehicles are driven more, the optimal age at which to start testing increases. The reason is simply that the benefit (in terms of abatement) of testing and repairing older vehicles becomes relatively higher so that it pays to target them relatively more intensively.

If we assume that the effectiveness of repairs declines or depreciates over time, the optimal starting age for testing increases. Clearly, the benefits (in terms of expected lifetime emissions reduction) of testing younger vehicles is reduced if repairs depreciate in effectiveness.

5. CONCLUSIONS

Mandatory vehicle emissions testing and maintenance programs are now a common example of pollution abatement policy in North America but we are not aware of any published estimates of their cost effectiveness. In many jurisdictions, the programs are applied very intensively. For example, mandatory testing often begins when a vehicle is relatively young (*e.g.*, three years of age) and must be repeated at regular intervals (*e.g.*, every two years). What motivated our research was a concern that the social cost of applying the testing policy so intensively may be quite high relative to the abatement benefits. We sought to address this concern by estimating the abatement cost function for a representative program so that we could estimate the social cost savings that would result from marginally reducing the intensity of the program.

We constructed a model of the statistical process that leads to non-compliance with a vehicle's emission standard and parameterized the model with data from a major program that has been in place since 1999 in Toronto, Canada and surrounding urban areas. We then used the model to simulate the reduction in abatement and in abatement costs that would occur if the program were applied less intensively. In other words, we constructed an estimate of the abatement cost curve. Our model suggests that the marginal cost of abatement is so high under the existing policy that even a small reduction in the abatement target would lead to substantial reductions in social costs (by requiring far fewer vehicles to be tested). In principle, these cost savings could be re-allocated to a different source of urban air pollution that has a lower marginal cost and so achieve an overall increase in pollution abatement. In addition, our model predicts that up to very high levels of abatement, the optimal age at which to begin mandatory testing is substantially higher than has been adopted in many jurisdictions. In addition, the cost minimizing solution seldom requires testing vehicles as frequently as is common in practice. For example, up to 70 percent of the maximum amount of abatement that is technically feasible to achieve can be obtained by testing only three age cohorts and this occurs at a cost of about one fifth of the total cost which is necessary to attain the maximum amount of abatement.

Table 2 (abatement rises with age)

Abatement	Cost	TA%	TC%	age 1%	age 2%	age 3%	age 4%	age 5%	age 6%	age 7%	age 8%	age 9%	age 10%	age 11%	age 12%	age 13%	age 14%	age 15%	age 16%	age 17%	age 18%	age 19%	age 20%
9178909.7	4306014.54	10	2.8	0	0	0	0	0	0	0	0	0	0	0	22.1	0	0	0	0	0	0	0	0
18357819.4	8612029.08	20	5.7	0	0	0	0	0	0	0	0	0	0	0	44.1	0	0	0	0	0	0	0	0
22947274.3	10765036.3	25	7.1	0	0	0	0	0	0	0	0	0	0	0	55.2	0	0	0	0	0	0	0	0
27536729.1	12918043.6	30	8.5	0	0	0	0	0	0	0	0	0	0	0	66.2	0	0	0	0	0	0	0	0
36715638.8	17224058.2	40	11.4	0	0	0	0	0	0	0	0	0	0	0	88.3	0	0	0	0	0	0	0	0
45894548.5	21665614.2	50	14.3	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0.3	0	0	0	0	0
55073458.2	29214789.1	60	19.3	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	99.1	0	0	0	0
64252367.9	37371234.2	70	24.7	0	0	0	0	0	0	0	0	100	0	0	0	100	0	0	0	17.5	0	0	0
68841822.8	43413276.9	75	28.7	0	0	0	0	0	0	0	0	100	0	0	0	100	0	100	0	0	11.1	0	0
75267060	53503752.09	82	35.4	0	0	0	0	0	0	0	100	0	0	100	0	0	100	0	3.1	100	0	0	0
81692296.3	73174580.5	89	48.4	0	0	0	0	0	0	74.2	0	100	0	100	0	100	0	100	0	100	0	0	0
83528078.3	78431288.2	91	51.9	0	0	0	0	0	0	100	0	100	0	100	0	100	0	100	0	100	0	50.3	0
84445969.2	82352855	92	54.5	0	0	0	0	0	0	100	0	100	0	100	0	100	0	100	93.4	100	0	100	0
85363860.2	86764433.2	93	57.4	0	0	0	0	0	0	100	0	100	0	100	0	100	59.5	100	100	100	0	100	0
86281751.2	91341459.5	94	60.4	0	0	0	0	0	0	100	0	100	0	100	2.7	100	100	100	100	100	100	100	0
87199642.2	96843707.3	95	64.1	0	0	0	0	0	0	100	0	100	0	100	53.8	100	100	100	100	100	100	100	0
88117533.1	102588332	96	67.9	0	0	0	0	0	0	100	0	100	5.4	100	100	100	100	100	100	100	100	100	0
89035424.1	110616911	97	73.2	0	0	0	0	0	0	100	0	100	62.2	100	100	100	100	100	100	100	100	100	0
89953315.1	120224047	98	79.5	0	0	0	0	0	100	0	100	12.4	100	100	100	100	100	100	100	100	100	100	100
90871206	130740031	99	86.5	0	0	0	0	0	100	0	100	80.3	100	100	100	100	100	100	100	100	100	100	100
91789096.9	151194114	100	100	0	0	0	0	0	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
84261560.7*	142653691*	91.8*	94.4*	20	20	100	20	100	20	100	20	100	20	100	20	100	20	100	20	100	20	100	20
84261560.7	**81521060.9**	**91.8**	**53.9**	**0**	**0**	**0**	**0**	**0**	**0**	**100**	**0**	**100**	**0**	**100**	**0**	**100**	**0**	**100**	**70.8**	**100**	**0**	**100**	**0**
88629997.8+	146096943+	96.6+	96.6+	20	20	20	20	100	20	100	20	100	20	100	100	100	100	100	100	100	100	100	100
88629997.8	**107070741**	**96.6**	**70.8**	**0**	**0**	**0**	**0**	**0**	**0**	**100**	**0**	**100**	**37.1**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**0**

