How Targeted Vehicle Scrappage Subsidies Can Reduce Pollution Effectively

1. Introduction

Policymakers are showing renewed interest in subsidizing scrappage of old and heavily polluting vehicles. In late 2019, Senator Schumer proposed spending almost half a trillion dollars over 10 years to subsidize scrapping older vehicles and replacing them with electric vehicles. The US House of Representatives Select Committee on the Climate Crisis and Joe Biden have mentioned similar ideas as part of comprehensive climate policy packages. At the same time, many states are considering scrappage programs to reduce transportation sector emissions and achieve long-term climate objectives.¹

In addition to providing economic stimulus by providing money to households, subsidizing scrappage appeals to policymakers because the subsidies can complement other environmental policies for the transportation sector. Most existing national climate policies focus on new vehicles, like setting emissions rate and fuel economy standards for new vehicles and offering tax credits for buying new electric vehicles. These policies cause newer vehicles to emit less pollution than older vehicles, and economy-wide transportation emissions decline over time as the new vehicles replace older ones. Subsidizing scrappage of older and higher-emitting vehicles can hasten the turnover of the vehicle fleet and further reduce emissions over time.

Notwithstanding this appeal, research on vehicle scrappage programs has shown that their environmental benefits to be disappointing. In the Car Allowance Rebate System (commonly known as “Cash for Clunkers”), during the summer of 2009, a new car buyer received $3,500-$4,500 to scrap an older vehicle and replace it with a new fuel-efficient one. The program cost about $3 billion (2009$) and reduced emissions at a fiscal cost of about $300 per metric ton of carbon dioxide, which is substantially higher than contemporaneous programs (Palmer and Burtraw 2005 and Li et al. 2013).²

Cash for Clunkers (and similar programs in other countries) had such small environmental benefits because they had little effect on scrappage behavior. Of the $3 billion of spending in Cash for Clunkers, most went to households who would have bought new vehicles anyway—either during the program period itself or later in the fall of 2009 (Mian and Sufi 2012). Older vehicles tend to be driven relatively little during the final years before they are scrapped, and many of the 700,000 vehicles that were scrapped under Cash for Clunkers probably would have been scrapped within the next few years anyway. Because those vehicles had few remaining miles (and emissions), the environmental benefits of scrapping them slightly earlier were modest. Or to put it another way, most of the subsidy money went to people who would have scrapped their vehicles soon regardless—akin to what economists refer to as

¹ See, for example, California’s Clean Cars for All program and other programs by states belonging to the US Climate Alliance.

² Aside from improving the environment, the program aimed to stimulate the economy during a deep economic recession by promoting new vehicle sales. However, Hoekstra et al. (2017) find that the environmental and stimulus objectives interfered with one another, severely hampering the stimulus effects.
“adverse selection.” This adverse selection also harmed the stimulus effects of the program (Li et al. 2013).

This paper evaluates hypothetical scrappage schemes and assesses whether linking subsidies to vehicle attributes such as age and emissions rates—which I refer to as “targeting the subsidies”—can reduce adverse selection and improve the efficacy of the subsidies at changing behavior and reducing emissions. Incentivizing scrappage is most effective when the scrapped vehicles have high emissions rates and would have otherwise been driven many miles in the future. The renewed interest in subsidizing scrappage raises the following question: how should scrappage subsidies be designed? While research on scrappage programs provides some general insights, I am not aware of quantitative analysis that answers this question.

Recent proposals have linked the purchase and scrappage subsidy—that is, a person receives the subsidy only if the scrapped vehicle meets certain criteria (such as a minimum age) and the new vehicle meets other criteria (such as being an all-electric vehicle). In this paper, I consider a scrappage subsidy that depends only on the attributes on the vehicle being scrapped and does not impose any requirements that the recipient purchase a new vehicle. I do this because considering an unlinked scrappage subsidy allows me to assess whether carefully selecting the eligibility criteria can improve emissions outcomes, without worrying about confounding influences of the new vehicle purchase decision. Also, although some recent proposals link scrappage and purchase, the ultimate policy may not do so, and it is worthwhile to consider each subsidy in isolation. Finally, because new vehicle prices are typically several times higher than used vehicle prices, the level of a scrappage subsidy needed to affect behavior is much lower than the level of a new vehicle subsidy needed to affect behavior.

Using a simple computational model of vehicle emissions, I reach two main conclusions:

- **Providing a single subsidy amount to all older vehicles is a costly way to reduce emissions.** Cash for Clunkers and recent proposals provide a fixed subsidy amount if the vehicle is drivable and exceeds a minimum age. A hypothetical scrappage program with these attributes would cost the government roughly $600 per metric ton of carbon dioxide reduced (2019$), which is probably substantially higher than the societal benefits from the lower emissions.

