The Entry Effects of Utilities in the Electric Vehicle Charger Market

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Abstract

Several U.S. states allow regulated electric utilities to install, own, and operate public electric vehicle (EV) chargers. Utility ownership may expand charging access in markets underserved by private providers, but regulatory approval and rate-base cost recovery may also change entry incentives. This paper studies how ownership structure shapes Maryland's public EV charging market. I combine reduced-form charger-supply estimates with a structural vehicle-demand model and distinguish between third-party and utility-owned chargers. Utility-owned chargers have lower semi-elasticities with respect to EV stock than third-party chargers, consistent with regulator screening and weaker sensitivity to local profitability under rate-base cost recovery. They are also concentrated in middle-income markets, while third-party chargers are more concentrated in higher-income markets. Counterfactual simulations show that pooling all chargers overestimates the equilibrium effects of EV purchase subsidies on EV sales and charger deployment. Utility-owned charger deployments substantially increase EV sales, EV stock, and public charger deployment, with larger percentage effects in lower- and middle-income markets. These results show that charger ownership matters for policy counterfactuals and for the distributional incidence of transportation-electrification policies.

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1 Introduction

The transportation sector remains one of the largest sources of greenhouse gas (GHG) emissions, and passenger gasoline vehicles account for a substantial share of these emissions. A central policy strategy for reducing transportation-sector emissions is the transition from internal combustion engine (ICE) vehicles to electric vehicles (EVs). Despite rapid growth in EV adoption, several frictions continue to limit diffusion, including high upfront purchase costs, uncertainty about a relatively new technology, and insufficient public charging infrastructure. A common policy response is to subsidize EV purchases or charging-station investment. A distinct approach is direct public-sector participation in the charging-station market. Several states have authorized or required regulated electric utilities to install, own, and operate public EV charging stations.

The economic rationale for charging-infrastructure policy extends beyond environmental externalities. The public charging market also features indirect network effects: charging availability affects EV purchase decisions, while local EV adoption affects charger profitability and siting incentives. Subsidies for EV purchases and charging-station investments are commonly used to address these market failures as a second-best policy. Utility ownership raises additional potential economic benefits and issues. Utility-owned chargers may either crowd out or complement third-party investment, depending on whether utility-owned and third-party chargers serve the same locations and consumers. In addition, because utility-owned charging investments may be recovered through the rate base, regulated utilities face incentives that differ from those of private charging providers. Rate-of-return (ROR) regulation can distort capital-investment incentives, as emphasized by the Averch-Johnson effect (Averch and Johnson, 1962), while regulatory approval may also constrain or redirect utility investment toward policy-priority locations. Thus, the ownership of charging infrastructure may matter for both market outcomes and the spatial distribution of access.

These issues are not only theoretical. The increasing role of regulated utilities in the charging-station market has raised concerns among private charging providers and incumbent fuel retailers. A *Wall Street Journal* article (Hiller, 2022) describes tensions between utilities and gas stations, emphasizing that regulated utilities may have an advantage because, subject to regulatory approval, they can recover infrastructure and electricity-service costs from ratepayers.[1] These concerns suggest that utility participation may change not only the size of the charging network but also the incentives of private providers to enter.

Maryland provides a useful setting for studying utility participation in the public charging market. The Maryland Public Service Commission (PSC) approved a pilot program requiring five major electric utilities to install and operate public chargers. The PSC's stated rationale is that utility-owned chargers should be deployed in locations where private firms are unlikely to invest. Utilities must obtain PSC approval

[1] Similarly, a *CNN* article (Mcfarland, 2022) highlights concerns that regulated monopolies could weaken competition in the emerging charging market.

before constructing utility-owned charging stations, and the approval process publicly documents proposed locations, approval decisions, and installation outcomes. This institutional setting makes it possible to study whether utility-owned chargers are deployed in markets that differ systematically from those served by third-party providers.

This paper studies how ownership structure shapes entry and market outcomes in the public EV charging market. The central questions are twofold. First, do utility-owned chargers enter the same markets as third-party chargers, or do they expand charging access in markets that private providers are less likely to serve? Second, how would EV sales, EV stock, and charger deployment change if utility-owned chargers were removed from Maryland's public charging network?

To answer these questions, I combine reduced-form charger-supply estimates with a structural vehicle-demand model. I first construct geographic markets using a spatial clustering algorithm that incorporates charging-demand shifters and geographic contiguity (Section 3.2). This market definition addresses a limitation of administrative boundaries, such as counties or zip codes, which may not correspond to local charging demand or substitution patterns. Using these markets, I estimate how third-party and utility-owned chargers respond to local EV stock and how their deployment varies with observable market characteristics (Section 4). The estimates show that utility-owned chargers have higher elasticities but lower semi-elasticities with respect to EV stock than third-party chargers. The lower semi-elasticity implies that, for a given percentage increase in EV stock, utility-owned charger deployment increases by less in levels than third-party deployment. This pattern is consistent with two mechanisms. First, utilities may face PSC screening and therefore may be unable to concentrate investment in the most profitable high-EV-stock locations. Second, because approved utility-owned investments may be recovered through the rate base, utilities may be less responsive to charging revenues and local profitability than third-party providers. Heterogeneity estimates further show that third-party chargers are more concentrated in higher-income markets, whereas utility-owned chargers are more commonly deployed in middle-income markets.

I then estimate a random-coefficients vehicle-demand model that incorporates the local public charging network (Section 5). The demand estimates indicate that consumers value public charging availability when choosing EVs, consistent with indirect network effects between charging infrastructure and EV adoption. I use the estimated supply and demand models to conduct counterfactual simulations (Section 6). A model that pools all chargers and ignores ownership distinctions produces larger point estimates of the equilibrium effects of EV purchase subsidies on EV sales and charger deployment, although the differences are not statistically significant. This overestimation arises because the pooled model does not account for the weaker level response of utility-owned chargers to EV stock. When part of the charging network is utility-owned, additional EV adoption induces less charger deployment than a pooled model would predict; through the

network effect, this weaker charger response also dampens the subsequent increase in EV sales. In a second counterfactual, removing utility-owned chargers substantially reduces EV sales, EV stock, and the public charging network. The effects are larger in lower- and middle-income markets, suggesting that utility-owned chargers may expand access in markets that are less attractive to private providers. The simulations also show that utility-owned charger deployment complements EV purchase subsidies: when the charging network is smaller, purchase subsidies generate fewer additional EV sales per dollar of public expenditure.

This paper contributes to two strands of literature. First, it contributes to the growing economics literature on EV adoption and charging infrastructure. Prior studies emphasize indirect network effects between EV adoption and charging-station deployment: consumers value larger charging networks, and charging providers have stronger incentives to enter markets with more EVs (Li et al., 2017; Springel, 2021; Remmy, 2026). Related work studies charging-standard compatibility, vertical integration, firms' incentives to invest in charging networks, and the effectiveness of investments in charging speed or charger density (Li, 2023; Dorsey et al., 2025). Most existing studies treat charging stations as a homogeneous network or focus primarily on the vehicle market. This paper instead distinguishes utility-owned and third-party chargers and shows that ownership-specific investment incentives matter for estimated supply responses and policy counterfactuals.

Second, this paper contributes to research on public-sector participation in local infrastructure markets. A large literature studies the economic effects of infrastructure investments, including electrification, water and sewerage systems, and transportation networks (Lipscomb et al., 2013; Alsan and Goldin, 2019; Donaldson, 2018). This literature shows that infrastructure can generate large externalities and that infrastructure placement is often endogenous to local demand. A related literature emphasizes that public involvement in infrastructure may be justified by capital-market frictions, externalities, natural-monopoly concerns, or the need to maintain service in markets that private providers may not serve (Glaeser and Poterba, 2020). However, less is known about how public or regulated entities enter local infrastructure markets relative to private firms when the market is still developing. The closest paper is Wilson (2025), who studies whether municipal broadband provision crowds out or induces private broadband investment. I study a different but related setting: public EV charging, where utility-owned chargers are deployed by regulated electric utilities, costs may be recovered through the rate base, and public intervention may either expand access in underserved markets or crowd out third-party investment. The results show that ownership structure matters for infrastructure deployment and that targeted utility participation can affect the distribution of EV adoption benefits.

2 Institutional Background

A conventional policy for promoting public EV charging infrastructure is to subsidize private investment.[2] Although charging-station subsidies can mitigate the market failure problem between EV adoption and charging-station deployment, their effectiveness depends on market primitives that are difficult for policymakers to observe. The optimal subsidy level varies with EV demand, the existing charging network, the costs of vehicle production, and the costs of charger installation and operation.[3] These uncertainties have led some policymakers to consider more direct forms of intervention to accelerate charging-infrastructure deployment.

One such intervention is to allow regulated electric utilities to install, own, and operate public charging stations. Under these programs, approved installation and operating costs may be recovered through the rate base and ultimately paid by electricity ratepayers. This policy differs from a standard charger subsidy because utilities do not rely solely on charging revenues and because investment decisions may be subject to regulatory review. Several states, including Florida, Georgia, and Maryland, have allowed some form of utility participation, although Florida and Georgia have recently restricted the use of ratepayer funds for utility-owned charging infrastructure.[4] These policy changes reflect concerns that utility ownership may impede private investment in the emerging public charging market.

Maryland provides a useful setting because it has maintained an active utility-owned charger program during the sample period. The program originated from the Electric Vehicle Working Group of the Maryland PSC. On January 13, 2019, the PSC approved a statewide EV portfolio with several components, including residential charging incentives, non-residential charging incentives, and a public sub-portfolio focused on utility-owned public charging stations. The public sub-portfolio is the focus of this study.[5]

The public sub-portfolio began on July 1, 2019. Under the PSC's order, five Maryland utilities—Baltimore Gas and Electric Company (BGE), Delmarva Power & Light Company (Delmarva), Potomac Electric Power Company (Pepco), The Potomac Edison Company (PE), and Southern Maryland Electric

[2] Throughout the paper, I distinguish among three related concepts of public EV infrastructure. "Public chargers" are charging stations that are accessible to the public, regardless of ownership. "Publicly owned chargers" are public chargers owned by government entities. I refer to privately owned public chargers as "third-party chargers" and focus on a distinct form of publicly supported infrastructure: "utility-owned chargers," which are installed, owned, and operated by regulated electric utilities. The analysis excludes private chargers with restricted access, such as chargers installed in private apartment complexes or workplaces.

[3] Meunier and Ponssard (2020) shows that the optimal refueling-station subsidy depends on market conditions, including EV demand, the number of charging stations and vehicle producers, range anxiety, refueling prices, and the costs of vehicle production and charging-station operation.

[4] In Florida, Tampa Electric and Florida Power & Light received approval to own and operate public chargers, but House Bill 1645 and Senate Bill 1624, enacted in 2024, made ratepayer-funded utility ownership more restrictive. In Georgia, Georgia Power invested in utility-owned chargers through its Community Charging Program, but Senate Bill 146, enacted in 2023, restricts the use of ratepayer funds for utility-owned charger ownership costs.

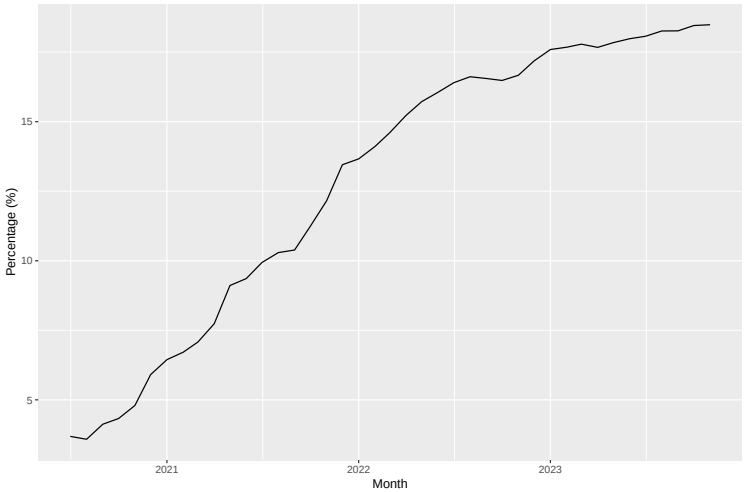
[5] In August 2024, the PSC indicated that it would be less likely to approve utility-owned chargers in the next phase of the program because of concerns about competition between utility-owned and third-party chargers. At the same time, the PSC stated that it would continue to allow utility-owned chargers in areas determined to be underserved. The cost-recovery structure continues to rely on future rate-base increases.

Cooperative (SMECO)—were authorized to install specified numbers of utility-owned public chargers. These chargers were to be located in public spaces leased, owned, or occupied by state, county, or municipal governments. The approval process begins when a utility proposes a site address and the number of chargers to be installed, typically after consulting with property owners and construction contractors. The PSC then decides whether to approve the proposed site.

The approval process is consequential. During the sample period, more than one-quarter of proposed sites were rejected. By December 2023, utility-owned chargers had been installed at 329 sites, corresponding to 708 chargers, while 127 proposed sites had ultimately been rejected. Proposed sites may be rejected because of engineering constraints, such as limited physical space or difficulty connecting to the distribution network, or because the PSC determines that the site does not align with the program's objective. The PSC states that the rationale for the public sub-portfolio is that "where private companies have been unable or unwilling to make initial capital investments in difficult and underserved areas, utility ownership can help reach these market segments faster" (Order No. 88997, Case No. 9478).[6] Thus, the approval process may reveal both engineering feasibility and the regulator's preferences over the spatial allocation of charging infrastructure.

Despite the rejected proposals, the share of utility-owned chargers in Maryland's public charging market increased substantially over the sample period. Figure 1 shows that the utility-owned share increased from approximately 4% in July 2020 to 19% in November 2023. The growing presence of utility-owned chargers makes Maryland a useful setting for studying whether regulated utility participation changes the geography of public charging infrastructure.

Figure 1: Percentage of Utility-Owned EVSEs over Time



Notes: The figure plots the percentage of utility-owned EVSEs in the Maryland EVSE market over the sample period.

[6]The PSC does not provide a precise definition of "underserved." The language in Case No. 9478 suggests that the PSC views underserved areas as locations where private firms are unlikely to enter absent utility participation.

Participating utilities submit semi-annual reports documenting proposed sites, approval decisions, installation status, and charger counts. I use these reports to construct the utility-owned charger data. Maryland's cost-recovery structure allows utilities to recover approved program costs through future rate-base increases, and utilities cannot modify charging fees without PSC approval. Appendix Table A.1 summarizes the main features of the public sub-portfolio, and Appendix A provides additional institutional history.

Maryland is especially useful for this study for four reasons. First, unlike Florida and Georgia, Maryland's utility-owned charger program remains active during the sample period. Second, the program includes five utilities that collectively cover most of the state, generating variation in utility service territories and proposed charger locations. Third, the program is administered through the PSC, so investment decisions are subject to centralized regulatory review. Fourth, the program is highly transparent: proposed sites, approval decisions, installation status, and program reports are publicly available through PSC filings. This transparency is useful for econometric analysis and may also affect market behavior because potential private entrants can observe the location and timing of utility-owned charger deployment.

3 Data and Market Definition

This section describes the data and geographic market definition used in the empirical analysis. Section 3.1 presents the primary data sources: public charging-station locations, utility-owned charger filings, vehicle registrations, and demographic characteristics. Section 3.2 constructs the geographic markets. Because EV registration and demographic data are observed at the zip-code level, while zip codes and counties may not correspond to the relevant market for public charging, I construct a spatial clustering-based market definition that incorporates charging-demand shifters and geographic contiguity.

3.1 EVSE Location and Vehicle Registration Data

The empirical analysis combines four primary datasets: (i) public charging-station data, (ii) regulatory filings on utility-owned chargers from PSC Case No. 9478, (iii) EV stock and vehicle registration data, and (iv) demographic data. The charging-station data come from the U.S. Department of Energy's Alternative Fuels Data Center (AFDC), which provides a national inventory of public charging stations. The AFDC data include station names, opening dates, geographic information, coordinates, charging speeds, numbers of outlets by charging level, connector types, facility types, and other station characteristics. Because the facility-type field is missing for many locations and does not consistently identify ownership, I supplement the AFDC data with PSC Case No. 9478 documents to identify chargers that are installed, owned, and operated by electric utilities. I classify other facility types using station names and location information.

The third data source is EV stock and vehicle registration data. EV stock data for July 2020 through November 2023 are publicly available from the Maryland Department of Transportation (MDOT) and the Maryland Motor Vehicle Administration (MVA). These data provide EV registrations by zip code and include registration date, vehicle make, vehicle model, service provider name, and drivetrain type. Because the public EV stock data do not include internal-combustion-engine vehicles, other non-EV vehicles, or full vehicle-model information, I also use a separate vehicle registration dataset covering all fuel types at the model-by-zip-code-by-month level from July 2020 to January 2025. This broader registration dataset is used for the demand estimation in Section 5 and is supplemented with vehicle attribute data from WardsAuto. The fourth data source is the American Community Survey (ACS), which provides zip-code-level demographic variables, including population, age, household income, commute time, educational attainment, labor-force participation, and land area.

3.2 Market Definition

A central empirical challenge is defining the relevant geographic market for public EV charging. In spatial retail markets, market boundaries should capture local substitution and competitive pressure. The retail gasoline literature provides a useful benchmark: because fuel-retailing competition is highly localized, prior studies define competition using nearby stations within fixed radii, driving-time neighborhoods, or isolated clusters (Hastings, 2004; Nishida and Remer, 2018). Recent evidence that the price effects of gasoline-station entry dissipate with distance further supports the view that fuel-retailing market definitions should reflect localized substitution rather than broad administrative boundaries (Taylor and Muehlegger, 2025).

The EV charging market raises similar spatial concerns but differs from gasoline retailing in ways that make gasoline-market definitions difficult to apply directly. Gasoline stations provide a relatively homogeneous refueling service, and consumers typically choose among nearby stations for short refueling stops. Public EV charging is more heterogeneous: charging demand depends not only on the proximity of chargers to one another but also on the likelihood that an EV driver needs to charge and the likelihood that the driver visits a given location. The first component is related to trip length and driving behavior, while the second is related to destination choice, since public chargers are often used when drivers park at workplaces, retail centers, restaurants, or other activity locations.[7]

For this reason, I do not define markets using contemporaneous charger locations or distances between active chargers. Such approaches are well-suited to mature fuel markets with relatively stable station networks, but the EV charging market is still expanding rapidly. If market boundaries changed mechanically as

[7] A 2023 survey by Boston Consulting Group reports that, among EV drivers who rely only on public charging, 63% charge at destinations rather than en route. See Boston Consulting Group (2023).

chargers entered, the market definition would be endogenous to the entry outcome studied in the empirical analysis. A fixed market definition is therefore preferable for estimating charger deployment responses over time and for combining supply estimates with structural demand estimation.

Existing EV and charging-infrastructure studies commonly define markets using counties (Springel, 2021) or metropolitan statistical areas (Li et al., 2017; Li, 2023). These definitions are transparent and comparable across regions, but they may be poorly suited to public charging. Counties and metropolitan areas may be too large relative to daily charging decisions, while zip codes may split nearby charging alternatives across boundaries or combine locations with different charging-demand conditions. For example, a charger near a zip-code boundary may serve drivers from adjacent zip codes, weakening the relationship between measured market-level EV stock and observed charger deployment. Administrative boundaries may therefore obscure both the demand-side geography of charging and the competitive environment faced by charging providers.

I address these issues by constructing fixed, contiguous markets using spatial clustering. The proposed market definition uses predetermined demand shifters rather than contemporaneous charger locations, allowing markets to capture spatial differences in potential charging demand while remaining fixed over time.[8] Specifically, I use the Spatial 'K'luster Analysis by Tree Edge Removal (SKATER) algorithm (Assunção et al., 2006), which groups adjacent spatial units into internally homogeneous regions based on distances in an attribute space. I apply SKATER to census tracts and aggregate them into charging markets in Maryland.

