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Technology progress and clean vehicle policies on fleet turnover and equity: insights from household vehicle fleet micro-simulations with ATLAS

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ABSTRACT

This paper documents the design and application of ATLAS (Automobile and Technology Lifecycle-Based ASsignment), a comprehensive household vehicle transaction and technology adoption micro-simulator in the San Francisco Bay Area. ATLAS evolves the fleet mix of individual households by simulating the vehicle transaction and choice decisions in response to co-evolving demographics, land use, and vehicle technology simulations. While most existing literature has focused on the aggregate clean vehicle uptake, this paper differentiates distributional effects and decomposes the underlying mechanisms across heterogeneous sub-populations of households. Using scenarios and sensitivity simulations that vary vehicle technology and policy assumptions, we find that Zero Emission Vehicles (ZEVs) penetrate into higher income groups at a faster rate than into lower income groups, which is intuitive and aligns with expectations. Interestingly, the relative income disparity in ZEV ownership shrinks over time across all scenarios, with a ZEV mandate coupled with declining battery cost leading to the greatest reduction in disparity of ZEV ownership by 2050. Federal, state, and local financial incentives influence the redistribution of ZEV uptake across income groups and contribute to narrowing income disparity. Vehicle transaction frequency and new versus used market dynamics are found to be important factors contributing to the income disparity.

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1. Introduction

Much of the world is moving toward increased transportation system electrification in order to decarbonize the transportation sector and mitigate the adverse effects of climate change. The European Union (European Commission n.d.) and the United States (Office of the Federal Register 2021) have both established targets for net-zero greenhouse gas emissions by 2050. There is increased interest in policies to expedite turnover of the passenger vehicle fleet to cleaner technologies, such as electric vehicles (EVs). For example, a number of U.S. states have passed legislation banning the sale of internal combustion engines (ICEs) by 2030 or 2035, such as California's 2035 Zero Emission Vehicle (ZEV) Mandate (Axsen, Hardman, and Jenn 2022; Reed 2021), and the Biden administration is pursuing stricter tailpipe standards, higher purchase subsidies, and other financial incentives to encourage EV adoption (The White House 2021). Although ZEVs are currently more expensive on average than ICE vehicles, purchase costs of EVs are declining rapidly, driven in part by declining battery costs. Between 2007 and 2014, industry-wide costs of lithium-ion battery packs fell by more than 50% (Nykvist and Nilsson 2015). However, significant uncertainty remains regarding how quickly clean vehicles will overtake ICE vehicles as the majority of the national fleet. This uncertainty is exacerbated by differences across alternative technology and policy pathways. Projecting how this transition of personal vehicles will unfold requires sufficiently comprehensive and robust modeling of vehicle transaction decisions made by households.

Households with different travel needs and constraints have different sensitivities to vehicle attributes and policy incentives (Coffman, Bernstein, and Wee 2017). Consequently, uncertainty also arises regarding the distributional and equity impacts of the clean vehicle transition across heterogeneous populations. The transportation engineering and environmental economics literature has reviewed the impacts of various clean vehicle incentives programs in recent years with a focus on these questions. The bulk of this literature, particularly in the transportation domain, uses stated preference methods. Potoglou and Kanaroglou (2007) used a choice experiment in an online survey aimed at residents of the Hamilton, ON, Canada metropolitan area, while Tal and Nicholas (2016) used ex-post survey data of clean vehicle buyers. In the environmental economics literature, DeShazo, Sheldon, and Carson (2017) leveraged a vehicle choice experiment from a representative survey of prospective new car buyers in California to calibrate a hedonic model for vehicle choice, and use this model to simulate the effects of various clean vehicle incentives on cost-effectiveness and distribution of benefits. Further research on the distributional impacts of various policy mechanisms is limited, which is the primary focus of this paper.

Specific outcomes pertaining to vehicle ownership are often the result of a sequential and circumstantial decision-making process. For example, vehicle ownership is influenced by life-stage transitions, such as the birth of a child (Jin et al. 2020; Oakil, Manting, and Nijland 2016; Yang et al. 2023), and changes in the number of adults in the household (Yamamoto 2008). The number and types of vehicles owned by a household are a result of a series of vehicle transactions (add, replace, and dispose of vehicles) and decisions which take place at different stages along the household's life-course (Jin et al. 2022) and co-evolve with the spatial context of residential and work locations (Rashidi, Mohammadian, and Koppelman 2011). Furthermore, adoption of clean vehicles is sensitive to evolving vehicle attributes such as price and performance (range, charging time, etc.) as well as supply side constraints (Coffman, Bernstein, and Wee 2017). For example, declining battery prices reduce ZEV upfront costs, making them more attractive to consumers. Several ZEV mandates require manufactures to accelerate ZEV supply (Axsen, Hardman, and Jenn 2022; Bhardwaj, Axsen, and McCollum 2022; 2021), subsequently increasing the clean vehicle options in the market. Therefore, accurate forecasting of technology adoption requires an integration of demographic, land use, vehicle technology, and vehicle market simulations to fully evolve households, their preferences, and household vehicle composition over time.

Current literature has inadequate emphasis on modeling these underlying processes of vehicle ownership especially at the household level. Most existing literature, relying on cross-sectional data, has provided only a snapshot of vehicle holdings and/or their utilization (Anowar, Eluru, and Miranda-Moreno 2014; de Jong and Kitamura 2009). While longitudinal models have been proposed (e.g. de Jong and Kitamura 2009), these models have either focused primarily on change of ownership levels rather than vehicle types (e.g. body type, powertrain, and vintage) as reviewed in (Paleti et al. 2011); or operated at a more aggregated level such as stock models (e.g. Brooker et al. 2015a; Muratori et al. 2021) and more reviewed in (Stephens et al. 2017). Aggregated models typically project market penetration and vehicle population (stock) at county – or national levels and for limited population segments. The lack of consideration of detailed household-level vehicle transaction processes in these aggregated models results in important caveats: (i) a primary focus on vehicle choices in the *new* vehicle market while ignoring transactions in the *used* vehicle market that could redistribute vehicles among households without changing the total stock; (ii) a limited ability to accommodate flexible distributional analysis at disaggregated spatial and sociodemographic resolutions; and (iii) inadequate behavioral realisms to interrogate the underlying drivers and identify potential intervention strategies along the full process chain of technology adoption from vehicle transaction to technology choice decisions.

This study seeks to address aforementioned uncertainties in both fleet turnover and its distributional and equity impacts under alternative technology and policy pathways, leveraging a newly developed vehicle transaction and technology adoption microsimulator ATLAS (**A**utomobile and **T**echnology **L**ifecycle-Based **AS**signment). Different from most existing vehicle choice models, ATLAS operates at fully disaggregated household and vehicle levels and is designed to capture the detailed household-level vehicle transaction processes in both new and used vehicle markets – following households' lifecycle stages.

ATLAS has been developed as part of a larger mesoscale agent-based transportation modeling system (BEAM CORE: Behavior, Energy, Autonomy, and Mobility Comprehensive Regional Evaluator) (Laarabi et al. 2023; Spurlock et al. 2024). The vehicle technology adoption processes in ATLAS are modeled through tight coupling with several other simulation modules in BEAM-CORE: the population evolution model Demographic Microsimulator (DEMOS) (Sun et al. 2023), running within the land use development model UrbanSim (Waddell et al. 2007), and the national vehicle technology and sales model Automotive Deployment Options Projection Tool (ADOPT) (Brooker et al. 2015a).

