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Heterogeneous Responses to Vehicle Replacement Subsidies: Evidence from Linked Vehicle-Owner Data

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Heterogeneous Responses to Vehicle Replacement Subsidies: Evidence from Linked Vehicle-Owner Data

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Abstract

This study examines how vehicle owners respond to vehicle replacement subsidies, using administrative data covering the universe of Finnish passenger vehicles and their owners to evaluate a subsidy program implemented in 2018. The subsidy increased new car purchases, with 66 percent of subsidized purchases estimated to be additional. The effects of the program on new car purchases varied across a number of vehicle and household characteristics, while the effects on the emissions of new vehicles did not differ significantly. On average, the program reduced CO_2 emissions at a cost of € 184 per ton, though cost-effectiveness varied substantially across vehicle-owner subgroups.

Keywords: vehicle replacement subsidies, climate policy, CO_2 emissions, transportation emissions, policy evaluation, administrative microdata, difference-in-differences

JEL codes: H23, H31, L91, R48, Q52, Q58

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1 Introduction

Passenger vehicles accounted for about 10 percent of global energy-related CO_2 emissions in 2023 (IEA 2024). Despite technological advances in electric vehicles and fuel efficiency, emissions from this segment continue to rise (IEA 2025). Ambitious policy measures are needed to align emissions with climate policy targets. While fuel carbon taxes would be a direct policy tool to reduce emissions, they often face public resistance (Carattini et al. 2018, Dechezleprêtre et al. 2025, Douenne and Fabre 2022). As a result, many countries have incorporated subsidies into their policy mix. One common approach is vehicle replacement subsidies, which aim to encourage consumers to trade in old, higher-emission vehicles for new, lower-emission vehicles.[1] Given their widespread use and potentially high costs, understanding what vehicle replacement subsidies deliver in terms of emission reductions, to whom, and at what cost, is important from environmental, equity, and public spending perspectives alike.

Although several papers have studied the overall effects of vehicle replacement subsidies on vehicle purchases and emission intensities (e.g., Grigolon et al. 2016, Hoekstra et al. 2017, Li et al. 2013, Mian and Sufi 2012), little is known about how these effects vary across trade-in vehicle attributes and owner characteristics. Improving policy design requires knowing which vehicle owners are most responsive to subsidies and how they respond. However, because comprehensive microdata on vehicles and vehicle owners have not been previously available, past research has not examined heterogeneity in how subsidies affect vehicle purchases and emission intensities, and the implications of such heterogeneity for policy cost-effectiveness and equity. This paper breaks new ground on these questions by using quasi-experimental variation created by a Finnish vehicle replacement subsidy program and population-wide administrative microdata on vehicles and vehicle owners.

The vehicle replacement subsidy program we study, implemented in January – August 2018, provided car owners a government subsidy of €1,000 to €2,000 if they scrapped a qualifying existing vehicle and purchased a new vehicle with a sufficiently low CO_2 emission intensity. Our main econometric strategy exploits the program eligibility criteria that scrapped vehicles had to be at least 10 years old and owned by the subsidy recipient for the previous 12 months. The eligibility criteria generate sharp quasi-experimental variation that allows us to identify program effects on new vehicle purchases and CO_2 emission intensities using difference-in-differences methods. For this analysis, we obtained access to Finland's full vehicle registry as well as administrative records on transactions that benefited from the vehicle replacement subsidy. These data are linked to individual- and household-level demographic and financial information for all vehicle owners.

We find that the Finnish vehicle replacement subsidy program increased new car purchases. The effect on new vehicle registrations starts to ramp up in the second month of the program, with no reversal in vehicle purchases in the months after the program expired. In February – August 2018, the growth in new car purchases relative to the same period in the previous year by program-eligible vehicle owners was 30 percentage points higher than it would have been in the

[1] Programs are currently in place or have recently been in place for example in China, Italy, France, Spain, Sweden, the province of British Columbia in Canada, and the states of California, Colorado, and Vermont in the United States.

absence of the program. We estimate that 66 percent of purchases by households that claimed the subsidy would not have occurred in the absence of the subsidy. The program's intention-to-treat effect on the CO_2 emission intensity of new vehicles purchased by eligible households is -3.6 percent. Taking into account that only a proportion of eligible households claimed the subsidy, the average treatment effect on the treated is -11 percent.

We obtain compelling evidence of heterogeneity in the program effect on new car purchases by current vehicle CO_2 emission intensity and by household income, location, and number of cars. Along these dimensions, the effect on purchases is the largest for households with a low current vehicle CO_2 emission intensity; low income; an urban location; or only one car. We find no significant differences in program effects by kilometers driven per year or by education level. We also find no evidence of heterogeneity in the program effect on new car CO_2 emission intensity across any of the dimensions studied. Nonetheless, heterogeneity in the purchase response suggests that targeting subsidies could yield efficiency gains, although equity concerns may also arise.

To explore quantitative differences in program-induced CO_2 emission reductions and the associated public costs across existing vehicle and vehicle owner characteristics, we supplement our main empirical analysis by estimating the residual lifetime of scrapped and new vehicles. This analysis draws on vehicle registry records covering Finland's entire vehicle fleet from 2013 to 2020, with months when vehicle replacement subsidies were in effect excluded. We estimate a survival model with lifetime vehicle kilometers – based on the last odometer reading of a vehicle – as the outcome variable. Using the survival model estimates, we predict lifetime vehicle kilometers for both scrapped and new vehicles, and combine these predictions with estimated program effects on new car purchases and CO_2 emission intensities to quantify the emission reductions attributable to the program.

Overall, the estimated fiscal cost of emission reductions is €184 per ton of CO_2 avoided. We find significant heterogeneity in the cost-effectiveness of the program. Importantly, the program's cost of reducing CO_2 emissions from households with high-emitting current vehicles is only 48 percent of the cost of reducing emissions from households with low-emitting vehicles. The results indicate that cost savings could also be achieved by targeting based on income, location, or the number of cars. However, efficiency gains would come at the expense of equity: the cost of reducing emissions from high-income households is 29 percent lower than that of reducing emissions from low-income households, and 15 percent lower for urban than for rural households. The estimated emission reductions generated by the program, in the Finnish context associated with savings in fuel carbon taxes, are also disproportionally concentrated among high-income and urban households.

This paper makes several contributions to both research and policy. Linked population-wide data for individuals, households, and vehicles allow us to examine heterogeneity in the effects of vehicle replacement subsidies in ways that have not been possible in prior studies. Previous literature has used data on vehicle sales (Grigolon et al. 2016, Li et al. 2013, Mian and Sufi 2012) or census-tract-level information on vehicle owners (Hoekstra et al. 2017).[2] While Muehlegger

[2]Linn (2020) presents a quantitative study of targeting a hypothetical vehicle scrappage subsidy. Linn's computational model suggests that targeting can reduce costs substantially. However, the computational model does not account for behavioral responses.

and Rapson (2022) study a program specifically targeting low- and middle-income buyers, they also only have information on income at the zip code level. None of these papers estimate how responses differ across the income and rural-urban continuums, and household vehicle holdings and usage. We show empirically that targeting subsidies could improve cost-effectiveness, but at the cost of potentially undesirable distributional effects.

Furthermore, most of the empirical evidence to date on vehicle replacement programs comes from the United States, where the Cash for Clunkers program in place in July – August 2009 appears to have shifted vehicle purchases forward only by a few months (Hoekstra et al. 2017, Li et al. 2013, Mian and Sufi 2012).[3] However, there is limited evidence from other vehicle markets and transport regimes.[4] Grigolon et al. (2016) study program effects on vehicle sales in seven European countries. In line with our results, they find that subsidies increased vehicle sales in most countries, with pronounced pull-forward effects in just one country. A common design feature of the programs studied by Grigolon et al. and the context of this study is substantially longer program duration than that of Cash for Clunkers. In terms of quantifying program-induced CO_2 reductions, we provide some of the first evidence from outside the United States.

This paper also contributes to the broader literature on government programs that subsidize energy-efficient durables. These programs also require evaluation of impacts on both durable goods purchases and energy efficiencies, and distinguishing between inframarginal participants and those who change behavior in response to subsidies (e.g., Boomhower and Davis 2014, Davis et al. 2014, Houde and Aldy 2017). As with vehicle replacement subsidies, understanding how consumer responses vary across market segments can inform policy design. Yet this dimension has received little attention in the existing literature.

2 Background

2.1 The car market and fleet in Finland

Finland has no large-scale car production of its own. There is only one car manufacturer, which produces select models of the Mercedes-Benz luxury brand. Thus, nearly all new cars are imported, and the auto industry consists mostly of wholesale and retail dealers. Altogether 120,500 new cars were registered in Finland in 2018, which is 0.9 percent of new cars registered in the European Union overall in the same year. The volume of used car trades is larger. Some 630,000 used cars were traded in within Finland alone in 2018, and an additional 40,000 used cars were imported into the country. Used car exports, on the other hand, are minimal, about 1,500 vehicles in 2018, up some from 1,200 vehicles in 2017. Overall, the motor vehicle retail industry employed 0.5 percent of Finland's workforce in 2018. This figure includes wholesale and

[3]Studies of earlier US scrappage policies include Alberini et al. (1996), Hahn (1995), and Sandler (2012). See also Adda and Cooper (2000) for an earlier policy in France.

[4]A related literature studies the impacts of tax incentives for low-emission vehicles. Gallagher and Muehlegger (2011) examine hybrid vehicle sales responses to state-level incentives in the United States, and Chandra et al. (2010) to province-level tax rebates in Canada. Structural studies of the sales effects of tax incentives include Beresteanu and Li (2011) and Xing et al. (2021) for the US, D'Haultfœuille et al. (2014) for France, Adamou et al. (2014) for Germany, and Huse and Lucinda (2014) for Sweden.

retail sales of both new and used cars and other light motor vehicles.[5] As for the vehicle fleet, the average car age in the beginning of 2018 was 12.1 years, slightly above the EU average of 10.5 years. Ninety-nine percent of cars still ran on gasoline or diesel, with an average CO_2-intensity of 160 g/km.[6]

2.2 The 2018 vehicle replacement program

Finland's 2018 vehicle replacement program aimed at incentivizing households to replace old, relatively CO_2-intensive vehicles with new, less CO_2-intensive vehicles. The nationwide program offered consumers a subsidy of €1,000 to €2,000 toward the purchase of a qualifying new vehicle, provided that they had scrapped a qualifying used vehicle. The car retail industry (dealers) participated with an additional €500 rebate for new car purchases that qualified for the government subsidy.

Eligibility criteria applied both to the scrapped vehicle and the new vehicle purchased. The scrapped vehicle had to be at least 10 years old (registered in year 2007 or earlier) and in the subsidy recipient's ownership for 12 months prior to scrappage.[7] The new vehicle had to be a passenger vehicle with CO_2 emissions below 110 g/km, or one powered either in full or in part by electricity, ethanol, or methane. The subsidy amount varied by the motive power of the new vehicle – gasoline and diesel cars received a €1,000 subsidy, and cars powered in full or in part by electricity, ethanol, or methane a €2,000 subsidy.

The program bill was brought to parliament on October 26, 2017 and signed into law on December 19, 2017.[8] The actual program began on January 1, 2018 and ended on August 31, 2018. The program eligibility criteria were strictly enforced: an information system that was developed specifically for administering the program used Finland's vehicle registry to verify that both the scrapped vehicle and the replacement vehicle satisfied the eligibility criteria. Altogether 6,677 new vehicles were purchased under the program. The total cost in terms of public spending was €7 million.[9]

3 Data and descriptive analysis

3.1 Data

Our principal data sources are administrative records provided by the Finnish Transport and Communications Agency Traficom and individual and household demographic and financial data

[5]Sources: Finnish Transport and Communications Agency Traficom's Statistics database for new and imported used cars in Finland (https://trafi2.stat.fi/PXWeb/pxweb/en/TraFi/); Eurostat Transport database for new cars in the EU (https://ec.europa.eu/eurostat/web/transport/database); Information Centre of Road Transport for used cars in the Finnish Market (https://www.aut.fi/en/statistics); Finnish Customs Statistical Database for used car exports (https://uljas.tulli.fi/v3rti/db/0), and Statistics Finland "Employment" and "Business and financial statement statistics" databases for employment (https://stat.fi/en/statistics/tyokay and https://stat.fi/en/statistics/yrti).

[6]Sources: Authors' calculations using Finnish Transport and Communications Agency Traficom data for Finland's vehicle fleet (see Section 3.1) and European Automobile Manufacturers Association (2018).

[7]The scrapped vehicle also had to be registered for road use in the preceding calendar year and at the time of scrappage, with the vehicle use tax imposed in Finland on cars in road use paid for the full year.