* Level of Abatement and Total Cost under the current Drive Clean program. The cost minimizing solution to achieve this level of abatement is shown under it.

+ Level of Abatement and Total Cost under the proposal Drive Clean program review. The cost minimising solution to achieve this level of abatement is shown under it. Based on the technical summary of the first three years of Drive Clean program 20% of vehicles change their ownership in each year.

Table 3 (abatement constant across age cohorts)

Abatement	Cost	TA%	TC%	age 1%	age 2%	age 3%	age 4%	age 5%	age 6%	age 7%	age 8%	age 9%	age 10%	age 11%	age 12%	age 13%	age 14%	age 15%	age 16%	age 17%	age 18%	age 19%	age 20%
13885585.7	5702505.1	10	2.3	0	0	0	0	0	0	0	0	23.8	0	0	0	0	0	0	0	0	0	0	0
27771171.4	11405010	20	4.6	0	0	0	0	0	0	0	0	47.5	0	0	0	0	0	0	0	0	0	0	0
34713964.3	14256263	25	5.8	0	0	0	0	0	0	0	0	59.4	0	0	0	0	0	0	0	0	0	0	0
41656757.1	17107515	30	6.9	0	0	0	0	0	0	0	0	71.3	0	0	0	0	0	0	0	0	0	0	0
55542342.8	22810020	40	9.3	0	0	0	0	0	0	0	0	95.1	0	0	0	0	0	0	0	0	0	0	0
68039369.9	30831744	49	12.5	0	0	0	0	0	0	0	100	0	0	0	43.2	0	0	0	0	0	0	0	0
83313514.2	41289013	60	16.8	0	0	0	0	0	0	100	0	0	0	0	100	0	0	15.9	0	0	0	0	0
97199099.9	55414166	70	22.5	0	0	0	0	0	100	0	0	0	100	0	0	100	0	0	14.2	0	0	0	0
104141893	64671102	75	26.3	0	0	0	0	0	100	0	0	100	0	0	100	0	0	100	0	6.1	0	0	0
113861803	84551537	82	34.3	0	0	0	0	100	0	0	100	0	31	100	0	100	0	100	0	100	0	0	0
123581713	113979378	89	46.3	0	0	0	100	0	100	0	100	0	100	0	100	20.9	100	100	100	0	100	0	0
126358830	127890228	91	51.9	0	0	100	0	100	0	100	0	100	0	100	20.9	100	100	100	100	0	100	0	0
127747388	134981779	92	54.8	0	0	100	0	100	0	100	0	100	0	100	86.7	100	100	100	100	0	100	0	0
137467298	213687932	99	86.8	0	100	31.4	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
138855857	246187197	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
127092452*	142653691*	91.5*	57.9*	20	20	100	20	100	20	100	20	100	20	100	20	100	20	100	20	100	20	100	20
127092452	**131636931**	**91.5**	**53.5**	**0**	**0**	**100**	**0**	**100**	**0**	**100**	**0**	**100**	**0**	**100**	**55.7**	**100**	**100**	**100**	**100**	**0**	**100**	**0**	**0**
127582488+	146096943+	91.9+	59.3+	20	20	20	20	100	20	100	20	100	20	100	100	100	100	100	100	100	100	100	100
127582488	**134139611**	**91.9**	**54.5**	**0**	**0**	**100**	**0**	**100**	**0**	**100**	**0**	**100**	**0**	**100**	**78.9**	**100**	**100**	**100**	**100**	**0**	**100**	**0**	**0**

* Level of Abatement and Total Cost under the current Drive Clean program. The cost minimizing solution to achieve this level of abatement is shown under it.

+ Level of Abatement and Total Cost under the proposal Drive Clean program review. The cost minimising solution to achieve this level of abatement is shown under it.

Based on the technical summary of the first three years of Drive Clean program 20% of vehicles change their ownership in each year.