This paper documents the modeling framework and application of ATLAS to simulate the fleet turnover among the households of the San Francisco Bay Area over a thirty-year horizon. To address uncertainties in both fleet turnover and its distributional and equity impacts, this study designs technology and policy scenarios and sensitivity simulations to investigate (i) the effects of vehicle technology progress and the California 2035 ZEV mandate on the fleet turnover in the San Francisco Bay Area, (ii) further differentiation among income groups in terms of their fleet turnover pathways and income disparity in ZEV ownership, and (iii) the relative effectiveness of financial incentives – tax credit versus. rebate – on income disparity in ZEV ownership.

ATLAS development and its application presented in this paper contribute to the existing transportation literature: (i) the study design addresses the uncertainties in the timeline of fleet turnover through simulating a range of policy and technology scenarios, (ii) while most existing literature has focused on the overall effect of technology progress and/or policy mechanisms on aggregate clean vehicle uptake, the process oriented micro-simulator we developed here answers questions regarding the distributional impacts among subpopulations and their underlying drivers, and (iii) in addition to new vehicle sales, our results reveal insights from transactions in the used vehicle market that play an important role contributing to income disparity in clean vehicle ownership.

The rest of the paper is organized as follows: Section 2 introduces the ATLAS modeling framework, its constituent modules, and validation; Section 3 describes the main input data from two upstream models to drive the long-term simulation; Section 4 presents the scenario simulations with ATLAS applied to the San Francisco Bay Area and discusses the results; Section 5 summarizes the paper and lays out future research directions.

2. Automobile and technology lifecycle-Based assignment (ATLAS) model framework

ATLAS consists of three major modules (Figure 1): (i) the static household fleet mix module; (ii) the dynamic vehicle transaction decision module; and (iii) the dynamic vehicle choice module. Currently, all constituent models are estimated and calibrated for the San Francisco Bay Area; the estimation and validation of each module is described in the Supporting Information (SI). Note that the models are 'dynamic' in their path dependent nature. The existing fleet attributes and ownership as well as household attributes at given time step and life events occurring between time steps are used to predict the vehicle transaction and choice decisions that evolve the household fleet composition into the next time step.

The static household fleet mix module determines a snapshot of vehicle choices for a given household. This module determines the initial state of vehicle ownership and household fleet composition when no historical vehicle ownership nor sociodemographics information are available. This module uses a Multiple Discrete Continuous Extreme Value (MDCEV) (Bhat 2008) model in conjunction with several other multinomial logit models that control and constrain the prediction of fleet mix to be representative of the observed fleet mix in the initial year. The output from this module is a prediction of the number of vehicles owned by individual households, and the body

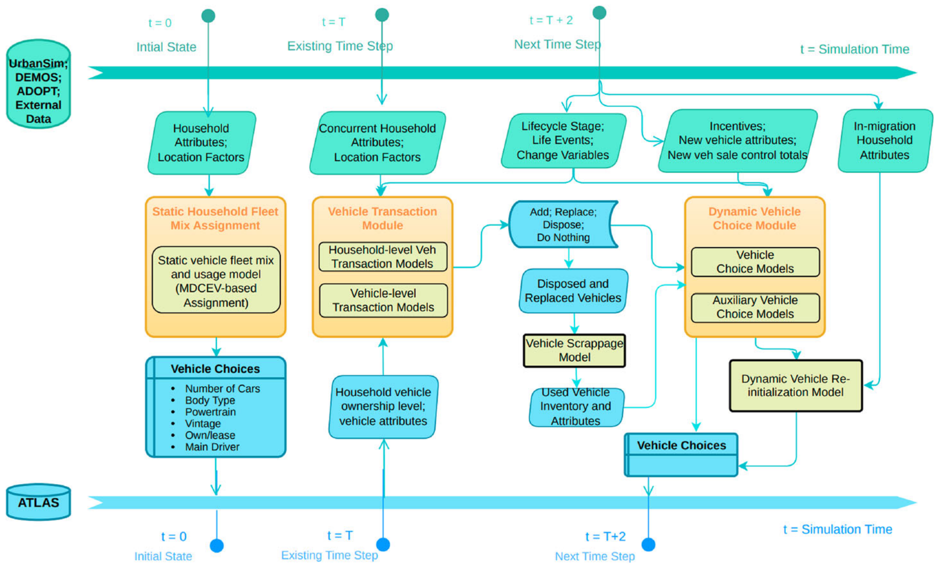

Figure 1. ATLAS modeling architecture.

type, vintage, powertrain, and tenure (own or lease) of each of these vehicles. The approach taken for this module is based on the Vehicle Fleet Composition (VFC) model developed by the Maricopa Association of Governments (Garikapati et al. 2014) with more detailed documentation in (Garikapati et al. 2016; 2014). The nine-county San Francisco Bay Area portion of the California sample (National Renewable Energy Laboratory n.d.) in the National Household Travel Survey (NHTS) 2017 (U.S. Department of Transportation n.d.) is used as the primary data source to estimate the constituent models. As a result, the initialization year of the household fleet mix is set to 2017.

After the household fleet composition is initialized by the static household fleet mix module, the two other modules, as described below, run sequentially at each evolution time step to dynamically evolve the fleet forward in time.

The vehicle transaction decision module dynamically predicts household decisions for vehicle addition, disposal, and/or replacement for each evolution timestep, based on households' existing vehicle attributes, concurrent sociodemographic and spatial context, and life-event changes between previous and current time steps. This module consists of two sub-models. The first is the vehicle level transaction choice model, which predicts whether a given vehicle in each household is disposed (disposed without replacement), kept, or replaced (disposed with replacement) in the next timestep using a series of multinomial logit models separately estimated for single vehicle and multiple vehicle households. The second sub-model is the household level transaction choice model that determines whether the family will acquire additional vehicle(s) to increase their level of vehicle holdings using an ordered logit model. We found vehicle transaction probabilities are associated with vehicle attributes, households' life cycle stages, and key life events. For example, disposal and/or replacement decisions are positively correlated with (i) the age of the vehicle coupled with the vehicle being leased rather than owned; (ii) sociodemographic characteristics such as families with a greater number of drivers, and/or lower income level; and (iii) key life cycle events such as childbirth (particularly for younger parents), residential relocation, and empty nesting. Vehicle acquisition is found to be positively associated with an increasing number of workers, and life cycle events such as childbirth and marriage, etc. The estimation and validation of this module are further described in (Jin et al. 2022) and supporting materials (**SI: Constituent Models and SI: Model Validation**) based on the revealed preference data collected in the Panel Survey of Income Dynamics (PSID) (University of Michigan 2021), which is a longitudinal survey.

A vehicle scrappage model following the transaction decision module applies a fleet level survival curve as a function of vehicle type (car versus truck) and vehicle age to determine whether the disposed and replaced vehicles exit the vehicle population. The survival curves are estimated using the fleet database maintained by the California Air Resources Board (California Air Resources Board n.d.). The surviving vehicles forming the 'used inventory' enter the used vehicle market. The market shares and vehicle attributes by body type, powertrain, and vintage characterized by the used vehicle inventory serve as inputs to the dynamic vehicle choice module as described next.

The dynamic vehicle choice module takes the output from the vehicle transaction decision module and predicts the vehicle choices in terms of vintage (new or used), body type, powertrain, and tenure (own or lease) for the added and replacement vehicles. This module uses multinomial logit models following the approach from Fowler et al. (Fowler et al. 2017) that were estimated mainly using the California Energy Commission (CEC) California Vehicle Survey. The specification of the vehicle choice multinomial logit models (**SI: Constituent Models**) aim to determine the parameters associated with vehicle attributes, policy incentives (tax credits and cash rebates for ZEVs), and their interactions with the household characteristics that predict vehicle choice decisions.

