ERCOT EV ALLOCATION STUDY

METHODOLOGY FOR DETERMINING EV LOAD IMPACT AT THE SUBSTATION LEVEL

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Executive Summary

Introduction

- The Brattle Group was retained by ERCOT to create and carry out a repeatable process for forecasting electric vehicle load impacts at the substation level out to 2029, for use in their System Planning Assessment.
- ERCOT requested that, in addition to presenting load impact findings in report format, Brattle provide an interactive "tool" that could be used to easily replicate and update the analysis in the future.
- Brattle has conducted a thorough review of ERCOT's existing electric vehicle assumptions, allocated those forecasts to ERCOT substations using Texas-specific and publicly accessible data, and generated representative 24-hour load profiles at each substation for 8 years, 4 seasons, and 2 day-types.
- Brattle has also corresponded at length with several of ERCOT's Transmission and Distribution Service Providers to gain perspective on their plans for EV adoption in the next 8 years.
- This report details Brattle's approach in carrying out the analysis from start to finish, and includes a summary of the final results.
- The Excel-based interactive tool will be passed off to members of ERCOT's Transmission Planning team at the conclusion of the engagement.

Methodology Overview

Brattle applied a 3-step approach to its analysis of EV load impacts at the ERCOT substation-level:

1 Establish Light, Medium, and Heavy-Duty EV Adoption Forecasts for 2022-2029

- Update and improve upon ERCOT's existing adoption assumption for LDV penetration.
- Build out adoption forecast for a more granular list of Medium and Heavy-Duty (MHDV) EVs

2 Allocate Adoption Forecasts to ERCOT Substations

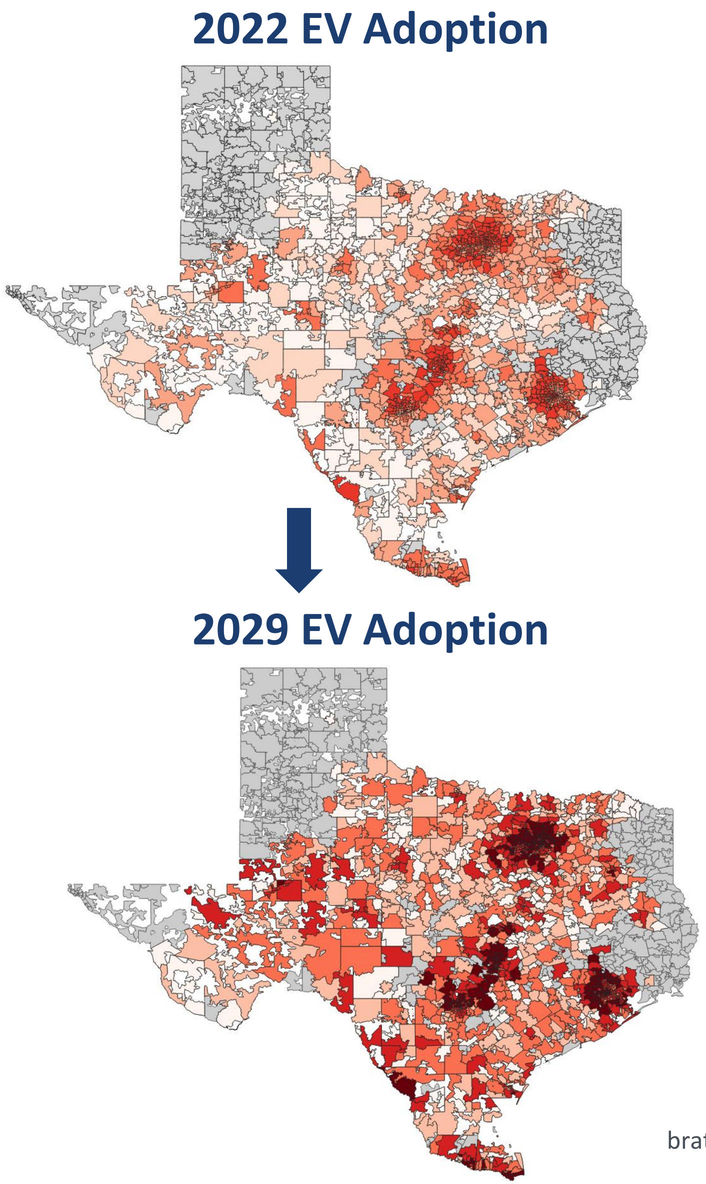
- Separate methodologies for LDV and MHDV allocation
- Vehicles first allocated to the zip-codes and then to the substations using data from ERCOT, the Census, and Moody's.

3 Calculate Load Impacts at the Substation-Level

- Calculate 64 representative load profiles for each substation, showing load throughout 4 seasons, 2 day types, and 8 years.
- Develop interactive tool that generates profiles for each substation and can be easily updated in the future.

Summary of Results

- **System-wide adoption and load impacts:**
  - ~770,000 LDVs and ~225,000 MHDVs are projected to be electric by 2029 in ERCOT's service territory, representing about **4%** of LDV stock and **6%** of MHDV stock, or **4%** of all vehicles on the road in TX. Approximately **96%** of electrified LDVs and **93%** of MHDVs across TX will be registered in ERCOT's service territory.
  - The total EV charging load in 2029 is approximately **6.7 TWh**, adding **1.36%** of load to ERCOT's electric load forecast in 2029, up from **0.14%** in 2022 .
- **Allocation to substations:**
  - LDV allocation is developed based on metrics capturing future propensity for adoption. Allocation is concentrated primarily in urban and suburban zip codes surrounding major cities such as Austin, Houston, DFW, San Antonio.
  - MHDV allocation is established by multiple bottom-up models for key use cases. Delivery vehicles and regional and long haul trucks add load to substations in the city outskirts and major highways. Buses, pickup trucks, and certain regional trucks will increase load in urban and suburban areas.



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Forecasting Approach

- The results of this analysis rely on carefully developed EV adoption forecasts
- After benchmarking ERCOT's existing adoption assumption against other jurisdictions around the U.S., Brattle determined that a "refresh" of ERCOT's existing assumption was needed to ensure that the resulting allocations to substations were accurate
- Brattle performed a thorough review of ERCOT's existing stock turnover models, which forecast Light-Duty (LDV) and Medium-Heavy-Duty (MHDV) Electric Vehicle adoption out to 2037
  - Brattle identified several areas for potential improvement of ERCOT's LDV stock turnover model and applied these to arrive at a "refreshed" LDV adoption forecast.
  - Improvements to the MHDV model were more substantial, as Brattle developed forecasts for more granular MHDV use-cases

LDV Stock Turnover Methodology Adjustments

LDV Stock = **Existing LDV Registrations** + **New Sales** - **Retirements**

Existing LDV Registrations

ERCOT Approach:
- Actual historical sales data from 2015-2021 sourced from ERCOT.

Brattle Approach:
- No change.

New Sales

ERCOT Approach:
- Apply market share forecast from *2020 BNEF Electric Vehicle Outlook* to a static estimate of Texas-level vehicle sales.
- Apply 4-year delay to resulting forecast to match actual sales trajectory.

Brattle Approach:
- Apply market share forecast from *2020 BNEF Electric Vehicle Outlook* to Passenger Sales Forecast from *2022 EIA Annual Energy Outlook, Table 38* (scaled down to TX-level).
- Apply 3-year delay to match actual sales trajectory.

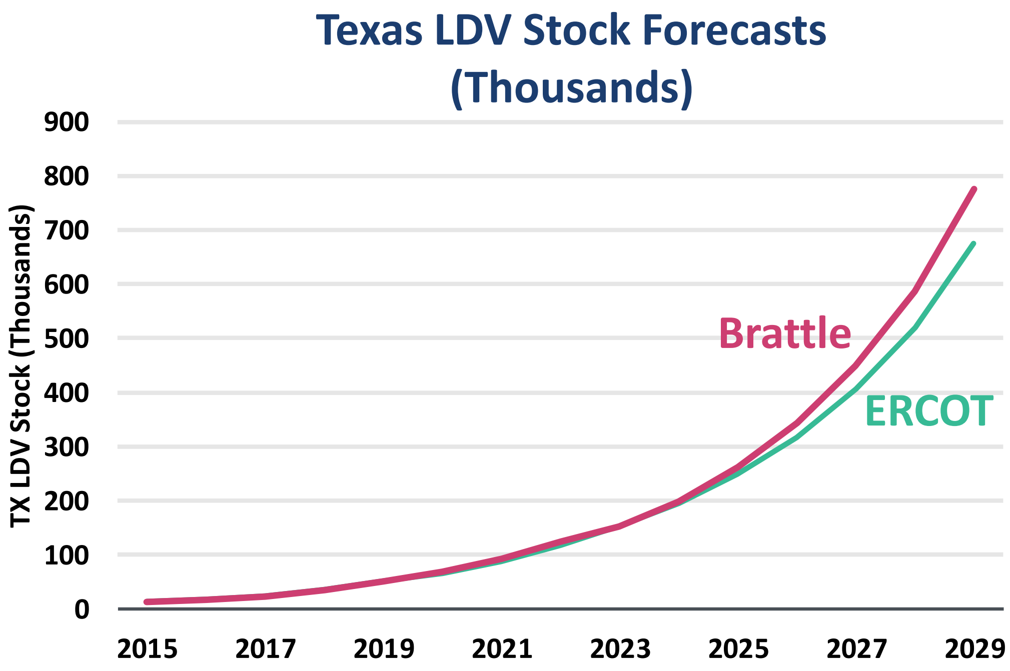
Retirements

ERCOT Approach:
- Assume 50% of vehicles sold in a given year retire after 10 years.

Brattle Approach:
- Apply annual retirement analysis using Survivability Data from National Highway Traffic Safety Administration.

Updated LDV Stock Forecast

- **Brattle's updated LDV stock forecast exceeds ERCOT's original assumption by about 100,000 vehicles in 2029 for several reasons:**
  - The AEO forecast of total LDVs sold in 2029 is higher than ERCOT's static assumption.
  - Brattle's light truck sales forecast exceeds ERCOT's.
  - These increases are somewhat offset by Brattle's retirement approach, which results in more vehicles retired by 2029 than in ERCOT's forecast, but the resulting stock forecast is still higher.



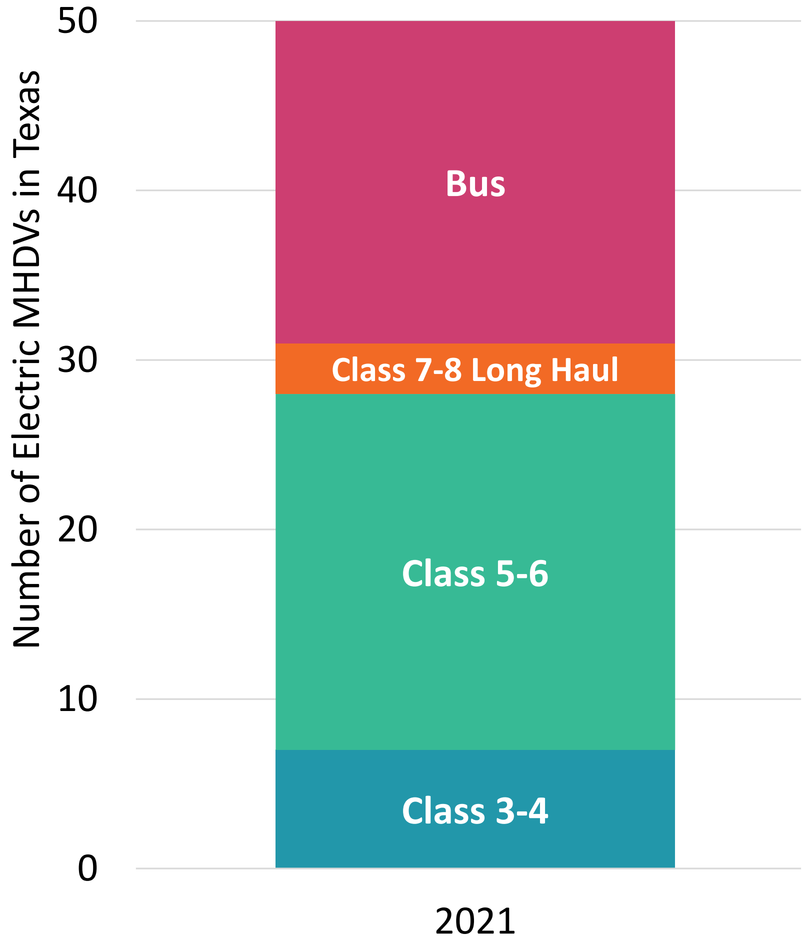
LDV Stock Turnover Model Input Updates

Assumption	ERCOT Approach	Brattle Update	Source for Update
Total US Vehicle Sales (Forecast)	17,865,773 (static value).	Time series personal vehicle sales data (includes passenger car and light truck sales).	EIA AEO 2022.
Light Truck Sales	5-year delay of BNEF market share data applied to static light truck sales value.	Split AEO forecast into passenger car and light truck sales using ERCOT assumed breakdown.	EIA AEO 2022 and ERCOT assumptions.
Retirements	50% of LDVs sold in year 0 retire in year 10.	In-house retirement analysis.	NHTSA Survivability Data
Market Share Data	BNEF 2017	BNEF 2021	Bloomberg New Energy Finance Electric Vehicle Outlook
Texas Share of National Vehicle Registrations	8.9%	9.4%	National Automobile Dealers Association (NADA) 2021 Report
Passenger Cars Sales Share of Total Vehicles (%)	55%	58%	Texas DMV Vehicle Titles and Registration Data
Light Truck Sales Share of Total Vehicles (%)	23%	24%	Texas DMV Vehicle Titles and Registration Data

Electric MHDV Adoption is Currently Low in Texas

MHDV electric vehicle adoption is currently much less advanced than LDV adoption.

- There were only 50 registered electric MHDVs in 2021.
- In class 2B, the largest MHDV class in our study, no EVs were registered in 2021.
- This poses a challenge for forecasting the adoption and allocation of vehicles
  - There is no historical adoption trend.
  - There is a high level of uncertainty about the development of these advanced technologies.



Medium and Heavy Duty Vehicles are Segmented into Classes

We group MHDVs into 5 classes, which largely align with the Federal Highway Administration's gross vehicle weight ratings (FHWA GVWR) and ERCOT's vehicle class segmentation.

- These classes were selected to align with the classes used for EV sales adoption forecasts in Brattle's Delphi Survey.
- We add additional granularity to ERCOT's breakdown by adding more categories to their Local HD class.
- We consider buses and school buses separately from the weight classes.

Weight less than or equal to (lbs)	**6,000**	**8,500**	**10,000**	**14,000**	**16,000**	**19,500**	**26,000**	**33,000**	**60,000**	**over 60,000**
FHWA GVWR Vehicle	Class 1	Class 2		Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	
ERCOT Vehicle Classes	Light Duty Trucks and Cars			Local HD					Long Distance HD	
Brattle Vehicle Classes			Class 2B	Class 3-4		Class 5-6		Class 7-8 Regional Class 7-8 Long Haul		

Forecasting Electric MHDV Adoption

We implement a stock turnover model to forecast electric MHDV adoption levels in each class.

- In this model, we use initial vehicle numbers sourced from EV Hub for 2021, which are very few.
- We then project vehicles in subsequent years by assuming a certain number of new vehicles enter, based on the assumed initial sales and sales growth rate projection.
- Vehicles are expected to retire after their expected lifetime (10-12 years for MHDVs), but this is longer than the study period from 2022-2029, so the model assumes no electric vehicles retire.
- The share of new vehicles that are EVs is forecasted based on the forecasted EV sales adoption rate.

Electric MHDV Stock	=	Existing Electric MHDV Registrations	+	New Sales	-	Retirements
		Because electric MHDV technology is new, these vehicles are assumed to have age 0 in 2021.		New sales are calculated as forecasted MHDV sales in the class times forecasted EV sales share for the class.		Because vehicle lifetimes are assumed to be longer than the study period (to 2029), retirements are 0.

Forecasting Electric MHDV Adoption: Data

Forecasts are based on data from a Delphi Survey conducted by Brattle in late 2020.

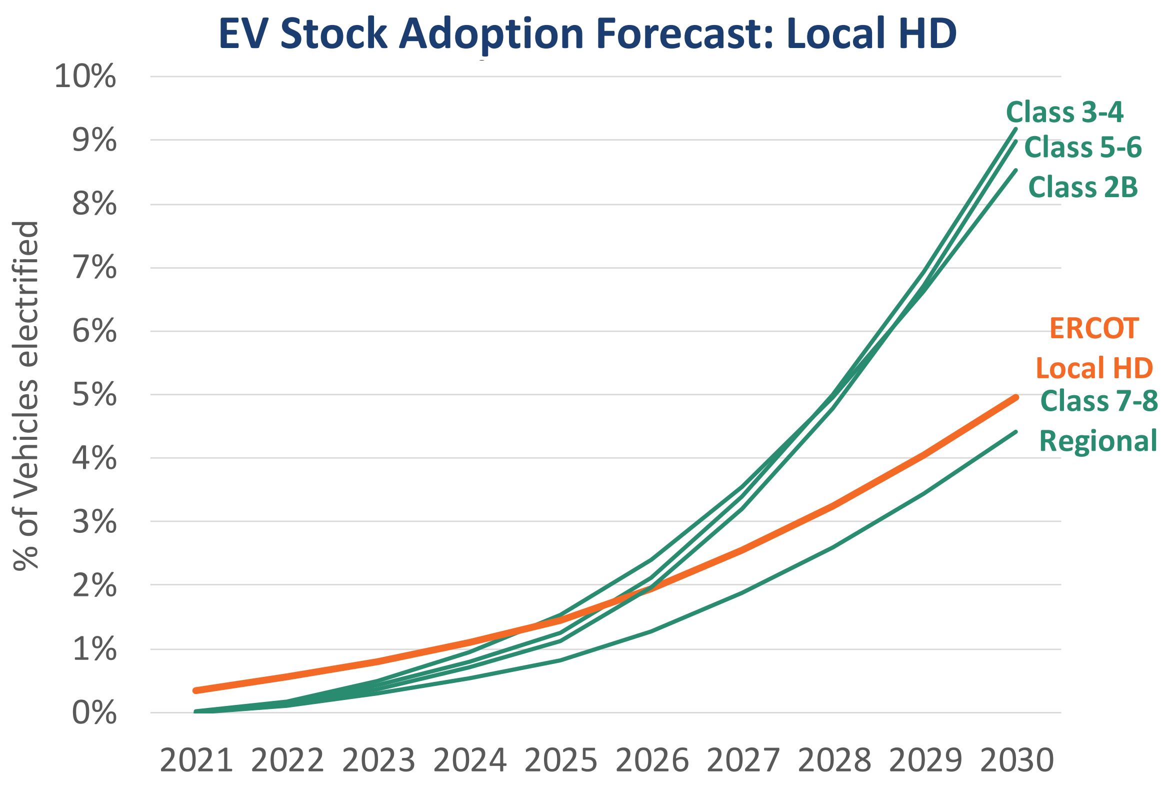
- A panel of experts was asked to predict MHDV sales adoption across classes in 2025, 2030, and 2035. Their responses were then aggregated in to high, base, and low scenarios.
- We use the base forecast for buses, and the low forecast for other vehicle types.
- We benchmark the stock adoption forecasts derived from these sales adoption forecasts through the stock turnover model against ERCOT's assumptions, which are less granular.