The clustering variables capture two components of potential public charging demand. The first is the likelihood that drivers need to charge away from home. I proxy for this component using average daily travel distance, measured at the county level from the Baltimore Metropolitan Council Maryland Travel Survey (MD MTS) and the Metropolitan Washington Council of Governments Regional Travel Survey (DC RTS). Because the number of EV drivers in the surveys is small, I compare EV and ICE travel patterns and find no statistically significant differences in daily travel distance or travel time after controlling for origin county, destination county, and household fixed effects (Appendix Table A.3). The median daily travel distance is 21.0 miles for EVs and 25.1 miles for ICE vehicles, suggesting that the spatial scale implied by the clustering-based markets is consistent with daily charging-relevant travel.[9]

The second component is the likelihood that a location is chosen as a destination. Public chargers are often used while drivers are parked at workplaces, retail centers, restaurants, or other activity locations. I therefore use the number of jobs to proxy for commuting destinations and the number of retail establishments to proxy for non-commuting destinations. The job measure comes from the Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES), produced by the U.S. Census Bureau. The

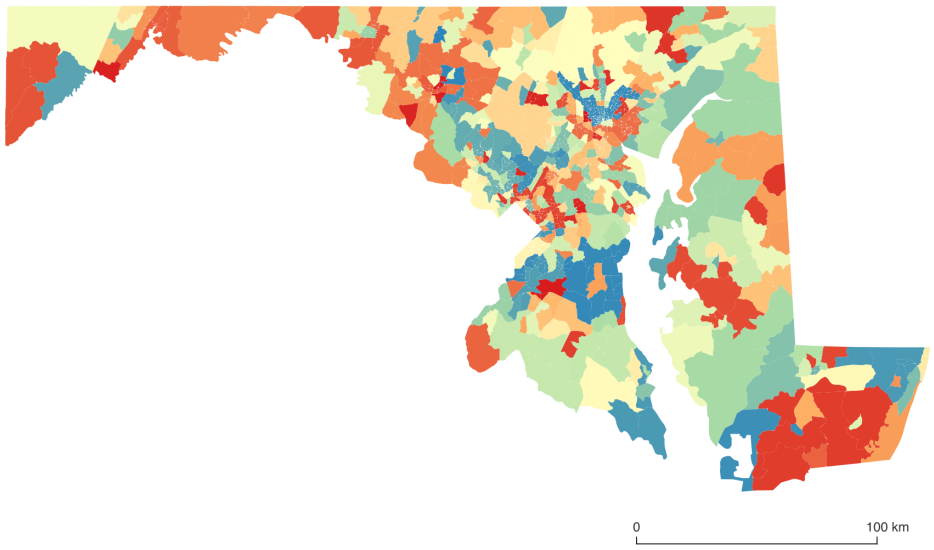
[8] I also construct a grid-based definition as a reference. The detailed discussion is in Appendix C.4.

[9] Appendix C.1 describes the travel survey data, reports the EV–ICE travel-pattern comparisons, and explains the construction of the travel-distance measure. Figure A.2 plots the distribution of daily travel distance for EVs and ICE vehicles.

retail-establishment measure comes from the National Neighborhood Data Archive (NaNDA), which reports retail establishments across a wide range of industries. I use 2017 values for both variables because the NaNDA retail data are available through 2017.[10]

Figure 2 displays the resulting clustering-based markets. The procedure groups census tracts with similar potential charging demand into contiguous markets, separating high-demand and low-demand areas in a way that administrative boundaries may not. Because the resulting markets incorporate persistent demand shifters, market fixed effects can absorb time-invariant differences in potential charging demand across markets in the empirical analysis below.

Figure 2: Clustering Market with EVSEs (203 Markets)



Notes: The map displays the clustering-based market. Each distinct color represents a market.

I assign charger locations from the AFDC data and utility-owned charger locations from PSC Case No. 9478 to the clustering-based markets using GIS. Because EV registrations and demographic variables are observed at the zip-code level, I convert them to census tracts and then aggregate them to the clustered markets using household-unit weights.[11] Count variables, such as EV registrations and population, are aggregated using weighted sums, while rate or average variables, such as age and educational attainment, are aggregated using weighted averages.

I compare the clustering-based markets with zip-code markets along two dimensions: market scale and boundary-related measurement error. Table 1 reports summary statistics for the two definitions. The

[10] I also considered adding housing-type variables, such as the share of single-family detached housing and owner-occupied housing, as proxies for home-garage access. Including these variables does not substantially change the resulting clustering patterns.

[11] Appendix C.2 describes the zip-code-to-census-tract conversion and aggregation procedure.

clustering-based and zip-code definitions contain 203 and 227 markets, respectively. The average clustering-based market has a geographic scale of roughly 8 to 10 miles per side, consistent with the travel-survey evidence on daily driving distances. The average number of chargers per clustering-based market is about five, comparable to local market sizes used in the retail gasoline literature (Assad et al., 2023; Nishida and Remer, 2018).

Table 1: Summary Statistics across Market Definitions

	Clustering-Based	Zip Code
Panel A: Market State Variables		
Third-Party EVSEs	4.94	4.15
	(10.31)	(6.70)
Utility-Owned EVSEs	0.81	0.71
	(1.11)	(0.81)
EV Stocks	217.92	178.34
	(395.76)	(239.99)
Panel B: Demographic Variables		
Population (1K)	25.60	23.46
	(46.46)	(17.32)
Age	40.42	40.81
	(4.73)	(6.76)
Income (1K)	102.12	102.36
	(31.61)	(36.56)
Commute Time (min)	33.77	34.44
	(6.03)	(6.83)
Education: Post-Secondary	0.66	0.66
	(0.12)	(0.14)
Area (sq. mile)	60.72	42.73
	(110.95)	(48.31)
Panel C: Variables for Clustering		
Number of Jobs (1K)	12.27	10.54
	(21.82)	(11.95)
Number of Retail Shops	71.02	59.86
	(104.42)	(52.46)
Number of Markets	203	227

Notes: The table reports the means for the variables of each market definition (clustering-based and zip code). Standard deviations are reported in parentheses. Panel A reports the market state variable, panel B shows demographic variables, and panel C lists the variables used for the clustering algorithm. The numbers of EVSEs and EV stocks are averages across markets and over time. Other variables are averages across markets as they are cross-sectional.

The clustering-based definition also captures more variation in potential charging-demand shifters. As shown in Panel C of Table 1, clustering-based markets generate more variation in jobs and retail establishments than zip-code markets. This variation is useful because the clustering procedure is designed to separate locations with high and low destination-based charging demand.

Finally, I examine whether chargers are located close to market boundaries. Boundary proximity matters

because a charger near a boundary may serve drivers from adjacent markets, weakening the relationship between measured market-level EV stock and observed charger deployment. I calculate the Euclidean distance from each charger to the nearest market boundary under both the zip-code and clustering-based definitions. The clustering-based definition places fewer chargers near market boundaries than the zip-code definition, suggesting that it reduces boundary-related measurement error. Appendix C.3 reports the corresponding distance distributions and distance-bin comparisons.

In summary, the clustering-based market definition addresses two limitations of administrative markets. First, it incorporates observable shifters of potential public charging demand, including travel distance, jobs, and retail establishments. Second, it reduces the extent to which chargers are located close to arbitrary administrative boundaries. For these reasons, I use the clustering-based market definition as the primary specification in the empirical analysis in Section 4.

4 Reduced-form Supply Estimation

This section investigates how public charger deployment responds to local EV adoption and how this response differs by ownership type. I estimate reduced-form supply equations relating charger counts to local EV stock and recover both elasticities and semi-elasticities of charger deployment. Section 4.1 describes the empirical specification and identification strategy. Section 4.2 presents the average and heterogeneous responses by ownership type, and Section 4.3 discusses the implied differences in investment patterns.

4.1 Empirical Strategy

This section describes the empirical framework used to estimate the elasticity and semi-elasticity of charging-station deployment with respect to EV adoption. The specification is related to the approaches in Li et al. (2017) and Springel (2021), but extends them by distinguishing utility-owned chargers from third-party chargers and by allowing responses to vary with observable market characteristics. I estimate separate equations for third-party, utility-owned, and all public chargers.[12] Estimating ownership-specific equations allows investment responses to differ across private charging providers and regulated utilities. For market m and month t, I estimate the following log-log specification:

$$\ln(N^k_{m,t}) = \alpha_1 \cdot \ln(Q_{m,t}) + \delta_m + \lambda_t + \varepsilon_{mt}, \tag{1}$$

[12] I do not control for the other charger type in each ownership-specific equation. For example, the third-party charger equation does not include utility-owned chargers as a control. Both charger types may respond to the same underlying EV demand conditions, so controlling for the other type could introduce a bad-control problem if both are functions of EV stock and unobserved market-level demand shocks.

and the following level-log specification:

$$N_{m,t}^{k} = \beta_1 \cdot \ln(Q_{m,t}) + \delta_m + \lambda_t + \varepsilon_{mt}, \tag{2}$$

where $k \in \{TP, UO, All\}$ denotes the charger type: third-party, utility-owned, and all public chargers. The variable $N_{m,t}^{k}$ is the number of chargers of type k in market m and month t, and $Q_{m,t}$ is the number of registered EVs in the same market and month.[13] The terms δ_m and λ_t denote market fixed effects and year-month fixed effects, respectively. Market fixed effects absorb time-invariant differences across markets, including persistent differences in charging demand, land-use patterns, local permitting conditions, and access to distribution infrastructure. This is particularly important because the clustering-based market definition may generate markets that differ in unobserved factors affecting charging-station investment. Year-month fixed effects absorb shocks common across markets, such as macroeconomic conditions, statewide EV policies, and aggregate trends in charging technology.

The coefficient α_1 in equation (1) is the elasticity of chargers with respect to EV stock: it measures the percent change in $N_{m,t}^{k}$ associated with a one-percent increase in $Q_{m,t}$. The coefficient β_1 in equation (2) is a semi-elasticity: $\beta_1/100$ measures the level change in the number of chargers associated with a one-percent increase in EV stock.

These specifications rely on two assumptions about charging demand and investment timing. First, EV stock is assumed to be proportional to the potential customer base for public chargers. This assumption may fail if charging providers use proprietary forecasts of customer arrivals or charging durations that differ systematically from observed EV stocks.[14] Second, the specifications assume that charging providers can forecast contemporaneous EV stock when making investment decisions. In practice, the final investment decision precedes the opening date because of site validation, permitting, construction, and inspection. Using contemporaneous EV stock is therefore consistent with forward-looking behavior if firms and utilities can forecast near-term EV registrations with reasonable accuracy.[15] To assess the sensitivity of the results to the timing between investment decisions and charger openings, I also estimate equations (1) and (2) using lagged EV stock.

Identification. — Identification comes from within-market changes over time in EV stocks and charging-station deployment, after controlling for market fixed effects and year-month fixed effects. The clustering-

[13] In the baseline estimation, I add one to both $N_{m,t}^{k}$ and $Q_{m,t}$ before taking logarithms to retain observations with zero chargers or zero EVs. The results are similar when observations with zero values are dropped.

[14] For example, Roland Berger provides EV charging-demand forecasting services, primarily in Europe. I do not find evidence that comparable forecasting services dominate the Maryland charging-station market.

[15] Potential entrants will form the expected payoff functions rather than the historical states before deciding to enter the markets.

based market definition is useful for this purpose because it groups locations with similar potential charging demand and allows market fixed effects to absorb persistent spatial differences in demand and investment conditions. The error term ε_{mt} captures time-varying unobserved shocks to charger deployment, such as changes in local permitting costs, community support for charging infrastructure, installer capacity, or local policies affecting charging-station entry.

Endogeneity may arise from omitted variables and simultaneity. For example, local electricity prices or utility policies may affect both EV adoption and charging-station investment. Similarly, EV stocks and charger deployment may be jointly determined if unobserved market-specific shocks increase both EV adoption and charger entry in the same month. Although $N^k_{m,t}$ and $Q_{m,t}$ are stock variables, their changes may reflect common time-varying shocks. As a result, ordinary least squares estimates of equations (1) and (2) may be inconsistent.

To address this concern, I use an instrumental-variables approach. The ideal instrument is a shifter of EV demand that affects charging-station deployment only through EV stock. I use regular gasoline prices as a time-series shifter of EV demand because higher gasoline prices increase the relative operating-cost advantage of EVs over ICE vehicles.[16] Monthly gasoline-price data are available for eight Maryland cities, which provides time-series variation but limited cross-sectional variation.[17] I therefore interact monthly gasoline prices with the market-level share of gas stations.[18] Markets with fewer gas stations may face higher gasoline search costs and less retail fuel competition, making EV adoption more attractive. The resulting shift-share instrument combines a time-series shock, monthly regular gasoline prices, with a cross-sectional exposure measure, the market's share of gas stations.

The identifying assumption is that gasoline-price exposure affects charging-station deployment only through EV stock, conditional on market and year-month fixed effects. Market fixed effects absorb time-invariant differences in charging profitability, entry costs, traffic patterns, and access to distribution infrastructure, while year-month fixed effects absorb aggregate shocks common to all markets. The remaining concern is that market-specific time-varying shocks may be correlated with both gasoline-price exposure and charger entry. For example, electricity prices could affect both EV adoption and charger profitability. However, gasoline and electricity prices are generally driven by different market forces (Kilian and Zhou, 2023), and distribution-rate adjustments in Maryland vary across utility service territories for reasons not directly tied to gasoline-price exposure (Office of People's Counsel, 2024). The empirical strategy, therefore,

[16] Li et al. (2017) uses gasoline prices over the previous three years as instruments. In this study, adding additional lagged gasoline-price instruments does not change the results.

[17] The eight cities are Annapolis, Baltimore, Bowie–St. Charles, Cumberland, Frederick, Hagerstown, Salisbury, and Washington, DC. The gasoline-price data are obtained from the American Automobile Association (AAA).

[18] I collect gas-station locations in Maryland as of August 2024. Most locations are obtained from All USA Gas Stations, and missing locations are hand-collected. I geocode the addresses, convert them to coordinates, and count the number of gas stations in each market using GIS.

assumes that residual time-varying shocks to charger investment costs or profitability are not systematically related to the shift-share instrument after conditioning on fixed effects.

Heterogeneity. — Equations (1) and (2) estimate average elasticities and semi-elasticities of charger deployment with respect to EV stock. These average responses may mask important heterogeneity across markets. Such heterogeneity is especially relevant for utility-owned chargers because their locations are determined through a regulatory process. As described in Section 2, utilities first propose sites for utility-owned chargers, and the PSC then approves or rejects those proposals. Utilities may prefer sites with higher expected charging demand or lower installation costs, while the PSC may prefer sites that it views as underserved by private providers. Because the PSC does not provide a precise definition of "underserved," heterogeneity analysis can help infer whether utility-owned chargers are disproportionately deployed in markets with specific demographic or land-use characteristics.

To examine heterogeneous investment responses, I estimate level-log specifications that augment equation (2) with an interaction between EV stock and a time-invariant market characteristic, D_m. I estimate a separate equation for each heterogeneity variable. The first set of variables includes demographic characteristics: household income, educational attainment, and population. The second set includes land-use shares: business, residential, public, and natural land.[19] The interaction coefficient measures how the semi-elasticity of charger deployment with respect to EV stock varies with D_m. Comparing interaction estimates across third-party and utility-owned chargers reveals whether the two ownership types respond differently to EV stock in markets with different observable characteristics.

The identification strategy follows the strategy used for equations (1) and (2). I instrument $\ln(Q_{m,t})$ with the baseline shift-share instrument based on monthly gasoline prices and the market-level gas-station share. Because the specification with market heterogeneity also includes the endogenous interaction $\ln(Q_{m,t}) \cdot D_m$, I instrument this interaction using the baseline shift-share instrument interacted with D_m.

4.2 Results

This section presents two sets of empirical results. The first set reports average elasticity and semi-elasticity estimates from equations (1) and (2). The second set reports semi-elasticity estimates with observable market heterogeneity. The heterogeneity results are used to compare the entry patterns of third-party and utility-

[19]The land-use data come from the 2020 Land Use and Land Cover shapefile produced by the Maryland Department of Planning. The original data classify land into 13 categories: very-low-, low-, medium-, and high-density residential; commercial; industrial; institutional; agriculture; forest; water; wetlands; barren land; and transportation. I aggregate these categories into four groups: business land, which includes commercial and industrial areas; residential land, which includes all residential density categories; public land, which includes institutional and transportation areas; and natural land, which includes agriculture, forest, water, wetlands, and barren land. I calculate the area of each land-use type within each market using GIS and convert these areas into market-level shares.

owned chargers and to infer which types of markets the PSC may prioritize when approving utility-owned charger proposals.

Elasticity and Semi-elasticity. — Table 2 reports the elasticity and semi-elasticity estimates for three dependent variables: third-party chargers, utility-owned chargers, and all public chargers. Columns (1)–(3) report the elasticity estimates from equation (1), and columns (4)–(6) report the semi-elasticity estimates from equation (2). The estimated elasticities for third-party and utility-owned chargers are 4.4 and 11.3, respectively. Thus, a one-percent increase in EV stock is associated with a 4.4% increase in third-party chargers and an 11.3% increase in utility-owned chargers. These elasticities are larger than those reported in prior studies (Li et al., 2017; Springel, 2021), likely because the markets in this study are smaller than counties or metropolitan statistical areas.

Table 2: Elasticity and Semi-Elasticity

	Elasticity			Semi-Elasticity		
	TP	UO	All	TP	UO	All
	(1)	(2)	(3)	(4)	(5)	(6)
log(EV Stock)	4.42***	11.25***	3.15***	129.63***	46.67***	176.30***
	(1.25)	(3.00)	(0.96)	(34.33)	(12.36)	(46.52)
F-stat	14.49	14.49	14.49	14.49	14.49	14.49
N	8323	8323	8323	8323	8323	8323

Notes: The table reports elasticity and semi-elasticity estimates. TP and UO denote third-party and utility-owned chargers, respectively. All denotes the total number of public chargers. The three regressions in each panel differ by the dependent variable, $N^k_{m,t}$, where $k = \{\text{TP}, \text{UO}, \text{All}\}$. EV stock is weighted by the number of household units.

The estimated semi-elasticities for third-party and utility-owned chargers are 129.6 and 46.7, respectively. These estimates imply that a one-percent increase in EV stock is associated with an increase of 1.30 third-party chargers and 0.47 utility-owned chargers. The first-stage statistics exceed the conventional rule-of-thumb threshold of 10, suggesting that weak instruments are not a primary concern in the baseline estimates.

The results imply that utility-owned chargers have higher elasticities, while third-party chargers have larger semi-elasticities. This pattern is partly mechanical: because the stock of utility-owned chargers is much smaller than the stock of third-party chargers, a given level increase in utility-owned chargers translates into a larger percentage increase. The lower semi-elasticity for utility-owned chargers is more informative because it indicates a smaller level of response to increases in EV stock. This pattern is consistent with two mechanisms. First, utility-owned deployment may be constrained by PSC approval, public-site availability, and program targets, limiting utilities' ability to concentrate investment in high-EV-stock markets. Second, because approved utility-owned investments may be recovered through the rate base, utilities may be less responsive to charging revenues and local profitability than third-party providers. Appendix Tables A.6–A.8

assess the sensitivity of the semi-elasticity estimates to the timing between investment decisions and charger openings. The qualitative patterns are similar to the baseline results in Table 2.

Heterogeneity. — The second part of the empirical analysis examines whether third-party and utility-owned chargers respond differently to EV stock across markets with different observable characteristics. This analysis is motivated by the PSC's stated objective of deploying utility-owned chargers in "underserved" locations where private capital is unlikely to invest. Because the PSC does not disclose a precise rule for classifying markets as underserved, the interaction estimates provide indirect evidence on the market characteristics associated with utility-owned deployment. I focus on two sets of heterogeneity variables: demographic characteristics and land-use shares. All specifications use the clustering-based market definition.

