An Analysis of British Columbia's SCRAP-IT Program: Emissions Savings, Participation, and Transportation Choice

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Abstract

In this paper we analyze British Columbia's accelerated vehicle retirement program (BC SCRAP-IT®) offering a uniquely wide range of post retirement options. In addition to cash or new-vehicle subsidies, BC SCRAP-IT also supports alternative forms of transportation: public transit, membership in ride-share or car-share programs, and/or the purchase of a bicycle. We evaluate the program's impact on carbon dioxide (CO_2), carbon monoxide (CO), hydrocarbon (HC) and nitrous oxides (NO_x) emissions. We also ask, was program participation higher among people belonging to lower income groups? And did different income groups choose different post-retirement options? We find that the average vehicle in the program is retired 9.4 years earlier than 'normal' and is driven approximately 12,100 km per year during the end of its life. We estimate an average savings of 10.5 tonnes of CO_2, 70 kg of NO_x, 28 kg of HC, and 402 kg of CO per program vehicle. Using a price of C$30 per tonne of CO_2 and C$3500 per tonne of NO_x emissions we value these savings at C$859. For participants who choose a new vehicle only (ignoring public transit, ride-share or bicycle options) the corresponding savings are 6 tonnes of CO_2, 65 kg of NO_x, 24 kg of HC, and 356 kg of CO per program vehicle. The corresponding value is C$666. We find no evidence that program participation is higher in areas with lower income levels. However, conditional on participation, we find that the the probability of choosing the transit option rises as the area's median income falls.

Keywords: accelerated vehicle retirement programs; vehicle emissions; voluntary environmental programs. **JEL Codes:** Q53, Q58.

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1 Introduction

In his July 2008 editorial in the *New York Times* titled, "A Modest Proposal: An Eco-Friendly Stimulus"[1] Alan Blinder outlines three benefits from an Accelerated Vehicle Retirement Program (AVRP). First, a cleaner environment, as old cars, especially those in poor condition, pollute more per mile than newer cars. Second, a more equal income distribution, as AVRP's naturally target the poor—the well-to-do rarely own the oldest cars. Finally, effective economic stimulus, as cash in the hands of the poor is the most effective way to increase consumer spending.

In this paper we evaluate the contribution of British Columbia's accelerated vehicle retirement program, BC SCRAP-IT® towards a cleaner environment and a more equal income distribution.

In effect since 1996, the BC SCRAP-IT program offers a uniquely wide range of post retirement options. Unlike traditional AVRPs that either provide cash, or subsidize the purchase of a new vehicle, BC SCRAP-IT also supports alternative forms of transportation. Participants can subsidize public transit use, membership in ride-share or car-share programs, or the purchase of a bicycle. In its most popular phase, the program provided a new vehicle subsidy determined by the difference in fuel economy of the new and retired vehicle. A wide range of post retirement options and significant program variation over the last two years made BC SCAP-IT an ideal candidate for evaluation. In 2008 a grant from the provincial government allowed an unprecedented expansion of incentives. Subsequent budgetary constraints, brought about by the recession, prevented a renewal of the grant. Incentives were drawn down in two phases thereafter. During our period of analysis, vehicle replacement incentives ranged from $550 to $2250.[2]

In analyzing BC SCRAP-IT's contribution to a cleaner environment, we estimate its impact on carbon dioxide (CO_2), carbon monoxide (CO), hydrocarbon (HC) and nitrous oxides (NO_x) emissions. In analyzing its contribution to a more equal income distribution we ask: was program participation higher among people in low income groups? Did different income groups choose different post-retirement options in the program? While the poor hold most of the old vehicles targeted by AVRPs, they also find the cost of purchasing a new vehicle, as required by traditional AVRPs, prohibitive. In principle, subsidizing public transit or ride-share and car-share programs should draw greater participation from cash constrained groups.

We analyze data on 17,993 vehicle retirements, processed between January 2008 and May 2010, representing approximately 72% of all vehicles in the program. Our information includes: the Vehicle Identification Number (VIN), the make, model, and year of manufacture, transmission and fuel type of the retired vehicle, information on the replacement option chosen (vehicle, transit etc.), and a postal code for the owner.

[1] http://www.nytimes.com/2008/07/27/business/27view.html

[2] All dollar figures are in Canadian Dollars, which at the time of writing is approximately at par with the US Dollar.

Our analysis of BC SCRAP-IT's impact on emissions is based on three estimates: the difference in emissions per kilometre between the retired vehicle and its replacement, the owner's annual kilometrage,[3] and the number of years the vehicle would have been driven in the absence of the program. We use a variety of data sources to construct these estimates.

Estimates for CO, HC and NO_x emissions per kilometre for the retired vehicle are from data provided by British Columbia's Motor Vehicle Emissions Inspection and Maintenance Program (AirCare).[4] Aircare requires annual or biennial inspections for vehicles registered in the populous Lower Mainland of British Columbia. We match 12,449 retired vehicles—approximately 70% of our sample—with their last AirCare inspection, to obtain vehicle-specific emissions estimates for CO, HC, and NO_x per-kilometre. For the remaining 30% not registered in the lower mainland, we use an average emissions profile from a separate study by Aircare. Here a randomly selected sample of 133 vehicles retired by BC SCRAP-IT are retested just before scrapping. For the same study, Aircare also tests a smaller sample of replacement vehicles. We use their average as an estimate of emissions for all replacement vehicles bought under the program. To estimate CO_2 emissions we match fuel economy estimates for scrapped and replacement vehicles using United States Environmental Protection Agency (US-EPA) data.

Our estimate of the owner's annual kilometrage reflects driving behaviour during the end of the life of the retired vehicle. Aircare test records include odometer readings. By comparing odometer readings from the vehicle's last two Aircare inspections we can construct an end-of-life annual kilometrage. We project this end-of-life annual kilometrage as the estimate for vehicles kilometres driven by the owner in both retired and replaced vehicles.[5] For those who choose non-vehicle options: public transit, ride-share, or bicycle, we assume that 50% of their pre-retirement kilometres occur on a vehicle bought outside the program. In other words, we assume that those choosing non-vehicle options (approximately 52% of our sample) also produce vehicle emissions, although at half the rate of their vehicle-choosing counterparts.

To estimate the number of years the vehicle would have been driven in the absence of the program, we construct a 'normal' retirement schedule based on highly detailed vehicle in operation data (years 2008 and 2009) from R.L. Polk Canada. The 'normal' retirement schedule is disaggregated by vehicle make (Toyota, BMW etc.) vintage (year of manufacture), and province. A comparison with retirement rates under the program yields the 'acceleration' in retirement caused by BC SCRAP-IT.

We find that the average vehicle in the program is retired 9.4 years earlier than 'normal' and is driven approximately 12,100 kilometres per year during the end

[3] As Canada is a metric country, we use the term 'kilometrage' instead of the term 'mileage.' One mile equals 1.609344 kilometres.

[4] http://www.aircare.ca/

[5] As long as vehicle kilometrage are largely determined by owner (instead of vehicle) characteristics, information on recent driving trends are a fairly good estimate for the replacement vehicle (see Tatsutani (1991) for evidence).

of its life. We estimate an average savings of 10.5 tonnes of Carbon Dioxide, 70 kilograms of Nitrous Oxides, 28 kilograms of Hydrocarbons, and 402 kilograms of Carbon Monoxide per program vehicle. Using a price of $30 per tonne of CO_2 and $3500 per tonne of NO_x emissions[6] we value these savings at $859. For participants who choose a new vehicle only (that is, ignoring public transit, ride-share or bicycle options) the corresponding savings are 6 tonnes of Carbon Dioxide, 65 kilograms of Nitrous Oxides, 24 kilograms of Hydrocarbons, and 356 kilograms of Carbon Monoxide per program vehicle. The corresponding value is $666.

In analyzing BC SCRAP-IT's impact on income distribution we cannot access individual socio-economic data. Instead, we use socio-demographic data for each participant's postal district from the Canadian Census. We find no evidence that program participation is higher in areas with lower income levels. However, conditional on participation, we find that the the probability of choosing the transit option rises as the area's median income falls. This might reflect that there is no capital outlay necessary for transit. We also find that the probability of choosing the bicycle option decreases as the unemployment rate in the area increases. This possibly reflects the purchase of bicycles for recreational rather than commuter use.

Through this paper we make three main contributions to the literature evaluating AVRPs. First, we use a unique and extremely detailed dataset to estimate the impact of BC SCRAP-IT. Second, we analyze a highly elaborate and sophisticated set of post-retirement options in a vehicle retirement program. Thirdly, we are the first to systematically analyze the reach of a vehicle retirement program across socio-demographic groups.

Our data is a significant improvement in two main areas. Earlier studies such as Alberini et al. (1996), Hahn (1995) and Li et al. (2010) estimate retired vehicle emissions using one of two (either the EMFAC or the MOBILE) simulation models.[7] These models predict averages for vehicles of a particular type and vintage. Predictions are not specific to the retiring sample.[8] With no information on end-of-life driving behaviour, earlier studies also assume that the retired vehicle is driven the average attributed to vehicles of the same vintage; see Hahn (1995) and Li et al. (2010). This average is often based on "Vehicle Survivability and Travel Mileage Schedules" (Lu, 2007) and is not specific to the retiring sample. Other papers use owner surveys from the program (see Alberini et al. (1996) and California Air Resources Board (1991), and Fairbank, Bregman & Maullin (1991)). Instead, we use vehicle-specific emission and end-of-life driving behaviour to create our estimates.

Recently Sandler (2011) also uses a detailed dataset that is a significant improvement over those used in earlier analyses of AVRPs. Sandler (2011) matches the retiring sample California's Bay Area's vehicle buyback program to a control

[6] HC and CO are tied to NO_x prices by 1:1 and 1:7 ratio's respectively.

[7] The EMFAC is California Air Resources Board (CARB)'s EMission FACtors model, and the MOBILE model is United States Environment Protection Agency's (EPA) corresponding model.

[8] Dill (2004) compares exhaust emissions from tests on vehicles that were a part of the CARB accelerated retirement pilot program with those from the EMFAC 2000 model and finds substantial differences.

group of vehicles in the region. He then aggregates the control group's emissions and mileage till the end of their life as the counterfactual estimate of emissions of the retired vehicle. Our analysis is different for two reasons. Firstly, similar to most other AVRPs the buyback program analyzed by Sandler (2011) provides a simple cash subsidy for participating vehicles alone. Secondly, he does not analyze the reach of the program across different socio-demographic groups.

Unlike all earlier studies, BC SCRAP-IT's program design allows us to analyze the impact of offering alternative transportation subsidies. This has significant implications not just for environmental benefits, but also for extending the reach of retirement programs to cash constrained households. We conduct a systematic analysis of the distributional impacts of the BC SCRAP-IT program. These have been mostly ignored in analyses of AVRPs until now. To our knowledge, only Shaheen et al. (1994) discuss the distributional impacts of AVRPs. The authors hypothesize inequities generated by possible impacts in the used vehicle market, and where emissions reductions are likely to occur. They do not provide any empirical evidence for their hypotheses.[9]

2 Institutional Background

2.1 The BC SCRAP-IT Program

The BC SCRAP-IT® Program is a voluntary early vehicle retirement program providing incentives for British Columbians to replace their older vehicles with cleaner forms of transportation. According to their website[10] "The program is designed to reduce greenhouse gas emissions and to lower exhaust pollutants across the province." The program offers incentives for retiring an old vehicle (model year 1993 or older for the time period of our analysis) contingent on the choice of: the purchase a new vehicle (model year 2004 or later) from a participating dealer, a public transit pass, the purchase of a bicycle, a combination of transit and bicycle subsidies, credit on a vehicle sharing program, or cash (typically the least desirable option).

BC SCRAP-IT has been operating as a not-for-profit organization since 1996. Initial funding was provided by a government-brokered grant from the Canadian Petroleum Products Institute, a grant from the South Coast British Columbia Transportation Authority (known as TransLink[11]) and local area car dealers. BC SCRAP-IT received a large cash injection through a one time $15million grant in February

[9] Other articles related to our research are those that analyze the $3 Billion Accelerated Vehicle Retirement Program (AVRP) titled Car Allowance Rebate System (CARS). These include Knittel (2009), Li et al. (2010), Mian and Sufi (2010), and Yacobucci and Canis (2010). While the main aim for this set is to evaluate the economic stimulus generated by CARS, Li et al. (2010), and Knittel (2009) also estimate the reduction in emissions associated with the program. The focus of these articles reflects that CARS, with a 25 years or younger vehicle eligibility, was primarily designed to increase vehicle sales. Environmental benefits were a footnote.

