Accelerating vehicle fleet turnover to achieve sustainable mobility goals

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Accelerating vehicle fleet turnover to achieve sustainable mobility goals

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Abstract

Achieving societal climate goals requires rapid reductions in greenhouse gas (GHG) emissions from transportation. Recent efforts by policymakers have focused on increasing consumer adoption of electric vehicles (EVs). Nevertheless, EV sales remain low. Worse, even if EV market share jumped dramatically, it would take decades to replace the existing vehicle fleet, during which time vehicle GHG emissions would continue, worsening climate change. Consequently, some argue for policies to accelerate the retirement of inefficient fossil-powered vehicles through "cash-for-clunkers" (C4C) programs. We examine C4C policies through a behavioral model of vehicle fleet turnover and EV market development in the United States. We find C4C policies can substantially reduce vehicle fleet emissions at reasonable cost per tonne of CO_2. To meet emissions reductions goals, C4C policies should apply only when consumers replace their fossil-powered vehicles with EVs. C4C policies incentivizing EVs accelerate cost reductions through scale economies, charging infrastructure deployment, model variety, and consumer awareness, boosting EV adoption beyond the direct effect of vehicle replacement. The result is a substantial synergy amplifying the impact of C4C and lowering unit cost of emissions reductions. C4C is further amplified when deployed together with complementary policies promoting renewable electricity production and a gas tax or carbon price.

KEYWORDS

accelerated vehicle retirement, automobile manufacturing, public policy, sustainable mobility

Highlights

- Promoting sales of electric vehicles will not be sufficient to meet 2050 climate goals due to slow turnover of the existing vehicle fleet.
- Incentivizing the early retirement of gasoline vehicles ("cash-for-clunkers") and replacing them with new electric vehicles can achieve greater emissions reduction at reasonable cost.

- The environmental benefits of cash-for-clunkers can be enhanced further through complementary policies such a carbon price and faster decarbonization of the electric grid.

1 | INTRODUCTION

Reducing greenhouse gas (GHG) emissions to achieve climate goals and limit global warming to no more than 2°C requires effective policies addressing the most polluting sectors of the world economy. However, global GHG emissions are not on track to achieve these goals. The United Nations Environmental Programme finds that the world is failing to meet the goals of the Paris Agreement (UNEP, 2020). Significantly, faster and deeper emissions cuts are needed (Farmer et al., 2019) throughout the economy. In April 2021, the United States announced its new Nationally Determined Contribution (NDC) under the Paris Agreement, pledging to reduce "its net greenhouse gas emissions by 50–52 percent below 2005 levels in 2030" (UNFCCC, 2021). Rapid reductions in carbon emissions from transportation are crucial to achieving these goals: the transportation sector is responsible for 29% of United States GHG emissions as of 2019, and ~58% of these emissions arise from the roughly 250 million light-duty vehicles (cars, SUVs, and pickup trucks) on the roads today (U.S. EPA, 2019a).

Most efforts by policymakers and automakers have so far focused on increasing the share of new vehicle sales going to low- or zero-tailpipe emissions vehicles, for example, by mandating the minimum fuel economy of new vehicles through the corporate average fuel economy (CAFE) standards (NHTSA, 2021a). The transportation section of the new U.S. NDC calls for

> tailpipe emissions and efficiency standards; incentives for zero emission personal vehicles; funding for charging infrastructure to support multi-unit dwellings, public charging, and long-distance travel; and research, development, demonstration, and deployment efforts to support advances in very low carbon new-generation renewable fuels (UNFCCC, 2021).

In addition to direct consumer subsidies, cost-effective policies might involve government investment in charging infrastructure or providing owner benefits, for example, special license plates with parking or driving privileges (Li et al., 2021).

Many other nations have adopted similar policies designed to increase the market share of electric vehicles (EVs). The most successful, Norway, achieved 64.5% EV market share in 2021 (Elbil, 2021a), the result of aggressive subsidies including zero VAT and purchase taxes on EVs, charge point deployment, and abundant, inexpensive hydropower (averaging approximately US$0.07–$0.10/kWh, inclusive of taxes (Statistics Norway, 2021). In August 2021, President Biden signed executive order 14037 establishing "a goal that 50 percent of all new passenger cars and light trucks sold in 2030 be zero-[tailpipe] emission vehicles…." (Federal Register, 2021).

However, the impacts of policies designed to accelerate EV adoption are inherently constrained by the slow turnover of the vehicle fleet. The average light-duty vehicle (LDV) in the United States has a useful life of about 17 years (Keith et al., 2019), and many remain in use for 30 years or more (especially more-polluting light trucks). Even if policies such as CAFE succeed in improving the fuel economy of new gasoline vehicles, and sales of zero-tailpipe emissions vehicles grow, decades will be required to replace the existing vehicle fleet, during which time GHG emissions will continue (Keith et al., 2019). Accelerating retirement and replacement of the vehicle fleet will be required to achieve the GHG emission reduction goals needed to limit climate change.

Policies seeking to accelerate the turnover of the vehicle fleet have most commonly focused on boosting the retirement of the oldest and most polluting vehicles from the fleet, known colloquially as "cash-for-clunkers" (C4C). And by stimulating new vehicle sales, C4C policies can have significant operational co-benefits, providing incentives that can accelerate the formation of the EV market (e.g., increasing EV sales that builds consumer awareness and creates demand for the roll-out of charging stations), and stimulating vehicle sales that sustain valuable blue-collar manufacturing jobs (Adamson & Roper, 2019; Kalkanci et al., 2019; Rothstein, 2016; Ton, 2014). Thus, properly designed C4C policies could yield "triple-bottom-line" benefits for profit, people, and the planet (Kleindorfer et al., 2009). Increasing interest in C4C in the mainstream media (Plumer et al., 2021) and C4C proposals in nations such as India (Shah & Monnappa, 2021) suggest C4C is gaining momentum as governments seek to accelerate the decarbonization of automotive transportation. However, policies to date have not been optimized from a climate perspective as yet, with real-world implementations pursuing conflicting objectives (such as reducing pollution and increasing vehicle production) and limited by the set of fuel-efficient and alternative-fuel vehicles available to consumers (Morrison et al., 2010). It therefore remains an open question as to how C4C policies should be optimally designed to maximize GHG emissions reduction with manufacturing and employment co-benefits. In particular, should we incentivize the adoption of fuel-efficient gasoline vehicles that are more attractive to consumers in the short-run, but have more limited long-run emissions benefit, or incentivize emerging zero-emissions vehicle (ZEV) technologies such as EVs and hydrogen fuel cell vehicles that are yet to achieve mainstream adoption?

Here, we extend a fully calibrated extant model of the US light-duty vehicle fleet turnover (Keith et al., 2019) to analyze the effectiveness of C4C policies. We simulate the turnover of the US light-duty vehicle fleet out to 2050 under different C4C policies. We provide guidance on the practical steps needed to achieve meaningful GHG emissions reduction from automotive transportation, contributing to the literature on sustainable and behavioral operations and climate change mitigation. We outline the opportunities and challenges in designing a C4C policy that addresses environmental, financial, and manufacturing objectives concurrently.

We find that C4C programs in which participants can purchase either EVs or fuel-efficient gasoline vehicles lead to small emissions reductions at a high cost. Much larger and more cost-effective emissions reductions are possible when C4C requires consumers replace their old, fossil-fuel powered vehicle with an EV. C4C policies incentivizing EVs yield benefits larger than the direct effect of C4C on fleet replacement by stimulating a set of powerful reinforcing feedbacks that speed the development of the EV market. EV-focused C4C policies bootstrap EV adoption by (i) accelerating EV cost reductions through scale economies and learning throughout the EV supply chain, (ii) expanding EV make and model variety, (iii) speeding deployment of charging infrastructure, and (iv) building consumer awareness and willingness to consider EVs. These improvements foster additional EV purchases beyond the direct impact of C4C on fleet turnover, which then drive further improvements in the attractiveness of EVs, yielding a substantial synergy that amplifies the direct benefits of C4C. These reinforcing feedbacks also increase the benefits of complementary policies that speed grid decarbonization. A gas tax or carbon price further enhances the emissions reductions from C4C, and the revenue can be used to help offset program costs or be rebated to the public to address equity issues. We perform a wide range of sensitivity analyses over the key uncertainties to examine the robustness of our results and establish guidelines for the most effective and efficient policy design to leverage synergies with complementary environmental policies.

2 | CASH FOR CLUNKERS

2.1 | The road to a low emission vehicle fleet

A variety of policies have been employed in the United States to promote sales of alternative, low- or zero-tailpipe emissions vehicles such as EVs. Tax credits for buyers of EVs offer up to $7500 from the federal government, and additional incentives of up to $2500 in several states (U.S. DOE, 2019). California and nine other states follow the ZEV mandate, requiring that the market share of ZEV increases from 4.5% in 2018 to 22% in 2025 (CARB, 2018, 2019). Despite this substantial policy support over many years, alternative fuel vehicles have only achieved low single-digit market shares in the United States to date (Figure 1).

Along with technology-specific policies, the CAFE standards aim to improve the average fuel economy of new light-duty vehicles (cars and light trucks). The CAFE standards were weakened in 2020 under the safer affordable fuel-efficient (SAFE) vehicles rule. Adjusting for credits and accounting for the difference between test and real driving conditions, those standards required the average fuel economy of new light-duty vehicle to increase by 1.5% per year with a goal of 37 miles per gallon (MPG) by 2026, with the fuel economy of new cars and light trucks to be 43.7 and 31.3 MPG by 2026, respectively (NHTSA, 2021a). On January 20, 2021, President Biden issued Executive Order EO 13990 directing the

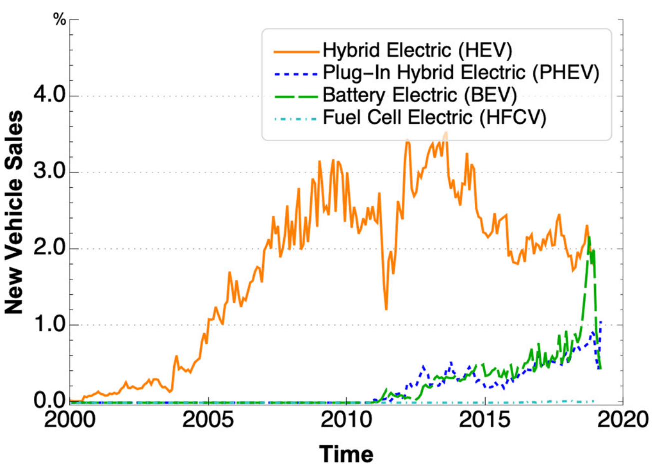

FIGURE 1 Sales of low- and zero-emission vehicles in the United States. *Source*: Auto Alliance, 2018; HybridCars.com, 2018; Automotive News, 2019

government to establish "Ambitious, Job-Creating Fuel Economy Standards" by "considering whether to propose suspending, revising, or rescinding" the SAFE standards, which apply through the model year 2026, and on August 5, 2021, the U.S. Department of Transportation's National Highway Traffic Safety Administration (NHTSA) proposed new CAFE standards for 2024–2026 that would boost the yearly increase in CAFE stringency to 8% per year from 1.5% per year set under the SAFE standards (NHTSA, 2021b). On August 5, 2021, President Biden issued EO 14037, "Strengthening American Leadership in Clean Cars and Trucks," directing the government to

> to establish new multi-pollutant emissions standards, including for greenhouse gas emissions, for light- and medium-duty vehicles beginning with model year 2027 and extending through and including at least model year 2030.

EO 14037 also established the goal that half of new vehicle sales be electric by 2030 (Federal Register, 2021). However, even if new vehicles sold in 2050 became 75% more fuel-efficient than today (implying average fuel economy of ~130 MPG), the expected reduction in fleet emissions will not exceed 40%, owing to the slow rate of fleet turnover (Keith et al., 2019).

2.2 | Lessons from the US CARS "Cash for Clunkers" program

Programs that accelerate the replacement of old and inefficient vehicles currently in the fleet provide an opportunity to reduce GHG emissions from the vehicle fleet. C4C programs began in the 1990s, including Sweden, Denmark, France, the United Kingdom, Canada ("Retire Your Ride"), China ("old swap new"), and others (ARC, 2012; BBC, 2009; Morrison et al., 2010; Zhang, 2009), with stated objectives of either reducing criteria pollutant emissions including GHGs, or stimulating the auto industry. All these accelerated vehicle retirement programs offered customers incentives to scrap their old cars, but differences in implementation time, program duration, incentives, budget, and mixed objectives have led to varying opinions about their success (Alberini et al., 1995; Dill, 2004; Lachapelle, 2015; Marin & Zoboli, 2020; Miller et al., 2020; Morrison et al., 2010; Zhou et al., 2019). To provide further context for this work, we summarize below the results of the most widely studied program: the US government's Cars Allowance Rebate System (CARS), commonly known as cash for clunkers.

CARS was introduced in 2009 to boost sales of new and domestically manufactured vehicles after the precipitous market decline during the economic crisis of 2008, when new vehicle sales plummeted 18%, to the lowest rate in a decade. US manufacturers were hit hardest, with sales declining between 28% and 36% (Vlasic, 2008). The CARS program provided incentives between $3500 and $4500 per vehicle to consumers who traded in a low fuel-efficiency vehicle and purchased a new and higher fuel-efficiency vehicle. Trade-ins were decommissioned (and the materials recycled) so that they could not re-enter the used vehicle market or be exported. Lasting only 8 weeks, from July 1, 2009, to August 24, 2009, CARS stimulated the replacement of 680,000 vehicles at a cost of $3 billion (Li et al., 2013).

While the government declared the program a success (U.S. DOT, 2009), subsequent research was less positive. The program did nominally achieve its stated objective of inducing additional vehicle sales. However, researchers estimated that only 370,000 of the 680,000 vehicles sold under the program would not have happened otherwise (54%), and sales of new vehicles dropped after the program expired (Mian & Sufi, 2012). Moreover, more than half the incentives are estimated to have gone to households that would likely have purchased a new vehicle in the next 2 months anyway (Hoekstra et al., 2017). Because the program required the purchase of a new fuel-efficient vehicle, many consumers chose to buy cheaper and more fuel-efficient vehicles such as the Toyota Corolla, boosting the sales of Japanese cars, and reducing the average selling price of new vehicles sold (Hoekstra et al., 2017; Simon, 2009), undermining the goal of boosting domestic car sales.

The CARS program required replacement vehicles purchased to be more fuel-efficient than the average vehicle available on the market, increasing the average fuel economy of all new vehicles by 0.6–0.7 MPG (Sivak & Schoettle, 2009) and preventing emissions of 4.4 million tonnes of CO_2 (tCO_2) (Lenski et al., 2010). However, estimates suggest program costs exceeded the value of the environmental benefits by about $2000 per vehicle, calculated as the difference between the subsidy and environmental benefits based on the then-current social cost of carbon (SCC) (Abrams & Parsons, 2009). Estimates of the cost per tonne of avoided CO_2 emissions vary widely, from about $90/tCO2 to over $500/$tCO_2$ (Knittel, 2010; Li et al., 2013). Further, 50% of the pollution reduction benefits went to just 2% of US counties—mostly urban centers (Lenski et al., 2013).