The first set of heterogeneity variables consists of demographic characteristics. I interact EV stock separately with three variables: (A) the logarithm of household income, (B) the share of residents with post-secondary education, and (C) population. Table 3 reports the estimates. Each panel corresponds to one demographic variable. Columns (1)–(3) in Panels A and B use the baseline shift-share instruments, while columns (4)–(6) add additional instruments to address weak first stages. For the income interaction, I add the baseline shift-share instrument interacted with the logarithm of market area; for the education interaction, I add the baseline shift-share instrument interacted with the labor-force participation rate. Panel C reports population-interaction estimates using the baseline instruments, which do not exhibit weak-instrument concerns.

Panel A of Table 3 reports estimates for the interaction between EV stock and the logarithm of household income. For third-party chargers, the interaction estimates are statistically insignificant or only weakly significant. This suggests that, conditional on EV stock, third-party charger deployment does not vary strongly with household income. In contrast, the interaction estimate for utility-owned chargers is negative and statistically significant, indicating that utility-owned deployment is less responsive to EV stock in higher-income markets. This result does not imply that third-party chargers avoid high-income markets. EV stock is itself likely correlated with income, and the interaction specification holds EV stock fixed. Section 4.3 therefore examines the relationship between predicted charger deployment and market demographics more directly.

Panel B reports estimates for the interaction between EV stock and the share of residents with post-secondary education. The interaction estimates are positive and statistically significant for third-party chargers. They are also positive and significant for utility-owned chargers when only the baseline instruments are used, but become statistically insignificant after adding the instrument interacted with the labor-force participation rate. These results suggest that, conditional on EV stock, markets with more educated residents

Table 3: Semi-Elasticity: Demographics Heterogeneity

	Semi-Elasticity: Demographics					
	TP	UO	All	TP	UO	All
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Income						
IV	Baseline SSIV			Baseline SSIV, SSIV × Market Area		
log(EV Stock)	131.66***	43.15***	174.81***	59.91***	4.03***	63.94***
	(34.01)	(11.30)	(45.13)	(8.18)	(1.10)	(8.80)
Int. w. log(Income)	2.01	-3.47***	-1.46	3.48*	-2.67***	0.81
	(3.93)	(1.31)	(5.22)	(1.83)	(0.25)	(1.97)
F-stat	7.56	7.56	7.56	19.42	19.42	19.42
Panel B: Education (Post-Secondary)						
IV	Baseline SSIV			SSIV, Baseline SSIV × Labor Force		
log(EV Stock)	149.04***	50.56***	199.60***	51.07***	10.07***	61.14***
	(43.15)	(14.73)	(57.71)	(8.00)	(1.82)	(9.52)
Int. w. Post-Secondary Rate	88.14***	17.69**	105.83***	44.83***	-0.21	44.62***
	(22.09)	(7.54)	(29.55)	(5.36)	(1.22)	(6.37)
F-stat	5.99	5.99	5.99	15.15	15.15	15.15
Panel C: Population						
Interaction with	log(Population)			Population Share		
log(EV Stock)	-4.79**	-5.84***	-10.63***	31.74***	-0.74	31.00***
	(1.88)	(0.90)	(2.37)	(4.19)	(0.73)	(4.11)
Int. w. log(Population)	4.11***	1.60***	5.71***			
	(0.19)	(0.09)	(0.24)			
Int. w. Population Share				247.17***	119.70***	366.87***
				(21.84)	(3.79)	(21.43)
F-stat	57.26	57.26	57.26	36.00	36.00	36.00

Notes: The table reports semi-elasticity estimates with interactions between EV stock and demographic variables. "TP" and "UO" denote third-party and utility-owned chargers, respectively. "All" denotes the total number of public chargers. The three regressions in each panel differ by the dependent variable, $N^k_{m,t}$, where $k = \{\text{TP}, \text{UO}, \text{All}\}$. EV stock is weighted by the number of household units. Baseline SSIVs include the original shift-share instrument, defined as the market share of gas stations in Maryland interacted with monthly city-level regular gasoline prices, and the corresponding interaction between this instrument and the focal demographic variable.

are associated with more third-party charger deployment, while the evidence for utility-owned chargers is weaker.

Panel C reports estimates for population heterogeneity. I consider two population measures: the logarithm of market population and the market's population share within Maryland. All interaction estimates are positive and statistically significant, indicating that the semi-elasticity of charger deployment with respect to EV stock is larger in more populous markets for both third-party and utility-owned chargers.

Overall, the demographic heterogeneity results suggest that utility-owned chargers are more likely to be deployed in lower-income markets, conditional on EV stock, while both ownership types are more responsive to EV stock in more populous markets. Educational attainment is more strongly associated with third-party deployment than with utility-owned deployment. The income result is particularly informative because it is the clearest distinction between third-party and utility-owned chargers and may reflect the PSC's preference for directing utility-owned investment toward markets it views as underserved.

I also examine heterogeneity by land use, using the shares of business, residential, public, and natural land. The detailed estimates are reported in Appendix Table A.9. The results show that third-party chargers respond more strongly to EV stock in markets with larger business-land shares, while the corresponding estimate for utility-owned chargers is not statistically significant. For the other land-use variables, the patterns are broadly similar across ownership types: both third-party and utility-owned chargers are more responsive to EV stock in markets with larger residential and public land shares and less responsive in markets with larger natural-land shares. Thus, unlike income heterogeneity, land-use heterogeneity does not reveal a sharp ownership-specific difference in deployment patterns.

In summary, the clearest difference by ownership type is income heterogeneity. Conditional on EV stock, third-party charger deployment is not strongly related to household income, whereas utility-owned charger deployment is stronger in lower-income markets. The next section discusses the implications of these heterogeneity results for investment patterns by ownership type.

4.3 Investment Pattern Difference by Ownership Type

This section discusses the policy implications of the empirical estimates in Section 4.2. Here, I use the heterogeneity estimates to describe how predicted charger deployment varies across market characteristics. The interaction coefficients in Section 4.2 show how the relationship between EV stock and charger deployment varies with observable characteristics, but they do not directly describe the unconditional relationship between charger deployment and those characteristics. EV stock is itself correlated with income, education, population, and land use. I therefore use the estimated parameters to predict the number of third-party and

utility-owned chargers across markets and plot these predictions against observable market characteristics.

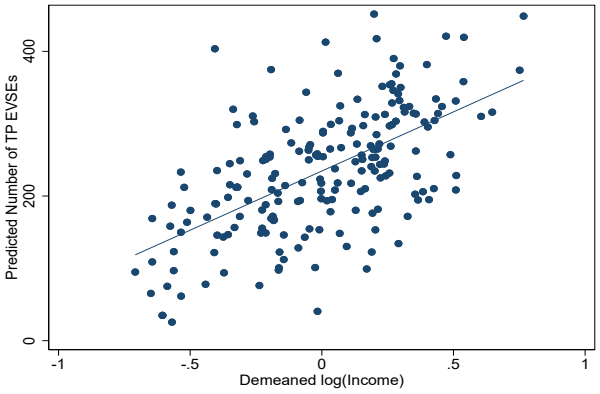
I use the parameter estimates from Table 3 to predict charger counts. To rely on specifications with stronger first stages, I use columns (4)–(6) in Panels A and B for income and education, and columns (1)–(3) in Panel C for population. Because the market characteristics are time-invariant, I focus on the November 2023 cross-section, the last month in the sample. Figure 3 plots the predicted number of chargers against demographics. As a robustness check, Figure A.9 reports analogous plots for July 2020 and November 2023.

Figure 3 plots predicted charger counts against income, education, and population. Panels 3a, 3c, and 3e report third-party chargers, while Panels 3b, 3d, and 3f report utility-owned chargers. The fitted lines for third-party chargers slope upward across all three demographic variables, indicating that third-party chargers are more concentrated in markets with higher income, higher educational attainment, and larger populations. This pattern is consistent with the expectation that EV adoption and charging demand are stronger in such markets (Hsu and Fingerman, 2021; Hardman and Tal, 2021).

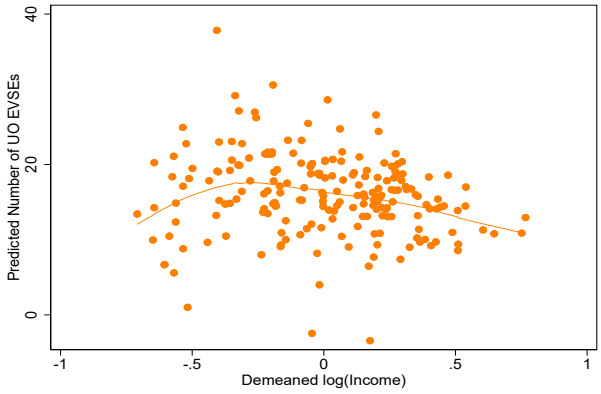
The predicted relationship for utility-owned chargers differs most clearly by income. The fitted line in Panel 3b is hump-shaped, suggesting that utility-owned chargers are concentrated in middle-income markets rather than the highest-income markets. This pattern is consistent with the PSC targeting markets that satisfy two conditions: they have sufficient potential charging demand to justify investment, but they may be less attractive to private charging providers than high-income markets. The fitted lines for utility-owned chargers are also flatter than those for third-party chargers with respect to education and population, as shown more directly in Appendix Figure A.9, which plots both ownership types in the same panels. This suggests that utility-owned deployment is less strongly concentrated in markets with high education and large population than third-party deployment, although these characteristics still appear positively related to predicted utility-owned charger counts. Appendix Figures A.10 and A.11 report analogous plots for land-use shares. Consistent with the interaction estimates, land-use patterns differ less sharply by ownership type than income patterns do.

Overall, the results provide partial support for the rationale behind utility-owned charger deployment. Utility-owned chargers are more concentrated in middle-income markets, whereas third-party chargers are more concentrated in higher-income, more educated, and more populous markets. This pattern is consistent with utility-owned deployment being directed toward markets with potential charging demand but weaker private-entry incentives. At the same time, utility-owned and third-party chargers display similar relationships with several other market characteristics, including education, population, and land use. These similarities suggest that utility-owned chargers may still compete with third-party chargers in some markets.

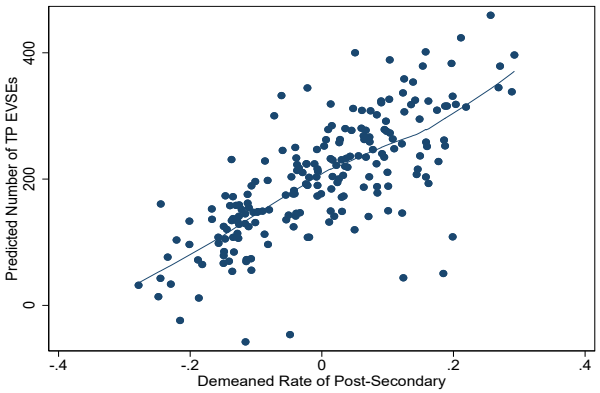
Figure 3: Predicted EVSE Numbers and Demographics



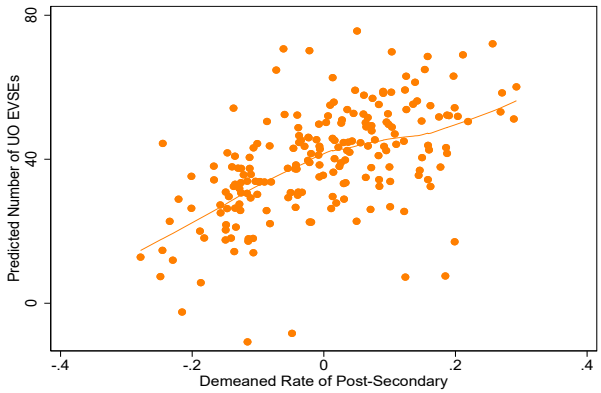
(a) Income: Third-party EVSEs



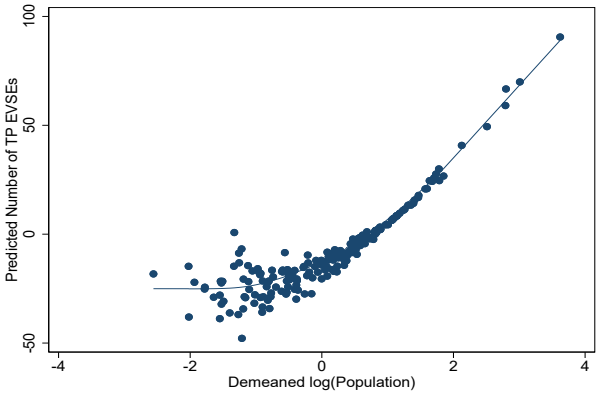
(b) Income: Utility-owned EVSEs



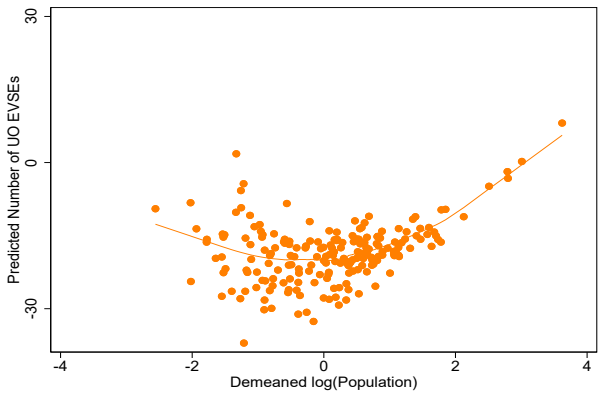
(c) Education: Third-party EVSEs



(d) Education: Utility-owned EVSEs



(e) Population: Third-party EVSEs



(f) Population: Utility-owned EVSEs

Notes: The figure presents the relationship between predicted numbers of third-party and utility-owned EVSEs and demeaned demographic variables. The predictions use the November 2023 cross-section. Blue and orange dots and fitted lines represent third-party and utility-owned EVSEs, respectively. For income and education heterogeneity, I use the parameter estimates in columns (4)–(6) of Panels A and B in Table 3. For population heterogeneity, I use the parameter estimates in columns (1)–(3) of Panel C.

5 Demand Estimation

This section estimates the effect of public charging infrastructure on EV adoption. I use a structural vehicle-demand model based on the random-coefficients logit framework of Berry et al. (1995). The model allows consumers to differ in their price sensitivity and in their valuation of the public charging network. The indirect utility that consumer i in market m obtains from purchasing vehicle j is

$$U_{ijm} = -\alpha_i p_{jm} + \gamma_i \mathbf{1}\{\text{EV}_j = 1\} \log N_m + \beta \boldsymbol{X}_{jm} + \xi_j + \delta_m + \varepsilon_{ijm}, \tag{3}$$

where p_{jm} is the effective price of vehicle j in market m. The price variable incorporates federal IRA subsidy eligibility rules for battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) and therefore allows effective prices to vary across markets.[20] The variable N_m denotes the number of public chargers in market m, including both third-party and utility-owned chargers. The charging-network term enters utility only for BEVs and PHEVs through the indicator $\mathbf{1}\{\text{EV}_j = 1\}$, so γ_i captures consumers' valuation of local public charging availability when choosing an EV. The outside option is not purchasing a vehicle, and market shares are computed as vehicle counts divided by the number of drivers in each market. The vector $\boldsymbol{X}_{jm}$ contains observable vehicle attributes, including future fuel costs, vehicle weight, and horsepower. The construction of future fuel costs follows the standard approach in the automobile-demand literature (Allcott and Wozny, 2014). Appendix E.3 reports the specification and average future fuel costs by fuel type.

The market in the demand estimation is defined as a year-by-spatial-market pair, where the spatial markets are the clustering-based markets constructed in Section 3.2. A limitation of the demand specification is that fully product-specific fixed effects cannot be included alongside year fixed effects, because prices and vehicle attributes exhibit little cross-sectional variation across markets within a year. I therefore specify ξ_j as fuel-type-by-body-style fixed effects and automaker fixed effects. The term δ_m includes year fixed effects and spatial-market fixed effects. These fixed effects absorb persistent differences across vehicle segments, automakers, years, and local markets.

The demand model in equation (3) contains two endogenous variables. First, vehicle prices are endogenous because prices and market shares are jointly determined. Second, public charging availability is endogenous because charging-station deployment and EV adoption are linked through positive feedback. Markets with stronger unobserved EV preferences may both adopt more EVs and attract more chargers. I therefore instrument both vehicle prices and public charging availability.

For vehicle prices, I use the differentiation instruments proposed by Gandhi and Houde (2020). These instruments are designed for differentiated-product markets with large choice sets, where traditional BLP-

[20] Appendix E.2 describes how local subsidized vehicle prices are constructed.

style instruments may be weak. This feature is useful in my setting because the demand model is estimated using spatially disaggregated markets, and some vehicle models have small market shares within individual markets.

For public charging availability, I use a shift-share instrument based on aggregate EV adoption and cross-sectional variation in the availability of potentially suitable charging locations. The shift is aggregate EV stock, which captures statewide growth in EV adoption and the corresponding expansion of charging demand. The share is based on predetermined market exposure to land-use categories and facility types where chargers are commonly installed. The instrument exploits the idea that markets with more suitable charging locations are more exposed to statewide growth in EV adoption and therefore experience larger changes in charging availability. Appendix E.4 describes the construction of this exposure measure and reports the facility-type and land-use patterns underlying the instrument.

Table 4 reports estimates from two random-coefficients demand specifications. Column (1) excludes public charging availability, while column (2) includes the number of public chargers in each market. I focus on the preferred specification in column (2). The estimate of public charging availability is positive, indicating that consumers value the local public charging network when choosing EVs. This result is consistent with the indirect-network-effect evidence in Li et al. (2017) and Springel (2021).

Table 4: Random Coefficient Model Estimates

Variables	(1)	(2)
Price ($1K)	-2.37	-2.80
	(0.28)	(0.25)
EVSE		0.71
		(0.33)
FFC ($1K)	-1.35	-0.73
	(0.08)	(0.03)
Price S.D.	1.09	1.07
	(0.14)	(0.11)
EVSE S.D.		0.66
		(0.51)
Num. obs.	58,005	58,005

Notes: The vehicle weights (tons) and horsepower (hp) are included in the demand estimation. FFC denotes future fuel costs. Both the price and future fuel costs are measured in thousands of US dollars. The specifications include spatial-market, year, body-type-by-fuel, and automaker fixed effects.

The estimated mean price coefficient is -2.80, indicating that consumers prefer lower-priced vehicles, all else equal. The coefficient on future fuel costs is also negative, implying that consumers prefer vehicles with lower operating costs. The magnitude of the price coefficient is larger than that of the future-fuel-cost coefficient, suggesting that consumers place less weight on future operating costs than on upfront purchase

prices when choosing vehicles. This pattern is consistent with parts of the automobile-demand literature documenting the incomplete valuation of future fuel savings. Although my market definition, sample, and specification differ from those in Springel (2021), the estimated magnitudes of the price and charging-network coefficients are broadly similar.

6 Counterfactual Simulations

This section combines the reduced-form charger-supply estimates with the structural vehicle-demand estimates to conduct counterfactual simulations. The simulations serve two purposes. First, they illustrate the model implications of accounting for charger ownership by comparing a pooled supply model, which treats all public chargers as a single type, with a split supply model, which distinguishes third-party and utility-owned chargers. Second, they quantify the equilibrium effects of removing utility-owned chargers from Maryland's public charging network.

In each simulation, I change either subsidized vehicle purchase prices or the availability of utility-owned chargers and then recompute the equilibrium levels of EV sales, EV stock, and charger deployment. The equilibrium is obtained using a fixed-point algorithm that combines the estimated demand model with the estimated charger-supply equations. These simulations should be interpreted as partial-equilibrium counterfactuals: they hold the estimated behavioral relationships fixed and do not incorporate all possible policy responses, changes in electricity rates, or welfare effects.

6.1 Model Implication

The first simulation examines how accounting for charger ownership changes the predicted effects of EV purchase subsidies. I simulate an additional $1,000 purchase subsidy for BEVs and PHEVs under two supply models. The pooled model does not distinguish charger ownership, whereas the split model used in the main empirical analysis estimates separate supply responses for third-party and utility-owned chargers.