- **Tying the subsidy amount to the scrapped vehicle’s estimated future emissions could reduce the cost by half, to roughly $300 per metric ton of carbon dioxide.** The program could be implemented by estimating future emissions from the vehicle’s make, model, age, and odometer reading at the time of scrappage.

Adverse selection explains these results; targeting the subsidy based on vehicle age, class, and emissions rate—or, even better, age, class, emissions rate, and odometer reading—can dramatically reduce (but not eliminate) the amount of adverse selection that occurs in response to the subsidy, improving environmental outcomes. Although the scenarios consider a national subsidy, similar conclusions would apply to any state that subsidizes scrappage. Section 4 at the end of this paper discusses a few caveats to these conclusions.

### 2. A Brief Look at the Economics of Scrappage

To provide some intuition for the scrappage policy analysis in the next section, this section discusses a hypothetical person deciding whether to scrap an old vehicle. Consider an individual who owns one old car that needs some repairs to continue operating. For concreteness, suppose the car was in an accident and that the uninsured repair costs amount to $2,000. Also, the individual could buy a car that is identical, except that it does not need to be repaired, for $1,000. In this situation, the individual would be better off scrapping the vehicle and buying a replacement for $1,000, rather than making the repairs and spending $2,000.

In an alternative scenario, if the replacement cost is $3,000 and repair costs are $2,000, the individual is more likely to make the repairs than in the first scenario. I am not suggesting that the individual will choose to repair as long as the repair costs are less than the replacement cost; many other factors are involved in this
decision, such as the time costs of having the repairs made or buying a replacement and any sentimental value the individual attaches to the car. The point is that the higher the replacement cost, the less likely the individual scraps the older vehicle.

Note that the individual considering scrapping the car does not have an economic incentive to consider the environmental implications of continuing to drive it rather than scrapping it. Emissions rates vary substantially across vehicles that have the same age, model, and odometer reading. Suppose the individual’s car has a higher emissions rate than its replacement. In that case, scrapping the car and replacing it would reduce pollution and benefit the public—in economic terms, repairing rather than scrapping the car has an external cost. In the absence of policy intervention, the individual does not have an incentive to consider the external environmental costs of repairing the vehicle.

In principle, a government-imposed emissions tax would correct the problem. The emissions tax would cause the individual to pay a tax that is proportional to the vehicle’s emissions. Consequently, if the individual scraps the car and replaces it with a lower-emitting one, the tax bill would decrease.

An alternative to taxing emissions would be to tax the registration of the vehicle according to its emissions rate; a high-emitting car would be subject to a higher tax than a low-emitting car. This would differ from emissions tax because the registration tax would depend only on the car’s emissions rate, whereas the emissions tax would depend on the emissions rate and how much the car is driven. That is, for two cars that have the same emissions rate, their owners would pay the same registration tax, but if one owner drives their car more than the other does, the high-driving owner would pay a higher emissions tax. Many European countries tax car registration according to emissions rates (Cerruti et al. 2019), although I am not aware of any research on whether these taxes affect scrappage decisions.

Subsidizing scrappage would have a similar effect to an emissions-based registration tax. Let’s return to the example of a car with repair costs of $2,000 and a replacement cost of $3,000. Taxing registration based on the vehicle’s emissions increases the likelihood that the individual scraps the car, because they would pay lower taxes by replacing it with a lower-emitting car. Subsidizing scrappage would also increase the likelihood of scrapping the car, because it reduces the total cost of scrapping the damaged car and replacing it. For example, a scrappage subsidy of $500 would reduce the replacement cost from $3,000 to $2,500. Consequently, either an emissions-based registration tax or a scrappage subsidy would increase scrappage and reduce emissions.

From a fiscal point of view, however, a registration tax and a scrappage subsidy differ widely; the registration tax raises revenue, whereas the scrappage subsidy must be funded from other sources of tax revenue. The two policies would also have different equity consequences because the taxes and subsidies for older and higher-emitting vehicles fall disproportionately on low-income households.

I conclude this section with a brief discussion of adverse selection. A household benefits from a vehicle’s comfort and convenience, and, generally speaking, the more the household drives the vehicle, the more the household benefits from owning it. As the preceding discussion suggested, the decision to scrap the vehicle depends partly on its value to the household (that is, the benefit of the specific vehicle to the household, as distinct from the replacement cost); the greater the value to the household, the less likely it is for the vehicle to be scrapped. Consequently, a household that expects to drive its vehicle many miles is less likely to scrap the vehicle needing repairs than a household expecting to drive the vehicle few miles (all else equal).