Although CARS and similar policies (see Morrison et al., 2010) provide important evidence regarding the impact of accelerated vehicle retirement programs, their impacts do not generalize to the current US market. New studies are needed to inform current (in California) or proposed (in Massachusetts) government programs (BAR, 2021; Rogers & Schmid, 2021).

For example, the short duration of CARS, only 8 weeks, allowed strategic consumers to accelerate replacement of an older car slightly so as to qualify for the program, undermining its net sales impact. The C4C program we examine would last far longer, on the order of a decade, limiting opportunities for strategic purchase timing. Further, the higher average fuel economy of vehicles in the fleet today, expanded makes and models of low emissions vehicles (including more low- and zero-tailpipe emission vehicles—103 in 2018 versus 20 in 2009 [see SAFE Vehicles Rule NHTSA, 2021a, p. 24237]), higher fuel economy standards, and more stringent climate objectives, create a different playing field.

Every older, inefficient fossil-powered vehicle replaced with an efficient electric vehicle generates direct environmental benefits (Kim et al., 2003; Morrison et al., 2010; Spitzley et al., 2005; Van Wee et al., 2000). However, C4C and other policies to promote EV adoption can also generate indirect benefits by accelerating market formation. To date, EV adoption in the US and most nations has been limited because EVs are unfamiliar to many consumers, who do not include them in their consideration sets when choosing a new vehicle (Hauser & Wernerfelt, 1990, explore the concept of consideration sets; Struben & Sterman, 2008, show how unfamiliarity limits adoption of alternative vehicles. See also Shafiei et al., 2012; Silvia & Krause, 2016; Hardman et al., 2020; Khurana et al., 2020; Shetty et al., 2020; Wu et al., 2020). Policies stimulating EV adoption will increase consumer familiarity through social exposure and network effects (Struben & Sterman, 2008). Further, increasing EV sales will stimulate R&D, learning-by-doing, and scale economies that lower EV costs and improve range, stimulate the deployment of charging infrastructure, and induce automakers to offer a wider variety of makes and models. These effects create self-reinforcing feedbacks that bootstrap the nascent EV market towards maturity and potentially amplify the impact of policies including C4C (Keith et al., 2020). To the best of our knowledge, no existing studies consider these indirect feedback effects of accelerated vehicle retirement programs.

3 | MODELING THE DYNAMICS OF ACCELERATED FLEET TURNOVER

To explore the dynamics of US vehicle fleet turnover with C4C policies, we extend and modify a fully calibrated model of the US light-duty vehicle fleet (Keith et al., 2019) to include the effect of C4C policies (see Figure 2). The fully documented model and data files (Rahmandad & Sterman, 2012) are available in an electronic supplement (Naumov et al., 2022) (Data S1). The model tracks cars and light trucks in the US fleet from initial sale until discard. The model incorporates established formulations from fleet diffusion and urban mobility models (Keith et al., 2017; Keith et al., 2020; Naumov et al., 2020; Struben & Sterman, 2008), discrete consumer choice (e.g., Archer & Wesolowsky, 1996; Ben-Akiva & Lerman, 1985; Brownstone et al., 2000; Coltman & Devinney, 2013; McFadden, 1981; Pullman et al., 2001; Verma et al., 2006), and behavioral decision-making (Bendoly et al., 2006; Morecroft, 1985; Sterman et al., 2015; Sterman & Dogan, 2015).

The model is calibrated to represent the light duty vehicle fleet of the US, which comprises two vehicle classes as defined by the US Department of Transportation (NHTSA, 2021a), cars and light trucks: $\mathcal{Z} = \{Cars, Light\ trucks\}$. We further consider two vehicle powertrain platforms, internal combustion engine (ICE) and electric (EV): $\mathcal{P} = \{ICE, EV\}$ available in each vehicle class. The model therefore tracks four fleets: two ICE (cars and light trucks), and two EV (cars and light trucks). The age structure of each of the four fleets is represented with one-year cohorts. The ICE fleets are calibrated to actual cohort-specific rates of vehicle retirement and vehicle-miles traveled (VMT) per year in the US light-duty vehicle fleet (Williams et al., 2017). We assume the same age-specific hazard rates of retirement and VMT per year for both the ICE and EV platforms.

The EV platform includes both battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEVs). PHEVs have a smaller battery than BEVs, with typical all-electric range of about 40 miles, but include a gasoline engine as a range extender. Approximately 55% of all miles driven by PHEVs are electric (AFDC, 2020), increasing GHG emissions relative to BEVs, but they also reduce range anxiety and require less time to charge. The effect of PHEVs is thus twofold—on the one hand, they increase GHG emissions from the combined EV fleet, but they also pose fewer barriers to adoption, accelerating EV market formation by building consumer awareness, creating demand for EV charging infrastructure, and fostering scale economies in EV components and supply chains, including motors, batteries, controls, and related subsystems (Keith et al., 2020; Struben, 2006).

3.1 | Vehicle fleet turnover

The total installed base of vehicles of class $i \in \mathcal{Z}$ with powertrain $p \in \mathcal{P}$ sums over N individual age cohorts a:

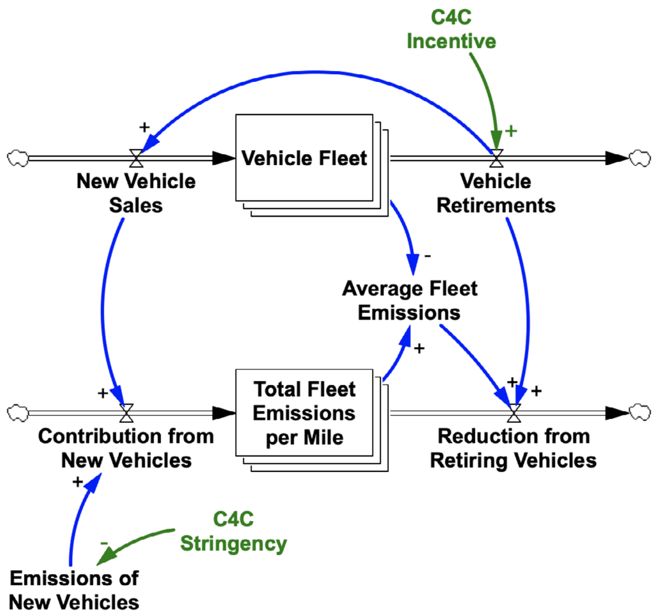

FIGURE 2 The C4C policy and fleet turnover. Signs at arrowheads indicate the polarity of the causal relationship: "+" indicates an increase in the independent variable causes the dependent variable to increase, ceteris paribus (and a decrease causes a decrease): $X \to^{+} Y \stackrel{\text{def}}{=} \partial Y/\partial X > 0$. Similarly, "–" indicates that an increase in the independent variable causes the dependent variable to decrease (and a decrease causes an increase): $X \to^{-} Y \stackrel{\text{def}}{=} \partial Y/\partial X < 0$. Boxes represent stocks (accumulations); double arrows "$\Longrightarrow$" with valves "$\bowtie$" represent flows, for example, $Vehicle\ Fleet(t) = \int_{t_0}^{t} (New\ \ Vehicle\ \ Sales(s) - \ Vehicle\ Retirements(s))ds + Vehicle\ Fleet(t_0)$

$$V_{ip} = \sum_{a=1}^{N} V_{ipa} \tag{1}$$

In the absence of the C4C program, the total installed base is changed through vehicle retirements r_{ipa} from each cohort a of class i with powertrain p, and the addition of vehicle purchases n_{ip} entering the cohort of new vehicles:

$$\frac{dV_{ip}}{dt} = n_{ip} - \sum_{a=1}^{N} r_{ipa} \tag{2}$$

where r_{ipa} is a function of the rate of vehicle retirements through natural turnover α_{ipa}, increasing with the age of the cohort a, estimated based on the existing data of the US fleet (Williams et al., 2017):

$$r_{ipa} = V_{ipa}\alpha_{ipa} \tag{3}$$

C4C policies add outflows of vehicles retired under the C4C program from qualifying age cohorts d_{ipa} and the inflow of mandatory replacement purchases m_{ip}:

$$\frac{dV_{ip}}{dt} = n_{ip} - \sum_{a=1}^{N} r_{ipa} + m_{ip} - \sum_{a=Q}^{N} d_{ipa} \tag{4}$$

where Q is the minimum age cohort qualifying for the C4C program.

Total new vehicle purchases for each vehicle and fuel type, n_{ip}, are given by the replacement of all discarded vehicles of each type, the share of replacements going to each platform (EV or ICE), σ_{ip}, and the increase in market size due to fleet growth, assumed to grow at fractional rate λ:

$$n_{ip} = \sigma_{ip}\left(\sum_{a=1}^{N} r_{ipa} + V_{ip}\lambda\right) \tag{5}$$

3.2 | Changing vehicle mix

Decommissioned vehicles are replaced with new vehicles. People can replace their old ICE vehicle with either a new ICE or a new EV. We do not allow for the possibility of switching back from EVs to ICE vehicles in light of recent mandates by many governments banning sales of gasoline vehicles in the next years. We model consumer choice based on the utility of EVs, $u_{i,EV}$, versus ICE vehicles, $u_{i,ICE}$ within vehicle class $i \in \mathcal{Z}$. Following the literature on new vehicle platform diffusion (Struben & Sterman, 2008; Keith et al., 2017, 2020), we use discrete consumer choice formulations (e.g., McFadden, 1981;

Ben-Akiva & Lerman, 1985; Brownstone et al., 2000; Verma et al., 2006) using a binomial logit model for the market share of each vehicle platform $\{ICE, EV\}$ for each class $i \in \mathcal{Z}$. Defining the utility of EVs, $u_{i,EV} \stackrel{\text{def}}{=} u_i$ and, without loss of generality, the utility of an ICE platform $u_{i,ICE} = 0, \forall i \in \mathcal{Z}$, the market share of each platform is:

$$\begin{cases} \sigma_{i,EV} \stackrel{\text{def}}{=} \sigma_i = \# \dfrac{1}{1+e^{-u_i}} \\ \sigma_{i,ICE} = \# 1 - \sigma_i \end{cases} \tag{6}$$

Following standard logit models, EV utility is a linear function of vehicle attributes, s, valued by consumers, x_{is}, weighted by coefficients β_s, with homoscedastic independent and identically distributed (i.i.d.) extreme value errors ϵ_i:

$$u_i = \sum_s \beta^s x_i^s + \epsilon_i \tag{7}$$

We assume no change in the mix of light trucks and cars. Some people might decide to purchase a light truck when they trade in an old car, as seen in the recent shift from sedans to SUVs (EIA, 2018), or potentially opt for a more efficient car when they trade in an old light truck. We leave consideration of this mechanism, and disaggregation to additional market segments (e.g., pickup trucks, full size SUVs, small SUVs, crossovers, etc.) for future studies, which may be feasible as more data become available.

We include covariates for the inconvenience of the EV platform relative to the ICE platform (reflecting lower driving range, longer refueling time, lack of recharging infrastructure, low consumer awareness, etc.), the price of EVs relative to ICE vehicles, and the relative fuel savings from driving an EV versus ICE vehicle, such that consumer utility becomes:

$$u_i = \beta^{market} x_i^{market} + \beta^{price} x_i^{price} + \beta^{fuel} x_i^{fuel} + \epsilon_i \tag{8}$$

The EV market is not yet mature, and multiple feedbacks exist that may cause the utility of EVs to increase as EV sales grow (Struben & Sterman, 2008; Keith et al., 2020). Growing EV sales generate more funds for R&D, speed learning-by-doing, and drive scale economies that reduce EV costs and improve range, inducing automakers to offer a wider range of EV makes and models. More EVs on the road increase demand for charging, stimulating the deployment of charging infrastructure, making EVs even more convenient. In addition, more EVs on the road increase social exposure to them, building familiarity with and consumer acceptance. All these effects increase EV sales further, forming reinforcing feedbacks potentially bootstrapping the EV market. For parsimony we do not disaggregate these multiple feedbacks, instead of aggregating them into the self-reinforcing *Market Formation* feedback, R1, shown in Figure 3 (Sterman (2000) provides an explanation of causal diagramming notation and the concepts of self-reinforcing (positive) and self-correcting (negative) feedbacks).

We capture these effects as reductions in the price of EVs and the inconvenience of the EV platform. We use a standard power-law learning curve in cumulative production experience, which serves as a proxy for the aggregate effect of all sources of learning (Argote & Epple, 1990). For the price attribute, we include both local market production of EVs, L, (here, US production), and rest-of-world EV production, W:

$$x_i^{price} = P_{i,0} \left(\frac{W}{W_0} \frac{L}{L_0} \right)^{\gamma_{price}} \tag{9}$$

where W_0 and L_0 are reference levels of rest-of-world and local production respectively, $P_{i,0}$ is the price premium of EVs at the reference level of experience, and γ_{price} is the strength of the learning curve for price. We further assume that world production W grows at rate λ_w:

$$\frac{dW}{dt} = W \lambda_w \tag{10}$$

We capture the effect of local market EV production on market formation dynamics, reflected in consumer acceptance, recharging infrastructure availability, quality of vehicle service, and other factors, jointly represented by the inconvenience of the EV platform. Because the EV platforms comprise both BEVs and PHEVs, the covariates of the utility of the EV platforms are modeled as a linear combination of the corresponding attributes of PHEVs and BEVs with the behavioral parameter PHEV Consideration, π, (Equations (11) and (16)) reflecting the availability, performance, and popularity of PHEVs as perceived by consumers. This formulation allows us to analytically determine the share of PHEVs versus BEVs in the EV platform (Equation (19)) and accurately capture EV market formation and the GHG impact of C4C policies. We assume that the inconvenience of PHEVs relative to ICE vehicles is 0, since PHEV drivers can also use the existing gasoline refueling infrastructure. The perceived inconvenience of an EV is therefore lower when PHEVs are present than in the absence of PHEVs through lower range anxiety, shorter charge times, and so forth:

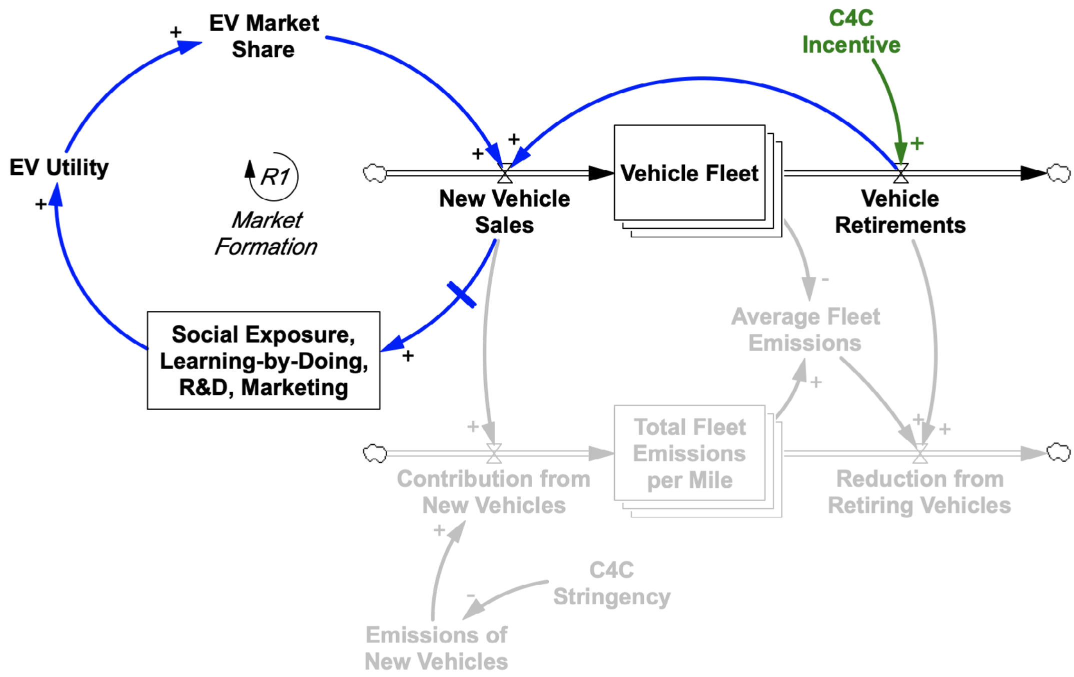

FIGURE 3 FIGURE EV market formation

$$x_i^{market} = I_{i,0}(1-\pi)\left(\frac{L}{L_0}\right)^{\gamma_{market}} \tag{11}$$

where $I_{i,0}$ is the reference inconvenience of BEVs at the reference level of experience, and γ_{market} is the strength of the learning curve for market formation.