Table 5 reports the effects of the $1,000 purchase subsidy under the two models. Both models predict that the subsidy increases BEV/PHEV sales, total vehicle sales, and public charger deployment. However, the pooled model predicts larger equilibrium effects. Relative to the split model, the pooled model overestimates the increase in BEV/PHEV sales by 549 vehicles, or about 7.4%, and overestimates the increase in total chargers by 7.1 chargers, or about 50.5%. The implied number of additional BEV/PHEV sales per $1 million of subsidy is also higher in the pooled model: 282.8 vehicles compared with 266.8 vehicles in the split model.[21] Although these differences are economically meaningful, the bootstrapped estimates show

[21]The cost-effectiveness estimate in the split model, 266.8 additional BEV/PHEV sales per $1 million, is larger than the

that they are statistically indistinguishable from zeros.[22]

Table 5: Counterfactual Effects of an EV Purchase Subsidy

	Supply model		Model diff.	
Outcome	Pooled	Split	Level	Percent
Δ BEV/PHEV sales	7,141	6,592	-549	-7.4%
	(1,314)	(1,168)	(435)	(5.5%)
Δ BEV sales	5,600	5,203	-397	-6.9%
	(962)	(872)	(299)	(4.9%)
Δ PHEV sales	1,541	1,389	-152	-8.9%
	(512)	(425)	(158)	(7.4%)
Δ Total vehicle sales	1,114	988	-126	-11.0%
	(308)	(272)	(97)	(7.2%)
Δ Total chargers	11.1	4.0	-7.1	-50.5%
	(5.8)	(1.4)	(5.5)	(34.0%)
Δ BEV/PHEV sales per $1 million	282.8	266.8	-16.0	-5.4%
	(27.4)	(21.5)	(12.3)	(4.0%)

Notes: The table reports effects of a $1,000 BEV/PHEV purchase subsidy relative to the corresponding no-subsidy baseline within each supply model. The sample is restricted to observed-ownership scenarios. "Level" reports the level difference between the split-supply and pooled-supply counterfactual effects. "Percent" reports the mean of the percentage differences in the bootstrap. Parentheses report bootstrapped standard errors.

These differences illustrate why ownership structure can matter for policy counterfactuals. Third-party and utility-owned chargers do not respond identically to EV stock. As shown in Table 2, utility-owned chargers have a smaller semi-elasticity with respect to EV stock than third-party chargers. This weaker level response is consistent with utility-owned deployment being shaped by regulatory approval, public-site availability, program targets, and rate-base recovery, while third-party deployment is more directly tied to private profitability. A model that pools the two ownership types imposes a common supply response and therefore overestimates the feedback from EV subsidies to charger deployment. Because consumers value public charging availability, this overestimated charger response also leads the pooled model to overestimate equilibrium EV adoption. The split model implies that purchase subsidies remain effective, but their predicted effects can be smaller once ownership-specific supply responses are taken into account.

6.2 Utility-Owned Charger Deployments

The second counterfactual quantifies the effect of utility-owned charger deployments by comparing the observed-ownership equilibrium with an equilibrium in which utility-owned chargers are removed. In the latter scenario, all public chargers are supplied by third-party providers, and the estimated third-party

41–115 additional EV sales per $1 million implied by the Norwegian subsidy estimates in Springel (2021). Because the market context, policy design, and model structure differ, this comparison is only suggestive.

[22]The subsidies to charging stations may make a greater difference because the model in this paper is improved on the supply side, but I need to implement a structural supply-side model to investigate these effects, as there are no variations in charger subsidies within the state.

charger supply equation is held fixed. This exercise measures the equilibrium contribution of utility-owned chargers to EV adoption and public charging availability, conditional on the estimated demand and supply relationships.

Table 6 reports the results. Without an additional purchase subsidy, utility-owned chargers increase BEV/PHEV sales by 6,965 vehicles, EV stock by 9,415 vehicles, and total public chargers by 481.3 chargers. The effect is larger for BEVs than for PHEVs: BEV sales increase by 6,118, compared with 847 for PHEVs. This pattern is consistent with BEV adoption being more dependent on public charging availability, while PHEVs remain closer substitutes for ICE vehicles because they can rely on gasoline. I find that the effect of utility-owned charger policy has the same level of impact to EV and total vehicle sales as $1,000 subsidies to EV purchase.

Table 6: Counterfactual effects of utility-owned chargers

	Utility-owned charger effect		
Outcome	No subsidy	$1,000 subsidy	Diff.
Δ BEV/PHEV sales	6,965	8,871	1,906
	(1,641)	(2,033)	(444)
Δ BEV sales	6,118	7,722	1,604
	(1,558)	(1,924)	(402)
Δ PHEV sales	847	1,149	302
	(260)	(353)	(114)
Δ Total vehicle sales	1,184	1,751	568
	(376)	(579)	(220)
Δ EV stock	9,415	11,966	2,551
	(2,211)	(2,697)	(600)
Δ Total chargers	481.3	477.3	-4.0
	(52.7)	(52.7)	(2.4)

Notes: The table reports the effect of utility-owned chargers in the split-supply model. Each entry in the first two columns is the difference between the observed-ownership counterfactual and the no-utility-owned counterfactual under the same purchase-subsidy regime. Positive values indicate that allowing utility-owned chargers increases the outcome relative to removing utility-owned chargers. "Diff." reports the difference in the utility-owned-charger effect between the $1,000-subsidy and no-subsidy scenarios. Parentheses report bootstrapped standard errors.

The results also indicate that utility-owned chargers complement EV purchase subsidies in promoting EV adoption. With an additional $1,000 BEV/PHEV purchase subsidy, the effect of utility-owned chargers increases to 8,871 BEV/PHEV sales and 11,966 EVs in stock. Relative to the no-subsidy scenario, these effects are larger by 1,906 BEV/PHEV sales and 2,551 EVs in stock. By contrast, the incremental effect on total public chargers changes little, declining from 481.3 to 477.3 chargers. Thus, the complementarity operates primarily through EV demand: purchase subsidies generate a larger adoption response when utility-owned charging infrastructure is available. The effect on total vehicle sales remains much smaller than the effect on BEV/PHEV sales, indicating that the main response is substitution between EVs and non-EVs rather than a large change in total vehicle demand.

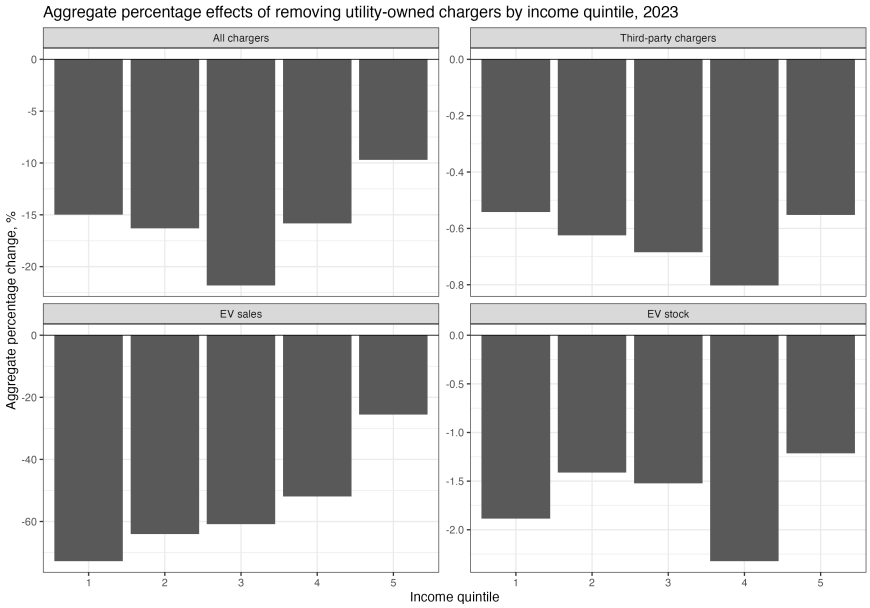
Appendix Figure A.15 extends the comparison to purchase subsidies ranging from $0 to $2,000. At each subsidy level, the increase in BEV/PHEV sales is larger when utility-owned chargers are present. Government expenditure is also higher in the observed-ownership scenario because more consumers take up the subsidy. The cost-effectiveness panel shows diminishing returns to larger purchase subsidies in both scenarios, while the no-utility-owned-charger scenario is consistently less cost-effective. This pattern reflects the network feedback in the model: purchase subsidies stimulate EV adoption, but the adoption response is weaker when the public charging network is smaller.

Utility-owned charger deployment also has distributional implications. Figure 4 reports the percentage changes in aggregate outcomes caused by removing utility-owned chargers, separately by income quintile. The decline in total chargers is the largest in middle-income markets, especially the third income quintile, where total chargers fall by more than 20%. EV sales also decline substantially in lower- and middle-income markets. The percentage decline in third-party chargers is small in all quintiles, indicating that endogenous third-party entry replaces only a limited portion of the removed utility-owned network. Appendix Figure A.16 reports the corresponding level comparisons.

These patterns are consistent with the descriptive and reduced-form evidence that utility-owned chargers are concentrated outside the highest-income markets (Figure 3b). Utility-owned chargers, therefore, appear to expand charging access in markets that may otherwise receive less private investment. At the same time, this counterfactual does not imply that all utility-owned chargers are welfare-improving. A full welfare analysis would need to quantify consumer surplus, ratepayer costs, charger operating profits, public expenditures, and any crowding out of private investment. The results instead show that utility-owned chargers can substantially affect EV adoption in lower- and middle-income markets and can change the effectiveness of purchase subsidies by altering the size and spatial distribution of the charging network.

In summary, the counterfactual simulations deliver two main findings. First, the point estimates indicate that a pooled supply model predicts larger purchase-subsidy effects than a model that accounts for ownership-specific supply responses, although the differences are not statistically significant. Second, utility-owned chargers meaningfully expand Maryland's public charging network and increase EV adoption, especially in lower- and middle-income markets. The interaction between purchase subsidies and utility-owned charger deployment further suggests that demand-side and supply-side policies are complements in markets with indirect network effects.

Figure 4: Percentage Effects of Removing Utility-Owned Chargers by Income Quintile



Notes: The figure reports percentage changes in four outcomes after removing utility-owned chargers: all public chargers, third-party chargers, EV sales, and EV stock. Outcomes are aggregated by income quintile.

7 Conclusion

This paper studies how ownership structure shapes entry and market outcomes in an emerging infrastructure market. The setting is Maryland's public EV charging market, where regulated electric utilities are allowed to install, own, and operate public chargers subject to PSC approval and rate-base cost recovery. This setting is economically important because the public charging market features indirect network effects between EV adoption and charger deployment, potential substitution or complementarity between third-party and utility-owned chargers, and investment incentives that differ across private firms and regulated utilities.

The reduced-form supply analysis shows that third-party and utility-owned chargers respond differently to local EV stock. Utility-owned chargers have higher elasticities but lower semi-elasticities than third-party chargers. The lower semi-elasticity indicates that, for a given percentage increase in EV stock, utility-owned charger deployment increases by less in levels than third-party deployment. This pattern is consistent with two mechanisms: utilities may face PSC screening and public-site constraints that limit investment in the most profitable high-EV-stock locations, and rate-base cost recovery may make utilities less responsive to charging revenues and local profitability than third-party providers. The heterogeneity analysis further shows that utility-owned chargers are concentrated in middle-income markets, whereas third-party chargers are more concentrated in higher-income, more educated, and more populous markets. These patterns are

consistent with utility-owned deployment being directed toward markets with potential charging demand but weaker private-entry incentives.

The structural demand estimates indicate that consumers value local public charging availability when choosing EVs, consistent with indirect network effects between charging infrastructure and EV adoption. Combining the estimated demand model with the ownership-specific supply estimates, the counterfactual simulations deliver two main findings. First, a supply model that pools all chargers produces larger point estimates of the equilibrium effects of EV purchase subsidies on EV sales and charger deployment because it ignores the weaker level response of utility-owned chargers to EV stock. Second, removing utility-owned chargers substantially reduces EV sales, EV stock, and the public charging network. The effects are larger in lower- and middle-income markets, and purchase subsidies become less cost-effective when utility-owned chargers are absent. These findings suggest that demand-side EV subsidies and supply-side charging-infrastructure policies can be complementary in markets with indirect network effects.

The analysis has several limitations. The counterfactual simulations are partial-equilibrium exercises that hold the estimated behavioral relationships fixed and do not provide a full welfare evaluation of utility-owned charger deployment. A complete welfare analysis would need to quantify consumer surplus, charger operating profits, public funds, electricity-rate impacts on ratepayers, and the extent to which utility-owned chargers crowd out or crowd in third-party investment. In addition, the reduced-form supply model captures third-party charger responses primarily through EV stock rather than through a fully specified strategic entry model. Future work could estimate a structural supply model that explicitly incorporates ownership-specific payoffs, strategic interaction between utility-owned and third-party chargers, PSC approval decisions, and ratepayer costs. Such an extension would allow a fuller assessment of whether utility-owned charging programs improve welfare and how they should be targeted across markets. Furthermore, the structural entry model would enable the evaluation of charger-subsidy policies. Because charger subsidies exhibit little within-state variation in the current setting, their effects cannot be credibly identified using the present reduced-form framework.

Disclosures

I have no financial relationships or other potential conflicts of interest to disclose.

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Appendices

A Institutional Detailed Background of Utility-Owned EVSE Policy in Maryland

Maryland's utility-owned EVSE policy was developed through a series of legislative and regulatory actions related to transportation electrification. In 2015, Governor Larry Hogan signed legislation extending the Maryland Electric Vehicle Infrastructure Council (EVIC). EVIC was tasked with evaluating incentives for EV and EVSE adoption, developing recommendations for a statewide EV infrastructure plan, and proposing policies to promote EV integration. This legislation was connected to Maryland's broader climate policy, including the Greenhouse Gas Emissions Reduction Act (GGRA), which established statewide emissions-reduction goals.

On September 26, 2016, the Maryland Public Service Commission initiated Public Conference No. 44 (PC44) to review electric distribution systems in Maryland. As part of this process, the Commission began considering EVSE expansion in January 2017 and launched the EV Work Group to coordinate with state agencies, utilities, and stakeholders. One proposed action from the EV Work Group was to allow limited utility infrastructure investment in EVSE, with an emphasis on working with private industry and identifying locations where private capital was unlikely to support EVSE investment.

In 2018, the Commission opened a docketed proceeding on statewide EV portfolio implementation in response to requests from the PC44 Electric Vehicle Work Group and the Maryland Office of People's Counsel (OPC). OPC expressed caution about utility-run EV programs and requested a transparent cost-benefit analysis, including analysis by the National Renewable Energy Laboratory (NREL), as well as a clear cost-recovery process. The Commission docketed the proceeding as Case No. 9478. After opening the case, the Commission held hearings and received public comments from state agencies, utilities, automobile companies, EVSE operators, research organizations, and other stakeholders.

The Electric Vehicle Work Group submitted a petition proposing a statewide EV portfolio. On January 13, 2019, the Commission issued Order No. 88997, approving several components of the portfolio: (i) a residential sub-portfolio, including residential EV charging incentives and time-of-use rates; (ii) a non-residential sub-portfolio, including non-residential EV charging incentives and demand-charge credits; (iii) a public sub-portfolio, focused on utility-owned EVSEs; (iv) an innovation sub-portfolio; and (v) a technology sub-portfolio. The public sub-portfolio is the component studied in this paper.

The public sub-portfolio authorized participating utilities to install, own, and operate a limited number

of public EVSEs. The initial participating utilities were BGE, Delmarva, Pepco, and PE; SMECO was later ordered to participate. The Commission approved utility ownership despite objections from OPC, Commission technical staff, and the Apartment and Office Building Association of Metropolitan Washington, who argued that the competitive market should play the primary role in expanding public EVSE deployment. In approving the public sub-portfolio, the Commission emphasized arguments from supporters that utilities could accelerate public EVSE deployment in underserved markets where private firms were unlikely to make initial capital investments.

Table A.1: Public Sub-Portfolio Project Description

	Description
IOU or Cooperatives	Baltimore Gas and Electric Company ("BGE") Delmarva Power & Light Company ("Delmarva") Potomac Electric Power Company ("Pepco") The Potomac Edison Company ("PE") Southern Maryland Electric Cooperative ("SMECO")
Location	Property leased, owned, or occupied by a unit of State, county, or municipal government for public use
Cost Recovery	Through distribution rates following a future base rate case
Tariff	Need the approvals of Commission
Progress Report	Each IOU reports progress in the semi-annual reports
# of EVSEs (Target)	BGE (500), DPL (100), Pepco (250), PE (59), SMECO (60)

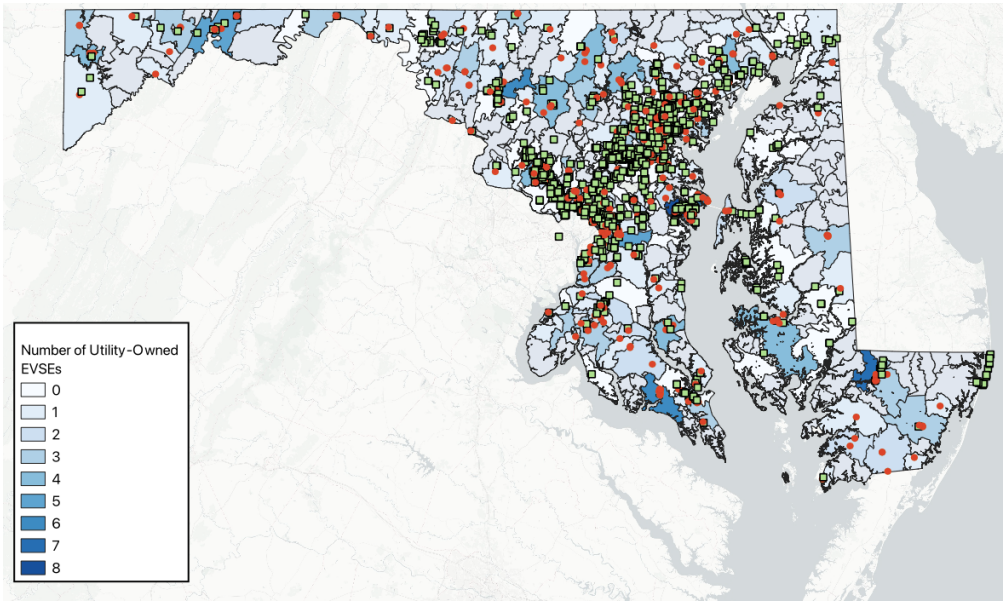
Notes: The table summarizes the public sub-portfolio project in Maryland. IOU stands for investor-owned utilities.

Under the program, utilities submit proposed sites to the PSC and report progress through semi-annual filings. These filings include proposed locations, approval status, construction progress, installation completion, and charger counts. The program, therefore, provides unusually detailed information on both approved and rejected utility-owned charger proposals, which makes it possible to study how regulatory approval shapes the spatial allocation of public charging infrastructure.

B Additional Data Description

Appendix Figure A.1 maps public charging stations in Maryland. Red points indicate utility-owned chargers, and green points indicate third-party chargers. The map also displays zip-code boundaries, with darker blue shading indicating zip codes that contain more utility-owned chargers. Utility-owned chargers are concentrated in several local areas, particularly in parts of southern and western Maryland and around the Chesapeake Bay. As of November 2023, the Maryland sample contains 1,398 third-party chargers and 317 utility-owned chargers.

Figure A.1: EVSE Locations and Number of Utility-Owned EVSEs



Notes: The figure maps EVSE locations (red: utility-owned EVSE, green: third-party EVSE). The blue color indicates the number of utility-owned EVSEs in each zip code.

