The fifth Bridging Transportation Researchers (BTR) Online Conference
9-10 August 2023
Publication website: http://bridgingtransport.org/

# Development and Application of a Household Vehicle Fleet Micro-simulator to Assess the Impact of Technology Progress and Clean Vehicle Policies on Fleet Turnover and Equity

Ling Jin[1], Connor P. Jackson[2*], Yuhan Wang[2*], Qianmiao Chen[2*], Tin Ho[1], Anna C. Spurlock[1], Aaron Brooker[3], Jacob Holden[3], Jeff Gonder[3], Mohamed Amine Bouzaghrane[2], Bingrong Sun[3], Shivam Sharda[3], Venu Garikapati[3], Tom Wenzel[1], Juan Caicedo[2]

*Equal contribution to the paper

1. Lawrence Berkeley National Laboratory
2. University of California at Berkeley
3. National Renewable Energy Laboratory

Email for the corresponding author: ljin@lbl.gov

## Abstract

This paper documented the modeling framework and its application of a comprehensive household vehicle fleet composition and evolution micro-simulator ATLAS in San Francisco Bay Area. ATLAS takes an innovative process-oriented approach and operates at a fully disaggregated level. It evolves individual households' vehicle ownership, transaction (vehicle addition, disposal, and replacement) and vehicle choice decisions in response to the coupled and co-evolving demographics, land use, and vehicle technology simulators. While most existing literature focused on the aggregated effects technology progress and policy mechanisms on clean vehicle uptake, this paper contributes to transportation equity literature by differentiating their distributional effects and underlying mechanisms across heterogeneous sub-populations. Using technology (whether battery cost declines) and policy (the 2035 Zero Emission Vehicle Mandate) scenarios and sensitivity simulations, we found Zero Emission Vehicles (ZEV) penetrated into the higher income groups at a faster pace than into lower income groups. However, the relative income disparity in ZEV ownership shrunk over time across all scenarios, with ZEV mandate together with technology success in the ZEV mandate scenario eventually reduced disparity most, while the stagnant battery price sustained income disparity the longest. ATLAS models several federal, state, and local financial incentives for ZEV adoption. Sensitivity simulations revealed the effects of these financial incentives on redistributing ZEV ownership among income groups and narrowing the income disparity. Cash rebate was found to be more effective for improving equity of ZEV ownership than tax credit. Application of ATLAS can be extended to other regions to support policy decisions to ensure an efficient, effective and equitable transition to a clean vehicle future.

**Key Words:** Household Fleet Evolution; Microsimulation; Panel Study of Income Dynamics; Long-term Forecasting; Agent based Model; Zero Emission Vehicle Mandate; Income Equity; Clean Vehicle Policies

# 1. Introduction

Much of the world is moving towards increased transportation system electrification in order to decarbonize and mitigate climate change. The European Union ("European Commission on Climate Action. 2050 long-term strategy" ) and the United States (Office of the Federal Register, 2021) have both established targets of net-zero greenhouse gas emissions by 2050. There is increased interest among policymakers to understand the most effective mechanisms to expedite turnover of the passenger vehicle fleet to cleaner technology, such as electric vehicles (EV). 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 et al., 2022), and the Biden administration is pursuing increasing subsidies and financial incentives for electric vehicle adoption (2021). Although ZEVs are on average pricier currently, the purchase costs of EVs are declining rapidly which is in part driven by the declining battery costs. Between 2007 and 2014, industry-wide costs of lithium-ion battery packs fell by over half (Nykvist and Nilsson, 2015). There is significant uncertainty regarding how long it will take under alternative technology progress pathways and policy mechanisms for the vehicle fleet to turn over sufficiently that the majority of vehicles on the road are no longer ICEs. Developing projections of how this fleet transition will unfold requires sufficiently comprehensive and robust modeling of vehicle transaction decisions.

Households with different travel needs and constraints have different sensitivity to vehicle attributes and policy incentives. As reviewed by (Coffman et al., 2017), consumer attributes are among the key external factors that influence clean vehicle adoption. Consequently, another uncertainty arises regarding to whether clean vehicle transition is just and equitable across the heterogeneous populations under alternative technology progress pathways and policy mechanisms. The transportation engineering and environmental economics literatures have reviewed impacts of various clean vehicle incentives programs in recent years with much of the research on these questions, particularly in the transportation literature, use 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 et al., 2017) leveraged a vehicle choice experiment from a representative survey of California prospective new car buyers 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 a main focus of this paper.

Vehicle ownership decisions have an underlying process orientation. For example, vehicle ownership is influenced by life-stage transitions, such as the birth of a child (Oakil et al., 2016), and changes in the number of adults in the household (Yamamoto, 2008). Vehicle transaction decisions (add, replace, and trade vehicles) take place at different stages along their life-course and co-evolve with the spatial context of residential and work locations (Rashidi et al., 2011). However, most existing literature, relying on cross-sectional data, has provided only a snapshot of vehicle holdings and/or their utilization (Anowar et al., 2014; de Jong and Kitamura, 2009). While dynamic models have been proposed (e.g. de Jong and Kitamura 2009), these models have focused primarily on vehicle transactions with inadequate emphasis on the vehicle body type and powertrain, and vintage considerations of the household fleet, as reviewed in (Paleti et al., 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 et al., 2017). For example, declining battery price reduces ZEV upfront costs, making it more attractive to consumers. Several ZEV mandates (Axsen et al., 2022) require manufactures to accelerate ZEV supply, making them increasingly accessible on the market.

Research on mobility biography and life-oriented approaches (Beige and Axhausen, 2017; Oakil et al., 2014; Rau and Manton, 2016; Zhang et al., 2014; Zhang and Van Acker, 2017) has long recognized the interdependency of choices across various life domains and recommended integrating the temporal dimensions into the analyses of long-term mobility in a comprehensive way. Therefore, accurate forecasting vehicle ownership will require integration with the demographic, land use, and vehicle technology and market simulations to fully evolve households and their vehicle fleet composition over time.

Recently, an advanced household vehicle fleet composition and evolution microsimulator - **A**utomobile and **T**echnology **L**ifecycle-Based **As**signment (ATLAS) was developed as part of a larger mesoscale agent-based transportation modeling system (with name hidden due to double-blind review requirement). ATLAS is designed to capture the underlying processes of vehicle ownership, such as vehicle transaction and choice decisions, along households' lifecycle stages, enabled by the closely coupled population evolution model, Demographic Microsimulator (DEMOS) (Sun et al., 2023) running within the land use model UrbanSim (Waddell et al., 2007), and a vehicle technology and sales model Automotive Deployment Options Projection Tool (ADOPT) (Brooker et al., 2015a). The evolution of fleet composition is simulated by ATLAS at individual household level with vehicle choice dimensions spanned by body type, powertrain, vintage, and tenure.

This paper documented the modeling framework and application ATLAS to simulate the fleet turnover in San Francisco Bay Area's households. Technology and policy scenarios and sensitivity simulations were designed to investigate (1) the effects of vehicle technology progress and the 2035 clean vehicle mandate on Bay Area's fleet turnover; (2) further differentiation among different income groups in terms of their fleet turnover pathways and income disparity in ZEV ownership; (3) relative effectiveness of financial incentives, tax credit v.s. rebate, on income disparity in ZEV ownership.

# 2. ATLAS Modeling Framework

## 2.1. Module Description

ATLAS consists of three major modules (**Figure 1**): (1) the static household fleet mix module; (2) the dynamic vehicle transaction decision module; and (3) the dynamic vehicle choice module. Currently, all models are estimated and calibrated for the San Francisco Bay Area.