This situation means that a flat scrappage subsidy that provides the same amount of money to all vehicles above a certain age will cause more scrappage of vehicles with few remaining miles—and emissions—than of vehicles with many remaining miles. This is an example of adverse selection, because the flat subsidy causes scrappage of many vehicles that would have been scrapped soon anyway.

The adverse selection can be reduced by targeting the subsidy such that the amount of the subsidy increases with the vehicle’s future emissions. For example, as I show in the next section, old vehicles have fewer remaining miles and greenhouse gas emissions than young or middle-aged vehicles, and a flat subsidy
causes more scrappage of old vehicles than other ones. As explained in more detail in the Appendix, targeting the subsidy so that it decreases with a vehicle’s age causes more scrappage of vehicles with high remaining miles and emissions. This makes a targeted subsidy more cost-effective than a flat subsidy.

3. Targeting Can Improve the Cost-Effectiveness of Scrappage Subsidies

This section begins by describing the framework used to compute the cost-effectiveness of alternative scrappage schemes. Then I show the results, which illustrate that targeting subsidy levels to estimated future emissions can substantially improve the cost-effectiveness of subsidizing scrappage.

3.1 Framework

Cost-effectiveness is defined as the fiscal cost per metric ton of carbon dioxide avoided. For a hypothetical scrappage subsidy program, a high cost means that the policy is expensive and that other policies could be more cost-effective. To estimate the cost-effectiveness of the scrappage schemes, I construct a model of the entire on-road vehicle fleet that covers 2017 through 2050. I summarize the model here and provide additional details in the Appendix.

The model is assembled from public data sources, particularly the National Household Travel Survey (NHTS), the Environmental Protection Agency’s (EPA) 2019 Automotive Trends Report, and the Energy Information Administration’s (EIA) Annual Energy Outlook (AEO). From these data sources, I compute the number of vehicles in the on-road fleet in 2017 by age and class (car or light truck). From the NHTS and EPA data, I compute miles traveled and emissions rates by age and class for 2017. Then I use EIA scrappage rates and projections of future new vehicle sales and fuel economy to iterate the model forward one year at a time through 2050. Using the vehicle counts, miles traveled, and emissions rates by age and class, I compute total greenhouse gas emissions each year. These emissions constitute the baseline, against which I compare emissions from hypothetical scrappage subsidies.

Figure 1. Projected Carbon Dioxide Emissions from Passenger Vehicles

Notes: The figure shows the estimated annual carbon dioxide emissions, in million metric tons, from passenger vehicles using data on the on-road vehicle fleet in 2017 from the NHTS and new vehicle sales, scrappage of older vehicles, miles traveled, and greenhouse gas emissions from 2017 to 2050 from the EIA and EPA. See Appendix for details on the calculations.

To estimate the effects of scrappage subsidies on scrappage rates, I use results from Jacobsen and van Benthem (2015), who examine the historical relationship between the market values of vehicles and their scrappage rates. The subsidies increase scrappage rates and reduce emissions, and I compute the fiscal costs and emissions changes relative to the baseline.

3.2 Results Using the On-Road Fleet Model

Using the model described in the previous subsection, I show that targeting scrappage subsidies based on vehicle age and class can substantially improve cost-effectiveness. Figure 1 shows the projected baseline emissions from 2020 through 2050. Baseline emissions decline gradually through 2035, after which they increase slightly. This pattern reflects the effect of the federal greenhouse emissions rate standards, which continue to reduce emissions as long as the emissions rates of the
new vehicles are lower than those of the older vehicles they replace.\footnote{That is, the emissions rates of new vehicles decline until 2026, after which they are flat. Because older vehicles were subject to higher (i.e., weaker) greenhouse gas standards when they were first sold, the emissions rates of new vehicles are lower than those of older vehicles. By 2035, nearly all the older vehicles that were subject to weaker standards have been scrapped, and the new vehicles have approximately the same emissions rates as older vehicles after 2035.} Emissions increase slightly after 2035 because new vehicle demand continues to rise due to rising incomes, and after 2035, the emissions rates of new vehicles are approximately equal to those of older vehicles. These patterns are similar to the emissions projections from the AEO 2020 for the entire light-duty fleet, although it should be noted that emissions in Figure 1 are lower, largely because the model I am using includes only household vehicles and excludes fleet-owned passenger vehicles, such as rental cars.

Against those baseline emissions, I estimate the change in emissions caused by a subsidy of $500 for scrapping any vehicle older than 10 years. This structure of the subsidy—offering the subsidy only to older vehicles and providing a flat dollar amount to any vehicle meeting that age requirement—was a feature of Cash for Clunkers and the recent scrappage subsidy proposals. I refer to this type of subsidy as a “flat subsidy,” because the dollar amount does not vary across vehicles older than 10 years.