C Market Definition

C.1 Travel Survey Data and Travel-Distance Measure

This appendix describes the travel survey data used to construct the travel-distance variable in the clustering-based market definition. I use two micro-level travel survey datasets: the Baltimore Metropolitan Council Maryland Travel Survey (MD MTS) and the Metropolitan Washington Council of Governments Regional Travel Survey (DC RTS). The DC RTS covers several Maryland counties adjacent to Washington, DC, including Prince George's County and St. Mary's County, that are not covered by the MD MTS. Both

surveys collect information from randomly selected households in Maryland and the District of Columbia about daily travel for work, school, shopping, errands, and social activities. Each survey consists of a recruitment questionnaire and a one-day travel diary recording all trips taken by household members on an assigned travel day. Because the two surveys were conducted over similar periods and use comparable questionnaire structures, I combine them to study travel behavior within and around Maryland.

The surveys collect household demographics, vehicle characteristics, and trip information between October 2017 and May 2019. Demographic variables include county of residence, age, gender, employment status, commuting mode, and workplace charging access. Vehicle information includes model year, body type, make, model, and fuel type, including gasoline, hybrid, plug-in hybrid, and battery electric vehicles. Trip records include origin and destination purpose, origin and destination state and county, departure and arrival times, and travel mode.

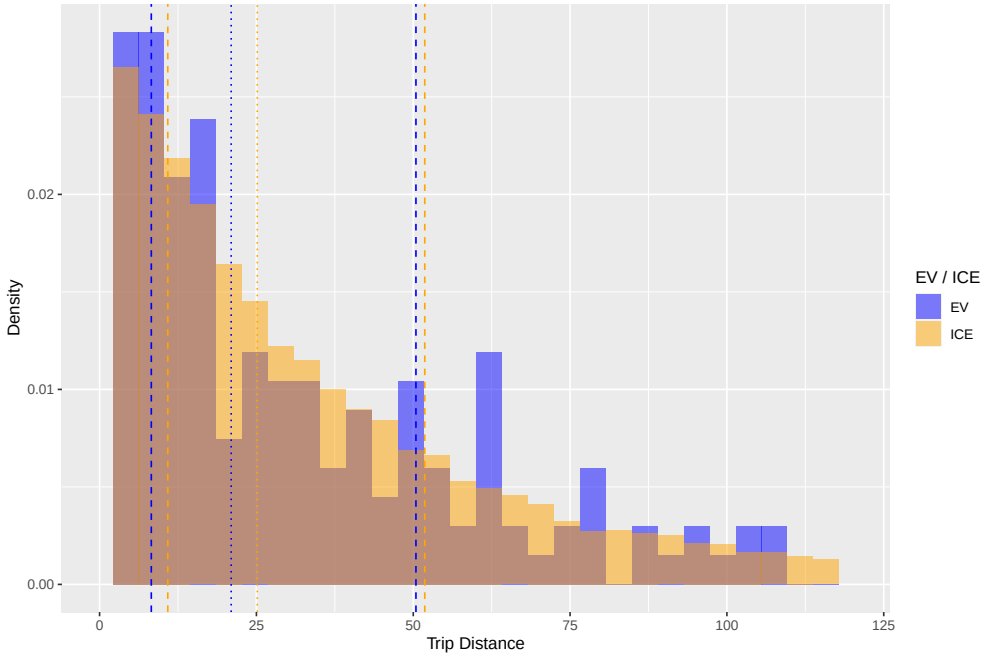
The purpose of this analysis is to construct a measure of daily travel distance that can proxy for the likelihood that drivers need public charging away from home. Charging providers may consider EV drivers' travel patterns when choosing where to locate public chargers, and daily travel distance provides guidance on the relevant geographic scale of charging markets. I aggregate the trip-level data to the person-day level and compare daily travel distance and travel time between EV and ICE drivers. Because the number of EV drivers in the survey is small, I also examine whether ICE travel patterns can be used as an informative proxy for EV travel patterns.

After aggregating the trip-level data to the daily level, the sample contains $20,726$ daily trip records for ICE vehicles and 168 daily trip records for EVs. Figure A.2 plots the distribution of daily travel distance for EVs and ICE vehicles. The EV distribution is noisy because of the small EV sample, but the quartiles are similar across fuel types. The first quartile is 8.2 miles for EVs and 10.9 miles for ICE vehicles; the median is 21.0 miles for EVs and 25.1 miles for ICE vehicles; and the third quartile is 50.4 miles for EVs and 51.8 miles for ICE vehicles, as shown in Table A.2. These distances suggest that a market with a geographic scale of roughly 8 to 10 miles per side is consistent with daily charging-relevant travel.

Table A.2 also reports trip purposes by fuel type. EVs and ICE vehicles are used for broadly similar purposes: approximately half of daily travel is commuting, and the remainder consists of shopping, meals, errands, and other activities. EVs are somewhat more likely to be used for commuting, but the overall trip-purpose distributions are similar. Travel-time distributions are also similar across fuel types, as shown in Figure A.3. The first quartile, median, and third quartile are 35, 70, and 121 minutes for EVs, compared with 45, 80, and 130 minutes for ICE vehicles.

Table A.3 reports regressions testing whether fuel type is correlated with daily travel distance and travel time. The key explanatory variable is an ICE indicator, with EVs as the omitted category. After control-

Figure A.2: Daily Trip Distance Distributions for EVs and ICE vehicles



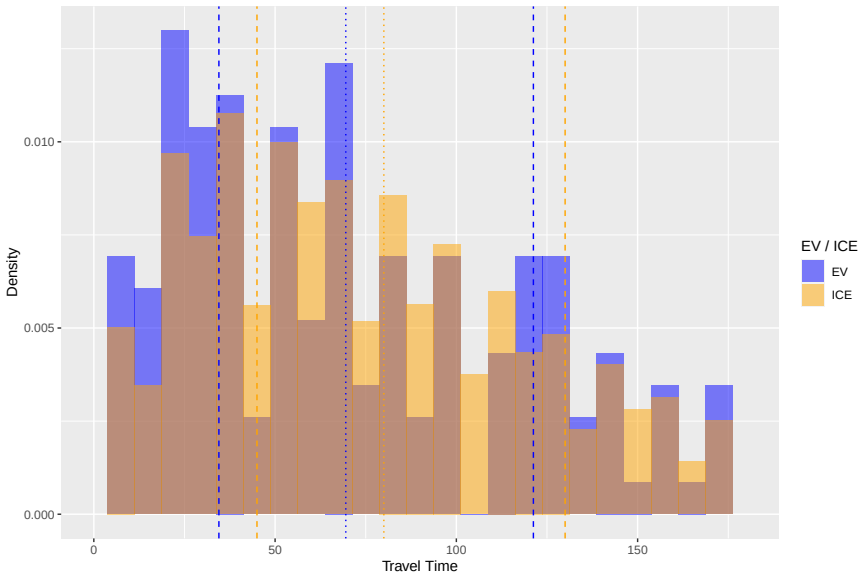
Notes: The figure plots a histogram of daily trip distance for EVs and ICE vehicles. Blue and orange represent EVs and ICE vehicles, respectively. Dotdash lines show median values of EV and ICE daily trip distances. The dotted lines represent 25% and 75% percentile values.

Table A.2: Trip Purpose of EV / ICE

	Total	Commute	Shopping / Meal	Others
Panel A: EV ($N = 168$)				
Share	100.00	58.33	17.26	24.41
Distance (1st Quartile)	8.24	13.32	4.46	5.98
Distance (Median)	20.98	34.11	18.07	9.33
Distance (3rd Quartile)	50.43	61.44	35.04	17.90
Panel B: ICE ($N = 20,726$)				
Share	100.00	49.15	27.05	23.81
Distance (1st Quartile)	10.87	13.41	9.56	8.60
Distance (Median)	25.14	29.73	21.03	21.51
Distance (3rd Quartile)	51.84	57.64	44.83	46.48

Notes: The table reports the share of travel purposes (commute, shopping/meal, and other usages) in the first row of each panel. Panel A is a summary of statistics for EVs, and panel B is for ICE vehicles. The first, second, and third quartiles of travel distance of each trip purpose are presented from the second to fourth rows in each panel.

Figure A.3: Daily Travel Time Distributions for EV and ICE



Notes: The figure plots a histogram of daily travel time for EVs and ICE vehicles. Blue and orange represent EVs and ICE vehicles, respectively. Dotdash lines show median values of EV and ICE travel time. The dotted lines represent 25% and 75% percentile values.

ling for origin county, destination county, and household fixed effects, the ICE indicator is not statistically significant. Because the specification with household fixed effects compares vehicles within the same household, it provides a useful check on whether EVs and ICE vehicles are used differently in daily travel. As robustness checks, Appendix Table A.4 reports analogous regressions for trips within Maryland and for the subsample of EV and ICE trips sharing the same origin-destination counties as observed EV trips. Across these specifications, I do not find statistically significant differences in daily distance or travel time between EVs and ICE vehicles.

Figure A.4 maps average daily travel distance by county. Figure A.4a uses the county of departure, and Figure A.4b uses the county of arrival. Red and orange counties indicate longer average travel distances, whereas blue and green counties indicate shorter average travel distances. Drivers in western Maryland, suburban Washington, DC, southern Maryland, and Baltimore tend to have shorter daily travel distances. Drivers in eastern Maryland and in counties near Baltimore, such as Carroll, Howard, and Anne Arundel, tend to have longer daily travel distances.

C.2 Aggregation from Zip Codes to Clustering-Based Markets

This appendix section describes how I assign charger locations, EV registrations, and demographic variables to the clustering-based markets. I first assign charging-station locations from the AFDC data and

Table A.3: Correlation between Travel Behaviors and Fuel Type

	Distance	Travel Time
	(1)	(2)
Fuel Type: ICE	2.58	5.32
	(4.66)	(8.48)
Trip Objective: Shopping/Meal	-3.49*	0.76
	(1.84)	(3.45)
Trip Objective: Others	-2.73	-1.99
	(1.97)	(3.95)
Dep. Mean	41.09	101.80
R^2	0.71	0.75
Observations	20,894	20,894

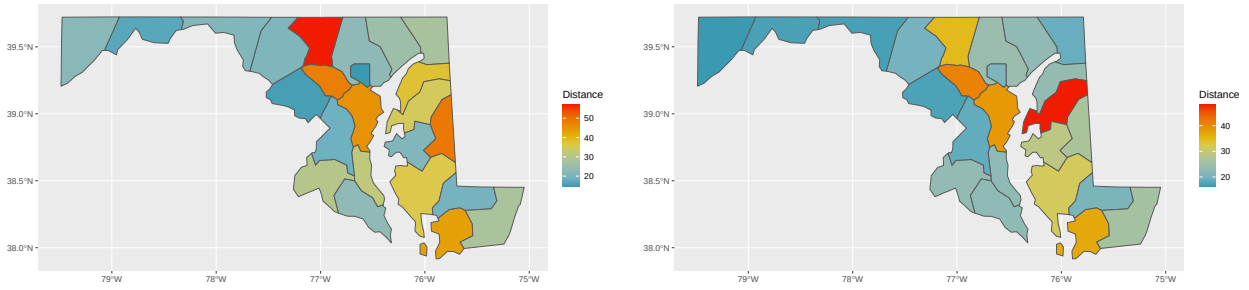
Notes: The table shows the correlation regression results for daily distance and travel time. The fuel type variable has two categories: "EV" or "ICE". Trip objective categories are "Commute," "Shopping/Meal," or "Others." Both regressions include origin/destination county and household fixed effects.

Table A.4: Robustness Check in Correlation between Driving Behaviours and Fuel Types

	Trip within MD				ICE Subset	
	Distance		Travel Time		Distance	Travel Time
	(1)	(2)	(3)	(4)	(5)	(6)
Fuel Type: ICE	5.05	3.10	7.76	10.45	-7.70	-8.81
	(5.27)	(2.32)	(12.52)	(8.59)	(4.46)	(9.00)
Trip Objective (Round): Others	-1.49	-3.87***	-3.37	-5.50**	3.14	9.92*
	(1.74)	(1.00)	(4.71)	(2.00)	(2.43)	(5.10)
Trip Objective (Round): Shopping/Meal	-3.56*	-5.09***	-5.10	-3.90	2.44	13.01**
	(1.95)	(1.18)	(5.53)	(2.35)	(1.84)	(4.46)
R^2	0.78	0.18	0.72	0.16	0.82	0.77
Observations	18,104	18,104	18,104	18,104	10,613	10,613
Origin County fixed effects	✓	✓	✓	✓	✓	✓
Destination County fixed effects	✓	✓	✓	✓	✓	✓
Household fixed effects	✓		✓		✓	✓

Notes: The table reports the correlation regression estimates of distance and travel time, using travel survey datasets. Columns (1)-(4) show the results for the subsample of trips within Maryland. Columns (5) and (6) report the results for the subsample of EVs and ICE vehicles sharing the same origin/destination as EVs.

Figure A.4: Distance (Origin/Destination Counties)



(a) Driving Distance (Origin County)

(b) Driving Distance (Destination County)

Notes: The figure maps a daily travel distance at the county level. The left panel (a) plots the daily driving distance of those who depart from the county. The right panel (b) is for those who arrive in the county. The blue-colored county has shorter trip drivers, and the red-colored county has longer trip drivers.

utility-owned charger locations from PSC Case No. 9478 to the clustering-based markets using a Geographic Information System (GIS). Because charging-station locations are observed with geographic coordinates, each charger can be directly mapped to the spatially clustered market in which it is located.

EV registration and demographic variables, however, are observed at the zip-code level. I therefore convert these variables from zip codes to census tracts and then aggregate them to the clustering-based markets. The zip-code-to-census-tract conversion uses household-unit weights for each zip-code-by-census-tract pair.[23] After converting variables to the census-tract level, I aggregate them to the market level using housing-unit weights. Count variables, such as EV registrations and population, are aggregated using weighted sums. Rate or average variables, such as age and the share of residents with post-secondary education, are aggregated using weighted averages.

C.3 Distance from Chargers to Market Boundaries

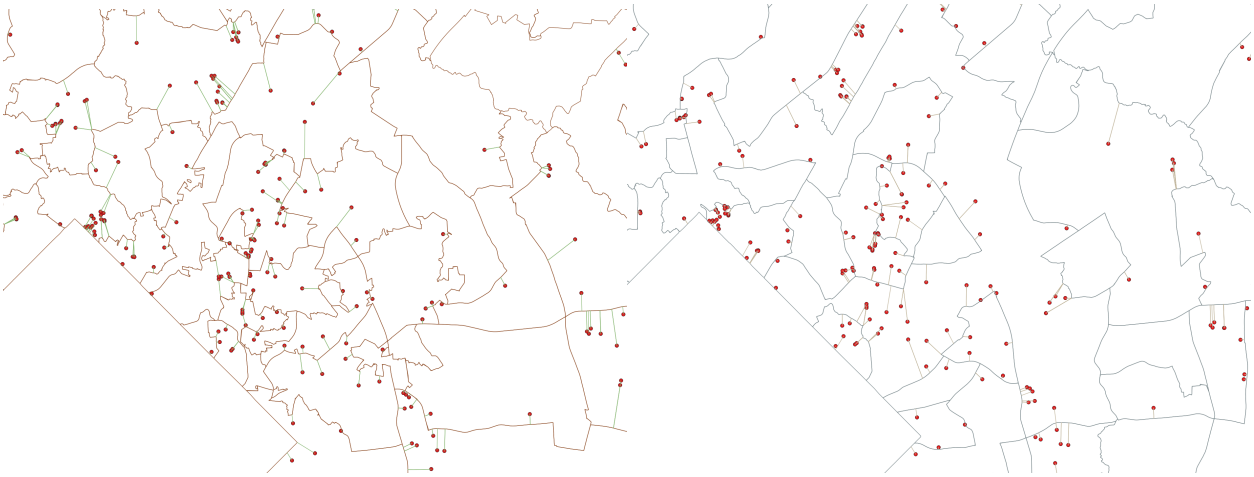
This appendix describes the boundary-distance diagnostic used to compare the clustering-based and zip-code market definitions. A concern with administrative markets is that their boundaries may be arbitrary from the perspective of charging demand. If many chargers are located very close to market boundaries, measured market-level demand may not correspond well to the customers served by those chargers, especially if drivers frequently cross boundaries to charge.

To examine this issue, I calculate the distance from each charger to the nearest market boundary under both the zip-code and clustering-based definitions. Figure A.5 illustrates the distance measure. For each

[23]Household-unit counts at the census-tract level come from the U.S. Census Bureau. I use a crosswalk matching ZIP codes to census tracts from the Stanford Center for Population Health Sciences.

charging-station location, I calculate the Euclidean distance to the closest market boundary. Figure A.5a shows the measurement under the zip-code definition, and Figure A.5b shows the measurement under the clustering-based definition.

Figure A.5: How to Compute Distance to Market Boundaries



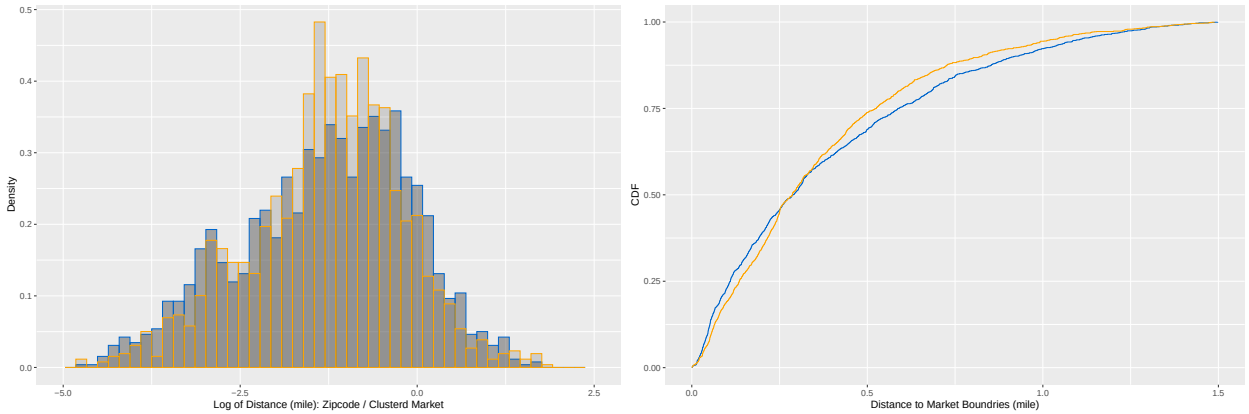
(a) Zip Code Market (b) Clustering-Based Market

Figure A.6a plots the distribution of the logarithm of the distance from chargers to market boundaries. The blue distribution corresponds to zip-code markets, and the orange distribution corresponds to clustering-based markets. The clustering-based definition has less mass near zero and a more concentrated distribution, indicating that chargers are less likely to be located very close to market boundaries. The cumulative distribution functions in Figure A.6b show the same pattern: zip-code markets place more chargers close to market boundaries than clustering-based markets do. Table A.5 reports the number of charger locations within distance bins of 0.05 miles. More chargers fall within the 0–0.05 mile and 0.05–0.10 mile bins under the zip-code definition than under the clustering-based definition.

Table A.5: Number of EVSEs with Small Distances to Boundaries

Distance to Boundaries (mile)	Zip Code	Clustering-Based
0 - 0.05	369	312
0.05 - 0.1	257	253
0.1 - 0.15	197	287
0.15 - 0.2	165	195
0.2 - 0.25	119	160

Figure A.6: Differences in Distance to Market Boundaries across Market Definitions



(a) Histogram of Logarithm Distance

(b) Cumulative Distribution Functions of Distance

Notes: Blue and orange colors correspond to zip code and clustering-based market definitions, respectively.