In addition to the income interaction with price specified in Fowler et al (Fowler et al. 2017), our choice models are specified to further account for the influence of the presence of children and previous vehicle ownership experience in body type and powertrain on current choices. Families with children are found more likely to choose light trucks (SUVs, minivans/vans, pickup trucks) relative to the car body type. Pickup truck owners are more likely to choose the same body type than owners of other body types. Two vehicle families are more likely to replace a vehicle with the same body type, while such behavior is not statistically significant in one vehicle and three or more vehicle families.

This module also calibrates the alternative-specific constants at each evolution time step to match the overall market shares of powertrain, body type, and vintage separately for (i) new vehicle sales totals provided externally by ADOPT (which will be described in Section 3.2) and (ii) used vehicles that are internally determined by the used vehicle inventories at each evolution time step. This approach allows ATLAS to capture the evolving supply side constraints while maintaining the relative adoption difference among the heterogeneous households differentiated by their vehicle transaction probabilities and vehicle preferences.

The above processes are applied to all continuing households in the region. For newly emerged households in a given evolution time step, such as in-migrating households and split-off households, a dynamic household fleet re-initialization model is used to determine their initial fleet mix using the most similar household within the residence census tract, based on sociodemographic and economic attributes.

ATLAS simulations are conducted on a *biennial* basis and generate fleet composition at each time step for individual households. The model creates each household's fleet, including the number of vehicles owned and choice of each vehicle described by body type, powertrain, vintage, and tenure (own or lease). The body type choices include car, sport utility vehicle (SUV), pickup, and van. The powertrain choices include internal combustion engine (ICE) vehicle, hybrid vehicle, battery electric vehicle (BEV) and plug-in hybrid electric vehicle (PHEV).

The input variables, the feed-in upstream models (discussed in Section 3), the estimation datasets, and their associated modules within ATLAS are all described in **Table A1** in the **Appendix**. The suite of constituent models within the ATLAS modules described above, and their estimation datasets and estimation results, are further described in detail in the Supporting Information '**SI: Constituent Models**'.

To increase confidence in its accuracy and applicability, the ATLAS model is validated both internally, using a hold-out sample of the estimation dataset, and externally, using datasets that are not used for estimation, following the model validation guidance by (Parady, Ory, and Walker 2020). For example, Figure 2 represents an external validation of ATLAS, indicating reasonable performance in the predicted vehicle ownership distribution as a result of the 'changes' introduced by ATLAS-predicted transactions (add, dispose, and trade vehicles) at each evolution time step, when compared to the observed external data (available up to year 2021 and not used for ATLAS model estimation) from the American Community Survey (ACS). The difference in the total number of households (i.e. the height of the bars in Figure 2) between predicted and observed is due to the performance of demographic model prediction described in the next section.

More importantly, the predicted transaction decisions result in a stable distribution in vehicle ownership levels over a long simulation period (16 evolution time steps) as seen in Figure 2. Note that ATLAS does not directly predict or calibrate the number of vehicles owned by individual households during the evolution time steps, so the stable distribution of ownership level over time helps rule out cumulative errors in the vehicle transaction module, which is critical for stable long-term simulations.

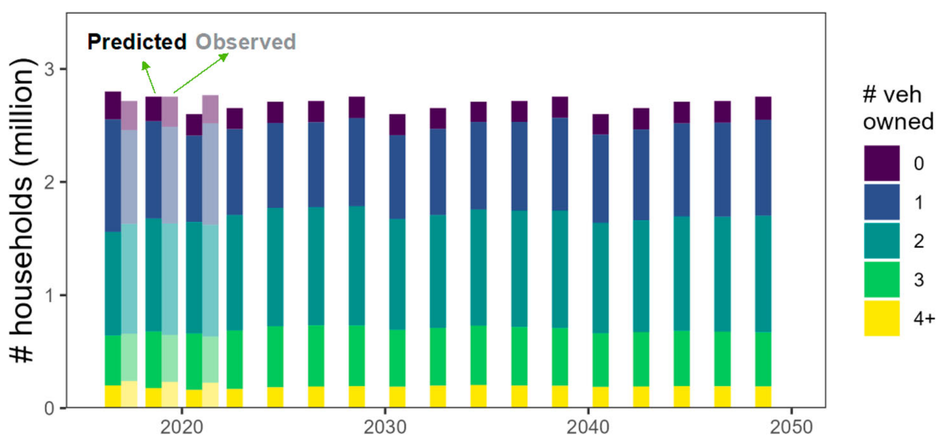

Figure 2. Distributions of household by number of vehicles held from 2017 to 2049 from the biennial ATLAS simulation. The observed number of households by vehicle ownership levels is from the ACS data available as a reference for years 2017, 2019, and 2021.

More detailed description of model validation results can be found in the Supporting Information '**SI: Model Validation**'.

3. Input data to drive ATLAS simulation

The primary data inputs that drive the evolution of household fleet composition are drawn from the co-evolving DEMOS-UrbanSim simulations, scenario outputs of new vehicle sales and sales weighted vehicle attributes from ADOPT, as well as ATLAS simulations from previous timesteps (Figure 1). These inputs include both cross-sectional and longitudinal demographic and socioeconomic variables, life-cycle events/contexts, built environment characteristics, vehicle technology characteristics (such as price and performance), aggregated new vehicle sales by vehicle type, purchasing incentives, and households' existing fleet characteristics.

3.1. Demographic evolution data

The demographic microsimulator DEMOS (Sun et al. 2023) running within the land use development model UrbanSim (Waddell et al. 2007) is a disaggregated modeling system that captures the evolution process of person and household sociodemographic attributes over time. The transition probabilities between consecutive years are derived using discrete choice models estimated from the PSID data (University of Michigan 2021).

The modeling framework of DEMOS is shown in Figure 3, and consists of three major components: (i) migration, (ii) individual-level demographic evolution, and (iii) household-level demographic evolution. The demographic evolution process is initiated with a baseline-year (t) synthetic population (which is validated using observed household – and person-level control distributions), and advances individuals and households through a host of lifecycle events. Household – and individual-level characteristics are updated and provided as inputs to the subsequent year's (t + 1) population evolution.

In this study, DEMOS-UrbanSim simulations upstream of ATLAS are conducted to generate a dynamically evolving synthetic population in the San Francisco Bay Area.

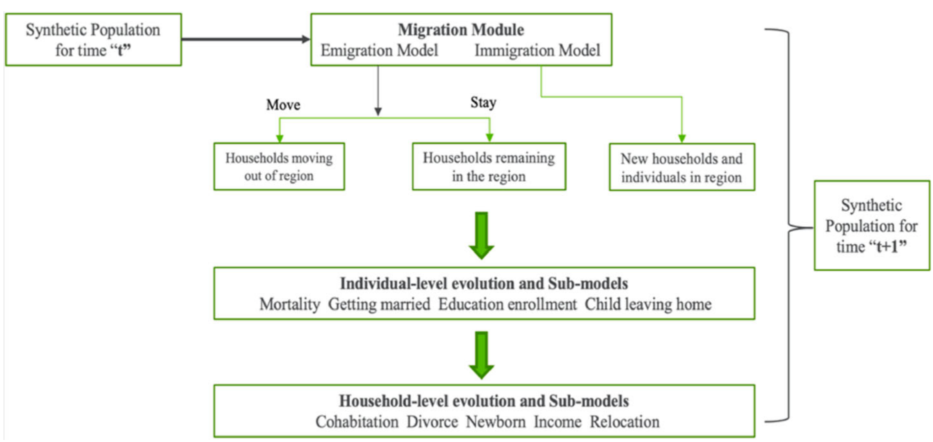

Figure 3. Representation of demographic microsimulation (DEMOS) model.