The static household fleet mix module determines a snapshot of vehicle choices of a given household. This module is useful for determining the initial state of the vehicle ownership when no historical vehicle ownership and social-demographics are available. This module uses a Multiple Discrete Continuous Extreme Value (MDCEV) model in conjunction with several other multinomial logit models that control and constrain the prediction of fleet mix such that it is representative of the observed fleet mix in the base year. The output from this module is a prediction the number of vehicles owned by individual households, body type of each of these vehicles, their vintage, the powertrain, and tenure (own or lease). The approach is based on the Vehicle Fleet Composition (VFC) model developed by Maricopa Association of Governments (2015) with more detailed documentation in (Garikapati et al., 2016, 2014). The National Household Travel Survey (NHTS) 2017 is used as the primary estimation data source.

The vehicle transaction decision module dynamically predicts the probability of household decisions on vehicle addition, disposal, and/or replacement at an evolution timestep based on existing vehicle attributes, sociodemographic and spatial context, and life-event changes. This model consists of two sub-models. The first one is the vehicle level transaction choice model. For each of the existing vehicles in the household fleet, vehicle transaction model predicts for next time step whether it is disposed (disposed without replacement), kept, or replaced (disposed with replacement) using series of multinomial logit models. The second model is the household level transaction choice model that determines whether the family will acquire additional vehicle to increase the level of vehicle holdings using an ordered logit. The development and validation of the module are further described in (Jin et al., 2022) based on the longitudinal survey Panel Data of Income Dynamics (PSID) (2021).

The dynamic vehicle choice module takes the transaction decision output from the dynamic vehicle transaction decision module and predicts the vehicle choices in terms of body type, vintage, powertrain, and tenure (own or lease) are predicted for the added vehicles and replacement vehicles. We followed the multinomial logit models published by (Fowler et al., 2017) that were estimated from the California Energy Commission (CEC) discrete choice experiment data. The specification of the sub-models aims to determine the parameters associated with vehicle attributes, policy incentives, and vehicle owners' characteristics that predict the vehicle choice decisions. This module also dynamically updates the alternative specific constants to match the overall market shares of powertrain, body type, and vintage in vehicle sales totals provided by ADOPT for new vehicles and by internally determined used vehicle inventories at each evolution time step. Such approach allows for capturing the evolving supply side constraints while maintaining the relative adoption difference among heterogeneous population reflected by the interacting parameters between the household socioeconomic attributes and vehicle alternatives.

Two additional auxiliary models are used to capture additional household fleet dynamics overtime. The first model is the vehicle scrappage model that applies a fleet level survival curve as a function of vehicle type (car vs truck) and vehicle age to determine whether the disposed and replaced vehicles exit the vehicle population. The survive curves are estimated using the fleet database maintained by California Air Resources Board (EMFAC n.d.). The survived vehicles form "used inventory" to enter the used vehicle market and are redistributed to the households in the vehicle choice module.

The second one is the dynamic household fleet re-initialization model that initializes the vehicle choices for immigrated families at the evolution time step. The household fleet composition for any newly emerged household is determined by the most similar household within the residence census tract according to the socio-demographic and economic attributes.

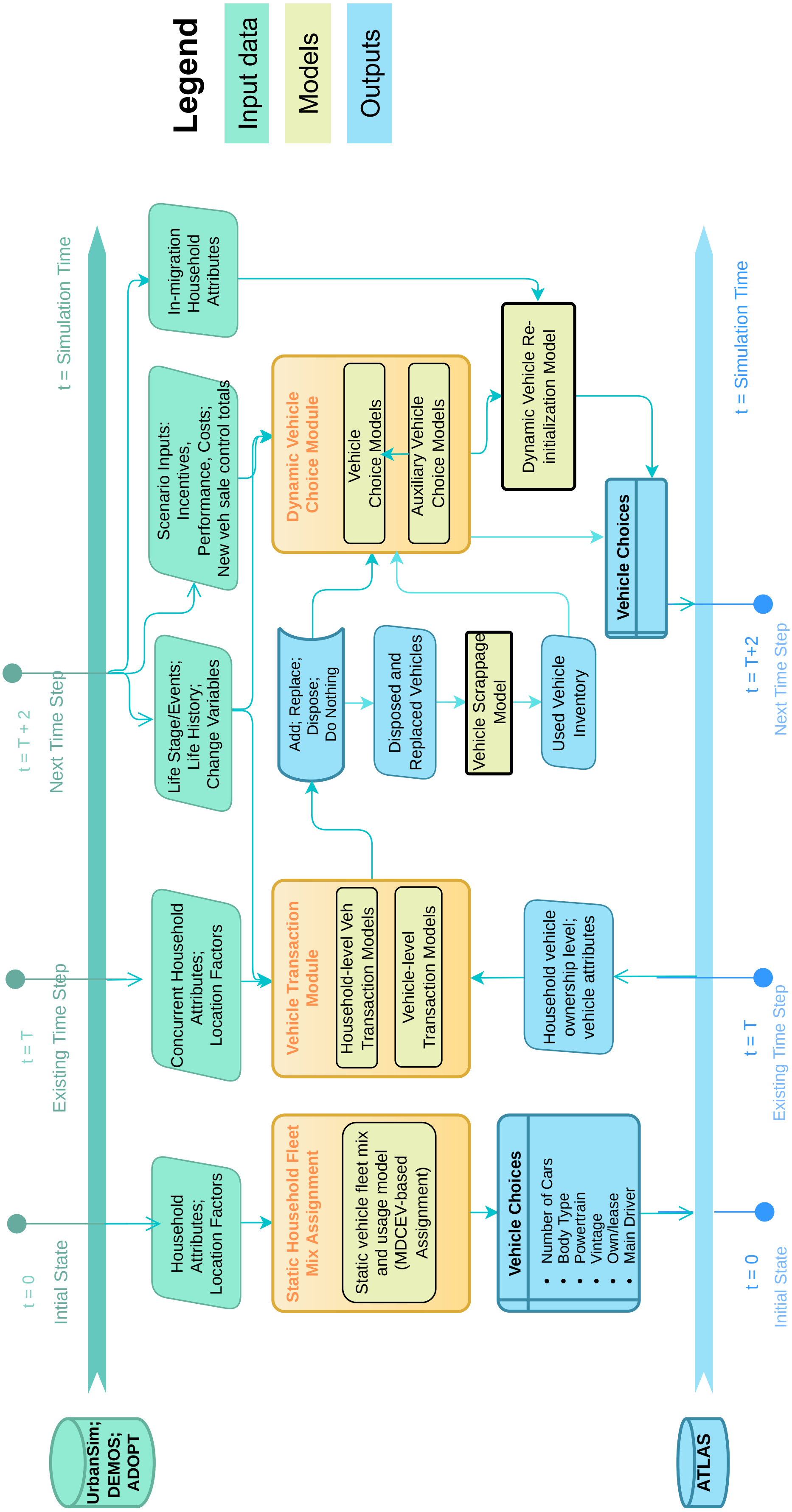


**Figure 1 ATLAS modeling architecture.**

## 2.2. Closely Coupled Input Streams and Output Variables

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

The demographic microsimulator DEMOS running inside of UrbanSim is a well-structured disaggregate evolution modeling system that captures the migration dynamics, evolution process of person level attributes and family behaviors. The transition probabilities between consecutive years are derived using discrete choice models estimated from the Panel Data of Income Dynamics (PSID) (2021) . The whole framework of DEMOS is shown in **Figure 2**.