Figure 2 illustrates the cumulative change in emissions each year after 2020 that is caused by either a subsidy that is offered in 2020 only or a subsidy that is offered from 2020 through 2024. The one-year subsidy causes an increase in scrappage in 2020, which continues to reduce emissions in subsequent years because those additionally scrapped vehicles would have been driven after 2020. By 2035, all of those additionally scrapped vehicles would have been scrapped without the subsidy, and the cumulative emissions change stops growing after that year. Not surprisingly, the five-year subsidy causes a larger decrease in emissions, and that decrease continues to grow in magnitude for several years longer than for the one-year subsidy. Note that the emissions change for the five-year subsidy is less than five times as large as that for the one-year subsidy, which indicates that the model exhibits diminishing marginal emissions benefits of the subsidies.

Notes: The figure shows the change in carbon dioxide emissions (in million metric tons) compared to emissions in Figure 1 caused by the indicated scrappage subsidy. The blue curve represents a scrappage subsidy of $500 per vehicle offered in 2020, and the red curve represents a $500 scrappage subsidy offered each year from 2020 through 2024. Subsidies are offered to vehicles older than 10 years.

---

Figure 2. Projected Cumulative Change in Carbon Dioxide Emissions Caused by Vehicle Scrappage Subsidies
Next, I consider a scrappage subsidy that is provided in 2020 and that depends on the vehicle’s estimated future emissions. As noted in Section 2, targeting the subsidy based on estimated future emissions causes it to be larger for vehicles with higher future emissions. This can reduce the fiscal cost per ton abated by causing greater scrappage of vehicles with higher future emissions, compared to the flat tax that was considered previously. I refer to this as a “targeted subsidy” based on age and class.

For each vehicle in the on-road fleet, the targeted subsidy is proportional to estimated future emissions, which is computed from the vehicle’s age and assumed scrappage rate, miles traveled, and emissions rates (see Appendix for further details). The subsidy is scaled to have the same fiscal cost as the flat subsidy.

In principle, the targeted subsidy could increase or decrease with vehicle age. On the one hand, older vehicles tend to have higher emissions rates than younger vehicles, which implies that the subsidy would increase with age. On the other hand, total emissions equal the emissions rate multiplied by miles traveled, and miles traveled tends to decrease with age. Figure 3 shows that the second effect is more important and that miles traveled decreases with age more quickly than the emissions rate increases with age. Consequently, future emissions—and hence, the subsidy—decrease with age.

The targeted subsidy causes more scrappage of younger vehicles than the flat subsidy. Figure 4 presents histograms for cars and light trucks of the number of vehicles scrapped by age. For younger vehicles, the bars are higher for the targeted subsidy (more so for light trucks than for cars), and the pattern reverses for older vehicles.

While economic theory predicts that the targeted subsidy is more cost-effective than the flat subsidy, it is important to quantify this difference. Table 1 shows the cost-effectiveness of the one-year flat and targeted subsidies.

<table>
<thead>
<tr>
<th>Table 1. Estimated Cost-Effectiveness of Vehicle Scrappage Subsidies Using Vehicle Fleet Model</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Flat Subsidy</strong></td>
</tr>
<tr>
<td><strong>2019 Dollars per Metric Ton Carbon Dioxide</strong></td>
</tr>
</tbody>
</table>

Notes: The table reports the cost-effectiveness in 2019 dollars per metric ton of carbon dioxide avoided. Cost-effectiveness is estimated using the vehicle fleet model used to construct Figures 1 and 2. The uniform and proportional subsidies are offered in 2020 and are the same as the subsidies used in Figure 3. See Appendix for details.

The flat subsidy has a fiscal cost of $610 per metric ton of carbon dioxide reduced. This is about twice the estimated cost of Cash for Clunkers from Li et al. (2013), which is primarily because it incentivized consumers to purchase new vehicles with higher fuel economy, in addition to scrapping older vehicles. The estimate in Table 1 is similar to the estimated cost-effectiveness of the federal tax credit for plug-in vehicles (Xing et al. 2019), although I note that the tax credit and scrappage subsidies have different objectives from one another.