C.4 Grid-Based Market

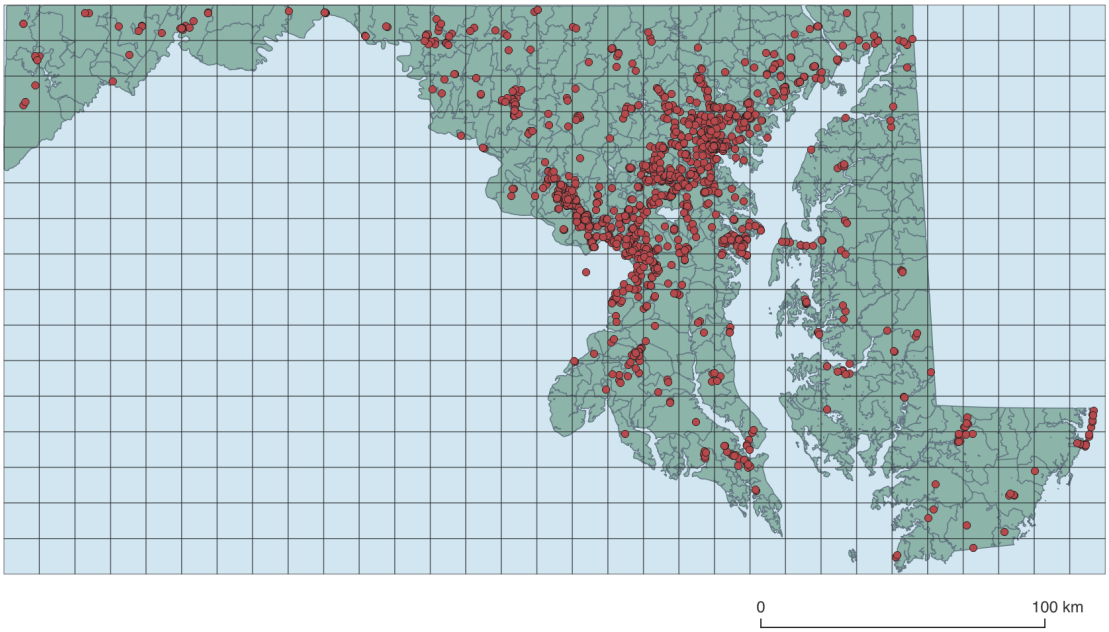
As an alternative market definition, I construct grid-based markets using only geographic distance. This approach does not incorporate the probability that a location is chosen as a destination, but it produces markets with more uniform area sizes. More uniform market areas may be useful because area size is related to potential market size and can affect comparability across markets. Guided by the travel-survey evidence above, I define grid cells as 10 miles by 10 miles. This scale is motivated by the median daily travel distance of EV drivers, approximately 21 miles, together with the assumption that many drivers make round trips and may charge once during the day.

Appendix C.4 describes the grid construction in detail. In brief, I generate a 10-mile grid in GIS and assign a grid identifier to each cell. I then compute the overlapping area shares for each zip-code-by-grid-cell pair and use these shares as weights to aggregate EV stock and demographic variables from zip codes to grid cells. Figure A.7 shows the grid-based markets. The green area represents Maryland, and grid cells that overlap with Maryland are included as markets.

The grid-based market is constructed on the GIS platform. GIS can generate a 10-mile grid overlapping a specific polygon. I assign grid IDs for all generated grids. For example, nine IDs ($1255-1257$, $1295-1297$, and $1335-1337$) are assigned into the right panel of Figure A.8. Then, I show the original zip code numbers in the right panel of Figure A.8. Here, the overlapping area share in each grid ID can be computed. For instance, grid 1296 are overlapping with three zip codes (20872, 20876, and 20882). Suppose that zip code 20872 overlaps 10% with grid ID 1296. Then, I put the 10% weighted values of EV stocks or demographic variables of zip code 20872 as the component of grid ID 1296. I conduct the same calculation procedure

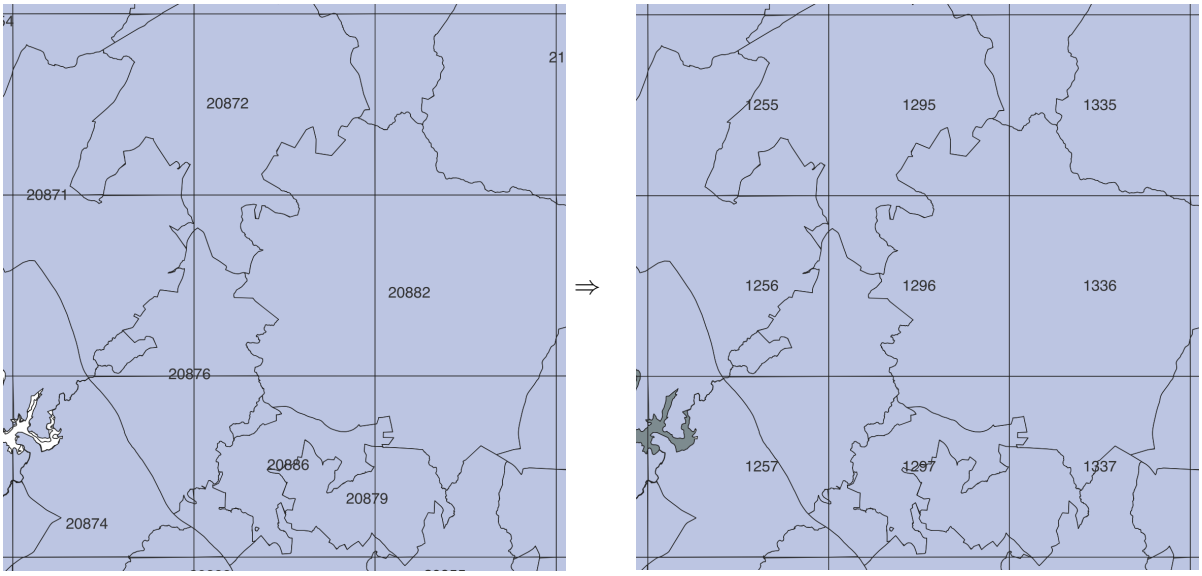
for other zip codes sharing the land of grid ID 1296. The stock variables (e.g., EV stock or population) are accumulated and the weighted means are taken for other variables (e.g., age or income). Applying this process to all grid IDs will generate the variables of the grid-based market.

Figure A.7: Grid Market (10 miles)



Notes: The map presents a grid-based market. The green-colored object is the state of Maryland. The red points are EVSE locations. The grid overlapping state of Maryland is defined as the market.

Figure A.8: Zip code to grid-based market



Notes: Those two figures are conceptual examples explaining how to convert zip code data to variables in the grid-based market.

D Results of Reduced-Form Analysis

D.1 Clustering-based Market: Lags

It is known that installing public EVSEs takes $9-18$ months (McKinsey & Company, 2022; SparkCharge, 2024). Overall, there are four steps to complete the installations: (1) make a plan and apply for grants/subsidies, (2) conduct site validation and discuss with EVSE installers, (3) apply for county permission, and (4) construction and inspection. Thus, I perform four types of lags: 3, 6, 12, and 18 months. These specifications replace $\ln(Q_{m,t})$ in equation (2) with lagged EV stock. For example, the three-month-lag specification replaces $\ln(Q_{m,t})$ with $\ln(Q_{m,t-3})$, corresponding to the assumption that charger owners make investment decisions three months before installation and do not form additional expectations about EV stock trends.

Appendix Tables A.6–A.8 show semi-elasticity estimates with lags for third-party, utility-owned, and all EVSEs, respectively. The estimates increase somewhat with longer lags, which is mechanically plausible because lagged EV stock is smaller in a growing market.[24] Overall, the qualitative patterns are similar to the baseline results in Table 2.

[24] As the lag length increases, $\ln(Q_{m,t-\ell})$ tends to be smaller because EV stock is growing over time. This can mechanically increase the estimated coefficient.

Table A.6: Semi-Elasticity with Lags: Third-Party EVSEs

	No Lag	Lag 3m	Lag 6m	Lag 12m	Lag 18m
	(1)	(2)	(3)	(4)	(5)
log(EV Stock)	129.63***	130.95***	132.91***	155.02***	179.38***
	(34.33)	(34.65)	(35.69)	(41.99)	(63.31)
F-stat	14.49	14.53	14.08	13.72	8.06
N	8323	7714	7105	5887	4669

Notes: The table reports the semi-elasticity parameter estimates when taking various lags of EV stock variables for third-party EVSEs. EV stock is weighted by the number of household units. "m" is an abbreviation of the month.

Table A.7: Semi-Elasticity with Lags: Utility-Owned EVSEs

	No Lag	Lag 3m	Lag 6m	Lag 12m	Lag 18m
	(1)	(2)	(3)	(4)	(5)
log(EV Stock)	46.67***	52.07***	55.01***	68.42***	76.78***
	(12.36)	(13.71)	(14.66)	(18.48)	(27.20)
F-stat	14.49	14.53	14.08	13.72	8.06
N	8323	7714	7105	5887	4669

Notes: The table reports the semi-elasticity parameter estimates when taking various lags of EV stock variables for utility-owned EVSEs. EV Stock is weighted by the number of household units. "m" is an abbreviation of the month.

Table A.8: Semi-Elasticity with Lags: Total EVSEs

	No Lag	Lag 3m	Lag 6m	Lag 12m	Lag 18m
	(1)	(2)	(3)	(4)	(5)
log(EV Stock)	176.30***	183.01***	187.91***	223.44***	256.16***
	(46.52)	(48.21)	(50.23)	(60.38)	(90.41)
F-stat	14.49	14.53	14.08	13.72	8.06
N	8323	7714	7105	5887	4669

Notes: The table reports the semi-elasticity parameter estimates when taking various lags of EV stock variables for total EVSEs. EV Stock is weighted by the number of household units. "m" is an abbreviation of the month.

D.2 Land Use Heterogeneity

This appendix reports heterogeneity results by land use. I consider four land-use shares: business, residential, public, and natural land. Business land includes commercial and industrial areas; residential land includes very-low-, low-, medium-, and high-density residential areas; public land includes institutional and transportation areas; and natural land includes agriculture, forest, water, wetlands, and barren land. Appendix Table A.9 reports estimates from specifications that interact EV stock with each land-use share. All regressions use the baseline shift-share instruments. Columns (1)–(3) report results for third-party chargers, utility-owned chargers, and all public chargers.

Panel A shows that the business-land share has a positive and statistically significant interaction with EV stock for third-party chargers, but not for utility-owned chargers. This pattern suggests that third-party providers respond more strongly to EV stock in markets with greater commercial and industrial activity. Such markets may be more attractive to private providers because they generate destination charging demand from workers, shoppers, and other visitors. The insignificant estimate for utility-owned chargers is consistent with the PSC placing less weight on business-oriented locations, possibly because these locations are more likely to attract private entry without utility participation.

For the other land-use variables, the estimated patterns are broadly similar across ownership types. Both third-party and utility-owned chargers are more responsive to EV stock in markets with larger residential and public land shares. These areas may generate charging demand from local residents or provide feasible public and institutional sites for charger installation. In contrast, both ownership types are less responsive to EV stock in markets with larger natural-land shares. This pattern is intuitive because forests, agricultural areas, water, wetlands, and barren land are less likely to contain destinations suitable for public charging.

Overall, the land-use heterogeneity results suggest that business activity matters more for third-party deployment than for utility-owned deployment, but the remaining land-use patterns are similar across ownership types.

D.3 Other Market Definitions: Elasticity/Semi-elasticity and Heterogeneity

I estimate the same specifications using two alternative market definitions: grid-based markets and zip-code markets. The results are reported in Tables A.10 and A.13. The grid-based markets generate elasticities and semielasticities similar to those from the clustering-based markets, whereas the zip-code markets generate a different pattern. The heterogeneity results are broadly robust across alternative market definitions.

Table A.9: Semi-Elasticity: Land Use Heterogeneity

	Semi-Elasticity: Land-Use		
	TP	UO	All
	(1)	(2)	(3)
Panel A: Business			
log(EV Stock)	104.94***	45.52***	150.46***
	(26.19)	(11.24)	(37.26)
Int. w. Share of Business Areas	24.57***	1.14	25.71**
	(7.39)	(3.17)	(10.52)
F-stat	8.34	8.34	8.34
Panel B: Residence			
log(EV Stock)	117.53***	41.62***	159.15***
	(28.26)	(10.02)	(38.10)
Int. w. Share of Residence Areas	13.60**	5.68**	19.27**
	(6.75)	(2.39)	(9.10)
F-stat	8.81	8.81	8.81
Panel C: Public			
log(EV Stock)	89.32***	34.41***	123.72***
	(18.10)	(6.98)	(24.91)
Int. w. Share of Public Areas	127.49***	38.78***	166.28***
	(21.13)	(8.15)	(29.07)
F-stat	12.57	12.57	12.57
Panel D: Nature			
log(EV Stock)	83.16***	34.84***	118.00***
	(16.68)	(6.99)	(23.49)
Int. w. Share of Nature Areas	-21.02***	-5.35***	-26.37***
	(3.80)	(1.59)	(5.35)
F-stat	12.90	12.90	12.90

Notes: The table reports semi-elasticity estimates with interactions between EV stock and land-use variables. "TP" and "UO" denote third-party and utility-owned chargers, respectively. "All" denotes the total number of public chargers. The three regressions in each panel differ by the dependent variable, $N^k_{m,t}$, where $k = \{\text{TP}, \text{UO}, \text{All}\}$. I aggregate the original 13 Maryland Department of Planning land-use classifications into four groups: business land (commercial and industrial), residential land (very-low-, low-, medium-, and high-density residential), public land (institutional and transportation), and natural land (agriculture, forest, water, wetlands, and barren land). EV stock is weighted by the number of household units.

Table A.10: Elasticity and Semi-Elasticity (Grid-based market)

	Elasticity			Semi-Elasticity		
	TP	UO	All	TP	UO	All
	(1)	(2)	(3)	(4)	(5)	(6)
log(EV Stock)	3.44***	7.86***	1.31***	154.92***	37.99***	192.91***
	(0.44)	(0.93)	(0.30)	(18.44)	(4.42)	(22.73)
F-stat	74.74	74.74	74.74	74.74	74.74	74.74
N	5535	5535	5535	5535	5535	5535

Notes: The table reports the elasticity and semi-elasticity parameter estimates. TP and UO represent the numbers of third-party and utility-owned, respectively. All means the total number of EVSEs. Three regressions in both elasticity and semi-elasticity are differentiated by the dependent variable, $N^k_{m,t}$ ($k = \{\text{TP}, \text{UO}, \text{All}\}$).

Table A.11: Semi-Elasticity: Demographics Heterogeneity (Grid-based market)

	Semi-Elasticity: Demographics					
	TP	UO	All	TP	UO	All
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Income						
IV		SSIV		SSIV, SSIV × log(Population)		
log(EV Stock)	156.65***	39.03***	195.68***	95.13***	26.92***	122.04***
	(19.48)	(4.91)	(24.24)	(9.72)	(2.77)	(12.29)
Int. w. log(Income)	-10.38*	-6.26***	-16.64**	3.46	-3.54***	-0.08
	(5.61)	(1.41)	(7.00)	(3.08)	(0.88)	(3.89)
F-stat	31.65	31.65	31.65	33.68	33.68	33.68
Panel B: Education (Post-Secondary)						
IV		SSIV		SSIV, SSIV × Labor Force Rate		
log(EV Stock)	119.15***	34.35***	153.50***	57.55***	23.15***	80.69***
	(13.11)	(3.66)	(16.59)	(5.84)	(2.04)	(7.61)
Int. w. Post-Secondary Rate	85.09***	8.66***	93.75***	70.09***	5.93***	76.02***
	(8.27)	(2.31)	(10.47)	(4.52)	(1.58)	(5.88)
F-stat	44.66	44.66	44.66	47.32	47.32	47.32
Panel C: Population						
Interaction with		log(Population)			Population Share	
log(EV Stock)	26.98***	15.74***	42.73***	25.98***	15.46***	41.44***
	(6.77)	(2.40)	(8.66)	(7.25)	(2.64)	(9.44)
Int. w. log(Population)	11.60***	2.02***	13.61***			
	(0.70)	(0.25)	(0.89)			
Int. w. Population Share				1479.91***	258.57***	1738.48***
				(72.59)	(26.44)	(94.48)
F-stat	30.77	30.77	30.77	29.59	29.59	29.59

Notes: The table reports the semi-elasticity parameter estimates with an interaction term of demographic variables. TP and UO represent the numbers of third-party and utility-owned, respectively. All means the total number of EVSEs. Three regressions in both elasticity and semi-elasticity are differentiated by the dependent variable, $N^k_{m,t}$ ($k = \{\text{TP}, \text{UO}, \text{All}\}$). EV Stock is weighted by the number of household units.

Table A.12: Semi-Elasticity: Land Use Heterogeneity (Grid-based market)

	Semi-Elasticity: Land-Use		
	TP	UO	All
	(1)	(2)	(3)
Panel A: Business			
log(EV Stock)	-56.67***	-13.86***	-70.53***
	(8.48)	(2.38)	(10.52)
Int. w. Share of Business Areas	159.34***	39.27***	198.62***
	(12.95)	(3.63)	(16.06)
F-stat	19.87	19.87	19.87
Panel B: Residence			
log(EV Stock)	-7.61***	3.37***	-4.24
	(2.89)	(0.82)	(3.34)
Int. w. Share of Residence Areas	75.70***	16.12***	91.82***
	(2.25)	(0.64)	(2.60)
F-stat	95.26	95.26	95.26
Panel C: Public			
log(EV Stock)	10.71***	2.69***	13.40***
	(3.01)	(0.85)	(3.49)
Int. w. Share of Public Areas	369.80***	90.51***	460.31***
	(12.28)	(3.46)	(14.22)
F-stat	79.04	79.04	79.04
Panel D: Nature			
log(EV Stock)	-47.79***	-4.84***	-52.63***
	(6.83)	(1.40)	(7.79)
Int. w. Share of Nature Areas	-58.84***	-12.43***	-71.28***
	(2.94)	(0.60)	(3.35)
F-stat	37.08	37.08	37.08

Notes: The table reports the semi-elasticity parameter estimates with an interaction term of land use variables. TP and UO represent the numbers of third-party and utility-owned, respectively. All means the total number of EVSEs. Three regressions in both elasticity and semi-elasticity are differentiated by the dependent variable, $N^k_{m,t}$ ($k = \{\text{TP}, \text{UO}, \text{All}\}$). I aggregate the original 13 classifications of the Maryland Department of Planning into four: (a) business (commercial and industrial), (b) residential (very low-/low-/medium-/high-density residential), (c) public (institutional and transportation), and (d) nature (agriculture, forest, water, wetlands, and barren land). EV Stock is weighted by the number of household units.

Table A.13: Elasticity and Semi-Elasticity (Zip code market)

	Elasticity			Semi-Elasticity		
	TP	UO	All	TP	UO	All
	(1)	(2)	(3)	(4)	(5)	(6)
log(EV Stock)	1.33***	1.07***	0.88***	12.53***	3.92***	16.45***
	(0.16)	(0.17)	(0.15)	(1.40)	(0.45)	(1.67)
F-stat	144.69	144.69	144.69	144.69	144.69	144.69
N	9307	9307	9307	9307	9307	9307

Notes: The table reports the elasticity and semi-elasticity parameter estimates. TP and UO represent the numbers of third-party and utility-owned, respectively. All means the total number of EVSEs. Three regressions in both elasticity and semi-elasticity are differentiated by the dependent variable, $N^k_{m,t}$ ($k = \{\text{TP}, \text{UO}, \text{All}\}$).