[10] http://scrapit.ca

[11] http://www.translink.ca

2008, leading to a substantial expansion starting June 4th 2008. While previously the program would provide only up to $750 towards a new vehicle, now up to $2250 was possible. Similarly, while the earlier program would fund up to 14 months of transit passes, now up to 28 months was funded. All options, besides cash (which stayed at $300) were similarly extended.

Gordon Campbell, then the Premier of British Columbia, first publicized this expansion in his weekly radio address on April 5, 2008. He said he hoped to remove 10,000 old and smog-forming vehicles over the next three years. Prior to the expansion, only 1000 cars were retired every year. However, in June 2008 alone, SCRAP-IT processed 1000 cars. By July 2009, over 11000 vehicles were retired under the expanded program. The grant ran out and incentives offered were drawn down starting August 1, 2009. On February 16, 2010 incentives returned to pre-expansion levels.

In Table 1 we provide an overview of the different program phases under BC SCRAP-IT. During Phase 1, before June 2008, the program offered incentives towards new and used vehicles bought from a participating dealer (capped at $750), public transit, bicycle and ride share options. In Phase 2, between June 2008 and July 2009, the subsidy for a replacement vehicle was $750, $1,250 or $2,250. The exact amount depended on the difference in fuel economy of the scrapped and replacement vehicle. Transit passes, worth just over $2,000, a transit-plus-bicycle combo package, worth about $1,900, a car-sharing membership, worth $750, or a cash-only incentive of $300, was also offered. Incentives were drawn down over the next two phases. In Phase 4, in place after February 2010, only $550 is offered for a new vehicle bought from participating dealers. Also offered are a transit subsidy worth approximately $1224, a bike subsidy worth $500, car-share incentives of $750, and $300 in cash.

2.2 AirCare Emissions Vehicle Emissions Testing Program

British Columbia's Motor Vehicle Emissions Inspection and Maintenance Program (AirCare) operates since 1992. Developed in partnership with the Ministry of Environment and Metro Vancouver Air Quality, AirCare is administered by Pacific Vehicle Testing Technologies (PVTT) Ltd., an operating subsidiary of the South Coast British Columbia Transportation Authority (TransLink).

For our analysis, details on the vehicle testing schedules are relevant. All light duty vehicles (5000 kg or lighter) registered in Metro Vancouver (Vancouver and the Fraser Valley) require AirCare inspections according to the following schedule.[12] Model year 1991 and older vehicles are inspected on a vehicle dynamometer annually (road simulator). If they cannot be tested on a dynamometer, they receive an idle-only test. 1992 and newer vehicles are either tested on the vehicle dynamometer or using information from their On-Board Diagnostic (OBD) system every second year. 1998 and newer vehicles receive an OBD system test every second year. We have data for 17,993 vehicles retired under SCRAP-IT, of these we

[12]See http://www.aircare.ca/inspinfo-desc.php for test definitions and procedures.

Table 1: Incentives During Different Program Phases of BC SCRAP-IT (Vancouver and Fraser Valley Regions)

Program Phase	1	2	3	4
Commenced on		2008-06-04	2009-08-01	2010-02-16
Ended on	2008-06-04	2009-07-31	2010-02-15	present
Vehicle				
New Vehicle	$750			$550
Used Vehicle	$500			$550
Low Greenhouse Gas Benefit		$750	$750	
Medium Greenhouse Gas Benefit		$1,250	$1,250	
High Greenhouse Gas Benefit		$2,250	$1,250	
Public Transit				
Translink / 1 zone	14 mo.	28 mo.		
Translink / 2 zones	10 mo.	21 mo.		
Translink / 3 zones	8 mo.	15 mo.	12 mo.	9 mo.
Translink / concession	20 mo.	48 mo.		
West Coast Expr. Inter-Suburban	8 mp	17 mp	14 mp	7 mp
West Coast Expr. Tri-Cities Area	6 mp	13 mp	10 mp	5 mp
West Coast Expr. Maple Ridge	5 mp	11 mp	8 mp	4 mp
West Coast Expr. Mission Area	4 mp	8 mp	6 mp	3 mp
Bicycle				
Discount Rate	50%	100%	100%	50%
Purchase Limit	$500	$1200	$700	$500
Bicycle/Transit Combo Package				
Translink / 1 zone		12 mo.		
Translink / 2 zones		9 mo.		
Translink / 3 zones		6 mo.		
Translink / concession		18 mo.		
Car/Ride Share				
Credit Towards Participation	$750	$1,250	$1,000	$750
Cash		$300	$300	$300

Note: Please see http://scrapit.ca/ for a description of the current phase 4 incentives. Also see http://www.translink.ca/ for a description of the transit framework relevant to the incentives. The Bicycle/Transit Combo allows for the purchase of a bicycle and one of the one/two/three/discount transit passes. Durations for translink passes are in months (mo). Durations for West Coast Express passes are expressed as the number of 28-day passes (mp).

Table 2: Distribution of Incentive Use During Different Program Phases

Program Period	Incentive Type: cash	new vehicle	combi package	public transit	bicycle	car sharing	none	All Applicants
Program Phase 1		166		202	4	1	66	439
before June 4, 2008		37.8%		46.0%	0.9%	0.2%	15.0%	100%
Program Phase 2	347	6,585	2,644	1,629		104	370	11,679
June 4, 2008 to July 31, 2009	3.0%	56.4%	22.6%	13.9%		0.9%	3.2%	100%
Program Phase 3	555	1,800		304	492	76	258	3,485
Aug. 1, 2009 to Feb. 15, 2010	15.9%	51.6%		8.7%	14.1%	2.2%	7.4%	100%
Program Phase 4	678			75	78	13	293	1,137
Feb. 16, 2010 to present	59.6%			6.6%	6.9%	1.1%	25.8%	100%
Retire Your Ride	1,253							1,253
overlaps with Phase 3	100%							100%
All Programs	2,833	8,551	2,644	2,210	574	194	987	17,993
	15.7%	47.5%	14.7%	12.3%	3.2%	1.1%	5.5%	100%

Note: Percentages sum up horizontally for each row that describes a different program phase.

match 12,449 with inspection records at AirCare.

3 Data Preview

Data on vehicle scrappage, from the BC SCRAP-IT program, contains information on 17,993 program participants from January 2008 through May 2010. Most of the data are from 2009. Half of the scrapped vehicles include just five car makes: Ford, Toyota, Honda, Chevrolet, and Mazda.[13] A list of scrapped vehicles by make appears in table TA-2 in our *Technical Appendix*.[14]

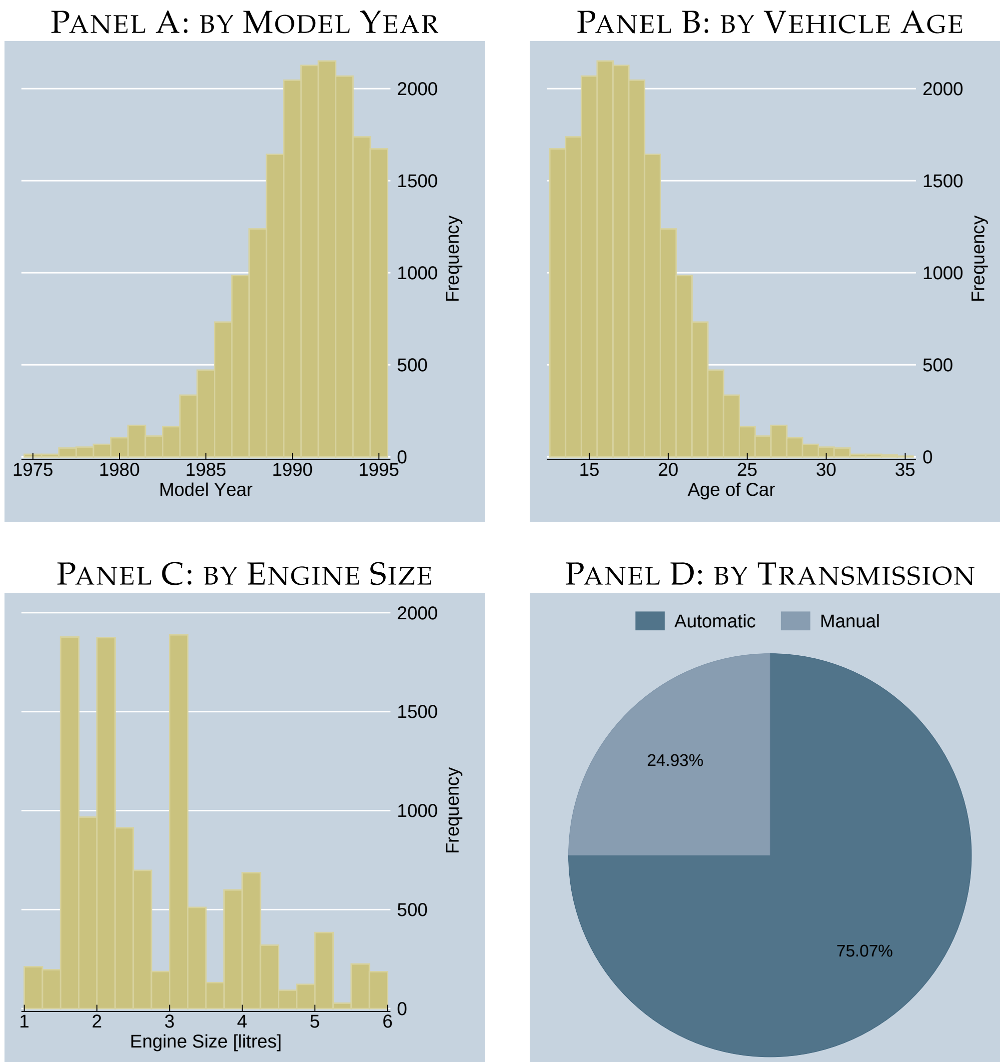
In Table 2 we provide a distribution of our observations under the different program phases and incentives. Almost 65% of our observations derive from Program Phase 2 (with the highest incentives offered). Program Phase 1 is least represented. Amongst incentives, the most popular option in phase 2 is replacement vehicle at 56%. Public transit and the combo package represent approximately 37% of our sample. In Table 2 we include a row for the national vehicle retirement program titled 'Retire Your Ride (RYR).' This program ran parallel to the provincial vehicle

[13]Most vehicle information is identified through the 17-character vehicle identification number (VIN) for post-1980 vehicles. Vehicles made prior to 1981 do not have standardized VINs.

[14]A detailed *Technical Appendix* provides more information about a variety of aspects of our data sets that will aid other researchers with replication of our results.

retirement program. It was also managed by BC SCRAP-IT. Similar to the provincial program, RYR also offers a cash incentive of $300. Residents can get either RYR or the provincial incentives, but not both.