Annual fuel costs for a new ICE vehicle depend on miles driven per year, l, the price of gasoline, p_g, and ICE fuel economy, determined by the CAFE standard, FE_i^{CAFE}. Annual fuel costs for a new EV depend on EV miles driven per year, l', which may differ from ICE miles per year (Equation (12)), the price of electricity, p_e, and EV fuel use (including electric power and, for PHEVs, gasoline for the non-electric miles driven), $FU'_{i,EV}$. Relative fuel cost savings for new EVs, x_i^{fuel}, are then given by:

$$x_i^{fuel} = 1-\left(FU'_{i,EV}\, l'\, p_e\right)\Big/\left(\frac{1}{FE_i^{CAFE}}\, l\, p_g\right) \tag{12}$$

It is well documented that people adjust their driving behavior when the fuel price, p changes relative to the reference fuel price, p', with the elasticity of miles driven to fuel price ε_l (Wang & Chen, 2014):

$$l = l'\left(\frac{p}{p'}\right)^{\varepsilon_l} \tag{13}$$

We model the fuel use of the aggregate EV platform, $FU'_{i,EV}$, as an average of the fuel use of new BEVs and PHEVs, weighted by the share of PHEVs in new EV sales, ρ, and accounting for the electricity and gasoline use of PHEVs. We assume the same fuel economy for BEVs and PHEVs. However, the gasoline fuel economy of new PHEVs is higher than that of new ICE vehicles by factor, ω_e, for two reasons. First, the internal combustion engine in a PHEV is more efficient than that of a conventional ICE vehicle because the engine is smaller and optimized for the PHEV (Zhang et al., 2019). Second, PHEV buyers often adjust their driving and charging behavior to use more all-electric miles, a phenomenon known as "gas anxiety"—the "desire of PHEV drivers to avoid using gasoline" (Ge et al., 2018). The parameter λ_e is the share of total PHEV miles driven on electricity. Thus, the average fuel use of the aggregate new EV is:

$$FU'_{i,EV} = (\rho+(1-\rho)\,\lambda_e)\frac{1}{FE_i^{BEV}} + (1-\rho)(1-\lambda_e)\frac{1}{FE_i^{CAFE}\,\omega_e} \tag{14}$$

We calculate the share of BEVs in new EV sales, ρ, in two steps: (1) compute what EV market share would be in the counterfactual scenario where the EV platform consists only of BEVs, and (2) compare it to the market share of the composite EV platform, which includes both BEVs and PHEVs. In the absence of PHEVs, the utility of the EV platform, u'_i, depends on the attributes, $\hat{x}^s$, of BEVs:

$$u_i' = \beta^{market}\widehat{x}_i^{market} + \beta^{price}\widehat{x}_i^{price} + \beta^{fuel}\widehat{x}_i^{fuel} + \epsilon_i \tag{15}$$

Specifically, pure BEVs increase the inconvenience of the EV bundle relative to a mix of BEV and PHEVs because BEVs induce greater range anxiety:

$$\widehat{x}_i^{market} = \frac{x_i^{market}}{(1-\pi)} \tag{16}$$

We assume BEV and PHEV prices are not materially different:

$$\widehat{x}_i^{price} = x_i^{price} \tag{17}$$

However, pure BEVs increase fuel savings of the EV platform relative to ICE because BEVs are more cost-efficient per mile than PHEVs:

$$\widehat{x}_i^{fuel} = 1 - \left(\frac{1}{FE^{BEV}} l' p_e\right) / \left(\frac{1}{FE_i^{CAFE}} l p_g\right) \tag{18}$$

The share of BEVs vs. PHEVs in aggregate EV sales for each vehicle class is then calculated from the utility to consumers of these two cases:

$$\rho = \frac{\sigma_i'}{\sigma_i} = \frac{1+e^{-u_i}}{1+e^{-u_i'}} \tag{19}$$

where u_i is the utility of an average EV of class i when PHEVs are present, given by Equation (8), and u_i' is the utility of an average EV in class i in the absence of PHEVs, given by Equation (15).

3.3 | Vehicle discards in the C4C program

Only ICE vehicles are retired through the C4C program, by vehicle age a, d_{ipa} (Equation (4):

$$d_{ipa} = \begin{cases} V_{ia}\beta_{ia}, \#p = ICE \\ 0, \#p = EV \end{cases} \tag{20}$$

where β_{ia} are the age-dependent hazard rates of vehicle retirement due to the C4C program. The hazard rate for ICE vehicle retirement through C4C is an age-dependent rate, β_{ia}', modified by the impact of the C4C policy, η_{ia}:

$$\beta_{ia} = \beta_{ia}' \eta_{ia} \tag{21}$$

The base hazard of retirement via C4C, β_{ia}', increases with age, a:

$$\beta_{ia}' = \beta_i' a^{\varepsilon_A} \tag{22}$$

where β_i' is the hazard of early retirement via C4C for 1 year old vehicles, and rises with vehicle age, with sensitivity of the hazard rate to vehicle age, ε_A.

The impact of C4C on early retirement, η_{ia}, is the product of three factors: the effect of the C4C incentive, θ^I, the effect of C4C stringency, θ_i^S, and the effect of additional fuel savings from the C4C program, θ_{ia}^{FE}:

$$\eta_{ia} = \theta_i^I \theta_i^S \theta_{ia}^{FE} \tag{23}$$

The incentive effect θ_i^I reflects how much the C4C incentive, I_i, affects the propensity of people to participate in the program:

$$\theta_i^I = \left(\frac{I_i}{I'}\right)^{\varepsilon_I} \tag{24}$$

where $\varepsilon_I > 0$ is the sensitivity of the incentive effect and I_i/I' is the incentive relative to a reference value.

The C4C program mandates the minimum fuel economy for new vehicles purchased under the program, FE_i^{min}. The stringency effect θ_i^S captures the fact that higher minimum fuel economy standards for replacement vehicles reduce the number of eligible replacement vehicles people can choose, therefore reducing the likelihood of participating in C4C:

$$\theta_i^S = \left(\frac{FE_i^{min}}{FE_i^{CAFE}}\right)^{\varepsilon_S} \tag{25}$$

where $\varepsilon_S < 0$ is the sensitivity of the stringency effect to the ratio of the minimum mandated fuel economy to the average fuel economy of new vehicles under the CAFE standard.

However, people choosing to participate in C4C might opt for an even more fuel-efficient vehicle than the minimum, especially if the C4C standard is not much higher than fuel economy under CAFE. We capture this effect by calculating the average fuel economy of new vehicle sales induced by C4C, FE_i^{C4C}, as the minimum mandated fuel economy, FE_i^{min}, adjusted upward by a fraction, δ_{FE}, of the effect of C4C stringency θ_i^S on the likelihood of participating in C4C:

$$FE_i^{C4C} = FE_i^{min}\left(1+\delta_{FE}\theta_i^S\right) \quad (26)$$

The less stringent the C4C program, that is, the higher θ_i^S, the higher the actual fuel efficiency of new cars purchased under C4C will be.

The effect of fuel savings on the hazard rate of C4C participation, θ_{ia}^{FE}, is based on the average fuel cost per mile of a new vehicle purchased under C4C, FC_i^{C4C}, versus that of an average ICE vehicle in the existing fleet $FC_{i,ICE,a}$, by age cohort and platform:

$$\theta_{ia}^{FE} = \left(1-\frac{FC_i^{C4C}}{FC_{i,ICE,a}}\right)^{\varepsilon_F} \quad (27)$$

where $\varepsilon_F > 0$ is the strength of the fuel savings effect.

New vehicles purchased under C4C can be either ICE or EV (as determined by market share σ_{ip} in Equation (6)). Therefore the average fuel cost per mile for new vehicles purchased under C4C is a linear combination of actual fuel cost per mile of an ICE vehicle purchased under C4C, FE_i^{C4C}, and perceived average fuel cost per mile of an EV, calculated as a weighted sum of BEVs electricity cost and PHEV electricity and gasoline cost ($FE_{i,EV}$ (Equation (14)):

$$\mathrm{FU}'_{\mathrm{i,EV}} = (\rho+(1-\rho)\,\lambda_e)\frac{1}{\mathrm{FE_i^{BEV}}} + (1-\rho)(1-\lambda_e)\frac{1}{\mathrm{FE_i^{CAFE}}\,\omega_e}$$

$$FC_i^{C4C} = (1-\sigma_i)\frac{1}{FE_i^{C4C}}\,p_g + \sigma_i\,\frac{1}{FE_{i,EV}}\,p_e \quad (28)$$

The average fuel cost per mile of an average vehicle in the existing fleet depends on the average fuel use of an ICE vehicle in the existing fleet, $\overline{z}_{i,ICE,a}$, by age cohort and platform:

$$FC_{i,ICE,a} = \overline{z}_{i,ICE,a}\,p_g \quad (29)$$

The model tracks the fleet and fuel economy of each cohort, and these are used to calculate total and average fuel economy of each platform and for the entire fleet (Appendix B: Co-flow Formulations).

3.4 | Vehicle replacement purchases under C4C program

We assume all vehicles traded in through C4C, d_{ipa}, are replaced with new vehicles, either ICE or EV, according to the market share of each platform, similar to Equation (5):

$$m_{ip} = \sigma_{ip}\sum_{a=\mathrm{Q}}^{N} d_{ipa} \quad (30)$$

Under different realizations of C4C people might qualify and be paid to discard their vehicle without buying a new one, and, having decided to go carless, fulfill their mobility needs through carpooling, ridesharing, bicycling, or other means. Estimating the potential for such mode-shifting and the resulting change in travel habits is beyond the scope of this paper, so we do not consider this possibility, establishing a lower bound on the potential reduction in GHGs achieved through the program.

3.5 | Greenhouse gas accounting

We capture full lifecycle emissions of vehicles in the model, including vehicle manufacturing, assembly, and disposal, fuel production (well-to-pump or plug), and tailpipe emissions from fuel consumption. We use the GREET 2020 model (ANL, 2020) to account for vehicle emissions from manufacturing and assembly, μ_{ip}^{mfg}, and disposal, μ_{ip}^{dis}, of vehicles, with the EV platform including the GHG footprint of the Li-Ion battery.

$$E_{ip}^{LCA} = E_{ip} + \left(n_{ip}+m_{ip}\right)\mu_{ip}^{mfg} + \left(\sum_{a=1}^{N} r_{ipa} + \sum_{a=\mathrm{Q}}^{N} d_{ipa}\right)\mu_{ip}^{dis} \quad (31)$$

We compute the emissions by vehicle class and powertrain platform, E_{ip}, by tracking fleet and emissions of each platform by each age cohort (Appendix B: Co-flow Formulations).

The emissions of new EVs are a weighted sum of the emissions attributable to BEVs and PHEVs. Emissions per mile from the electric drive of PHEVs are assumed to equal those of a BEV, but the emissions from the PHEV internal combustion engine are lower than those of a conventional ICE vehicle by a factor ω_e as discussed in Section 3.2. On average, tailpipe emissions of new EVs are:

$$\mu_{i,EV} = (\rho+(1-\rho)\,\lambda_e)\,\nu_e\,\eta_e + (1-\rho)(1-\lambda_e)\left(\frac{\nu_{gas}}{FE_i^{CAFE}\,\omega_e} + \nu_{gas}^0\right) \quad (32)$$

with the emission factor of gasoline vehicles, ν_{gas} (U.S. EPA, 2019b), in grams CO_2 per gallon, the fuel economy required by CAFE, FE_i^{CAFE}, well-to-pump emissions of gasoline, ν_{gas}^0 (ANL, 2020), the emissions factor of electricity, ν_e, the share of total miles PHEVs drive on electricity, λ_e, and the energy efficiency of the electric drivetrain, η_e, in kWh per mile.

Thus, tailpipe emissions from the composite EV platform (Equation (32)) is an implicit function of the mix of BEVs and PHEVs in EV sales, which depends on the PHEV consideration parameter, π. PHEVs comprise about 26% of all EV sales in the United States (Gohlke & Zhou, 2020; U.S. DOT, 2020), but are more popular in other markets (e.g., some European countries [EEA, 2021]). However, PHEVs are likely to be phased out to meet climate goals. For example, the European Commission proposes "all new cars registered as of 2035 will be zero-[tailpipe] emission" (European Comission, 2021). Phase-out is likely to be slower in the United States. We therefore set π such that PHEVs represent about one-quarter of all EV sales at the beginning of the simulation and decrease it linearly to 0 by 2050.