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Appendix

A. 1. The Failure Distribution:

In the presence of the emission tests and when failed vehicles are repaired/restored to compliance, the failure rates will be different from the initial ones (*e.g.* the hazard rate can have a Weibull distribution with different parameters). Let us assume that h_a denotes the initial hazard rate:

$$h_a = 1 - p^{a^{\pi} - (a-1)^{\pi}} \qquad \text{(A.1. 1)}$$

Therefore, h_a is the hazard rate corresponding to the vehicles before the introduction of the program; or if the emission tests are present, to the vehicles younger than the minimum testing age; and also to the vehicles that have never failed their emission tests.

Additionally, assume that g_a represents the hazard rate of the restored vehicles defined as:

$$g_a = 1 - v^{a^{\beta} - (a-1)^{\beta}} \qquad \text{(A.1. 2)}$$

where $0<v<1$ is the probability of remaining in compliance at the age a after being repaired at the age a-1 (*i.e.* the scale parameter) and β is the shape parameter.

If vehicles are tested only on one occasion at age t_1, the failure rate at any time t_2 where $t_2 > t_1$ can be calculated as:

$$\Psi_{t_2} = S_{t_1}\left[1 - \prod_{i=t_1+1}^{t_2}(1-h_i)\right] + F_{t_1}\left[1 - \prod_{i=t_1+1}^{t_2}(1-g_i)\right] \qquad \text{(A.1. 3)}$$

It is not difficult to show that for $t_1 = 1,2,...,T$, if $g_{t_1} < h_{t_1}$ (*i.e.* $v>p$ or $\beta<\pi$ or both; which means that a repaired vehicle is less likely to fail in successive tests), then $g_{t_2} < \Psi_{t_2} < h_{t_2}$ and if $g_{t_1} > h_{t_1}$ (*i.e.* $v<p$ or $\beta>\pi$ or both; this scenario can be, for instance, due to a shoddy repair and it means that a repaired vehicle is more likely to fail in successive tests), then $g_{t_2} > \Psi_{t_2} > h_{t_2}$. Finally, if $g_{t_1} = h_{t_1}$ (*i.e.* v=p and β=π), then $g_{t_2} = \Psi_{t_2} = h_{t_2}$ which means that in successive test cycles, a repaired vehicle is as likely to fail a test as a vehicle that remained in compliance up to that age.

However, if tests are only conducted on one occasion, it follows that Ψ_{t_2} will almost always closely follow the initial failure probability, h_{t_2}. Figure A.1. 1 depicts g_{t_2}, Ψ_{t_2} and h_{t_2} for the first case where g_{t_1} is 30% less than h_{t_1} (*i.e.* the hazard rate for the repaired vehicles is 30% less than the hazard rate for the un-repaired vehicles that pass the inspection tests) and t_1=4.

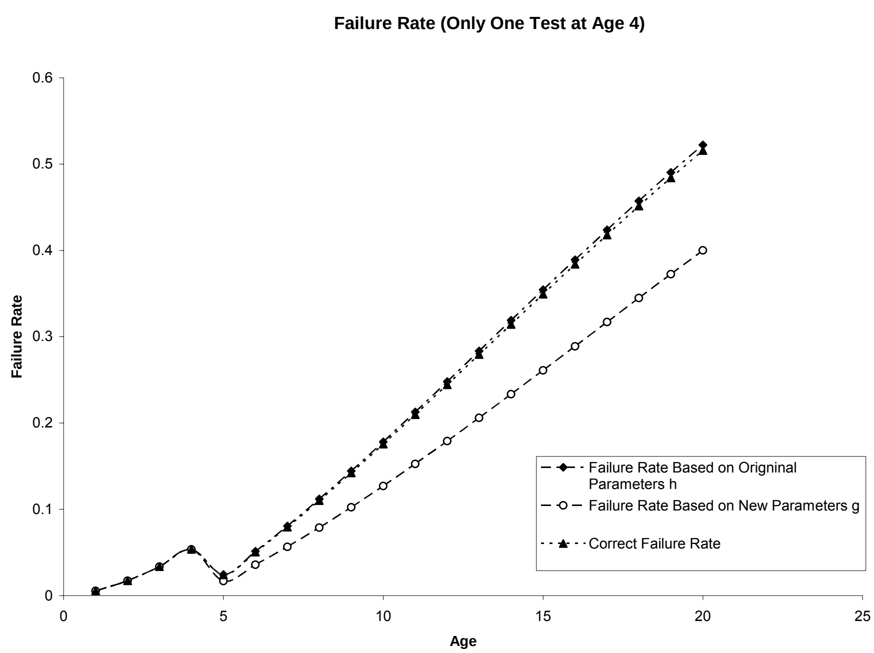

Figure A.1. 1

If vehicles are tested at age t_1 and every successive year after t_1, the failure rate at any time t_2 where $t_2 > t_1$ can be calculated as:

$$\Psi_{t_2} = S_{t_1} h_{t_2} + F_{t_1} g_{t_2} + S_{t_1} \left[1 - \frac{\prod_{i=t_1+1}^{t_2} (1 - h_i)}{(1 - h_{t_2})} \right] (g_{t_2} - h_{t_2}) \qquad \text{(A.1. 4)}$$