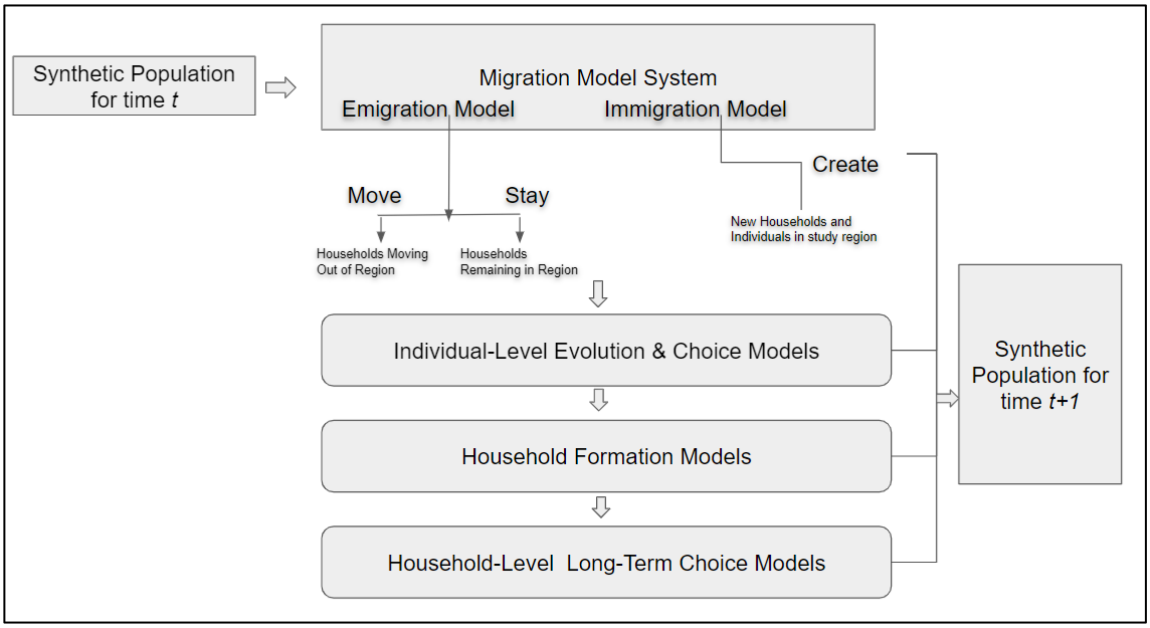


**Figure 2 Representation of Demographic Microsimulation**

Another key upstream model to ATLAS is ADOPT, which evolves vehicle market and forecasts vehicle attributes and total new vehicle sales. An overview of key elements is shown in **Figure 3**. The model starts by applying input assumptions including technology improvements, fuel emission factors, and fuel prices, to the vehicles. Simulations start with all of the over 700 existing vehicle makes, models, and options. 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 the predicted 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 options in the future. This leads to market-driven vehicle options and attributes that are indirectly influenced by the input assumptions. For example, as battery prices decrease, ADOPT tends to create battery electric vehicles (BEVs) with larger batteries that provide longer range and better acceleration. The sales of the evolving vehicle options are used to generate sales weighted averaged vehicles and attributes as an input to ATLAS.

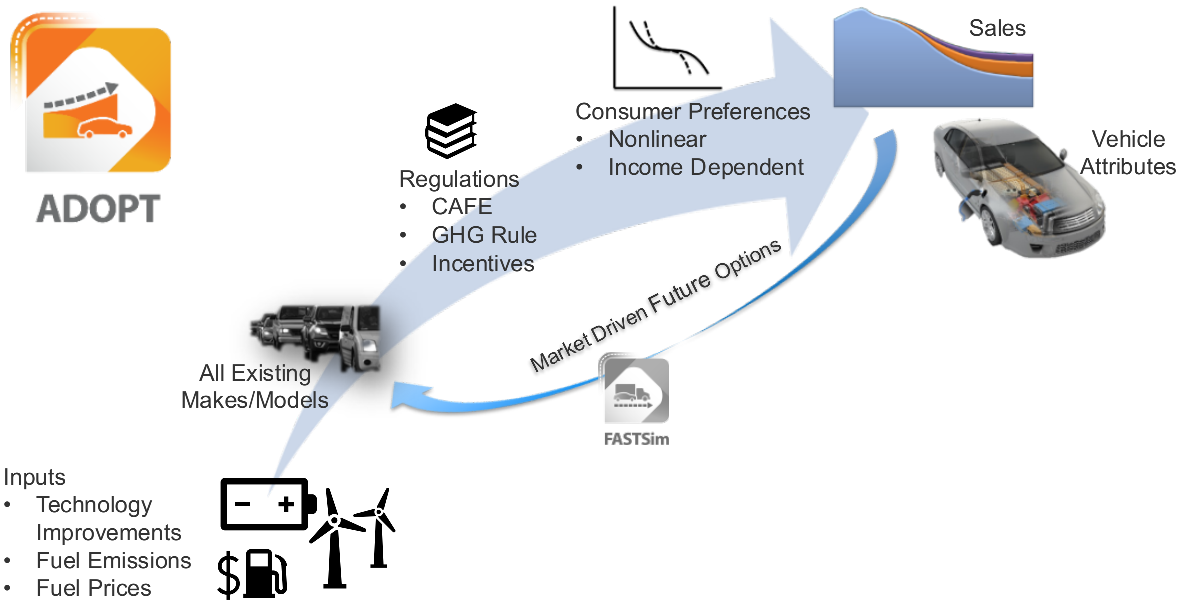


**Figure 3 ADOPT's approach to estimating future vehicle attributes and sales.**

While ADOPT data, available for vehicle sold in 2015 and later, is used to populate the vehicle attributes for the set of new vehicle choices at each evolution time step, the used vehicle attributes are prepared by combining ADOPT attributes and external 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. (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. Therefore, we use fleet averages from the EPA Automotive Trends report (Hula et al., 2021).

ATLAS simulations are conducted on a bi-annual basis and output fleet composition at each simulation time step for individual households. The output variables are household fleet compositions for individual households including the number of vehicles owned and choice of each vehicle described by body type ∈ {Car, SUV, Pickup, Van}, powertrain ∈ {ICE, BEV, PHEV, Hybrid}, vintage (a continuous variable at the simulation time step), and tenure ∈ {own, lease}.

Three primary datasets used for calibrating the ATLAS sub-models are:

- National Household Travel Survey 2017 (NHTS): a cross-sectional survey conducted in 2017 that collected information on household social-economics, demographics, travel behavior, vehicle ownership and usage. Three files are used in this project:
    - Household: contains household level socio-demographic characteristics such as household size, income, vehicle ownership, life cycle, etc.
    - Person: contains person level characteristics such as age, gender, worker status, driver status, walk or bike frequency, etc.
    - Vehicle: contains vehicle characteristics of all vehicles owned by a household such as year, make, model, powertrain, etc.
- Panel Study of Income Dynamics (PSID): a national level longitudinal panel survey of American families. It measures the social, economic, demographic, and vehicle

ownership over their life-course of families over multiple generations starting from 1968 – 2019. Vehicle data were collected more consistently from 2003 to 2019.
- California Energy Commission (CEC) dataset: Vehicle Survey data collected in 2017 to forecast vehicle fleet composition and fuel consumption in California. It contains (1) a cross-sectional survey of revealed household vehicle choices and usage; (2) a stated intention survey of potential vehicle transactions; and (3) a stated preference survey of vehicle choices upon future transactions.

A list of input variables, the feed-in upstream models, the calibration datasets, and their associated modules within ATLAS are provided in **Table A1** in **Appendix** at the end of the paper.