	Initial Total Vehicles	Initial Electric Vehicles	Initial Total Vehicle Sales	Vehicles Sales Growth Rate	Vehicle Lifetime	EV Sales Market Share
Class 2B Class 3-4 Class 5-6 Class 7-8 Regional Class 7-8 Long Haul	EV Hub Texas data, 2021	EV Hub Texas data, 2021	EV Hub Texas data, 2019-2021 average	EIA national forecast	10 years	Delphi Low Case
Bus School Bus			FHWA Texas data, 2016-2019 average	FHWA Texas data, 2016-2019 average	12 years	Delphi Base Case

MHDV Stock Adoption Forecast Benchmarking: Local HD

Brattle forecasts are generally more ambitious than ERCOT's Local HD assumptions

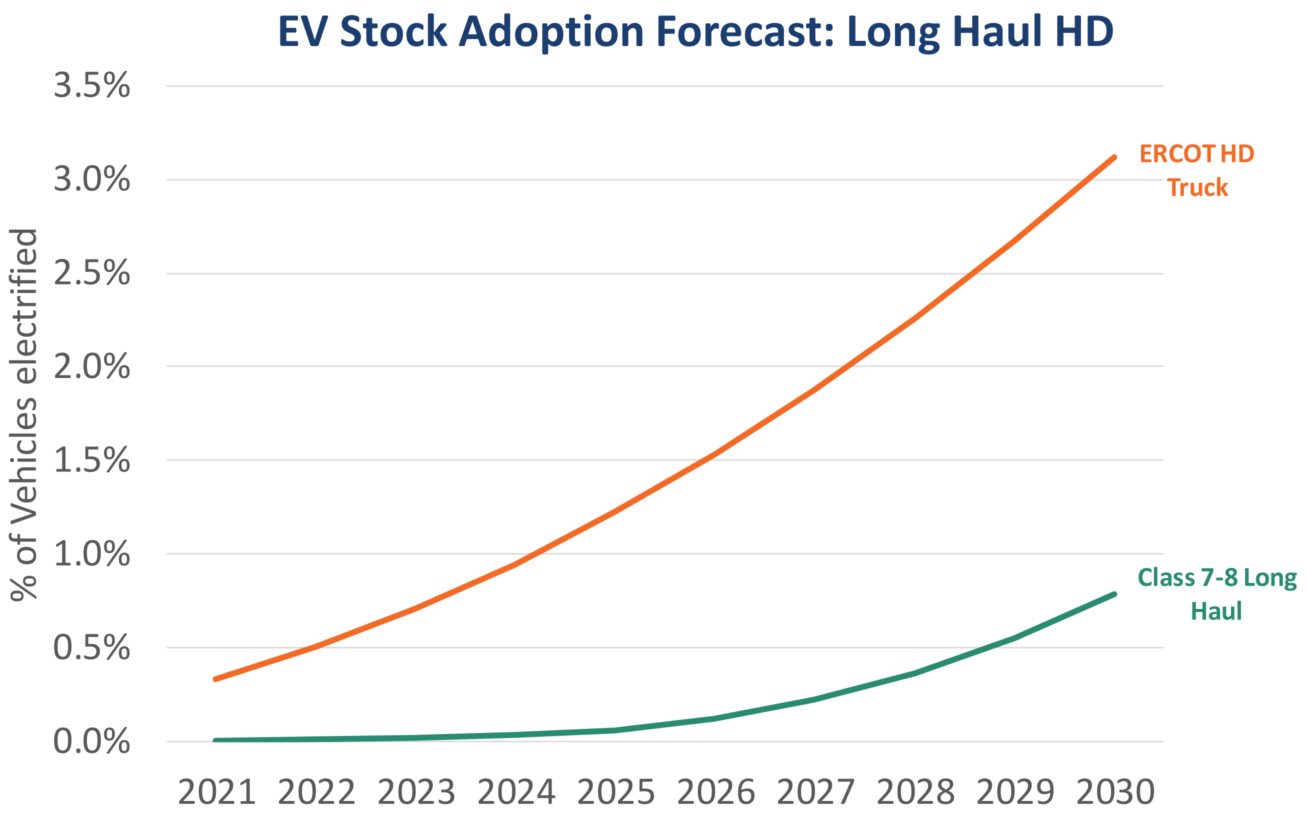
- We benchmark our forecast of MHDV adoption for classes 2B through 7-8 regional against ERCOT's Local HD vehicle assumptions
- Our forecasts were developing using Low Case Delphi survey sales adoption forecasts. The Delphi Base Case forecast would yield about twice as much stock adoption by 2030
- Because our forecast is more recent, it integrates information about historical adoption levels for 2021, and as a result, adoption is lower in our forecast compared to ERCOT's in early years of the period.



MHDV Stock Adoption Forecast: Long Haul HD

Our forecast for long haul heavy duty trucks is less ambitious than ERCOT's

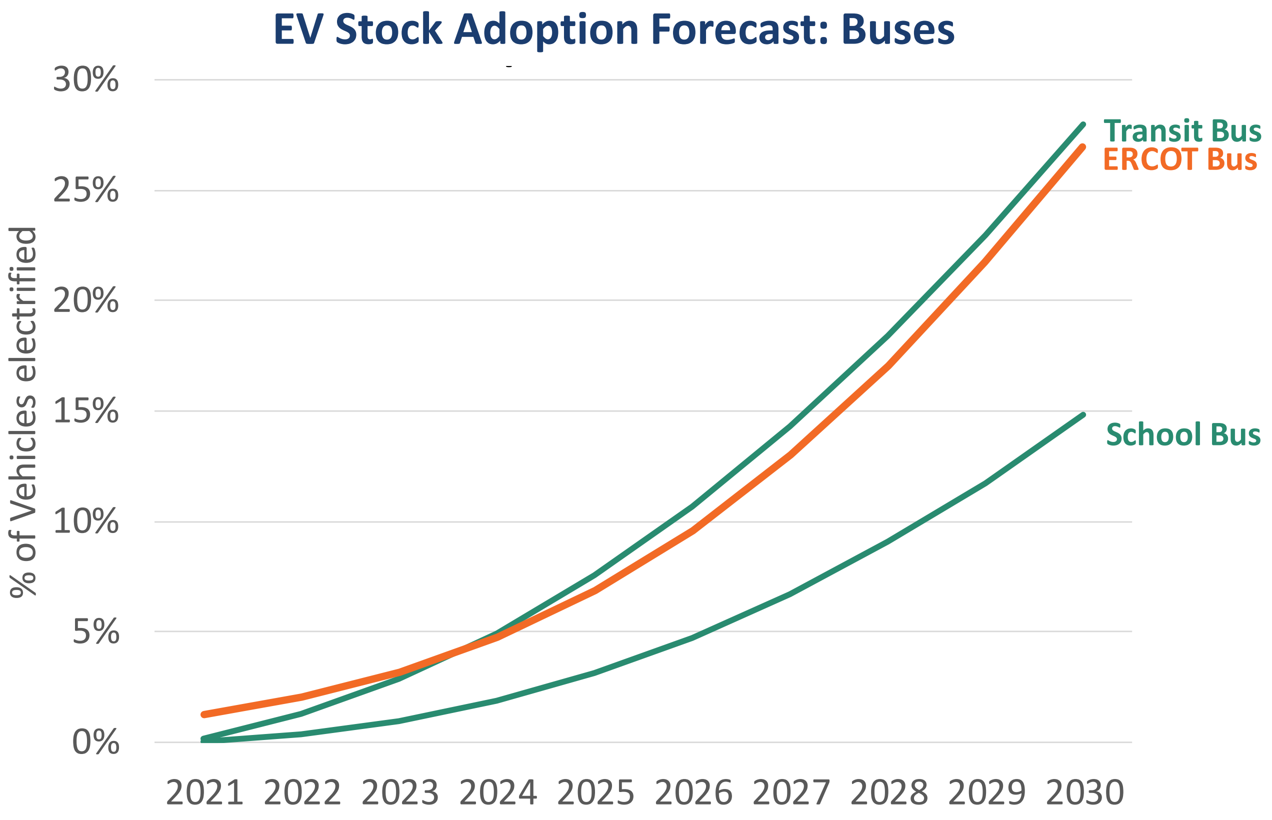
- Our forecasts were developed using Low Case Delphi survey sales adoption forecasts for consistency with the methodology used for lighter duty trucks. The Delphi Base Case forecast would yield about six times as much stock adoption by 2030.
- Because our forecast is more recent, it integrates information about historical adoption levels for 2021, and as a result, adoption is lower in our forecast compared to ERCOT's in early years of the period.



MHDV Stock Adoption Forecast: Buses

Our forecast for transit buses aligns well with ERCOT's.

- Our forecasts were developing using Base Case Delphi survey sales adoption forecasts because of expected policy-driven electric bus adoption.
- School bus adoption is expected to occur at about half the rate of transit buses.



Step 2: Allocating EV Adoption to ERCOT Substations

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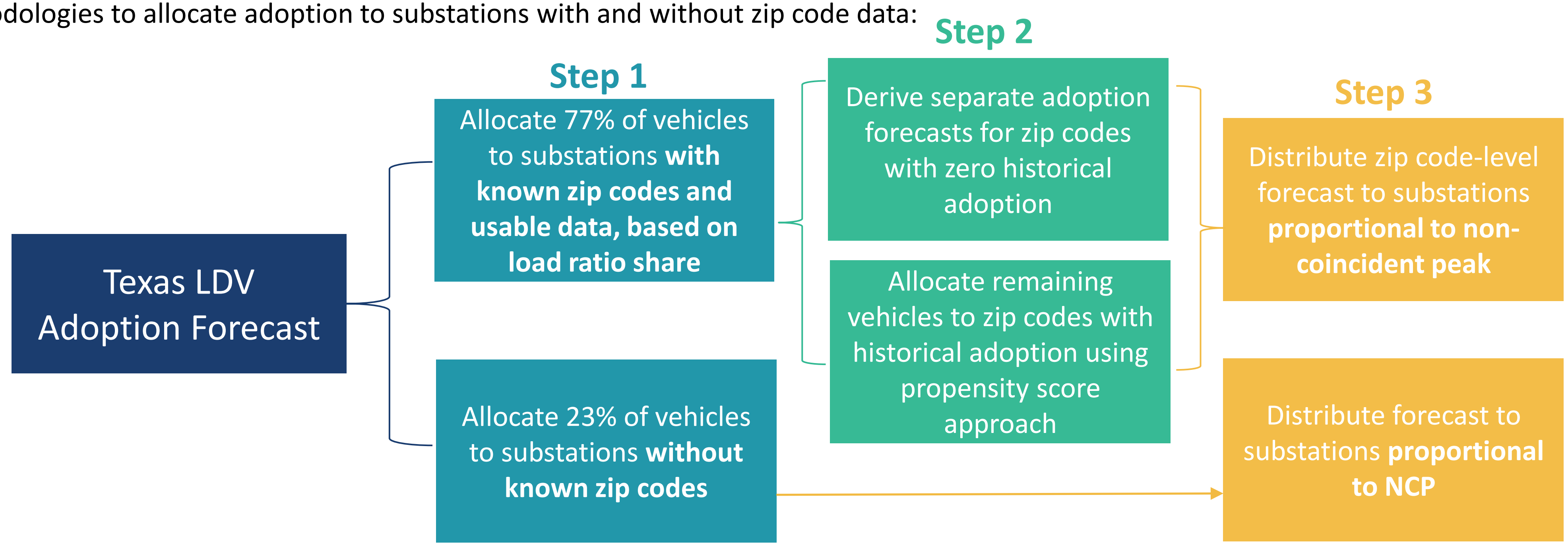
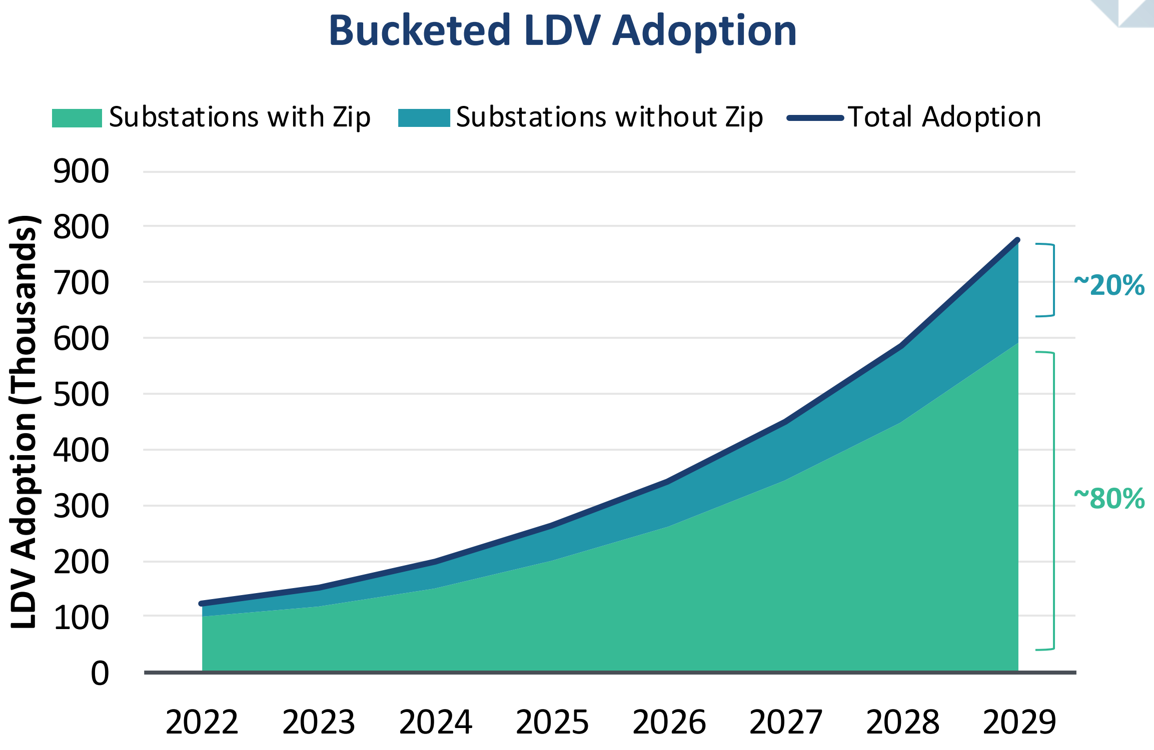
LDV Allocation Methodology

- The objective of this step in the analysis is to allocate our Texas-level LDV forecast to each of ERCOT's substations.
  - We first allocated adoption to all zip codes in ERCOT's service territory, and then further allocated to the substations serving each zip code.
- ERCOT Substations fall into three categories:
  - **ESIID Substations** – Existing ERCOT substations with loads associated with competitive choice areas within ERCOT.
  - **NOIE Substations** – Existing ERCOT substations with loads associated with Non Opt-In entities within ERCOT.
  - **Planned Substations**
- From ERCOT, we received a mapping of ESIID substations to the zip codes they serve, as well as non-coincident peak forecasts (in MW) for each substation. ERCOT does not track the zip codes served by Non Opt-In entities (NOIE) or Planned substations. For this reason, we applied varying methodologies to allocate adoption to substations with and without zip code data:



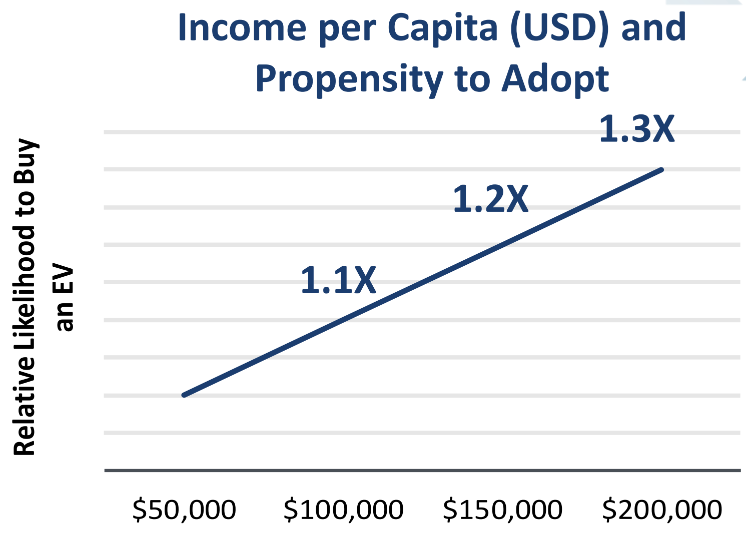
Step 1: Allocate Adoption into "Buckets"

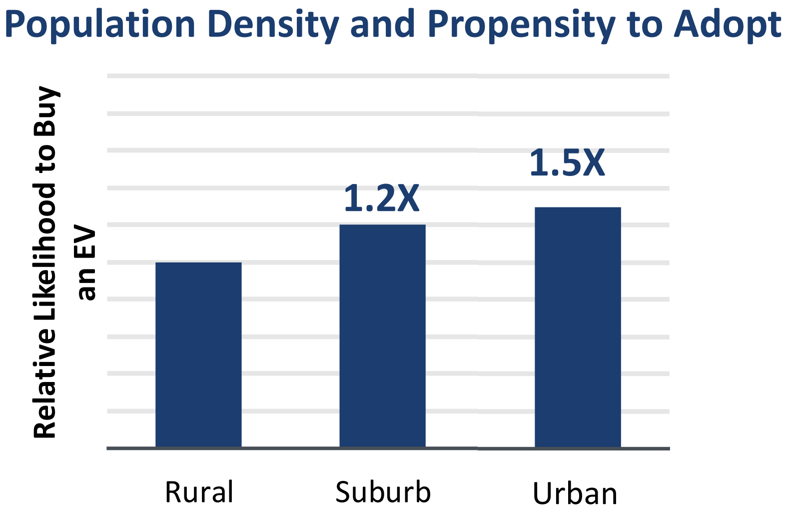
- **In the absence of zip code data for all of ERCOT's substations, it was necessary to separate our LDV adoption forecast into two "buckets," so we could allocate one bucket to substations with zip code data, and one bucket to substations without zip code data.**
- We received zip code data for approximately 75% of ERCOT's substations. These substations account for **80% of the non-coincident peak load** across all ERCOT substations.
  - We therefore allocated 80% of our forecasted LDV adoption to these substations and the **remaining 20%** to the substations without associated zip code data.
  - This process, in effect, left us with two sub-forecasts, one for zip code substations and one for non-zip code substations.