[8]See Government Proposal HE 156/2017 vp and Act 971/2017, Finlex Data Bank

[9]See Government Proposal HE 201/2020 vp, Finlex Data Bank

from Statistics Finland. The Traficom data include information on the full vehicle fleet and a listing of cars scrapped and cars purchased under the vehicle replacement subsidy program. Scrapped cars and subsidized new cars can be linked to the vehicle fleet data using identifiers common to the two data sets. The vehicle fleet data contain vehicle registered owner, vehicle technical information, and odometer readings from mandatory annual check-ups.[10] As only individuals were eligible for the vehicle replacement subsidy, we exclude cars registered to firms. To characterize new and used car prices, we use data from Netwheels, the Finnish car retail industry's market database, and Nettiauto, the largest car website in Finland, respectively.[11]

Statistics Finland's FOLK Base data set contains detailed individual-level demographic and financial information for the full Finnish population, including age, education, income (both salaries and capital income), and benefits. Statistics Finland's FOLK Household data set contains household-level information for the full Finnish population, including household size, the number and ages of children, and residence location. The residence location information includes a ready-made urban-rural indicator that divides locations into seven categories along the urban-rural axis based on geographic information.[12]

Identifiers common to the Traficom vehicle fleet data and the Statistics Finland data allow each car in the vehicle registry with an individual owner to be linked to the Statistics Finland records on the individual and the individual's household. The detailed data allow us to identify program effects by comparing the car purchase behavior of car owners who were eligible for the subsidy and those who were not, as well as studying possible effect heterogeneity across several important dimensions of car-owner and vehicle characteristics.

3.2 Summary statistics

Table 1 presents summary statistics for scrapped and new vehicles in 2018. Vehicles scrapped by subsidy recipients were on average 17 years old, slightly younger than the overall average scrappage age of 20 years. They comprised 7.6 percent of passenger vehicles scrapped in 2018. New vehicles purchased by subsidy recipients had an average CO_2 emission intensity of 100 g/km, while that of new passenger vehicles overall was 118 g/km. The most popular car bought by subsidy recipients was the Toyota Yaris in its hybrid version, chosen by 10 percent of program beneficiaries. Subsidized new vehicles comprised 7.9 percent of new passenger vehicles purchased in 2018.

Car prices cannot be linked to subsidized transactions directly, but the price data allow us to characterize the prices of cars that satisfied the CO_2 emission intensity threshold of 110 g/km for subsidized new vehicles. The average transaction price for program-eligible new vehicles was €24,879. The total of the government subsidy and dealer rebate of €1,500 for gasoline- and diesel-powered cars amounted to 6 percent of the average price of eligible new vehicles.

[10] In addition to the registered owner, the vehicle fleet data also list the legal owner of the vehicle. Due to financing arrangements, the legal owner of a vehicle may differ from the registered owner: In some car financing agreements, the legal owner is the entity that provides the financing. The registered owner is still responsible for vehicle taxes, for insuring the car, and for maintaining compliance with other laws and regulations. The registered owner is considered the vehicle owner in our analysis.

[11] The data include asking price, odometer reading, some car characteristics, the time of posting and the time of sale. The data can be linked to the vehicle fleet data using license plate numbers.

[12] The seven categories comprise inner urban area, outer urban area, peri-urban area, local center in a rural area, rural area close to an urban area, rural heartland, and sparsely populated rural area.

Table 1: Summary statistics of scrapped and new vehicles in 2018

Panel 1. Average scrapped vehicle characteristics

	Subsidized	**Nonsubsidized**	**All**
Vehicle age (years)	17	20	20
Odometer reading (km)	226,074	276,228	271,588
CO_2 emission intensity (g/km)	170	172	172
Weight (kg)	1232	1283	1280
Share gasoline	0.90	0.79	0.80
Share diesel	0.10	0.21	0.20
Observations	6569	79,288	85,857

Panel 2. Average new vehicle characteristics

	Subsidized	**Nonsubsidized**	**All**
CO_2 emission intensity (g/km)	100	119	118
Weight (kg)	1176	1438	1402
Share gasoline	0.91	0.79	0.80
Share diesel	0.03	0.16	0.15
Share methane	0.04	0.01	0.01
Share PHEV and BEV	0.02	0.04	0.04
Share SUV or pickup	0.06	0.27	0.26
Observations	6569	75,497	82,066

Panel 3. Average new vehicle prices

	Eligible	**Ineligible**	**All**
Transaction price (€)	24,879	40,829	35,879
Observations	35,354	78,559	113,913

Notes: Panels 1 and 2 report the mean of each variable for subsidized, nonsubsidized, and overall scrapped and new vehicles in Finland's vehicle registry in year 2018. To be consistent with our analysis, we exclude vehicles with a firm as the registered owner. Data on CO_2 emission intensities are only available for 68 percent of vehicles scrapped by subsidy recipients and for 42 percent of scrapped vehicles overall. Odometer readings are available for 95 percent of vehicles scrapped by subsidy recipients and for 70 percent of scrapped vehicles overall. Panel 3 reports the mean transaction prices for vehicles below (eligible) and above (ineligible) the CO_2 emission intensity threshold for subsidy-eligible vehicles, 110 g/km. As firm-owned vehicles cannot be identified in the price data, the observations in Panel 3 include both individual-owned and firm-owned new vehicles.

Table 2: Summary statistics of vehicle owners in 2017

	Age of household's oldest vehicle (years)			
	10 or above	**0-9**	**5-9**	**0-4**
Total number of households	1,100,962	698,642	411,521	287,121
Purchased new vehicle (quantity)	22,688	47,657	20,691	26,966
Purchased new vehicle (share)	0.02	0.07	0.05	0.09
Purchased used vehicle (quantity)	261,890	108,319	75,942	32,377
Purchased used vehicle (share)	0.24	0.16	0.18	0.11
Panel 1. Household characteristics				
Household size (persons)	2.34	2.32	2.40	2.20
Income (€)	42,614	53,634	52,113	55,820
Urban location (share)	0.49	0.62	0.59	0.65
Homeowner (share)	0.73	0.84	0.83	0.86
Owns more than one car	0.37	0.15	0.19	0.09
Number of vehicles	1.45	1.15	1.20	1.09
Owns SUV or pickup	0.02	0.10	0.08	0.14
Km driven per year (total all cars)	18,713	18,216	18,845	not available
Panel 2. Registered owner characteristics				
Income (€)	32,885	46,041	44,002	48,954
Age (years)	51	54	52	57
College education (share)	0.25	0.39	0.38	0.40

Notes: The table shows vehicle owner characteristics in the last pre-program year (2017). Household income refers to disposable income (income and benefits net of taxes and transfers). Owner income includes gross earned and capital income. Urban location includes inner urban and outer urban areas in the Statistics Finland urban-rural classification. Kilometers driven are calculated based on the most recent odometer readings from mandatory vehicle inspections, approximately one year apart, and take into account all vehicles owned by the household. Odometer readings are not available for most 0-4-year-old vehicles as the first mandatory inspection takes place at vehicle age 4.

Table 2 presents summary statistics for vehicle owners in the pre-program year 2017. The table groups vehicle owners by the age of the household's oldest vehicle, as the replaced vehicle had to be at least 10 years old to qualify for the subsidy. In 2017, 1.1 million households owned a vehicle aged 10 years or above. Among these households, 2 percent purchased a new vehicle, a somewhat smaller share than that among households with younger cars. On average, owners of older cars have slightly lower income and education and are less likely to live in an urban location than owners of younger vehicles.

3.3 Mileage, used car prices, and program take-up by vehicle age

Figure 1 displays mean odometer readings by vehicle age for the entire vehicle fleet and for scrapped vehicles in the pre-program year 2017. Vehicles that were scrapped at age 10, the program eligibility threshold for the 2018 subsidy program, had been driven notably more than the average vehicle of the same age. The average odometer reading for 10-year-old scrapped vehicles was 233,141 km, whereas the average for 10-year-old vehicles overall was 187,759 km.

Thus, vehicles scrapped close to the eligibility threshold age of 10 years are not representative of the fleet overall in terms of how much they had been driven given their age.

Figure 2 shows the mean used-car asking price by car age for the pre-program year 2017. The mean asking price for 10-year-old vehicles was close to €10,000, significantly more than the government vehicle replacement subsidy and the associated retailer rebate, €1,500 in total for for gasoline- and diesel-powered replacement vehicles and €2,500 in total for ethanol, methane and electric replacement vehicles. While the asking price is only a proxy for the actual transaction price, Figure 2 suggests that the resale value of the average 10-year-old vehicle was much higher than what could have been obtained by participating in the program and scrapping the vehicle. Figure 3 shows program take-up by existing vehicle age. Take-up is relatively low right above the eligibility threshold and increases with car age up to age 14, concurrently with the decrease in used car asking prices shown in Figure 2.

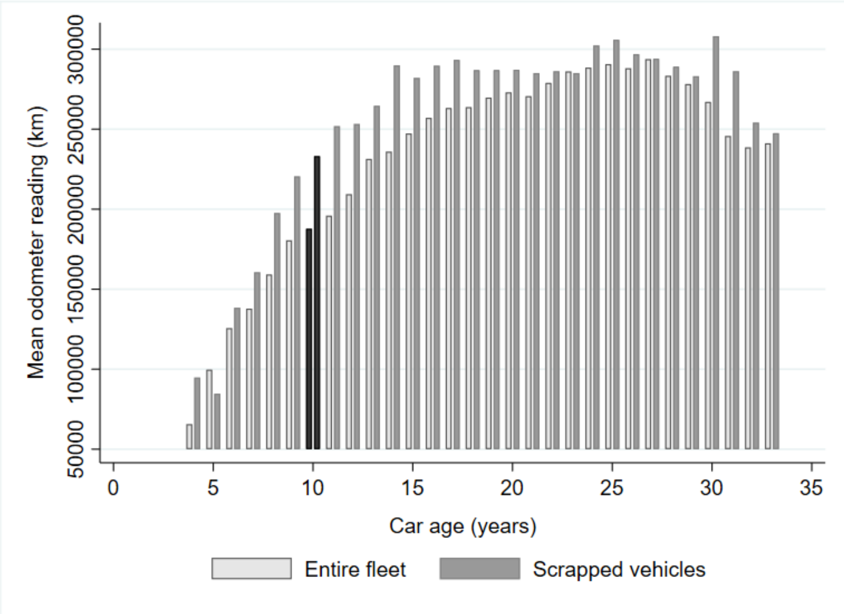


Figure 1: Mean odometer reading by car age in 2017.

Notes: The dark-shaded bars denote the fleet and scrapped vehicle averages for ten-year-old vehicles. Odometer readings are only available for vehicles that are at least four years old, as the data come from mandatory vehicle inspections that start at age four. The oldest 1 percent of cars is omitted to avoid a long tail with few observations.

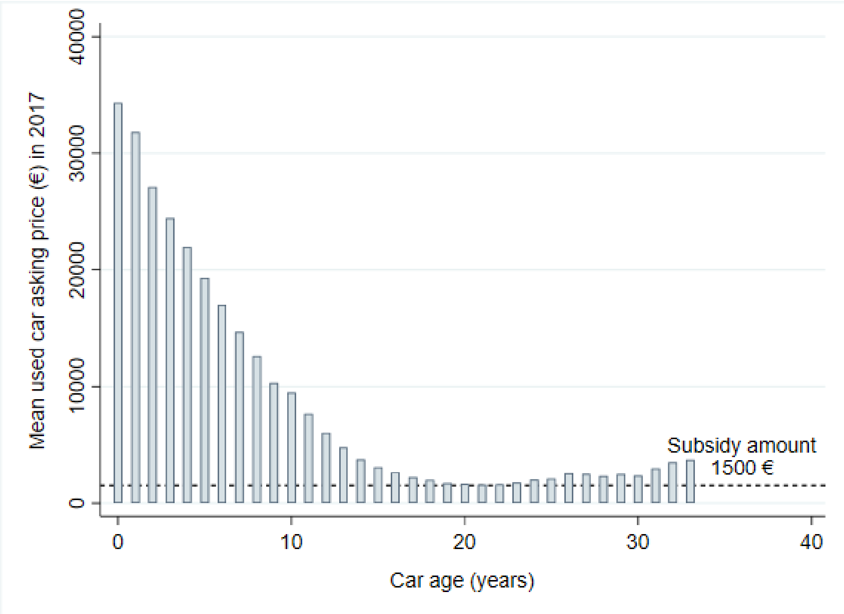


Figure 2: Mean used car asking price by car age in 2017.

Notes: The total of the government subsidy and retailer rebate was €1,500 for gasoline- and diesel-powered replacement vehicles, which formed 94 percent of subsidized transactions. Ethanol, methane and electric vehicles received €2,500 in total. Asking prices for cars aged above 25 years reflect a high proportion of classic collector cars. The oldest 1 percent of cars is omitted to avoid a long tail with few observations.

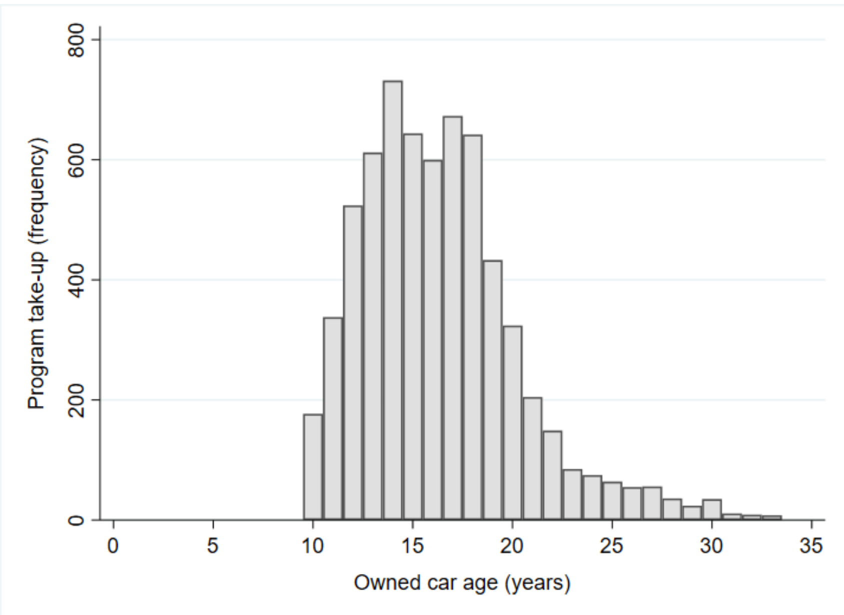


Figure 3: Program take-up frequency by existing vehicle age.