These include both cross-sectional (initial year 2017) and longitudinal (forecasting 2018–2050) demographic and socioeconomic attributes of individuals and households, their residence locations, and the associated built environment characteristics.

3.1. Vehicle market and vehicle attributes evolution

Another key upstream model to ATLAS is ADOPT (Brooker et al. 2015a), which evolves the overall market for new vehicles and forecasts vehicle attributes and total new vehicle sales. An overview of key elements is shown in Figure 4. The model starts by applying input assumptions including technology improvements, fuel emission factors, and fuel prices to the vehicles. Simulations start with all existing vehicle makes, models, and options – over 700 in total. The attributes, including price, fuel cost per mile, acceleration, size and range, are used to estimate consumer preferences and sales. The model evolves the market by using estimated consumer preferences to create new future vehicle options based on market conditions. ADOPT pairs with the integrated Future Automotive Systems Technology Simulator (FASTSim) (Brooker et al. 2015b), a vehicle powertrain model to create new vehicle technology options in the future. This combination of models leads to market-driven vehicle options and attributes that are indirectly influenced by input assumptions. For example, as battery prices decrease, ADOPT tends to create battery electric vehicles (BEVs) with sales-weighted larger batteries that provide longer range and better acceleration. The sales of the evolving vehicle options are used to generate sales weighted averaged vehicles attributes, including price, range, acceleration, fuel economy, cost per mile, annual maintenance cost, and refueling time, as inputs to ATLAS. ADOPT new vehicle sale totals by powertrain and body type at the national level are regionalized to the San Francisco Bay Area using observed light duty vehicle sales data provided by the California Energy Commission (California Energy Commission n.d.).

While ADOPT simulated data, available for new vehicles sold in 2015 and later, is used to populate the vehicle attributes for the set of new vehicle choices at each evolution time

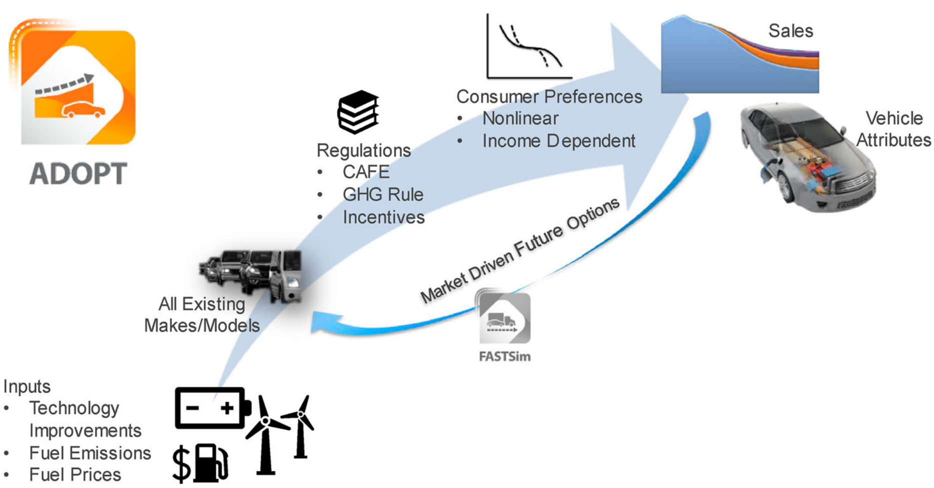

Figure 4. ADOPT's approach to estimating future vehicle attributes and aggregated sales.

step, the used vehicle attributes are prepared by combining ADOPT attributes and observed historical data. For vehicles of model years 2015 and newer, we use the ADOPT data for new vehicles, and simply depreciate the price according to the schedule estimated by Burnham et al. (2021) according to vehicle vintage at the simulation year. For vehicle model years 2014 and earlier, we do not have detailed data (either real or simulated) on attributes of specific vehicles, and therefore use fleet averages from the EPA Automotive Trends report (Hula et al. 2021). A detailed description of vehicle attribute input preparation for both new and used vehicles is provided in the supporting information '**SI: Vehicle Attributes Preparation**'.

4. Scenario simulations and results

The sub-modules discussed earlier are integrated into the workflow in Figure 1. The full model is applied to the San Francisco Bay Area in California at a biennial time step, from 2017 to 2049 as a case study, in order to understand the effects of vehicle technology progress and clean vehicle policies on fleet turnover and equity in ZEV ownership. More specifically, scenario and sensitivity simulations are designed to investigate (i) the effects of vehicle technology progress and the California 2035 ZEV mandate on the San Francisco Bay Area's fleet turnover; (ii) further differentiation among income groups in terms of their fleet turnover pathways and income disparity in ZEV ownership; and (iii) the relative effectiveness of financial incentives – tax credit versus rebate – on income disparity in ZEV ownership.

4.1. Technology and policy scenario definitions

The supply side of the market including new vehicle sales and sales weighted vehicle attributes are generated from ADOPT for three scenarios: (i) a central baseline scenario representing technology success (referred to thereafter as 'Tech Success Baseline'), where battery prices drop to levels where BEVs become successful and electricity generation becomes clean. The detailed battery price drop trajectories are further described in Supporting Information '**SI: ADOPT Scenario Assumptions'**; (ii) a more conservative scenario where battery prices (inclusive of a 1.5x markup to translate cost to consumer vehicle price contribution) stagnate at $220/kWh from 2025 to 2050 ('Stagnant Battery Price'); (iii) a more optimistic scenario ('ZEV Mandate') based on vehicle attributes of the Tech Success scenario and additionally assumed establishment of a clean vehicle mandate, where all vehicle production except clean vehicles is discontinued by 2035. The three scenarios were chosen to provide a wide variety of possible outcomes, but couched in relevant and realistic technology and policy contexts.

Vehicle attributes differ across scenarios with the difference most pronounced between the Stagnant Battery Price scenario and the other two scenarios that followed the same technology success trajectory. For example, the prices of electric SUVs in 2035 ($44,970) and 2050 ($44,752) are higher due to higher battery price in the stagnant battery scenario than in the Tech Success baseline scenario ($37,059 in 2035 and $35,750 in 2050). ADOPT also considers federal purchasing incentives under the Inflation Reduction Act (2022) that affect the trajectories of national sales totals of ZEVs. The complete list of technology assumptions, incentive assumptions, and vehicle attribute

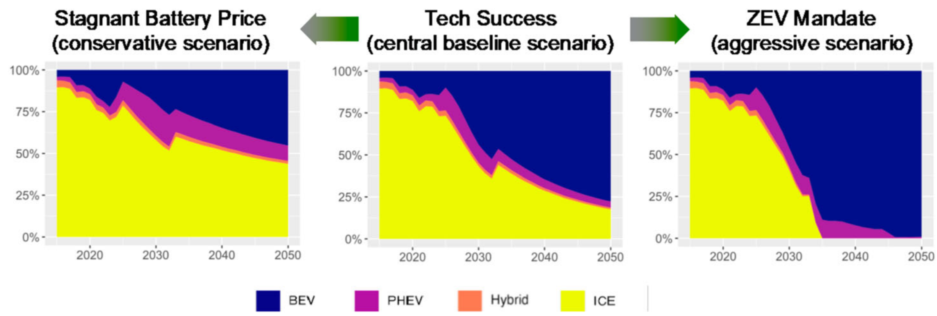

Figure 5. ADOPT predicted powertrain market share of new vehicles over time under three scenarios.

comparison are provided in the Supporting Information '**SI: ADOPT Scenario Assumptions**'.