We assume that the electric grid used to charge EVs becomes "greener" over time, so that the GHG emissions factor of electricity, ν_e, in grams CO_2 per kWh (ANL, 2020; Gómez Vilchez & Jochem, 2020), falls from the initial emissions intensity of the grid, ν_0, to the emissions factor of renewable power, ν_r, as the share of renewable, low GHG electricity, σ_t^r, increases over time:

$$\nu_e = \nu_0\left(1-\sigma_t^r\right) + \nu_r \sigma_t^r \tag{33}$$

Fuel-related emissions of new vehicle sales, μ_{ip}, are:

$$\mu_{ip} = \begin{cases} \dfrac{\nu_{gas}}{FE_i^{CAFE}} + \nu_{gas}^0, \#p = ICE \\ \mu_{i,EV}, \#p = EV \end{cases} \tag{34}$$

Average fuel-related emissions of vehicle sales induced by the C4C program, μ_{ip}^{C4C}, is calculated similarly using the average fuel economy in Equation (26):

$$\mu_{ip}^{C4C} = \begin{cases} \dfrac{\nu_{gas}}{FE_i^{C4C}} + \nu_{gas}^0, \#p = ICE \\ \mu_{i,EV}, \#p = EV \end{cases} \tag{35}$$

4 | ANALYSIS

After describing model parameters and initialization (Section 4.1), we simulate fleet evolution and emissions from 2021 through 2050 through natural fleet turnover, given the CAFE standards and EV adoption in the absence of any additional policies (Section 4.2). Next, we consider C4C policies with different incentive levels (Section 4.3) and contrast C4C policies allowing replacement vehicles to be ICE or EVs versus requiring replacement purchases to be EVs (Section 4.4). In Section 4.5, we consider the impact of complementary policies including accelerating the transition to renewable electricity and introducing a gasoline tax or price on carbon (Section 4.6). In Section 4.7, we explore the sensitivity of results to the magnitude of the C4C incentive, minimum qualifying age, and required fuel efficiency of replacement vehicles, and to major uncertainties: consumer responsiveness to C4C incentives and the strength of the EV Market Formation feedbacks.

4.1 | Parameterization

To parameterize the model we use the best available data and previous work on vehicle fleet turnover (Keith et al., 2017, 2019), data on scrap rates, and vehicle miles traveled from NHTSA and Oak Ridge National Laboratory (NHTSA, 2006; Williams et al., 2017; Davis & Boundy, 2021), vehicle life-cycle emissions (ANL, 2020), and multiple studies of the 2009 US CARS program (Abrams & Parsons, 2009; Sivak & Schoettle, 2009; Morrison et al., 2010; Lenski et al., 2013; Li et al., 2013; Hoekstra et al., 2017). However, the EV market is still nascent. Data related to consumer EV adoption, the impact of access to charging, and market development are sparse. To estimate the parameters governing market formation and consumer choice we use prior analyses and data from similar settings (e.g., Keith et al., 2020) and recent research estimating the impact of charging station availability on electric vehicle utility (Wei et al., 2021). Where empirical estimates are not possible, we make plausible evidence-based assumptions, placing a premium on assumptions that are qualitatively and directionally robust, recognizing that we are studying the future behavior of the vehicle market where prior relationships might not hold (Appendix A: Parameterization of the Model), and explore the sensitivity of the results to key assumptions (Section 4.7).

4.2 | Baseline (CAFE only)

First, we consider the baseline emissions reduction resulting from rising fuel efficiency for new ICE vehicles under the CAFE standards. We assume that CAFE standards follow the rule proposed by the EPA under President Biden's executive order 13990, which would lower fleet-wide CO_2 emissions standards from 220 gCO_2/mile for model year 2022 to 171 gCO_2/mile for model year 2023–2026 (U.S. EPA, 2021). Standards for later years

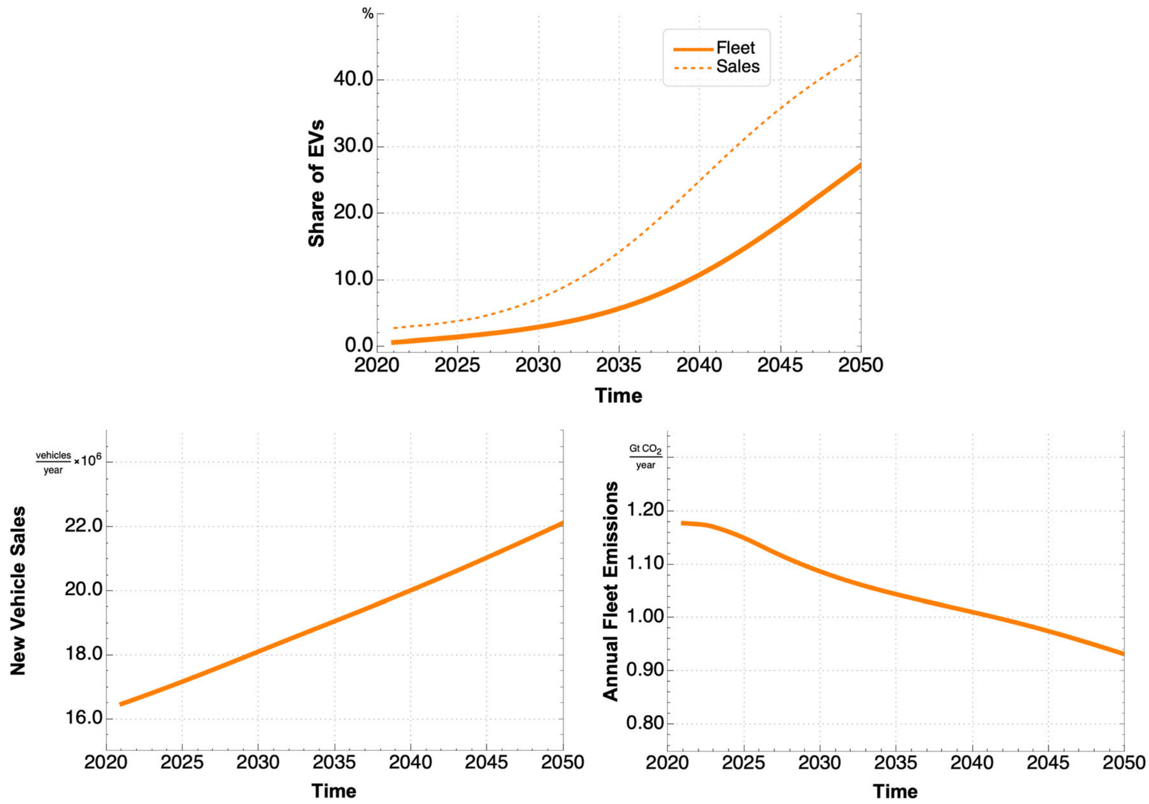

FIGURE 4 Baseline scenario (CAFE only)

have not yet been proposed. We therefore assume a conservative scenario in which emissions per mile fall an additional 25% by 2050. Real-world driving is about 20% less fuel-efficient than laboratory EPA tests (Lattanzio et al., 2020), so we adjust fuel economy for new ICE vehicles accordingly. Finally, we apply CAFE to gasoline vehicles only, excluding EVs so that growing EV sales do not have the unintended consequence of allowing automakers to sell less fuel-efficient vehicles, as current regulations permit (Jenn et al., 2019). In the baseline simulation (Figure 4), total new vehicle sales grow to about 22 million/year by 2050. EV market share rises to 44% by 2050, but the EV share of the fleet rises only to 27% of the installed base by 2050 due to the slow rate of vehicle turnover. The emissions of an average new vehicle fall 59% due to the effect of CAFE and the increasing share of EVs, but total annual fleet emissions drop only 21%, the result of the long life of vehicles and the assumed growth in total fleet size.

4.3 | C4C for the purchase of efficient gasoline or electric vehicles

We now introduce an accelerated vehicle retirement program (C4C). We assume the program operates for 10 years, starting in 2022 (Figure 5). To qualify we assume that the trade-in vehicle must be at least 5 years old, and that the replacement vehicle be at least 50% more efficient than the CAFE standard at that time (which qualifies efficient gasoline vehicles and EVs). In the results below, the cumulative reduction in CO_2 emissions through 2050 in each scenario is defined as the accumulation of the difference between emissions in the baseline case and emissions in the policy scenario (see, e.g., the right panel in Figure 5). The unit cost of C4C per tonne of avoided CO_2 emissions ($/t$CO_2$) of each policy scenario is given by the cumulative cost of C4C vehicle incentives divided by the cumulative emissions reduction in each scenario, both assessed through 2050.

Setting the incentive at $4000 per vehicle, roughly equal to the average incentive in the 2009 CARS program (Li et al., 2013), the C4C policy, denoted C4C ICE/EV, replaces 12.3 M vehicles by 2032 and reduces cumulative CO_2 emissions in 2050 by 0.08 GtCO_2, 0.3% of simulated cumulative emissions in the baseline case, at a unit cost of $613/t$CO_2$. Annual fleet emissions jump immediately after the C4C policy is introduced relative to the baseline as a result of additional emissions incurred with accelerated scrappage and new vehicle manufacturing (Figure 5). When we increase the C4C incentive to $8000 per vehicle, similar to the federal incentives available

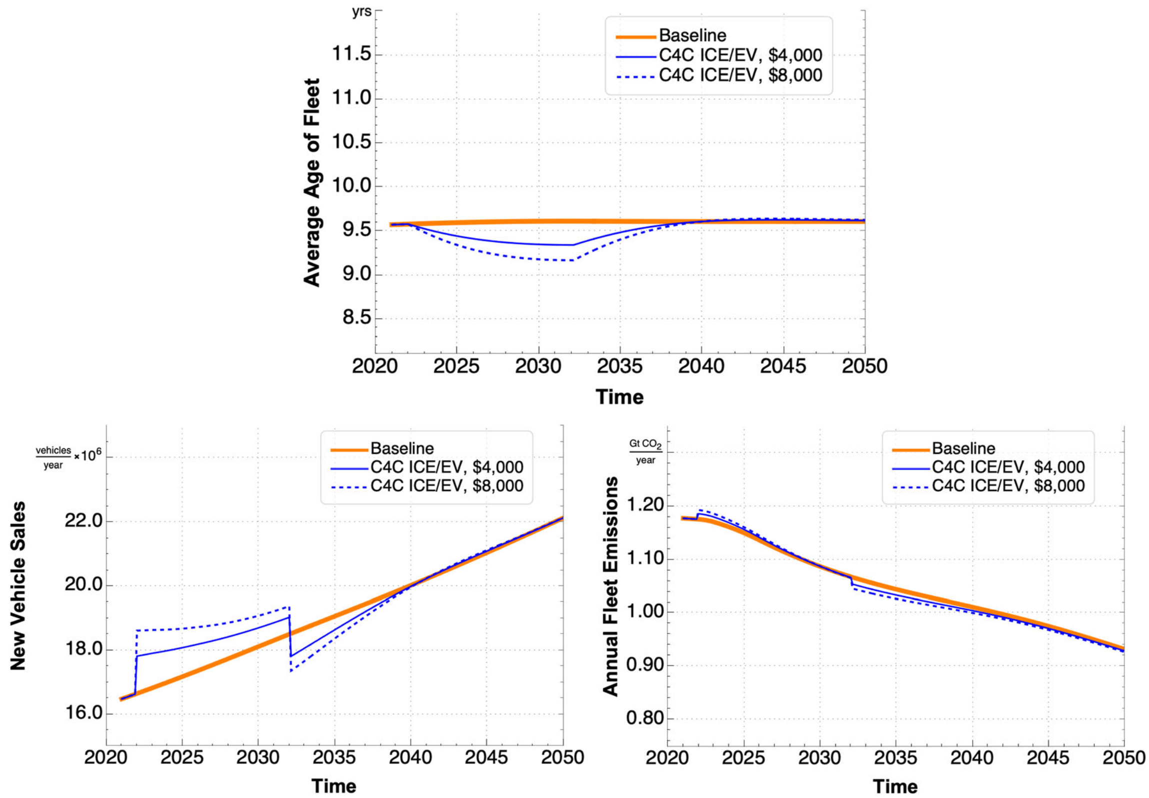

FIGURE 5 C4C policy mandating replacement with efficient ICE vehicles

today for purchasing alternative fuel vehicles (U.S. DOE, 2019), the policy replaces 20.4 M vehicles by 2032 and reduces cumulative emissions by 2050 by 0.13 $GtCO_2$ (Figure 5), at a unit cost of \$1233/tCO_2. A larger incentive encourages more people to participate and increases total avoided emissions, but the unit cost of those emissions reductions increases substantially.

As expected, the introduction of the C4C policy in 2022 immediately increases new vehicle sales, a “shot in the arm” for automotive production and manufacturing jobs. However, new vehicle sales drop below the Baseline in 2032 when C4C ends. Because C4C increases new vehicle sales, the average age of the fleet falls relative to the Baseline, beginning in 2022 (Figure 5). Consequently, when the C4C policy ends in 2032, the fleet is younger, reducing vehicle retirements. Sales eventually return to the baseline level as vehicles age (Figure 5). Cumulative sales under the C4C policy in 2032 when C4C ends are about 13 million higher than in the baseline and stabilize at 9.2 million vehicles above baseline by 2050. C4C, therefore, induces a permanent increase in cumulative auto production.

Despite the overall boost for the auto industry, C4C could create transient challenges. The demand surge when the policy begins would require production, and possibly manufacturing capacity, to ramp up, and when the program ends, the temporary drop in demand would require production to fall for some period. These impacts would ripple throughout the automotive supply chain (Vickery et al., 2003; Holweg & Pil, 2008). While the pull-forward effect on vehicle sales has been identified elsewhere, it's impact has been downplayed as insignificant, or affecting only “distant future” sales (Böckers et al., 2012; Li et al., 2013). In contrast, our results suggest policymakers should consider how to design C4C to mitigate these disequilibrium shocks. The start-up sales surge could be moderated by gradual phase-in, for example, by starting the program with eligibility restricted to older vehicles, then expanding it over a few years. Similarly, gradual phase-out of the incentive over a few years could moderate the demand reduction on program termination. Such policies would reduce the likelihood of transient production and employment problems on program start and sunset and provide time for effective planning and coordination across the supply chain.

Although outside the boundary of our model, strategic buyers already considering a new vehicle might wait until the C4C program starts, reducing sales just beforehand and increasing them further in the first few months of the program. Similarly, strategic buyers might accelerate a purchase they intended to make in the months after the program ends so as to qualify for C4C. As discussed above, such behavior was prevalent in the 2009 CARS program. However, in contrast to the eight-week CARS program of 2009, the long duration of the program minimizes the opportunity for such behavior—while some can defer the replacement of an old vehicle for a few months, fewer can delay replacement for years. To the extent strategic purchase timing occurs, it would slightly increase the short-run volatility in automobile purchases compared with the results in Figure 5. Coordination on program timing between policymakers and automakers would provide the time for auto OEMs and their supply chain partners to prepare for C4C, reducing the need for rapid, unplanned changes in production schedules.

4.4 | Targeting electric vehicle adoption with C4C

How effective would C4C be if it were specifically targeted to encourage the purchase of BEVs only? In the next scenario, denoted C4C EV, we assume people receive the incentive only if they purchase a BEV to replace their old vehicle. We retain the minimum qualifying age of 5 years, and keep the C4C incentive at \$8000, on the order of the \$7500 federal tax credit available today for many EVs.

As expected, mandating C4C trade-ins be replaced with BEVs leads to a smaller increase in new vehicle sales compared with the policy allowing replacement vehicles to be ICE or EV (Figure 6), because fewer people are willing to purchase a BEV due to their initially lower utility (e.g., fewer makes and models, shorter range, limited availability of recharging stations). Similarly, the drop in sales when the program ends is smaller under C4C EV. Note that the C4C EV \$8 K policy replaces 9.9 M vehicles by 2032, more than 50% fewer than when consumers can choose ICE or EVs under C4C, but reduces cumulative emissions through 2050 by 0.64 $GtCO_2$, about 385% more. Further, the smaller initial jump in total sales moderates the overall production and supply chain challenges automakers would face on program startup, but could create bottlenecks for batteries and other EV-specific components. Coordination between the government, automakers, and supply chain partners will be critical to mitigate the possibility of transient shortages, spot price increases, and other startup problems.