4 Empirical strategy

Our empirical strategy exploits granular data on vehicles and vehicle owners to estimate the effect of the vehicle replacement subsidy on vehicle purchase behavior. The strategy leverages the program rule requiring ownership of a vehicle at least 10 years old to be eligible for the subsidy. While subsidy eligibility is defined at the level of an individual car owner, we set out to identify program effects at the household level. This internalizes spillovers that may arise between program-eligible and ineligible car owners within the same household. We use a differences-in-differences approach, with households that did not own a subsidy-eligible vehicle as a control group, to assess the counterfactual car purchase behavior of subsidy-eligible households in the absence of the program.

While there is a well defined vehicle age cutoff for treatment assignment, regression discontinuity design is not well suited to the data. Figures 1 and 2 above suggest that in the absence of subsidies, vehicles scrapped close to the cutoff age differ systematically from vehicles further above the cutoff age in terms of mileage and resale value. Figure 3 shows that subsidy take-up is relatively low at the cutoff and increases notably when moving on to vehicle ages a few years beyond the cutoff. Thus, regression discontinuity treatment effects might not be representative of treatment effects further away from the cutoff. An initial investigation of the relationship between existing vehicle age and program take-up using regression discontinuity tools shows that there is no discontinuity in take-up at the cutoff and that take-up increases notably further above the cutoff, amplifying concerns about the external validity of local regression discontinuity estimates (see Appendix Figure A.1). Differences-in-differences analysis is more plausibly informative about the effects of the program across the group of subsidy-eligible households.

Our differences-in-differences analysis proceeds in two steps. We first analyze new vehicle purchase volumes to assess the time window within which the vehicle replacement subsidy program affected new vehicle purchases. We call this time period the "program window", similarly to Hoekstra et al. (2017). Importantly, the program window may differ from the actual program period due to intertemporal substitution in vehicle purchases. Subsidy-eligible individuals may have postponed new vehicle purchases from the end of 2017, when the program bill was introduced, to the program year 2018. Similarly, eligible individuals may have pulled forward purchases from post-program months to the program months. Earlier studies on the US CARS scrappage subsidy program by Mian and Sufi (2012), Li et al. (2013), and Hoekstra et al. (2017) have documented such intertemporal shifts in new car purchases. Accounting for potential intertemporal substitution is necessary to correctly assess the impacts of the program on the types of vehicles purchased. Once the program window has been identified, we proceed to the second step and analyze purchase characteristics within this time window to assess the impact of the program on new vehicle emission intensity.

We define the treatment group as households with an existing vehicle that satisfied the program eligibility criteria for vehicle age and ownership duration, minimum 10 years and 12 months, respectively. Of the vehicles eligible in terms of age, 7.8 percent did not satisfy the 12-month ownership requirement. Households that owned these vehicles were excluded from the analysis. The control group includes households whose oldest existing vehicle was not old enough to qualify for the subsidy. In the main analysis, we exclude households whose oldest existing vehicle was four years old or younger. The vehicle purchase behavior of these cohorts differs from that of the other vehicle owner cohorts in that the propensity to purchase a new car is notably higher (see Table 2).[13] A robustness test adds the households with vehicles at most four years old in the control group and shows that the results on new car purchase pattern and emission intensity are materially unaffected.

In order to consistently compare households whose oldest car was at least 10 years old to households whose oldest car was younger, we redefine the treatment and control groups at the beginning of each year. A concern here is that if households move from the control group to the treatment group, or vice versa, at a time when information about the subsidy program was already available or right after the end of the program, the composition of the treatment and control groups might change as a result of the treatment (Abbring and Van Den Berg, 2003). The effects of the program on new car purchase behavior could then be incorrectly estimated. In our case, households whose oldest vehicle was nine (but not yet 10) years old in 2017 could have self-selected into the treatment group by deferring the purchase of a new vehicle from when the program was announced in 2017 until the program year 2018. To avoid program-related changes in the treatment and control groups, we exclude this vehicle owner cohort from the analysis.

The main identifying assumption is that new car purchases and new car emission intensities in the treatment and control groups would have followed parallel trends after October 2017 (the date when the the program bill was first brought to parliament) in the absence of the vehicle replacement subsidy program. Sections 5.1 and 5.2 below present graphical analysis that allows assessing the validity of the parallel trends assumption. Another critical assumption is that treatment effects do not spill from the treated to the untreated (the Stable Unit Treatment Value Assumption or SUTVA). The SUTVA could be violated if the program had an effect on the car market overall, such that the prices faced by untreated households, or their income, would also change as a result of the program. Given the size of the program relative to the relevant new car market and the economy on the whole, such effects are unlikely. Altogether 6,677 new cars were purchased under the program, while the number of new passenger cars registered in the European Union in 2018 was 13.1 million (Eurostat 2024). The number of subsidized transactions is also small relative to the used car market, with 670,000 trades in Finland alone in 2018 (see Section 2.1).

5 Overall effects of the vehicle replacement subsidy

5.1 New car purchases

Figure 4 shows the monthly shares of households in the treatment and control groups who purchased a new car. The monthly new car purchase shares are scaled by the average monthly purchase shares from July 2016 to June 2017. The figure thus traces growth in new car purchases in the two groups relative to the group-wise average purchases in the period July 2016 - June 2017. We chose this base period to avoid confounding by a previous vehicle replacement subsidy program implemented in 2015, which could still be reflected in car purchases in early 2016, and

[13] The first mandatory vehicle inspection takes place at car age four. The observed purchase behavior is consistent with a subset of new car buyers replacing their car before the mandatory inspections begin.

by anticipation of the 2018 program, which could be reflected in car purchases toward the end of 2017.[14]

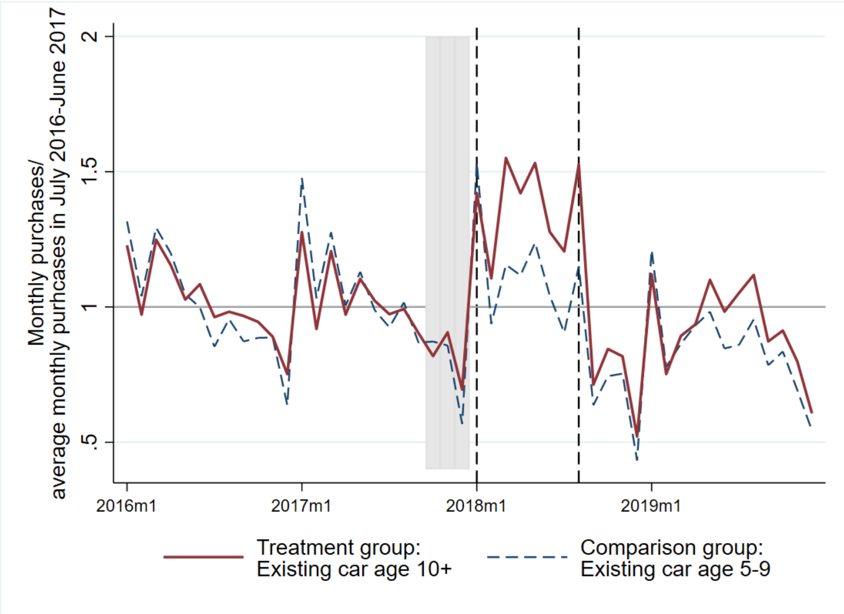


Figure 4: Monthly new car purchases.

Notes: The figure depicts the share of households in the treatment and control groups that purchased a new car, by month. The shares have been scaled by the group-wise monthly average new car purchase shares in July 2016 - June 2017. The dashed vertical lines mark the beginning and the end of the vehicle replacement subsidy scheme. The shaded region marks the potential anticipation period, the three months prior to the beginning of the program, starting from when the program bill was brought to parliament.

The pattern of new car purchases in Figure 4 is similar in the two groups until February 2018. After the typical January peak in new car registrations, common to the two groups, new car purchases in the treatment group were about 11 percent above the monthly average in July 2016 - June 2017. In contrast, new car purchases in the control group were 6 percent below the July 2016 - June 2017 monthly average. In March 2018, new car purchases in the treatment group increased dramatically, to 55 percent above the monthly average in July 2016 - June 2017, while there was a much smaller simultaneous increase in purchases in the control group. Once the program period ended in August 2018, purchases in the treatment group returned to levels similar to those in the control group.

Figure 5 shows the regression version of Figure 4. The figure depicts estimates of the following specification, estimated separately for each month m from January 2016 to December 2018:

$$q_{amt} = \alpha_{am} + \lambda_t + \delta_{mt} P_{mt} E_{amt} + \varepsilon_{amt}, \tag{1}$$

where q_{amt} denotes the share of households in each car age group a (car age 10+, car age 5-9) who purchased a new vehicle in month m and year t, relative to group-specific average monthly

[14]The 2015 program had the same car age eligibility criterion as the 2018 program but did not impose the restriction that the scrapped vehicle must have been in the subsidy beneficiary's ownership for a year prior to scrappage. The vehicle fleet data suggest that some program beneficiaries purchased an old vehicle and scrapped the vehicle only days after the change of ownership. As this type of gaming makes it difficult to credibly trace the impacts of the program, our analysis focuses on the 2018 program only.

purchase shares during July 2016 - June 2017. On the right-hand side, α_{am} denotes group-month fixed effects that capture seasonality in the purchase behavior of the owners of relatively old versus new cars, and λ_t year fixed effects that control for month-invariant overall demand trends. Coefficient δ_{mt} on the term $P_{mt}E_{amt}$ captures the program effect on new car purchases in the treatment group of eligible households (with car age 10+) during potential program window months. The full estimation results are presented in Panel A of Appendix Table B.1.

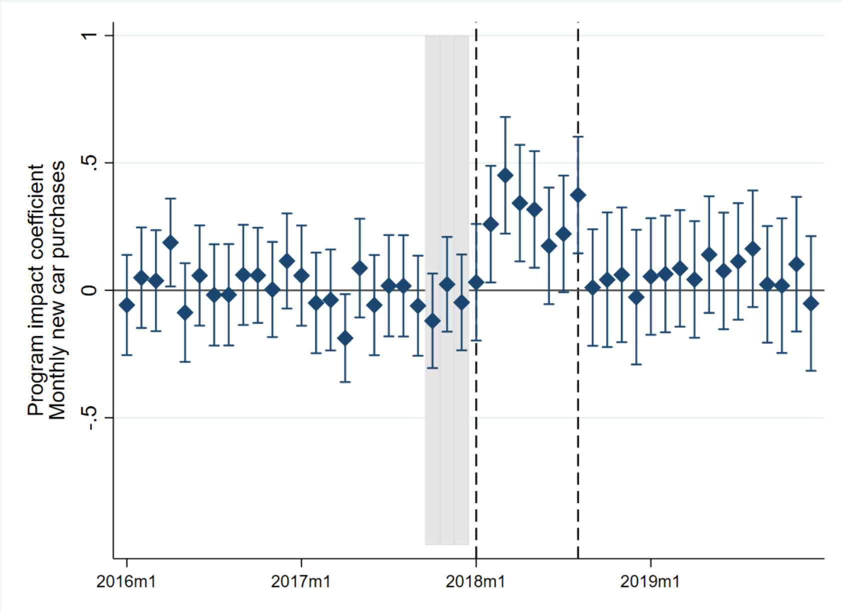


Figure 5: Program effect on monthly new car purchases.

Notes: The figure displays coefficient estimates for the impact of the program on monthly new car purchases from Equation (1). The dashed vertical lines mark the beginning and end of the program. The shaded region marks the potential anticipation period, the three months prior to the beginning of the program, starting from when the program bill was brought to parliament.

Intertemporal substitution could result in a negative program impact on purchases before or after the actual program period – any shifting of purchases to program months in order to benefit from the subsidy would mean reduced purchases in pre- and post-program periods. Estimating Eq.(1) separately for each month allows us to identify the program window as all the months within which the program had a statistically significant effect on new car purchases. That is, any months during which the program reduced purchases due to intertemporal shifts would also be included in the program window over which we expect the program to affect new car emission intensity.[15] The program bill was only introduced in October 2017, but we estimate Eq.(1) for all the months in our data, starting from January 2016, as this allows us to assess whether trends in car purchases in the two groups were parallel prior to the program.

Two results stand out from Figure 5. First, there is no statistically significant difference in the monthly car purchases in the treatment and control groups in the pre-program period. Therefore, assuming that absent the vehicle replacement subsidy program the two groups would have followed parallel trends in 2018 program months seems like a reasonable assumption. There is also no program effect in the potential anticipation period, from when the program bill was first

[15] Mian and Sufi (2012) and Li et al. (2013) used a similar approach.

brought to parliament in October 2017 till the onset of the program in January 2018. Second, once the program period begins, purchases in the treatment group increase substantially relative to those in the control group, albeit only starting in February 2018. The difference between the two groups disappears once the program ends in August 2018. Hence, the program window period during which the subsidy had an effect on new car purchases spans February 2018 – August 2018.