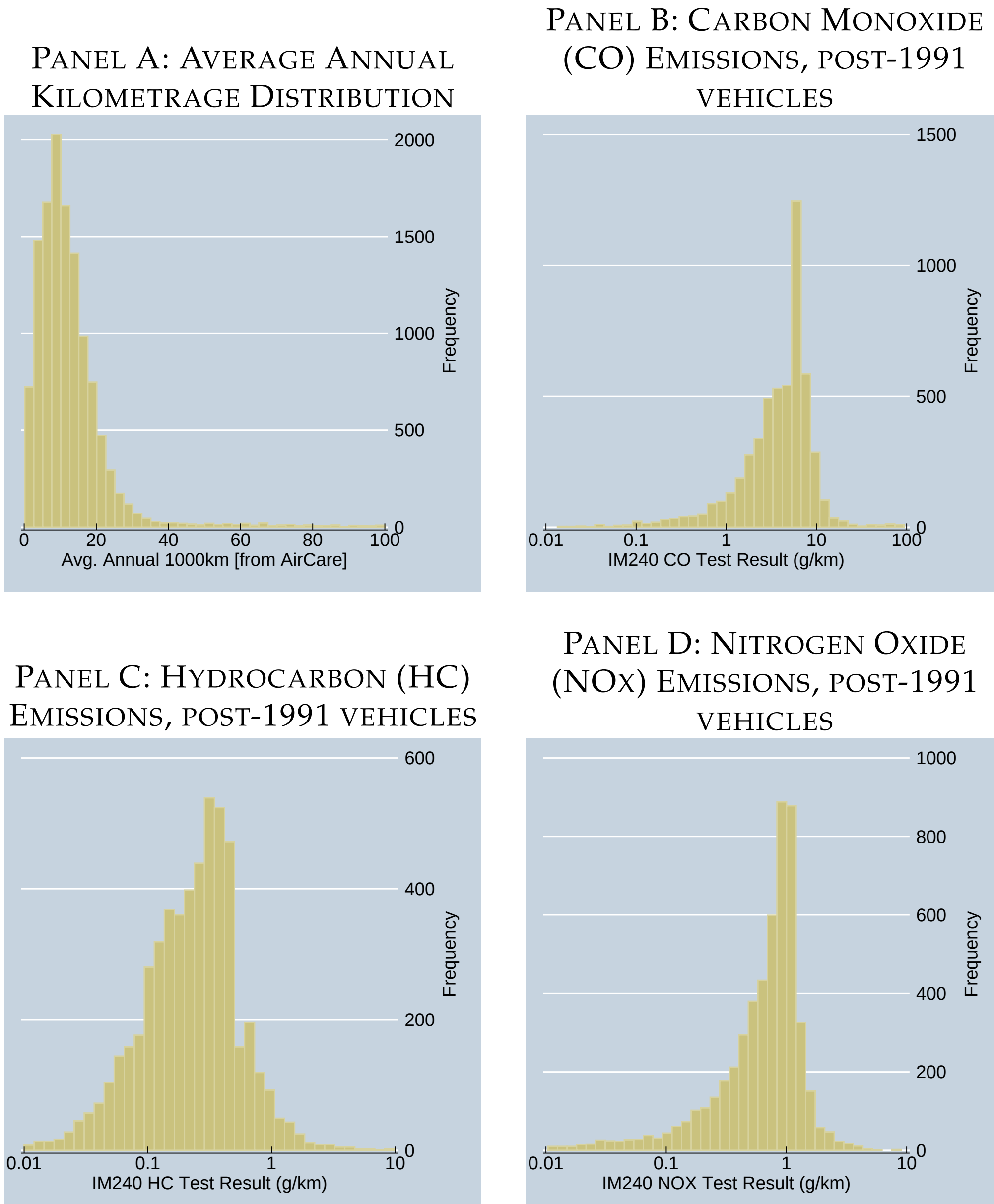
Figure 1: Profile of Scrapped Vehicles



In Figure 1 we illustrate the composition of scrapped vehicles. In Panels A and B we illustrate the age composition by model year or vehicle age. Retired vehicles span twenty model years, between 1975 and 1995. Most retired vehicles are 13 to 23 years old, with the mean age of 19.6 years. In Panel C we illustrate the range of engine sizes, and in panel D we show a 3-to-1 ratio of automatic to manual transmissions among the retired vehicles.

In Panel A of Figure 2 we show the distribution of annual average kilometrage using two consecutive AirCare inspections prior to scrappage. On average our scrapped vehicles are driven 12,100 km per year, with a median kilometrage of about 10,500 km. A long tail in the distribution exists due to a very small number of vehicles driven more than 100,000 km per year.

Figure 2: Emission and Usage Profile of Scrapped Vehicles



Panel A: Average annual kilometrage is imputed from the odometer reading between the two most recent AirCare inspections prior to scrappage of the vehicle. Panels B-D: the emission readings are for the post-1991 vehicles subjected to the IM240 test; older vehicles are tested with the ASM test.

In Panels B, C and D of Figure 2 we depict emissions profiles for scrapped vehicles from dynamometer (road simulator) tests for carbon monoxide, hydrocarbons, and nitrogen oxides, respectively. The horizontal axis has a logarithmic scale of emissions (measured in grams per kilometre). The distribution has strong peaks with left-skewness. Vehicles on the right to the peak have significant emission performance problems, and many fail the test.

Socio-demographic data derives from the 2006 Canadian Census. Using the postal code of program participants, we use forward sortation area (FSA, the first three letters of a postal code) information to link census data to the BC SCRAP-IT data. There are 185 FSAs in British Columbia. We compute distances between each FSA and its nearest neighbour in order to capture the effect of population density; FSAs with a near neighbour tend to be small and dense.

There are a number of interesting, sometimes obvious, correlations within these socio-demographic variables. For example, FSAs with a high share of immigrants also have a high share of foreigners (non-citizens). FSAs with a high share of immigrants from other FSAs also have a high share of renters. FSAs with a high share of married couples have a low share of renters. For measures of income we utilize both mean and median household income. We use the log-ratio of mean-to-median income as a measure of the skewness of the income distribution. FSAs with a high degree of income skewness have a high proportion of very wealthy households. FSAs with a high median income tend to have a high proportion of married couples, a low proportion of renters and migrants from other FSAs, and tend to be slightly younger. There are also strong correlations between population density (as captured by our measure of distances between an FSA and its nearest neighbour) and several socio-economic variables. Dense FSAs tend to have high proportions of immigrants, foreigners, renters, and migrants from other FSAs. [15]

4 Emission Reductions

A measure of emissions reductions from an AVRP equals: emissions forgone from the scrapped vehicle attributed to the AVRP, less emissions of the replacement mode of transportation during the scrapped vehicle's forgone lifetime. We derive this difference by estimating (i) the per kilometre emissions differential between the scrapped vehicle and its replacement; (ii) the vehicle owner's average annual kilometrage; and (iii) the number of years the vehicle would have been driven in the absence of the AVRP. Mathematically, for individual i, scrapping a vehicle and replacing it with another mode of transportation imply emission savings ΔE_i,

$$\Delta E_i = \left[e_i^{\text{old}} - e_i^{\text{new}}\right] M_i F^{\text{old}} \quad (1)$$

where e is the emission factor for a vehicle/mode of transportation per kilometre, M_i is the average annual kilometrage (in km), and F^{old} is the expected future

[15] In Table TA-3 of our *Technical Appendix* we provide an overview of the most important correlations in descending order of the Pearson correlation coefficient.

lifetime of the old vehicle. Superscript $^{\text{new}}$ denotes either the new vehicle or the new mode of transportation. In this simple mathematical formulation we are assuming that the new mode of transportation will be utilized for the same number of kilometres as estimated for the old vehicle.[16] It is possible that as the marginal cost per kilometre changes with the new mode of transportation this assumption is violated.[17] We now explore the above three (i–iii) steps in succession.

4.1 Emission Differentials

What is the difference in emission per kilometre driven between the scrapped vehicle and new mode of transportation $\left[e_i^{\text{old}} - e_i^{\text{new}}\right]$?

For differences in criteria air pollutants (CO, HC, and NO_x) we use a combination of vehicle specific AirCare test results and data from a study by the same program. In this study, the AirCare program measured emissions from a randomly selected sample of 133 scrapped and 15 new vehicles. These data provide average emission factors for each kilometre travelled (see table below). Scrapped vehicles

Table 3: Vehicle Emission Factors from *Air Care* Sample

[gramme/km]	CO	HC	NO_x
Scrapped Vehicles	2.6203	0.1808	0.4412
New Vehicles	0.2487	0.0209	0.0089

have significantly higher emissions factors that differ in magnitude by a factor of about 8-10 for CO and HC and about 50 for NO_x. The group of scrapped vehicles shows a much wider dispersion of emissions than the group of new vehicles. For the group of scrapped vehicles the median is significantly smaller than the average, which suggests that the average is strongly influenced by a small group of very polluting vehicles.

For vehicles scrapped outside the Lower Mainland (which are not covered by the AirCare program) we use averages reported in Table 3 above. We also use the averages reported above for all replacement new vehicles. However, for vehicles in the Lower Mainland of British Columbia we use vehicle-specific data from their most recent mandatory AirCare inspection.

For difference in CO_2 emissions we use a combination of carbon emissions per litre of fuel and fuel economy estimates for scrapped and replacement vehicles. Formally,

$$\left[e_i^{\text{old}} - e_i^{\text{new}}\right] = \left[(l/km)_i^{\text{old}} - (l/km)_i^{\text{new}}\right] e_{FAC}, \tag{2}$$

[16]In some cases emissions per kilometre are calculated as a function of fuel used. In those cases e is a product of an emissions factor per litre of fuel used, and fuel used for every kilometre.

[17]This phenomenon is known as the 'rebound effect.' As driving gets cheaper on a per-kilometre basis, drivers may increase their annual kilometrage due to a substitution effect (the relative price change with respect to other consumption goods) and an income effect (more available income). The empirical validity of the rebound effect (also known as the Khazzoom-Brookes postulate or the Jevons Paradox) remains the subject of considerable debate.

where (l/km) represents litres of fuel used per kilometre, and e_{FAC} represents the carbon emission factor per litre of fuel used.

Our estimates of emissions per litre of fuel derive from the US Energy Information Administration.[18] Gasoline has an emission factor of 2.354 kg CO_2(e) per litre, and diesel fuel has an emission factor of 2.681 kg CO_2(e) per litre (about 14% more than gasoline). We obtain fuel economy data from the United States Environmental Protection Agency (US-EPA) for vehicle model years 1978-2011.[19] Vehicles are identified by make, model, and model year. In addition, the US-EPA data also provide key vehicle characteristics that include engine displacement, transmission type, and fuel type. We match the US-EPA data with our data on retirement and replacement. We encounter several problems with the matching. In our scrapping data 'make' sometimes refers to manufacturer and sometimes to brand (or subsidiary). There are also inconsistent spelling and abbreviations. We use several string matching techniques and are able to match fuel economy data for 8,653 observations, and for the remaining 9,189 observations we predict fuel efficiency based on key vehicle characteristics: engine displacement (Dsp, in litres), vintage (Vtg, years before 2010), transmission type (Trm, manual=1, automatic=0), and fuel type (Flt, diesel=1, gasoline=0). Using the US-EPA data we estimate the fuel economy f_j (expressed in litres/100km) for vehicle type j using

$$\begin{aligned} \ln(f_j) \;=\; & \underset{(153.)}{4.198} + \underset{(256.)}{1.569}\ \ln(\mathrm{Dsp}_j) + \underset{(60.6)}{.0525}\ \ln(\mathrm{Vtg}_j) \\ & - \underset{(5.46)}{.0964}\ \mathrm{Trm}_j - \underset{(82.3)}{3.593}\ \mathrm{Flt}_j. \end{aligned} \tag{3}$$

The R^2 of this OLS regression with 29,837 observations is 0.72, which provides confidence in the reliability of the imputed fuel efficiencies.

We also need to account for emission differentials for participants opting for public transit or bicycle incentives in the program. If these participants, forgo individual vehicles during the expected remaining lifetime of their scrapped vehicle, their contributions to emissions are negligible at the margin—as long as public transit is not operating at full capacity. Unfortunately, we do not observe post-scrapping behaviour. While some participants might switch modes of transportation, it is possible that the choice of other incentives is just a means to maximize personal gains. A vehicle incentive is only paid out for relatively new vehicles bought from participating dealers. This might be undesirable for some participants. People who have limited access to participating dealers, or wish to buy a cheaper or different vehicle than available might take one of the transit or bicycle incentives and purchase a replacement vehicle as well. In essence, we cannot rule out their purchase of a replacement vehicle outside the program.

We make a subjective (with no empirical basis) assumption that those choosing incentives for public transit or bicycles reduce 50% of their pre-participation vehicle kilometres. We are assuming that no additional public transit vehicles are

[18] Please see http://www.eia.doe.gov/oiaf/1605/coefficients.html

[19] Please see http://www.epa.gov/otaq/fedata.htm

brought into service due to these marginal customers. This makes sense considering the relatively small size of the SCRAP-IT program. We thus assume that the 'effective fuel efficiency' is 50% of the average new-vehicle fuel efficiency from our sample of replacement vehicles. We also assume that and effective emission rate or emission intensity is 50% of that reported for new vehicles in table 3.

4.2 Annual Kilometrage

What would have been the average annual kilometrage M_i for the expected lifetime of the scrapped vehicle?