Step 2: Calculate "Propensity Score" for Each TX Zip Code

- **A "Propensity Score" is a metric that calculates the likelihood of EV adoption in a given geographic area. We rely on this metric to determine where LDV adoption is most likely to occur across Texas in each of our forecasted years.**
  - We forecast and assign a "propensity score" of EV adoption to each of the **1,935 active zip codes** in Texas for each year between 2022-2029.
  - Each zip code's "score" is equal to the product of a number of key economic indicators specific to that zip code, as well as adjustments for historical EV adoption levels.
  - Once each zip code is assigned a score, we translate each zip code's propensity score into a share of statewide adoption.
- According to prior Brattle work with EPRI, **income** and **population density** are two key indicators of a given geographic location's propensity to adopt an EV.
  - The study indicates that a **$50,000 increase** in income per capita results in a **10% increase** in the likelihood that an individual will purchase an EV over an internal combustion engine (ICE) vehicle, relative to a $50,000/year baseline. A zip code with an average income per capita of **$100,000/year therefore receives a score of 1.1.**
  - Similarly, a person living in a **suburb** is **20% more likely** to adopt an EV relative to a person living in a rural area.
  - We received county-level forecasts of income and population density from ERCOT, and calculated the year-over-year growth rate of both indicators in each county. We sourced zip-code level income and population density data from the U.S. Census and applied the relevant county-level growth rate to each zip code to forecast our economic data.





Source: McFadden et. al., The Impact of Incentives on Electric Vehicle Adoption: National Average Results. EPRI 2019.

Step 2: Calculate "Propensity Score" for Each TX Zip Code

- Additional propensity score considerations include:
  - **Historical EV Adoption Levels**: We multiply each zip code's propensity score by its LDV adoption level as of April 2022, via data from Atlas EV Hub. This adjustment ensures that our propensity scores are well-aligned with the existing EV market in each zip code.
    - If two zip codes have identical incomes per capita and population densities, but one zip code has far higher historical adoption than the other, we allocate more EVs to the zip code with higher historical adoption.
  - **Total Registered Vehicles:** We multiply each propensity score by the total number of vehicles registered in each zip code.
    - In lieu of sufficient vehicle registration forecasts at the zip code level, we calculate this value by calculating the number of vehicles registered per person in each TX county, then multiplying this value by the population forecast for each zip code.
    - This adjustment allows us to consider the relative prevalence of vehicle ownership across zip codes. If a zip code has high vehicle ownership to begin with (as is the case in suburbs, for example), there is a higher amount of vehicles to be electrified in that zip code.
    - Cities, on the other hand, have very high population densities but often have lower vehicle ownership rates, leading to lower potential for electrification.

Propensity Score = Income per Capita Score × Population Density Score × Historical Adoption × Total Vehicle Registrations

Zip Codes with No Historical EV Adoption

- Approximately **1%** of our LDV vehicle forecast in each year is allocated to zip codes with **0 historical adoption**. These zip codes require a different allocation method, since there is little precedent to be able to predict adoption here.
- A primary limitation of the propensity score approach is that it assigns a score of 0 to the 428 zip codes with zero historical EV adoption.
  - Excluding the historical adjustment from the propensity score equation results in an unrealistic ramp-up rate for zip codes with 0 EVs.
- We derive standardized adoption forecasts for each of these zip codes separately, using the following “rules”:

1. Identify most common level of EV entry using EV Hub historical data

- We find it is most common for 1 EV to enter at a time across one year and ramp up from there

2. Identify a “rule” that will dictate the first year of entry for the first EV

- We find that the majority of zip codes with existing EV adoption in 2022 had propensity scores over 1,000. So we assign each no adoption zip code with a propensity score over 1,000 one EV in 2022. We work backwards from there, zip codes with propensity scores from 500-1000 see adoption starting in 2023, and propensity scores from 0-500 start in 2024.

3. Set a limit on the maximum number of EVs that can be electrified in a given no adoption zip code in 2029

- The system-wide electrification level we forecast with our ERCOT-wide forecast is 5% of total registrations by 2029.
- We cut this in half to account for delayed adoption in these zip codes.

4. Calculate linear growth from the year that the first EV comes online to the maximum adoption level

Example Allocation to Zip Code with Historical Adoption

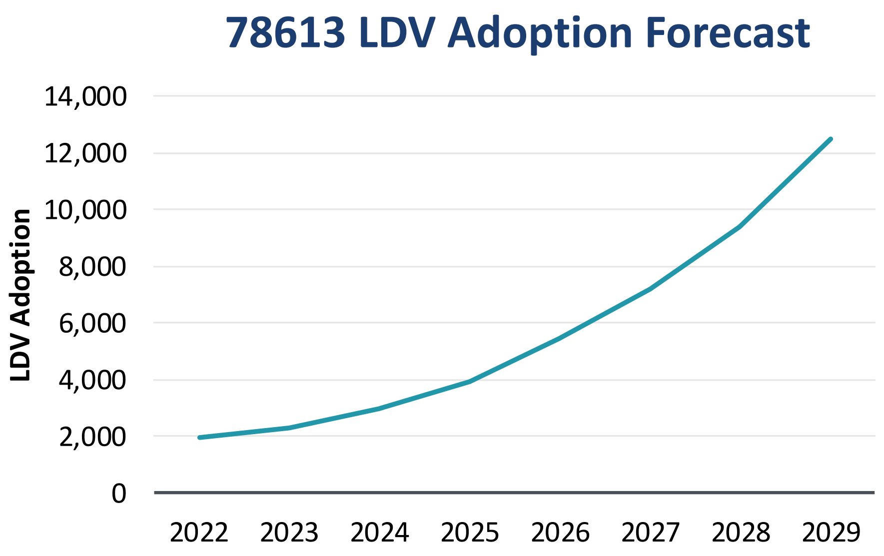
1. **78613** is a zip code located in the Austin metro area, primarily in Williamson County.
   - Population 2022: 65,099 (U.S. Census Bureau).
   - Land Area: 28 sq. miles (U.S. Census Bureau).
   - Population Density: ~2,351 residents per sq. mile ("Urban").
   - Income per capita 2022: $43,375 (U.S. Census Bureau).
   - Approx. Total Registered Vehicles 2022: 30,490.
   - Current LDV Adoption, as of April 2022: 1,130 vehicles (Atlas EV Hub).

2. **2022 Propensity Score = (Income Score = 1) * (Pop. Density Score = 1.5) * 30,940 * 1,130 = 51,681,225**

3. Propensity Score Share of Total = **1.9%** (Share of forecast allocated to this zip code)
   - Calculated by summing propensity scores across all zip codes and calculating each zip code's share of total.

4. Vehicles Allocated in 2022 = **1,947**

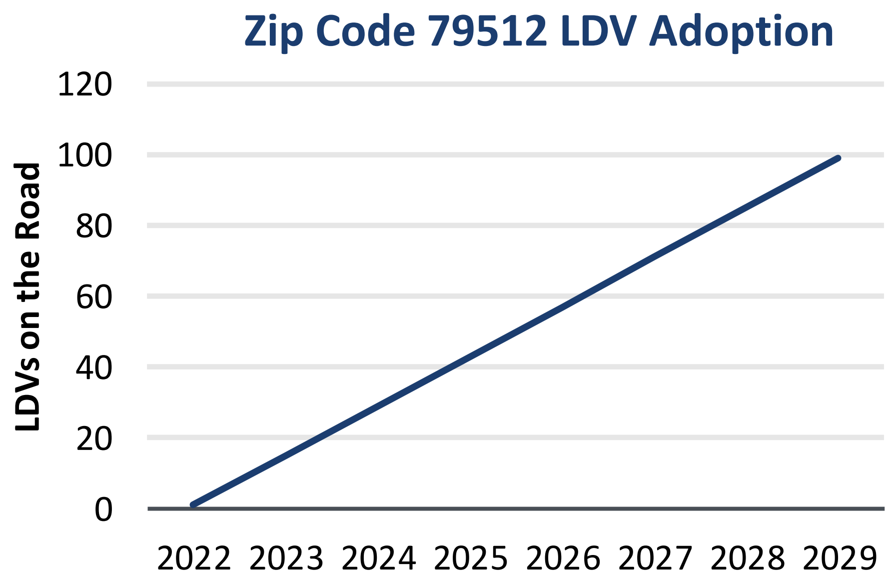
We repeat this process for all Texas zip codes with historical EV adoption.



Note: Adoption ramps up in later years due to increasing forecasted income per capita in this zip code, which increases its Income Score from 1 to 1.05 and boosting its propensity score relative to other zip codes.

Example Allocation to Zip Code without Historical Adoption

- **79512** is a zip code located in the Abilene – Sweetwater metro area, primarily in Mitchell County.
  - Population: 8,197 (U.S. Census Bureau).
  - Land Area: 599 sq. miles (U.S. Census Bureau).
  - Population Density: ~14 residents per sq. mile (“Rural”).
  - Income per capita 2022: $21,658 (U.S. Census Bureau).
  - Approx. Total Registered Vehicles 2022: 4,153.
- 2022 Propensity Score = 1 * 1 * 4,153 = **4,153**
  - Propensity score exceeds 1,000, so we assign 1 EV to be adopted in this zip code by end of 2022.
- Forecasted total registered vehicles in 2029 = **3,980**
- 3,980 * 2.5% EV penetration = **99** EVs adopted by 2029
- We use this approach for all 428 zero-adoption zip codes and add up the total number of EVs forecasted to be adopted in each year.
  - We find that this results in roughly 1% of LDVs being allocated to these zip codes by 2029.



Step 3: Allocate from Zip Codes to Substations

- The objective of this part of the analysis is to allocate LDVs at the **substation level**, one level deeper than the zip code level allocation we just developed.
  - We received from ERCOT a mapping of zip codes and the substations that serve them. In most cases, a given zip code is served by multiple substations, and one substation can serve multiple zip codes.
  - For each zip code, we calculate the aggregate **non-coincident peak load (NCP)** of all substations serving it, and calculate each substation's share of the zip code's total NCP.
  - Here, we use NCP as a proxy for the relative "popularity" of a substation – that is, if one substation's NCP is higher than another, it serves more load than the other substation, and can therefore be expected to serve more load from EVs.
  - For substations that serve multiple zip codes, we assume their NCP is distributed evenly.
    - Example: A substation with an NCP of **15 MW** serving **3 zip codes** would be assumed to contribute **5 MW** to each zip code's "total" NCP.
- For our bucket of substations without associated zip code data, we simply allocate our reduced forecast to all substations in the bucket, proportional to their NCP.

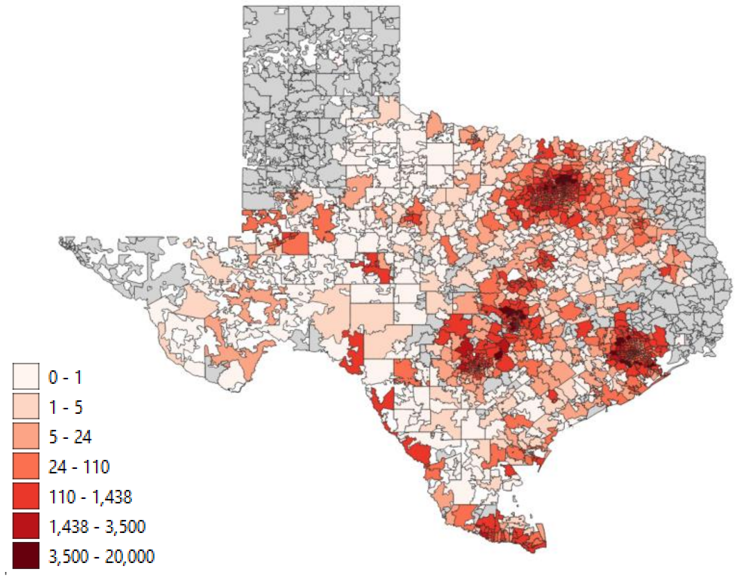
LDV Allocation: Summary of Results

- Our resulting allocation concentrates adoption primarily in urban and suburban zip codes surrounding major cities. The highest adoption zip codes in 2029 all started out with relatively high adoption in 2022.
  - Note that these values do not include additional adoption that may be served by NOIE or Planned substations.
  - Once the TX zip codes are pared down to just ERCOT zip codes, we find that **96%** of LDVs adopted in TX will fall in ERCOT's service territory.

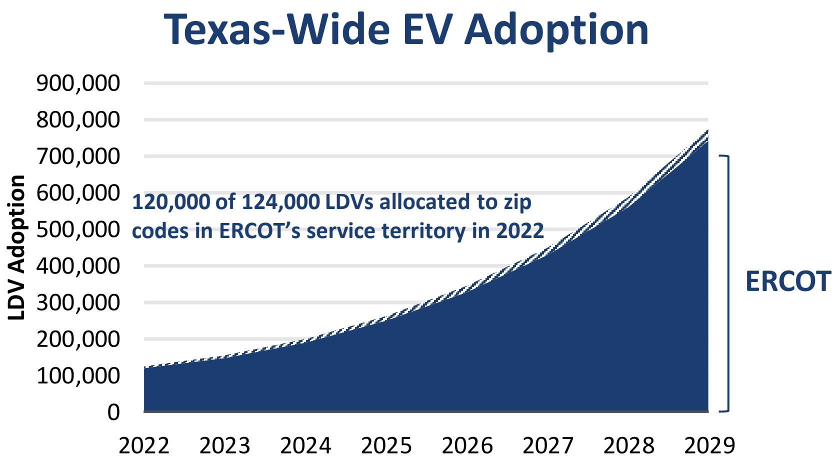
Top 10 Zip Codes by LDV Adoption in 2029

Rank	Zip Code	Current (2022) Adoption Level	2029 Adoption	Nearest City
1	77479	1,401	16,638	Houston
2	78613	1,130	12,501	Austin
3	75034	959	11,305	Dallas
4	75035	1,438	11,084	Dallas
5	77494	1,027	10,083	Houston
6	78660	892	8,740	Austin
7	75070	709	8,589	Dallas
8	78665	642	7,329	Austin
9	77584	589	7,046	Houston
10	78704	1,068	6,712	Austin

2029 LDV Allocation by Zip Code



Note: Figure is only showing adoption allocated to substations with zip code mappings. Adoption allocated to NOIE and Planned substations is not included, which is likely why some zip codes show 0 adoption.



LDV Allocation: Summary of Results

- We find that, in general, ESIID substations are expected to serve the most LDVs.

Top 10 Substations by 2022 Modeled LDV Adoption

Rank	Substation	Substation Type	2022 Adoption	County
1	CARDINAL	NOIE	1,133	Travis
2	SALEM WALK AEN	NOIE	877	Travis
3	CRABB RIVER ROAD	ESIID	860	Fort Bend
4	ROUND ROCK	ESIID	841	Williamson
5	CRAIG RANCH	ESIID	821	Collin
6	PFLUGERVILLE	ESIID	739	Travis
7	OBRIEN	ESIID	713	Fort Bend
8	CUSTER	ESIID	712	Collin
9	BALCONES	ESIID	706	Williamson
10	ROUND ROCK SOUTH	ESIID	687	Williamson

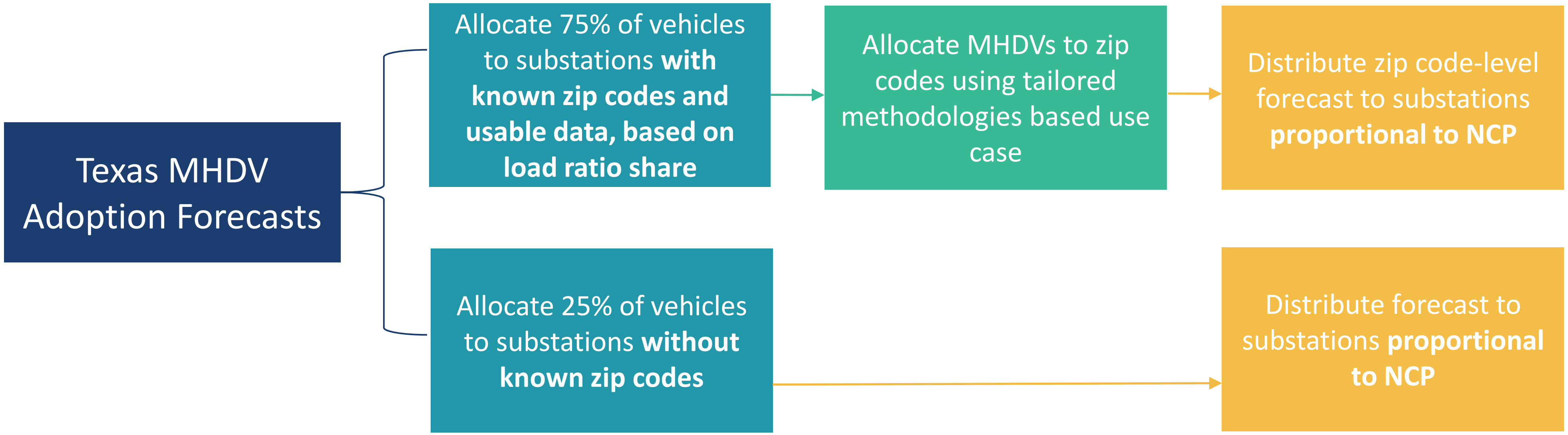
Top 10 Substations by 2029 Modeled LDV Adoption

Rank	Substation	Substation Type	2029 Adoption	County
1	CARDINAL	NOIE	6,712	Travis
2	CRAIG RANCH	ESIID	5,544	Collin
3	SALEM WALK AEN	NOIE	5,205	Travis
4	ROUND ROCK	ESIID	4,404	Williamson
5	OBRIEN	ESIID	4,385	Fort Bend
6	CRABB RIVER ROAD	ESIID	4,361	Fort Bend
7	PFLUGERVILLE	ESIID	4,356	Travis
8	ROUND ROCK SOUTH	ESIID	4,329	Williamson
9	BALCONES	ESIID	4,315	Williamson
10	DEWALT	ESIID	4,219	Fort Bend

MHDV Allocation Methodology: Overview

As in the LDV methodology, we allocate 25% of vehicles directly to the NOIE substations proportionally to the NCP load served by those substations, because ERCOT does not track the zip codes served by these substations.