# 3. Case Study and Results

The sub-modules discussed in Section 3 are integrated into the workflow in **Figure 1**. The combined effects of the interactions among all sub-models are simulated for the San Francisco Bay Area in California from 2017 to 2050 in a case study to understand the effects of vehicle technology progress and clean vehicle policies on fleet turnover and equity in ZEV ownership among the heterogeneous population in this region. More specifically, scenario and sensitivity simulations are designed to investigate (1) the effects of vehicle technology progress and the 2035 clean vehicle mandate on Bay Area's fleet turnover; (2) further differentiation among different income groups in terms of their fleet turnover pathways and income disparity in ZEV ownership; (3) relative effectiveness of purchasing incentives (tax credit vs rebate) on income disparity in ZEV ownership.

## 3.1. Scenario Definition and Input Data

DEMOS-UrbanSim simulations upstream of ATLAS are conducted to generate a dynamically evolving synthetic populations in the Bay Area. These include both cross-sectional (intitial year 2017) and longitudinal (forecasting 2018 to 2050) demographic and social-economic attributes of individual persons and households, their residence locations and associated built environment.

Sales and sales weighted vehicle attributes were generated from ADOPT for three scenarios: (1) Technology success (Tech Success baseline scenario), where battery prices drop to levels where BEVs become successful and electricity generation becomes clean, reflecting Department of Energy (DOE) goals; (2) A more conservative variation where battery prices stagnate at $220/kWh (Stagnant Battery Price scenario); (3) A more optimistic variation that assumes a clean vehicle mandate (ZEV Mandate scenario), where all vehicles except clean vehicles (BEVs, PHEVs, and FCVs) get discontinued by 2035. The three scenarios were chosen to provide a wide variety of possible outcomes.

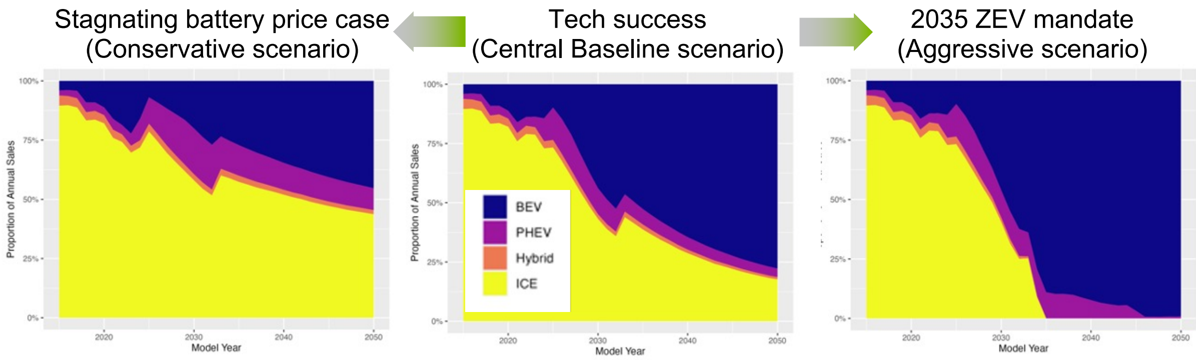


**Figure 4 ADOPT predicted powertrain market shares overtime under three scenarios**

As shown in **Figure *4*** ADOPT forecasts an increasing share of new ZEVs sold in this region across all scenarios. However, the Stagnating battery price scenario reduces the ZEV market share relative to the Technology success baseline scenario, while the 2035 ZEV mandate increase the ZEV market share to 100% after 2035. Vehicle attributes differ across scenarios with the difference mostly pronounced between the stagnant battery price scenario vs others. As shown in **Figure *5***, the price of electric cars is higher due to higher battery price in the stagnant battery scenario than in the Tech success baseline scenario. ATLAS then distributes these new vehicle sales as supply-side control totals together with the internally generated used vehicle inventory to individual households that are predicted to have a purchasing transaction (to add or replace a household vehicle) and generates the updated household fleet composition at each time step.

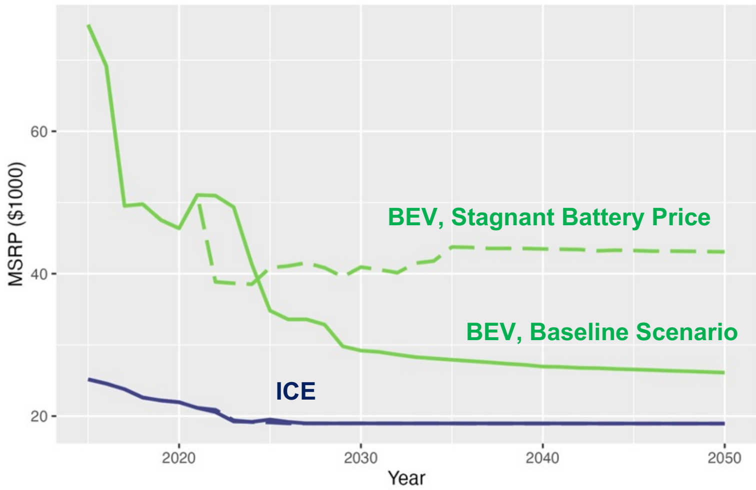


**Figure 5 Sales weighted car price for BEV (green) and ICE (blue) vehicles under the baseline (solid lines) and stagnant battery price (dashed lines) scenarios.** *Showing car price as an example and plots for other body types, such as SUV, have similar trends.*

Several incentives for the purchase of clean vehicles are modeled across the scenarios. These include (1) The federal tax credit for BEVs and PHEVs with batteries of at least 5 kWh before 2023; (2) Tax credits for both new and used vehicle purchase of all manufacturers subject to meeting particular sourcing requirements for battery materials and minerals starting from 2023 (*Inflation Reduction Act*, 2022); (3) two main rebate/grant programs: the California Clean Vehicle Rebate Project (CVRP, California Air Resources Board, 2010) which funds new vehicles only, and the Clean Vehicle Assistance Program (CVAP, California Air Resources Board, 2018), which funds the purchase of both new and used vehicles. More detailed description of these incentives is presented in **Table A2 and Table A3** in the **Appendix** at the end of the paper.

Around the Tech Success Baseline scenario where both tax credit and rebate are modeled, three additional sensitivity simulations are conducted to further understand the distributional effects of purchasing incentives on ZEV ownership across income groups of different eligibility: (1) baseline simulation absent of rebate; (2) baseline simulation absent of tax credit; and (3) baseline simulation absent of both incentives.

## 3.2. Simulation Results and Discussions

Driven by the demographic attributes and scenarioized inputs described earlier, ATLAS generates the biannual outputs of household fleet composition from 2017 to 2050 for individual households in San Francisco. We combine the electric and plugin hybrid vehicles into the "ZEV" category shown in the figures in this section, while the rest powertrains belong to the "nonZEV" category.
At an aggregate level, ZEV penetrates the Bay Area fleet over time in all scenarios, although at different paces. As shown in **Figure 6** the fleet share of nonZEV steadily declines and ZEV increases. The Tech Success Baseline scenario alone results in 40% ZEV share by 2037, while Stagnating battery price declines delay the process by 5~6 years. On the other hand, Implementing the 2035 ZEV mandate along with technology success accelerates the turnover (to reach the 40% ZEV share) by 4~5 years. The cross-scenario variations are primarily driven by the differences in technology and policy pathways represented by the new vehicle sales input from ADOPT. As shown earlier in **Figure *4***, the Stagnant battery price reduces the ZEV market share relative to the Technology success baseline scenario, while the 2035 ZEV mandate increase the ZEV market share to 100% after 2035. Comparing the ZEV shares in fleet mix in **Figure *6*** with the market shares in **Figure *4***, it is worth noting that ZEV ownership levels in 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 same level of ZEV market shares was introduced. This is because vehicle ownership is a median to long term household behavior and existing nonZEVs in the fleet will keep operating until they are disposed or replaced by ZEVs. Policy effectiveness of decarbonization through electrification of household vehicles should consider this time lag between market share and fleet turnover.