Data from the mandatory AirCare program for scrapped vehicles registered in the Lower Mainland of British Columbia includes vehicle-specific emission information, whether the vehicle passed the emissions test, and the odometer reading. AirCare inspections are typically two or one year apart, depending on the age of the vehicle. With exact inspection dates and data on odometer readings from the last two AirCare tests, we calculate the average yearly kilometres driven during the end of the vehicles lifetime. We project this average onto the replacement vehicle as well. In other words, we assume that the replacement vehicle is driven at the same annual average as the scrapped vehicle.[20]

The AirCare data covers the Lower Mainland; 12,207 observations out of a total of 17,993 participating in SCRAP-IT. We do not have exact kilometrage data for the remaining vehicles. In these cases we infer the average based on vehicle age. Concretely, we predict kilometrage for these vehicles using the following equation estimated using the 12207 observations for which we have kilometrage data,

$$\ln(M_i) = \underset{(37.92)}{5.05} - \underset{(22.10)}{0.991} \ln(\text{Age}_i) + \underset{(12.12)}{0.101} \ln(\text{Dst}_i) + \underset{(3.21)}{0.054} \text{Trm}_i. \tag{4}$$

where 'Age' is the vehicle age, 'Dst' is the distance to the nearest neighbouring FSA, and 'Trm' is a binary indicator for manual transmissions. T-ratios are given in parentheses, and all estimates are statistically significant at the 99.9% confidence level. The additional regressors capture the effect that vehicles are driven more in rural than urban areas and that vehicles with manual transmissions are driven slightly more. Unfortunately, this regression captures very little variation; the R^2 is only about 0.05. Most of the variation is idiosyncratic to the vehicle owner. Attempts to use indicator variables for vehicle type or vehicle make only improve the fit insignificantly. Because of the problems with estimating kilometrage, we present separate results for the group of observed and imputed kilometrage in table 7 as robustness checks.

[20]It has been shown that the average annual kilometrage declines with vehicle age in the aggregate; see Lu (2007). It is important to understand that this is not necessarily true at the individual level. In the aggregate, this likely reflects a composition (selection) effect. Vehicles with a higher annual kilometrage are more likely to get scrapped at a younger age, while those that remain are those that are driven less. However, this selection effect does not change the annual kilometrage of an individual driver.

4.3 Expected Future Lifetime

Given vehicle age y at the time of scrappage, what is the expected future lifetime $F(t)$ without scrappage? Of our three estimates, this is probably the most challenging.

We use two years (2008–2009) of vehicle inventory data from *R. L. Polk & Co.* as our main source for this estimate. The data set provides vehicle counts by province (as registered with the local licensing body) disaggregated by make, model and model year. If n_{ist} is the number of vehicles of type i and age s in year t, then the unconditional hazard rate for scrapping vehicles of vintage s is $h_{is} = (n_{is,t+1} - n_{ist})/n_{ist}$. Using the Polk data we calculate age-dependent hazard rates of vehicle retirement and infer a corresponding survival function for the vehicle fleet. We aggregate our discrete hazard rates by major manufacturer. An estimated survival function yields the expected future lifetime $F(t)$.

There are two main challenges in estimating future lifetimes using vehicle fleet inventory data.

First, our empirical hazard rates capture more than new vehicle purchases and vehicle retirements. Vehicle imports and exports of used cars also influence inventory changes. This is especially true for relatively new vehicles and for subnational data. In practice, this can lead to apparent negative hazard rates, as the inventory for a vintage of vehicles may actually increase if net imports exceed vehicle retirements. Even in the case of positive hazard rates, a positive import balance means that older vehicles may get replaced by older imported vehicles of the same vintage, thus prolonging the apparent lifetime of vehicles in the importing jurisdiction.

To deal with this issue, we constrain the hazard rate to be non-negative. In other words, our estimates of the survival function only use data points with positive net vehicle retirements. Our exclusion of negative data implicitly reduces the weight given to early lifetime years of a vehicle model. Hazard rates increase with age. Thus, by excluding early years, the statistical fit of a survival function depends largely on the points where the hazard of vehicle retirements is high. This also reduces the influence of imports on the hazard rate curve. Limited data from *R. L. Polk & Co.* and the registrar of imported vehicles suggests that international imports to BC and Canada mostly comprise relatively new (5 years or younger) vehicles. Thus, as the vehicle age rises, imports have a smaller influence on the hazard rate.[21] Recall that we wish to estimate the residual expected lifetime of vehicles in the BC SCRAP-IT program. These are vehicles from vintage 1995 or older. It thus makes sense to weight the late lifetime of the vehicle more heavily towards the estimation of its survival function.

The second challenge of our estimation is deciding on the assumed distribution of the survival function. Parametric assumptions on the survival function have

[21] It is possible that exports from BC and Canada largely comprise vehicles of older vintage. Unfortunately, we do not have any data on exports. However, if exports play a large role, we would over-estimate the hazard rate. For reasons we shall discuss later, this does not qualitatively alter our results.

a large role to play in its later years. This is especially important for our right-censored dataset that provides observations only for 28 vehicle vintage years. As a certain fraction of vehicles will exceed this age, we need to be able to estimate the survival function for these older vehicles. Estimates of function parameters lead to a survival function $\hat{S}(t)$, which in turn can be used to calculate the expected remaining lifetime $F(t)$ of a vehicle at age t:

$$F(t) = \frac{1}{S(t)} \sum_{s=t+1}^{\infty} (s-t) \left[\hat{S}(s) - \hat{S}(s-1)\right] \tag{5}$$

Conditional on a vehicle surviving until age t, this vehicle can be expected to last for another $F(t)$ years. We employ three widely-used parametric distributions for our estimation of the survival function: the Weibull distribution, the log-logistic function, and the complementary log-log function.[22] We also use the observed empirical distribution.[23] They are denoted by subscripts w, l, c, and e, respectively.

Using the data for the vehicle fleet in British Columbia, we illustrate the issues discussed above in Table 4. Corresponding numbers for all of Canada are listed in Table TA-5 of our *Technical Appendix*. The first two columns show the model year and age. The most recent model year overlaps with the previous year, which results in large additions to the vehicle fleet in that year. For example, model year 2009 starts selling during the autumn of 2008. Column $h(t)$ shows the observed hazard rate in percent, column $S(t)$ shows the implied survival rate in percent, and $F(t)$ is the predicted expected lifetime in years.

Using an empirical survival function avoids making use of distributional assumptions, while imposing distributional assumptions smoothes the hazard rate and provides meaningful predictions beyond the right-censoring point. We find that the log-logistic function offers a very good fit to our observed hazard rate. The Weibull hazard rate is monotonically increasing, whereas the log-logistic function in non-monotonic and hump-shaped. This means that that the hazard rate increases, reaches a maximum, and then gradually decreases over time. The complementary log-log function used by the US-EPA is similar to the log-logistic but does not fit our British Columbia data as well.

Each distribution is characterized by its cumulative distribution function $F(t; \alpha, \beta)$, where α and β are the scale and shape parameter respectively. The survival function is given by $S(t) = 1 - F(t)$. In continuous-time notation, the hazard function is $h(t) = -S'(t)/S(t)$. Table TA-4 in our *Technical Appendix* provides closed form expressions for the survival and hazard functions. It should be noted that the scale parameter α equals the median in the log-logistic survival function. The

[22] The US Environmental Protection Agency (EPA) uses the complementary log-log function to estimate hazard rates of the US vehicle fleet.

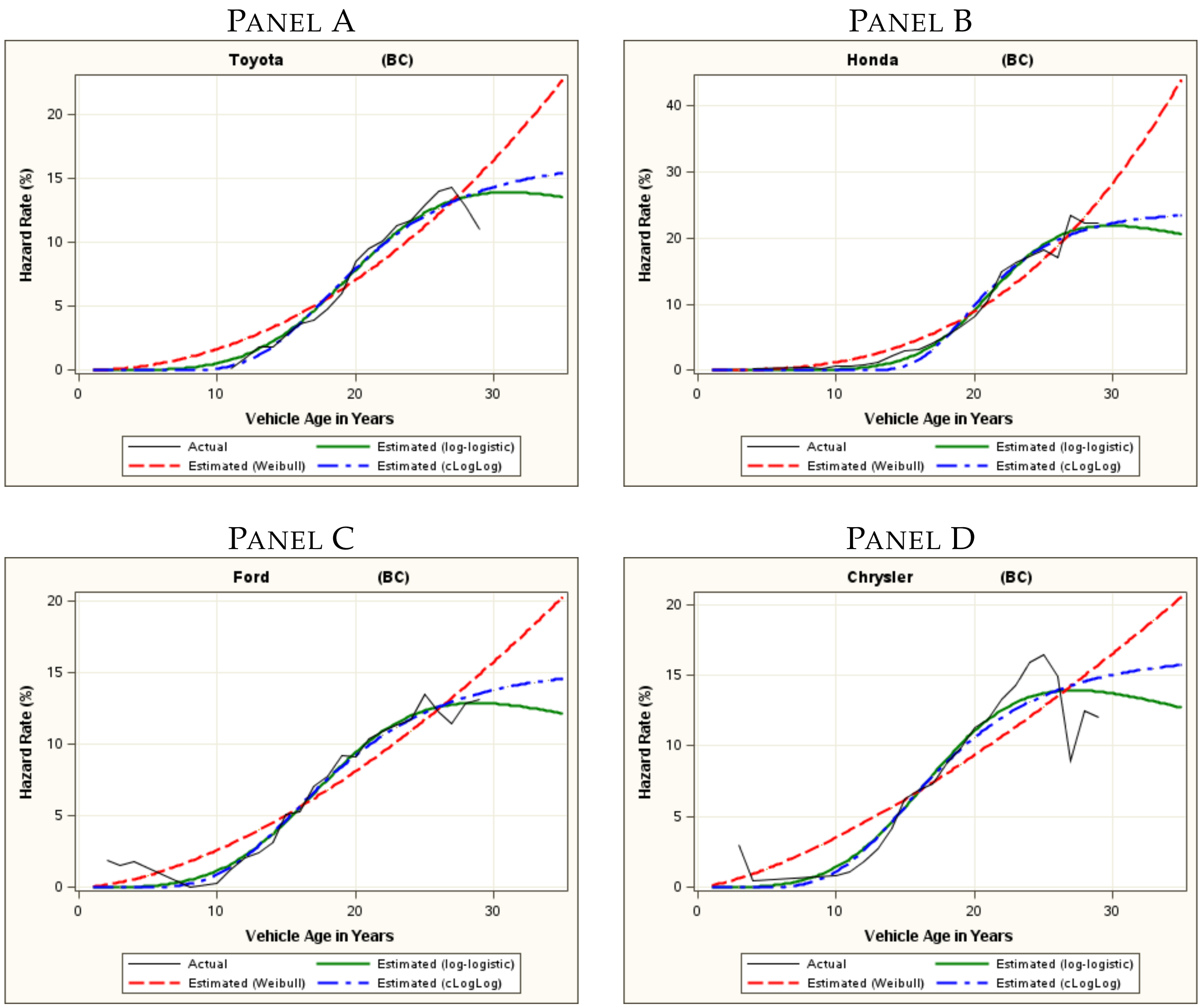
[23] We use the observed hazard rate for vehicle ages through 28, and then apply a constant hazard rate for all following years based on the average hazard rate recorded in the right-censored observation point. Note that a constant hazard rate implies that the remaining future lifetime $F(t)$ is constant. This is true for the vehicle at any point of its lifetime, conditional on its surviving to that point. Thus a vehicle "at birth" has the same expected future lifetime as a vehicle at year t that has survived through year t.