For the remaining 75% of vehicles, we developed a 4-step methodology to allocate MHDVs to zip codes and then to substations.



MHDV Allocation Methodology: Overview

Step 1: Identify primary use cases within each class

Step 2: Identify proxies for number of vehicles at a given location

Step 3: Allocate system-wide vehicle numbers to locations

Step 4: Assess results and model limitations

We developed a 4-step methodology to allocate MHDVs to substations.

1. In the first step, we identify the primary use cases of each vehicle weight class.
2. Understanding use cases is key to elucidating the economic factors that affect MHDV locations, driving patterns, and electrification likelihood, which is step 2.
3. Once proxies and corresponding data sources are identified, we use them in step 3 to develop quantitative metrics to allocate vehicles in each class to zip codes and then substations.
4. Lastly, we produce data visualizations and assess the results in the context of acknowledged model limitations.

MHDV Allocation Methodology: Step 1

Step 1: Identify primary use cases within each class

Step 2: Identify proxies for number of vehicles at a given location

Step 3: Allocate system-wide vehicle numbers to locations

Step 4: Assess results and model limitations

We identify primary use cases of vehicles by weight class using Texas-specific registration data.

- Segmenting vehicles by use case is essential for understanding the diversity of vehicles represented and the most common types that should be represented in our model.
- Atlas EV Hub data breaks down Texas MHDV registrations by use case, weight class, and fuel type.
  - Due to limited MHDV EV adoption, we identify primary use cases based on current registrations of vehicles across all fuel types.

Composition of Vehicle Classes (I)

By identifying a set of primary use cases in each vehicle class, we group the vehicles into categories that share similar geographic distributions and driving patterns.

- These groups combine vehicle types whose charging locations are expected to depend on common factors and proxies.
- We develop seven "Allocation Methods," A-G, for these key use case groups.

Vehicle Class	# EVs projected by 2029	Primary Use Cases	Share of Vehicles in Class in 2021	Allocation Method
Class 2B	95,592	Pickup Truck	78%	A: Pickup Trucks
		Cargo Van	22%	B: Regional Delivery Vehicles
Class 3-4	40,390	Pickup Truck	83%	A: Pickup Trucks
		Dump Truck	9%	C: Dump Trucks
		Cargo Van	4%	B: Regional Delivery Vehicles
		Straight Truck	4%	B: Regional Delivery Vehicles
Class 5-6	9,643	Straight Truck	57%	B: Regional Delivery Vehicles
		Dump Truck	40%	C: Dump Trucks
		Step Van	4%	B: Regional Delivery Vehicles
Class 7-8 Regional	4,044	Dump Truck	38%	C: Dump Trucks
		Tractor	33%	D: Regional Heavy Duty Trucks
		Straight Truck	29%	D: Regional Heavy Duty Trucks
Class 7-8 Long Haul	841	Tractor	58%	E: Long Haul Heavy Duty Trucks
		Straight Truck	42%	E: Long Haul Heavy Duty Trucks
Buses	3,476	Transit Bus	100%	F: Transit Buses
School Buses	5,609	School Bus	100%	G: School Buses

Composition of Vehicle Classes (II)

The breakdown of vehicle classes also highlights the relative size of each class and primary use cases.

- EV adoption is highly concentrated amongst lighter vehicle classes.
  - Nearly 2/3 of all MHDV EVs expected by 2029 are Class 2B vehicles.
  - Over 75% of these Class 2B vehicles are pickup trucks, primarily for individual rather than commercial use.

Vehicle Class	# EVs projected by 2029	Primary Use Cases	Share of Vehicles in Class in 2021	Allocation Method
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		Straight Truck	42%	E: Long Haul Heavy Duty Trucks
Buses	3,476	Transit Bus	100%	F: Transit Buses
School Buses	5,609	School Bus	100%	G: School Buses

MHDV Allocation Methodology: Step 2

Step 1: Identify primary use cases within each class	Step 2: Identify proxies for number of vehicles at a given location	Step 3: Allocate system-wide vehicle numbers to locations	Step 4: Assess results and model limitations

Two central data limitations drive the challenge of projecting the spatial distribution of future electric MHDVs. We identify data proxies for both of the following parameters to allocate electric MHDVs to substations.

1. **MHDV locations (all fuel types)**
   - Unlike with LDVs, we do not have data on where MHDVs (across all fuel types) are currently registered or located.
2. **Electric MHDV adoption level by location**
   - Historical electric MHDV adoption has been extremely limited.
   - As a result, empirical relationships between economic variables and electric MHDV adoption level have not been established.

Proxies for MHDV Location and EV Adoption

We identified public data sources that inform estimation of:

1. Where MHDVs are located
2. Where EV MHDV adoption is likely

We use these identified proxies to develop a quantitative allocation metric for each method, A-G.

Allocation Method	1. Proxies for Vehicle Location	2. Proxies for EV Adoption Likelihood
A: Pickup Trucks	1. Population Density 2. Number of LDVs	1. Population Density 2. Income
B: Regional Delivery Vehicles	1. Employment in the transportation and warehousing industry	1. Distribution center locations
C: Dump Trucks	1. Employment in mining and construction industries	1. Assumed uniform adoption likelihood across zip codes
D: Regional Heavy Duty Trucks	1. Employment levels in the transportation and warehousing industry 2. Truck traffic on roads 3. Corridor charging station locations	1. Distribution center locations
E: Long Haul Heavy Duty Trucks	1. Truck traffic on major roads 2. Corridor charging station locations	1. Assumed uniform adoption likelihood across zip codes
F: Transit Buses	1. Buses registered at a transportation authority level 2. Population	1. Population density 2. Income
G: School Buses	1. Population of school aged children 2. Population density	1. Population density 2. Income

MHDV Allocation Methodology: Step 3

Step 1: Identify primary use cases within each class	Step 2: Identify proxies for number of vehicles at a given location	Step 3: Allocate system-wide vehicle numbers to locations	Step 4: Assess results and model limitations

Using the identified proxies, we transform the available data to estimate at a zip code level:

1. The current number of vehicles in each class and use case
2. The relative rate of EV adoption

These two metrics are then combined to calculate the number of forecasted EVs.

Lastly, we convert zip code level vehicle projections to substation level projections based on the non-coincident peak load of each substation.

A: Pickup Trucks

Estimate total 2022 pickup trucks (all fuel types) at zip code level

Develop metric to represent rate of EV adoption in category at a zip code level for 2022-2029

Allocate EV forecast to zip codes

Map forecast from zip codes to substations

Estimate the number of pickup trucks per zip code by multiplying (a) and (b):

a. An estimate of pickup truck share of personal vehicles in each zip code
   – Find by joining data on pickup truck ownership relative to other vehicle types based on population density range (Natl. Household Travel Survey) with population density data by zip code (Census)

b. An estimate of total personal vehicles of all types in each zip code
   – Found by mapping data on vehicle registrations per county (TX DOT) to zip code level based on county to zip code relationship (Census)

Estimate relative likelihood to buy an EV conditional on buying a personal vehicle in each zip code for 2022-2029 by multiplying (a) and (b):

a. Income adoption propensity score (mapped from census zip code income data)

b. Population density adoption propensity score (mapped from census zip code population density data)

1. Calculate EV pickup truck adoption propensity scores for 2022-2029 by multiplying total pickup trucks per zip code by relative likelihood to buy an EV, conditional on buying a personal vehicle, in each zip code

2. Allocate Brattle **low case** EV stock adoption forecast in each weight class to zip codes proportional to metric calculated in (1)

Allocate vehicles from zip codes to substations proportionally to substations' non-coincident peak load.

B: Regional Delivery Vehicles

Estimate distribution of 2022 vehicles (all fuel types) at zip code level for each category and class

Develop metric to represent rate of EV adoption in category at a zip code level for 2022-2029

Allocate EV forecast to zip codes

Map forecast from zip codes to substations

Estimate the number of regional delivery vehicles per zip code by considering employment level in the transportation & warehousing industry as a proxy. Calculate:

a. An estimate of transportation & warehousing employment by workplace zip code
   - Found by converting census tract level employment data by industry (Census) to zip codes using US Housing & Urban Dev. geographic mapping data.

b. A sum of Texas-wide employment in transportation & warehousing

c. Divide (a) by (b) to obtain relative estimated shares of 2022 vehicles in each zip code.

Model high vs low EV adoption zip codes based off whether the zip code has a warehouse of a major company expected to be an early EV adopter.

a. Identified warehouse coordinates using Google Maps.

b. Mapped coordinates to zip codes using Census zip code locations.

c. Flagged zip codes with one of the identified warehouses.

1. *Zip codes with warehouses:* Allocate Brattle **base case** EV stock adoption forecast proportionally to the zip code's employment share
2. *Zip codes without warehouses:* Allocate Brattle **low case** EV stock adoption forecast proportionally to the zip code's employment share
3. Rescale forecasts so that they sum to the Brattle low case forecast across all zip codes.

Allocate vehicles from zip codes to substations proportionally to substations' non-coincident peak load.

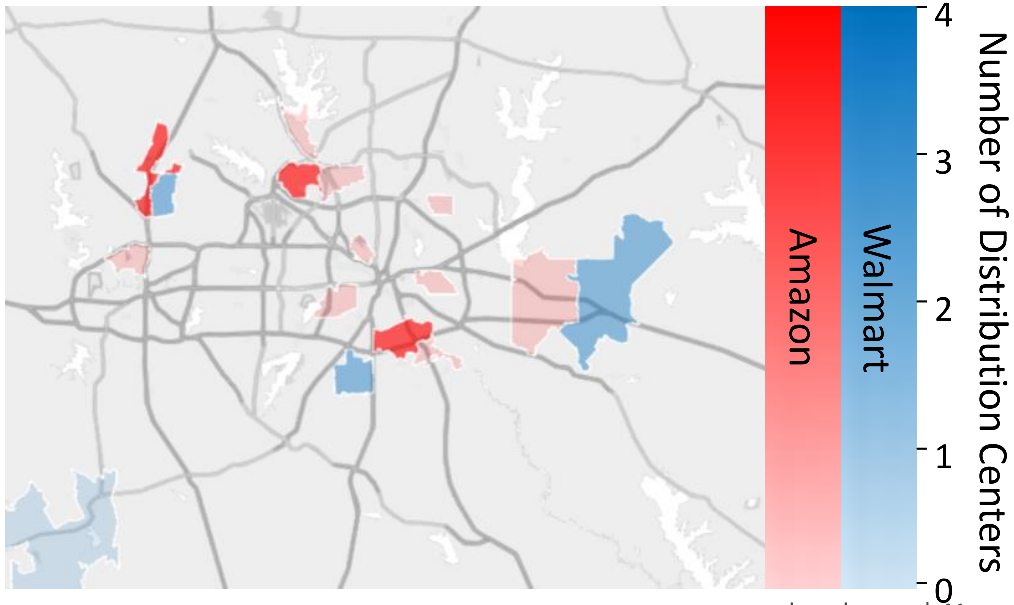
Additional Detail: Distribution Center Approach

- We identified companies in Texas expected to be early or major adopters of EVs based on information from TDSPs and ERCOT.
- For straight truck allocation, we consider the warehouses of Walmart, HEB, Frito Lay, Amazon, UPS, and FedEx. For cargo and step van allocation, we only consider Amazon, UPS, and FedEx locations.

Expected Early or Major Adopters of Electric Trucks by TDSPs

	CPS	Oncor	TNMP	Austin Energy
Consumer Goods	Walmart, AT&T, Verizon, Ikea	Amazon	Amazon	Amazon, Ikea, Staples, J.B. Hunt
Food	Frito Lay, Pepsi	Frito Lay		Frito Lay, Coca Cola, Pepsi, Nestle
Transport	UPS	FedEx, UPS, Ryder		DHL, UPS, FedEx, USPS

Amazon and Walmart Distribution Center Density in DFW Area



C: Dump Trucks

Estimate distribution of 2022 dump trucks (all fuel types) at zip code level for each class → **Develop metric to represent rate of EV adoption at a zip code level for 2022-2029** → **Allocate EV forecast to zip codes** → **Map forecast from zip codes to substations**

Estimate distribution of 2022 dump trucks (all fuel types) at zip code level for each class	Develop metric to represent rate of EV adoption at a zip code level for 2022-2029	Allocate EV forecast to zip codes	Map forecast from zip codes to substations
Estimate the number of dump trucks per zip code by considering employment level in the construction and mining industries as a proxy. Calculate: a. An estimate of construction and mining employment by workplace zip code – Found by converting census tract level employment data by industry (Census) to zip codes using US Housing & Urban Dev. geographic mapping data. b. A sum of Texas-wide employment in construction and mining c. Divide (a) by (b) to obtain relative estimated shares of 2022 dump trucks in each zip code.	Due to lack of information, EV dump truck share is assumed to be the same as the dump truck share of the zip code (i.e. if the dumb truck share of the zip code is 1%, then that zip code is also assigned 1% of the EV dump trucks)	Allocate Brattle **low case** EV stock adoption forecast proportionally to the zip code's employment share.	Allocate vehicles from zip codes to substations proportionally to substations' non-coincident peak load.

E: Long Haul Heavy Duty Trucks

Estimate distribution of 2022 long haul trucks (all fuel types) at zip code level

Estimate the number of long haul trucks per zip code by considering truck highway traffic as a proxy.

- Use GIS to calculate relative truck vehicle miles traveled (VMT) in each zip code based off data on:
  a. Truck VMT on major highway road segments throughout Texas (TX DOT)
  b. Texas zip code locations (Census)

Develop metric to represent rate of EV adoption in category at a zip code level for 2022-2029

Assume EV charging will only occur at or around corridor charging stations.

a. Identified forecasted LDV corridor charging station locations in each year (TX DOT)
   – Assume that MHDV charging stations will be developed at the same rate in the same locations.
b. Mapped coordinates to zip codes using Census zip code locations.
c. Flagged zip codes with at least one charging station in each year.

Allocate EV forecast to zip codes

Allocate Brattle ***low case*** EV stock adoption forecast across zip codes proportionally to truck VMT.

- Exclude zip codes without charging stations forecasted for that year

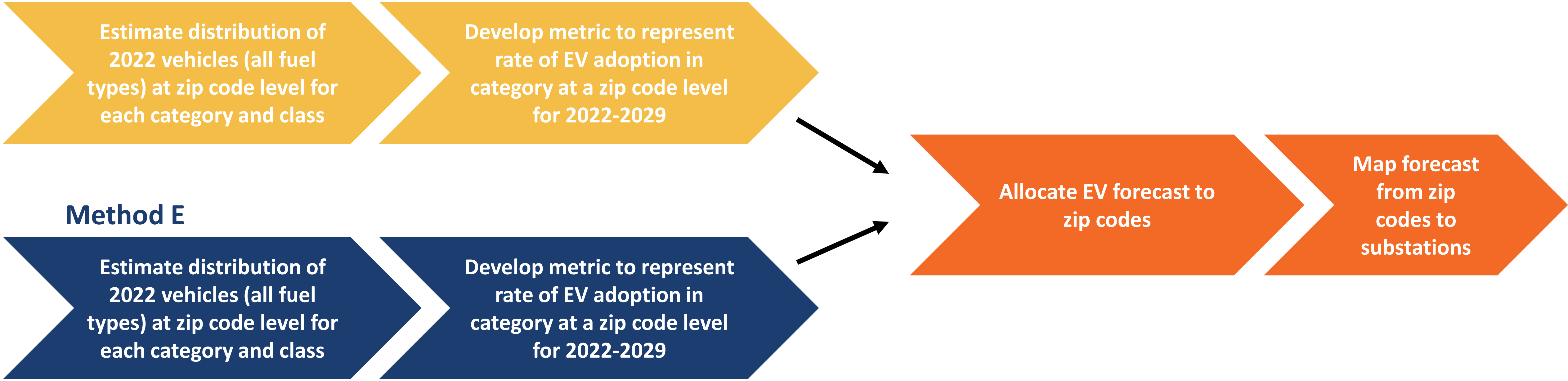
Map forecast from zip codes to substations

Allocate vehicles from zip codes to substations proportionally to substations' non-coincident peak load.

D: Regional Heavy Duty Trucks

- We assume that regional heavy duty trucks will charge either at distribution centers or along major corridors with charging stations.
- Therefore, we take an average of the percentage allocation to zip codes of regional heavy duty trucks according to method B (regional delivery vehicles) and according to method E (long haul heavy duty trucks).