The finding that the vehicle replacement subsidy had no impact on auto purchases in post-program months contrasts with prior studies on the United States' 2009 Cars Allowance Rebate System (CARS), which documented negative intertemporal substitution effects in the months following the program's conclusion (see Mian and Sufi 2012, Li et al. 2013, and Hoekstra et al. 2017).[16] With a program period of eight months, Finland's vehicle replacement subsidy program was notably longer than the US CARS program, which only lasted two months. Given the longer program period, the Finnish program may have induced some auto purchases to be pulled forward from the very near future such that they also fell within the program period. Such short-run intertemporal substitution effects could be outweighed by the positive effects of the program in program months. Future reductions in auto purchases could also be spread out over a long period of time after the end of the subsidy program, making it difficult to detect the impact of the program in post-program periods (see House and Shapiro 2008).

Another possible explanation for the absence of intertemporal substitution effects is that the additional purchases in the program months might have come from the substitution of new cars for used cars. Appendix Figure B.1 displays coefficient estimates for the impact of the program on monthly used car purchases and Appendix Figure **??** repeats the analysis for used cars that were at most five years old, potentially closer substitutes for new cars than older used vehicles.[17] We do not find evidence that the positive program effect on new car purchases is driven by substitution away from used cars – the estimation results show no statistically significant program impact on used car purchases.

To identify the overall effect of the subsidy program on the quantity of new vehicles purchased, needed later to assess the additionality of the program, we estimate a cumulative version of Equation 1:

$$q_{amt}^{cum} = \alpha_{am} + \lambda_t + \delta_{mt} P_{mt} E_{amt} + \varepsilon_{amt}, \tag{2}$$

where q_{amt}^{cum} denotes the cumulative share of households in each car age group a (car age 10+, car age 5-9) who purchased a new vehicle between February of year t and month m of the same year. All other notation is as in Equation 1. We estimate Equation 1) for the February 2018 – August 2018 program window months and scale the cumulative new car purchase shares by the group-specific cumulative purchase shares in February 2017 – August 2017. The outcome variable then measures growth in cumulative purchases during the program window months relative to the same period in year 2017. The regression results, presented in Panel B of Appendix Table B.1, imply that the program increased relative new car purchases in the February 2018 – August 2018 program window period by 30 percentage points.

[16] In contrast, Houde and Aldy (2017), who examined the effects of energy efficiency rebates on household appliance purchases, found no pull-forward effects but estimated that some consumers waited a few weeks before replacing their current appliance in anticipation of the rebates becoming available.

[17] The results are similar for used cars that were at most three or at most four years old.

Figure 6 displays the trends in cumulative new car purchase shares in the treatment and control groups. The patterns in cumulative purchases are similar in the two groups prior to the onset of the program in January 2018. There is a notable relative increase in cumulative purchases in the treatment group during the program months that persists through the months following the end of the program in August 2018.

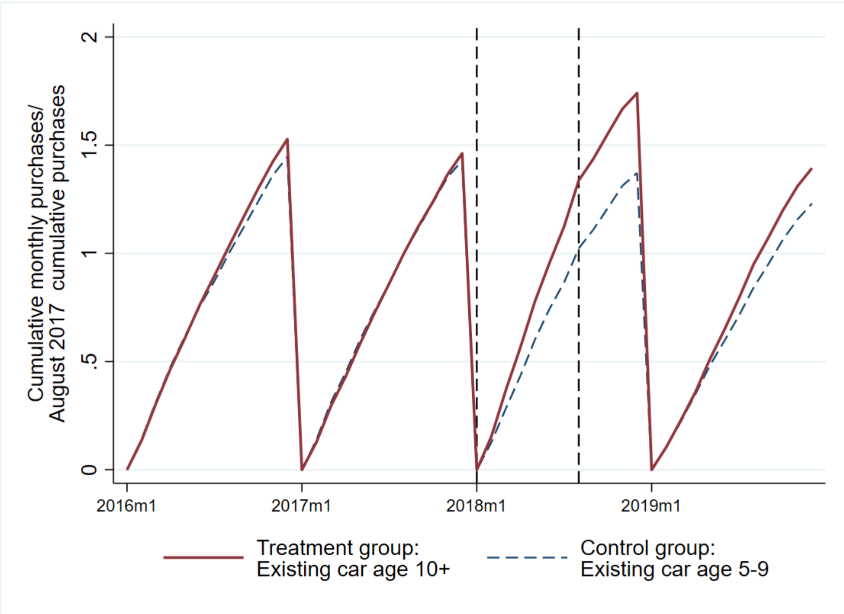


Figure 6: Cumulative new car purchases.

Notes: The figure shows the cumulative share of households in treatment and control groups who purchased a new car by a specific month of a year. The shares are scaled by the group-wise cumulative new car purchase shares in February 2017 – August 2017 to measure growth relative to cumulative purchases in year 2017 months that correspond to the 2018 program window months. The dashed vertical lines mark the beginning and end of the program.

5.2 New car CO_2 emission intensity

Our second outcome of interest is the effect of the vehicle replacement subsidy on the CO_2 emission intensity of new vehicles purchased. To analyze this outcome, we focus on households that purchased a new vehicle during the February 2018 – August 2018 program window period identified in Section 5.1, in a differences-in-differences design that compares new car buyer households whose oldest existing vehicle was at least 10 years old to those whose oldest vehicle was five to nine years old. We now use household-level data on new car emission intensities and car buyer household characteristics. Appendix Table B.2 shows summary statistics for the sample of households that purchased a new vehicle during the program window period. Altogether 19,891 new car buyer households were eligible for the vehicle replacement subsidy. Of them, 29 percent used the subsidy.

Figure 7 displays the trends in the CO_2 emission intensities of new cars purchased by households in the two groups. The vertical lines indicate the beginning and the end of the vehicle replacement subsidy program. The figure shows that new car buyer households in the subsidy-eligible group systematically bought cars with a lower CO_2 emission intensity than new car buyers in the control group. While the high-frequency data exhibit some month-to-month variation, the trends over time are similar across the two groups in the pre-program period, up to January 2018. When the program begins, the gap between the emission intensities of the two groups opens up. The fact that the change happens right when the program begins suggests that this effect is indeed program-driven.

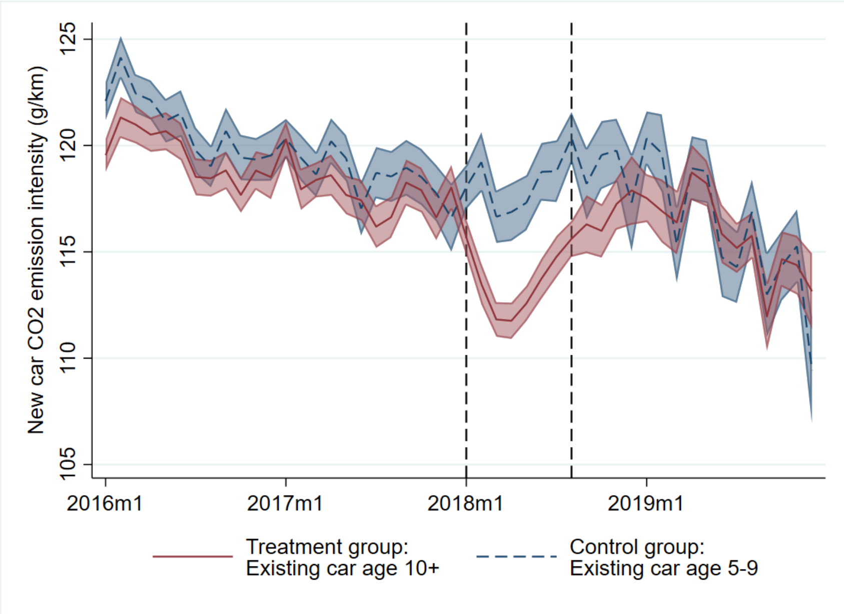


Figure 7: Trends in the CO_2 emission intensity of new cars.

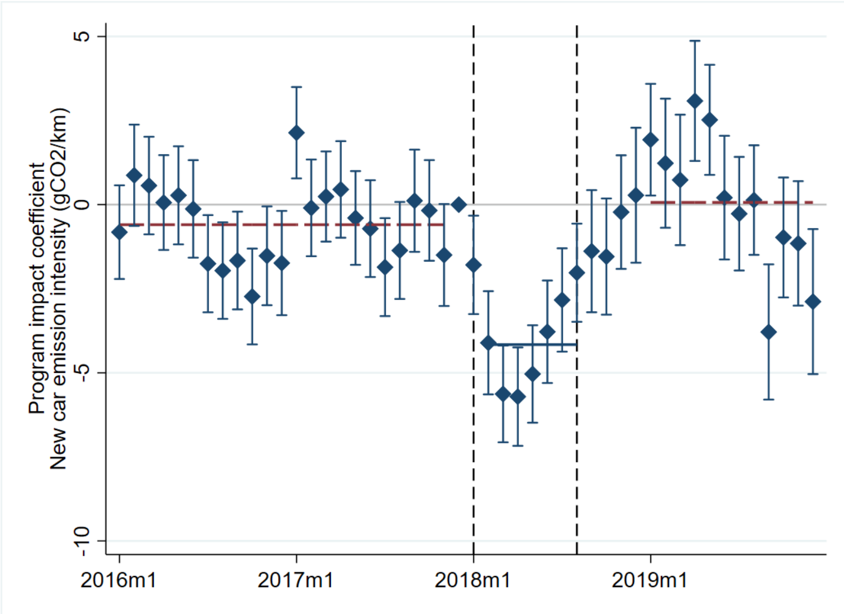
Notes: The figure displays the monthly mean CO_2 emission intensities (g/km) of new cars purchased by households in the treatment and control groups. The shaded area indicates the 95% confidence interval of the mean. The vertical lines mark the beginning and the end of the program.

Figure 8 presents the regression version of Figure 7. The figure shows coefficient estimates for program impact on new vehicle CO_2 emission intensity, by month, estimated using the following equation:

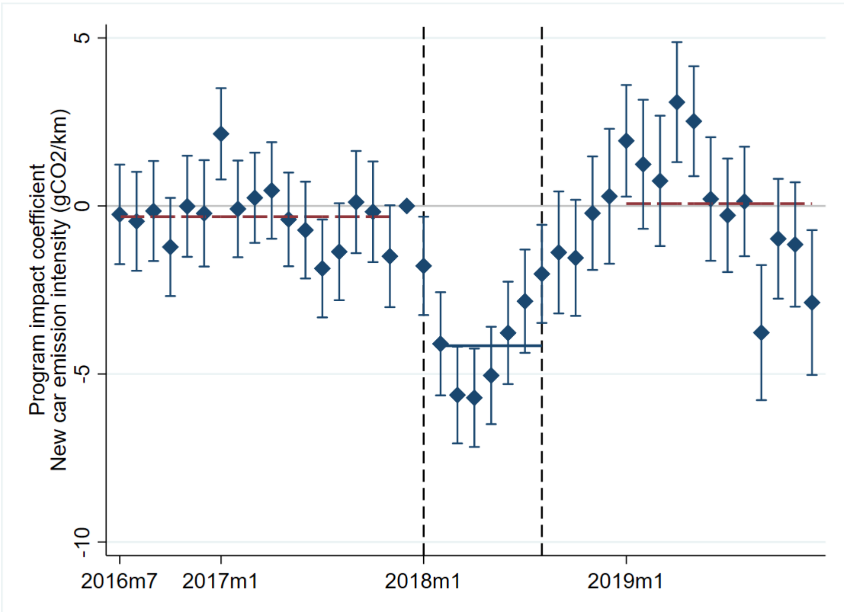
$$y_{iamt} = \alpha_a + \lambda_t + \delta_{mt} P_{mt} E_{imt} + \boldsymbol{\beta} \boldsymbol{X}'_{it} + \varepsilon_{iamt}. \tag{3}$$

The dependent variable y_{iamt} is the emission intensity of a new vehicle purchased by household i with an existing car in age group a (car age 10+, car age 5-9) in month m and year t. On the right-hand side, α_a are group fixed effects that control for time-invariant observed and unobserved vehicle attribute preferences by households with relatively old versus new cars, and λ_t are year fixed effects to capture trends in vehicle attributes and emission intensity. Coefficient δ_{mt} on the term $P_{mt}E_{imt}$ measures the effect of the program on new vehicle emission intensity, with P_{mt} taking on value one for months in the February 2018 – August 2018 program window period identified in Section 5.1. Controls in $\boldsymbol{X}'_{it}$ include household disposable income, number of cars, and annual vehicle kilometers driven.

Panel (a) in Figure 8 uses data for the period January 2016 – December 2018. The dashed red line depicts the average of the pre-program coefficients and the solid blue line the average of the program window coefficients. January 2018 is not included in either average. While the program officially began in that month, the results in Section 5.1 are most in line with no significant program impact on new car purchases in the first official program month, possibly due to delays between new car purchases and registrations. Some of the coefficients for the pre-program period in Figure 8 are statistically different from zero, which is not surprising given the high-frequency household-level vehicle registration data used in the estimation. But the average of the program-window coefficients is considerably smaller in absolute terms than that of the pre-program coefficients.



(a) Full sample



(b) Shorter sample

Figure 8: Program impact on new car CO_2 emission intensity.

Notes: The figure displays regression coefficients for leads and lags of program effect on new car CO_2 emission intensity (g/km). Panel (a) includes vehicle registrations from January 2016 onward, panel (b) excludes January 2016 – June 2016 vehicle registrations. The dashed red line depicts the average of the pre-program coefficients and the solid blue line the average of the program window coefficients, with January 2018 excluded. The vertical lines mark the beginning and the end of the program.