As shown in Figure 5, ADOPT forecasts an increasing share of new ZEVs sold in this region across all scenarios. However, the Stagnant Battery Price scenario reduces the ZEV market share relative to the Tech Success baseline scenario, while the 2035 ZEV Mandate scenario increases the ZEV market share to 100% in 2035 and later. The sales changes in 2025 and 2035 reflect the federal tax credit assumptions applied in ADOPT throughout the scenarios.

ATLAS then distributes these new vehicle sales together with the internally generated used vehicle inventory as supply-side control totals across all individual households with predicted vehicle acquisition needs and generates the updated household fleet composition at each time step.

4.2. Incentives modeled in atlas and sensitivity analysis

Financial incentives address the cost differential between ZEVs and conventional vehicles at different levels across income groups. Several federal and state level incentives for the purchase of clean vehicles are modeled in ATLAS across the scenarios. These include: (i) the federal tax credit for BEVs and PHEVs with batteries of at least 5 kWh before 2023; (ii) federal tax credits for both new and used vehicle purchases of all manufacturers starting from 2023 under the Inflation Reduction Act (2022); (iii) two main rebate/grant programs – the California Clean Vehicle Rebate Project (CVRP) (California Air Resources Board 2010), which funds new vehicles only, and a rebate program modeled after both the Clean Vehicle Assistance Program (CVAP) (California Air Resources Board 2018), and the PG&E Pre-Owned Electric Vehicle Rebate Program (Pacific Gas and Electric Company 2023), which funds the purchase of both new and used vehicles. A summary of these incentives is presented in **Table A2 and A3** in the Appendix at the end of the paper. A more detailed description of incentive modeling is provided in the Supporting Information '**SI: Modeling Purchase Incentives**'.

Under the total sales constraints provided by ADOPT, the incentives modeled by ATLAS redistribute the ZEV sales among different income groups. To further quantify the resulting effects on income disparity in ZEV ownership, three additional sensitivity simulations are conducted around the Tech Success baseline scenario in which both the tax credits and rebates are modeled, including (i) baseline simulation without rebates; (ii) baseline simulation without tax credits; and (iii) baseline simulation without any financial incentives. It is important to note that these sensitivity simulations are hypothetical and subject to the same control total of new vehicle sales provided by ADOPT with federal tax credit considered. As a result, the comparison among the sensitivity simulations should be interpreted in a relative sense.

4.3. Simulation results and discussion

Driven by the demographic attributes and input scenarios described earlier, ATLAS generates biennial outputs of household fleet composition from 2017 to 2050 for individual households in the nine-county San Francisco Bay Area. We combine the electric and plugin hybrid electric vehicles into the 'ZEV' category shown in the figures in this section, while the remaining powertrains are combined into the 'non-ZEV' category. In this paper, 'fleet turnover' refers to the process of non-ZEVs being replaced by ZEVs from the entire fleet or in the fleet owned by a given segment of the population.

4.3.1. Technology progress and ZEV mandate on fleet turnover

At an aggregate level, ZEVs penetrate the San Francisco Bay Area fleet over time in all scenarios, but at different rates. As shown in Figure 6, the fleet share of non-ZEVs steadily declines and that of ZEVs increases. By 2040, ZEV fleet share reaches 37%, 50%, and 67% in the three scenarios, respectively. These fleet share results are within the range reviewed by Kah (2019) which considers 17 studies and shows EV share of the global passenger vehicle fleet is projected to be from 10 to 70% in 2040.

More importantly, differences in the fleet turnover schedule are revealed across the scenarios. The Tech Success baseline scenario results in 40% fleet share for ZEVs by 2037, while Stagnant Battery Price scenario delays the process by *five to six* years. A similar acceleration (about 5 years) in fleet turnover schedule induced by battery technology progress was also reported by Naumov, Keith, and Sterman (2023). On the other hand, the 2035 ZEV mandate along with technology success,

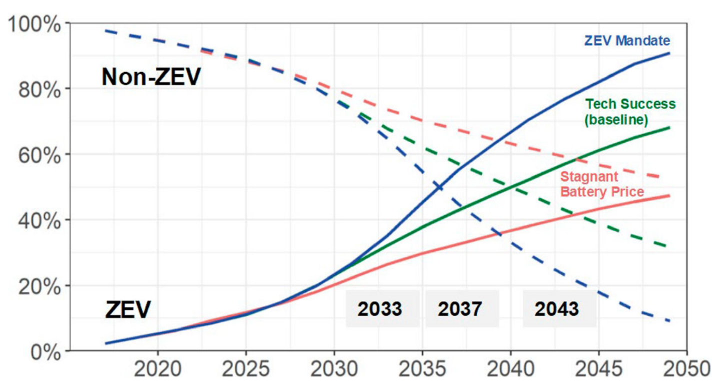

Figure 6. Fleet nonZEV turnover (dashed lines) and ZEV penetration (solid lines) predicted under three scenarios. Solid lines: ZEV% (all electric and plug-in hybrid vehicles) and dashed lines: fleet share of non-ZEV% in the fleet mix.

captured in the ZEV Mandate scenario, accelerates the turnover (to reach the 40% ZEV share) by four to five years. The cross-scenario variation is primarily driven by the differences in the new vehicle sales input from ADOPT scenarios representing different technology and policy pathways. As shown earlier in Figure 5, Stagnant Battery Price reduces the ZEV market share relative to the Tech Success baseline scenario, while the 2035 ZEV Mandate increases the ZEV market share to 100% after 2035.

Comparing the ZEV fleet shares in Figure 6 with the new vehicle market shares in Figure 5, it is worth noting that ZEV ownership levels in the fleet mix significantly lag behind the ZEV market shares in new vehicle sales. For example, in the baseline scenario, ZEV share in the fleet mix reaches 40% about 10 years after the ZEV new vehicle market shares reaches the same level. This is because changes in vehicle ownership is a medium – to long-term household behavior, and existing non-ZEVs will remain in the fleet until they are disposed or replaced by ZEVs. Policy effectiveness of decarbonization through electrification of household vehicles should consider this long lead time in turning over the on-road passenger fleet.

4.3.2. Income disparity in ZEV ownership

As ATLAS predicts vehicle ownership and fleet composition at the individual household level, the fleet turnover and ZEV penetration can be analyzed by household income levels as shown in Figure 7. As expected, ZEVs penetrate into higher income groups at faster rates than lower income groups, in all scenarios. Tech Success and the ZEV Mandate scenarios both enable all income groups to transition to ZEV-dominant ownership (i.e. > 50% ZEV) by 2050, with top earners transitioning to ZEV-dominant ownership about five years earlier than the bottom income group. In the Stagnant Battery Price scenario, however, vehicle ownership of all income groups remains dominated by non-ZEVs throughout the simulation period.