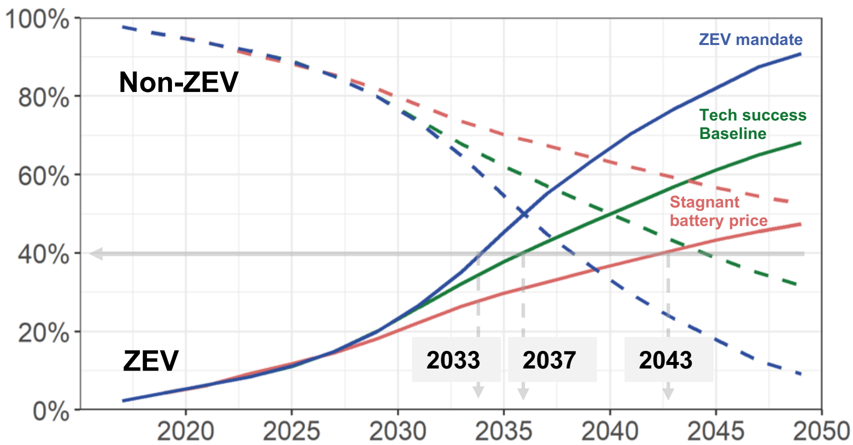


**Figure 6 Fleet turnover and ZEV penetration predicted under three scenarios. Solid lines: ZEV% (all electric and plug-in hybrid vehicles) and dashed lines: fleet share of non-ZEV% in the fleet mix.**

As ATLAS predicts vehicle ownership and fleet composition at individual household level, the fleet turnover and ZEV penetration can be aggregated from household level to different subpopulation differentiated by income levels as shown in **Figure** *7*. Across scenarios, ZEV penetrates into the higher income groups at a higher pace than lower income groups. Technology success and ZEV mandate both enable all income groups to transition to ZEV dominant ownership (i.e. >50% ZEV) by 2050. Because of its faster fleet turnover, the top income subpopulation transitions to ZEV dominant ownership about 5 years earlier than the bottom income group in both baseline and ZEV mandate scenarios. In the stagnant battery price scenario, however, vehicle ownership of all income groups remains dominated by nonZEVs throughout the simulation period.

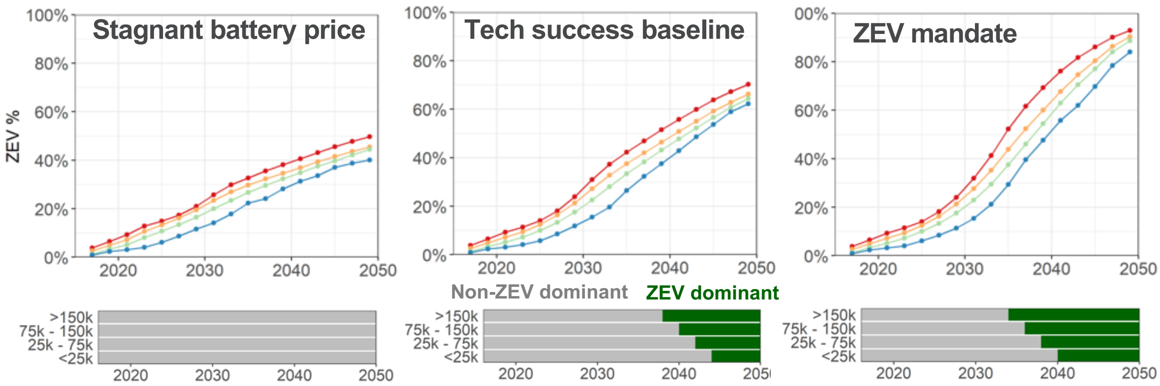


**Figure 7 ZEV ownership levels within different income groups over time (upper panel) and transition from nonZEV dominant (grey) to ZEV dominant (green) ownerships by income groups (bottom panel) under three scenarios.**

Existing literature, with most of them through stated preference surveys, investigated factors affecting ZEV uptake. Review by (Coffman et al., 2017) identified most important factors including internal factors (e.g. costs, range, charging time) and external factors (e.g. relative fuel prices, consumer attributes, charging infrastructure, etc.) that influence clean vehicle adoption. These factors are mostly conditioned on the vehicle purchasing occasions. Following the literature, factors such as vehicle attributes, incentives and their interaction with demographic attributes (Table A1) at the purchasing occasion are represented by the dynamic vehicle choice module in ATLAS. Vehicle price and incentives are interacted household income in the multinomial logit model used, we will see later in the sensitivity simulations that the incentives address the price differentials in ZEV vs nonZEV, converging the income differences in ZEV ownership. This means the simulated income differences in ZEV ownership dynamics in **Figure** *7* cannot be explained by powertrain preferences only upon the purchasing occasions.

In addition to the preferences conditioned on the purchasing occasion, the overall probability of ZEV uptake by individual households is also influenced by the full chain of decision-making processes of vehicle purchase, that is, how often the purchasing occasion occurs (whether a household needs to buy vehicles) and ZEV availability in the choice set (e.g. in new v.s. used market) considered by the households. Using a process-oriented approach, ATLAS offers unique new insights in ZEV uptake behavior in these areas.

Firstly, as shown in **Figure** *8*a, the transaction frequencies, to replace an existing vehicle or to add a vehicle, increase with household income. Higher income households are less financially constrained to make a purchasing decision and their higher vehicle ownership levels also require more frequent vehicle replacement. This means higher income groups are exposed to more frequent opportunities (or transaction windows) to considering ZEV adoption concurrent with the increasing ZEV availability on the market.

Secondly, as shown in **Figure *8***b, when considering the vehicle markets, higher income households are more likely to choose from new vehicle market, while lower income households are more likely to buy from the used market with vehicles of lower upfront costs. In fact, our simulations indicate that households with income less than $150k purchase vehicles primarily from the used market.

Thirdly, related to the new vs used markets, **Figure *8***c shows the availability of ZEV in respective markets. ZEV shares in the whole fleet is also shown as a reference. We can see the relative amount of ZEVs available to purchase is much higher in new vehicle market indicated by the red line, while the ZEV share in used market (blue line) slightly lags behind fleet averages (black line), which lags far behind the new vehicle market.

Taking these factors together, we can see lower income groups buy vehicles less often, and when they do, they are more likely to consider cheaper used vehicle market where ZEVs are not as available as the new vehicle market. These decision processes coupled with the new and used market evolutions, dynamically differentiate the fleet turnover patterns across the income groups.