Method B



F: Transit Buses

Estimate total 2022 transit buses (all fuel types) at zip code level

Estimate the number of transit buses per zip code through the following steps:

1. Obtain number of buses by transportation authority (TX DOT)
2. Estimate number of buses by city (urban areas) or county (rural areas) based on transportation authority to county and city mappings (TX DOT)
3. Estimate number of buses by zip code based on county to zip code mappings (US Housing & Urban Dev.) and city to zip code mappings (USZip.com), allocating to zip codes based on the relative numbers of addresses in each zip code (US Housing & Urban Dev.)

Develop metric to represent rate of EV adoption at a zip code level for 2022-2029

Estimate relative likelihood of EV adoption conditional on number of buses in each zip code for 2022-2029 by multiplying (a) and (b):

a. Income adoption propensity score (mapped from census zip code income data)
b. Population density adoption propensity score (mapped from census zip code population density data)

Allocate EV forecast to zip codes

1. Calculate EV transit bus adoption propensity scores for 2022-2029 by multiplying total transit buses per zip code by relative likelihood of EV adoption conditional on number of buses in each zip code
2. Allocate Brattle **base case** EV stock adoption forecast to zip codes proportional to metric calculated in (1)

Map forecast from zip codes to substations

Allocate vehicles from zip codes to substations proportionally to substations' non-coincident peak load.

G: School Buses

Estimate the relative shares of 2022 school buses (all fuel types) between zip codes

Develop metric to represent rate of EV adoption at a zip code level for 2022-2029

Allocate EV forecast to zip codes

Map forecast from zip codes to substations

Use number of children who ride the school bus in a zip code as a proxy for the number of school buses (assume equal school bus to child ratio across zip codes).

Estimate the relative share of school buses per zip code by multiplying (a) and (b):

a. An estimate of school bus ridership rate by zip code
   - Find by joining data on school bus ridership rate among children reported for different population density ranges within Texas (Census) with population density data by zip code (Census)

b. Data on the number of school aged children by zip code (Census)

Estimate relative likelihood of EV adoption conditional on number of school buses in each zip code for 2022-2029 by multiplying (a) and (b):

a. Income adoption propensity score (mapped from census zip code income data)

b. Population density adoption propensity score (mapped from census zip code population density data)

1. Calculate EV transit bus adoption propensity scores for 2022-2029 by multiplying total school buses per zip code by relative likelihood of EV adoption conditional on number of buses in each zip code
2. Allocate Brattle **base case** EV stock adoption forecast to zip codes proportional to metric calculated in (1)

Allocate vehicles from zip codes to substations proportionally to substations' non-coincident peak load.

MHDV Allocation Methodology: Step 4

Step 1:
Identify primary use cases within each class

Step 2:
Identify proxies for number of vehicles at a given location

Step 3:
Allocate system-wide vehicle numbers to locations

Step 4:
Assess results and model limitations

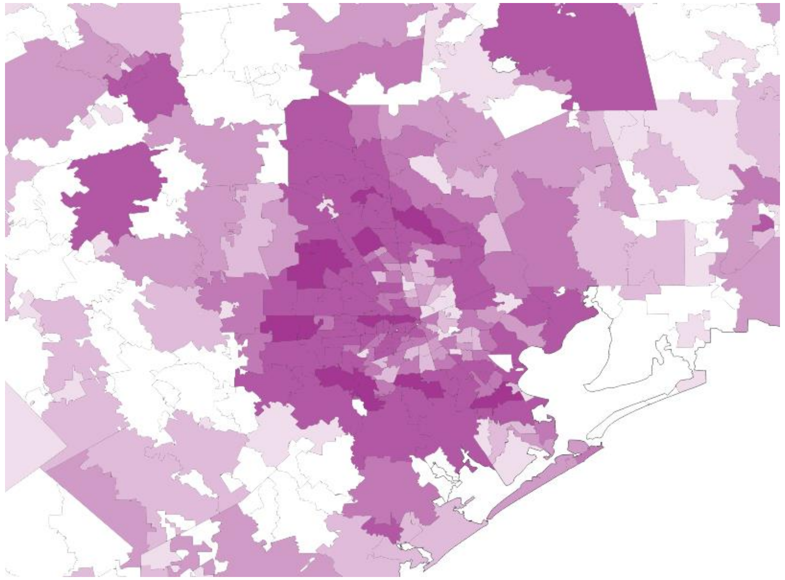
We map the allocations at a zip code level in order to assess the reasonableness of our assumptions and quality of the results.

Results: Pickup Trucks

Pickup truck ownership is more common in rural areas. However, conditional on owning a pickup truck, an individual buying an electric pickup truck is more likely in urban areas. Combining these two factors, we see the highest EV pickup truck adoption in suburban and city outskirt zip codes.

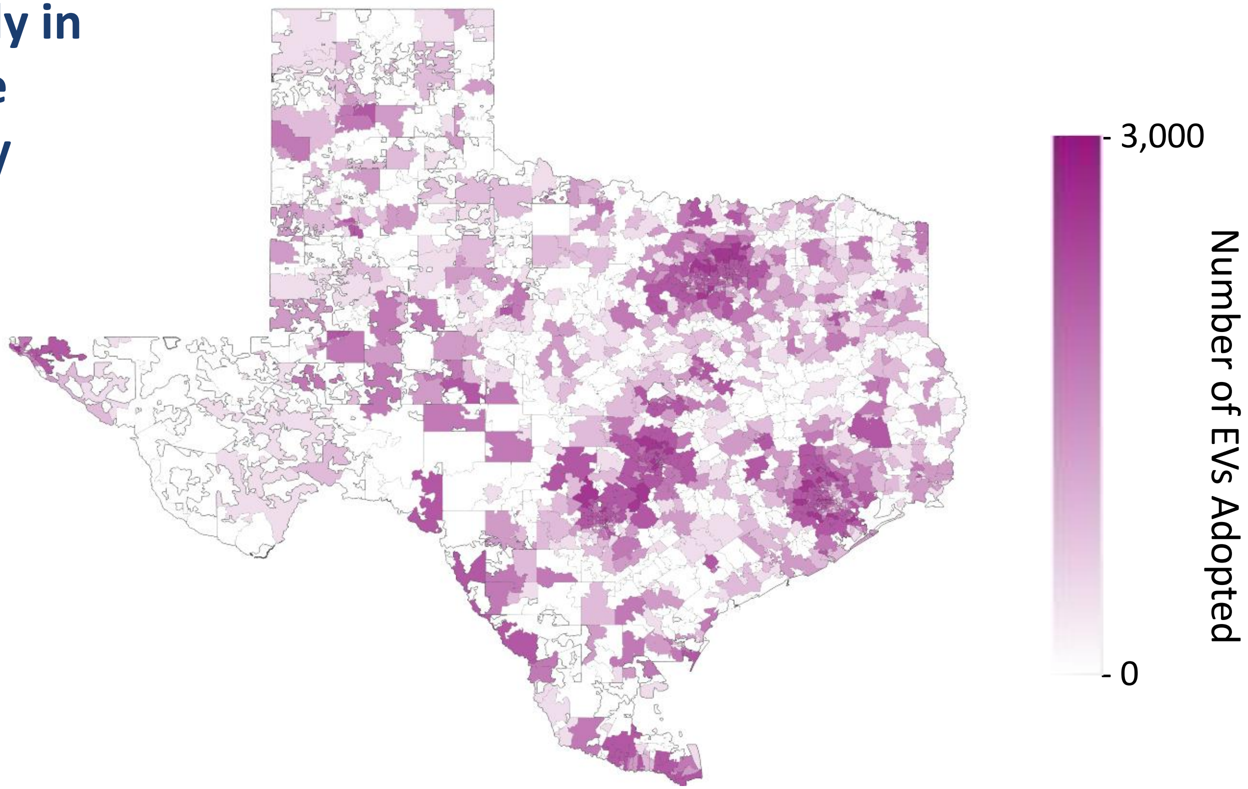
Forecasted EVs by Zip Code Detail: Houston

2029, Pickup Trucks



Texas Forecasted EVs by Zip Code

2029, Pickup Trucks

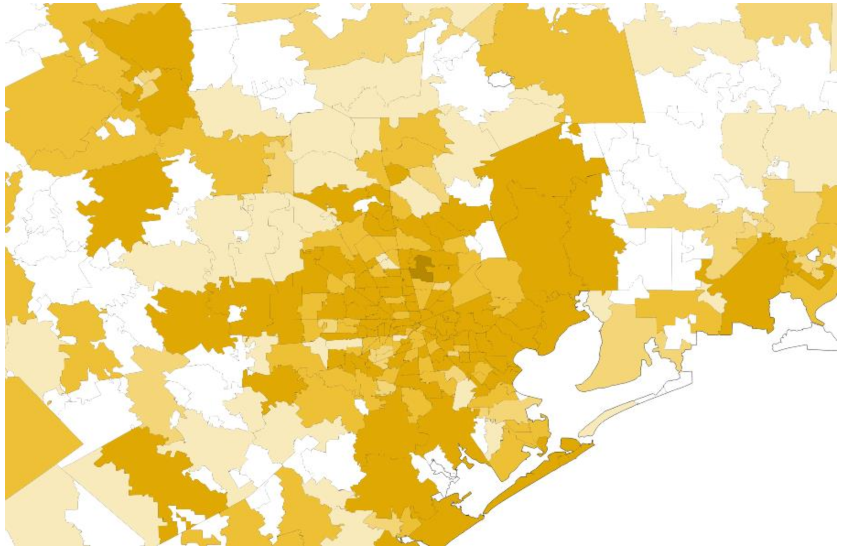


Results: Regional Delivery Vehicles

Electric regional delivery vehicle adoption is projected to occur around city outskirts and along major highways where distribution centers tend to be located.

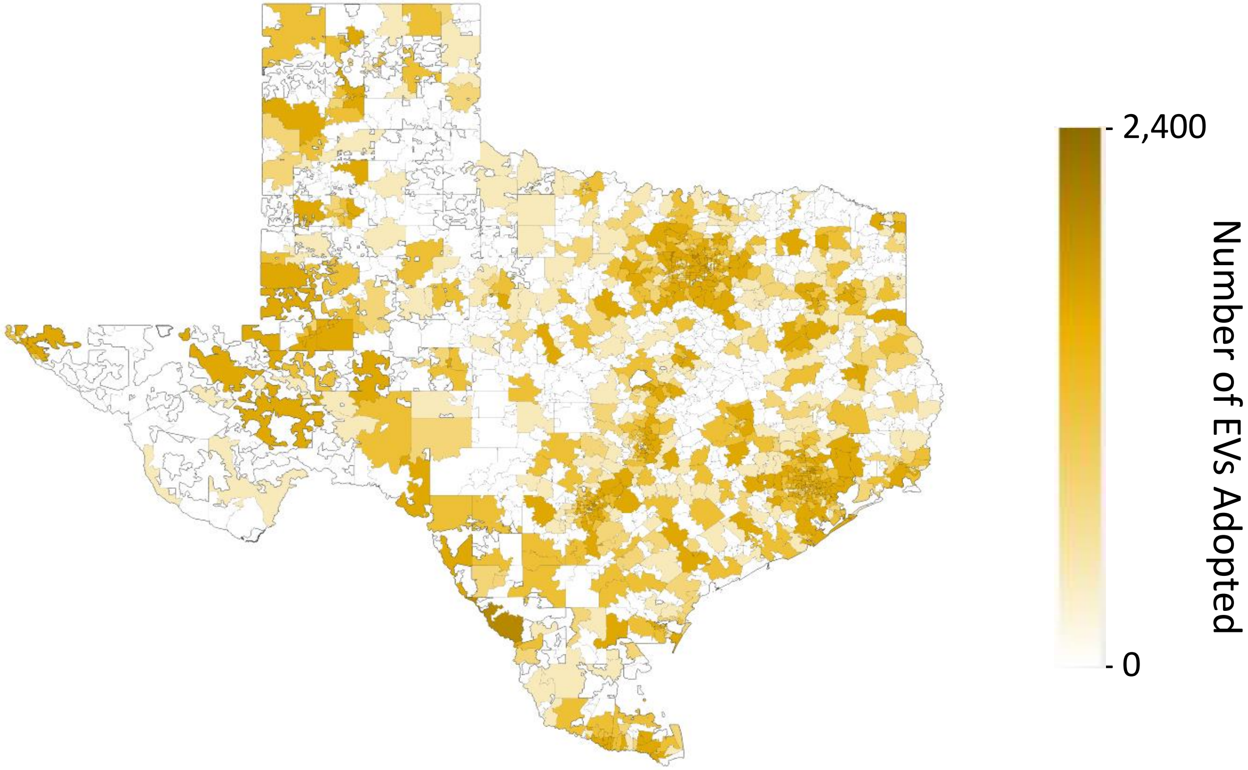
Forecasted EVs by Zip Code Detail: Houston

2029, Regional Delivery Vehicles



Texas Forecasted EVs by Zip Code

2029, Regional Delivery Vehicles

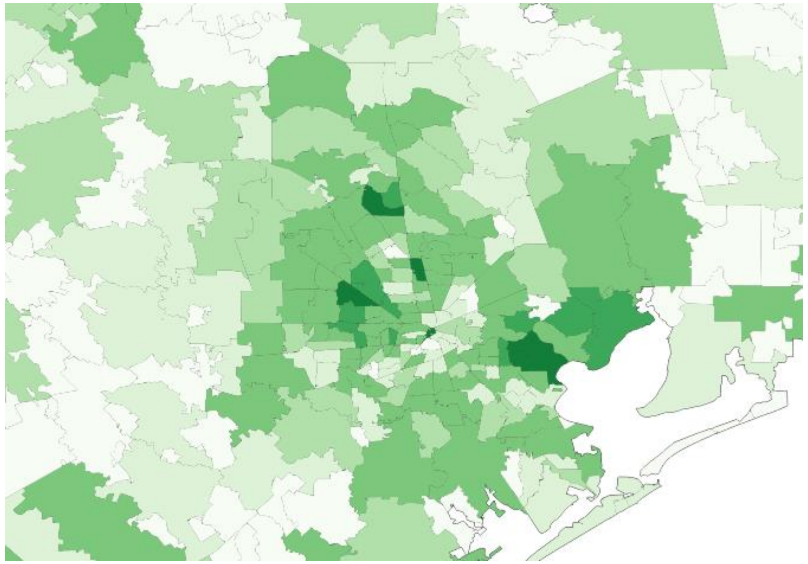


Results: Dump Trucks

Electric dump truck adoption is generally clustered around cities.

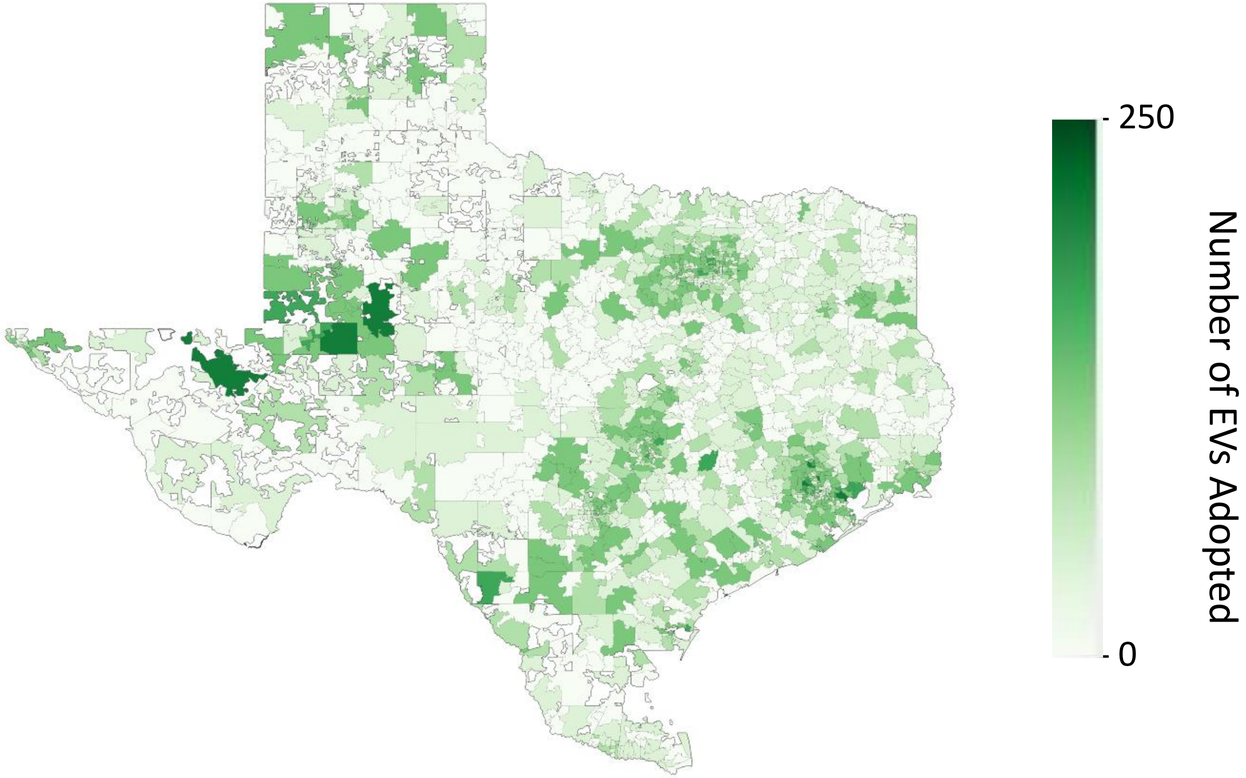
Forecasted EVs by Zip Code Detail: Houston

2029, Dump Trucks



Texas Forecasted EVs by Zip Code

2029, Dump Trucks

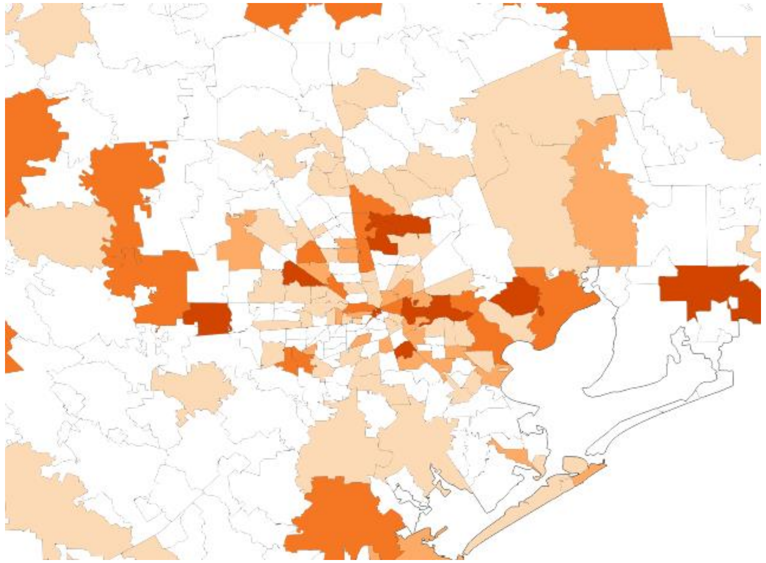


Results: Regional Heavy Duty Trucks

Electric regional trucks are projected to be located around city outskirts and along major highways where distribution centers tend to be located and where more large trucks tend to drive.