Table 4: British Columbia Vehicle Fleet

Year	Age	2008	2009	Δ	$h(t)$	$S(t)$	$\hat{F}_e(t)$	$\hat{h}_l(t)$	$\hat{S}_l(t)$	$\hat{F}_l(t)$	$\hat{h}_w(t)$	$\hat{S}_w(t)$	$\hat{F}_w(t)$	$\hat{h}_c(t)$	$\hat{S}_c(t)$	$\hat{F}_c(t)$
2009	1	36,794	145,862	109,068		100.0	22.7	0.0	100.0	23.1	0.0	100.0	21.3	0.0	100.0	23.2
2008	2	189,331	195,553	6,222		100.0	21.7	0.0	100.0	22.1	0.2	99.9	20.3	0.0	100.0	22.2
2007	3	218,028	217,869	-159	0.1	99.9	20.7	0.0	100.0	21.1	0.3	99.6	19.4	0.0	100.0	21.2
2006	4	192,810	191,431	-1,379	0.7	99.2	19.9	0.0	100.0	20.1	0.5	99.2	18.4	0.0	100.0	20.2
2005	5	190,622	192,340	1,718		99.2	18.9	0.1	99.9	19.1	0.7	98.6	17.5	0.0	100.0	19.2
2004	6	166,713	169,407	2,694		99.2	17.9	0.2	99.8	18.2	1.0	97.8	16.7	0.0	100.0	18.2
2003	7	183,936	184,901	965		99.2	16.9	0.3	99.5	17.2	1.3	96.6	15.9	0.1	99.9	17.2
2002	8	174,457	174,318	-139	0.1	99.1	15.9	0.5	99.2	16.3	1.7	95.2	15.1	0.2	99.8	16.2
2001	9	144,349	144,244	-105	0.1	99.1	14.9	0.8	98.5	15.4	2.0	93.5	14.4	0.4	99.5	15.2
2000	10	142,220	141,451	-769	0.5	98.5	14.0	1.1	97.6	14.5	2.4	91.4	13.7	0.8	98.9	14.3
1999	11	121,665	120,659	-1,006	0.8	97.7	13.1	1.6	96.3	13.7	2.8	89.1	13.0	1.3	97.9	13.5
1998	12	130,182	128,102	-2,080	1.6	96.1	12.3	2.1	94.5	12.9	3.3	86.4	12.4	1.9	96.3	12.7
1997	13	128,182	125,429	-2,753	2.1	94.1	11.5	2.8	92.2	12.2	3.8	83.4	11.8	2.7	94.2	11.9
1996	14	96,945	94,063	-2,882	3.0	91.3	10.8	3.6	89.4	11.6	4.3	80.1	11.2	3.5	91.3	11.3
1995	15	117,696	112,335	-5,361	4.6	87.1	10.3	4.4	85.8	11.0	4.8	76.6	10.7	4.5	87.7	10.7
1994	16	109,909	104,191	-5,718	5.2	82.6	9.8	5.4	81.7	10.5	5.3	72.8	10.2	5.4	83.5	10.2
1993	17	108,178	101,278	-6,900	6.4	77.3	9.4	6.3	77.1	10.1	5.9	68.8	9.7	6.4	78.7	9.7
1992	18	110,703	102,663	-8,040	7.3	71.7	9.1	7.3	72.0	9.7	6.5	64.7	9.3	7.3	73.5	9.4
1991	19	101,768	93,402	-8,366	8.2	65.8	8.8	8.3	66.6	9.5	7.1	60.4	8.9	8.2	68.0	9.0
1990	20	97,450	88,495	-8,955	9.2	59.8	8.6	9.2	61.0	9.2	7.8	56.1	8.5	9.0	62.4	8.8
1989	21	78,772	70,480	-8,292	10.5	53.5	8.5	10.0	55.4	9.1	8.5	51.7	8.1	9.7	56.9	8.5
1988	22	64,384	56,947	-7,437	11.6	47.3	8.5	10.7	50.0	8.9	9.1	47.3	7.8	10.4	51.4	8.3
1987	23	48,072	42,251	-5,821	12.1	41.6	8.5	11.3	44.8	8.9	9.9	43.0	7.4	11.0	46.2	8.1
1986	24	42,337	37,021	-5,316	12.6	36.4	8.6	11.8	39.9	8.8	10.6	38.9	7.1	11.5	41.3	8.0
1985	25	27,521	23,845	-3,676	13.4	31.5	8.7	12.2	35.4	8.8	11.4	34.8	6.8	12.0	36.7	7.9
1984	26	20,925	18,349	-2,576	12.3	27.6	8.8	12.4	31.3	8.9	12.1	31.0	6.6	12.4	32.5	7.7
1983	27	11,883	10,502	-1,381	11.6	24.4	8.8	12.6	27.6	8.9	12.9	27.3	6.3	12.8	28.6	7.6
1982	28	9,949	8,820	-1,129	11.3	21.6	8.8	12.7	24.3	9.0	13.8	23.9	6.1	13.1	25.2	7.6
1981	29	16,095	14,275	-1,820	11.3	19.2	8.8	12.8	21.4	9.1	14.6	20.7	5.8	13.4	22.0	7.5

Note: Subscript l refers to the log-logistic distribution, subscript w refers to the Weibull distribution, subscript c refers to the complementary log-log distribution, and subscript e refers to the empirical distribution. Hazard rates and survival rates are expressed in percent. Expected future lifetime is expressed in years.

Figure 3: B.C. Vehicle Fleet Hazard Rate Estimates



median is also closely related to α in the Weibull function. As we observe interval-censored annual data of changes in the vehicle fleet, the observed discrete hazard rate can be used to approximate the continuous-time equivalent. The parameters α and β are estimated directly from the observed hazard rates through iterative OLS or maximum likelihood. We list these estimated parameters by manufacturer in Table 5 for British Columbia; Table TA-6 in our *Technical Appendix* shows corresponding estimates for all of Canada.

Figure 3 shows graphs for actual and estimated hazard functions for four car manufacturers (Toyota, Honda, Ford, and Chrysler). The estimated log-logistic hazard function appears a generally better approximation of the empirical hazard function than the estimated Weibull. For most manufacturers there is a notable flattening of the observed hazard function at high vehicle ages, and in some case there is a reversal. The hump-shaped log-logistic function is better able to capture the observed patterns in the data.

The estimated residual vehicle lifetime for the average BC vehicle is reported

Table 5: B.C. Vehicle Fleet Hazard Rate Estimates

	Log-Logistic Distribution				Weibull Distribution				Comp. Log-Log Distribution			
Make	$\hat{\alpha}_l$		$\hat{\beta}_l$		$\hat{\alpha}_w$		$\hat{\beta}_w$		$\hat{\alpha}_c$		$\hat{\beta}_c$	
Mercedes-Benz	30.186^c	(23.0)	3.744^c	(6.22)	33.706^c	(27.5)	2.701^c	(5.33)	2.189^c	(5.56)	0.086^c	(7.75)
BMW	26.692^c	(58.4)	8.506^c	(13.3)	28.011^c	(71.7)	5.224^c	(12.3)	5.811^c	(11.6)	0.230^c	(13.7)
Suzuki	25.895^c	(14.5)	2.849^c	(5.79)	30.675^c	(15.4)	2.042^c	(4.22)	1.774^b	(3.93)	0.083^c	(6.09)
Navistar	25.362^c	(13.8)	3.417^c	(6.12)	27.785^c	(12.4)	1.920^c	(4.93)	1.419^b	(3.03)	0.081^c	(6.73)
Volvo	25.060^c	(53.4)	6.058^c	(18.0)	27.069^c	(49.5)	3.713^c	(12.4)	3.964^c	(15.8)	0.173^c	(20.6)
White	24.553^c	(20.8)	7.863^c	(6.04)	24.447^c	(14.7)	3.530^c	(5.01)	5.483^c	(5.52)	0.236^c	(6.57)
Toyota	23.584^c	(79.1)	5.322^c	(33.0)	25.782^c	(36.2)	3.090^c	(11.7)	3.524^c	(26.4)	0.163^c	(36.5)
Honda	23.290^c	(116.)	7.537^c	(43.8)	24.474^c	(55.7)	3.862^c	(18.5)	5.251^c	(31.7)	0.239^c	(41.0)
Volkswagen	23.125^c	(33.7)	4.024^c	(16.5)	25.972^c	(22.8)	2.400^c	(8.52)	2.574^c	(11.5)	0.125^c	(18.0)
Nissan	22.276^c	(76.6)	5.928^c	(34.5)	23.754^c	(28.7)	3.061^c	(11.4)	3.935^c	(26.0)	0.192^c	(36.6)
Subaru	22.023^c	(31.0)	6.963^c	(13.5)	23.030^c	(16.2)	3.302^c	(6.64)	4.778^c	(11.2)	0.231^c	(15.2)
All Manuf.	21.996^c	(89.7)	4.708^c	(45.1)	24.507^c	(33.3)	2.690^c	(13.2)	3.021^c	(29.6)	0.152^c	(44.4)
Ford	21.806^c	(78.1)	4.706^c	(39.8)	24.053^c	(37.7)	2.637^c	(15.7)	2.996^c	(30.0)	0.153^c	(45.7)
Freightliner	21.792^c	(28.1)	4.762^c	(11.8)	23.885^c	(21.2)	2.681^c	(7.92)	3.030^c	(9.69)	0.155^c	(13.6)
GM	21.555^c	(71.5)	4.455^c	(38.0)	24.119^c	(28.2)	2.517^c	(12.0)	2.828^c	(22.7)	0.146^c	(35.1)
Mazda	21.327^c	(23.9)	4.912^c	(12.5)	23.148^c	(14.3)	2.518^c	(6.61)	3.171^c	(8.87)	0.163^c	(13.5)
Paccar	20.879^c	(13.3)	4.241^c	(6.77)	22.524^c	(14.8)	2.473^c	(6.40)	1.888^c	(4.54)	0.125^c	(8.66)
Chrysler	20.666^c	(40.8)	4.799^c	(22.5)	22.222^c	(18.5)	2.406^c	(9.38)	3.040^c	(14.7)	0.163^c	(23.0)
Hyundai	18.207^c	(44.0)	6.241^c	(22.8)	19.148^c	(27.3)	2.926^c	(13.7)	4.048^c	(18.9)	0.243^c	(27.9)

Note: The table is sorted in descending order of the estimated parameter α, which is equal to the median of the survival rate function in the case of the log-logistic distribution. Subscript l refers to the log-logistic function, subscript w refers to the Weibull function, and subscript c refers to the complementary log-log function. Statistical significance at the 95%, 99%, and 99.9% confidence levels is indicated by the superscripts ^{a}, ^{b}, and ^{c}, respectively.

in table 4. Estimated future lifetimes are usually shorter for Weibull estimates than for log-logistic estimates due to the fact that the hazard rate for older vehicles continues to rise with age in a Weibull, and declines in log-logistic. This leads to slight differences in the estimates. For example, the expected lifetime for the average 15-year old vehicle (model year 1995) ranges from 10.3 to 11 years depending on the choice of survival function. In Table 6 we list the conditional expected remaining lifetime for vehicles in our sample. The average remaining lifetime ranges from 8.62 years under Weibull to 9.39 years under log-logistic.

Table 6: Characteristics of Retired and New Vehicles

Variable	Mean	S.V.	Q1	Q2	Q3
All Vehicles [N=17866]					
Effective new fuel economy [l/100km]	5.33	2.01	3.61	3.61	7.21
Fuel Economy [litres/100km]	9.19	2.03	7.72	8.90	10.3
Kilometrage [1000km/year]	12.1	9.11	7.68	10.7	14.1
Remaining Lifetime (compl-loglog) [years]	8.95	2.09	7.90	8.75	9.60
Remaining Lifetime (empirical) [years]	8.88	2.24	7.96	8.96	9.53
Remaining Lifetime (log-logistic) [years]	9.39	2.08	8.36	9.31	9.96
Remaining Lifetime (weibull) [years]	8.62	2.00	7.45	8.53	9.53
Vehicle Age [years]	19.6	3.52	17.0	19.0	22.0

Amongst other caveats, we are using fleet averages that are not disaggregated by vehicle type (car, light truck and vans). Further, SCRAP-IT participation slightly inflates retirement numbers. If participation accounted for a large share of vehicle retirements, our estimates of expected future lifetime are biased downward. These vehicles might not have not been retired until later.

Ideally, we would use a control group of vehicles rather than an aggregate that includes the treatment group. While we could use another region in Canada, idiosyncratic differences of weather and road conditions stop us from using other regions. Nevertheless, to the extent that SCRAP-IT participation biases the expected future lifetime, it will bias it downward. This errs on the conservative side as our objective is to estimate emission savings from accelerated retirement. To consider the impact of including SCRAP-IT participants, for 2008-2009 we have a maximum of 12,000 SCRAP-IT participants. The total number of vehicle retirements (for vehicles older than 10 years) was just over 90,000 in the same period. Thus SCRAP-IT accounts for about 13% of vehicle retirements. This is a significant share, but no large enough to dominate the picture.

Our estimates of expected future vehicle lifetime $F(t)$ are significantly higher than used in other studies. Based on national fleet-wide retirement rates, coupled with the assumption that program vehicles are likely to be retired earlier than normal, California Air Resources Board (1991) and Hahn (1995) assume a three year acceleration.[24] Others, including Alberini et al. (1996) and Kavalec and Setiawan

[24]Deysher and Pickrell (1997) just uses fleet-wide survivability schedules such as those in Lu (2007) as an estimate for the normal life of the retired vehicle.

(1997), assume that the decision to retire the vehicle depends on the difference between the ownership price and the offer price from the program. Alberini et al. (1996) finds that an offer price of US$1,400 is likely to induce vehicles with a three year life into the program. Using data from California's Bay Area, Sandler (2011) estimates survival probabilities of a control group of vehicles not participating in the accelerated vehicle retirement program. He estimates a 3.4 year expected lifetime.