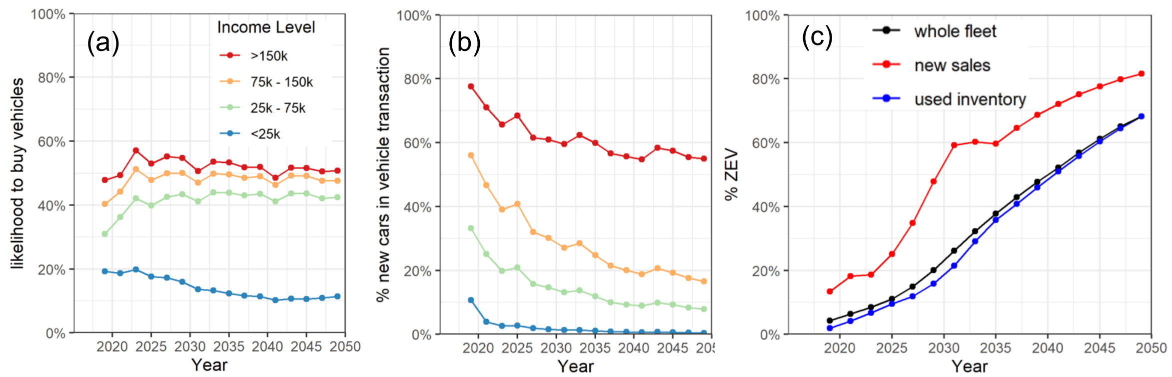


**Figure 8 Dynamics that affect differential ZEV ownership evolution across income groups: (a) transaction probability by income groups; (b) likelihood by income group to purchase new vehicles; (3) ZEV shares in new vehicle sales, used vehicle inventory, and whole fleet. Data shown are from the Baseline scenario (plots under other scenarios showed similar trends and are available upon request).**

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

$$D_{i,s} = \frac{ZEV_{i,s}\% - ZEV_{pop,s}\%}{ZEV_{pop,s}\%} \quad (1)$$

Where $D_{i,s}$ is the disparity metric of income group $i$, measuring the difference between percent of ZEV owned by income group $i$ ($ZEV_{i,s}\%$) and the population average ownership level $ZEV_{pop,s}\%$ under scenario $s$. The difference is normalized by population average of respective scenarios $ZEV_{pop,s}\%$ so that this metric can be compared across scenarios. A positive value of $D_i$ indicates higher than population average ZEV ownership and vice versa.

As expected, the top income groups showed consistent higher than average ZEV ownership throughout the simulation period across all scenarios (red lines in the disparity metric time series in **Figure *9***). The relative income disparity in ZEV ownership, however, shrinks over time across all scenarios as indicated by the narrowing gap between the income groups. ZEV mandate together with technology success in the ZEV mandate scenario eventually reduce disparity most, while the stagnant battery price sustains income disparity the longest. This finding suggests that although technology progress and ZEV mandate result in faster ZEV penetration into the higher income households, they eventually narrow the relative gaps in ZEV ownership across income groups.

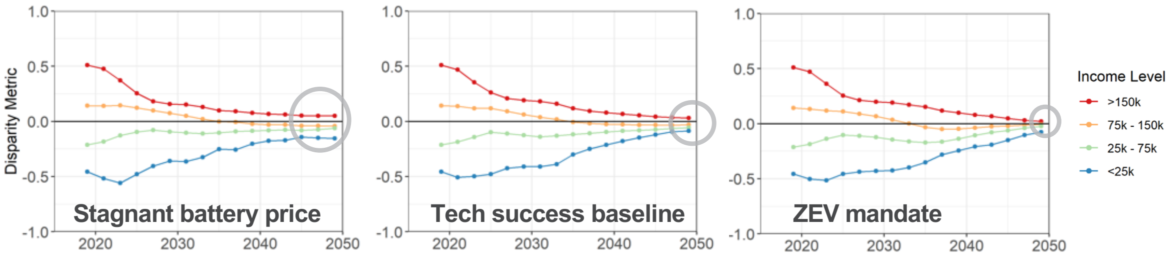


**Figure 9 Disparity metrics of ZEV ownership by income groups under three scenarios.**

Lastly, purchase incentives that aim to induce consumers to adopt pricier ZEVs have heterogeneous effects across income groups. Subpopulations are faced with different levels of incentives due to income eligibility with *opposite* trends in tax credit vs cash rebate.

As shown in **Figure *10*** ab, available tax credit per household for new or used vehicles depends on household income, as the tax credits are nonrefundable. An income cap is instantiated in 2023, and in 2032 the tax credit phases out entirely. Lower income consumers are unable to fully capture the tax credit because their tax liability is too low, while high income consumers become ineligible starting in 2023.

Available cash rebate per household for new vehicles (**Figure *10***cd) is independent of scenario and is reduced for higher income categories because of the programs' income caps. The vehicle rebates increased in 2023 with the introduction of PG&E's rebate program.

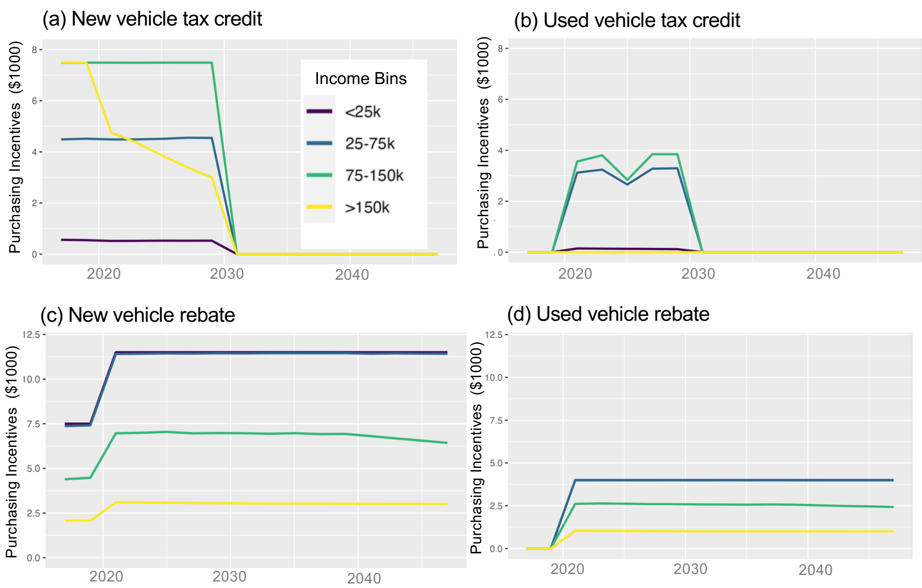


**Figure 10 Available per household purchasing incentives in the form of (a) new vehicle tax credit; (b) used vehicle tax credit; (c) new vehicle rebate; and (d) used vehicle rebate; averaged over the households with predicted purchasing occasion at each simulation time step.**

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 of these subpopulations have not been well investigated in the literature. Sensitivity simulations performed here are focused on understanding how the ZEV ownership are redistributed by the financial incentives to affect the income disparity we observed earlier.

**Figure** ***11*** shows the difference in ZEV ownership levels between the top income group and each of the rest three income groups simulated under the combinatorial of incentive types. Greater values indicate larger gaps between the income groups and vice versa. We can see federal tax credit and state and local rebate programs reduce income disparity in ZEV ownership, as indicated by lower ZEV ownership differences. Tax credit alone only slightly redistributed the ZEV ownership as indicated by small difference between "tax credit only" simulation and "no incentives" simulation. In contrast, the re-distribution of ZEV ownership via cash rebate is more pronounced, as indicated by the greater reduction of ZEV ownership gaps in the "rebate only" simulation relative to the "no incentives" case. This finding suggests that cash rebate improves equity more than tax credit. It is also worth noting that purchasing incentives are more effective at increasing adoption in mid-range income groups compared to lowest income groups. This is partly because the bottom income group prefers used and aged vehicles of much lower costs that are more likely to be nonZEVs and therefore is not sensitive to ZEV incentives. Incentivizing the ZEV adoption by poorer households merits further research.