Then, for $t_1 = 1,2,...,T$, if $g_{t_1} < h_{t_1}$ (*i.e.* $v>p$ or $\beta<\pi$ or both), then $g_{t_2} < \Psi_{t_2} < h_{t_2}$ and if $g_{t_1} > h_{t_1}$ (*i.e.* $v<p$ or $\beta>\pi$ or both), $g_{t_2} > \Psi_{t_2} > h_{t_2}$ and finally, if $g_{t_1} = h_{t_1}$ (*i.e.* $v=p$ and $\beta=\pi$), $g_{t_2} = \Psi_{t_2} = h_{t_2}$ but contrary to the former case, the failure rate Ψ_{t_2} will be close to the hazard rate h_{t_2} only for initial values of t_2 and as t_2 increases Ψ_{t_2} will approach g_{t_2}. Figure A.1. 2 shows g_{t_2}, Ψ_{t_2} and h_{t_2} for the first scenario where g_{t_1} is 30% smaller than h_{t_1} and there are successive tests in each year after age 4 (t_1=4).

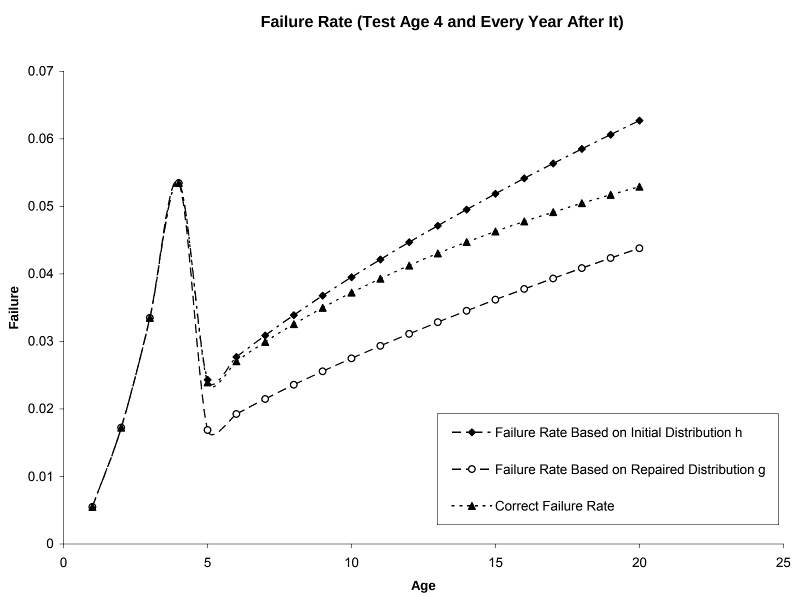

Figure A.1. 2

However, in the literature, there is no evidence to suggest whether g_{t_1} should be smaller, greater, or equal to h_{t_1}. Thus, for simplicity, we assume that g_{t_1} and h_{t_1} are equal. This is the same as saying the hazard rate for a repaired vehicle also follows the Weibull distribution and with the same parameter values as the hazard rate for the vehicles that never failed the inspection. Nevertheless, if only a few age cohorts are tested, the effects of assuming g_{t_1} equal h_{t_1} will be insignificant since Ψ_{t_2} will closely follow the initial failure rate and in the second scenario the effects will be negligible. Consequently, we assume that the hazard function for the repaired vehicles has the same parameters as never-repaired vehicles and hence in the presence of the emission tests and when failed vehicles are repaired to compliance, the failure distribution can be expressed as:

$$
\begin{aligned}
&F_1 = h_1 \\
&F_a = h_a + (1 - h_a)(1 - x_{a-1})F_{a-1} \qquad\qquad a = 2, 3, ..., T
\end{aligned}
\tag{A.1. 5}
$$

A. 2. Age Distribution of Vehicles:

The actual number of Drive Clean tests is the only record in our data that can be used to estimate the number of vehicles in each age cohort. In each year of the Drive Clean program, the tests were conducted for the odd age cohorts between the age of 3 and 20. Vehicles in the even age cohorts in this range and the age cohorts younger than 3 years old were tested only if the ownership of the vehicle was transferred. Unfortunately, this information is insufficient to build a vehicle age distribution that would be needed for our simulation. This is because 1) the data is available just for the first three years of the Drive Clean program, 2) the data only covers vehicles in the odd age cohorts between the age of 4 and 20, and 3) each year data is a snapshot of the vehicle age distribution and therefore sensitive to the boom and bust.

To overcome this problem, we use findings from other studies (*e.g.* the report to Ontario Ministry of the Environment by Eastern Research Group, Inc.) and incorporate data from surveys (*e.g.* Canadian Vehicle Surveys for 2000-2005 by Statistics Canada) as follows.