We posit the following reasons for our estimates being higher than those in the literature. First, B.C. climate is milder than in other parts of Canada and the United States, and thus vehicles suffer less wear and tear than vehicles exposed to rough winter conditions. Second, vehicles in BC are on average driven significantly less every year than the average vehicle in the US. Third, and perhaps most importantly, most programs in the US offered approximately $500 for a vehicle scrapped. Compare this to an average payout of approximate $1,800 in our program. The vehicles scrapped in the programs analyzed earlier had a much lower expected value than those scrapped in our program.

4.4 Estimated Emission Reductions

In Table 6 we list the characteristics of retired and new vehicles in our sample. The table reports the mean, standard deviation (S.D.), and three quartile points (Q1, median Q2, Q3). The vehicles bought under the program were significantly more fuel efficient than those retired (fuel consumption of 5.33 versus 9.19 l/100km). On average retired vehicles were driven 12,100 km during the final years of their life, and were retired at the age of 19.6 years. Remaining lifetime for the average vehicle retired ranged from 8.62 to 9.39 years, depending on distributional assumption. Our results presented below are all based on the log-logistic specification.

In Tables 7 and 8 we report our findings on the net reduction of emissions from the BC SCRAP-IT program. In Table 7 we report the overall results, results within sample sub-groups by replacement type (scrapped vehicle replaced with new vehicle or switch to alternative transportation mode), fuel economy (estimated or matched by make/model name), and kilometrage (observed or estimated). Each table reports reductions for three pollutants and carbon dioxide. In Table 8 we report robustness of emissions reductions under different survival distributions discussed earlier.

Our main result is that the average participant in the BC SCRAP-IT program contributes a 10.5 tonne net reduction in carbon dioxide emissions.[25] The median reduction is 7.64 tonnes. Approximately 18,000 participants in our data (over approximately 2 years) contributed 180 kilo-tonnes reductions of carbon dioxide. Of course, the contribution of the SCRAP-IT program pales in comparison to the 68,000 kilo-tonnes CO_2(e) emissions overall in B.C. in 2008. Keeping in mind that the ten-tonne reduction of CO_2(e) accrues over a period of nine years, a SCRAP-IT

[25]Depending on the distributional assumption for the remaining lifetime of the vehicle, the mean ranges from 9.67 (Weibull) to 10.5 (log-logistic).

Table 7: Net Emission Reductions from Scrapping (by kilometrage imputation, by fuel economy imputation, and by replacement type)

Variable	Mean	S.V.	Q1	Q2	Q3
All Vehicles [N=17866]					
CO Reduction [kg]	402.	927.	166.	249.	369.
CO_2 Reduction [tonnes]	10.5	13.0	3.32	7.64	13.7
HC Reduction [kg]	27.6	84.3	8.98	15.1	23.7
NO_x Reduction [kg]	70.3	96.9	33.3	48.9	73.4
Vehicles replaced with new vehicles [N=8493]					
CO Reduction [kg]	356.	810.	169.	246.	346.
CO_2 Reduction [tonnes]	5.98	7.73	1.40	4.35	8.90
HC Reduction [kg]	24.1	96.7	8.99	15.0	22.0
NO_x Reduction [kg]	64.6	79.5	34.1	48.6	68.5
Vehicles scrapped for altern. transp. [N=9373]					
CO Reduction [kg]	444.	1,020	164.	252.	400.
CO_2 Reduction [tonnes]	14.7	15.3	6.21	10.9	18.0
HC Reduction [kg]	30.7	71.1	8.96	15.2	26.3
NO_x Reduction [kg]	75.5	110.	32.4	49.2	78.9
Vehicles with fuel economy estimated [N=9173]					
CO Reduction [kg]	432.	1,100	173.	255.	378.
CO_2 Reduction [tonnes]	11.0	14.7	2.92	7.65	14.4
HC Reduction [kg]	30.0	99.2	9.60	15.8	24.6
NO_x Reduction [kg]	74.1	107.	34.1	50.1	75.3
Vehicles with fuel economy matched [N=8669]					
CO Reduction [kg]	370.	700.	160.	242.	359.
CO_2 Reduction [tonnes]	10.1	11.0	3.74	7.64	13.1
HC Reduction [kg]	25.0	65.0	8.41	14.3	22.4
NO_x Reduction [kg]	66.3	85.1	32.3	47.5	71.1
Vehicles with kilometrage estimated [N=5659]					
CO Reduction [kg]	265.	127.	192.	248.	313.
CO_2 Reduction [tonnes]	9.20	8.04	3.78	7.87	13.0
HC Reduction [kg]	18.3	10.7	13.0	16.7	21.2
NO_x Reduction [kg]	47.3	19.2	34.5	44.5	56.4
Vehicles with kilometrage observed [N=12207]					
CO Reduction [kg]	466.	1,113	148.	250.	430.
CO_2 Reduction [tonnes]	11.2	14.7	3.11	7.47	14.3
HC Reduction [kg]	31.9	101.	7.01	13.3	27.3
NO_x Reduction [kg]	81.0	115.	32.2	53.1	88.9

Table 8: Net Emission Reductions from Scrapping with Different Distributional Assumptions about the Remaining Vehicle Lifetime

Variable	Mean	S.V.	Q1	Q2	Q3
All Vehicles [N=17866]					
CO Reduction [kg] (compl-loglog)	381.	843.	157.	238.	354.
CO Reduction [kg] (empirical)	380.	873.	156.	236.	348.
CO Reduction [kg] (log-logistic)	402.	927.	166.	249.	369.
CO Reduction [kg] (weibull)	363.	772.	151.	232.	345.
CO_2 Reduction [tonnes] (compl-loglog)	10.0	12.2	3.15	7.25	13.1
CO_2 Reduction [tonnes] (empirical)	10.0	12.4	3.08	7.18	13.1
CO_2 Reduction [tonnes] (log-logistic)	10.5	13.0	3.32	7.64	13.7
CO_2 Reduction [tonnes] (weibull)	9.67	11.6	3.02	6.92	12.7
HC Reduction [kg] (compl-loglog)	25.9	74.1	8.50	14.3	22.7
HC Reduction [kg] (empirical)	26.1	78.3	8.27	14.3	22.3
HC Reduction [kg] (log-logistic)	27.6	84.3	8.98	15.1	23.7
HC Reduction [kg] (weibull)	24.5	65.7	8.08	13.9	22.0
NO_x Reduction [kg] (compl-loglog)	66.7	88.7	31.4	46.7	70.6
NO_x Reduction [kg] (empirical)	66.6	92.2	31.2	46.1	69.4
NO_x Reduction [kg] (log-logistic)	70.3	96.9	33.3	48.9	73.4
NO_x Reduction [kg] (weibull)	63.9	81.7	30.1	45.6	68.6

Table 9: Calculation of Program Benefits

		Average		New Vehicle		Public Transit	
Pollutant	Price	Reduct.	Value	Reduct.	Value	Reduct.	Value
Carbon Dioxide	30$/mt	10.5 mt	$315	5.92 mt	$178	14.7 mt	$441
Carbon Monoxide	0.50$/kg	402. kg	$201	356. kg	$178	444. kg	$222
Hydrocarbons	3.50$/kg	27.6 kg	$97	24.1 kg	$84	30.7 kg	$107
Nitrogen Oxides	3.50$/kg	70.3 kg	$246	64.6 kg	$226	75.5 kg	$264
Total			$859		$666		$1034

Note: Abbreviations: kg=kilogram; mt=metric tonne. Assumptions: $30/mt is the BC carbon tax. For NO_x, $3.50/kg is the value of NO_x given by Krupnick et al. (2005). HC and CO match the NO_x price in 1:1 and 1:7 ratios respectively.

participant contributed approximately 1.1 tonnes of CO_2(e) reduction per year. For comparison, in 2008 the emission intensity was estimated as about 14.9 tonnes of CO_2(e) per capita per year in British Columbia.[26]

We also find that the average participant reduces emissions of carbon monoxide by about 400 kg, hydrocarbons by about 27 kg, and nitrogen oxides by about 70 kg. Sandler (2011) estimates a reduction of 350 kg of carbon monoxide, 35 kg of hydrocarbons, and 26 kg of nitrogen oxides for a vehicle retirement program in the San Francisco Bay Area. Our results are fairly similar for CO and HC, but are significantly higher for nitrogen oxides.

A vehicle scrapped in exchange for a new vehicle contributes 6.0 tonnes of CO_2(e) reductions, whereas a scrapped for alternative transport vehicle contributes roughly 15 tonnes of CO_2(e). The ten-tonne average reported earlier reflects the composition of program participants. Differences for the other pollutants are not quite as large: 356 kg versus 444 kg for carbon monoxide; 24.1 kg versus 30.7 kg for hydrocarbons; and 64.6 kg versus 75.5 kg for nitrogen oxides. While the difference for carbon dioxide is roughly a factor of two, the difference for the criteria air pollutants is the range of 20-25%. The gap for carbon dioxide strongly reflects the choice of fuel efficiency adjustment factor: we assume that emissions for alternative transportation are half the emissions for the average new vehicle. On the other hand, as new vehicles produce such small amounts of criteria pollutants, most of the emission reductions derive from scrappage, and the transportation mode choice does not matter as much.

To create a single metric for all pollutants, we assign economic values to emissions reductions. By itself this exercise is challenging. There are several valuation options available in the literature and due to differing underlying assumptions it is difficult to choose one as appropriate. In addition, for local air pollutants that do not mix uniformly in the atmosphere (such as NO_x, CO, HC) valuations differ not just based on underlying assumptions but also on local concentrations.

The meta study by Yohe (2007) argues that an appropriate price for CO_2 emissions is \$50 per metric tonne. BC's Carbon Tax will reach its maximal value of \$30 per tonne of CO_2 emissions on July 1st 2011. We choose the more conservative option of \$30 per tonne. There are several options available for NO_x. At the low end, Muller and Mendelsohn (2009) argues a US wide average marginal damage for NO_x is US\$260 per tonne. At the high end, Holland et al. (2005) estimates NO_x damages for Europe ranging from €4,400 to €12,000. We use damage estimates provided by Krupnick et al. (2005), Table 5. They estimate a shadow value of NO_x reduction at US\$3,226 per tonne, which translates to approximately \$3.50 per kilogram in Canadian dollars in 2010 prices. The standard conversion ratio for Hydrocarbon emissions with NO_x is 1:1, and for carbon monoxide emissions to NO_x is 1:7.

In Table 9 we list value of emissions reductions via the BC SCRAP-IT based on the assumptions discussed above. In this table, we aggregate savings by the type of

[26] British Columbia Greenhouse Gas Inventory Report 2008, Ministry of Environment, Victoria BC, Sept 2010.

participant. The average program participant in the BC SCRAP-IT program generates emission savings of $859. Those choosing a new vehicle create average emissions reductions of $666, and those choosing alternative modes of transportation create emissions reductions worth $1,034. Currently, the BC SCRAP-IT program offers approximately $550 for someone purchasing a new vehicle. Car-share participants get a subsidy of $750, and those choosing transit get passes valued over $1,000.

5 Program Participation Decision

In this section we explore the factors underlying program participation. In particular, is program participation higher among people belonging to lower income groups? In the next section we explore program participation further by looking at the different incentive choices. There we explore whether different income groups sort into different incentive choices offered by the program.

In an ideal world we would link individual socio-economic variables to the decision to participate. Our data does not allow identification of individual level socio-economic variables. It also does not include information on non-participants—owners of vehicles eligible for BC SCRAP-IT who chose to keep driving these cars. However, our data identifies participants by their place of residence. Thus to answer our questions, we aggregate participants geographically to a postal Forward Sortation Area (FSA) and link these data to socio-economic and socio-demographic data from the 2006 Canadian Census.

Our objective is to explain the determinants of the the number of vehicles participating from a particular FSA. Aggregate participation depends on two basic factors: the number of eligible cars, and the propensity for replacement. However, we do not have data on the number of eligible vehicles in each FSA and need to proxy for it. We assume that the number of eligible cars is driven by an FSA's population size and age and income distribution. All else being equal, an FSA with a higher population should also have more cars of vintage 1995 or older. The age distribution of this population is likely to influence the number of old vehicles either through preferences or through income differentials. The income distribution influences the number of eligible cars, as old cars are on average cheaper than newer vehicles.

We further assume that the propensity of vehicle replacement is governed by an FSA's income distribution and economic conditions, program incentives, and participants' preferences. Income distribution affects the propensity for replacement as new vehicles are costly, and the size of the program's incentive influences this replacement cost.