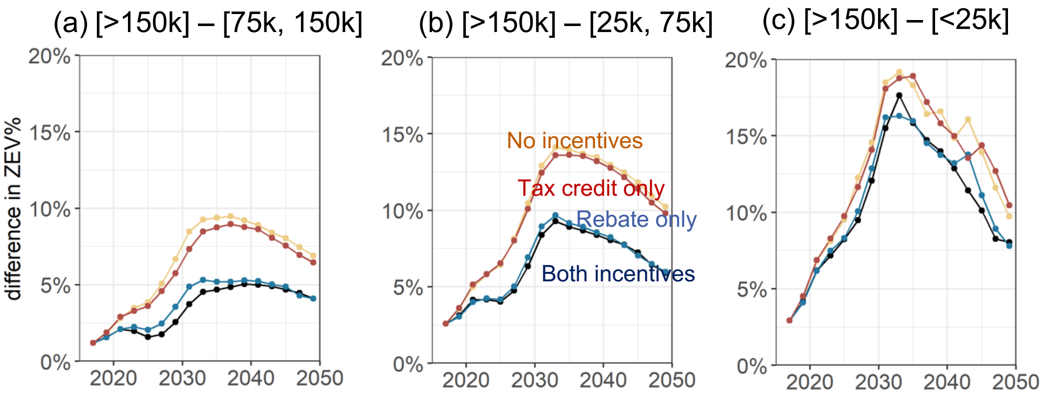


**Figure 11 Difference in ZEV ownership level between the top income group (> $150k) and households with (a) income of $75k to $150k, (b) income of $25k to $75k, and (c) income less than $25k, under different sensitivity simulations.**

# 4. Summary and Future Steps

This paper documented the modeling framework and its application of a comprehensive household vehicle fleet composition and evolution microsimulator ATLAS. ATLAS takes an innovative process-oriented approach and operates at a fully disaggregated level. It evolves individual households' vehicle ownership, transaction and choice decisions in response to the coupled and co-evolving demographics, land use, and vehicle technology simulators. While most existing literature focused on the aggregated effects technology progress and clean vehicle policies on ZEV uptake, ATLAS enables a deeper understanding of their distributional effects and underlying mechanisms across heterogeneous sub-populations and thus contribute to the transportation equity literature.

ATLAS was calibrated and applied the San Francisco Bay Area in California to simulate vehicle fleet composition of individual households from 2017 to 2050. Technology and policy scenarios and sensitivity simulations were designed to investigate (1) the effects of vehicle technology progress and the 2035 clean vehicle mandate on Bay Area's fleet turnover; (2) further differentiation among different income groups in terms of their fleet turnover pathways and income disparity in ZEV ownership; (3) relative effectiveness of financial incentives, tax credit v.s. rebate, on income disparity in ZEV ownership.

We found that at an aggregate level, ZEV penetrates the Bay Area fleet over time in all scenarios, although at different paces. For ZEV to reach 40% of fleet share, stagnant battery prices delay the process by 5~6 years relative to the technology success scenario where battery prices drop to levels where BEVs become successful. On the other hand, Implementing the 2035 ZEV mandate along with technology success accelerates the turnover by 4~5 years.

ZEV shares in the fleet mix significantly lag behind those in new vehicle sales. For example, in the baseline scenario, ZEV shares in the fleet mix reach 40% about 10 years after the same level of ZEV market shares was introduced. This is because vehicle ownership is a median to long term household behavior and existing nonZEVs in the fleet will keep operating until they are disposed or replaced by ZEVs. Policy effectiveness of decarbonization through electrification of household vehicles should consider this time lag between market share and fleet turnover.

Across scenarios, ZEV penetrates into the higher income groups at a faster pace than lower income groups. In particular, technology success and ZEV mandate both enable all income groups to transition to ZEV dominant ownership (i.e. >50% ZEV) by 2050. The top income subpopulation transitions to ZEV dominant ownership about 5 years earlier than the bottom income group. Vehicle ownership in the stagnant battery price scenario, however, remains dominated by nonZEVs across all income groups throughout the simulation period.

We found that the full chain of vehicle transaction and choice processes drove the income differences in ZEV ownership evolution. Lower income groups are exposed to fewer vehicle transaction opportunities to adopting and gaining experiences of ZEV, and are more likely to consider cheaper vehicles in the used market where ZEVs are not as available as the new vehicle market. These decision processes coupled with the new and used market evolutions, dynamically differentiate fleet turnover patterns among the income groups.

The ATLAS application demonstrated here also contributes to transportation equity literature. Despite of faster ZEV penetration into the higher income groups, we found the relative income disparity in ZEV ownership shrunk over time across all scenarios. ZEV mandate together with technology success in the ZEV mandate scenario eventually reduced disparity most, while the stagnant battery price sustained income disparity the longest.

ATLAS modeled both federal and state and local financial incentives for clean vehicle adoption. These financial incentives address the cost differential between ZEVs and conventional vehicles at different levels across income groups. Sensitivity simulations revealed the effects of these financial incentives on redistributing ZEV ownership among income groups that consequently narrowed the income disparity. We found cash rebate was more effective for improving equity of ZEV ownership than tax credit.

The current implementation of ATLAS could merit further development. Examples include implementing additional policy intervention levers such as charging infrastructure and modeling additional dimensions around vehicle choices such as level of automation. Parameter calibration is an ongoing effort to more accurately capture the preferences in consumer transaction and vehicle choices as observational data becomes more abundant with increased ZEV adoption over time. In future work, we will expand the ATLAS deployment to other regions to support policy decisions that ensure an efficient, effective and equitable transition to a clean vehicle future.

# Reference

Anowar, S., Eluru, N., Miranda-Moreno, L.F., 2014. Alternative Modeling Approaches Used for Examining Automobile Ownership: A Comprehensive Review. Transport Reviews 34, 441–473. https://doi.org/10.1080/01441647.2014.915440

Axsen, J., Hardman, S., Jenn, A., 2022. What Do We Know about Zero-Emission Vehicle Mandates? Environ. Sci. Technol. 56, 7553–7563. https://doi.org/10.1021/acs.est.1c08581

Beige, S., Axhausen, K.W., 2017. The dynamics of commuting over the life course: Swiss experiences. Transportation Research Part A: Policy and Practice 104, 179–194. https://doi.org/10.1016/j.tra.2017.01.015

Biden faces pressure to drive gasoline and diesel cars out of the US | Pollution | The Guardian [WWW Document], n.d. URL https://www.theguardian.com/us-news/2021/apr/30/biden-administration-cars-emissions (accessed 11.30.21).

Brooker, A., Gonder, J., Lopp, S., Ward, J., 2015a. ADOPT: A Historically Validated Light Duty Vehicle Consumer Choice Model (No. NREL/CP-5400-63608). National Renewable Energy Lab. (NREL), Golden, CO (United States). https://doi.org/10.4271/2015-01-0974

Brooker, A., Gonder, J., Wang, L., Wood, E., Lopp, S., Ramroth, L., 2015b. FASTSim: A Model to Estimate Vehicle Efficiency, Cost and Performance (No. NREL/CP-5400-63623). National Renewable Energy Lab. (NREL), Golden, CO (United States). https://doi.org/10.4271/2015-01-0973

Burnham, A., Gohlke, D., Rush, L., Stephens, T., Zhou, Y., Delucchi, M., Birky, A., Hunter, C., Lin, Z., Ou, S., Xie, F., Proctor, C., Wiryadinata, S., Liu, N., Boloor, M., 2021. Comprehensive Total Cost of Ownership Quantification for Vehicles with Different Size Classes and Powertrains (No. ANL/ESD-21/4, 1780970, 167399). https://doi.org/10.2172/1780970

California Air Resources Board, 2018. Clean Vehicle Assistance Program [WWW Document]. URL https://cleanvehiclegrants.org/ (accessed 8.12.22).

California Air Resources Board, 2010. Clean Vehicle Rebate Project [WWW Document]. URL https://cleanvehiclerebate.org/en (accessed 8.12.22).