- Figure A.2.1 (Source: Figure 3-1 in the Evaluation of Ontario Drive Clean Program by Eastern Research Group, Inc. that is provided by DesRoisers Automotive Consultants) shows the historical trends and future projections of the light-duty vehicle fleet in Ontario and Drive Clean areas. According to the figure, there are almost 6 million vehicles registered in the Drive Clean areas as of 2004. The reported number of gasoline fuel vehicles registered in Ontario is further divided in to 4 areas, 1) not in Drive Clean area with 794,636 vehicles, 2) in phase 1 area with 3,099,700 vehicles, 3) in phase 2 area with 1,849,320 vehicles, and 4) in phase 3 area with 1,130,398 vehicles. Consequently, number of registered vehicles in area 1 and 2 that is consistent with our emission data is about 5 million vehicles.

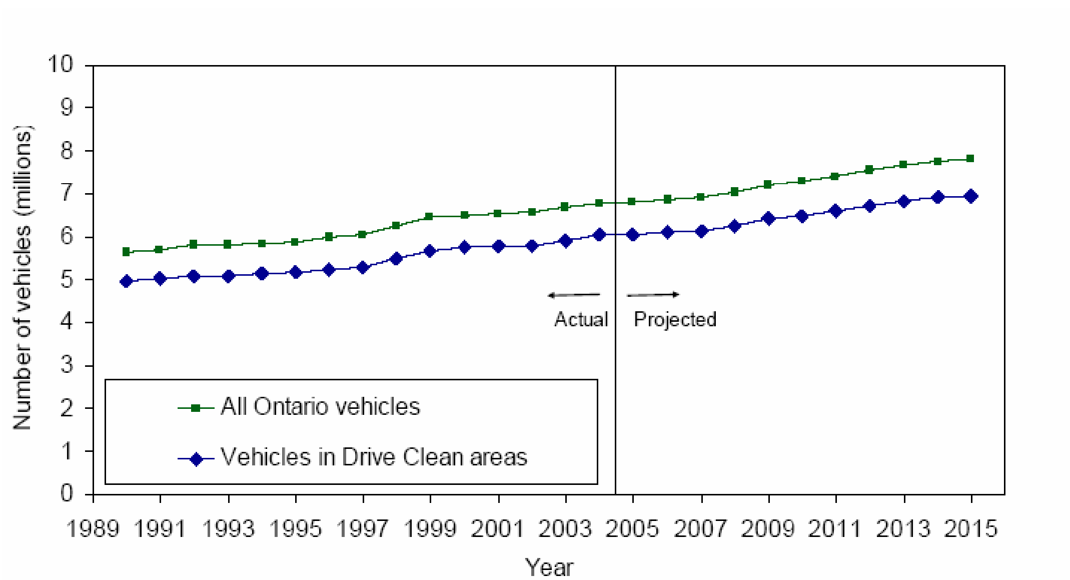

Figure A.2. 1

Table A.2.1 shows the vehicles age distribution of the light-duty vehicle fleet in Ontario for 2000 to 2005 from Canadian Vehicle Survey by Statistics Canada.

Table A.2. 1

Age Cohorts	2000	2001	2002	2003	2004	2005
1	500,040	597,112	522,819	570,572	592,552	488,270
2	495,767	490,714	582,621	510,664	571,973	593,110
3	431,995	471,557	455,409	547,044	490,995	554,384
4	341,569	435,642	470,190	449,588	548,989	486,203
5	413,887	340,492	432,972	468,505	448,498	546,274
6	388,364	410,482	337,024	427,206	463,276	444,782
7	390,585	381,085	402,208	329,582	417,236	453,392
8	414,734	381,230	372,255	390,180	320,897	408,170
9	385,979	397,540	365,467	355,907	370,448	306,881
10	399,053	364,097	377,149	343,559	334,431	350,406
11	397,230	361,667	332,575	342,819	308,981	304,074
12	367,964	348,085	322,809	293,197	302,475	273,843
13	256,487	302,927	290,882	270,122	242,414	253,950
14	208,027	204,151	247,393	231,813	217,841	198,337
15	136,314	154,319	156,283	187,379	173,724	168,373
16	88,344	101,999	117,413	114,210	137,925	130,809
17	41,433	63,887	75,642	84,318	80,798	100,015
18≥	209,200	213,883	242,339	260,486	278,792	295,781

- As can be seen in table A.2.1, the vehicles age distribution shows little variation from one year to another and therefore, no change in the age distribution can be deduced by it. (Furthermore, we could not find any indication that suggests the vehicle age distribution will considerably change over time and the impact of minor changes should be negligible in our analysis).

We used Canadian Vehicle Survey data to calculate the percentage changes in number of vehicles by age and run an OLS regression to fit a curve for the average empirical percentage changes. Table A.2. 2 shows the result from the OLS estimation and figure A.2.2 shows the empirical versus estimated percentage change in number of vehicles.