Targeting the subsidy based on vehicle class and age reduces the cost by about 25 percent. As Figure 3 shows, this improvement occurs because the targeted subsidy provides greater incentive to scrap younger vehicles, which have higher future emissions than do older vehicles.4

4 As discussed in the Appendix, in the policy simulations, I assume that the subsidies do not affect total miles traveled in the subsidy year. Therefore, an increase in scrappage caused by the subsidy also causes an increase in new vehicle sales, so that total miles traveled is unaffected by the subsidy. Because the targeted subsidy causes scrappage of younger vehicles compared to the flat subsidy, the targeted subsidy causes a larger increase in new vehicle sales. The emissions calculations include the emissions from the fuel consumption of those vehicles, but it does not include the emissions of manufacturing and selling the vehicles. However, because new vehicle sales vary little across scenarios, and fuel consumption accounts for nearly all the life-cycle emissions of a vehicle (particularly for gasoline-powered vehicles, which represent 98 percent of vehicles sold in 2020), accounting for the full life-cycle emissions probably would not affect the qualitative conclusions.
Figure 3. Normalized Emissions Rate, Remaining Miles, and Remaining Emissions versus Vehicle Age for Vehicles in 2020

**Notes:** For vehicles in 2020, the figure plots the emissions rate, remaining miles, and remaining emissions against the vehicle's age. All data series are normalized to equal one for one-year-old vehicles. See Appendix for details on variable construction.

Figure 4. Counts of Scrapped Vehicles by Age for Flat and Targeted Subsidies

**Notes:** The figure compares a flat scrappage subsidy of $500 per vehicle with a subsidy that is proportional to the estimated future emissions of the vehicle. The two subsidies are offered in 2020, and the targeted subsidy is scaled so that the total fiscal costs of the two subsidies are the same. The vertical axes are the counts of vehicles scrapped, and the horizontal axis shows vehicle age.
3.3 Results Using the NHTS Data on Odometer Readings

Targeting the subsidy by class and age improves cost-effectiveness, but this targeted subsidy treats all vehicles that share a class and age as the same. Figure 5 shows that in the NHTS data, odometer readings vary substantially within a class and age. The figure plots the estimated probability density functions of the log of odometer readings after removing the overall mean (blue) or removing age by class means (orange). Comparing the two curves, we see that even after controlling for class and age, odometer readings vary quite a lot; age and class account for just about half the overall odometer reading variation in the NHTS.

One can use the odometer readings to predict the vehicle’s future emissions. For example, suppose there are two 20-year old cars that are identical (same model, trim, etc.), except that one of them has been driven 100,000 miles and the other 150,000 miles. It is reasonable to suppose that the former vehicle has more remaining miles than the latter. I assume that lifetime miles traveled do not vary within a model and vintage, so that in this example, the former vehicle would have 50,000 more remaining miles. Underlying this assumption is the idea that for most vehicles that are reasonably well maintained, the power train will last a certain number of miles before needing to be replaced—at which point the repair costs would likely exceed the replacement cost. This is a simplifying assumption, but it is sufficient for showing that targeting the subsidy based on odometer readings can improve cost-effectiveness; future research using data on scrappage and odometer readings could refine this analysis.

To assess the implications of targeting based on odometer readings, I use an alternative (and simpler) model to the one in the previous subsection. In this model, the NHTS vehicle-level data constitute the primary data source. I consider a one-time subsidy imposed on all vehicles that were included in the survey data in 2017, comparing three subsidies: a) a flat subsidy of $500 for all vehicles older than 10 years; b) a subsidy targeted on age, class, and emissions rate; and c) a subsidy targeted on odometer reading and emissions rate. The three subsidies are normalized to have the same total fiscal cost. I compute the effect of each.
subsidy on the scrappage probability of each of the vehicles in the NHTS data, using the same scrappage elasticity and market value as in the first model. Based on the change in scrappage probability and estimated remaining emissions for each vehicle, I compute the cost-effectiveness of each policy. Note that this analysis is static, in that I do not keep track of the change in emissions over time. Moreover, I use the odometer readings rather than assumed miles traveled to compute emissions, which causes the results to differ between this model and the first one.

Table 2 shows the results of these calculations. The cost-effectiveness of the first two subsidies is broadly similar to those shown in Table 1, although targeting by age, class, and emissions rate improves cost-effectiveness by somewhat more in Table 2. The third column shows that targeting based on odometer reading improves cost-effectiveness by an additional 32 percent, relative to targeting by age, class, and emissions rate.

Taken together, Tables 1 and 2 show that targeting the subsidies can dramatically improve their cost-effectiveness. I have noted the simplifying assumptions that support these calculations, and these numbers should be taken as rough estimates. Nonetheless, the results demonstrate that scrappage subsidies have much larger effects on behavior when they depend on estimated future emissions of the vehicle.

### 4. Discussion

A flat scrappage subsidy, which offers a fixed dollar amount for vehicles exceeding a particular age, appears to be an expensive approach to reduce greenhouse gas emission. The problem is that the subsidy pays a lot of money for vehicles that would have been scrapped soon, so the scrappage causes a relatively small reduction in emissions.

However, targeting the scrappage subsidy based on an estimate of the vehicle’s future emissions can reduce those costs substantially. In the data I assembled from the NHTS, EPA, and EIA, such a scrappage subsidy would be relatively high for newer vehicles and decline with age. Providing the larger subsidy to vehicles with higher future emissions creates a larger behavioral effect—that is, pulling forward in time the scrappage of relatively new but still high-emitting vehicles. Calculations show that targeting can reduce costs by roughly half, depending on how the targeting is done.