Table A.14: Semi-Elasticity: Demographics Heterogeneity (Zip code market)

	Semi-Elasticity: Demographics					
	TP	UO	All	TP	UO	All
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Income						
IV		SSIV		SSIV, SSIV × log(Population)		
log(EV Stock)	13.48***	3.62***	17.10***	2.11***	2.44***	4.55***
	(1.34)	(0.41)	(1.58)	(0.59)	(0.23)	(0.65)
Int. w. log(Income)	1.42***	-0.45***	0.97*	2.81***	-0.31***	2.50***
	(0.44)	(0.13)	(0.52)	(0.29)	(0.11)	(0.32)
F-stat	81.38	81.38	81.38	131.65	131.65	131.65
Panel B: Education (Post-Secondary)						
IV		SSIV		SSIV, SSIV × Labor Force Rate		
log(EV Stock)	15.97***	3.93***	19.90***	14.22***	2.58***	16.81***
	(1.59)	(0.46)	(1.89)	(1.35)	(0.36)	(1.53)
Int. w. Post-Secondary Rate	16.79***	0.06	16.86***	16.59***	-0.10	16.49***
	(1.23)	(0.36)	(1.46)	(1.14)	(0.30)	(1.29)
F-stat	69.88	69.88	69.88	55.78	55.78	55.78
Panel C: Population						
Interaction with		log(Population)			Population Share	
log(EV Stock)	-0.49	2.41***	1.92***	0.37	2.94***	3.32***
	(0.61)	(0.23)	(0.65)	(0.63)	(0.27)	(0.68)
Int. w. log(Population)	1.61***	0.19***	1.79***			
	(0.10)	(0.04)	(0.11)			
Int. w. Population Share				453.57***	36.46***	490.03***
				(26.47)	(11.43)	(28.57)
F-stat	175.83	175.83	175.83	155.51	155.51	155.51

Notes: The table reports the semi-elasticity parameter estimates with an interaction term of demographic variables. TP and UO represent the numbers of third-party and utility-owned, respectively. All means the total number of EVSEs. Three regressions in both elasticity and semi-elasticity are differentiated by the dependent variable, $N^k_{m,t}$ ($k = \{\text{TP}, \text{UO}, \text{All}\}$). EV Stock is weighted by the number of household units.

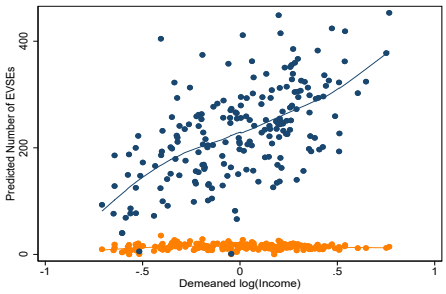
Table A.15: Semi-Elasticity: Land Use Heterogeneity (Zip code market)

	Semi-Elasticity: Land-Use		
	TP	UO	All
	(1)	(2)	(3)
Panel A: Business			
log(EV Stock)	13.38***	6.16***	19.54***
	(1.91)	(0.75)	(2.43)
Int. w. Share of Business Areas	7.66***	-3.32***	4.34***
	(1.28)	(0.50)	(1.63)
F-stat	46.28	46.28	46.28
Panel B: Residence			
log(EV Stock)	15.63***	5.47***	21.10***
	(2.05)	(0.70)	(2.54)
Int. w. Share of Residence Areas	0.29	-0.60*	-0.31
	(1.06)	(0.36)	(1.32)
F-stat	45.38	45.38	45.38
Panel C: Public			
log(EV Stock)	11.56***	4.93***	16.49***
	(1.46)	(0.56)	(1.81)
Int. w. Share of Public Areas	31.74***	1.37	33.12***
	(2.57)	(0.98)	(3.18)
F-stat	63.10	63.10	63.10
Panel D: Nature			
log(EV Stock)	10.48***	6.46***	16.93***
	(1.58)	(0.76)	(2.10)
Int. w. Share of Nature Areas	-5.05***	1.28***	-3.78***
	(0.62)	(0.30)	(0.82)
F-stat	48.62	48.62	48.62

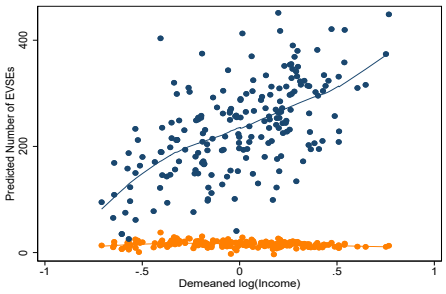
Notes: The table reports the semi-elasticity parameter estimates with an interaction term of land use variables. TP and UO represent the numbers of third-party and utility-owned, respectively. All means the total number of EVSEs. Three regressions in both elasticity and semi-elasticity are differentiated by the dependent variable, $N^k_{m,t}$ ($k = \{\text{TP}, \text{UO}, \text{All}\}$). I aggregate the original 13 classifications of the Maryland Department of Planning into four: (a) business (commercial and industrial), (b) residential (very low-/low-/medium-/high-density residential), (c) public (institutional and transportation), and (d) nature (agriculture, forest, water, wetlands, and barren land). EV Stock is weighted by the number of household units.

D.4 Policy Discussion

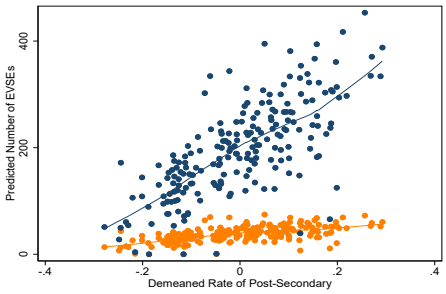
Figure A.9: Predicted EVSE Numbers and Demographics



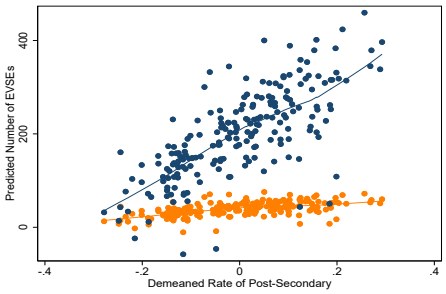
(a) Income (Jul, 2020)



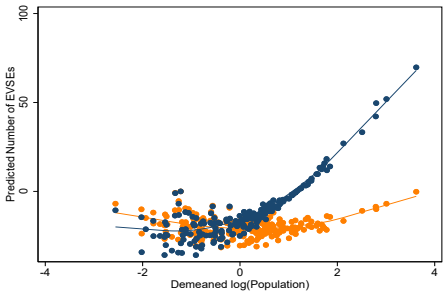
(b) Income (Nov, 2023)



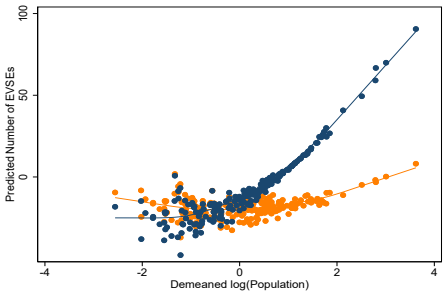
(c) Education (Jul, 2020)



(d) Education (Nov, 2023)



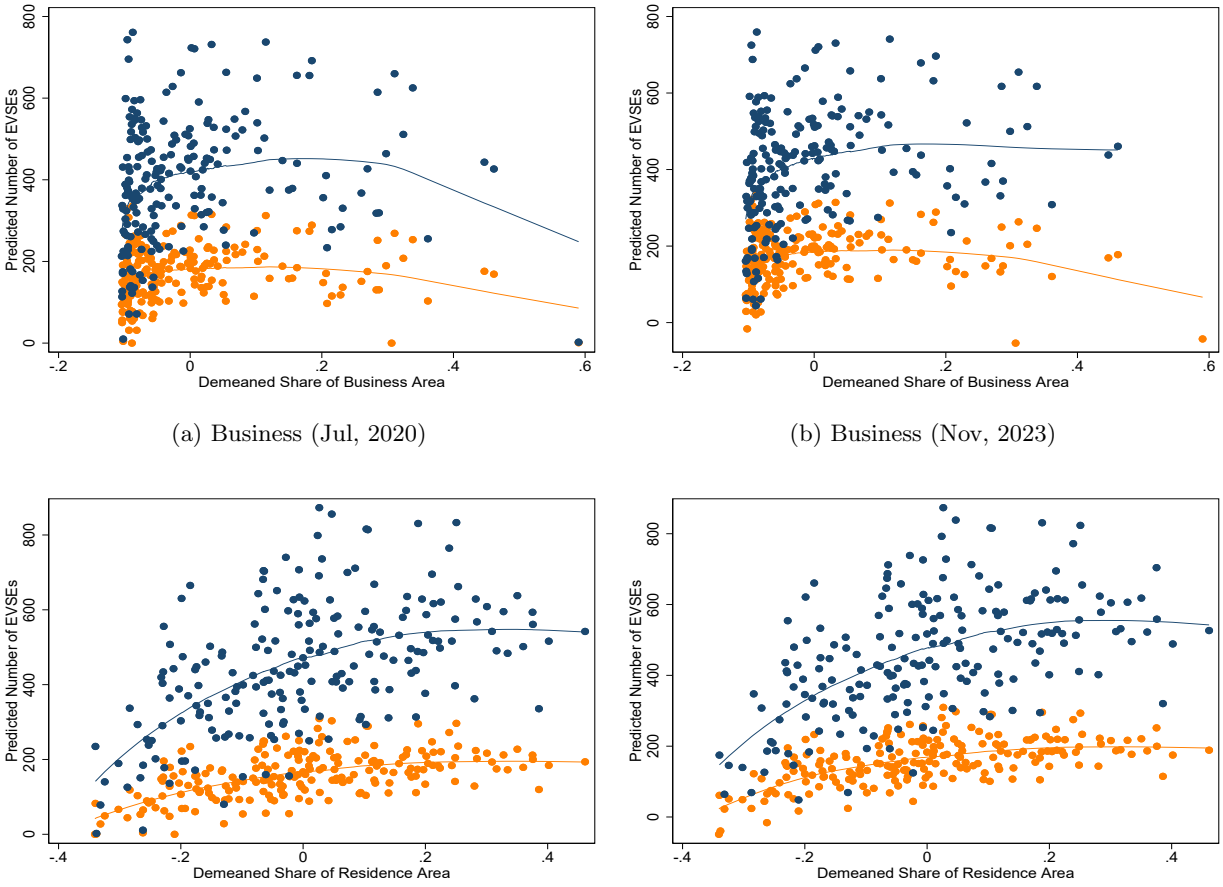
(e) Population (Jul, 2020)



(f) Population (Nov, 2023)

Notes: The figure presents the relationship between the predicted numbers of third-party and utility-owned EVSEs and demeaned demographic variables. Blue and orange dots and lines represent third-party and utility-owned EVSEs, respectively. I use the parameter estimates in columns (4)-(6) in Panels A and B for income and education heterogeneity, and columns (1)-(3) in Panel C for the population heterogeneity, in Table 3.

Figure A.10: Predicted EVSE Numbers and Land Use (I)



(a) Business (Jul, 2020)

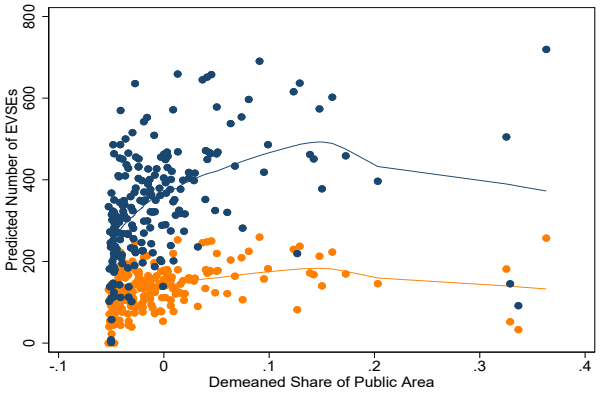
(b) Business (Nov, 2023)

(c) Residence (Jul, 2020)

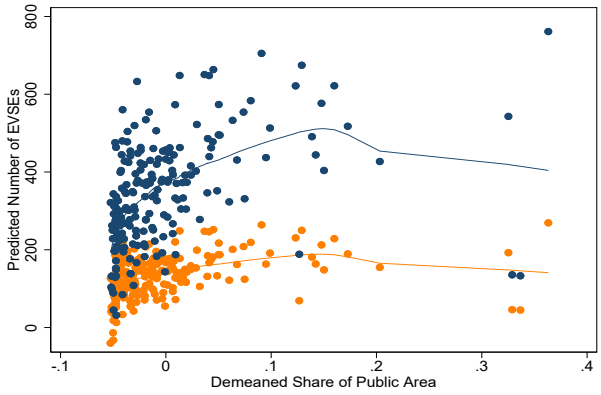
(d) Residence (Nov, 2023)

Notes: The figure presents the relationship between the predicted numbers of third-party and utility-owned EVSEs and demeaned land use variables. Blue and orange dots and lines represent third-party and utility-owned EVSEs, respectively. I use the parameter estimates in Table A.9.

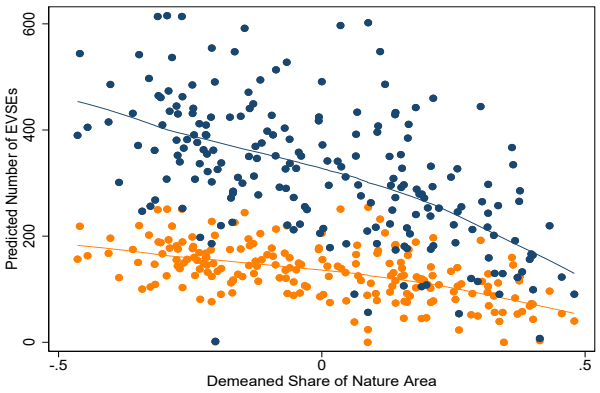
Figure A.11: Predicted EVSE Numbers and Land Use (II)



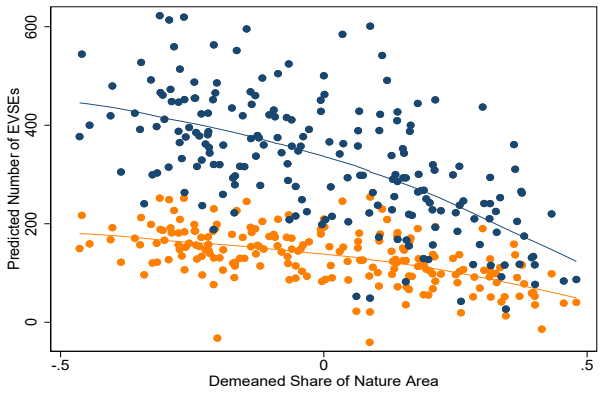
(a) Public (Jul, 2020)



(b) Public (Nov, 2023)



(c) Nature (Jul, 2020)



(d) Nature (Nov, 2023)

Notes: The figure presents the relationship between the predicted numbers of third-party and utility-owned EVSEs and demeaned land use variables. Blue and orange dots and lines represent third-party and utility-owned EVSEs, respectively. I use the parameter estimates in Table A.9.

E Appendix for Demand Estimation

E.1 Data Description of Registration and EV Charger Data

Table A.16 summarizes annual vehicle sales from 2021 to 2024 across the clustering-based markets. Standard deviations are reported in parentheses and show substantial heterogeneity in vehicle sales across markets. ICE vehicle sales decline from 2021 to 2022, while the shares of hybrid vehicles and BEVs/PHEVs increase steadily over the period. The growth in BEV/PHEV sales is driven in large part by Tesla sales. For example, the Tesla Model Y was the ninth-best-selling vehicle in Maryland in 2024.

Table A.16: Vehicle Counts per Each Market (Clustering-Based Market)

Year	ICE	HEV	BEV+PHEV
2021	991.69	23.13	17.97
	(2122.43)	(52.38)	(43.82)
2022	771.55	25.77	23.82
	(1664.62)	(57.39)	(57.65)
2023	776.31	35.12	51.97
	(1669.94)	(81.11)	(129.64)
2024	795.02	52.46	54.35
	(1701.84)	(124.08)	(123.7)

Notes: The table reports average annual vehicle sales from 2021 to 2024 across clustering-based markets. The standard deviation is in parentheses.

Table A.17: Facility Types where EVSEs are installed

Facility Type	Percent Share (%)	Facility Type	Percent Share (%)
Utility	20.19	Hotel/Inn	5.49
Office	11.50	Uni/Research-Lab	4.46
Shopping Center/Restaurant	10.30	Hospital	3.55
Fed/State/Municipal Gov't	7.55	C-Store/Gas-Station	3.49
Parking Lot/Garage	6.92	Public	2.97
Retail/Grocery	6.46	Rec. Center	2.80
Car Dealer/Auto-shop	5.84	Park	1.43
Residential Complex	5.72	Others	1.32

Notes: Some facilities are a complex of government and business offices. Some residential complexes include the office, retail, and restaurants. The category of facility types "Others" includes airports, arenas, churches, convention centers, museums, and so forth.

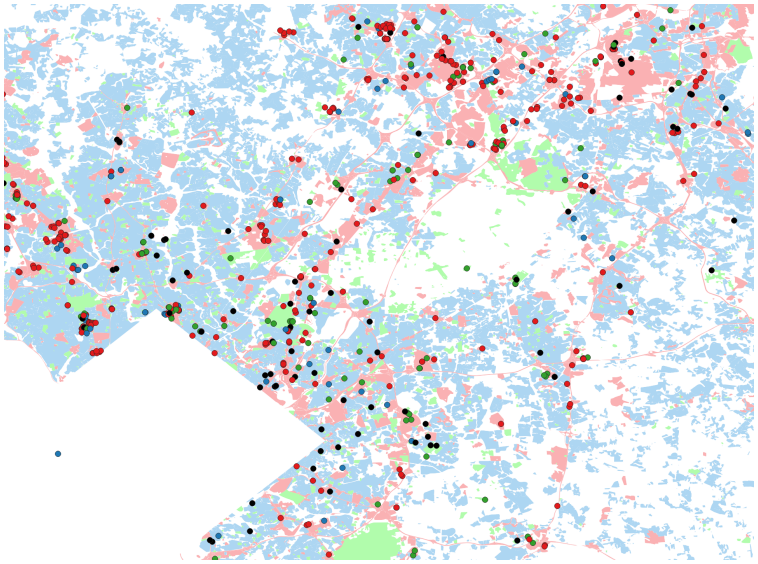
E.2 Subsidies and Price Variation

During the data period, both federal (IRA) and state subsidies were provided. IRA has made multiple changes to the eligibility requirements for attributes and has imposed household-income eligibility based on

Table A.18: Facility Type and Land Use

Facility Type	1st Land-Use	Percent Share (%)	2nd Land-Use	Percent Share (%)
Utility	Institutional	33.14	Commercial	30.31
Office	Commercial	37.31	Industrial	25.37
Shopping Center/Restaurant	Commercial	63.89	Forest	11.67
Fed/State/Municipal Gov't	Institutional	33.33	Commercial	32.58
Parking Lot/Garage	Commercial	51.24	Institutional	19.01
Retail/Grocery	Commercial	64.60	Industrial	19.47
Car Dealer/Auto-shop	Commercial	81.37	Industrial	9.80
Residential Complex	Residential	53.00	Commercial	20.00

Figure A.12: EVSE Locations and Land-Use



Notes: Points show EVSE locations by facility type: commercial, residential, public, and utility-owned. Colored areas show land use: commercial, residential, institutional, and other land uses, including agriculture, forest, and water.

family type since January 2023, to the end of the subsidy program (Table A.19). The tax reimbursement amount of each vehicle, depending on the vehicle models, was available in fueleconomy.gov and summarized in Table A.20. The state subsidy is fixed ($3,000) for eligible vehicles (Table A.21).