The larger drop in cumulative emissions arises for two reasons. First, BEV emissions are lower than emissions from ICE vehicles meeting the CAFE standard. Second, and more importantly, C4C EV increases EV sales more than C4C ICE/EV, bootstrapping the overall EV market by driving costs down faster and speeding growth in make and model variety, charging infrastructure deployment, and consumer familiarity with EVs. The result is far more EV sales than C4C induces alone (Figure 7). The synergy created by the reinforcing market formation feedbacks is large compared with the direct impact of C4C on vehicle replacement, contributing 84% of the total impact of C4C EV \$8 K on the cumulative emissions reduction. The additional EV sales induced by the self-reinforcing market formation feedbacks drive the unit cost of emissions reductions down to \$124/tCO_2.

4.5 | C4C with complementary policies

We next consider a policy that combines the C4C program with a gasoline tax and policies accelerating the decarbonization of the electric grid. A gas tax or price on CO_2 emissions would correct (part of) the unpriced carbon emissions externality and generate tax revenue to offset the cost of C4C implementation. Although gas tax increases have historically been politically unpopular in the United States (Hammar et al., 2004), even the American Petroleum Institute now supports carbon pricing to help reduce GHG emissions (API, 2021). Combining C4C

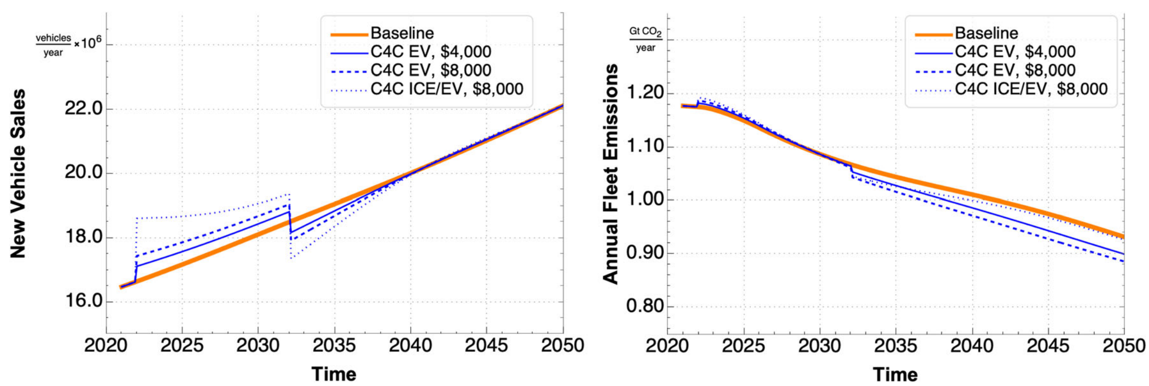

FIGURE 6 C4C policy mandating replacement with EVs only

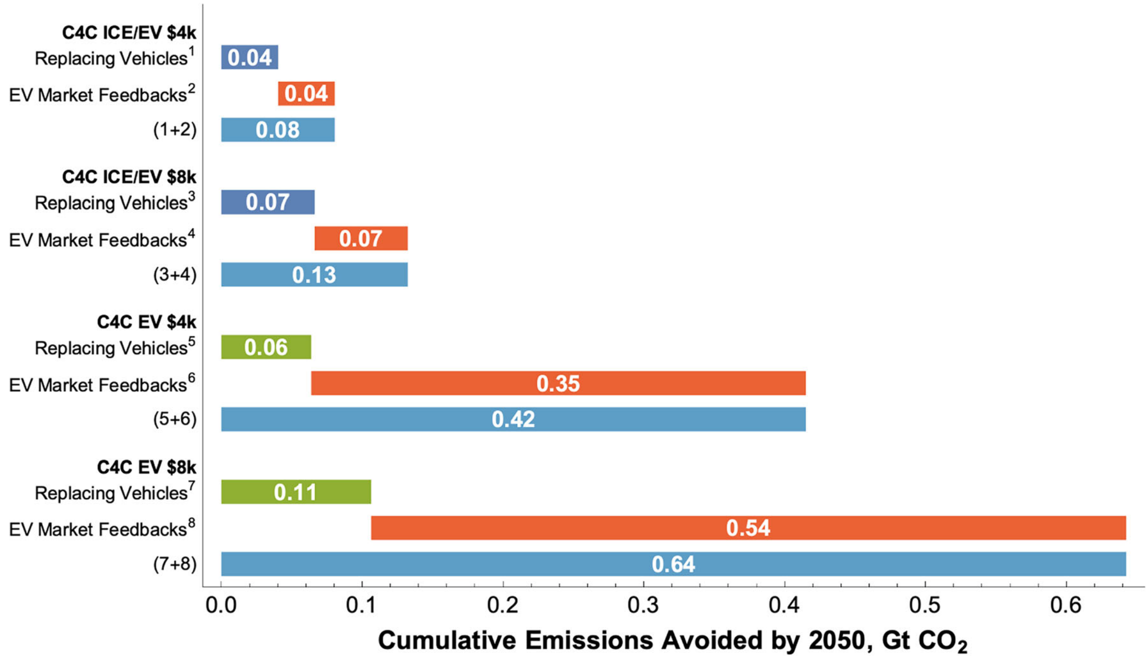

FIGURE 7 Comparison of C4C policies

and a price on carbon or gas tax creates a "carrot and stick" approach further increasing the attractiveness of EVs. Further, the revenue from a carbon price can be used to pay for the cost of C4C and/or rebated to consumers as a carbon dividend to address concerns that gas taxes are regressive. A large literature in operations management examines tax policy to promote environmentally responsible technology (e.g., Zhu & Sarkis, 2004; Krass et al., 2013; Drake et al., 2016). The results are largely driven by assumptions about emissions prices and the availability of additional incentives, such as production and cost subsidies, consumer rebates, and so forth. For example, Krass et al. write:

> using a combination of the environmental tax, consumer rebate, and fixed cost subsidy, the regulator can always induce [the clean] technology ... and achieve the highest possible welfare value of social welfare achievable with this technology.

Here, we consider the impact of a gas tax on the performance of C4C. The broader welfare and equity implications of these policies, however, are beyond the scope of our model.

Figure 8 shows the C4C EV $8 K policy together with a gasoline tax. We assume the new tax rises linearly from $0.00 to $0.30/gallon by 2050. Increasing fuel prices trigger a behavioral response as consumers reduce miles driven per Equation (13). However, the gas tax tested here is small, amounting to only 10% of the price of gasoline in 2050, so with an assumed price elasticity of demand of -0.3 (e.g., Gillingham & Munk-Nielsen, 2016), the maximum impact is a 3% reduction in ICE vehicle miles traveled (VMT) in 2050. Although the VMT reduction is small, the policy increases the attractiveness of EVs relative to ICE vehicles, and leads to large emissions reductions, particularly in later years (Figure 8).

Combining C4C EV and the gas tax raises the EV share of new vehicle sales to 52% by 2050, with the EV fleet share reaching 39%. Cumulative avoided emissions rise to 0.97 $GtCO_2$ by 2050, and the cost falls to $81/$tCO_2$. That cost is the cumulative cost of the C4C incentives per tonne of avoided emissions and does not include the revenue from the gas tax. In that scenario, cumulative gas tax revenues are approximately $318 billion, and could pay for the C4C program with a large surplus remaining.

Because EVs have zero tailpipe emissions, their climate benefits are governed by the emissions intensity of the electricity for recharging. We now consider the impact of a faster transition to renewable, low-carbon power production. The proposed Clean Electricity Payment Program seeks 80% low/zero emissions power by 2030 (Clean Air Task Force, 2021). We assume a more modest transition, achieving about 50% by 2030 and a maximum of 90% by 2040, compared with about 28% and 41% in the base case, respectively. Adding the renewable electricity (RE) policy to C4C EV and the gas tax reduces cumulative emissions by 1.31 $GtCO_2$ by 2050 (Figure 8), and further reduces the average cost to $61/$tCO_2$.

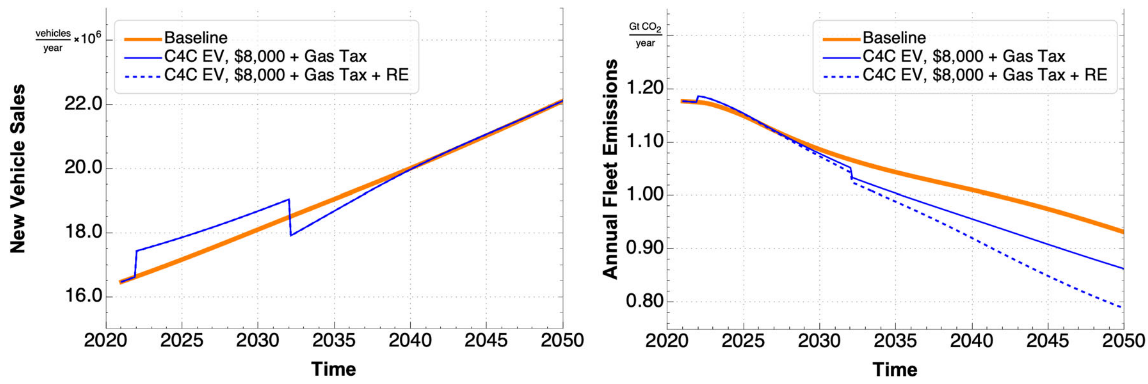

FIGURE 8 C4C policy with EVs, a gas tax, and renewable electricity

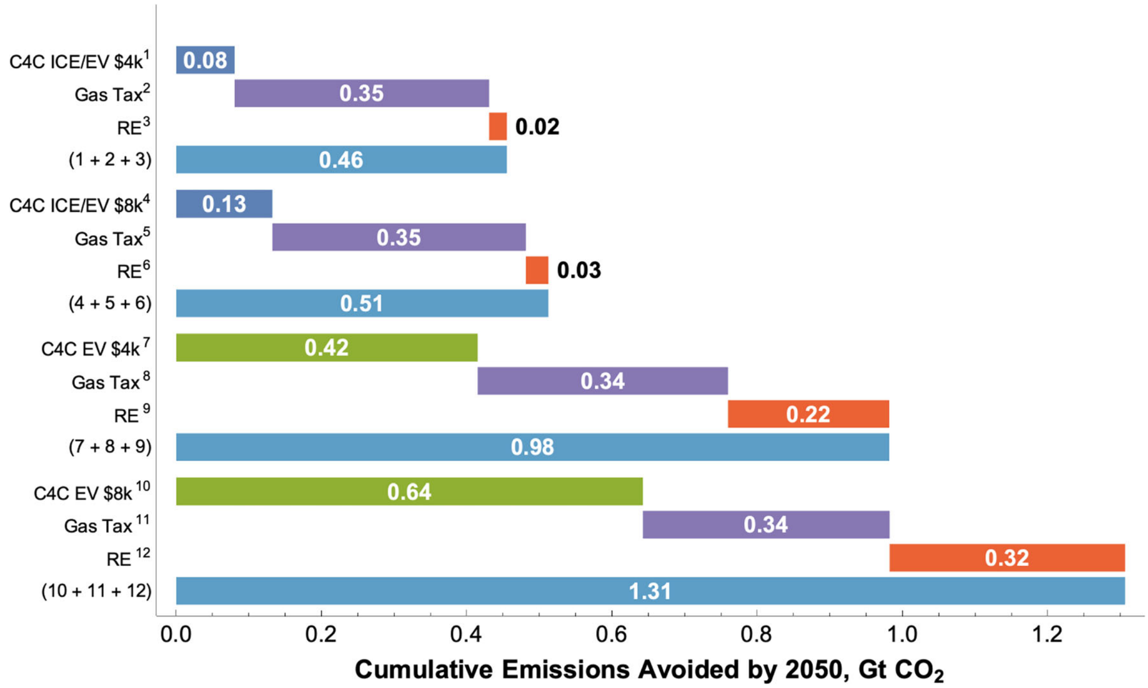

FIGURE 9 C4C policy synergies

Figure 9 shows the impact of the C4C policies with the complementary gas tax and renewable electricity policies. The impact of faster electric system decarbonization is much larger with the C4C EV policies: With C4C ICE/EV \$8 K, RE reduces cumulative emissions by 2050 by ≈0.03 $GtCO_2$, but C4C EV \$8 K increases the impact of renewable electricity to 0.32 $GtCO_2$, nearly 11 times larger (Figure 9). The synergy from the gas tax is negligible because the tax is small, reaching only \$0.09/gallon (< \$10/tCO_2) by 2030 and \$0.30/gallon (≈\$34/tCO_2) by 2050.

4.6 | Factors affecting C4C effectiveness

The impact and cost-effectiveness of C4C is contingent on three main parameters: (1) the C4C incentive; (2) C4C stringency, that is, the minimum fuel economy required for replacement vehicles under C4C; and (3) C4C qualifying age, that is, the minimum age of vehicles eligible to participate in the C4C program.