Table A.2. 2

Parameters	Estimates	Standard Error	P-Value
Intercep	3.647821	1.412639	[0.022758]
age	-1.33059	0.382462	[0.004075]
age^2	0.187515	0.021871	[1.04E-06]
R Square	0.974791		
Adjusted R Square	0.970913		
Observations	16		

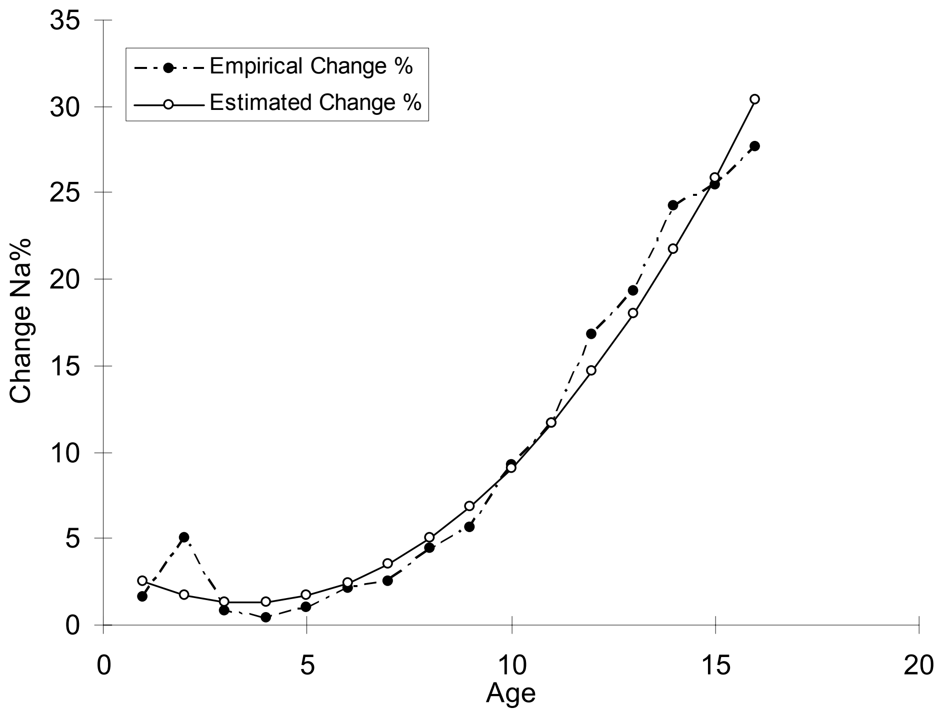

Figure A.2. 2 – Empirical percentage changes in number of vehicles vs. estimated percentage changes

Therefore, number of vehicles in each age cohort can be calculated as:

$$N_a = N_0 \left[1 - \left(3.647821 - 1.33059a + 0.187515a^2\right)\right] \quad \text{(A.2. 1)}$$

Where $N_0 = 400{,}000$ and for $a = 1,...,20$

Figure A.2. 3 depicts this function versus the actual number of Drive Clean tests for phase 1 and 2 in 2001, as well as the total number of vehicles in Ontario (*i.e.* vehicles in phase 1, 2, 3 and in non Drive Clean areas) based on Canadian Vehicle Survey 2001.

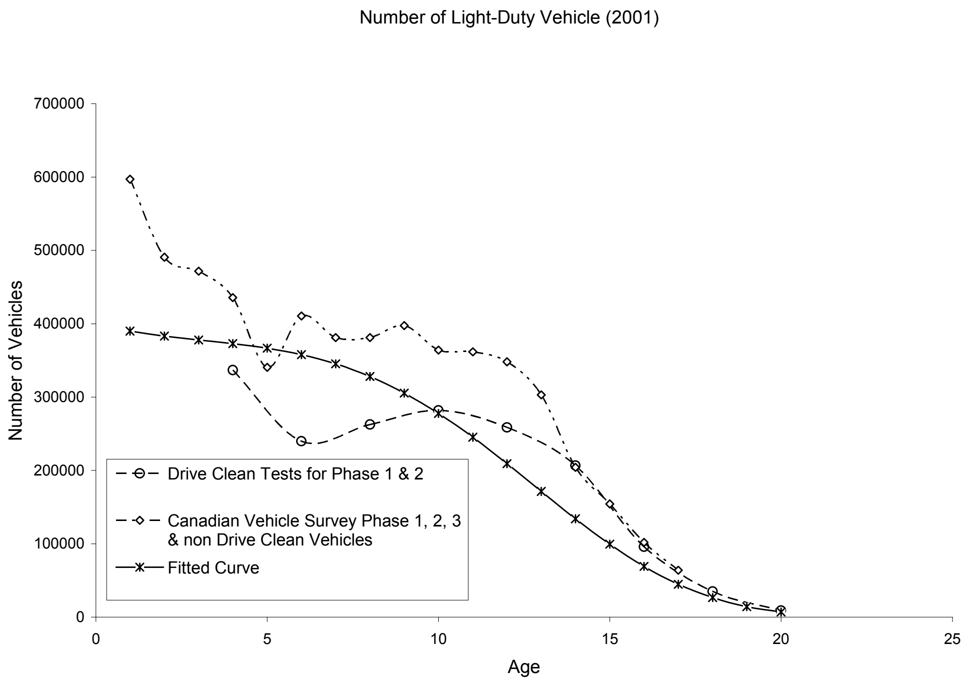

Figure A.2. 3

We did not use the EPA estimation for fleet distribution by age in the technical report of Fleet Characterization Data for MOBILE6 for several reasons. First, it was a poor fit for our data, second, it assumes an unjustified structural break at age 13 and third it was based on a year of data whereas our estimation gives us a better fit, it will not assume a structural break and it takes advantage from 5 years data.[15]