We estimate a relationship between the number of participating vehicles in a FSA and the groups of covariates mentioned above. The first group includes population and age distribution (average age). The second group captures income and income distribution, and we proxy these through median income and a skewness measure of the income distribution (the ratio of mean-to-median income).

The third group captures participant preferences by including the share of married households, immigrants, renters, and a proxy for population density (the distance to the nearest FSA). Some of the preference indicators may also capture aspects of the income distribution. For instance, it is possible that immigrants belong to a more homogenous income level than the average, or that renters have lower income than those who own houses. Also note that the indicator for population density captures access to the program. This is due to two reasons. First, most scrapyards associated with the program are in urban centres. As population density falls access to the yards falls. Second, incentives on transit and ride-share have very little value outside urban centres. The fourth and last group captures local economic conditions, by including the rate of unemployment.

In this section we analyze participation in the largest program phase 2 (June 2008 to July 2009) during which nearly 12,000 vehicles were retired. As incentive levels do not change over one program phase, we leave an analysis of the impact of incentive levels for future research.

Figure 4 illustrates the relationship between scrappage intensity (vehicles retired under the BC SCRAP-IT program per capita) and six key covariates. Each dot in the diagram represents one of the 187 forward sortation areas (FSAs) in our analysis. A simple linear fit line indicates pattern in the data. Panels A and B focus on two income variables, the median household income and a measure of the skewness of the income distribution. There is no obvious pattern, although there is a weak upward trend. Nevertheless, the weakness of the *prima facie* correlation is no indication of the lack of importance, as these diagrams do not adjust for the presence of multiple covariates. Nevertheless, panels C and E indicate a weak positive relationship between scrappage intensity and immigrant share as well as home-renter share, while panel D indicates a weak negative relationship between scrappage intensity and the share of married couples in an FSA. A strong negative correlation exists between scrappage intensity and the log-distance to the nearest FSA; this indicates that vehicle scrappage is strongest in densely-populated (urban) areas and less common in sparsely-populated (rural) areas.

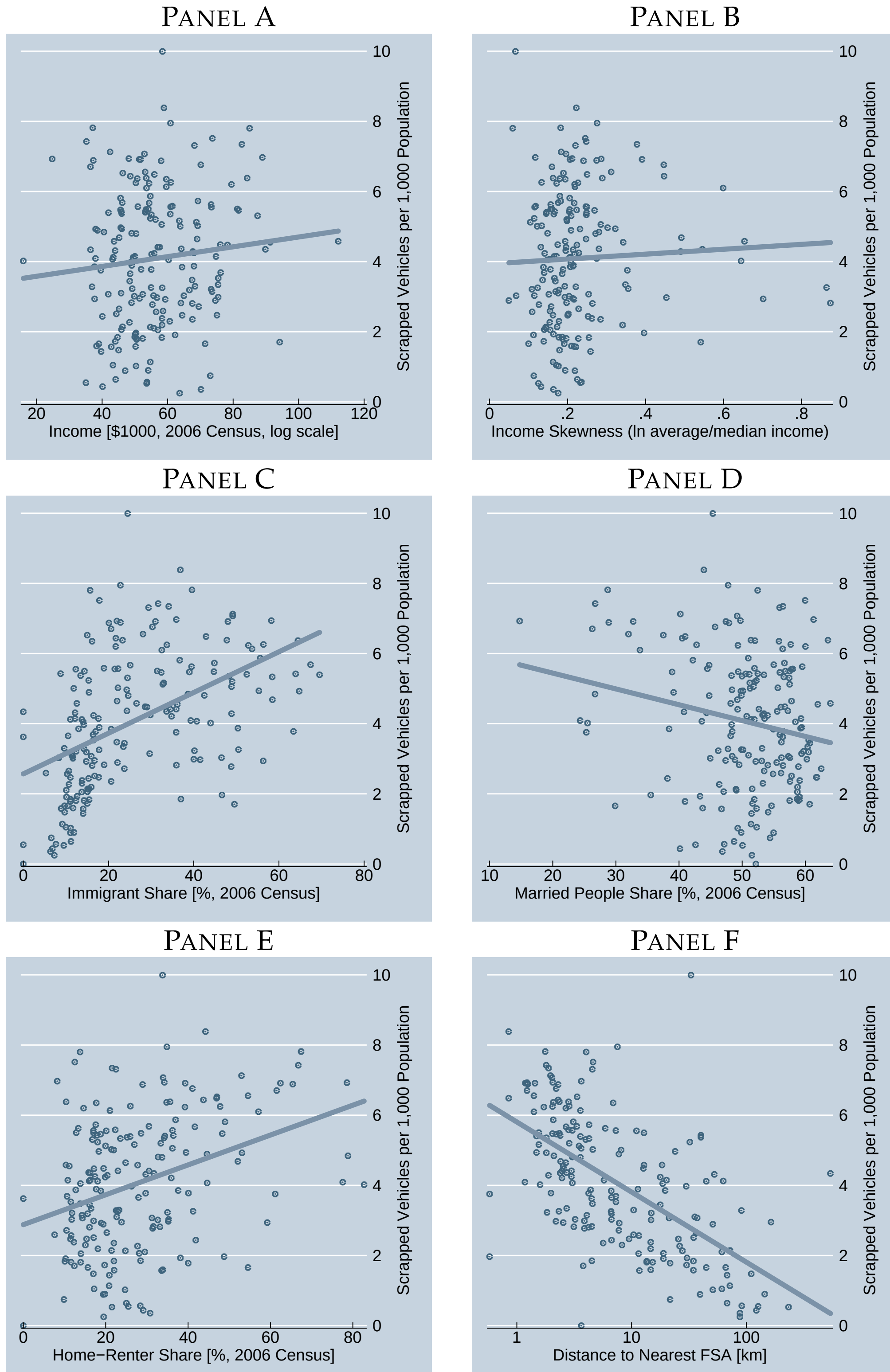
We employ three separate econometric approaches to estimate the effect of socio-economic characteristics on the program participation decision. Our dependent variable is either the count of scrapped vehicles in a given FSA, or the log of the scrappage intensity, i.e., the number of scrapped vehicles per capita in a given FSA. For count data we employ either a Poisson regression or a negative binomial regression, and for the intensity data we employ ordinary least squares.

The most widely used model for count data analysis is Poisson regression where the dependent variable y_i is a non-negative count and is independently Poisson distributed, given the vector $\mathbf{x}_i$ of covariates. The parameter vector $\mathbf{b}$ corresponds to these covariates. The conditional mean is given by $\mu = \exp(\mathbf{x}_i'\mathbf{b}) \geq 0$, i.e., the mean number of events. The estimating equation

$$\ln\left[E(y_i|\mathbf{x}_i)\right] = \ln(\mu_i) = \mathbf{x}_i'\mathbf{b}. \tag{6}$$

has a log-linear form and is estimated by maximizing a corresponding log-likelihood function; see (Greene, 2011, ch. 18) for the econometric details.

Figure 4: Per-Capita Scrappage Intensity & Census Statistics



Note: The figures show the per-capita scrappage intensity for the reference period (January-August 2009) in all 187 postal forward sortation areas (FSAs) in B.C. Linear fits are superimposed.

The Poisson model imposes the restrictive property that the conditional mean equals the conditional variance. However, typical applications often exhibit overdispersion where variance exceeds the mean. In the presence of overdispersion it is common to employ the negative binomial model, which generalizes the Poisson regression by allowing observations to differ randomly in a manner not fully accounted for by the observed covariates. Specifically, it is often assumed that the conditional variance exceeds the conditional mean μ_i by an additive term $\alpha\mu_i^2$ that is quadratic in the mean. The negative binomial model can also be estimated by maximum likelihood; see (Greene, 2011, ch. 18) for the econometric details.

Results for our regression analysis are reported in table 10. The top panel focuses exclusively on the income variables (in addition to population size and population density). [27] Columns (A), (B), and (C) of table 10 report the results of the Poisson, Negative Binomial, and OLS intensity regressions. The bottom panel includes the socio-economic status variables, which may confound the effect of income. Columns (D), (E), and (F) report the results of the corresponding Poisson, Negative Binomial, and OLS intensity regressions. Overdispersion is present in our data set—the estimated α is in the range of 0.10–0.15 and highly significant. This indicates that the results from the negative binomial regression (columns B and E) should be preferred over the results from the Poisson regression (columns A and D). Several socio-economic status covariates lose their statistical significance under the negative binomial regression.

In the count regressions, population size enters explicitly as a covariate, whereas it does not in the per-capita intensity regression. In the two sets of count regressions, the log of population has nearly unit elasticity on the dependent variable—the log of the expected count. This result, in conjunction with the fact that all FSAs had non-zero counts of scrapped vehicles, suggests that the intensity-form OLS regression is a plausible, and slightly easier to interpret, alternative to the count models.

The statistical analysis demonstrates convincingly and robustly that the strongest determinant of scrappage is the urban-rural divide. Interpreting the coefficient in column (C), a 10% increase in distance to the nearest FSA decreases the scrappage rate by 3.3%. While the scrappage decision does not depend on an area's median household income, it is strongly and negatively correlated with the presence of a disproportionate large share of high-income households. Presumably, high income households do not own old vehicles, but newer vehicles and are less likely to make a vehicle scrappage decision.

Four socio-economic variables provide statistically-significant explanatory power. Vehicle scrappage increases with the presence of a larger share of immigrants and the average age of the population. This possibly reflects a tendency of immigrants and older owning older vehicles. The age-related result is only significant in the Poisson and OLS regressions, but not the negative binomial regression.

[27] This is because income is strongly related to a wide range of socio-economic status variables, as discussed earlier and summarized in table TA-3 in our *Technical Appendix*.

Table 10: Vehicle Scrapping Decision

	(A)		(B)		(C)	
Estimation Method	Poisson		Neg.Bin.		OLS	
Dependent Variable	SV		SV		ln(SV/Pop)	
Intercept	-3.752^c	(8.60)	-3.933^a	(2.54)	2.038	(1.28)
ln(population)	0.900^c	(59.7)	0.908^c	(18.4)		
ln(distance nearest FSA)	-0.270^c	(39.0)	-0.290^c	(11.8)	-0.331^c	(11.9)
ln(median HH income)	-0.015	(.432)	0.000	(.002)	0.003	(.022)
ln(mean/median income)	-0.497^c	(6.30)	-0.658^a	(2.51)	-0.699^a	(2.29)
Number of observations	183		183		183	
R^2					0.452	
Log Likelihood	-1548.2		-870.03			

		(D)		(E)		(F)	
Estimation Method		Poisson		Neg.Bin.		OLS	
Dependent Variable		SV		SV		ln(SV/Pop)	
Intercept		-8.788^c	(8.42)	-7.583^a	(2.50)	-2.208	(.632)
ln(population)		0.978^c	(56.8)	0.907^c	(20.0)		
ln(distance nearest FSA)		-0.129^c	(9.91)	-0.136^c	(3.44)	-0.183^c	(4.00)
Foreigners	%	-0.020^c	(4.41)	-0.007	(.515)	-0.006	(.350)
Immigrants	%	0.017^c	(12.4)	0.013^b	(2.89)	0.012^a	(2.25)
Married	%	-0.026^c	(7.59)	-0.020	(1.90)	-0.012	(.934)
Migration (last 5 years)	%	-0.011^c	(6.67)	-0.010	(1.95)	-0.013^a	(2.10)
Average Age		0.035^c	(5.70)	0.027	(1.46)	0.054^a	(2.42)
Renting	%	0.002	(.830)	0.007	(1.02)	0.008	(1.05)
ln(median HH income)		0.429^c	(4.80)	0.460	(1.85)	0.310	(1.08)
ln(mean/median income)		-1.040^c	(10.3)	-1.365^c	(4.57)	-1.446^c	(4.05)
Participation rate	%	-0.004	(.920)	-0.016	(1.31)	-0.004	(.248)
Unemployment rate	%	-0.079^c	(9.79)	-0.093^c	(4.05)	-0.082^b	(3.14)
Number of observations		183		183		183	
R^2						0.587	
Log Likelihood		-1224.8		-841.55			

Note: The dependent variable is the number of scrapped vehicles (SV) or its logged per-capita counterpart. Poisson and negative binomial (Neg.Bin.) refer to the respective distributional assumptions for count data regressions. OLS is ordinary least squares. Unit of observation are postal Forward Sortation Areas (FSA) in British Columbia, except those suppressed by Statistics Canada in the 2006 census data. All socio-demographic characteristics are from the 2006 census. T-ratios are given in round parentheses. Statistical significance at the 95%, 99%, and 99.9% confidence levels is indicated by the superscripts ^{a}, ^{b}, and ^{c}, respectively.