Figure 10 shows the impact of C4C ICE/EV and C4C EV as a function of the incentive. Larger incentives induce large increases in C4C participation (the cumulative number of vehicles traded in under the program). Participation is much lower under C4C EV, but shows similar responsiveness to the incentive. The magnitude and sensitivity of emissions reductions to incentive size are low when replacement vehicles can be either ICE or EVs, while the average cost per tonne of avoided emissions is high and rises steeply with larger incentives, even when C4C ICE/EV is combined with the carbon price and faster grid decarbonization. In contrast, the

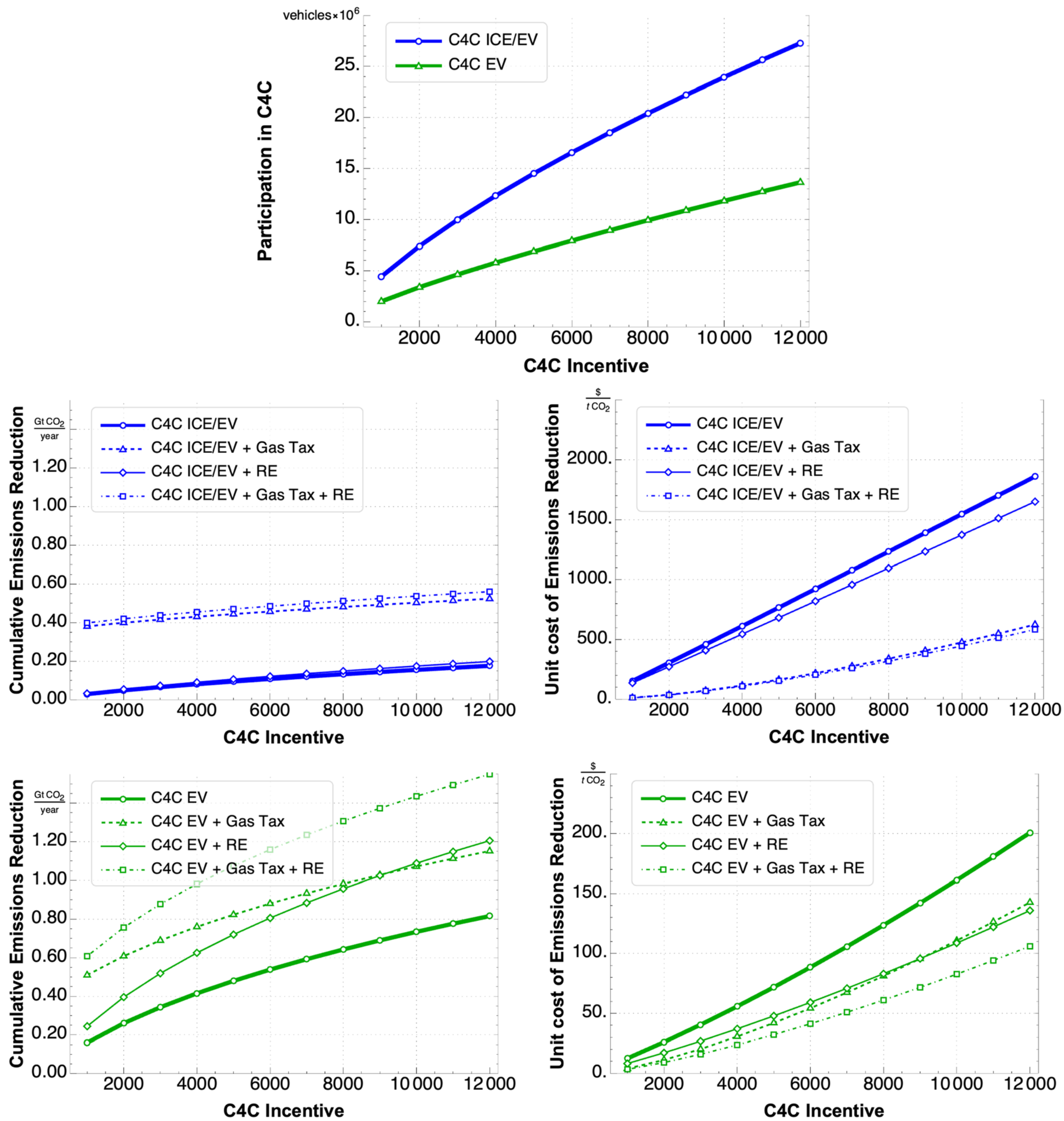

FIGURE 10 Impact of the C4C incentive. Note the different scales for the two graphs of average costs (right panels)

emissions reductions from C4C EV are far larger and rise steeply as the incentive grows, and the average cost is far lower and rises less rapidly. As expected, emissions reductions show modest diminishing returns as the incentive rises. Adding the complementary gas tax and renewable electricity policies boosts emissions reductions substantially for any incentive level and creates large reductions in the average cost per tonne of avoided emissions.

Program stringency is the required reduction in replacement vehicle emissions per mile relative to the CAFE standard at the time of trade-in and applies only to the case where participants can choose either an EV or a qualifying ICE vehicle. Perhaps a sufficiently stringent C4C program, together with the reduction in emissions per mile under the CAFE standards, would enable emissions reductions under C4C ICE/EV to surpass those of the EV only policy due to C4C higher participation when participants can choose EVs or ICE vehicles. However, while greater stringency lowers the emissions of replacement ICE vehicles, it reduces people's propensity to participate in the program because it will be harder to find makes and models meeting people's needs. Figure 11 shows that greater stringency has weak effects on emissions reductions because C4C participation falls as stringency rises. As a result, although cumulative emission savings rise for small increases in stringency, they remain far below the emissions reductions from C4C EV even

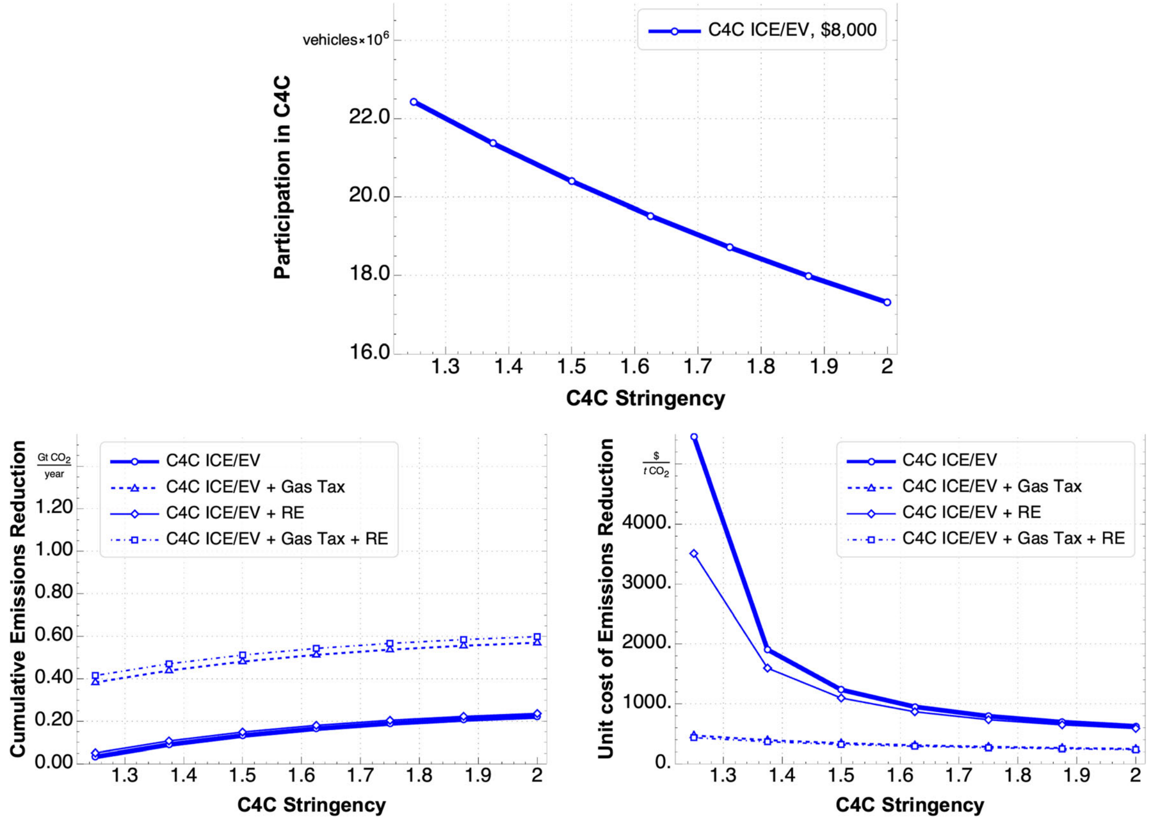

FIGURE 11 C4C impact as it depends on program stringency. Efficiency of replacement vehicle under C4C relative to CAFE standard at time of replacement

when the new ICE vehicles must be 50% better, or more, than the average new vehicle under CAFE (compare against Figure 9). The unit cost of emissions reductions under C4C ICE/EV also remain far higher than the EV only case and exhibit strong diminishing returns as stringency increases. These results hold even when C4C ICE/EV is combined with the complementary gas tax and renewable electricity policies.

The effect of the minimum qualifying age is similarly nonlinear (Figure 12). Older vehicles emit more CO_2 per mile, improving emissions reductions and cost effectiveness per vehicle, but limiting eligibility to very old vehicles reduces participation because there are fewer older vehicles, and reduces cost effectiveness because those vehicles are already near end-of-life and replacement without C4C. On the other hand, including younger vehicles might be inefficient because they are less emission-intensive than older ones, reducing the emissions benefits of early retirement. As expected, participation in C4C falls sharply as qualifying vehicle age increases from 1 to 15 years and approaches zero as qualifying age is increased further. Consequently, emission reductions are lowest for higher qualifying ages. Under C4C ICE/EV, extending eligibility to the youngest vehicles yields a negligible improvement in cumulative emissions reductions, and high cost per tonne of avoided emissions, because most replacement vehicles chosen under that policy are ICE, and the emissions intensity of young ICE vehicles is closer to that of the replacement ICE vehicle. In contrast, under C4C EV, extending eligibility to the youngest vehicles yields a large increase in cumulative emissions reductions, with only a small increase in the unit cost of avoided emissions, because even young ICE vehicles generate far more emissions than an EV.

4.7 | Sensitivity analysis

Uncertainty is inherent in all models, but particularly relevant for emerging technologies and markets where data are not yet available. Key areas of uncertainty here include parameters affecting EV market formation and consumer responsiveness to C4C programs.

4.7.1 | EV market evolution

The growth and maturation of the EV market is controlled by the strength of the learning curves governing (i) EV cost reductions and (ii) market formation, the

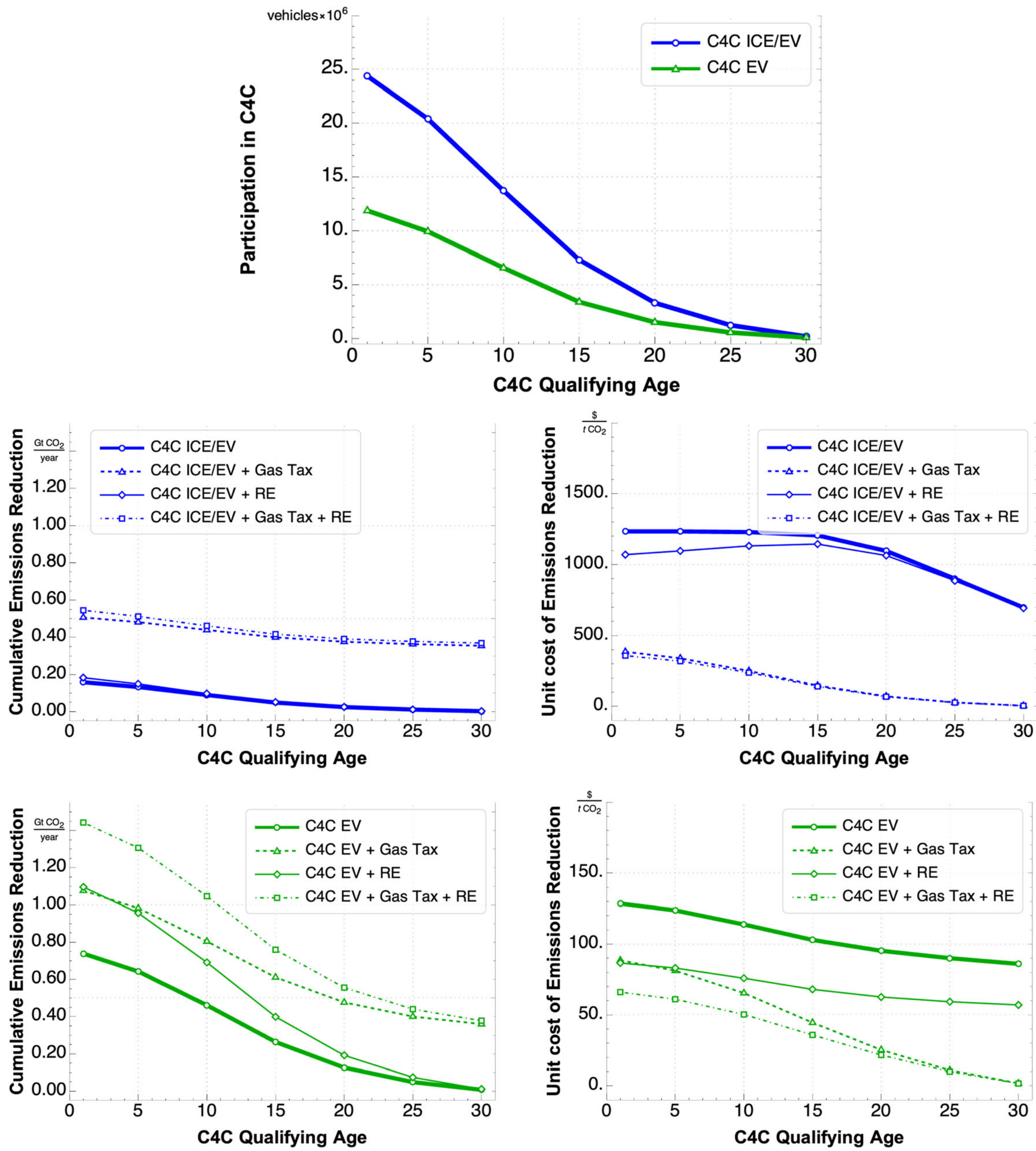

FIGURE 12 C4C impact as it depends on program qualifying age. Note the different scales for the two graphs of average costs (right panels)

latter comprising the impact of growing vehicle range and performance, make and model variety, charging infrastructure deployment, consumer awareness and willingness to consider EVs, and related factors. Figure 13 shows the effect of large variations on the assumed rate at which EVs achieve cost parity with ICE vehicles. Today, EVs are more expensive than comparable conventional vehicles, largely due to the cost of batteries. EV cost reductions in the model depend on the assumed growth rate in rest-of-world EV sales, λ_w, Equation (10), and strength of the cost reduction learning curve strength, γ_{price}, Equation (9). The baseline scenario (thick solid line) takes the default values for the worldwide market growth (10%/year) and strength of the cost reduction learning curve (25% cost reduction per doubling of cumulative sales). The Sluggish scenario assumes 50% slower rest-of-world EV market growth rate and a 50% weaker cost reduction learning curve. The optimistic case assumes 50% faster market growth and a 50% stronger learning curve, and the breakthrough case assumes 100% faster market growth and a learning curve twice as strong as the base case. The effect of these large changes is relatively modest. In the base case, the EV share of the fleet in 2050 is 27%. It varies from 21% in the sluggish scenario