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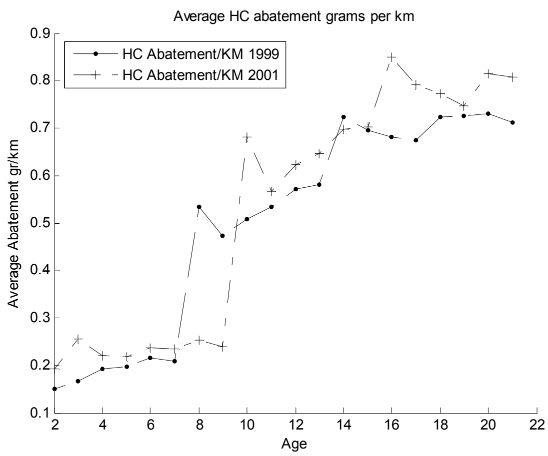
[15] EPA estimation for U.S. Fleet Distribution by age is as follows:

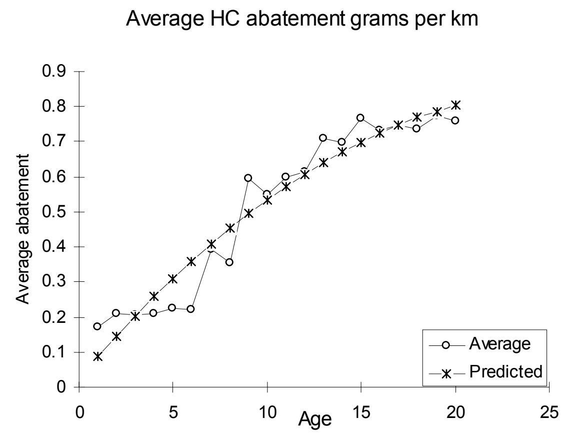
$$\begin{cases} N_a = 8{,}517{,}910e^{-\left(\frac{a}{16.100505}\right)^{4.45489164}} & \text{for } 1 \le a \le 12 \\ N_a = 112{,}855{,}609.5568e^{-0.2321a} & \text{for } 13 \le a \le 25 \end{cases}$$

A.3. Abatement Per Kilometre:

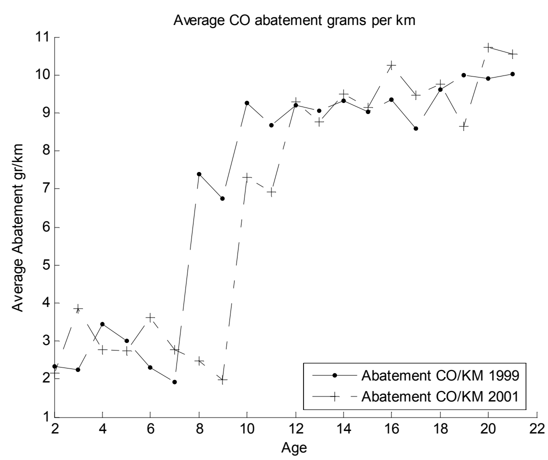
The average abatement of HC, NO_x and CO per kilometre can be calculated from the Technical Summary of the First Three Years of Light-Duty Vehicle (1999-2001) by vehicles age. Figure A.3. 1 depicts the calculated average abatements per kilometre. While part I-III of figure A.3.1 depict the average abatement per kilometre for each one of these three gases separately, part IV-VI portray the fitted curve for the average abatement per kilometre for each one of them. The estimation result is presented in table A.3.1.



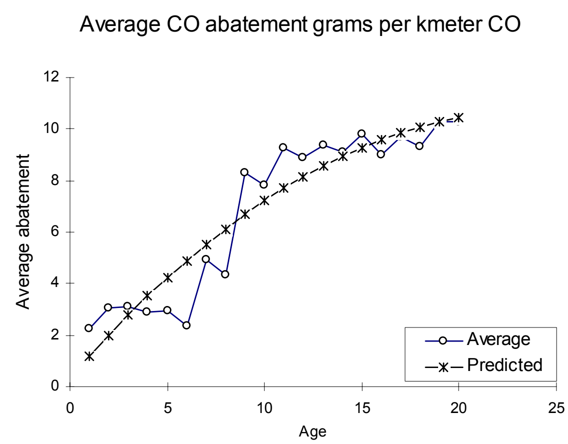
(I)