A potential explanation for some of the pre-program coefficients diverging from zero is also the previous vehicle replacement subsidy program implemented in 2015, which ended in December 2015. Due to delays between new vehicle purchases and registrations, new vehicle registrations in early 2016 could include some vehicles purchased under the previous subsidy program. To address potential bias due to lingering effects of the previous program, we also present results from a specification that excludes the first six months of 2016. Panel (b) in Figure 8 shows coefficient estimates for program impact by month for this shorter sample. Here, the average of the pre-program coefficients is very close to zero. Overall, the evidence shows that the vehicle replacement subsidy program was successful in reducing new vehicle CO_2 emission intensity.

Table 3 provides regression estimates of the average program effect, obtained by estimating a differences-in-differences specification corresponding to Equation (3). The full sample includes vehicles registered during January 2016 – August 2018 and the shorter sample vehicles registered during July 2016 – August 2018. Columns (1) and (3) show estimates from two-way fixed effects regressions of new vehicle CO_2 emission intensity on indicators for program eligibility, program window months, and their interaction. Columns (2) and (4) display estimates from regressions that add household income, number of cars, and annual vehicle kilometers driven as controls.

In Column (1), the vehicle replacement subsidy reduces new car CO_2 emission intensity by 3.61 g/km, a precisely estimated effect with a standard error of 0.34 g/km. Column (2) shows that adding the control variables has virtually no impact on the treatment effect estimate. Column (3) shows that the estimated program impact increases to approximately -3.84 g/km when the first six months of 2016 are excluded. Thus, excluding the six months following the previous subsidy program that ended in December 2015 changes the estimates only slightly. Adding controls again has virtually no impact on the estimated program effect. In terms of magnitude, the estimates in Columns (1) to (4) all translate into a decrease of about 3 percent in the emission intensity of new cars purchased by subsidy-eligible individuals.

Table 3: Effect of vehicle replacement subsidy on new car CO_2 emission intensity

	Full sample		**Shorter sample**	
Coefficient	(1)	(2)	(3)	(4)
Eligible x program window	-3.606***	-3.564***	-3.844***	-3.806***
	(0.343)	(0.343)	(0.357)	(0.357)
Eligible	-1.237***	-1.874***	-0.999***	-1.616***
	(0.150)	(0.156)	(0.180)	(0.186)
Year effects				
2017	-1.967***	-1.977***	-0.678***	-0.691***
	(0.148)	(0.148)	(0.181)	(0.181)
2018	-2.731***	-2.760***	-1.310***	-1.339***
	(0.287)	(0.287)	(0.311)	(0.311)
Constant	120.964***	118.864***	119.544***	117.643***
	(0.130)	(0.199)	(0.177)	(0.247)
Controls	No	Yes	No	Yes
Observations	107 868	107 868	85 787	85 787

Notes: The table presents regression coefficients from estimating a differences-in-differences version of Equation 3 on household-level data. The full sample includes vehicles registered during 1/2016-8/2018 and the shorter sample vehicles registered during 7/2016-8/2018. The program window variable takes on the value of one for 2/2018-8/2018, with 1/2018 excluded. The coefficient on Eligible x program window measures the average program effect (intention-to-treat). The controls include household income (total earned income and benefits net of taxes and transfers), number of cars, and annual vehicle kilometers driven. Heteroscedasticity-robust standard errors are reported in parentheses. * indicates $p < 0.05$, ** indicates $p < 0.01$, and *** indicates $p < 0.001$.

The estimates in Table 3 are intention-to-treat estimates. In order to assess the average treatment effect on the treated, we scale the intention-to-treat estimates by the program take-up rate, 29 percent for February 2018–August 2018. The subsidy induced participating households to choose a car with a CO_2 emission intensity on average 12.3 g/km (e.g., 3.564/0.29 g/km) lower than that of the counterfactual vehicle they would have purchased otherwise. In percentage terms, the scaled estimate corresponds to an about 11 percent reduction in the emission intensity of new cars purchased by subsidy-receiving households. Thus, the vehicle replacement subsidy significantly reduced the CO_2 emission intensity of new cars purchased by subsidy recipients.[18]

[18]To complement this analysis, Appendix Table B.3 shows two-stage least squares estimates of the effect of the vehicle replacement subsidy on new car CO_2 emission intensity. At 18.9 and 19.8 g/km (without controls and with controls, respectively), the two-stage least squares estimates are slightly larger than the values obtained by scaling the differences-in-differences estimates by the subsidy take-up rate, but of a similar magnitude.

5.3 Robustness checks

Sensitivity to vehicle owner cohorts included in the control group. The analysis presented above is based on comparing vehicle purchases in the program-eligible group of households with vehicles of at least 10 years of age to a control group of households with vehicles of five to nine years of age. We do not include households whose oldest vehicle was less than five years old in the control group in the main analysis because the propensity to purchase a new vehicle is notably higher in these cohorts than in those with vehicles five to nine years or at least 10 years old (see Table 2). In this section, we test the robustness of our main results on new car purchases and CO_2 emission intensity to the choice of which vehicle owner cohorts are included in the control group. We consider two alternative control groups: households with vehicles one to nine years old, and households with vehicles eight to nine years old.

Columns (2) and (3) of Table B.4 show that the results are robust to alternative choices concerning the control group. The program window period during which the vehicle replacement subsidy had a discernible effect on new car purchases does not change. The effects of the program on cumulative new car purchases and new car CO_2 emission rates are similar to our main analysis, although the smaller control group of households with eight- to nine-year-old vehicles reduces precision in the estimated effect on CO_2 emission intensity some.

Sensitivity to month of year when treatment and control groups are redefined. Our analysis period spans several years. In order to consistently compare households whose oldest car was at least 10 years old to households whose oldest car was newer, we redefine the treatment and control groups each year. Next, we test the robustness of our results to changing the time at which the treatment and control groups are redefined from January to July. The treatment and control groups are now fixed for each 12-month period from July to June of the following year. The treatment group includes households whose oldest car was at least 10 years old on June 30th, and the control group households whose oldest car was five to nine years old on that date. Households whose cars reached the program-eligible age of 10 years during the second half of 2017 are excluded from the analysis for the first half of 2018. Column (4) of Table B.4 shows that the results are almost identical to the results obtained when the treatment and control groups are redefined at the beginning of each year. As Table 3 demonstrates, the results are also robust to the inclusion of controls and to considering a shorter sample of vehicles registered during 7/2016–8/2018.

6 Effect heterogeneity by car and household characteristics

The effectiveness and perceived distributional impacts of climate policies have been found to be major predictors of policy support (Dechezleprêtre et al., 2025). Whether and how the effect of vehicle replacement subsidies varies across vehicle attributes and households is thus an important question from the perspectives of both public spending and the acceptability of climate policy. Could the effectiveness of vehicle replacement subsidies in reducing emissions be improved by linking them to current vehicle attributes? Do responses to vehicle replacement subsidies differ across the socioeconomic or urban-rural continuums? Having population-level data for individuals, households, and vehicles allows us to examine heterogeneity in the effects of vehicle replacement subsidies in ways that have not been possible in other related work prior to this point. We study heterogeneity in responses to the program along the following dimensions: current vehicle CO_2 emissions; household income, annual vehicle kilometers driven, number of cars, and residence location (urban or rural); and vehicle owner education.[19] Unfortunately, while we observe the CO_2 emission intensities of new vehicles, the information is missing for about 30 percent of the old vehicles in the data. We impute the missing CO_2 emission intensities based on fuel type (9 categories), make and model, registration year, weight, and cylinder volume.[20]

Panel (a) in Figure 9 summarizes the effect of the program on cumulative new car purchases by household current vehicle attributes and household characteristics. The estimates in panel (a) come from a triple difference version of Equation (2), estimated on aggregate data split into subgroups g by each household characteristic separately:

$$q^{cum}_{agmt} = \alpha_{am} + \lambda_t + \boldsymbol{G'_g}\gamma_1 + \gamma_2 P_{mt}E_{amt} + P_{mt}\mathbf{G'_g}\boldsymbol{\gamma_3} + E_{amt}\boldsymbol{G'_g}\gamma_4 + P_{mt}E_{amt}\boldsymbol{G'_g}\boldsymbol{\gamma_5} + \varepsilon_{agmt}, \quad (4)$$

where $\mathbf{G'_g}$ is a vector of group indicators for the heterogeneity dimension analyzed (for example, household's income group) and all other variables are as previously defined. We estimate Equation (4) for the February 2018 – August 2018 program window period and scale the cumulative new car purchase shares by the group-specific cumulative purchase shares in February 2017 – August 2017, to measure growth in overall purchases.[21] The coefficients in vector $\boldsymbol{\gamma_5}$ measure how the impact of the program on cumulative new car purchases in group g differs from that in the baseline group. With three subgroups, these regressions are based on 120 aggregate observations, and with two subgroups, on 80 aggregate observations.

Panel (b) in Figure 9 shows the effect of the program on new car CO_2 emission intensity by household current vehicle attributes and household characteristics. For easier comparison of panels (a) and (b), we flip the sign of the emission intensity effect so that a more positive outcome is better in terms of reaching program objectives. The estimates in panel (b) come from a triple difference version of Equation (3), estimated on household-level data:

$$\begin{aligned} y_{iagmt} = {} & \alpha_a + \lambda_t + \mathbf{G'_g}\boldsymbol{\gamma_1} + \gamma_2 P_{mt}E_{imt} + P_{mt}\mathbf{G'_g}\boldsymbol{\gamma_3} + E_{imt}\boldsymbol{G'_g}\gamma_4 \\ & + P_{mt}E_{imt}\boldsymbol{G'_g}\boldsymbol{\gamma_5} + \boldsymbol{\beta X'_{it}} + \varepsilon_{iagmt}, \end{aligned} \quad (5)$$

where $\mathbf{G'_g}$ is a vector of indicators for household i's group along the heterogeneity dimension

[19] The kilometers traveled for each vehicle are calculated using odometer readings from the two latest mandatory vehicle inspections. Household vehicle kilometers driven sum up the kilometers for all of a household's vehicles.

[20] To predict the missing CO_2 emission intensities, we use data for cars whose emission intensities are observed and regress CO_2 emission intensity on dummies for fuel type, make and model, registration before 2008 (year when the legislative proposal for EU CO_2 emission standards was negotiated); and linear controls for weight, cylinder volume, and registration year, as well interactions between the variables. The model produces CO_2 emission intensity estimates with a correlation of 0.94 between predicted and observed values for the sample of cars whose CO_2 emission intensities are observed.

[21] We first estimate a triple difference version of Eq. (1) for each heterogeneity dimension and each month from January 2016 to December 2019 to examine whether there are between-group differences in the program window period. The results (not shown) indicate that in each group along each heterogeneity dimension the program increases new car purchases starting February 2018 and that the effect disappears once the program ends in August 2018.

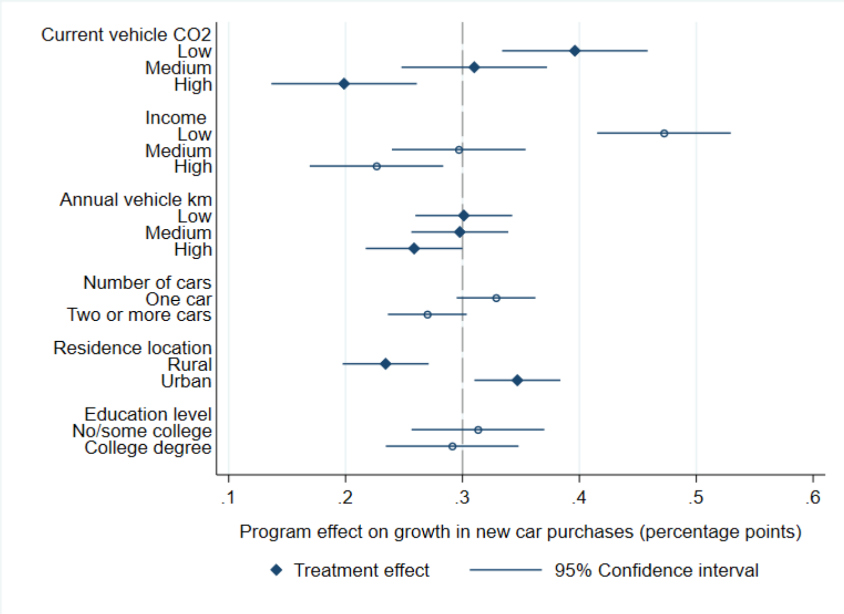
analyzed, P_{mt} equals one for months in the February 2018 – August 2018 program window period, and all other notation is as previously defined. The controls in $\boldsymbol{X}'_{it}$ are household disposable income, number of cars, and annual vehicle kilometers driven, with existing vehicle CO_2 emissions added when examining heterogeneity along this dimension. We estimate Equation (5) using the full sample of vehicles registered January 2016 – August 2018.

The results in panel (a) of Figure 9 indicate that the vehicle replacement subsidy increased new car purchases across all groups along all the heterogeneity dimensions examined. But the magnitude of the program effect differs across groups along several heterogeneity dimensions. Households with relatively low CO_2 emission-intensity vehicles responded significantly more to the program than households with high-emission vehicles. Households in the lowest income group also responded more to the program than households in the middle- or high-income groups. The differences are smaller in magnitude but statistically significant for households with one car versus several cars or in urban versus rural locations. In contrast, the results for households with different kilometers driven per year or education levels are not statistically different from each other. The results in panel (b) of Figure 9 for program effect on new car emission intensity are qualitatively different from those for program effect on new car purchases, in that the between-group differences are not statistically significant at conventional levels.