This paper provides the first quantitative analysis of a hypothetical scrappage subsidy. The Appendix notes that these calculations omit certain behavioral responses (such as changes in driving) that may cause me to underestimate the costs of the subsidies, but the underestimation applies to all the subsidies considered in this paper. Future research should refine this analysis and include those behavioral responses.
Moreover, the distributional consequences of scrappage policies, and the extent to which they benefit low-income households, have not yet been analyzed carefully. Subsidizing scrappage reduces the supply of older used vehicles, raising prices of used vehicles. This effect, which I did not consider in this paper, would likely be regressive because low-income households are more likely to buy used vehicles than are high-income households. Subsidizing new electric vehicles is probably regressive because most consumers of those vehicles have incomes higher than a typical US household. Consequently, combining an electric vehicle subsidy with a scrappage subsidy could yield a more equitable policy, but this is a topic for future research.

References


Acknowledgments

This work was supported in part by the Energy Foundation and the Merck Family Fund.

Resources for the Future (RFF) is an independent, nonprofit research institution in Washington, DC. Its mission is to improve environmental, energy, and natural resource decisions through impartial economic research and policy engagement. The views expressed here are those of the individual authors and may differ from those of other RFF experts, its officers, or its directors.

Joshua Linn is an associate professor in the Department of Agricultural and Resource Economics at the University of Maryland and a senior fellow at RFF. His research centers on the effects of environmental policies and economic incentives for new technologies in the transportation, electricity, and industrial sectors. His transportation research assesses passenger vehicle taxation and fuel economy standards in the United States and Europe. He has examined the effects of Beijing’s vehicle ownership restrictions on travel behavior, labor supply, and fertility.
Appendix

A.1. Stylized Model of Scrappage and Adverse Selection

This section describes a stylized conceptual model to illustrate how a targeted subsidy can be more effective than a flat subsidy at reducing emissions. To simplify the notation, I focus on a single vehicle model (such as a Hyundai Sonata) that is owned by a set of households who are indexed by \( i \).

Let \( P_i \) be the private value the household receives from the vehicle. This value may include comfort, sentimental value, and the services the vehicle provides by transporting people and cargo. Some components of \( P_i \) increase with the number of miles the vehicle will be driven in the future, and other components do not. I can express these two components as \( P_i = a + \beta m_i \), where \( a \) is the component that does not depend on future miles traveled, \( m_i \) is the number of future miles traveled, and \( \beta \) is a coefficient that links miles traveled to value. Note that \( a \) can be negative, such as when the vehicle requires expensive repairs to continue operating.

If the household decides to scrap the vehicle and replace it, the household receives a scrappage subsidy \( S \) and pays a replacement cost of \( V \). The subsidy is flat because it does not depend on \( m_i \). Note that \( V \) does not depend on \( m_i \) either, which simplifies the analysis.

The household scraps the vehicle if the private value is less than the scrappage subsidy less the replacement cost: \( a + \beta m_i < S - V \). Panel A of Appendix Figure 1 depicts this situation. The figure plots dollars on the vertical axis and miles along the horizontal axis. The upward sloping line is the private value of the vehicle, and the horizontal line is the difference between the subsidy and the replacement cost. Given the scrappage subsidy, a household scraps its vehicle if future miles lie to the left of the intersection of the two lines. As the figure shows, only vehicles with low future miles are scrapped—that is, there is adverse selection.

Panel B shows a targeted subsidy that depends on future miles. The targeted subsidy is scaled so that the two subsidies have the same total fiscal cost. The line showing the difference between the subsidy and the replacement cost is upward sloping because the subsidy increases with \( m_i \). The vertical intercept of this line is lower than the vertical intercept of the corresponding line in Panel A because the targeted subsidy offers a smaller subsidy to low-mileage vehicles than the flat subsidy does. Point B in Panel B is the intersection of the two lines, and all vehicles with mileage to the left of point B are scrapped. Comparing the two panels, we can see that the targeted subsidy causes more scrappage because it offers smaller subsidies to low-mileage vehicles.

Notes: Panel A shows a flat subsidy, and Panel B shows a targeted subsidy. In both panels, the vertical axis is measured in dollars and the horizontal axis is the miles the vehicle will be driven, \( m \). Both diagrams show the private value of the vehicle. The replacement cost of the vehicle is \( V \). The flat subsidy amount is \( S \), and \( \sigma \) is the coefficient on miles that is used to compute the targeted subsidy. Points A and B indicate the maximum number of miles of a vehicle scrapped because of the flat subsidy and the targeted subsidy, respectively.