To further quantify the income disparity of ZEV ownership and scenario influences, we use a simple normalized disparity metric defined as:

$$D_s = \frac{ZEV_{\geq \$150k,s}\% - ZEV_{<\$150k,s}\%}{ZEV_{pop,s}\%} \quad (1)$$

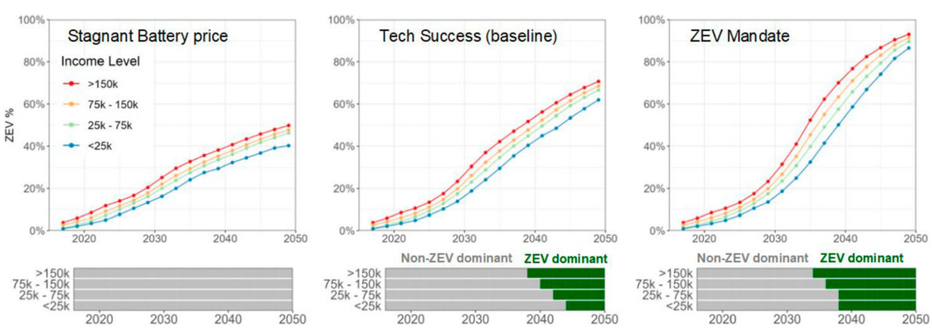

Figure 7. ZEV ownership levels within different income groups over time (upper panel) and transition from non-ZEV dominant (gray) to ZEV dominant (green) ownerships by income groups (bottom panel) under three scenarios.

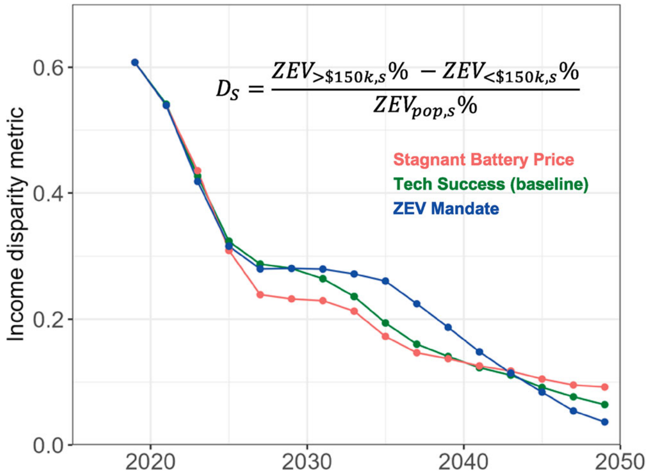

Figure 8. Disparity metrics of ZEV ownership under three technology and mandate scenarios.

where D_s is the disparity metric under scenario $\boldsymbol{s}$, measuring the difference between percent of ZEVs owned by households above ($ZEV_{\geq\$150k,s}\%$) and below ($ZEV_{<\$150k,s}\%$) \$150k, normalized by the population average ownership level $ZEV_{pop,s}\%$ under scenario $\boldsymbol{s}$. The normalization enables comparisons across scenarios. A positive value of D_i indicates relatively higher than population average ZEV ownership among high earners relative to low earners, and vice versa.

Despite the top income group holding consistently higher than average ZEV ownership throughout the simulation period across all scenarios (red lines in Figure 7), the relative difference between the top income group and the rest of the population, as indicated by the income disparity metric, shrinks over time across all scenarios as indicated by the downward trends in Figure 8. However, the comparative equity implications are path-dependent and differ by time frame considered. In the first 10 years after the scenarios begin to diverge, lower ZEV penetration as a result of stagnant battery prices actually shows a larger reduction in the income disparity compared to the other two scenarios; however, the Stagnant Battery Price scenario has the highest income disparity in the last six years (last three time steps) of the simulation. In contrast, under the Tech Success and ZEV Mandate scenarios, lower income earners overcome early disparities in ZEV adoption to ultimately reach the lowest levels of income disparity in the long run (in the 2040s and onward). These findings suggest that, although technology progress and a ZEV mandate might result in faster ZEV penetration into the higher income households, they eventually narrow the relative income gaps in ZEV ownership. Additional clean vehicle policies (such as income-based purchase incentives as shown in Guo and Kontou (2021)) concurrent with the ZEV mandate and technology progress should be considered – particularly in the first decade of the transition – to accelerate ZEV uptake by lower income households when the relative income disparity is the highest.

4.3.3. Effects of purchasing incentives on income disparity

Purchase incentives that aim to induce consumers to adopt pricier ZEVs have heterogeneous effects across income groups. Subpopulations are faced with different levels of

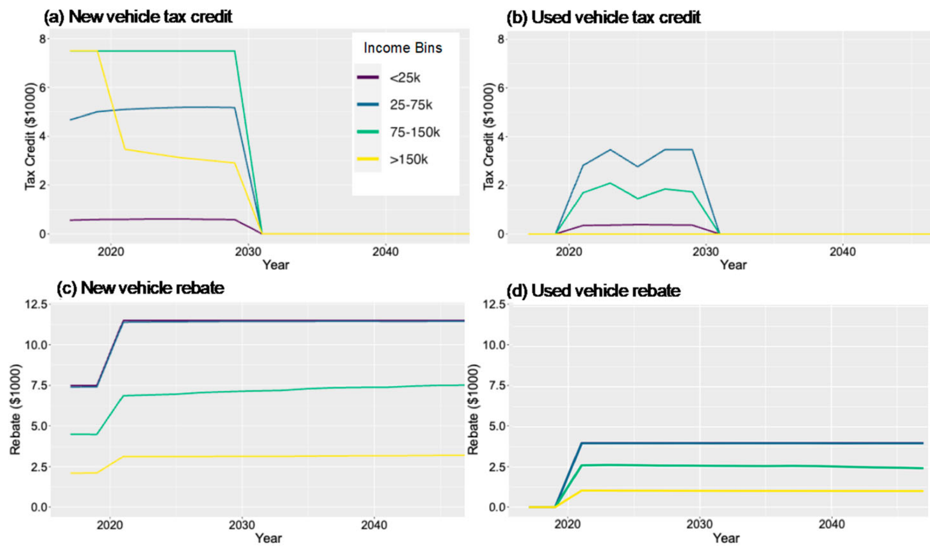

Figure 9. Maximum available per household purchasing incentives in the form of (a) new vehicle tax credit; (b) used vehicle tax credit; (c) new vehicle rebate; and (d) used vehicle rebate; averaged over the households with predicted purchasing occasion at each simulation time step.

incentives due to income eligibility with *opposite* trends in tax credit versus cash rebate for new vehicle purchases.

As shown in Figure 9(a,b), the available tax credit averaged across households of different income bins for new or used vehicles depends on each household's tax liability (driven primarily by their income), as tax credits are nonrefundable. Prior to 2023, any household could qualify for a tax credit of up to $7,500 for the purchase of a qualifying EV. The Inflation Reduction Act of 2022 imposed an income cap of $150,000/$350,000 for single/married couple filers in 2023, with the tax credit phased out entirely in 2032. Lower income consumers are unable to fully capture the tax credit because their tax liability is too low, while some high-income consumers become ineligible starting in 2023.

Available cash rebate per household for new vehicles (Figure 9c,d) is independent of scenario and is reduced for higher income categories because of the programs' income caps. Vehicle rebates increased in 2023 with the introduction of the second rebate program modeled after CVAP and PG&E rebate programs. A more detailed description of the income eligibility of incentives is provided in Tables A2 and A3 in the Appendix.

These financial incentives address the cost differential between ZEVs and conventional vehicles at different levels across income groups. However, their distributional effects on the ultimate ZEV adoption for these subpopulations have not been well investigated in the literature. Sensitivity simulations performed here are focused on understanding how ZEV ownership is redistributed by different types of financial incentives, which affects the observed income disparity.