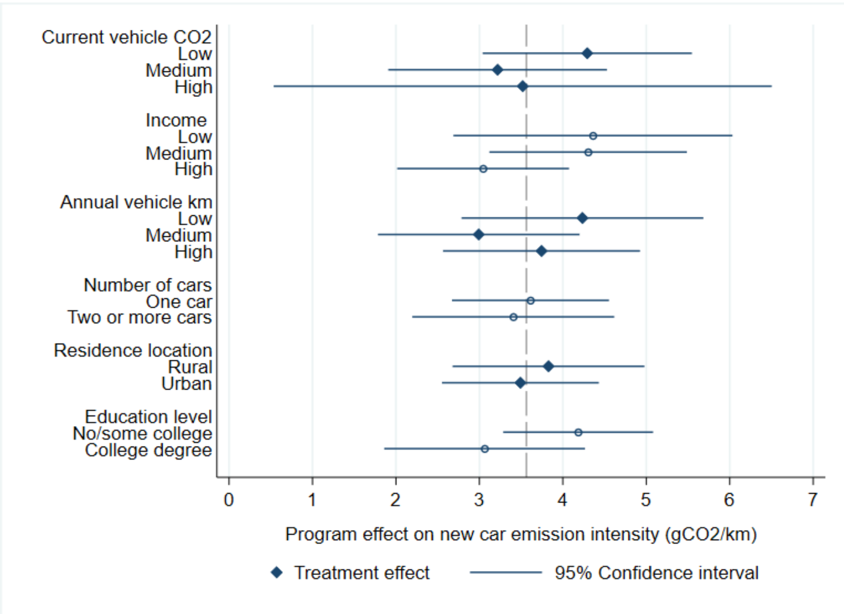
The regression results for program effects across vehicle and household subgroups, including p-values for the null of equal effects across groups, are collected in Table 4. The new car CO_2 emission intensity estimates in Figure 9, panel (b) are intention-to-treat estimates. Column (7) shows subsidy take-up by subgroup and column (8) scales the intention-to-treat estimates by take-up. While the take-up rates differ some across groups along several heterogeneity dimensions, scaling the intention-to-treat estimates by groupwise take-up rates does not change the finding of no significant differences across groups.

Do differences in the effects of the program on new car purchases across current vehicle CO_2 emission rates or the socioeconomic or rural-urban spectrums translate into differences in the cost-effectiveness of subsidies? Could targeting reduce the costs of vehicle replacement subsidies as a tool to reduce CO_2 emissions?[22] Could they be used as a social cushioning measure to lighten the burden of carbon taxes on rural or low-income households? The next section evaluates the cost-effectiveness of Finland's 2018 vehicle replacement subsidy in reducing CO_2 emissions overall and assesses the magnitude of differences in cost-effectiveness across current vehicle and household characteristics.

[22]See Linn (2020) for computational modeling of hypothetical vehicle scrappage schemes showing that tying the subsidy amount to scrapped vehicles' estimated future emissions could significantly reduce costs.



(a) New car purchases



(b) New car CO_2 emission intensity

Figure 9: Program impact on new car purchases and CO_2 emission intensity by subgroup.

Notes: The figure collects results from estimating Equations (4) and (5) by the heterogeneity dimensions indicated on the vertical axes. The dashed vertical lines in each panel show the overall average program effects.

Table 4: Program effects by vehicle and household subgroups

	Effect on new car purchases			**Effect on new car emission intensity (full sample)**						
	Estimate	P-value gr2=gr1 gr3=gr1	P-value gr3=gr2	Estimate	P-value gr2=gr1 gr3=gr1	P-value gr3=gr2	Take-up rate	Scaled estimate	P-value gr2=gr1 gr3=gr1	P-value gr3=gr2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Average effect	0.30			-3.56			0.30	-12.87		
Effect by subgroup										
Current vehicle CO_2										
Low	0.40			-4.29			0.42	-10.31		
Medium	0.31	0.04		-3.22	0.25		0.33	-9.76	0.83	
High	0.20	0.00	0.01	-3.52	0.64	0.86	0.24	-14.77	0.50	0.45
Income										
Low	0.47			-4.36			0.46	-9.40		
Medium	0.30	0.00		-4.30	0.96		0.31	-14.03	0.09	
High	0.23	0.00	0.07	-3.04	0.19	0.12	0.25	-12.20	0.32	0.53
Annual vehicle km										
Low	0.30			-4.24			0.33	-12.82		
Medium	0.30	0.90		-2.99	0.20		0.30	-10.12	0.38	
High	0.26	0.13	0.16	-3.74	0.61	0.38	0.26	-14.39	0.63	0.17
Number of cars										
One car	0.33			-3.61			0.36	-9.91		
Two or more	0.27	0.01		-3.40	0.79		0.25	-13.83	0.17	
Residence location										
Rural area	0.23			-3.83			0.26	-14.45		
Urban area	0.35	0.00		-3.49	0.66		0.33	-10.62	0.15	
Education level										
No/some college	0.31			-4.18			0.30	-14.04		
College degree	0.29	0.55		-3.06	0.14		0.32	-9.58	0.07	

Notes: The table shows results from estimating triple difference specifications (4) and (5) with heteroskedasticity-robust standard errors. The estimation of the effect on new car CO_2 emission intensity uses the full sample of new car purchases in the period 1/2016-8/2018. Take-up rates are calculated from new car purchases and subsidy uptake in the population of subsidy-eligible households in each subgroup. Scaled estimates are obtained by dividing the estimated program effects in Column (4) by the take-up rates in Column (7). Take-up rates are considered constants when calculating the p-values for equal scaled program effects across groups. The results on new car purchases with three subgroups are based on 120 aggregate observations, those with two subgroups on 80 aggregate observations. The results on new car CO_2 emission intensity are based on 107 868 household-level observations.

7 Cost-effectiveness of the vehicle replacement subsidy

How much is society paying to reduce CO_2 emissions when using vehicle replacement subsidies as a policy tool? The European Union's Fit for 55 climate package sets binding national targets for CO_2 emission reductions in sectors that are not covered by the union's energy and manufacturing sectors' emissions trading system. For many countries, including Finland, road transport is the largest of these sectors. Understanding the costs of emission reductions achieved by vehicle replacement subsidies can help improve the efficacy of policies aiming to change consumer behavior and mitigate climate change.

The vehicle replacement subsidy program affected CO_2 emissions through two channels. First, the program caused some households to pull forward the replacement of an old, relatively emission-intensive vehicle. Second, the program caused some households to purchase a lower-emission-intensity new vehicle than they would have bought otherwise. We examine the two channels based on our estimation results and some simplifying assumptions. The main assumption is that the program did not increase the overall number of vehicles in the vehicle fleet. If the program increased the number of vehicles, our analysis would overestimate the environmental benefits.

We proceed by evaluating the overall emission reductions that can be attributed to vehicle replacements by households that used the subsidy. However, not all subsidy recipients purchased a new vehicle because of the subsidy - some would have replaced their existing vehicle during the program window period anyway, in which case their new vehicle purchases were not additional. We therefore adjust the overall emission reduction estimate for additionality.

7.1 Emission reductions produced by the subsidy

To assess overall CO_2 emission reductions attributable to the subsidy, we compare emissions in actual (with the program) and counterfactual (without the program) scenarios. The actual emissions of the new vehicles purchased by subsidy recipients are given by

$$CO_2 = \sum_j y_j^{NEW} \cdot VKT_j^{NEWlife} \tag{6}$$

where j indexes subsidy recipient households and y_j^{NEW} is the CO_2 emission intensity and and $VKT_j^{NEWlife}$ the lifetime vehicle kilometers (VKT) of the new vehicle purchased by household j.

Counterfactual emissions consist of two components – the emissions that would have been produced over the remaining lifetime of the vehicles scrapped under the program, and the emissions produced by new vehicles eventually purchased to replace them. We calculate the counterfactual emissions as follows:

$$\widetilde{CO}_2 = \sum_j z_j^{OLD} \cdot VKT_j^{OLDremain} + \sum_j \widetilde{y}_j^{NEW} \cdot \widetilde{VKT}_j^{NEWcf}, \tag{7}$$

where z_j^{OLD} is the CO_2 emission intensity of the vehicle that household j scrapped under the program and $VKT_j^{OLDremain}$ its remaining lifetime kilometers. The emission intensity of the counterfactual new vehicle that household j would eventually have purchased to replace the clunker is denoted by $\widetilde{y}_j^{NEW}$ and the vehicle kilometers attributed to it in the counterfactual scenario by $\widetilde{VKT}_j^{NEWcf}$. To assess household j's counterfactual and actual emissions over the same horizon of vehicle kilometers driven, we account for the kilometers of the counterfactual new vehicle only to the point where the total of the remaining kilometers of household j's scrapped vehicle and the kilometers of its counterfactual new vehicle sum up to the lifetime kilometers of the actual new vehicle purchased under the program. That is, $\widetilde{VKT}_j^{NEWcf} = VKT_j^{NEWlife} - VKT_j^{OLDremain}$.

We predict the lifetime kilometers of household j's new and scrapped vehicles from a survival model estimated on vehicle-level data for the Finnish car fleet in years 2013-2020. A unique feature of the data is that we observe odometer readings for vehicles removed from the fleet, which allows us to estimate a survival model with lifetime kilometers as the outcome variable and vehicle make and model, weight, and fuel type (diesel or gasoline) as covariates. Appendix C.1 provides details of the survival model estimation. We do not explicitly consider rebound effects in the cost-effectiveness analysis, but including vehicle weight, make, and model in the survival model and the prediction of vehicle lifetime kilometers in part accounts for the association of lower emission rates with higher lifetime vehicle kilometers, due to higher fuel efficiency and lower fuel cost per kilometer of travel. We observe the emission intensities of the new vehicles, whereas emission rates are missing for about 50 percent of the scrapped vehicles. We impute the missing values based on fuel type, make and model, registration year, weight, and cylinder volume (see footnote 20). The remaining lifetime kilometers of household j's scrapped vehicle are calculated as the difference between the vehicle's predicted lifetime kilometers and its last odometer reading. The emission rate of household j's counterfactual new vehicle is obtained by summing up the observed emission intensity of the new vehicle purchased under the program and the negative of the estimated program effect on new car CO_2 emission intensity. The CO_2 emission reductions attributable to subsidized vehicle replacements are given by the difference between the objects in Equations (7) and (6), $\widetilde{CO_2} - CO_2$.

Additionality To address additionality, we use the estimation results on program effect on cumulative new car purchases and determine the number of cars that would have been purchased by the treatment group without subsidies. We then calculate additional new car purchases as the difference between the observed new car purchases and the counterfactual new car purchases over the program window period February 2018 – August 2018. Additionality refers to the ratio of additional new car purchases to subsidized transactions.

Co-pollutants Road transport is also a significant source of nitrogen oxide, carbon monoxide, and particulate matter emissions (i.e., NO_x, CO, and PM). The vehicle registry data include NO_x and CO emission rates for new cars. We use this information to estimate Equation 3 with NO_x and CO emission rates as outcome variables. The results are most in line with no important effects on the new-car emission rates of these pollutants (see Appendix Table C.1). Unfortunately, NO_x and CO emission rates are missing for about 40 percent of the scrapped vehicles. We use the EU exhaust emission limits for the vehicle's first registration year to proxy missing NO_x and CO emission rates. As the vehicle registry includes PM emission rates only for a subset of cars, we are unable to assess program effects on PM emissions.[23] For the monetary measure of co-benefits, we include only the damage cost of NO_x, for which we use the estimate for Finland provided by the European Commission, 3.5 €/kg (see the report by DG MOVE, 2020). CO concentrations in Finland are well below the European ambient air quality standard, so the adverse effects are likely to be limited.[24]

7.2 Cost-effectiveness overall and by heterogeneity dimensions

Table 5 presents the results for the cost-effectiveness of CO_2 emission reductions, both overall and by household subgroups for the heterogeneity dimensions for which Section 6 indicated between-group differences in program effects. The analysis uses the estimation results from the full sample of vehicles registered January 2016 – August 2018. Column (1) reproduces the subsidy take-up rates. Column (2) reports the additionality of the subsidy overall and by subgroup along each heterogeneity dimension. The results indicate that 66 percent of subsidized purchases were additional overall. This is somewhat higher than estimates from other comparable programs: a little over 40 percent reported by Hoekstra et al. (2017) and 55 percent by Li et al. (2013) for the CARS program in the United States, and 46 percent by Boomhower and Davis (2014) and 30 percent by Houde and Aldy (2017) for appliance energy efficiency programs in Mexico and the United States.[25] Only one heterogeneity dimension stands out in terms of differences in additionality across household subgroups: while 60 percent of subsidized purchases were additional among one-car households, the rate was 74 percent for households with two or more cars.[26]

Column (3) in Table 5 shows the reduction in total CO_2 emissions attributable to the subsidy and Column (4) the fiscal cost of a per ton CO_2 emission reduction. Emission reductions are calculated using the scaled estimates for the program's effect on new car emission intensity (see Table 4) and adjusted for additionality. The reduction in overall CO_2 emissions is approximately 36,000 metric tons, representing about 14 percent of the counterfactual emissions of subsidy recipients. The reductions in NO_x and CO due to earlier scrappage are 28 tons and 234 tons, or about 54 percent and 45 percent of the counterfactual emissions, respectively. The overall cost of CO_2 emission reductions is estimated at €184/tCO_2 without co-benefits; incorporating the NO_x reduction co-benefit lowers the cost only marginally, to €182/tCO_2. These estimates

[23] EU emission limits for PM only apply to diesel vehicles and to gasoline vehicles with a direct injection engine. PM emissions are not part of the EU vehicle type approval for other engine types and are hence not recorded in the vehicle registry. PM emission rates are missing for about 40 percent of new and over 90 percent of used gasoline cars.