The assumption that the replacement cost does not vary across households is equivalent to assuming that the replacement cost is uncorrelated with the miles traveled. Because of limited data availability, I must maintain this assumption in the computational models. If the replacement cost is positively correlated with future miles, this would exacerbate adverse selection and increase the fiscal cost of a flat subsidy, but it would also harm the cost-effectiveness of a targeted subsidy.
vehicles and higher subsidies to high-mileage vehicles, compared to the flat subsidy. Thus, this discussion illustrates how the targeted subsidy can improve the cost-effectiveness of a scrappage subsidy by reducing adverse selection.

A.2. Data

This section provides additional information about the data used in the computational model in Section 3.2. The model is similar to the one I developed for the RFF analysis in support of the 2019 Annual Report of the US Climate Alliance; additional documentation can be found there.

The main data sources are the National Household Travel Survey (NHTS), the Energy Information Administration’s (EIA) Annual Energy Outlook (AEO), and the Environmental Protection Agency’s 2019 Automotive Trends Report. The NHTS is a household survey administered by the Federal Highway Administration, and the public data provide information about household vehicle ownership and miles traveled. Using the 2017 wave of the NHTS, I compute counts of vehicles by age and class using the sample weights. I also use the data to estimate vehicle miles traveled by age and class. Age is top-coded at 25 because of the small sample for older vehicles.

The AEO 2020 provides data from the EIA’s simulations of the National Energy Modeling System. The public data include projections of new vehicle sales through 2050, and the projections include assumptions on economic growth and new vehicle demand. The public data also include projected new vehicle fuel economy by class through 2050, which assumes that automakers are subject to the recently finalized fuel economy and greenhouse gas standards. The Trends Report includes the estimated on-road greenhouse gas emissions rate (in grams of carbon dioxide per mile) of new vehicles by class and year from 1975 through 2018. I use the data to compute emissions rates by vehicle age and class in 2017 and to convert the EIA fuel economy projections to emissions rates.

I assume that a vehicle’s miles traveled depends only on its age and class. While I could estimate average miles traveled by age and class from the NHTS, the sample size of older vehicles is small, and the estimates are correspondingly noisy. Consequently, I use a third-order polynomial in age to predict vehicle miles traveled separately for each class, and I compute the average predicted miles traveled by age and class.

The AEO 2020 includes assumptions on scrappage rates by vehicle age and class, which I use as inputs in the model. These scrappage rates imply longer vehicle lifetimes than in prior iterations of the AEO. I use projections of vehicle sales for cars and light trucks from the AEO 2020. The AEO classification of cars and light trucks is somewhat different from that in the NHTS; the AEO definition implies a larger share of cars. To harmonize the two data sets, I compute an adjustment factor that equals the difference in market share of cars between the 2017 NHTS and the AEO 2017. I assume this adjustment factor does not change through 2050, and I adjust the sales projections accordingly.

The final data source is the EPA 2019 Automotive Trends Report, which provides the estimated on-road greenhouse gas emissions rate and fuel economy of new vehicles sold by class and year from 1975 through 2018. I assume that the emissions rate of a vehicle cohort does not change over time. For example, cars sold in 2017 are assumed to have the same emissions rate in 2017 as they do in subsequent years. This assumption is necessary, given the available data, and it amounts to assuming that scrappage rates are uncorrelated with emissions rates within a cohort. Using this assumption, I impute the emissions rate by vehicle age and class for 2017. For example, I use the emissions rate of new cars

---

6 The EIA makes projections using policies that are in place at the time of the analysis. Consequently, the projections include the assumption that fuel economy and greenhouse gas standards tighten through 2026 but do not change afterward.

7 The NHTS data include the make and model of each vehicle, from which I could impute fuel economy and an emissions rate. This would allow for the possibility that scrappage rates are correlated with emissions rates within an age cohort. However, this would introduce an inconsistency in the model because I must assume that the emissions rates of all vehicles sold after 2017 do not change over time after those vehicles are sold.
sold in 2002 to impute the emissions rate of cars that are 15 years old in 2017.

Finally, I use the EPA emissions and fuel economy data to convert the projected new vehicle fuel economy in the AEO to emissions rates, which are on-road estimates.

### A.3. Computational Models

This section provides additional detail about the two computational models in Sections 3.2 and 3.3. Vehicles are distinguished by vehicle age and class (car or light truck). Each year, emissions depend on the number of miles traveled and the emissions rate of each vehicle in the on-road fleet. The emissions rates of new vehicles are equal to the emissions rates determined by fuel economy and greenhouse gas standards in the year that those vehicles are purchased.