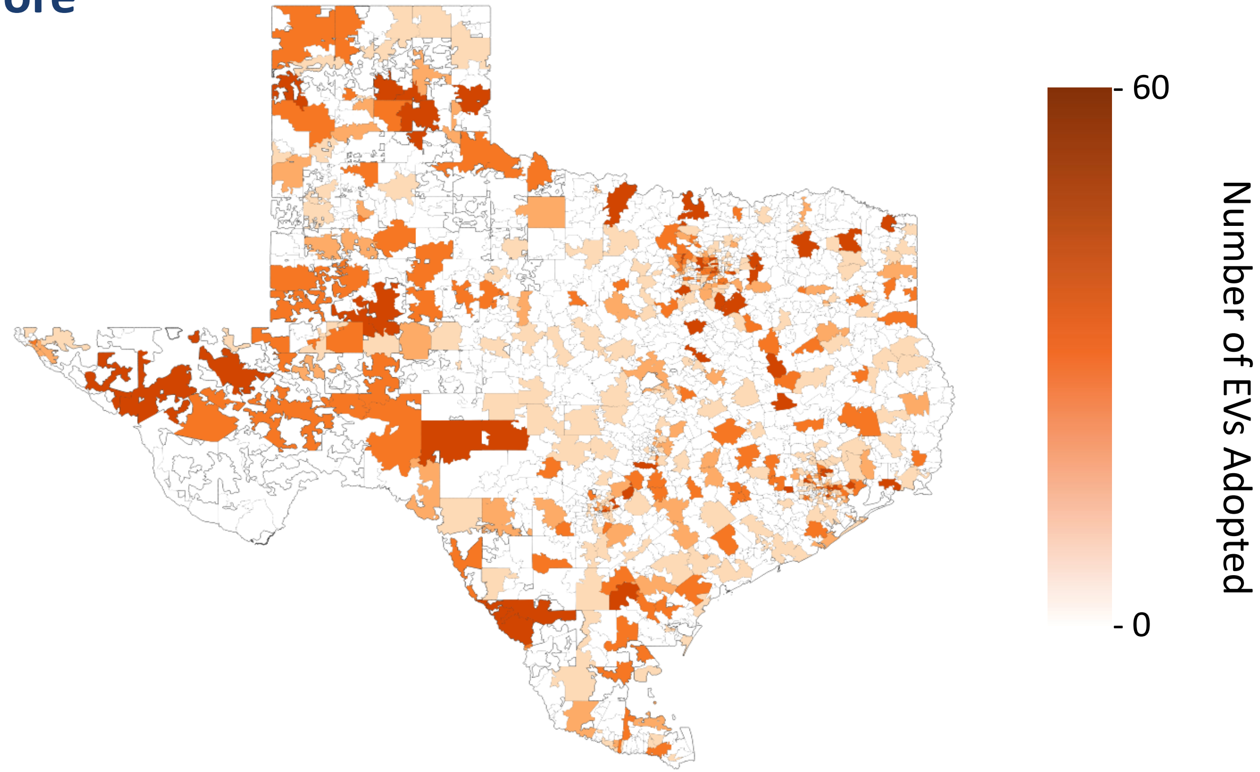
Forecasted EVs by Zip Code Detail: Houston

2029, Regional Heavy Duty Trucks



Texas Forecasted EVs by Zip Code

2029, Regional Heavy Duty Trucks

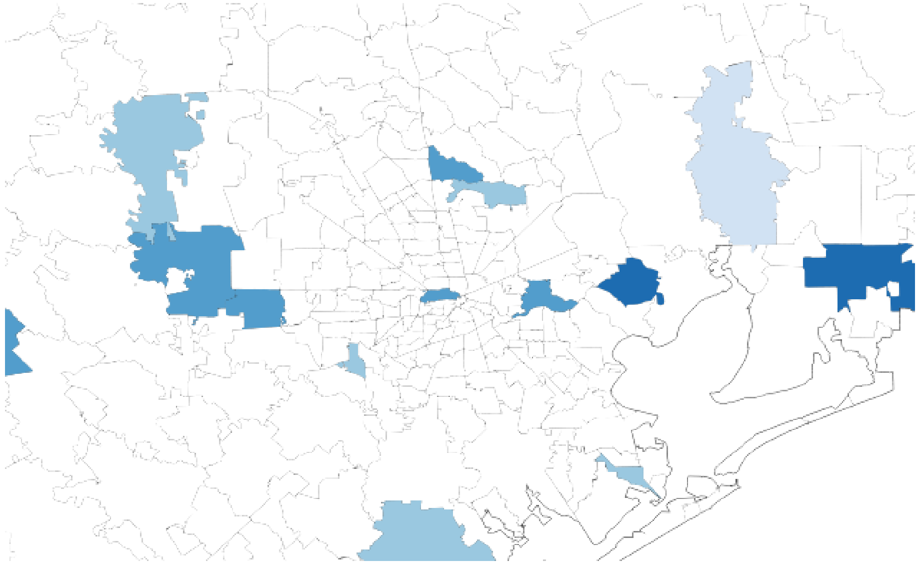


Results: Long Haul Heavy Duty Trucks

Electric long haul trucks are projected to be located along major highway corridors.

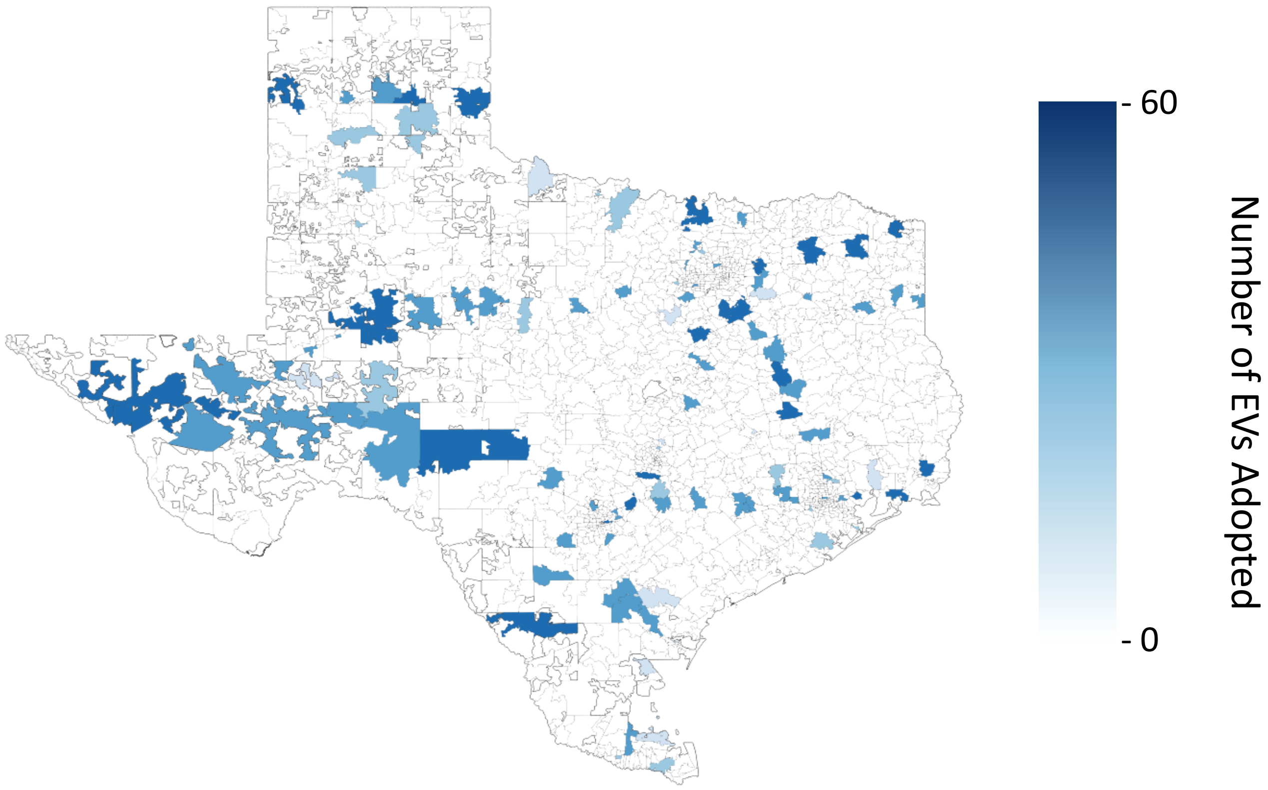
Forecasted EVs by Zip Code Detail: Houston

2029, Long Haul Heavy Duty Trucks



Texas Forecasted EVs by Zip Code

2029, Long haul Heavy Duty Trucks

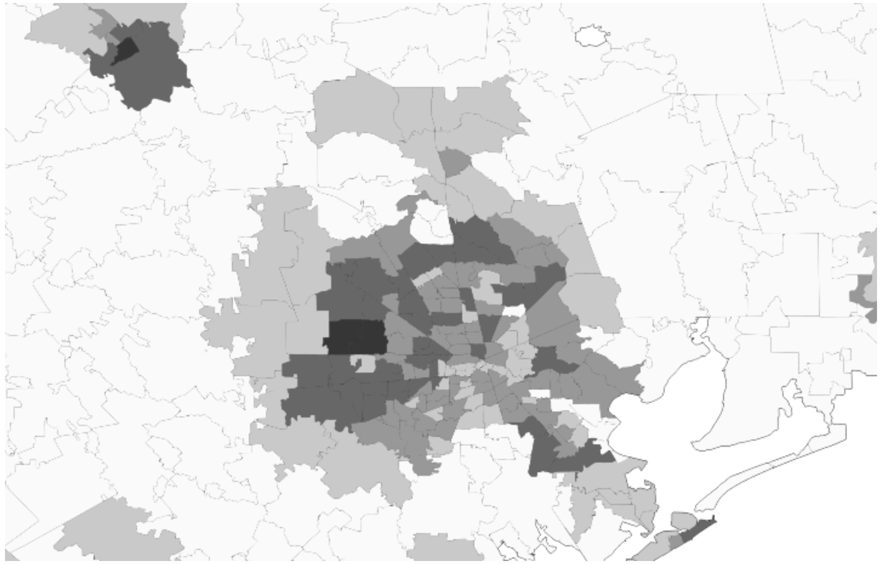


Results: Transit Buses

Electric transit bus adoption is expected to occur primarily in cities and areas with higher average income. Because depot charging locations were not identified, charging was assumed to occur where bus driving occurs.

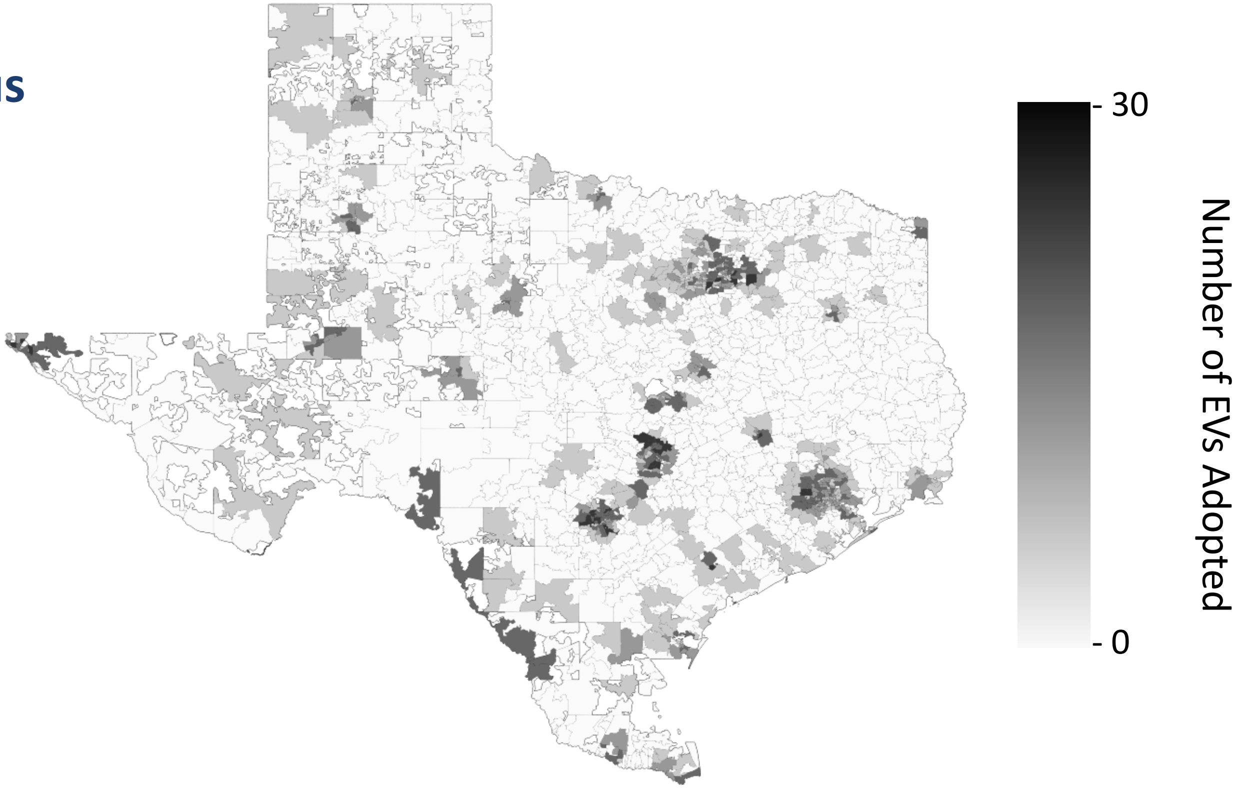
Forecasted EVs by Zip Code Detail: Houston

2029, Transit Buses



Texas Forecasted EVs by Zip Code

2029, Transit Buses



Results: School Buses

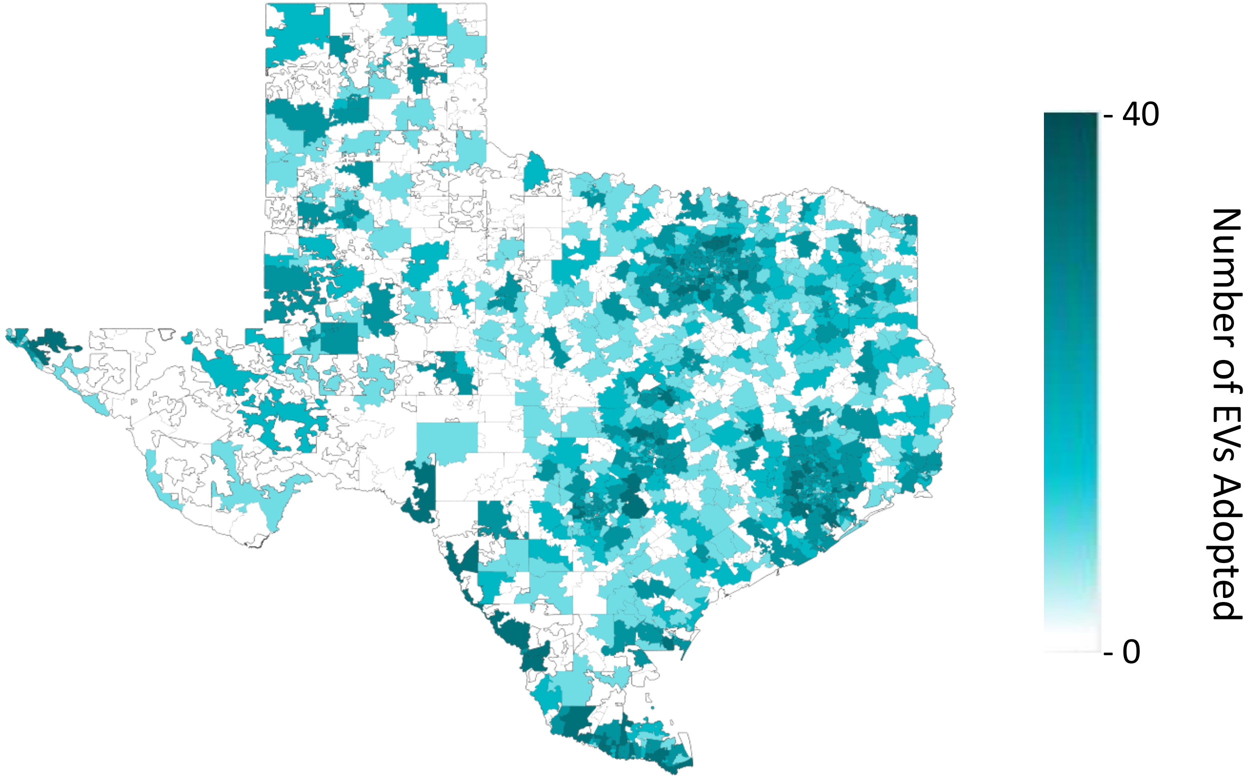
We project the most electric school bus adoption in suburban areas where children are more likely to ride the school bus and where there may be more public support for EV adoption among higher income households living in high density zip codes.