[24] The European ambient air quality standard for maximum 8-h average CO is 10 mg/m^3. The measures for Finland closest to the program period are for 2019. Average CO concentrations varied between 0.160 and 0.164 mg/m^3 and maximum concentrations between 0.281 and 0.355 mg/m^3 (Komppula et al., 2021).

[25] The additional purchases found by Hoekstra et al. (2017) and Li et al. (2013) were concentrated in the program months, with no net gain over a longer horizon comprising pre- and post-program months. Houde and Aldy (2017) find that about 70 percent of rebate recipients would have purchased a qualifying appliance during the rebate period even in the absence of rebates and that an additional 15-20 percent of the rebate recipients only changed the timing of a purchase they planned to make anyway. Boomhower and Davis (2014) estimate that the proportion of inframarginal participants varies across pre-program energy consumption thresholds that assign different subsidy amounts, while 54 percent of participants would have replaced their appliances even with no subsidy whatsoever.

[26] Note that as counterfactual purchases overall and by subgroups are predicted from different models, groupwise counterfactual purchases do not sum precisely to overall counterfactual purchases. The average of the groupwise values of additionality and CO_2 emission reductions obtained may thus differ from the overall values.

Table 5: Cost-effectiveness analysis

	Take-up rate	Additional transactions (share)	Total CO_2 reductions (tons)	Cost CO_2 reductions (€/tCO_2)	CO_2 reductions (tons) – from scrapped vehicles	– from new vehicles
	(1)	(2)	(3)	(4)	(5)	(6)
Overall results	0.30	0.66	35,644	184	22,193	13,451
Results by subgroups						
Current vehicle CO_2						
Low	0.42	0.61	4,277	322	2,597	1,680
Medium	0.33	0.62	14,081	207	9,204	4,877
High	0.24	0.58	13,618	166	8,380	5,238
Income						
Low	0.46	0.63	6,594	241	4,786	1,808
Medium	0.31	0.66	10,092	194	6,316	3,776
High	0.25	0.64	17,264	172	10,246	7,018
Residence location						
Rural area	0.26	0.62	11,694	207	6,435	5,259
Urban area	0.33	0.69	23,394	175	15,843	7,550
Number of cars						
One car	0.36	0.60	15,350	212	10,667	4,683
Two or more	0.25	0.74	19,943	158	11,200	8,744

Notes: The table is based on estimation results from the full sample of vehicles registered January 2016 – August 2018. Analysis by subgroups is presented for the heterogeneity dimensions for which the results in Section 6 indicate between-group differences in program effects. Additional transactions refer to the ratio of additional new car purchases to subsidized transactions. Only additional vehicle replacements are accounted for when calculating CO_2 emission reductions. Columns (5) and (6) split the total CO_2 emission reductions into those generated by earlier scrappage of vehicles, and those attributable to lower emission rates of new replacement vehicles. Both actual and counterfactual emissions for each household are calculated over the predicted lifetime kilometers of the new vehicle purchased under the program. Co-benefits from reduced NO_x emissions are not reported due to the relatively small monetary benefit.

are similar in magnitude to those reported for the US CARS program by Li et al. (2013), \$260/tCO_2 without co-benefits and \$247/tCO_2 with co-benefits. They are somewhat smaller than the estimate for Mexico's appliance replacement program reported by Davis et al. (2014), which exceeds \$500/tCO_2.[27] More than half of the CO_2 emission reductions attributable to the vehicle replacement subsidy come from replacing old, relatively emission-intensive vehicles with new, lower emission rate vehicles, rather than from the program-induced reduction in the emissions of the replacement vehicles (Columns (5) and (6)).

The results by subgroups reveal significant heterogeneity in the cost-effectiveness of the subsidy in reducing CO_2 emissions. A key finding concerns the potential gains from targeting subsidies based on current vehicle attributes. Economic theory predicts that targeted subsidies can be more cost-effective than uniform ones, and our results provide empirical support for this prediction. The fiscal cost per ton of CO_2 mitigated is nearly 50 percent lower among households with high-emission vehicles than among those with low-emission vehicles - despite the fact that the high-emission group responded less strongly to the program in terms of new car purchases. This suggests that removing some of the most polluting vehicles from the fleet can improve cost-effectiveness, even when behavioral responses are relatively modest among owners of high-emission vehicles. Once differences in take-up (column (1) in Table 5) are accounted for, both the counterfactual emissions from the remaining lifetime of the scrapped vehicles and the program-induced reduction in the emissions of their replacements are notably larger in the high-emission subgroup than in the low-emission subgroup (columns (5) and (6)). The differences across subgroups are less pronounced – but still substantial – along income, rural–urban, and household vehicle count dimensions. The cost per ton of CO_2 mitigated in the high-income subgroup is about 30 percent lower than in the low-income subgroup, and about 16 percent lower in urban areas than in rural areas. Hence, targeting by income or location could also improve cost-effectiveness, though to a lesser extent.

Table 6, column (1) shows how the emission reductions generated by the vehicle replacement subsidy were distributed across subgroups. Along the income dimension, about 50 percent of the program-induced emission reductions accrued to the high-income group. Along the rural-urban dimension, nearly 70 percent were realized in urban areas. Column (2) presents group-wise emission reductions in per capita terms, accounting for differences in subgroup size. The disproportionate share of reductions accruing to high-income and urban subgroups persists even after adjusting for the number of car-owning households in each group.

The finding that emission reductions were skewed toward high-income and urban subgroups suggests that a uniform vehicle replacement subsidy may not be well suited to cushioning the potential regressive effects of other climate policies, such as carbon taxes. In this case, high-income and urban households benefited disproportionally through greater reductions in emissions – and thus in carbon tax payments. A likely explanation is that eligibility for the subsidy was conditional on purchasing a new vehicle. Column (3) shows the share of car-owning households in each subgroup that purchased a new car in the pre-program year 2017. New car purchases were far more common in the high-income subgroup than in the low-income subgroup. The difference between urban and rural households is smaller, but follows a similar pattern. Conditioning

[27] These comparisons are illustrative and not adjusted for exchange rates or inflation, as the purpose is to compare orders of magnitude rather than exact values.

Table 6: Distributional analysis

Heterogeneity dimension and subgroup	Distribution of emission reductions		New car buyers 2017
	Share of total	Per capita (kg)	Share in subgroup
	(1)	(2)	(3)
Existing vehicle CO_2			
Low	0.13	7	0.058
Medium	0.44	24	0.034
High	0.43	23	0.025
Income			
Low	0.19	11	0.020
Medium	0.30	17	0.040
High	0.51	29	0.071
Residence location			
Rural area	0.33	15	0.037
Urban area	0.67	24	0.048
Number of cars			
One car	0.43	12	0.034
Two or more	0.57	38	0.050

Notes: Column (1) shows how the total program-induced emissions reductions were distributed across subgroups. The shares were calculated using the results from column (3) in Table 5. Column (2) divides the emissions reductions in column (3), Table 5 by the number of car owner households in each subgroup. Column (3) shows descriptive statistics for the share of car-owning households that bought a new car in the last pre-program year 2017.

subsidy eligibility on new car purchases may limit the usefulness of vehicle replacement subsidies as a tool for mitigating the distributional impacts of other climate policies.

8 Conclusion

Vehicle replacement subsidies are a commonly used policy tool to reduce vehicle fleet emission intensity and road transport emissions. Yet whether these policies could be made more cost-effective through targeting, and whether they could help cushion the potential regressive effects of other climate policies, remains empirically underexplored. This paper examines the impact of a vehicle replacement subsidy program implemented in Finland on new car purchases and CO_2 emissions. By linking data for the entire Finnish vehicle fleet with owner-level demographic and socioeconomic information, we are able to study heterogeneity in behavioral responses in ways not explored in prior research.

Overall, we find that the subsidy program led to a significant increase in new vehicle purchases during the program period. We estimate that 66 percent of purchases by households that claimed the subsidy would not have occurred in the absence of subsidies. We find no evidence of intertemporal substitution – that is, of car owners merely shifting the timing of purchases they would have made even without the program. We also estimate that the program reduced the emission intensity of vehicles purchased by beneficiary households by about 11 percent. Accounting for emission reductions from the expedited scrappage of old vehicles, we estimate that the program reduced CO_2 emissions at a cost of €184 per ton of CO_2.

The average estimates mask meaningful heterogeneity in program effects on new car purchases across some household characteristics. The subsidy increased purchases substantially more among households whose existing vehicles had relatively low CO_2 emission intensity, compared to those with high-emission vehicles, and more among low-income than high-income households. In contrast, the program effect on the CO_2 emission intensity of new cars did not differ significantly across household characteristics. However, once differences in program take-up across subgroups are accounted for, the pattern reverses: the subsidy appears more cost-effective among households with high-emission existing vehicles than those with low-emission vehicles, and among high-income compared to low-income households. The cost-effectiveness is also greater for urban households and for those with two or more cars.

The finding of no intertemporal substitution contrasts with earlier evaluations of the US Cash for Clunkers program, which found that subsidies mainly pulled purchases forward from the post-program period. The longer duration of the Finnish program may have absorbed short-term shifting within the program window. Another possible explanation is that future reductions in purchases were spread over a longer horizon, making them difficult to identify statistically.

This empirical analysis indicates that vehicle replacement subsidies involve a tradeoff between cost-efficiency and distributional equity. As the European Union extends emissions trading to the transport sector, it has established the Social Climate Fund (SCF) to help cushion the social impacts of carbon pricing. Several EU countries are considering or planning to use SCF funding for vehicle replacement programs. Similarly, some U.S. states tie eligibility for vehicle replacement subsidies to income. With vehicle replacement subsidies increasingly turned to as a tool for addressing equity concerns arising from other climate policies, policymakers will need to weigh the efficiency–equity tradeoff when designing subsidy eligibility criteria.

Appendix A Regression discontinuity

Figure A.1 presents a regression discontinuity plot of treatment take-up against the eligibility criterion of car age expressed in days. The cutoff is at 3650 days (10 years).

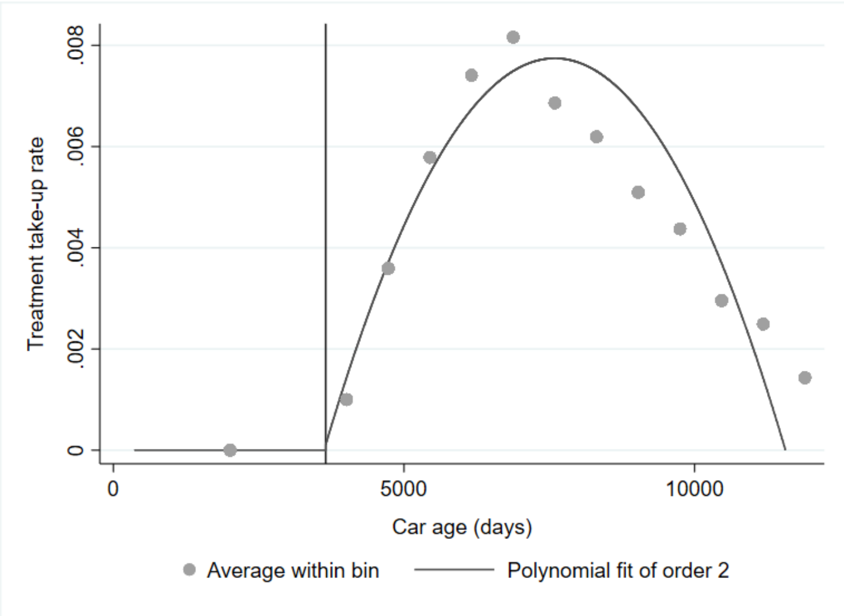


Figure A.1: Regression discontinuity plot: First stage – subsidy take-up.

Notes: The figure plots binned rates of program take-up and a second-order global polynomial fit against car age expressed in days, with an integrated mean squared error optimal number of evenly spaced bins (one below the car age cutoff and 12 above the cutoff), following Cattaneo et al. (2019). Higher-order polynomial fits yield qualitatively similar results.