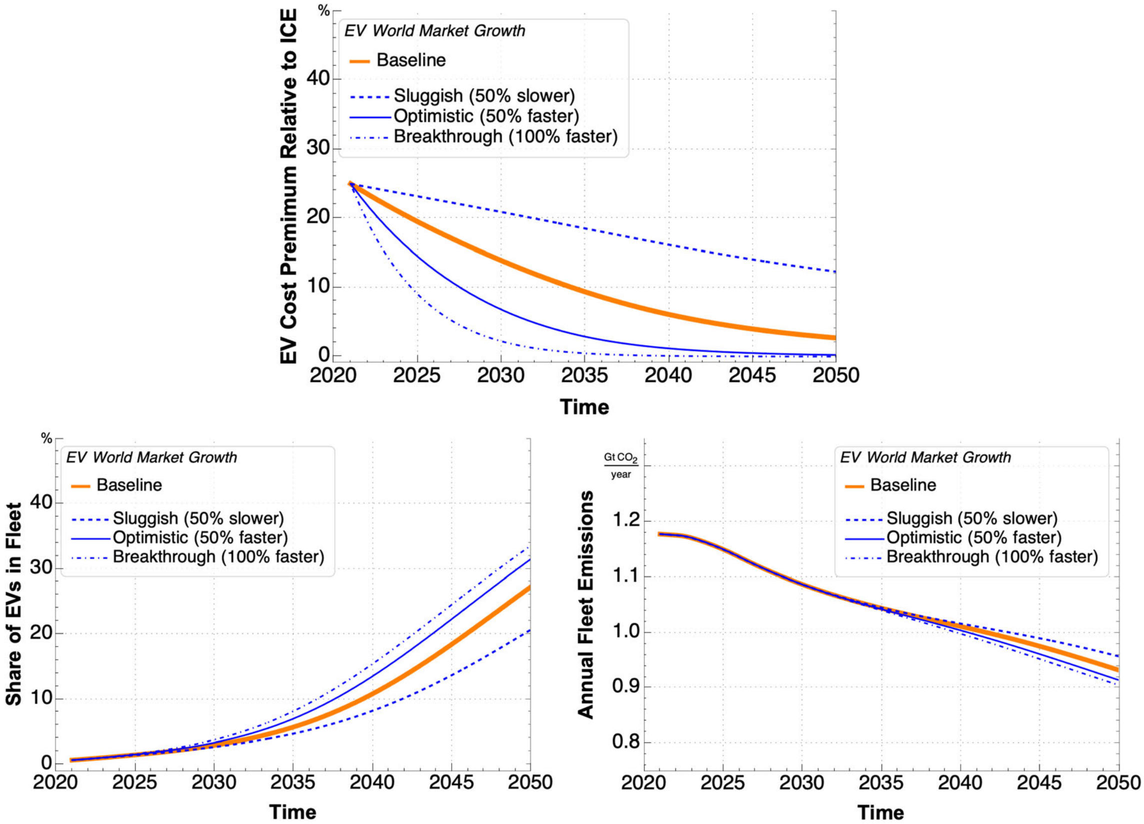

FIGURE 13 Effect of EV market on price

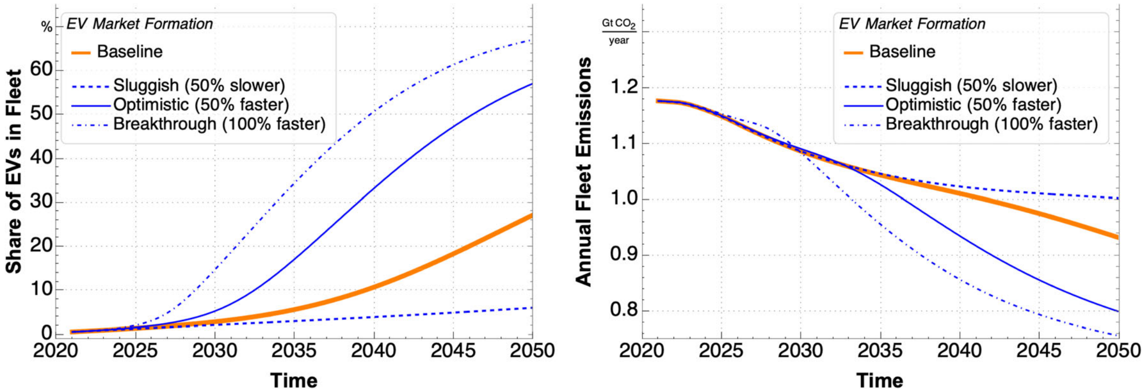

FIGURE 14 Effect of EV market formation

to 34% in the breakthrough scenario, with annual emissions in 2050 varying by approximately ±3% of the base value.

We next vary the strength of the reinforcing EV market formation feedbacks by adjusting the strength of the learning curve, γ_{market}, Equation (11). Figure 14 contrasts the baseline scenario ($\gamma_{market} = 0.35$) against Sluggish, Optimistic, and Breakthrough scenarios with $\gamma_{market} = 0.175$, 0.525, and 0.7, respectively. The impact is large. The EV share of the fleet by 2050 is 27% in the base case, but only 6% in the Sluggish case and 57% and 67% in the optimistic and breakthrough scenarios, respectively, reducing annual emissions, particularly after 2030. Cumulative emissions by 2050 are 1.3% higher in the Sluggish case than the base case and reduced by 4.5% and 8.3% for the Optimistic and Breakthrough cases respectively.

How does the strength of the market formation feedbacks affect the impact of C4C? Intuitively, C4C should be less effective when these reinforcing feedbacks are

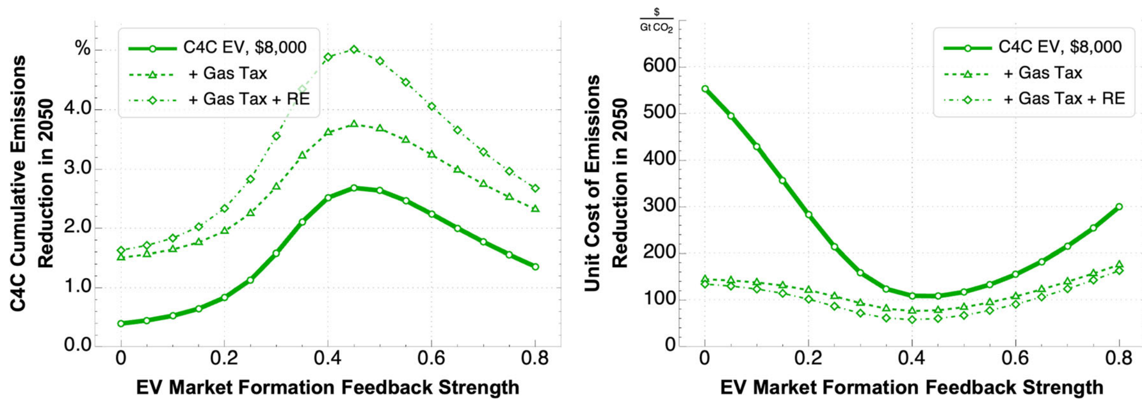

FIGURE 15 Effect of EV market formation feedbacks on C4C program

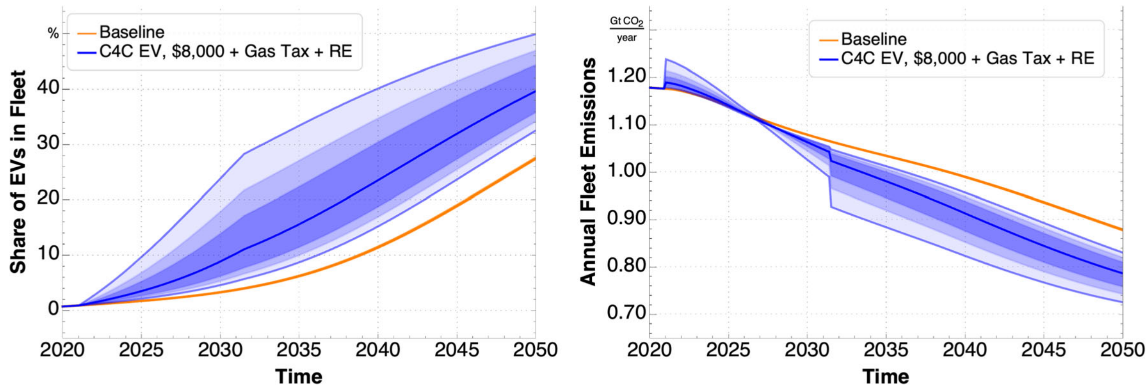

FIGURE 16 Full factorial sensitivity analysis of C4C program parameters. Darker to lighter shades encompass 50%, 75%, and 95% of all runs, respectively

weak because the synergy of additional EV sales stimulated by C4C will be smaller. However, C4C should be less beneficial when the market formation feedbacks are so strong that the EV market grows rapidly even without the stimulating effect of C4C. Figure 15 shows how C4C impact varies with the strength of the market formation feedbacks (γ_{market}) for C4C policy with $8000 incentive and additional complementary policies as in Figure 8. As expected, cumulative emissions reductions rise, peak, and then decline, and the average cost of these reductions per tonne fall to a minimum, then rise.

Note, however, that the benefits of C4C fall only slowly as the market formation feedbacks become very strong. For example, when the market formation feedbacks are twice as strong as the base case (as in the Breakthrough scenario in Figure 14), cumulative emissions reductions with the C4C EV $8000 policy in 2050 are still 0.49 GtCO2. Stronger EV market formation feedbacks cause EV market share to rise faster even without C4C, but has its greatest impact after 2030 and does not affect the existing inefficient fleet today. By removing older, more polluting vehicles in the fleet today, C4C continues to have a large impact on emissions even under highly optimistic assumptions about the speed of EV market maturation. These results hold for C4C EV alone and when the gas tax and renewable electricity policies are added. With these complementary policies, emissions reductions are much larger, and unit costs are far lower.

4.7.2 | Consumer responsiveness to C4C

Consumer response to C4C programs is governed by three main and uncertain parameters: how responsive people are to the incentive offered (ε_I), how much people value the fuel savings from replacing their vehicle (ε_F), and how much the likelihood of participating in C4C increases with vehicle age (ε_A). The smaller the magnitude of each parameter, the smaller the increase in the hazard rate of participating in C4C as incentives, fuel savings, or vehicle age increase. To explore the impact of these uncertainties, we vary each parameter between 0 (not responsive, ignoring increasing benefits) and 1 (highly responsive, proportional to benefits), in

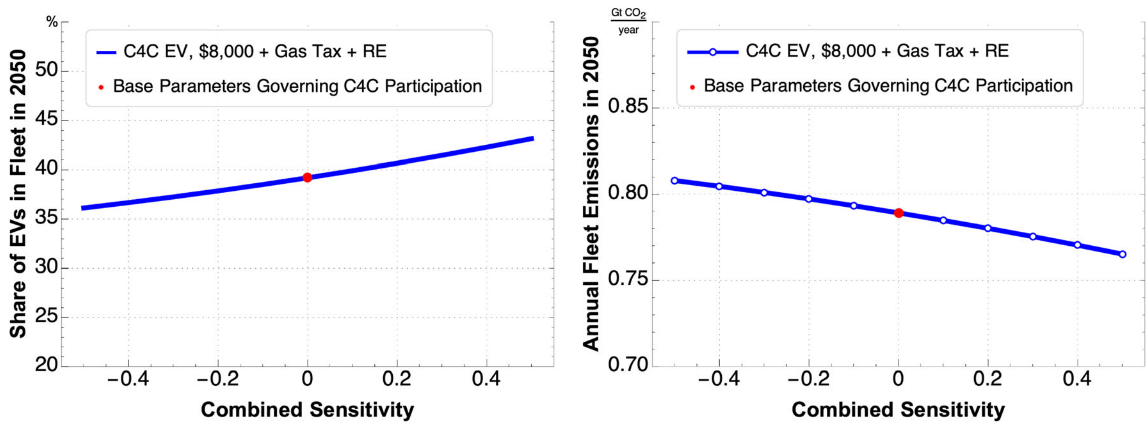

FIGURE 17 Sensitivity analysis assuming parameters affecting C4C participation are perfectly correlated

increments of 0.05 in a full factorial sensitivity analysis generating $21^3 = 9261$ simulations. Figure 16 shows the results for C4C EV $8 K with the gas tax and accelerated renewable electricity policies. Importantly, C4C increases EV adoption and cuts emissions under all combinations of parameters, even those in which their values are least favorable.

While the full factorial design varies the parameters governing the hazard rate of C4C participation independently, they are likely to be highly correlated: all three (incentive, fuel savings, and vehicle age) affect the financial impact of participating in C4C. Individuals more aware of and responsive to incentive are also more likely to be more aware of and respond to the fuel savings and to the maintenance costs, breakdown risk, and lack of modern safety features and other technologies in their older vehicle. Figure 17 shows the results of assuming the parameters governing the hazard rate of C4C participation are perfectly correlated, varying from 50% less responsive to 50% more responsive than the base values.

With the base values of these parameters, the share of EVs in the fleet in 2050 is 39% under the combined C4C $8 K, gas tax, and renewable electricity policy, compared with 27% in the baseline scenario without C4C. When all three parameters vary from −50% to +50% of their base values the EV share of the fleet in 2050 under the combined C4C policies ranges from 36% to 43%, and annual emissions range from 0.81 to 0.77 $GtCO_2$/year, compared with 27% and 0.93 $GtCO_2$/year without C4C. The combined C4C policies speed EV adoption and reduce annual emissions even when the parameters governing C4C participation are most pessimistic.

5 | DISCUSSION

The long life of automobiles means policies promoting purchase of more efficient and zero-tailpipe emissions vehicles will not reduce fleet emissions fast enough to meet current US goals. C4C programs can accelerate fleet turnover and speed the transition to low-emissions transportation. Designing a C4C policy that simultaneously addresses environmental, financial, and manufacturing objectives create opportunities but also challenges. Several tensions must be resolved. Increasing the incentive paid to each participant boosts participation, but raises program costs and may create a surge of sales at the start of the program that could strain automotive supply chains. The more stringent the eligibility requirements for C4C, the larger the emissions reductions from each vehicle traded in under the program, but fewer people will qualify, reducing participation. Allowing people to choose a qualifying EV or ICE replacement vehicle increases the variety of makes and models available, increasing participation, but reduces the emissions savings per vehicle and slows the maturation of the EV market.

Here we address these issues by extending an existing simulation model of the US light-duty vehicle fleet to include behavioral feedback governing consumer choice among BEV, plug-in hybrid electrics (PHEV), and internal combustion engine (ICE) vehicles as they depend on attributes such as price, fuel economy, and convenience, the latter encompassing make and model variety, charge time and availability, range anxiety, and other factors. We also model the dynamics of EV market formation. Higher EV sales lead to cost reductions and performance improvements through scale economies, learning, and R&D; boost growth in the variety of EV makes and models and increase EV attractiveness to a heterogeneous driving public; create demand for deployment of ubiquitous charging infrastructure, reducing range anxiety; and increase social exposure to EVs, increasing consumer familiarity with them and people's willingness to consider an EV in their next purchase. These effects create multiple reinforcing feedback processes driving the formation and maturation of the EV market. As EV sales grow, these feedbacks improve the attractiveness of EVs, leading to still more sales in a virtuous cycle.