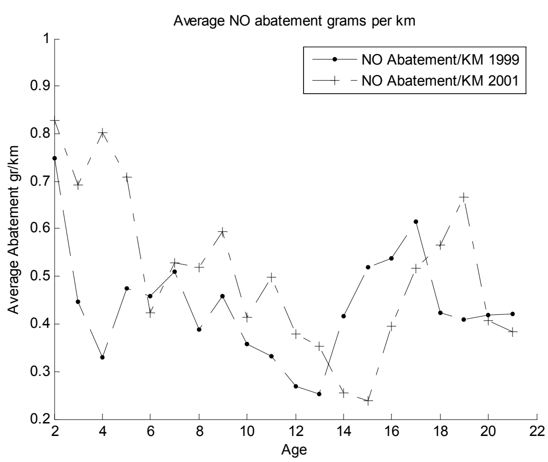
(IV)



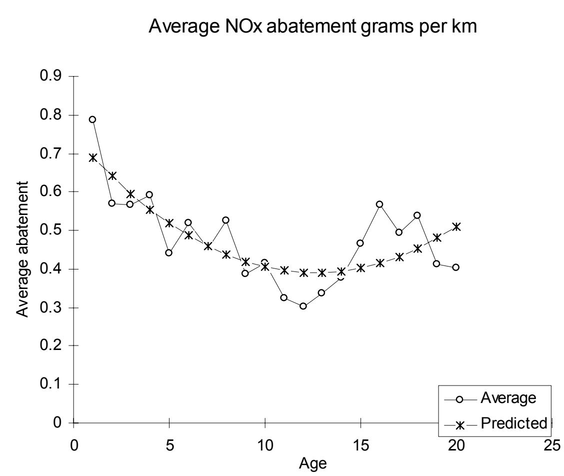
(II)



(V)



(III)



(VI)

Figure A.3. 1

Table A.3. 1

Parameter	Estimates	Standard Error	P-value
Carbon Monoxide			
Parameter	Estimates	Standard Error	P-value
Intercept	0.31625	0.84922	0.714197
age	0.872308	0.186247	0.000214
age^2	-0.01829	0.008615	0.048678
R Square	0.881217		
Adjusted R Square	0.867243		
Observations	20		
Volatile Organic Compounds			
Parameter	Estimates	Standard Error	P-value
Intercept	0.025068	0.049007	0.615563
age	0.062994	0.010748	1.89E-05
age^2	-0.0012	0.000497	0.026889
R Square	0.929391		
Adjusted R Square	0.921084		
Observations	20		
Nitrogen Oxides			
Parameter	Estimates	Standard Error	P-value
Intercept	0.744257	0.05805	3.63E-10
age	-0.05609	0.012731	0.000386
age^2	0.002221	0.000589	0.001524
R Square	0.585332		
Adjusted R Square	0.536547		
Observations	20		

We use the estimate of CO abatement per kilometre by age as a representative equation for Abatement per kilometre (Equation A.3.1). .

$$q_a = 0.31625 + 0.872308a - 0.01829a^2 \tag{A.3. 1}$$

Furthermore, we consider an additional scenario where the abatement per kilometre by age is constant and equal to 8.5 grams per kilometre (q_a=8.5). This is the case that the implemented emission standards for older vehicles are much higher than those for younger vehicles and hence the emission reductions of repairs can possibly remain constant regardless of age.

A.4. Number of Age Cohorts (T):

Choosing T as 20 can limit our analysis in two ways. First, the expected lifetime abatement of a vehicle repaired at any age between 1 and 20 will be underestimated because the expected benefits are forced to be truncated at age 20. Second, we will not consider the cost-effectiveness of testing vehicles older than 20 years. However, considering T equal to 20 should have negligible impact on our analysis. This is because vehicles older than 20 years account for a small percentage of vehicles in the fleet. For example, according to the Canadian Vehicle Survey by Statistics Canada, vehicles older than 20 years roughly account for two to three percent of the fleet. For this reason, emissions from vehicles older than 20 years should account for a very small percentage of the total flow of emissions.

Figure A.4. 1 shows the distribution of emission and abatement flows by model year in the first year of drive clean program, 1999 (only even model year vehicles were subject to tests). As can be seen in this figure, 1980 model year vehicles (19 years old vehicles) represent 0.84% of the flow of emissions and around 1% of Abatement. These percentages would be much smaller once we include the actual number of vehicles in the fleet (*i.e.* if we include odd model year vehicles and those younger than 3 years).

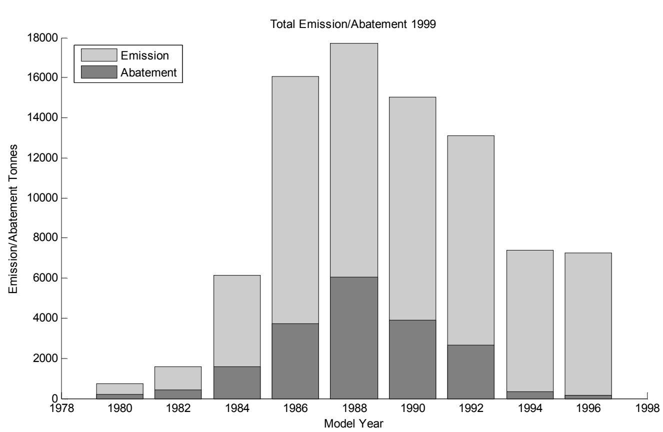


Figure A.4. 1