Forecasted EVs by Zip Code Detail: Houston

2029, School Buses

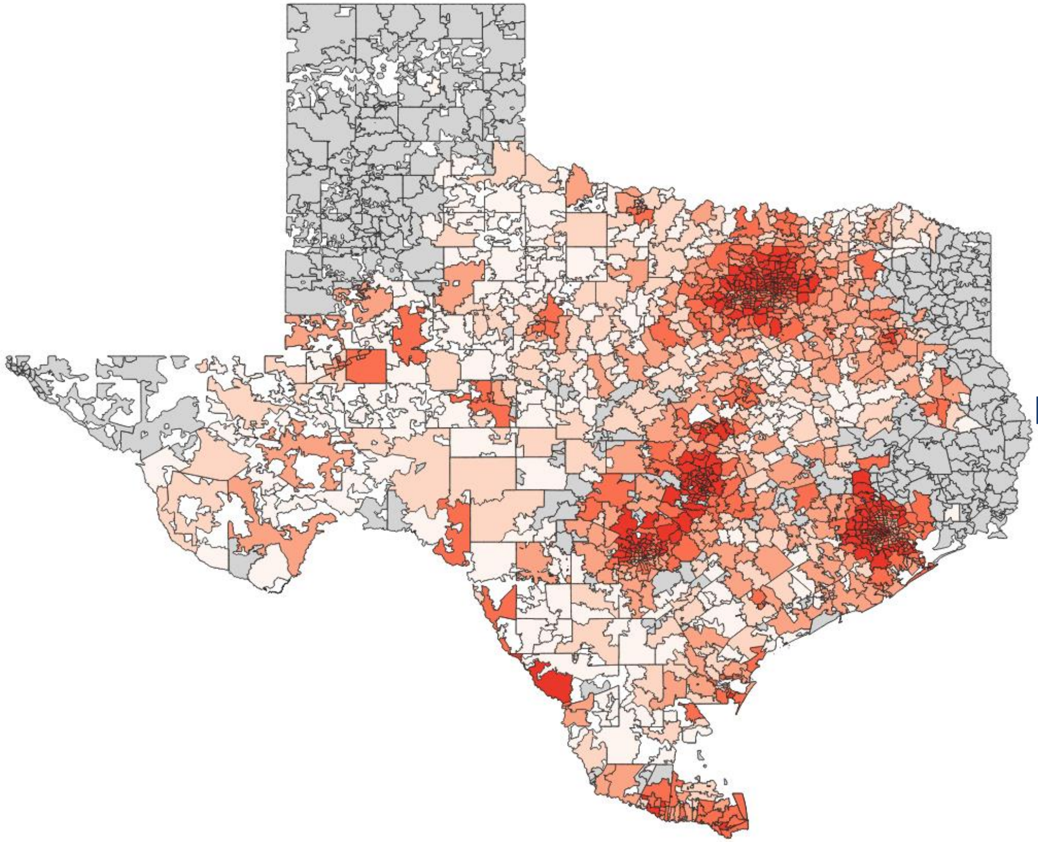
Texas Forecasted EVs by Zip Code

2029, School Buses



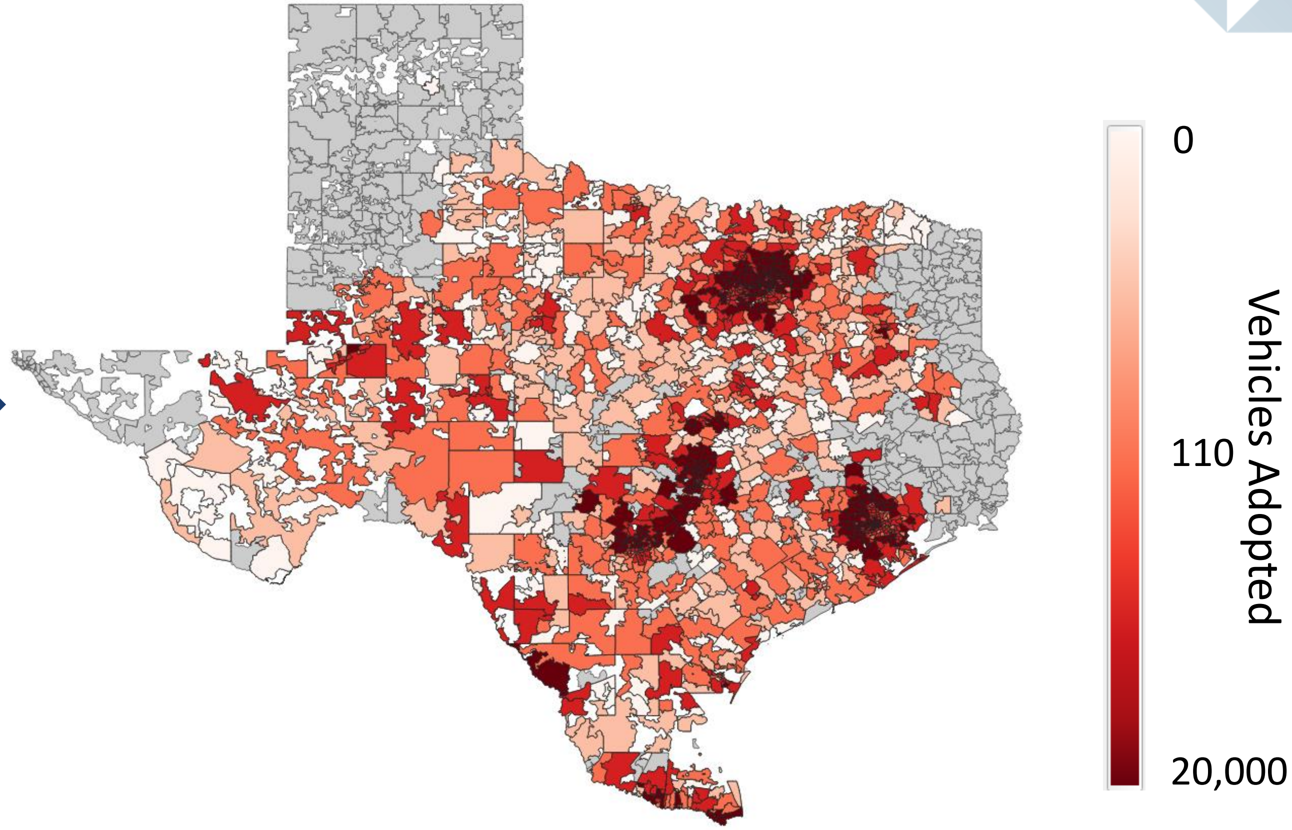
Final Electric Vehicle Allocation to ERCOT Zip Codes

2022 Electric Vehicle Adoption



Note: Showing actual LDV adoption as of April 2022 via Atlas EV Hub. MHDV adoption is currently very low in TX (~50 EVs total) and is not shown on the figure.

2029 Electric Vehicle Adoption



Note: Showing modeled LDV and MHDV adoption in 2029. LDV adoption includes only vehicles allocated to ESIID substations (75% of forecast). Due to data limitations we cannot show the location of LDVs allocated to NOIE/Planned substations serving these zip codes.

Step 3: Load Impact Analysis

Step 3: Load Impacts at the Substation-Level

1 Establish Light, Medium, and Heavy-Duty EV Adoption Forecasts for 2022-2029

- Update and improve upon ERCOT's existing adoption assumption for LDV penetration.
- Build out adoption forecast for a more granular list of Medium and Heavy-Duty (MHDV) EVs

2 Allocate Adoption Forecasts to ERCOT Substations

- Separate methodologies for LDV and MHDV allocation
- Vehicles first allocated to the zip-code level and then to the substation-level using data from ERCOT, the Census, and Moody's.

3 Calculate Load Impacts at the Substation-Level

- Calculate 64 representative load profiles for each substation, showing load throughout 4 seasons, 2 day types, and 8 years.
- Develop interactive tool that generates profiles for each substation and can be easily updated in the future.

EV Load Profile Model Flow

Primary Texas-specific inputs:
- Total EVs
- Mix of EV types (Battery Electric (BEV)/Plug-in Hybrid (PHEV), sedan/SUV, battery size)

Output:
- Total hourly EV demand at each substation by season/day
- Can break down load by location/charging type

Daily Electric Vehicle Miles Traveled (VMT) (per vehicle, quarter, day) → **Daily Energy Demand** (per vehicle, quarter, day) → **Daily Energy Charger Demand** (per vehicle, quarter, day) → **24-hr Energy Charger Demand** (per vehicle, season, day)

Inputs:
- % electric miles for PHEV
- Daily VMT for TX LDV drivers
- Seasonal VMT (% of annual)
- Weekday vs weekend VMT

Inputs:
- Vehicle average efficiency
- Seasonal ambient temperature by Weather Zone
- Efficiency vs temperature

Inputs:
- % of demand by location, for each vehicle, season, and day

Inputs:
- 24 hour normalized demand by charger type for each vehicle and day

LDV Load Profiles: Assumptions & Sources

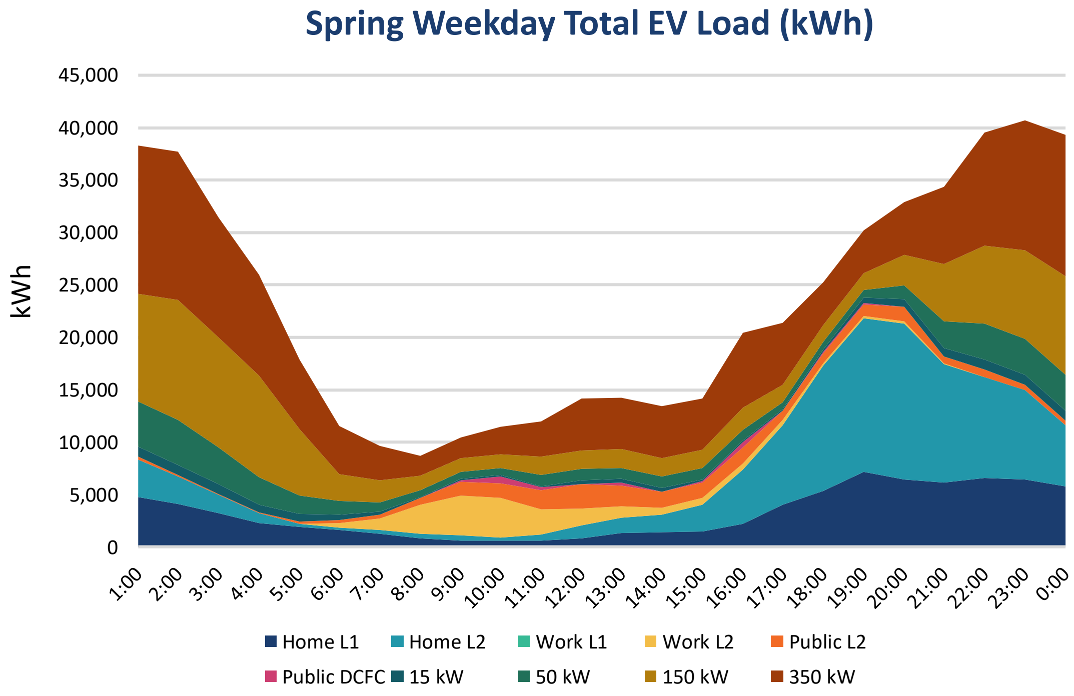
Input	Value	Source
Mix of LDV types	75% BEV, 25% PHEV	Austin Energy.
% Annual PHEV Electric Miles	55% electric	AFDC, ICCT. (Publicly Available) https://afdc.energy.gov/vehicles/electric_emissions_sources.html, https://theicct.org/wp-content/uploads/2021/06/PHEV-FS-EN-sept2020-0.pdf
Annual VMT per capita	Rural – 11,380 mi/vehicle/year Suburban – 11,190 mi/vehicle/year Urban – 11,000 mi/vehicle/year	National Household Travel Survey 2017. (Publicly available)
Seasonal share of VMT	Winter = 25% Spring = 25% Summer = 33% Fall = 17%	Provided by ERCOT, based on number of days in each season.
Weekday vs. Weekend VMT	Calculated in-model	National Household Travel Survey 2017. (Publicly Available)
Vehicle Battery Efficiency	PHEV – 2.0 miles/kWh. Efficiency is the weighted average efficiency of 35 available PHEV models in the US as of 2022 BEV – 3.7 miles/kWh. Efficiency is weighted average efficiency of 26 available BEV models in US as of 2022.	EV Adoption. (Publicly Available) https://evadoption.com/ev-models/available-phevs/ https://evadoption.com/ev-models/bev-models-currently-available-in-the-us/
Seasonal average ambient temperature	By ERCOT Weather Zone	Provided by ERCOT.

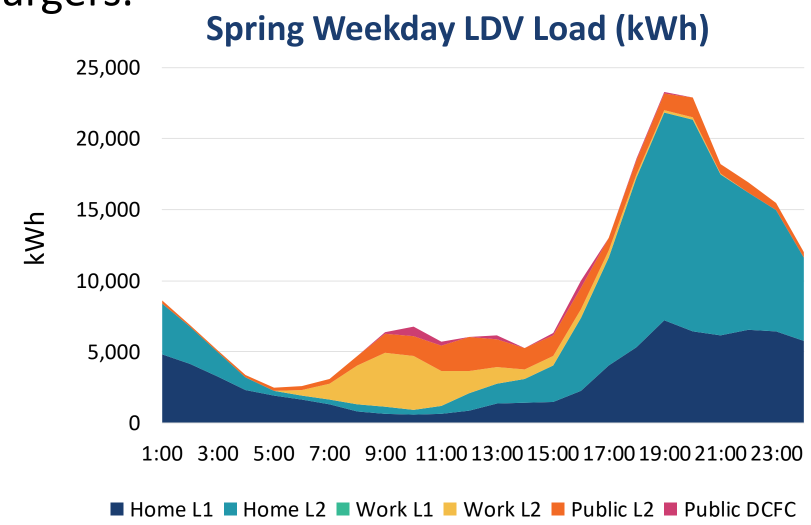
MHDV Load Profiles: Assumptions & Sources

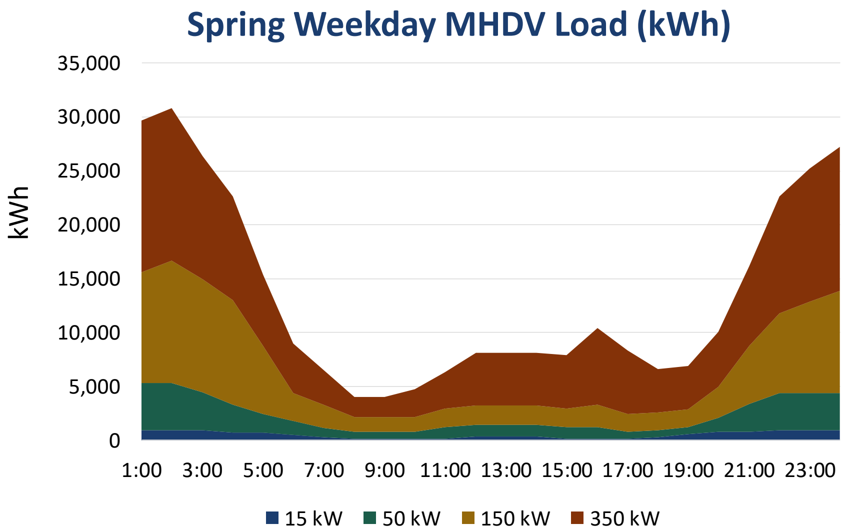
Vehicle Type	Weight Class/Use Case	Load Profile	Daily Energy Usage	Charging Type	Source
Transit Bus		Segment F: Transit – Bus Fleets	167 kWh/EV (89 mi/day at 1.88 kWh/mi)	150 kW	West Monroe
School Bus		Segment E: Schools – Bus Fleets	95 kWh/EV (70 mi/day at 1.30 kWh/mi)	15 kW	West Monroe
Pickup Trucks	Class 2B, Class 3-4 Pickup trucks	BEV250 Charging Profile	Vary by urban size (~30 mi/day at 2-3 kWh/mi)	Same as LDV	EVI Pro-Lite
Regional Delivery Vehicles and Lighter Trucks	Class 2B/3-4 Cargo Vans Class 5-6 Step Vans Class 3-4/5-6 Straight Trucks	Segment C: Texas-Based Companies – LD Local Delivery Fleets	60 kWh/EV (100 miles/day at 0.60 kWh/mi)	50 kW and 150 kW depending on weight class	West Monroe
Dump Trucks	Class 3-4, 5-6, 7-8 Dump Trucks	GVWR7,8	15 kWh/EV (25 miles/day at 0.60 kWh/mi)	50 kW and 150 kW depending on weight class	CEC 2019 Load Shape Study
Heavy Duty Regional Trucks	Class 7-8 Regional straight trucks, regional tractors	GVWR7,8	260 kWh/EV (200 miles/day at 1.30 kWh/mi)	350 kW	CEC 2019 Load Shape Study
Heavy Duty Long Haul Trucks	Class 7-8 Long Haul straight trucks, Class 7-8 Long Haul tractors	Segment D: Texas-Based Companies – Long Haul HD Fleets	1,200 kWh/EV (600 miles/day at 2 kWh/mi)	350 kW	West Monroe

Example Load Profiles

Takeaways: Our load profiles assume that substations will serve high levels of evening and overnight load due to charging from Long Haul trucks and LDVs plugging in at Home L2 chargers.