Coffman, M., Bernstein, P., Wee, S., 2017. Electric vehicles revisited: a review of factors that affect adoption. Transport Reviews 37, 79–93. https://doi.org/10.1080/01441647.2016.1217282

de Jong, G.C., Kitamura, R., 2009. A review of household dynamic vehicle ownership models: holdings models versus transactions models. Transportation 36, 733–743. https://doi.org/10.1007/s11116-009-9243-7

DeShazo, J.R., Sheldon, T.L., Carson, R.T., 2017. Designing policy incentives for cleaner technologies: Lessons from California’s plug-in electric vehicle rebate program. Journal of Environmental Economics and Management 84, 18–43. https://doi.org/10.1016/j.jeem.2017.01.002

EMFAC [WWW Document], n.d. URL https://arb.ca.gov/emfac/fleet-db/fc0f0bad04c20b37fbbf52df54fd97f32217ac87 (accessed 4.30.22).

European Commission on Climate Action. 2050 long-term strategy, n.d.

Fowler, Mark, Cherry, Tristan, Adler, Thomas, Bradley, Mark, Richard, Alex, 2017. 2015–2017 California Vehicle Survey.

Garikapati, V.M., Sidharthan, R., Pendyala, R.M., Bhat, C.R., 2014. Characterizing Household Vehicle Fleet Composition and Count by Type in Integrated Modeling Framework. Transportation Research Record 2429, 129–137. https://doi.org/10.3141/2429-14

Garikapati, V.M., You, D., Pendyala, R.M., Jeon, K., Livshits, V., Bhat, C.R., 2016. Development of a Vehicle Fleet Composition Model System: Results from an Operational Prototype. Presented at the Transportation Research Board 95th Annual MeetingTransportation Research Board.

Hula, A., Maguire, A., Bunker, A., Rojeck, T., Harrison, S., 2021. The 2021 EPA Automotive Trends Report: Greenhouse Gas Emissions, Fuel Economy, and Technology since 1975. United States Environmental Protection Agency, Ann Arbor, Michigan.

Inflation Reduction Act, 2022.

Jin, L., Lazar, A., Brown, C., Sun, B., Garikapati, V., Ravulaparthy, S., Chen, Q., Sim, A., Wu, K., Ho, T., Wenzel, T., Spurlock, C.A., 2022. What Makes You Hold on to That Old Car? Joint Insights From Machine Learning and Multinomial Logit on Vehicle-Level Transaction Decisions. Frontiers in Future Transportation 3.

Nykvist, B., Nilsson, M., 2015. Rapidly falling costs of battery packs for electric vehicles. Nature Clim Change 5, 329–332. https://doi.org/10.1038/nclimate2564

Oakil, A.T.M., Ettema, D., Arentze, T., Timmermans, H., 2014. Changing household car ownership level and life cycle events: an action in anticipation or an action on occurrence. Transportation 41, 889–904. https://doi.org/10.1007/s11116-013-9507-0

Oakil, A.T.M., Manting, D., Nijland, H., 2016. Dynamics in car ownership: the role of entry into parenthood. European Journal of Transport and Infrastructure Research 16. https://doi.org/10.18757/ejtir.2016.16.4.3164

Office of the Federal Register, N.A. and R.A., 2021. DCPD-202100095 - Executive Order 14008-Tackling the Climate Crisis at Home and Abroad [WWW Document]. govinfo.gov. URL https://www.govinfo.gov/app/details/https%3A%2F%2Fwww.govinfo.gov%2Fapp%2Fdetails%2FDCPD-202100095 (accessed 11.30.21).

Paleti, R., Eluru, N., Bhat, C.R., Pendyala, R.M., Adler, T.J., Goulias, K.G., 2011. Design of Comprehensive Microsimulator of Household Vehicle Fleet Composition, Utilization, and Evolution: Transportation Research Record. https://doi.org/10.3141/2254-06

Panel Study of Income Dynamics, public use data. (2021). Produced and distributed by the Survey Research Center, Institute for Social Research, University of Michigan. Ann Arbor, MI: University of Michigan, Institute for Social Research. https://psidonline.isr.umich.edu/guide/default.aspx Accessed April 2021, n.d.

Potoglou, D., Kanaroglou, P.S., 2007. Household demand and willingness to pay for clean vehicles. Transportation Research Part D: Transport and Environment 12, 264–274. https://doi.org/10.1016/j.trd.2007.03.001

President Biden Announces the Build Back Better Framework [WWW Document], 2021. . The White House. URL https://www.whitehouse.gov/briefing-room/statements-releases/2021/10/28/president-biden-announces-the-build-back-better-framework/ (accessed 11.30.21).

Rashidi, T.H., Mohammadian, A., Koppelman, F.S., 2011. Modeling interdependencies between vehicle transaction, residential relocation and job change. Transportation 38, 909. https://doi.org/10.1007/s11116-011-9359-4

Rau, H., Manton, R., 2016. Life events and mobility milestones: Advances in mobility biography theory and research. Journal of Transport Geography 52, 51–60. https://doi.org/10.1016/j.jtrangeo.2016.02.010

Sun, B., Sharda, S., Garikapati, V.M., Bouzaghrane, A., Caicedo, J., Ravulaparthy, S., Viegas De Lima, I., Jin, L., Spurlock, A., Waddell, P., 2023. Demographic Microsimulator for Integrated Urban Systems: Adapting Panel Survey of Income Dynamics to Capture the Continuum of Life (No. NREL/PO-5400-84809). National Renewable Energy Lab. (NREL), Golden, CO (United States).

Tal, G., Nicholas, M., 2016. Exploring the Impact of the Federal Tax Credit on the Plug-In Vehicle Market. Transportation Research Record 2572, 95–102. https://doi.org/10.3141/2572-11

Waddell, P., Bhat, C., Eluru, N., Wang, L., Pendyala, R.M., 2007. Modeling Interdependence in Household Residence and Workplace Choices. Transportation Research Record 2003, 84–92. https://doi.org/10.3141/2003-11

Yamamoto, T., 2008. THE IMPACT OF LIFE-COURSE EVENTS ON VEHICLE OWNERSHIP DYNAMICS: The Cases of France and Japan. IATSS Research 32, 34–43. https://doi.org/10.1016/S0386-1112(14)60207-7

Zhang, J., Van Acker, V., 2017. Life-oriented travel behavior research: An overview. Transportation Research Part A: Policy and Practice 104, 167–178. https://doi.org/10.1016/j.tra.2017.06.004

Zhang, J., Yu, B., Chikaraishi, M., 2014. Interdependences between household residential and car ownership behavior: a life history analysis. Journal of Transport Geography 34, 165–174. https://doi.org/10.1016/j.jtrangeo.2013.12.008

# 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 | UrbanSim location combined with external accessibility data (PSID, NHTS) | x | x | |
| Urbanization | 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 (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 | ADOPT and External Data (CEC) | | | x |

| Output Variables | Calibration/validation Data Source | Used in Modules | | |
|---|---|---|---|---|
| | | **Static fleet mix module** | **Transaction module** | **Dynamic vehicle choice module** |
| ***Vehicle Choice*** | | | | |
| Body type | PSID, NHTS, CEC, DMV | x | | x |
| Powertrain | PSID, NHTS, CEC, DMV | x | | x |
| Vintage | PSID, NHTS, CEC, DMV | 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**

| Credit | Qualified Plug-In Electric Drive Motor Vehicle | New Clean Vehicle | 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: 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 |
| Battery minerals requirement | | 40% from US or Free Trade nation in 2023 50% in 2024 60% in 2025 70% in 2026 80% in 2027 No credit for batteries with minerals from "foreign entity of concern" | |

| | | | |
|---|---|---|---|
| Battery components requirement | | 50% from US or Free Trade nation in 2023 60% in 2024 70% in 2026 80% in 2027 90% in 2028 100% in 2029 | |
| 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 rebate modeled in ATLAS**

| **Credit** | **Clean Vehicle Rebate Project** | **PG&E Clean Vehicle Rebate Project** |
|---|---|---|
| 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 | 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 |