The model transitions from one year to the next by adding new vehicles to the fleet and scrapping older vehicles. The numbers of new cars and light trucks that are added to the fleet are exogenous to the model, as are the baseline scrappage rates that vary by vehicle age and class.

A key input to the model is the elasticity of the scrappage rate to the value of the vehicle, where the elasticity is the percent change in the scrappage rate given a 1 percent increase in the value of the vehicle. As discussed in Section 2, this elasticity should be negative, because more valuable used cars are less likely to get scrapped. Jacobsen and van Benthem (2015) use historical data on used vehicle prices and scrappage rates to estimate this elasticity, which they find to be equal to about -1 (they also report that the elasticity varies with vehicle age).

I use the average values and scrappage elasticities in their paper to compute the change in scrappage rate caused by a particular vehicle subsidy. For example, if the baseline value of a 20-year-old car is $3,000, a $500 subsidy reduces the value to $2,500, which is a decrease of almost 20 percent (the subsidy reduces the replacement value because it represents the opportunity cost of replacing rather than scrapping the vehicle). Because the elasticity of the scrappage rate with respect to the value is -1, the 20 percent decrease in value causes the scrappage rate to increase by 20 percent. I use their instrumental variables estimates of scrappage elasticities by vehicle age group and the mean market value by age group that they report in the paper.

The miles traveled and emissions rates are exogenous input assumptions, meaning that these parameters are not affected by the subsidy. The exogeneity assumption could cause me to overstate the emissions reduction caused by a scrappage subsidy. For example, suppose a household has two cars that are 10 and 20 years old, respectively. If a subsidy causes the household to scrap the older car, it may drive the remaining car more intensively or buy a new car.

To approximate the resulting increase in emissions, I assume that in aggregate when a scrappage subsidy causes an increase in scrappage, there is a simultaneous increase in new vehicle sales such that total miles traveled across the entire fleet during the year of the subsidy are the same as miles traveled without the subsidy. This assumption introduces two sources of bias, relative to a hypothetical model that explicitly characterizes vehicle ownership, scrappage, and driving decisions. On the one hand, new vehicles have lower emissions rates than older vehicles, so to the extent that the example household from the preceding paragraph drives its 10-year-old car rather than buying a new one, I would understate emissions. On the other hand, the new car would be driven more miles than the 10-year-old car would in subsequent years, causing me to overstate emissions. If the two sources of bias offset one another, the estimated emissions would be unbiased. Even if that is not the case, because my main interest is in showing how targeting scrappage subsidies can improve cost-effectiveness, the main concern would be that one source of bias is more important for one type of subsidy than for another.

An important part of the analysis of targeted subsidies is computing remaining emissions of the vehicles in the on-road fleet. For the model in Section 3.2, which characterizes emissions over time, I use the assumed scrappage rates and miles traveled by age and class to compute expected miles traveled. I multiply the
expected miles traveled by the corresponding emissions rate (which does not vary by age) to obtain the remaining emissions.

For the model in Section 3.3, which incorporates the NHTS vehicle odometer readings, I predict the lifetime miles traveled of each model using the methodology described in Linn (2020). Essentially, I assume that a vehicle’s odometer reading is a fourth-order polynomial function of the model’s age and vintage, and I use the 2001, 2009, and 2017 NHTS data to estimate separate parameters for each model. I use the estimates to predict the lifetime models as the maximum predicted odometer reading between ages 1 and 25. I assume that the maximum is the number of miles the vehicle is driven over its lifetime. The remaining miles represent the difference between that maximum and the vehicle’s odometer reading (setting negative values to zero). Remaining emissions equal remaining miles multiplied by the vehicle’s emissions rate.

There are a few things worth noting about the assumptions underlying both models. First, I assume that households respond equally and oppositely to a scrappage subsidy of a certain amount as to a change in the value of the vehicle. This assumption seems like a reasonable approximation, and it is necessary because I am not aware of any direct estimates of the effect of vehicle scrappage subsidies on scrappage decisions.8

Second, the structure and assumptions of the model in Section 3.2 are similar to the models that the National Highway Traffic Safety Administration and EPA used to evaluate the benefits and costs of federal fuel economy and greenhouse gas emissions standards for passenger vehicles. Similar to their models, I assume that scrappage and miles traveled are exogenous.

Third, because of the limitations of available public data, for the model in Section 3.2, I abstract from variation in emissions rates or miles traveled within a vehicle class and age. This is the issue that motivates the odometer-based analysis in Section 3.3, which shows that targeting based on odometer readings can reduce adverse selection.

---

8 Antweiler and Gulati (2015) estimate the effect of British Columbia’s scrappage subsidies, but it unfortunately is not possible to extrapolate their results to the on-road fleet model because of insufficient information about market values of the vehicles in their data.