Figure 10 shows the income disparity metric – the relative difference in ZEV% between income groups above and below $150K – simulated under the combinatorial of incentive types. Greater values indicate larger gaps between the income groups. We can see both federal tax credits and state and local rebate programs reduce income disparity in ZEV

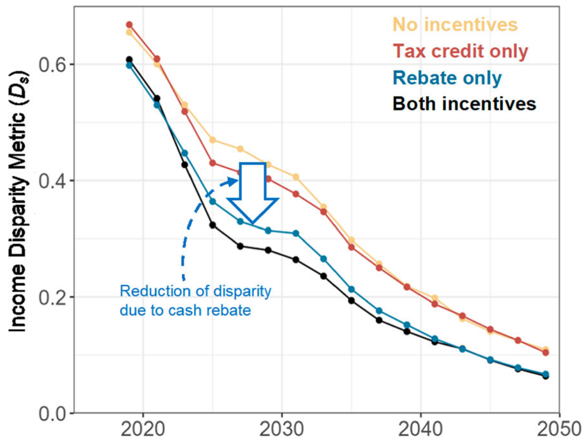

Figure 10. Income disparity metric under different incentive simulations around the baseline scenario.

ownership over time, as indicated by lower values of the disparity metric in later simulation years. Tax credits alone are seen to only slightly redistribute ZEVs to lower income households, as indicated by a small decrease in the income disparity metric from the 'no incentives' case to the 'tax credit only' simulation. This is understandable owing to the complexities involved in leveraging tax credits, as explained above. In contrast, cash rebates result in a more pronounced redistribution of ZEVs to lower income households, with a larger reduction in the income disparity metric from the 'no incentives' case to the 'rebate only' simulation. In fact, cash rebates account for about 80% of the total reduction in the simulated income disparity. This finding indicates that cash rebates improve equity more than tax credits, which is consistent with existing literature on lower income groups being more responsive to rebates (DeShazo, Sheldon, and Carson 2017). With both the tax credit and the rebate applied, income disparity is cut in half by 2025 relative to the base year level, which is about 8 years sooner than if the only incentive is a tax credit. This underscores the role of cash rebate in accelerating improvement in ZEV ownership equity.

In this analysis, we have modeled the tax credits as nonrefundable. However, the U.S. Department of the Treasury has recently put forth new guidance that will allow consumers to transfer the full value of the tax credits – regardless of their tax liability – to the vehicle dealer (U.S. Department of the Treasury 2023). This change, set to take effect in 2024, will allow consumers to receive the full value of the credit as an upfront payment at the point of sale. While not modeled here, this change will likely have significant impacts on uptake, particularly among low-income buyers, as consumers prefer point of sale rebates to tax credits, and the full value of the credit becomes available to consumers with small or no tax liability.

4.3.4. A process-oriented explanation of ZEV uptake by income

In addition to the purchase incentives, the overall probability of ZEV uptake by individual households is also influenced by the full chain of decision-making processes of vehicle purchase. The frequency of the purchasing occasion (how often a household needs to shop for vehicles) and ZEV availability in the choice set (e.g. in the new versus used market) considered by the household are both major factors influencing ZEV uptake.

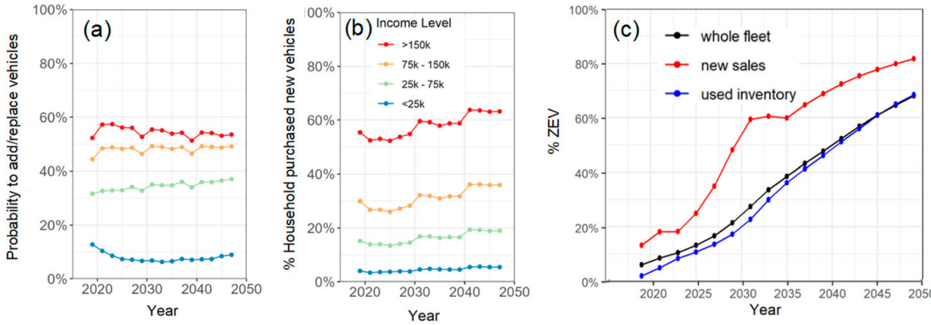

Figure 11. Dynamics that affect differential ZEV ownership evolution across income groups: (a) transaction probability by income groups; (b) likelihood by income group to shop for new vehicles; (3) ZEV shares in new vehicle sales, used vehicle inventory, and whole fleet. Data shown are from the Baseline scenario (plots under other scenarios showed similar trends and are available upon request).

Using a process-oriented approach, ATLAS offers unique new insights in ZEV purchasing behavior in these areas.

First, as shown in Figure 11(a), the frequency at which households replace an existing vehicle or add a vehicle increases with household income. Higher income households are less financially constrained and their higher vehicle ownership levels also lead to more frequent vehicle replacement. This means higher income groups are exposed to more frequent opportunities (or transaction windows) for considering ZEV adoption concurrent with the increasing ZEV availability on the market.

Second, as shown in Figure 11(b), when considering households that shop for a vehicle, higher income households are more likely to choose a new (~ 60%) rather than used (~ 40%) vehicle, while lower income households are more likely to acquire a used rather than new vehicle, likely because of the lower upfront costs. Our simulations indicate that households with annual income less than \$150k purchase vehicles primarily from the used market (> 0.5 probability), with only 5% of the lowest income households (with income less than \$25k) obtaining a new vehicle, and 95% obtaining a used vehicle.

Finally, Figure 11(c) shows the availability of ZEVs in the new and used vehicle markets. ZEV shares in the whole household vehicle fleet are also shown as a reference. We see that the share of new vehicle purchases that are ZEVs is much higher than the equivalent share in the used vehicle market, with ZEV shares in the used market about 10 years behind those in the new vehicle market.

In summary, lower income groups shop for vehicles less often, and when they do, they are more likely to consider the cheaper used vehicle market, where ZEVs are not as readily available. These decision processes, coupled with the new and used market evolution, dynamically differentiate the fleet turnover patterns across income groups. Policies that promote retirement of aging vehicles and increase ZEV supplies in the used market may further help address the income disparity in ZEV adoption.

5. Summary and future steps

This paper documents the design and application of ATLAS, a comprehensive household vehicle fleet composition and evolution micro-simulator in the San Francisco Bay Area.

Technology and policy scenarios investigate the effects on overall fleet turnover, distribution of impacts, and underlying mechanisms. While most existing literature focuses on the aggregated effects of technology progress and/or clean vehicle policies on ZEV uptake, ATLAS enables a deeper understanding of their distributional effects and the underlying mechanisms across heterogeneous sub-populations, and thus contributes to the transportation equity literature.

The simulation results indicate that, at an aggregate level, ZEVs penetrate the San Francisco Bay Area fleet over time in all scenarios, although at different rates. Technology progress accelerates the fleet turnover to ZEVs by *five to six* years, relative to the Stagnant Battery Price Scenario, which is consistent with the literature reported by Naumov, Keith, and Sterman (2023). On the other hand, the 2035 ZEV mandate along with technology success accelerates the turnover (to reach the 40% ZEV share) by four to five years.

Households with the highest incomes transition to ZEV-dominant ownership about five years earlier than households with the lowest incomes. If battery prices continue to fall, then all income groups transition to ZEV-dominant ownership by 2050. Despite the persistence of income gaps, the relative income disparity in ZEV ownership shrinks over time across all scenarios. In the long run, the high ZEV penetration enabled by technological progress and a ZEV Mandate reduces income disparity the most.