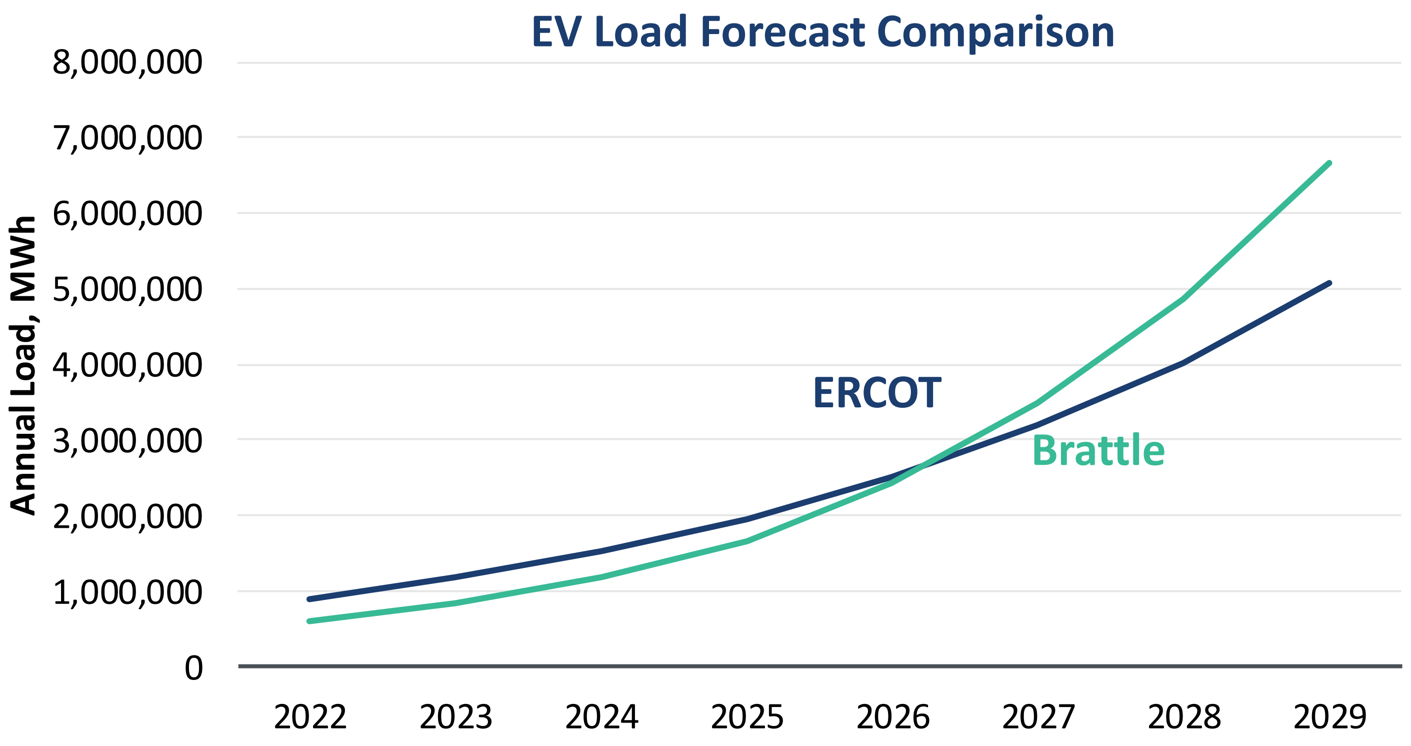






Comparison to ERCOT Load Impact Assumptions

- Brattle's annual EV load forecast aligns closely with ERCOT's original load impact assumption at the system level.
- ERCOT's forecast reports an annual total system load impact of approximately **5.1 TWh** in 2029, while Brattle's approach comes in slightly higher at **6.7 TWh**.

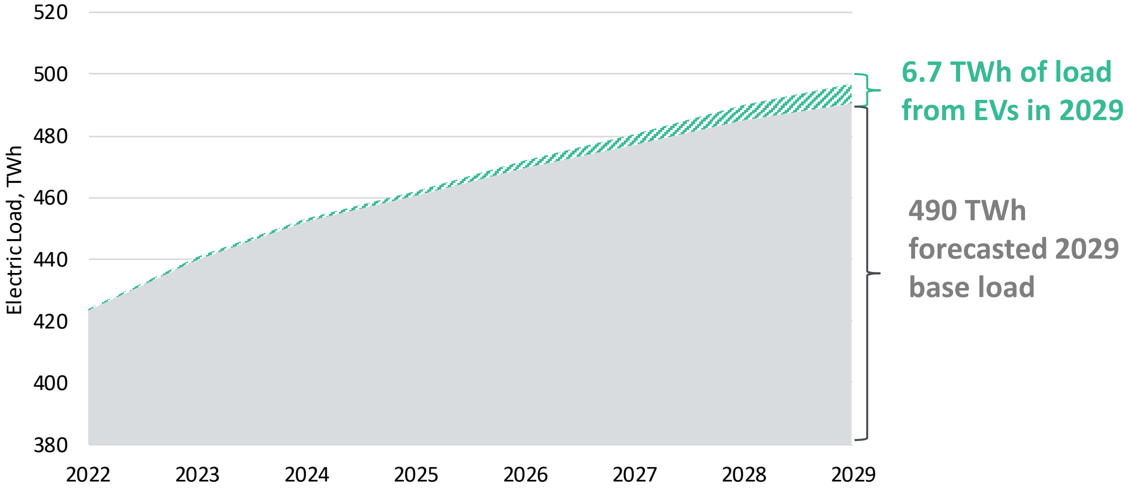


ERCOT Electric Load Forecast Impacts

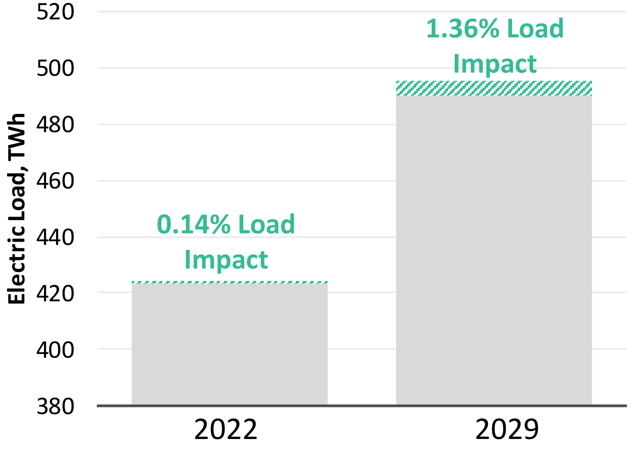
- EV adoption across all ERCOT substations is expected to add about 0.14% of load to ERCOT's electric load forecast in 2022 and about 1.36% of load in 2029.
  - By 2029, EV load will add approximately **6.7 TWh** of load to ERCOT's base load forecast.
  - This is the combined charging load estimated to come from **~750,000 LDVs** and **~208,000 MHDVs.**
- ERCOT's electric load will grow at a rate of **2.1%/year** without EV load, and **2.3%/year** with EV load.

Vehicle Type	Annual MWh
Passenger BEV	3.4
Passenger PHEV	2.0
Passenger Light Truck	3.9
MHDV Pickup Truck	7.4
Transit Bus	188
School Bus	17
Regional Delivery Truck	25
Dump Truck	6
HD Regional Truck	106
HD Long Haul Truck	488

ERCOT Electric Load Forecast Plus Added EV Load

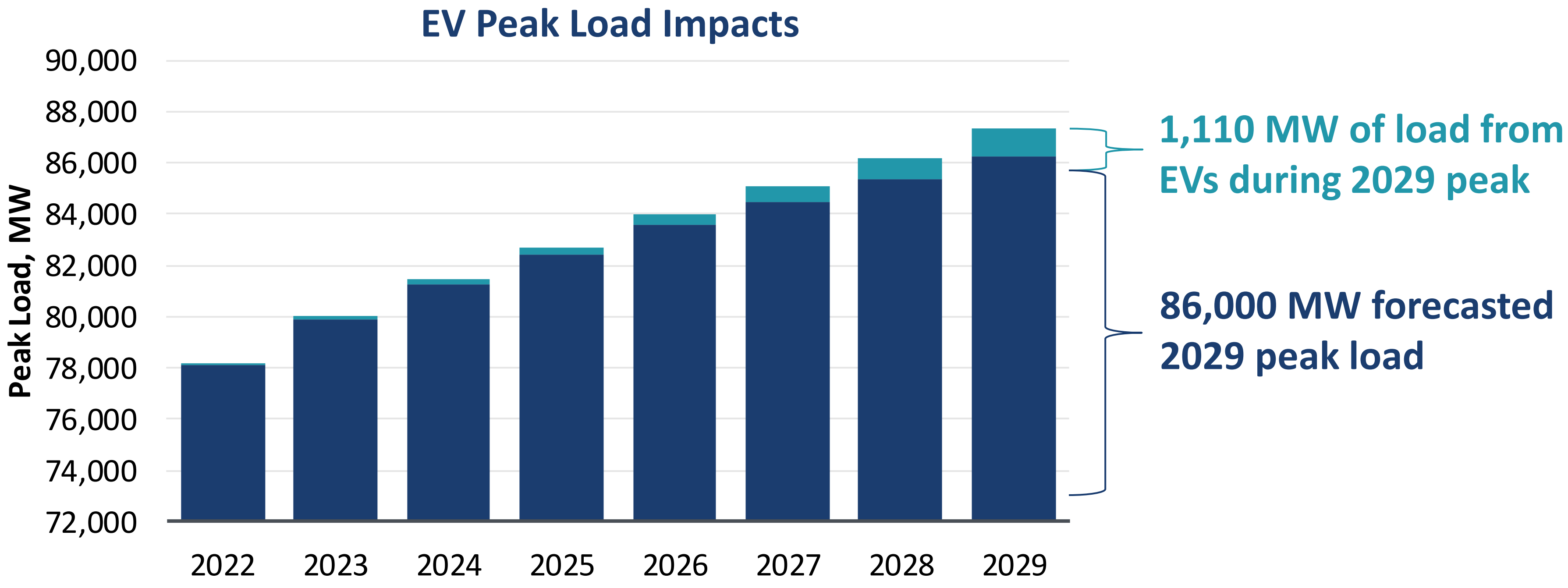


2022 vs. 2029 EV Load Impact Comparison



Peak Load Impacts by Weather Zone

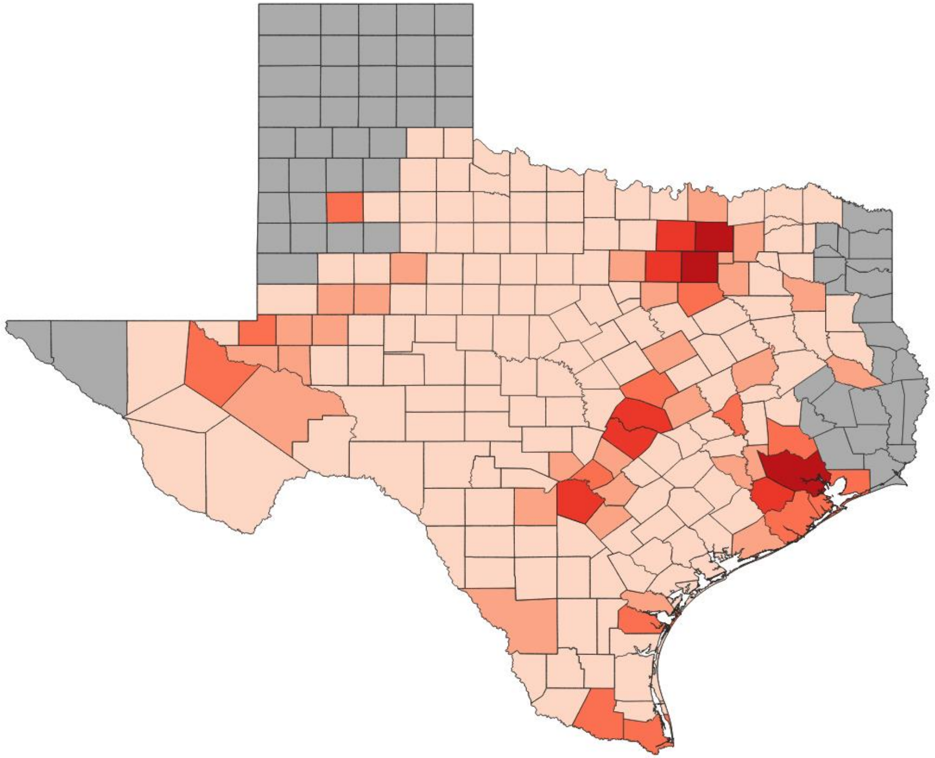
- According to 2021 Four Coincident Peak Load Calculation, ERCOT's coincident peak occurred on Tuesday, August 24th at HE 17.
  - We see that at the system level, CP impacts are quite similar to total load impacts, totaling roughly 1.3% of the annual coincident peak in 2029.
  - With EV load, ERCOT's peak load cumulative average growth rate (CAGR) will increase from **1.4%/year** to **1.6%/year**.



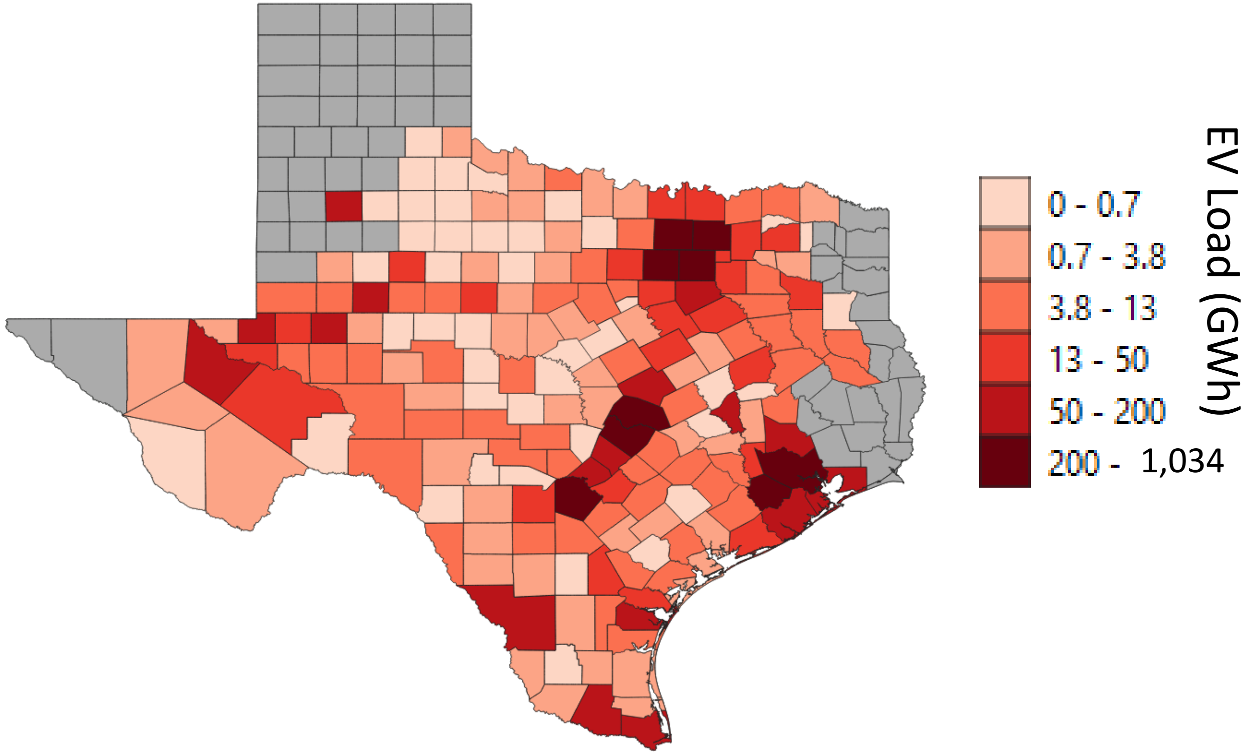
Total EV Load Distribution by County

- In 2029, Harris County is expected to have the most load from EVs at ~1,034 GWh.

2022 (Modeled) EV Load Impacts



2029 (Modeled) EV Load Impacts



Note: Based on modeled 2022 adoption of LDVs and MHDVs. Historical load impacts unavailable.

Recap

- Brattle team developed a new methodology to allocate light, medium and heavy duty vehicles to ERCOT substations to understand the extent of additional load on substation peaks
- We utilized the most recent and best available information to guide our methodology, largely relying on publicly available data sources
- We took into account the characteristics as well as use cases for each vehicle category for defining an allocation method for that category
- This is still a very nascent research area, and there are not publicly available precedents to the allocation of EVs to more granular locations
- While our allocation method resulted in allocations consistent with a priori expectations (i.e. higher LDV allocations to urban and suburban zip codes surrounding major cities such as Austin, Houston, DFW and higher allocations of delivery vehicles and regional and long haul trucks add load to substations in the city outskirts and major highways), the accuracy of the approach should be evaluated periodically and adjusted as more data becomes available

LDV Analysis Key Limitations

- Lack of zip code data for all substations causes us to make approximations for load at substations for which we do not know the associated zip code
- Approximation of adoption at zip codes with no historical adoption is speculative and assumes no-historical-adoption zips will experience adoption at a faster rate than zips with historical adoption
- List of active zip codes in TX and appropriate mappings to counties, census tracts, etc. is inconsistent across sources
- Propensity score approach could capture more economic variables in future iterations to produce more granular and diverse results across zips

MHDV Analysis Key Limitations

Allocation Method	Limitations and Areas for Future Development
Pickup Trucks	• Did not have pickup truck registrations at a county or zip code level- estimated based on a population density relationship.
Regional Delivery Vehicles	• In the future, could consider additional companies, distribution center size, and the specifics of expected announced adoption timelines.
Dump Trucks	• Did not identify centers where dump trucks are likely to charge • In the future, could add differentiation of EV adoption rates of dump trucks by zip code
Heavy Duty Trucks	• Assumed charging stations will be deployed as forecasted by the Texas DOT charging plan. • Assumed MHDV chargers will be deployed at the same rate and in the same locations as LDV chargers – MHDV report will be released this fall. • Assumed regional trucks will charge 50% along roads where they travel and 50% at distribution centers. • Assumed long haul vehicles will only charge along major highways.
Transit Buses	• Did not have information on bus depot and charging locations. • In the future, could incorporate information about which areas have announced electric bus adoption plans.
School Buses	• Did not have data on actual school bus registrations by zip code- estimated based on population density relationship. • Did not identify school bus charging locations or depots.