Appendix B Appendices to the main estimation results

B.1 Program effect on car purchases, full estimation results

Table B.1: Program effect on new car purchases

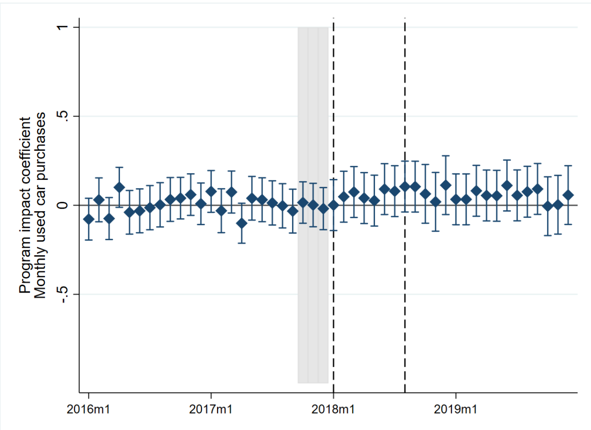
Month	Effect	Standard Error
Panel A: Program effect on monthly car purchases		
January 2016	-0.058	0.093
February 2016	0.049	0.093
March 2016	0.038	0.093
April 2016	0.187	0.081
May 2016	-0.087	0.091
June 2106	0.058	0.093
July 2016	-0.018	0.094
August 2016	-0.017	0.094
September 2016	0.061	0.093
October 2016	0.059	0.089
November 2016	0.003	0.089
December 2016	0.115	0.089
January 2017	0.058	0.093
February 2017	-0.049	0.093
March 2017	-0.038	0.093
April 2017	-0.187	0.081
May 2017	0.087	0.091
June 2107	-0.058	0.093
July 2017	-0.018	0.094
August 2017	0.017	0.094
September 2017	-0.061	0.093
October 2017	-0.120	0.088
November 2017	0.024	0.088
December 2017	-0.048	0.090
January 2018	0.032	0.108
February 2018	0.260 **	0.108
March 2018	0.451 ***	0.108
April 2018	0.342 ***	0.108
May 2018	0.317 ***	0.108
June 2018	0.174	0.108
July 2018	0.222 *	0.108
August 2018	0.374 ***	0.108
September 2018	0.011	0.108
October 2018	0.042	0.125
November 2018	0.061	0.125
December 2018	-0.027	0.125
Panel B: Program effect on cumulative purchases		
August 2018	0.298 ***	0.019

* indicates $p < 0.10$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.
Table notes on the following page.

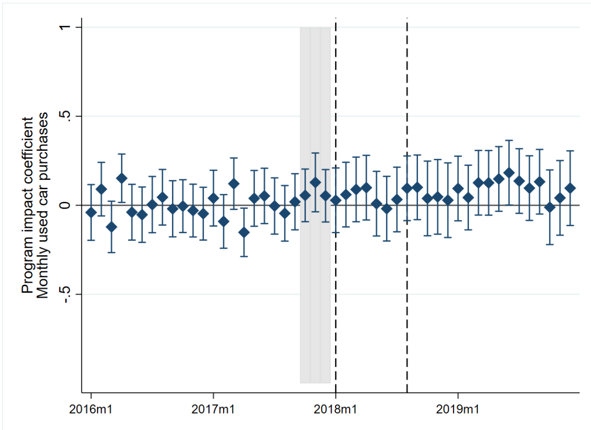
Estimations are based on 44 aggregate observations. Panel A shows results for Equation 1. The outcome variable is the share of car owners in group a (treatment or control) who purchased a new car in month m of year t. New car purchase shares are scaled by the group-wise average monthly new car purchase shares in July 2016 – June 2017. The program effect on new car purchases in each month comes from a separate estimation of Equation 1 for that month. Panel B shows results for Equation 2. The outcome variable is the cumulative new car purchase share in group a (treatment or control) by month m of year t, relative to the August 2017 cumulative new car purchase share. The estimated coefficient for August 2018 measures program effect on cumulative purchases during the program window period indicated by the estimated coefficients in Panel A. All estimations include month-by-group and year fixed effects. The standard errors are heteroscedasticity-robust.

B.2 Program impact on used car purchases

Figure B.1 presents results from estimating Equation 1 on used car purchases. Panel B.1a is based on data on all used car purchases. Panel B.1b is based on data that only inlude used cars that are 1 to 5 years old, as these may be a closer substitute for new car purchases.



(a) All used cars.



(b) Up to 5 years old used cars.

Figure B.1: Program impact on monthly used car purchases

Notes: The figure displays coefficient estimates for program impact on monthly used car purchases, estimated from Equation (1) with used car purchases as the outcome variable. The dashed vertical lines mark the beginning and the end of the program and the shaded region the potential anticipation period, starting from when the program bill was brought to parliament.

B.3 Summary statistics of new car buyers

Table B.2: Summary statistics of new car buyers, February 2018 – August 2018

	Age of household's oldest vehicle (years)			
	10 or above	**0-9**	**5-9**	**0-4**
Total number of households	19,891	33,014	12,273	20,741
Program take-up (share)	0.29	0	0	0
Panel 1. Household characteristics				
Household size (persons)	2.62	2.37	2.49	2.28
Income (€)	65,755	71,544	77,561	67,016
Urban location (share)	0.57	0.55	0.63	0.51
Homeowner (share)	0.86	0.89	0.90	0.89
Owns more than one car (share)	0.58	0.36	0.36	0.36
Number of vehicles	1.73	1.28	1.40	1.19
Owns SUV or pickup (share)	0.02	0.13	0.11	0.14
Km driven per year (total all cars)	21,661	19,015	20,021	not available
Panel 2. Registered owner characteristics				
Income (€)	48,690	58,879	63,168	55,653
Age (years)	52	55	54	56
Upper secondary education (share)	0.37	0.40	0.43	0.37

Notes: The table shows characteristics for households that purchased a new vehicle during the program window, measured in 2018. Household income refers to taxable income and benefits net of taxes and transfers. Owner income refers to annual gross total of salaries and capital income. Urban location includes inner urban and outer urban areas. Kilometers driven are calculated based on the most recent odometer readings from mandatory vehicle inspections and take into account all vehicles owned by the household. Odometer readings are not available for most 0-4 year old vehicles as the first mandatory inspection takes place at vehicle age 4.

B.4 Two-stage least squares estimates for new car emission intensity

Table B.3: Two-stage least squares estimates for new car emission intensity

	Estimated program effect (2SLS)	
	(1)	(2)
CO_2 emission intensity (g/km)	-18.897***	-19.792***
	(1.116)	(1.104)
Controls	No	Yes
Observations	29 450	29 450

Notes: The table shows regression coefficients from two-stage least squares regressions of new car CO_2 emission intensity on an indicator for vehicle replacement subsidy receipt, instrumented for subsidy eligibility. The estimations include the program window months 2/2018-8/2018. The controls are household income, number of cars, and annual vehicle kilometers driven. Heteroscedasticity-robust standard errors are reported in parentheses. * indicates $p < 0.05$, ** indicates $p < 0.01$, and indicates *** $p < 0.001$.

B.5 Robustness checks

Table B.4 presents results from robustness checks on the choice of the control group (columns 2 and 3) and the cutoff date for redefining the control and treatment groups each year (column 4). The main results, based on a control group of 5- to 9-year-old vehicles, are documented in column 1 for comparison. Column 2 reports results when including 1- to 9-year-old vehicles in the control group. Column 3 reports results when 8- to 9-year-old vehicles are included in the control group. Column 4 reports results using an alternative date for defining car age: in this robustness check, car age is defined at the end of June each year, and the control and treatment groups are fixed for each 12-month period from June to July. In the main analysis, car age is defined at the end of December each year, and the composition of the groups is fixed for the duration of a calendar year.

Table B.4: Robustness checks

	Main analysis	Control group 1- to 9-year-old vehicles	Control group 8- to 9-year-old vehicles	Redefining groups mid-year
	(1)	(2)	(3)	(4)
Panel A. Program window				
Months with program effect on new car purchases	2/2018 - 8/2018	2/2018 - 8/2018	2/2018 - 8/2018	2/2018 - 8/2018
Program effect on cumulative new car purchases	0.298*** (0.019)	0.317*** (0.021)	0.264*** (0.016)	0.300*** (0.018)
Panel B. Program effect on new car CO_2 intensity				
CO_2 emission intensity (g/km)	-3.564*** (0.343)	-3.406*** (0.288)	-3.814*** (0.715)	-3.592*** (0.350)
Controls	Yes	Yes	Yes	Yes

Notes: Column (1) reproduces the results from the main analysis. Columns (2) and (3) use alternative control groups. Column (4) redefines the treatment and control groups in July each year. Panel A summarizes the results for Equation 1, estimated month by month, and for Equation 2. Panel B shows regression coefficients from estimating a differences-in-differences version of Equation 3 on household-level data. The estimations use the full sample of new vehicles registered during 1/2016–8/2018. The program window variable takes on the value of one for 2/2018–8/2018, with 1/2018 excluded. The controls include household disposable income (total earned income and benefits net of taxes and transfers), number of cars, and annual vehicle kilometers traveled. Heteroscedasticity-robust standard errors are reported in parentheses. * indicates $p < 0.05$, ** indicates $p < 0.01$, and indicates *** $p < 0.001$.

Appendix C Appendices to the cost-effectiveness calculations

C.1 Expected lifetime vehicle kilometers

Given a vehicle's odometer reading at the time of scrappage, what would have been its expected remaining vehicle kilometers without the vehicle replacement subsidy program? What are the expected lifetime vehicle kilometers of a new car purchased under the program? To assess these values, we estimate a vehicle survival model with lifetime vehicle kilometers (odometer reading at scrappage) as the outcome variable, using administrative records for the vehicle fleet for years 2013-2020. We exclude cars that were scrapped during the 2018 program months or during the previous vehicle replacement subsidy program in 2015 from the estimation sample, as these scrappage decisions may have been policy-driven.

We define a vehicle as scrapped if it disappears from the vehicle registry records or if its registration status changes permanently to being decommissioned from road use. Odometer readings are missing for the scrappage year for the cars that were scrapped before the mandatory vehicle inspection of that year took place. We use the last two odometer readings observed for these cars to calculate the average kilometers traveled per day and impute the kilometers for the days between the dates of the vehicle's last observed odometer reading and the last vehicle registry record based on this figure.

We estimate the survival model using three different parametric survival functions: the log-log function, the log-normal function distribution and the Weibull function. We define vehicle kilometers traveled as the analysis-time variable. Vehicles are scrapped when the costs of operating and repairing make their economic value vanish. While both vehicle age and kilometers driven influence the rate at which these failures occur, we proceed from the assumption that kilometers driven are the more significant measure. We include vehicle make by model fixed effects, weight, and fuel type (gasoline, diesel or other) as covariates in the estimation.

Figure C.1 displays the observed distribution of odometer readings at scrappage and the distribution produced by predictions from the three estimated survival functions. Our interest is in predicting final odometer readings for the cars scrapped and bought with the subsidy; the Weibull survival function matches the observed data best and therefore we choose this parametrization.

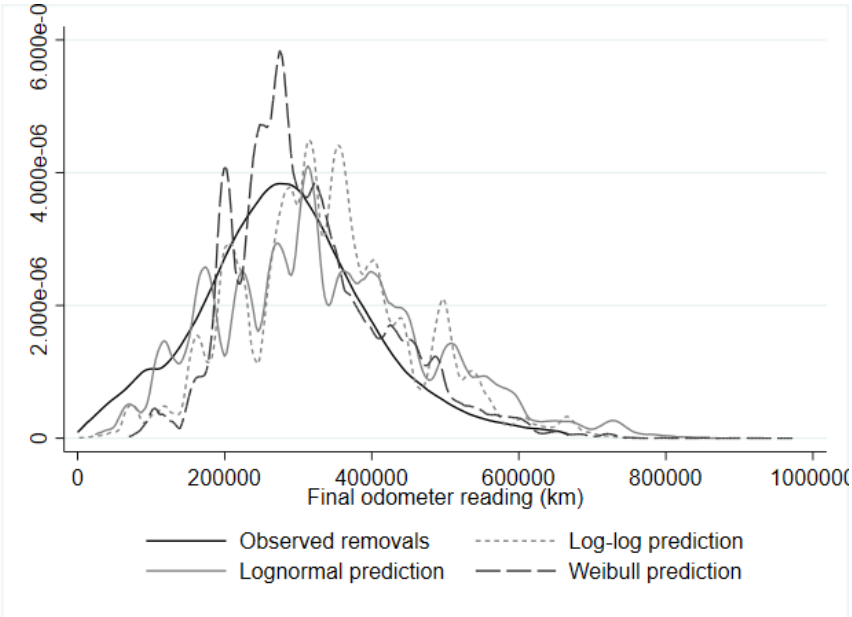


Figure C.1: The distribution of observed odometer readings at scrappage and model predictions

Notes: The figure shows the distribution of observed final odometer readings for cars removed from the fleet and the estimated values from three parametric survival model specifications: log-log, lognormal, and Weibull.

C.2 Co-pollutants

Table C.1: Program effect on new car local pollutant emission rates

	Full sample		**Shorter sample**	
	(1)	(2)	(3)	(4)
Panel A: NO_x emission rate (mg/km)				
Eligible x program window	-0.213	-0.222	-0.232	-0.241
	(0.205)	(0.204)	(0.215)	(0.214)
Observations	106,751	106,751	85,028	85,028
Panel B: CO emission rate (mg/km)				
Eligible x program window	2.670	2.646	2.718	2.692
	(1.974)	(1.963)	(2.075)	(2.063)
Observations	107,190	107,190	85,071	85,071
Controls	No	Yes	No	Yes

Notes: The table presents regression coefficients from estimating a differences-in-differences version of Equation 3 with the NO_x or CO emission rate as the outcome variable. The full sample includes vehicles registered during 1/2016-8/2018 and the shorter sample vehicles registered during 7/2016-8/2018. The program window variable takes on the value of one for 2/2018-8/2018, with 1/2018 excluded. The coefficient on Eligible x program window measures the average program effect (intention-to-treat). The controls include household income, number of cars, and annual vehicle kilometers driven. Heteroscedasticity-robust standard errors are reported in parentheses. * indicates $p < 0.05$, ** indicates $p < 0.01$, and indicates *** $p < 0.001$.

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