Federal, state, and local financial incentives address the cost differential between ZEVs and conventional vehicles to different degrees across income groups. Sensitivity simulations reveal the effects of these financial incentives on redistributing ZEV ownership from higher to lower income groups, which consequently lowers the income disparity in ZEV ownership. Cash rebates are found to be more effective accelerating the equity improvement of ZEV ownership than tax credits. With both the tax credit and the rebate applied, income disparity is cut in half by 2025 relative to the base-year level, which is about 8 years sooner than if the only incentive is a tax credit.

In addition to purchase incentives, we find that the full chain of vehicle transaction and choice processes contributes to income differences in the evolution of ZEV ownership. Lower income groups are exposed to fewer vehicle transaction opportunities to adopt ZEVs, and are more likely to consider cheaper vehicles in the used market, where shares of ZEVs are about 10 years behind the new vehicle market. These decisions, coupled with the evolution of the new and used vehicle markets, dynamically differentiate fleet turnover patterns among income groups. Policies that promote retirement of aging vehicles and increase ZEV supply in the used vehicle market may help address the income disparity in ZEV adoption.

The current implementation of ATLAS could merit further development. Examples of future work include implementing additional policy intervention levers, such as charging infrastructure deployment, and modeling additional dimensions of vehicle choice, such as level of automation. Parameter calibration is an ongoing effort to more accurately capture consumer preferences as observational data pertaining to ZEV sales and/or stated preference surveys become more abundant. In future work, ATLAS can be deployed to other regions, with parameters being calibrated and validated under the same framework, to support policy decisions that encourage an efficient, effective, and equitable transition to a clean vehicle future.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix

Table A1. Input and output variables and data sources.

Input variables	Data feed from Model (Estimation and Calibration Data Source in parenthesis)	Used in modules: Static fleet mix module	Transaction module	Dynamic vehicle choice module
Concurrent Household Demographics				
Income	DEMOS (PSID, NHTS, CEC)	x	x	x
Household size/composition	DEMOS (PSID, NHTS, CEC)	x	x	x
Marital status	DEMOS (PSID, NHTS, CEC)	x	x	
Children	DEMOS (PSID, NHTS, CEC)	x	x	x
Education	DEMOS (PSID, NHTS, CEC)	x	x	
Employment	DEMOS (PSID, NHTS, CEC)	x	x	
Race	DEMOS (PSID, NHTS, CEC)	x	x	
Dynamic Variables: Life events				
Marriage change	DEMOS (PSID)		x	
Child birth	DEMOS (PSID)		x	
Education change	DEMOS (PSID)		x	
Employment change	DEMOS (PSID)		x	
Residence relocation	DEMOS (PSID)		x	
Income change	DEMOS (PSID)		x	
Location factors/Built environment				
Job density	UrbanSim, DEMOS (NHTS, PSID)	x	x	
Residential density	UrbanSim, DEMOS (NHTS, PSID)	x	x	
Single or multi-family units and/or housing tenure	UrbanSim, DEMOS (NHTS, PSID)	x	x	
Transit access		x	x	

(*Continued*)

Table A1. Continued.

Input variables	Data feed from Model (Estimation and Calibration Data Source in parenthesis)	Used in modules Static fleet mix module	Transaction module	Dynamic vehicle choice module
	UrbanSim location combined with external accessibility data (PSID, NHTS)			
Is CBSA	UrbanSim location combined with external accessibility data (NHTS, PSID)	x	x	
Vehicle Technology Characteristics				
Price	ADOPT for new vehicles and external data for used vehicles (CEC)			x
Cost (O&M)	ADOPT for new vehicles and external data for used vehicles (CEC)			x
Acceleration	ADOPT for new vehicles and external data for used vehicles (CEC)			x
Vehicle range	ADOPT for new vehicles and external data for used vehicles (CEC)			x
Refueling/charging time	ADOPT battery size dependent (CEC)			x
Existing Fleet Characteristics				
Body type	ATLAS previous time step (PSID, CEC)		x	x
Powertrain	ATLAS previous time step (PSID, CEC)		x	x
Vintage	ATLAS previous time step (PSID, CEC)		x	
Number of cars	ATLAS previous time step (PSID, CEC)		x	x
Lease/Own	ATLAS previous time step (PSID, CEC)		x	
Policy Scenarios				
New Sales control totals	ADOPT (CEC)			x
Incentives (rebate and tax credit)	ADOPT and External Data (CEC)			x

Output Variables	Estimation Data Source	Modules Static fleet mix module	Transaction module	Dynamic vehicle choice module
Vehicle Choice				
Body type	PSID, NHTS, CEC	x		x
Powertrain	PSID, NHTS, CEC	x		x
Vintage	PSID, NHTS, CEC	x		x
Tenure (own/lease)	PSID, CEC	x		x
Transaction Probability				
Dispose	PSID		x	
Add	PSID		x	
Replace	PSID		x	

Table A2. Tax credits modeled in ATLAS.

Tax credit	Qualified plug-in electric drive motor vehicle	New clean vehicle credit	Used clean vehicle credit
Max credit	$7,500	$7,500	$4,000
Years Active	2015–2022	2023–2032	2023–2032
Credit calculation	$2917 + $417 per kWh over 5 kWh	$3750 for each of the battery sourcing requirements (Not currently enforced) (two battery requirements, each gets half of the 7500)	30% of vehicle price
Min battery size (kWh)	5	7	7 (or fuel cell)
Assembly Requirements	Final assembly in North America	Final assembly in North America	Final assembly in North America
Manufacturer Qualifications	GM: full prior to April 2019, $0 after April 2020 Tesla: full prior to Jan 2019, $0 after Jan 2020 Toyota:		

(*Continued*)

Table A2. Continued.

Tax credit	Qualified plug-in electric drive motor vehicle	New clean vehicle credit	Used clean vehicle credit
	partial Oct – Dec 2022 All other manufacturers: full credit		
Gross Vehicle Weight (lbs)	14,000	14,000	14,000
Income Qualifications		$300,000 Married filing jointly $225,000 head of households $150,000 other filers	$150,000 married filing jointly $112,500 head of household $75,000 other filers
MRSP Caps		Vans, SUVs, Pickups: $80,000 Cars: $55,000	$25,000
Model year requirement			at least 2 model years prior to year of purchase
Sale requirement			second sale only, bought from a dealer

Table A3. Cash rebates modeled in ATLAS.

Cash rebate	Clean vehicle rebate project	**Rebate** modeled after clean vehicle assistance program and PG&E pre-owned EV rebate program
BEV Credit	$2000, $7500 increased	$1000, $4000 increased
PHEV Credit	$1000, $6500 increased	$1000, $4000 increased
Hydrogen Credit	$4500, $7500 increased	
Hybrid Credit		
new/used	new	New and used
Years Active	2015 – (amounts and income thresholds have changed a lot over the years)	2023 –
Income Qualifications	$135,000 for single filers $175,000 for head-of-household $200,000 for joint filers increased credit <400% federal poverty level	County HUD Low Income threshold (usually 80% of AMI) gets increased award
MRSP Caps	Beginning Feb 2022 cars: $45,000 SUVs, pickups, vans: $60,000 Hydrogen vehicles exempt	
model year requirements		
mileage requirements		(if no prior sale) > 7,500 miles
ownership requirements		one rebate per vehicle over its lifetime