Before summarizing the results, we consider the limitations of this study and opportunities for additional research. First, our model assumes existing patterns of car ownership and use continue in the coming decades, even though a wide range of future worlds are possible with the emergence of technologies such as on-demand mobility platforms, and self-driving cars. The impact of these technologies is highly uncertain—the emergence of safe and shared robotaxis could accelerate the removal of vehicles off our roads, but they could also make driving more attractive and more accessible, leading to an increase in VMT (Naumov et al., 2020). The COVID-19 pandemic triggered a shift to work-from-home business models and changes in settlement patterns, which, if they persist, could have lasting impacts on patterns of vehicle ownership and use. Second, our model uses an aggregated representation of EV market formation, abstracting away from dynamics such as the chicken-and-egg problem around charging infrastructure rollout that could be a further barrier to EV adoption (see e.g., Struben & Sterman, 2008, for a spatially explicit model of the coevolution of alternative fuel vehicles and fueling infrastructure). Third, our analysis does not capture variations in policies across the US caused by different state- and municipality-level incentives, EV mandates, and other preferences for EVs that could influence the effectiveness of C4C. Fourth, other policies complementary to C4C, gas or carbon taxes, and policies to promote zero- and low-carbon power generation could be considered, including subsidies for automakers to retool production lines, retrain workers, and develop the new supply chains and vehicle servicing capacity needed for EVs. Fifth, other policies can increase the relative attractiveness of EVs, including tolls and congestion pricing, registration fees and taxes, in which EVs would be charged less or be exempt. EVs can also be given access to HOV lanes without passengers. Such policies are more common in Europe than in the United States (e.g., "the polluter pays principle" in Norway (Elbil, 2021b) and London's "congestion charge" (Errity, 2021)), though some (e.g., HOV lane access for low-emission vehicles) have been successfully deployed in various US states (AFDC, 2021). We welcome additional research that addresses these topics and brings climate-oriented C4C closer to implementation.

Notwithstanding these opportunities for model extensions, we find that C4C policies can contribute significantly to US automotive emissions reductions. However, the impact depends strongly on program characteristics. The most important by far: we find C4C policies should require trade-ins under the program be replaced with electric vehicles, even with the stronger CAFE standards implemented in 2021 and the assumption of continued drops in ICE vehicle emissions per mile through 2050. Requiring replacement vehicles purchased under C4C be electric ("C4C EV") reduces overall program participation, but has two critical benefits. First, C4C EV boosts EV sales more than when participants can purchase an EV or ICE vehicle ("C4C ICE/EV"), and EVs reduce emissions more than ICE vehicles, even with the current emissions intensity of the electric power system. Second, and far more important, by increasing EV sales in the near term, C4C EV speeds and strengthens the multiple reinforcing feedback processes that accelerate the growth of the EV market and supply chain. Consequently, C4C EV increases EV sales far more than the direct impact it has on vehicle replacement by bootstrapping the maturation of the EV market, cutting emissions significantly even after the C4C program ends and lowering the cost per tonne of avoided emissions.

The impact of C4C EV is further enhanced when deployed together with complementary policies including a price on carbon (or gas tax), and policies that accelerate the decarbonization of the electric power system. The joint impact of C4C and these policies is larger than the sum of their individual impacts because of the additional synergy they generate by further promoting the multiple market formation feedbacks described above.

How cost-effective could C4C programs be? The cost per tonne of avoided emissions ranges from \$124/tCO_2 for C4C EV with an \$8000 per vehicle inventive to \$61/tCO_2 when deployed with the carbon price and accelerated transition to renewable electricity (and with a \$4000 incentive, \$56/tCO_2 alone and just \$24/tCO_2, with the complementary policies). These costs are within the range of values for the SCC estimated by the EPA during the Obama administration, \$14–\$138/tCO_2 in 2007\$ (U.S. EPA, 2016), ~\$18–\$175/tCO_2 in 2020\$ using the CPI). However, several considerations suggest those estimates of the SCC are too low. First, SCC estimates are highly sensitive to the social discount rate (SDR); EPA used SDRs from 2.5 to 5%/year, while Drupp et al. (2018) found "more than three-quarters" of experts surveyed found "the median risk-free SDR of 2 percent acceptable." Lower social discount rates increase the SCC. Second, SCC estimates are highly sensitive to the assumed climate damage function. Later work (e.g., Weitzman, 2010; Burke et al., 2015; Dietz & Stern, 2015) supports damage functions and SCC estimates much higher than those used by EPA a decade ago. Third, models accounting for uncertainty in key climate and economic parameters, the possibility of crossing climate tipping points, and risks that emissions reductions may be further delayed by technical, political, or other factors yield much higher estimates of SCC: Dietz et al. (2021) found that the risk of climate tipping points, such as thawing permafrost, ice sheet disintegration, and changes in atmospheric circulation, increase the expected value of SCC by about 25%. Daniel et al. (2019), accounting for uncertainty in key climate and economic parameters, and risks of delays in emissions reductions estimate SCC through 2050 to be approximately \$100–\$150/tCO_2, even for low-end damage functions and social discount rates >2%/year. Bressler (2021) finds that including the "mortality cost of carbon"—the economic value of the additional deaths caused by the warming induced by a tonne of CO_2 emissions—yields an SCC up to \$295/tCO_2, while Kikstra et al. (2021), accounting for climate-economy feedbacks and temperature variability, estimate the SCC to be \$307/tCO_2 (interquartile range \$147–\$349/tCO_2). We conclude that properly designed C4C policies offer emissions reductions at costs lower than or comparable to the value of the avoided climate damage.

Additional complementary policies not examined here could further reduce the costs of emissions reductions. Plautz (2021) reports that electrifying federal, state, city, and postal service fleets could yield about \$4 billion in savings, savings that could be used to offset the costs of C4C policies aimed at the general population. Even more important, electrifying government fleets would further speed EV market development, enhancing the synergy arising from the reinforcing market formation feedbacks and leading to larger synergies from C4C.

Even if C4C policies are cost effective, the distributional and equity impacts of these, and any, climate policies must be considered. Gas taxes and carbon prices are often seen as regressive, disproportionately harming lower-income individuals. The distributional impact of a gas tax or carbon price, however, depends on the fate of the revenue. Many proposals, across the political spectrum, call for 100% of the revenue be rebated to the public as a "carbon dividend." These include the Republican Baker-Schultz plan (e.g., Climate Leadership Council, 2019), the non-partisan Citizens Climate Lobby plan (CCL, 2021), and the Energy Innovation and Carbon Dividend Act (H.R. 2307, U.S. Congress, 2021), co-sponsored by 40 Democratic representatives as of 5 May 2021, among others (Reynolds, 2021). The gasoline consumption and carbon footprints of low-income individuals are lower than those of the affluent. Consequently, the net cost of a gas or carbon tax with dividend is low or negative for lower-income individuals and positive for the affluent. C4C programs will also primarily benefit more affluent individuals who buy the majority of new cars, while low-income individuals tend to purchase used vehicles or forgo car ownership altogether, instead of relying on public transportation. However, by accelerating fleet turnover, C4C policies speed reductions in harmful tailpipe emissions. The adverse health impacts of these emissions are disproportionately borne by the poor and especially by people of color (Tessum et al., 2021). Reductions in fossil fuel use induced by C4C help these groups by reducing morbidity, mortality, days of lost income, and health care costs, among other co-benefits.

Intuition suggests that C4C programs should focus on the oldest, most polluting vehicles, with relatively new vehicles ineligible for the program. We find, however, that C4C programs requiring the replacement vehicle be electric yield larger emissions reductions at reasonable cost per tonne even when all existing ICE vehicles are eligible: the emissions reductions of EVs are large even compared with the newest ICE vehicles, and, by increasing participation, universal eligibility further speeds the maturation of the EV market, boosting the synergies created by the reinforcing market formation feedbacks around EV costs, range, performance, make and model variety, charging infrastructure, and consumer awareness.

The potential to implement an environmental policy that stimulates manufacturing employment is a particularly appealing aspect of C4C. Our simulations show that C4C will lead to an immediate increase in new vehicle sales, and a permanent increase in cumulative production even after C4C ends. However, the physics of fleet turnover cannot be avoided. C4C accelerates trade-ins, causing a surge in new vehicle sales when the program starts, potentially stressing manufacturing capacity and creating supply chain bottlenecks. Such bottlenecks would be most severe for the EV supply chain, particularly under C4C EV. Policymakers could mitigate the potential for transient bottlenecks when the program begins through gradual phase in, for example, by starting the program with eligibility restricted to older vehicles and expanding it over a few years. Likewise, a temporary drop in sales is inevitable when the program ends. However, running C4C over a decade, as in our simulations, both increases the cumulative emissions reductions from the program and reduces the pull-forward effect and possibilities for strategic purchase timing by consumers, reducing the sales decline when the program ends. The temporary sales drop at program end and its transient impacts on automakers and the supply chain could be mitigated by, for example, gradually reducing the incentive or eligibility. Coordination among government, automakers, and suppliers will be important in any scenario.

The results also have methodological implications. The large synergy created by the market formation feedbacks means models that assume exogenous rates of improvement and adoption of new technologies will underestimate the impacts of policies such as C4C. Effective models should capture fleet turnover and other constraints imposed by the "physics" of the system, but should also have a broad boundary that includes the many endogenous feedback processes that condition consumer choice and manufacturer behavior. Although we examined the automobile industry here, the need for a broad boundary including such behavioral feedback would apply to models designed for any new technologies and novel markets.

Limiting global warming and avoiding the worst impacts of climate change require global GHG emissions fall as quickly and deeply as possible. Transportation constitutes a major source of emissions, but the long lifetime of vehicles means emissions reduction targets cannot be met even assuming optimistic reductions in new vehicle emissions and a rapid increase in the market share of zero-tailpipe emissions vehicles. C4C programs designed to speed the transition to electric vehicles can speed emissions reductions and bootstrap the maturation of a robust zero-tailpipe emissions vehicle fleet, automobile industry, and supply chain, helping to make the transition to sustainable transportation a reality.

OPEN RESEARCH BADGES

This article has been awarded Open Data Badge for making publicly available the digitally-shareable data necessary to reproduce the reported results. Data is available at Open Science Framework

This article has been awarded Open Materials Badge for making the components of the research methodology needed to reproduce the reported procedure and analysis publicly available at Open Science Framework

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SUPPORTING INFORMATION

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APPENDIX

A. Parameterization of the model

TABLE A1 Model parameters

Parameter	Value
Initial price surcharge of EVs relative to ICE	0.25
Reference inconvenience of EVs (Car)	−1
Reference inconvenience of EVs (light truck)	−1.8
Weight of market maturity	2
Weight of price surcharge	−1
Weight of fuel savings	1
Sensitivity of market share to utility	2
Grid electricity cost, $/kWh	0.1054 (U.S. EIA, 2020)
Current share renewable electricity	0.15
Max share renewable electricity	0.9
Learning curve strength price	0.25
Learning curve strength market formation	0.35
Aggregate market growth rate, 1/year	0.01
Elasticity of VMT to fuel price	(Gillingham & Munk-Nielsen, 2016)
Hazard rate of vehicle discards, 1/year	(Williams et al., 2017; Davis & Boundy, 2021)
Initial vehicle fleet, vehicles	(Keith et al., 2019; Davis & Boundy, 2021)
Initial emissions, grams CO_2/mile*vehicles	(Keith et al., 2019)
Baseline fuel price, $/gallon	3.0
CAFE standards	(Volpe, 2015; Keith et al., 2019; NHTSA, 2021a; U.S. EPA, 2021)
Reference C4C hazard rate	0.002

(Continues)

TABLE A1 (Continued)

Parameter	Value
Sensitivity of C4C hazard rate to vehicle age	0.5
Reference C4C incentive value, $/vehicle	$4000
Sensitivity of incentive effect	0.75
C4C policy start year	2022
C4C policy end year	2032
Minimum age to qualify for C4C, years	5
C4C stringency multiplier	1.5
Gas tax ramp start year	2022
Gas tax ramp end year	2050
Gas tax start value, $/gallon	0
Gas tax end value, $/gallon	0.3
Year of fully renewable electricity	2075
Maximum share renewables	0.9
Sensitivity of C4C stringency effect	−0.75
Sensitivity of fuel savings effect	0.75

B. Co-flow formulations

We calculate the emissions and fuel use of vehicles in the existing fleet using standard co-flow formulations (Sterman, 2000). The co-flow structure tracks fuel use from each age cohort arising from age-specific fuel-efficiency, improving fuel-efficiency of new vehicles, and changing the mix of vehicle platforms. Total fleet fuel use sums over N individual age cohorts a:

$$FU_{ip} = \sum_{a=1}^{N} FU_{ipa} \tag{B1}$$

Emissions from each cohort accumulate and deplete following vehicle sales and retirements:

$$\frac{dFU_{ip}}{dt} = n_{ip} z_{ip} - \sum_{a=1}^{N} r_{ipa} \overline{z}_{ipa} + m_{ip} z_{ip}^{C4C} - \sum_{a=Q}^{N} d_{ipa} \overline{z}_{ipa} \tag{B2}$$

where z_{ip} and z_{ip}^{C4C} are fuel use of new vehicle sales from natural fleet turnover and induced by the C4C program respectively for vehicle class i, gallons per mile, and $\overline{z}_{ipa}$ is the average fuel use of vehicles of class i with powertrain p in age cohort a,:

$$\overline{z}_{ipa} = \frac{FU_{ipa}}{V_{ipa}} \tag{B3}$$

Fuel use of new EVs is a reciprocal of the average fuel economy of a new EV which we calculate as a weighted sum of the fuel economy of BEVs and PHEVs. The fuel economy of the electric drive of a PHEV equal that of a BEV, but the fuel economy of the PHEV internal combustion engine is higher than that of a conventional ICE vehicle by a factor ω_e as discussed in Section 3.2. On average, fuel use of new EVs is:

$$z_{i,EV} = \frac{1}{(\rho + (1-\rho)\,\lambda_e)\,FE_{i,EV} + (1-\rho)(1-\lambda_e)\,FE_i^{CAFE}\,\omega_e} \tag{B4}$$

with the share of total miles PHEVs drive on electricity, λ_e, and the share of PHEVs in new EV sales, ρ, calculated in Equation (19).

Fuel use of new vehicle sales, z_{ip}, is:

$$z_{ip} = \begin{cases} \dfrac{1}{FE_i^{CAFE}}, \#p = ICE \\ z_{i,EV}, \#p = EV \end{cases} \tag{B5}$$

Average fuel use of vehicle sales induced by the C4C program, z_{ip}^{C4C}, is calculated similarly using the average fuel economy in Equation (5):

$$z_{ip}^{C4C} = \begin{cases} \dfrac{1}{FE_i^{C4C}}, \#p = ICE \\ z_{i,EV}, \#p = EV \end{cases} \tag{B6}$$

Fuel-related vehicle GHG emissions from the vehicle fleet use the same co-flow structure. Total emissions sum over N individual age cohorts a:

$$E_{ip} = \sum_{a=1}^{N} E_{ipa} \tag{B7}$$

The emissions accumulate and deplete following vehicle sales and retirements:

$$\frac{dE_{ip}}{dt} = n_{ip}\mu_{ip} - \sum_{a=1}^{N} r_{ipa}\overline{\mu}_{ipa} + m_{ip}\mu_{ip}^{C4C} - \sum_{a=Q}^{N} d_{ipa}\overline{\mu}_{ipa} \tag{B8}$$

where μ_{ip} and μ_{ip}^{C4C} are emissions of new vehicle sales from natural fleet turnover and induced by the C4C program respectively for vehicle class i, in grams CO_2 per mile, and $\overline{\mu}_{ipa}$ is the average emissions of vehicles of class i with powertrain p in age cohort a:

$$\overline{\mu}_{ipa} = \frac{E_{ipa}}{V_{ipa}} \tag{B9}$$