A strong negative predictor of scrappage is the unemployment rate. As unemployment rises, scrappage declines. Intuitively, individuals who lose employment are financially constrained and tend to delay a vehicle replacement decision. It is more affordable to continue driving the current old vehicle than to buy a new vehicle.

6 Incentive Choice Decision

The BC SCRAP-IT Program offers a variety of incentive choices that differ from program stage to program stage. Our analysis focuses on program phase-II (June 2008 to July 2009) during which nearly 12,000 vehicles were retired through the program. The most-frequent incentive choice is the replacement vehicle credit. A small share (3%) opt for a simple cash payment, and just over a third of participants opt for a public transit pass or a pass+bicycle combination package.

To analyze the incentive choice problem for pairs of choices (option j relative to baseline choice 0) we employ a simple logit model of the form

$$\ln\left(\frac{\Pr(y_i = j|\mathbf{x}_i)}{\Pr(y_i = 0|\mathbf{x}_i)}\right) = a_j + \mathbf{b}_j'\mathbf{x}_i \tag{7}$$

which can be estimated by maximum likelihood. The term on the left-hand side is the log odds function of the covariates $\mathbf{x}$. A problem with binary choice variables is the interpretation of the estimation results because the marginal effects depend on the actual values of each observation $\mathbf{x}_i$. A common way to deal with this is to evaluate marginal effects at sample means. Another way to deal with this problem is to report the regression results in odds-ratio form, as each estimated parameter represent the logs of the odds ratio. By expressing estimates b_k in odds-ratio form $\exp(b_k)$, the odds ratio can be interpreted as the change in the odds for any increase of one unit in the corresponding covariate. When a covariate is itself expressed as a logarithm, the interpretation is even more straight-forward: the estimated parameter is the odds ratio elasticity with respect to the covariate.

Table 11 reports the results of our empirical analysis of the incentive choice. Our reference category is the vehicle replacement incentive option. The results in column (1) identify the odds of choosing cash over the replacement vehicle, results in column (2) identify the odds of choosing public transit over the replacement vehicle, and results in column (3) identify the odds of choosing a bicycle & transit option combination over the replacement vehicle incentive. Note that the car share option has been left out. This is because only 0.9% of participants chose it.

We employ socio-economic and socio-demographic variables (mapped to each observation based on the participant's postal code) along with vehicle-specific information about the vehicle's age (in years) and annual vehicle kilometrage. The latter two are expressed in logarithmic form. Age and annual kilometrage affect the scrappage decision in different ways. Age influences the value of the vehicle scrapped, and may reflect owners income or preferences. Annual kilometrage can influence the choice of replacement. An owner with a high annual kilometrage probably requires a replacement vehicle; public transit or bicycle options are an

Table 11: Scrappage Incentive Choice (Program Phase 2 Only)

	(1)		(2)		(3)	
Incentive Choice Reference Category	cash vehicle		transit vehicle		combo vehicle	
Intercept	6.417^b	(8.35)	18.282^c	(28.9)	0.676	(.046)
ln(distance nearest FSA)	−0.014	(.337)	-1.278^c	(335)	-0.342^c	(80.7)
	[0.986]		[0.279]		[0.711]	
Married %	0.005	(.543)	0.029^a	(5.75)	-0.025^b	(6.72)
	[1.005]		[1.029]		[0.975]	
Average Age	-0.070^c	(17.8)	-0.129^c	(20.9)	−0.008	(.116)
	[0.933]		[0.879]		[0.992]	
ln(median HH income)	−0.270	(1.32)	-0.772^a	(4.10)	0.309	(.869)
	[0.763]		[0.462]		[1.362]	
ln(mean/median income)	0.290	(1.08)	0.105	(.072)	0.664	(3.76)
	[1.336]		[1.111]		[1.943]	
Participation rate %	−0.003	(.056)	-0.044^a	(4.65)	0.013	(.698)
	[0.997]		[0.957]		[1.014]	
Unemployment rate %	−0.037	(2.80)	0.089^a	(4.48)	-0.093^b	(8.00)
	[0.964]		[1.093]		[0.911]	
ln(vehicle age)	−0.037	(.259)	-0.856^c	(57.4)	-1.497^c	(269)
	[0.963]		[0.425]		[0.224]	
ln(annual mileage)	-0.128^c	(34.2)	-0.080^a	(6.10)	0.202^c	(16.1)
	[0.879]		[0.923]		[1.223]	
Number of observations	10,756		10,756		10,756	

Note: The categorical dependent variable is the choice of scrappage incentive: 'vehicle' for a replacement vehicle, 'cash,' 'transit' for public transportation, 'combo' for a bicycle+transit combination package. Estimation method is multinomial logit. All socio-demographic characteristics are from the 2006 census, merged with the program participation data by postal forward sortation area. Wald-χ^2 statistics are given in round parentheses. Odds-ratio estimates are given in square brackets. Statistical significance at the 95%, 99%, and 99.9% confidence levels is indicated by the superscripts ^{a}, ^{b}, and ^{c}, respectively.

unlikely replacement for such a person. Annual kilometrage helps us understand whether the program participant uses vehicles intensely or not.

Let us first look at column (1) for the odds of choosing the cash incentive over a vehicle replacement option. Note that the value of the cash incentive is significantly lower than the external valuation of any other incentive offered. As a result, in this phase a very small percentage of participants, 3%, choose it. Its choice reveals that the participant also assigns a low implicit value to all other alternatives. Transit passes, bicycle subsidies, and the option of buying a vehicle from participating dealers are all worth less than $300 to this participant. This could be because the owner is permanently retiring travel in this jurisdiction, will not—or cannot—use public transit or bicycles, or has purchased a replacement vehicle outside the program. It must also hold that the participating vehicle has a resale value lower than $300.

We find that two variables predict the choice of cash over a replacement vehicle. Cash incentives are more likely to be chosen when the average age of the population in the area is low. Cash options are also more likely to be chosen over vehicle replacement when the scrapped vehicles has a low annual kilometrage. A low annual kilometrage could imply a low travel requirement of the participant. This could support the notion that the participant is retiring travel. However we are unable to explain how the average age of the area's population increases the likelihood of choosing cash.

Now consider column (2), the odds of choosing the transit option relative to vehicle replacement. Transit options in this phase are all valued at over $2,000, higher than the value of most other options. The choice of this option implies that the participant also implicitly values transit passes higher than all other alternatives. We find that several variables help explain the choice of transit over a replacement vehicle. Participants from areas with a higher population density, a greater proportion of married households, a younger population, a lower median household income, a lower participation rate, and a higher unemployment rate are more likely to choose transit over a vehicle option. We also find that participants who trade in younger vehicles with lower annual kilometrage are also more likely to choose transit over vehicle replacement.

We can offer several explanations for the observed statistical effects. Areas with higher population density are likely to have higher transit frequency and options. This result indicates that accessibility to transit influences its choice. Married households (especially those with kids) tend to have multiple travel demands. Public transit is thus valuable for families. Younger participants are more likely to use transit. The income and unemployment variables reflect the reach of the transit option amongst the poor. Conditional on participation, if a participant is from an area with a lower median income and a higher unemployment rate she is more likely to choose transit over a vehicle replacement option. This might be because, transit does not require capital costs of purchasing and running a vehicle. In this phase the public transit option can allow a participant to ride public transit for up to 28 months at no cost. We believe that participants probably trade in younger vehicles due to the high explicit and implicit value of this option. And finally, the low annual kilometrage reflects the ability of participants to replace vehicle kilometres with transit.

Now consider column (3), the choice of the bicycle-plus-transit combination relative to vehicle replacement. In this option, participants can claim a subsidy for standard bicycles for up to $1,100 (up to $1,200 for an electric bicycle), and approximately $800 in transit passes. The choice of this option implies that the participant implicitly values either the bicycle subsidy—or its combination with transit passes—higher than receiving a potentially more valuable set of transit passes. We find that participants from areas with a higher population density, a lower proportion of married households, and a lower unemployment rate are more likely to choose combination packages over a vehicle option. We also find that participants who trade in a younger vehicle with a higher annual kilometrage are also likely to choose the combination package over vehicle replacement.

Areas with higher population density are likely to have higher transit frequency and options. As earlier, this results indicates that accessibility to transit influences its choice. This is where the similarity with public transit on this choice ends. We find the opposite impacts on married households and unemployment rates. We also find that vehicles with a high annual kilometrage are are more likely to choose this option. The likely story underlying these results is that the choice of the combination option reflects a demand for recreational bicycles. Single, and gainfully employed owners are more likely to demand recreational bicycles. Further, if you have a vehicle with high end-of-life annual kilometrage you are less likely to be able to replace those kilometres with a bicycle or public transit. It could be that some participants are using the combination incentive to subsidize a recreational bicycle, and are buying another vehicle outside the program.

We take away two observations from this analysis. Firs, the choice between transit options and vehicle replacement options is strongly driven by the urban-rural divide. The availability of public transit determines whether program participants choose this option, as public transit availability correlates very strongly with population density. Second, conditional on participation, having the public transit option extends the reach of BC SCRAP-IT among the poor and cash-constrained.

7 Conclusions

The British Columbia SCRAP-IT Program is a novel Accelerated Vehicle Retirement Program (AVRP). Unlike AVRPs in other jurisdictions, notably the cash-for-clunkers program in the United States, an explicit objective of the BC program is to encourage transportation mode switch: making people retire their cars in exchange for taking up public transport or cycling. The program has been quite successful in that regard. Only about half of all participants opted for the new-vehicle incentive, while the other half opted for one of the alternative incentives.

We had set out answering three research questions. First, what is the environmental impact of the BC SCRAP-IT program? We find significant positive impacts of retiring pre-1995 vehicles. The environmental benefits arise from a number of factors. Older vehicles emit much higher amounts of carbon monoxide, hydrocarbons, and nitrogen oxides than newer vehicles. Taking pre-1995 vehicles off the street therefore contributes much to reducing air pollution particularly in urban areas. Vehicles in British Columbia also tend to be owned for longer periods than in other parts of Canada, likely due to more favourable weather conditions. Accelerated vehicle scrappage therefore results in larger emission savings than in other jurisdictions where vehicles have shorter lifetimes than in BC. Furthermore, the success of the SCRAP-IT program in diverting participants into alternative transportation modes that are much less carbon-intensive than automobiles contributes greatly to reducing carbon dioxide. On balance, we estimate conservatively that the program generates emission savings worth about $850. The difference in emission savings between those who continue driving a vehicle and those who switch to public transit or biking is around $350.

Second, who participates in SCRAP-IT and does it have income-distributional effects? Our analysis reveals that household income does not have a strong effect on program participation. However, participation rates are lower in regions with a high proportion of affluent households, which is consistent with the notion that high-income households do not participate much in scrappage programs because these households tend to drive newer cars. The strongest factor influencing participation is population density. There are two reasons for this. Vehicles in urban areas are subject to AirCare monitoring and thus face stricter emission standards, and public transit and bicycle use is more feasible in urban areas. Participation is also slightly higher in regions with higher levels of immigrants and older people, and lower levels of unemployment.

Lastly, which participants prefer alternative transport mode incentives over new-vehicle incentives? Here the answer again depends strongly on population density. Unsurprisingly, the choice of alternative transportation mode options depends on the availability of such options. Public transit is denser and more frequent in urban than in rural areas, and the same is true for cycling, car-share programs, and train service. In particular, the choice of public transit increases with lower household income and higher unemployment rates, and is also more readily chosen by married households. The choice of public transit incentives increases when the scrapped vehicles are younger or or driven less per year. This suggests that perhaps household's second cars are more readily traded in for alternative transportation options. Bicycle options are more readily chosen by younger and unmarried participants, and strongly so for participants scrapping younger vehicles.

Our analysis has shown that the BC SCRAP-IT has been, and continues to be, an environmentally useful program. While at some point the program may have been somewhat too generous, incentive levels are probably at a level now that is concordant with the environmental benefit we have identified. Importantly, providing a differentiated incentive level for new vehicles at a lower level than for alternative transportation modes remains a worthwhile policy. The BC SCRAP-IT program provides a number of useful new insights that AVRPs in other jurisdictions should take to heart.

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