Table A.19: Federal Subsidy Description (IRA)

Period	Requirements	Amounts
– Dec 31, 2022	At least 5 kwh battery capacity	$2,917 ∼ $7,500
Jan 1, 2023 – Apr 17, 2023	At least 7 kwh battery capacity	$2,500 ∼ $7,500
Apr 18, 2023 – Sep 30, 2025	Critical mineral & Battery Component	$3,750 ∼ $7,500
Period	**Family Type**	**Income Eligibility**
– Dec 31, 2022	—	No threshold
Jan 1, 2023 – Sep 30, 2025	Married Couples	< $300,000
	Heads of HHs	< $225,000
	Others	< $150,000

Table A.20: IRA Tax Credits

Eligibility group	Models	Before 8/17/22	12/31/2	1/1/23- 4/17/23	After
Excluded Aug 2022	**Audi** (Q4 e-tron, Q8 e-tron); **BMW** (530e PHEV, i4, i5, iX, X3 PHEV); **Ford** (Fusion PHEV); **Honda** (Clarity PHEV); **Hyundai** (Ioniq 5, Ioniq 6, Kona, Tucson PHEV, Sonata PHEV, Santa Fe PHEV); **Kia** (EV6, Niro, Sorento PHEV, Sportage PHEV); **Lexus** (NX PHEV); **Mercedes-Benz** (EQB, GLE PHEV); **Mitsubishi** (Outlander PHEV); **Nissan** (ARIYA); **Polestar** (Polestar 2); **Porsche** (Taycan); **Subaru** (Solterra); **Toyota** (Prius PHEV, RAV4 PHEV, bZ4X); **Volvo** (C40, XC40, XC60 PHEV, XC90 PHEV)	$3,750–$7,500			
Included Jan 2023	**Chevrolet** (Blazer EV, Bolt, Bolt EUV, Equinox EV); **Tesla** (Model 3, Model Y); **Volvo** (S60 PHEV)			$7,500	
Included After Apr 2023	**Honda** (Prologue); **Jeep** (Wagoneer); **Kia** (EV9); **Tesla** (Model X)				$7,500
Excluded/ reduced Apr 2023	**Ford** (E-Transit, Escape PHEV, Mustang Mach-E); **Jeep** (Grand Cherokee PHEV, Wrangler PHEV); **Rivian** (R1S, R1T)	$3,750–$7,500			$3,750
	Audi (Q5 PHEV); **BMW** (X5 PHEV); **Nissan** (Leaf)	$7,500			
Excluded Jan 2023	**Cadillac** (Lyriq); **Genesis** (G80); **Lincoln** (Corsair); **Lucid** (Air); **Mercedes-Benz** (EQS)	$3,750–$7,500			
Always included	**Chrysler** (Pacifica PHEV); **Ford** (F-150 Lightning); **Volkswagen** (ID.4)	$7,500			
Always excluded	**Alfa-Romeo** (Tonale PHEV); **Dodge** (Hornet); **GMC** (Hummer SUV); **Lexus** (RZ); **Tesla** (Model S); **Volvo** (EX40)				

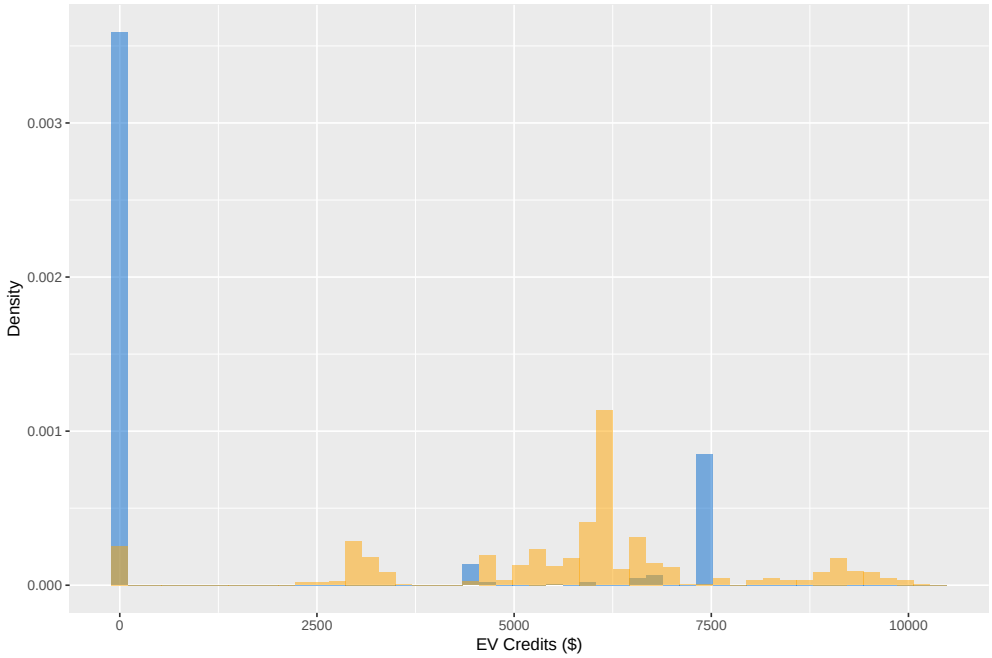
The changes in the total EV credit are stark. First, more EVs were eligible in later periods of the subsidy programs. Second, the IRA EV credit shows greater variation in later periods than in earlier ones. For instance, the comparisons between 2021 and 2023 (Figure A.13) visually show those two points. The blue and orange bars in the Figure represent the densities for 2021 and 2023, respectively. The share without any subsidies dramatically reduced in 2023, and the amounts of EV credits widely vary. The increase in the

Table A.21: State Subsidy Description

Period	Requirements	Amounts
July 1, 2023 − July 1, 2027	At least 5 kwh battery capacity Base price $< \$50,000$	$\$3,000$

share of subsidized vehicles is driven by the change in that the most popular model, Tesla vehicles, were subsidized in 2023, as shown in Table A.22. Table A.22 presents the sold numbers in Maryland state, list price, total EV credits, and batteries (kWh) for the top 10 popular vehicle models in 2021 and 2023.

Figure A.13: Total EV Credit Variations (2021 and 2023)



Notes: The densities of total EV credit, federal plus state subsidies, in each vehicle model are depicted. The blue and orange bars in the Figure represent the densities for 2021 and 2023, respectively.

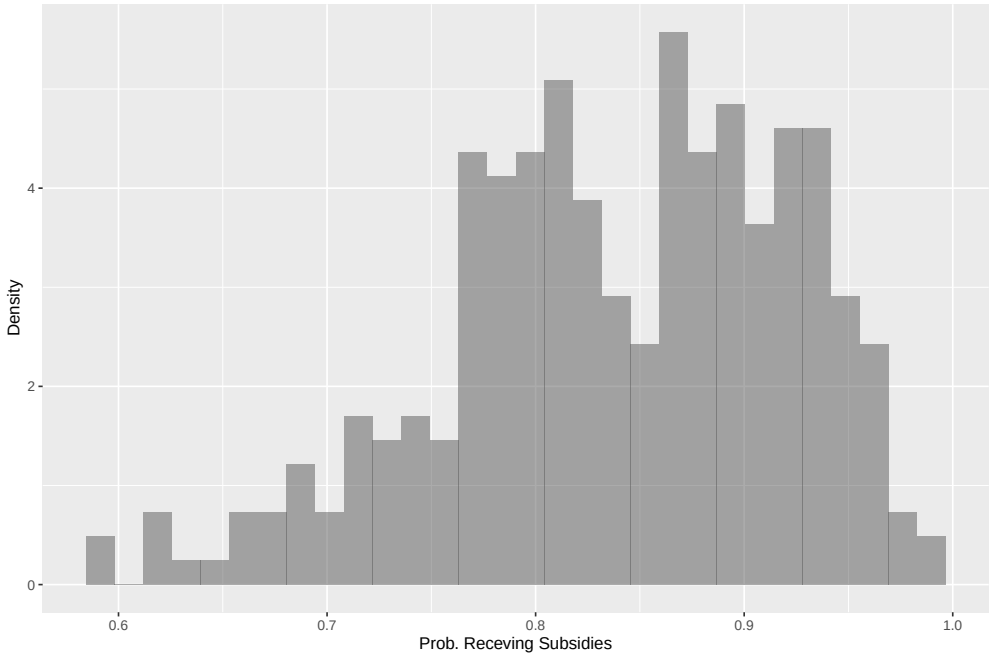
Table A.22: Price and EV Credits for Top 10 Share Vehicles in 2021 and 2023

Year	Maker	Fuel	Model	Counts	MSRP	EV Credit	Battery (kwh)
2021	Tesla	E	Model Y	1125	54323	0	70.00
2021	Tesla	E	Model 3	1121	51657	0	62.25
2021	Hyundai	E	Kona	224	41663	7500	64.00
2021	Toyota	P	RAV4 Prime	126	40012	7500	18.10
2021	Chrysler	P	Pacifica	109	48274	7500	16.00
2021	Toyota	P	Prius Prime	88	30740	4502	8.80
2021	Tesla	E	Model S	70	107276	0	100.00
2021	Polestar	E	Polestar 2	42	59900	7500	78.00
2021	Ford	P	Escape	40	35925	6843	14.40
2021	Mitsubishi	P	Outlander	29	38762	6587	13.80
2023	Tesla	E	Model Y	5922	50740	5991	67.50
2023	Tesla	E	Model 3	3058	48490	7677	70.50
2023	Jeep	P	Grand Cherokee	627	69280	3188	17.30
2023	Chrysler	P	Pacifica	618	55745	5934	16.00
2023	Jeep	P	Wrangler	416	58715	3593	17.00
2023	Hyundai	E	Kona	308	37467	1922	64.00
2023	Mitsubishi	P	Outlander	206	44315	1297	20.00
2023	Chevrolet	E	Bolt EUV	121	30050	7063	65.00
2023	Hyundai	P	Tuscon	99	41130	3000	13.80
2023	Hyundai	P	Santa Fe	77	45040	3000	13.80

Notes: "E" and "P" in the fuel column mean EV and PHEV, respectively. Counts show the new vehicle numbers in the entire state. EV Credit is a weighted average because it varies over time.

Household income and family type create cross-sectional variation in subsidized vehicle list prices. First, I compute the household median income for all clustered markets using ACS census-tract-level household income data. Given the calculated household median income and the assumption of the same income distribution at each family type level across markets within the state and within the same year, I generate the income distribution for each market in each year. Then, using the household income and family type eligibility in Table A.19, I generate the probability of receiving IRA EV credits in each market and year. Figure A.14 shows the probability distribution of receiving IRA EV credits across markets in 2023. For subsidized BEV/PHEV, I deduce the probability-weighted subsidy amounts from the list price in each market and year.

Figure A.14: Probability of Receiving IRA across Markets in 2023



E.3 Future Fuel Costs

This section describes the future fuel cost variables included in the demand estimation. The future fuel cost is specified as present discounted value of annual fuel costs:

$$G_j = \mathbb{E}\left[\sum_{s=0}^{S}(1+r)^{-s} me_j g_s\right],$$

where S is the vehicle lifetime, r is a discount rate, m is an annual mileage, e_j is a vehicle j's fuel consumption, and g_s is a fuel price at the purchase period. I exploit the common values in the literature for a vehicle lifetime ($S = 15$) and a discount rate ($r = 0.06$), and use the Highway Statistics from the Federal Highway Administration for an average vehicle mileage.

Table A.23 reports the average operating fuel costs by fuel type. BEVs have substantially lower operating costs than ICE vehicles, with average future fuel costs approximately half as large as those of comparable gasoline vehicles. This pattern is consistent with commonly reported comparisons of EV and gasoline operating costs.

Table A.23: Average Future Fuel Costs by Fuel Types

Fuel Type	Future Fuel Costs ($)
ICE	19450
HV	11564
PHEV	15379
BEV	8342

E.4 Construction of the Charging-Availability Instrument

This appendix describes the shift-share instrument for public charging availability used in the demand estimation. The instrument interacts with aggregate EV stock with predetermined market exposure to locations suitable for public charger installation. The shift is aggregate EV stock, which captures statewide growth in EV adoption and the corresponding expansion of charging demand. The exposure measure is based on market-level land-use categories and facility types where chargers are commonly installed.

Appendix Table A.17 summarizes the facility types associated with observed public charger locations. Utility-owned chargers account for approximately 20% of public chargers during the sample period, as shown in Figure 1. Other common facility types include offices, shopping centers and restaurants, federal, state, and municipal government facilities, parking lots and garages, and retail or grocery stores. These patterns suggest that public charger deployment is concentrated in locations that attract commuting, shopping, public-service, and other destination-based trips.

The mapping between charger facility types and land-use categories shows that most chargers are located in commercial, industrial, and institutional areas, as reported in Appendix Table A.18. Appendix Figure A.12 illustrates this relationship by overlaying charger locations on land-use classifications in Maryland. Red, blue, green, and black points represent chargers located in commercial, residential, public, and utility-owned locations, respectively. Red, blue, and green polygons represent commercial, residential, and institutional

land-use areas. Uncolored areas correspond to other land uses, such as agriculture, forest, water, and protected areas.

The identifying logic is that markets with more land and facilities suitable for charging-station installation are more exposed to aggregate EV adoption growth and therefore experience larger changes in charging availability. The instrument does not use contemporaneous charger locations to define exposure; instead, it relies on predetermined or slow-moving market characteristics that affect the feasibility of charger deployment.

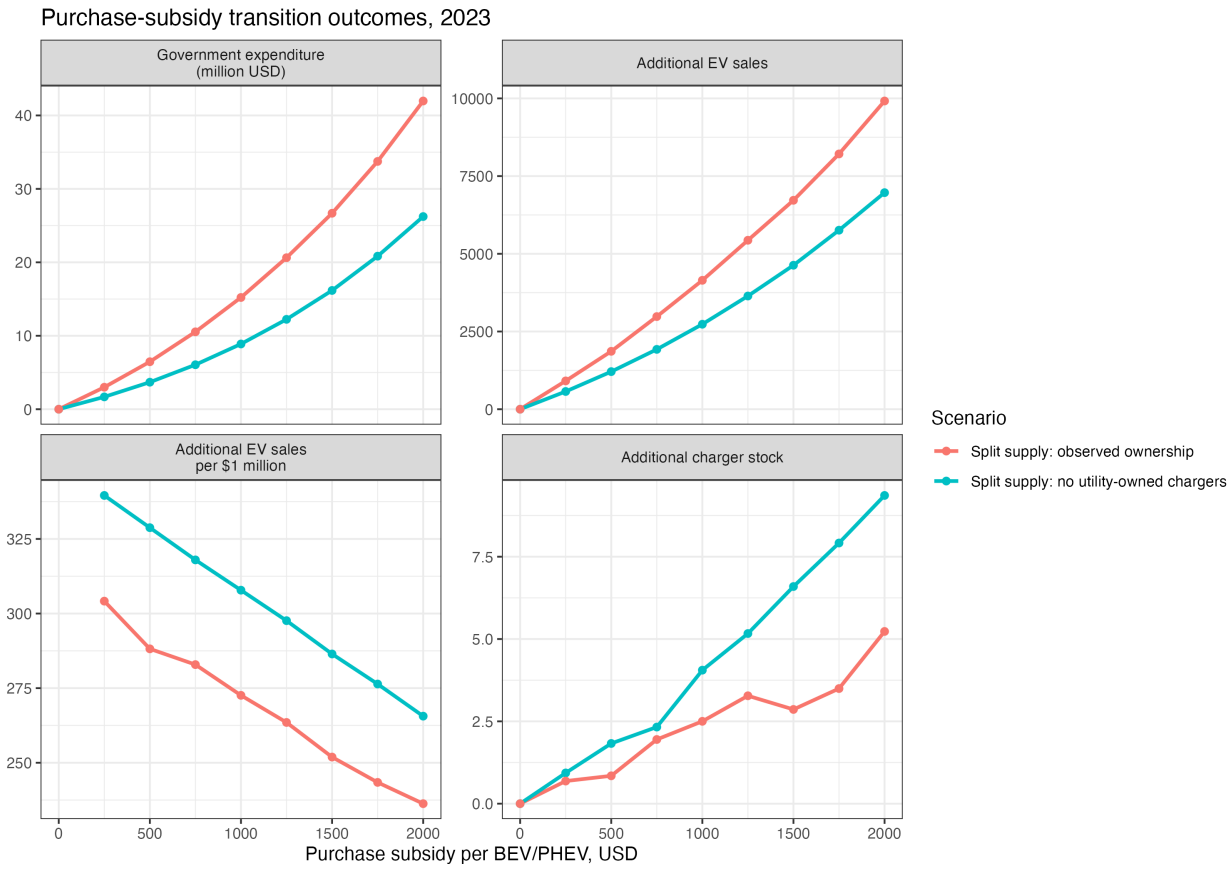
F Appendix for Counterfactual Simulations

Table A.24: Counterfactual Effects of an EV Purchase Subsidy (Percentage to the Market)

	Supply model		Diff.
Outcome	Pooled	Split	Diff
Δ BEV/PHEV sales	39.63%	36.50%	-3.13
	(5.43%)	(4.05%)	(2.5)
Δ BEV sales	36.81%	34.15%	-2.66
	(4.36%)	(3.41%)	(1.98)
Δ PHEV sales	55.06%	49.57%	-5.49
	(13.05%)	(9.30%)	(5.62)
Δ Total vehicle sales	0.16%	0.15%	-0.02
	(0.03%)	(0.03%)	(0.01)
Δ Total chargers	0.32%	0.11%	-0.20
	(0.16%)	(0.04%)	(0.16)

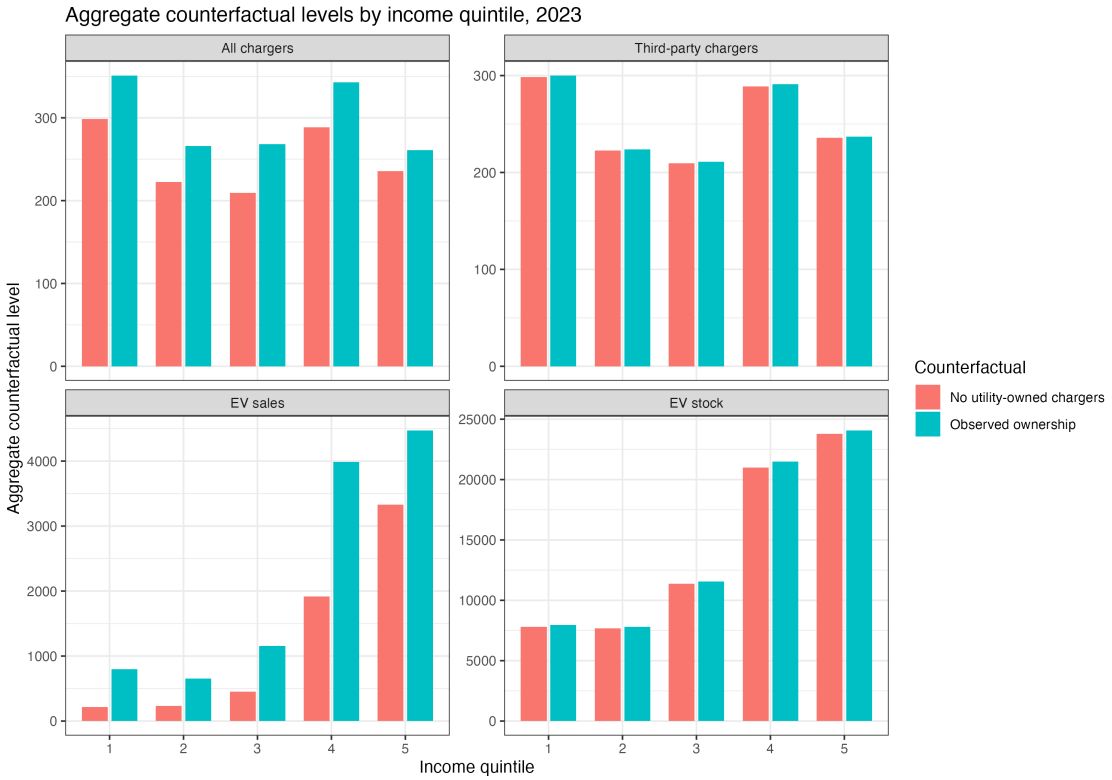
Notes: The table reports effects of a $1,000 BEV/PHEV purchase subsidy relative to the corresponding no-subsidy baseline within each supply model at the percentage to the baseline level. The sample is restricted to observed-ownership scenarios. The parenthesis shows the bootstrapped standard errors.

Figure A.15: Purchase-Subsidy Effects with and without Utility-Owned Chargers



Notes: The figure plots four equilibrium outcomes by BEV/PHEV purchase-subsidy level: government subsidy expenditure, additional EV sales, additional EV sales per $1 million of subsidy expenditure, and additional charger stock. The red series corresponds to the observed-ownership scenario, and the blue series corresponds to the no-utility-owned-charger scenario. Subsidies increase in $250 increments up to $2,000.

Figure A.16: Level Comparisons of Removing Utility-Owned Chargers by Income Quintile



Notes: The bar plots compare the levels in four outcomes after removing utility-owned chargers: all public chargers, third-party chargers, EV sales, and EV stock. Outcomes are aggregated by income quintile.