Apex Analytics Electric Vehicle Study for the Regional Technical Forum

April 24, 2025

Agenda

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Study Objectives	Why do this work?
Background and definitions	Review EV background and definitions
EV Efficiency	EV energy efficiency analysis
EV Load	EV loads and managed charging

Study Objectives

Research Objective

- Characterize the electric vehicle (EV) market to **identify EV efficiency**
- Answer the Question: Does it make sense for a "**Unit Energy Savings**" measure?
- Update **L2 charger DR** potential estimates
- Develop various **EV loadshapes** (currently in development)

Considerations

- **Technology is changing… rapidly**
  - Findings today likely to be outdated soon; e.g., solid state batteries, new EV drive systems and motors, new charging infrastructure.

- **Data availability greater than most efficiency measures, but large and significant gaps remain**
  - Cannot think of another emerging technology with so much public data. Yet…
    - Not all manufacturers, EV models, EV attributes represented in analysis
    - Matching EV model "trims" across data sources is imperfect, and leads to broad assumptions that we know are inaccurate

Brief Review of Key Data Sources

Data Source	Data Type	Description
EPA	Vehicle attribute and efficiency data	EPA **certified and lab-tested** efficiency values, range, class, motor power, drive type
State registration data	State vehicle counts (proxy for sales)	Statewide registration data reports up-to-date** vehicle counts for WA, OR, and MT. Varying levels of "model" granularity
Rolling Energy Resources (RER)	Charging session summaries/telematics	Real-world session level charging data for 6,000 EVs. Detailed EV attributes (make, model, battery size).
VIN decoding (Vehicle Identification Number)	Vehicle attribute data	VIN "decoding" process matches to EV attribute data. RER has **full** VINs for over 6,000 vehicles WA registration has **partial** VIN data (first 10 of 19 digits) for 50,000 EVs. Attributes include make, model, drive type
Apex secondary research	Additional EV Attributes	Weight, drag, EV model verification
DOE EERE Alternative Fuels Data Center	Maximum Power Acceptance	Also used Chargehub if vehicle model not listed in DOE dataset

*** OR allows initial four-year registration, and then is every other year.*

EV Background and Definitions

Vehicle Classification Hierarchy

Study focused on passenger cars and light-duty trucks as defined by DOE

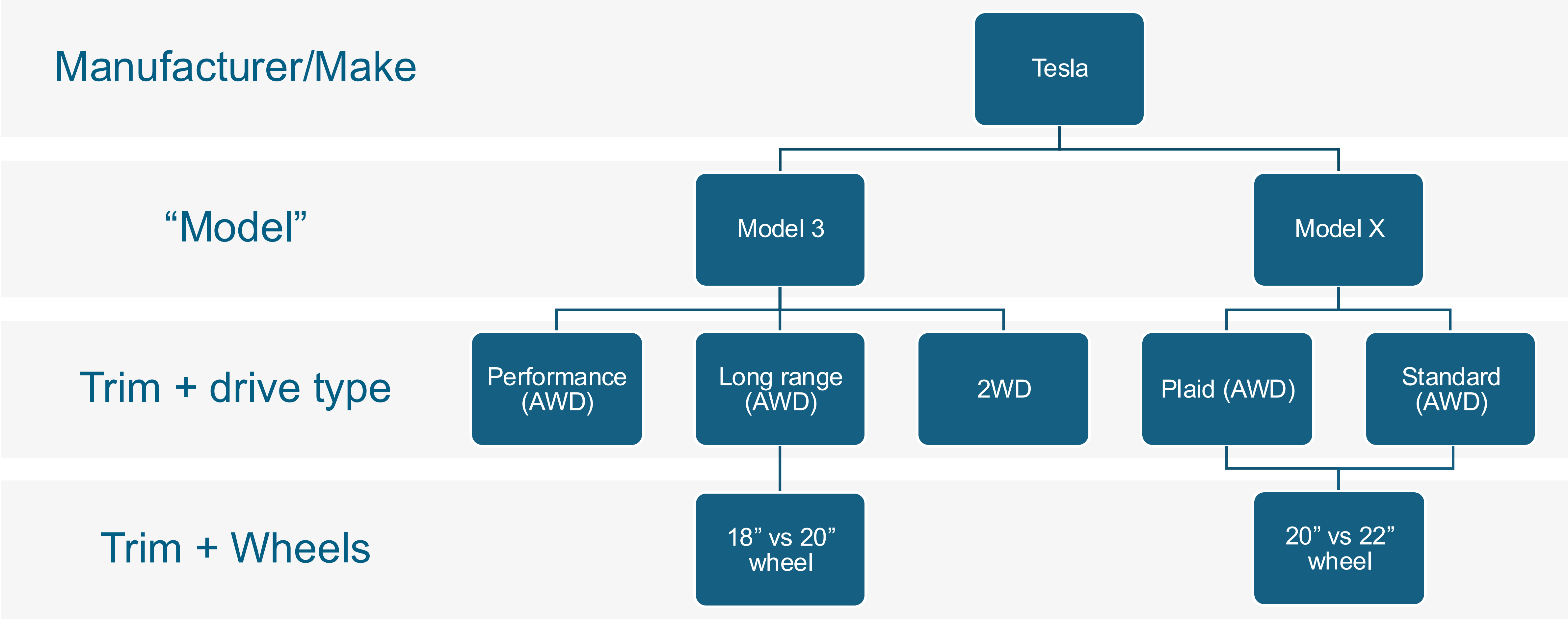
Passenger cars: Classified by cargo volume (Cu. Ft.)

- Compact
- Midsize
- Large

Trucks: Classified by gross weight (GVWR)

- Light duty (class 1+2): Trucks & SUVs
- Medium and heavy duty (class 3-8)

EV “Model” Is Generic, “Trim” Levels Detailed & Important!



EPA Monroney Labels Provide Fuel Efficiency for All Vehicles

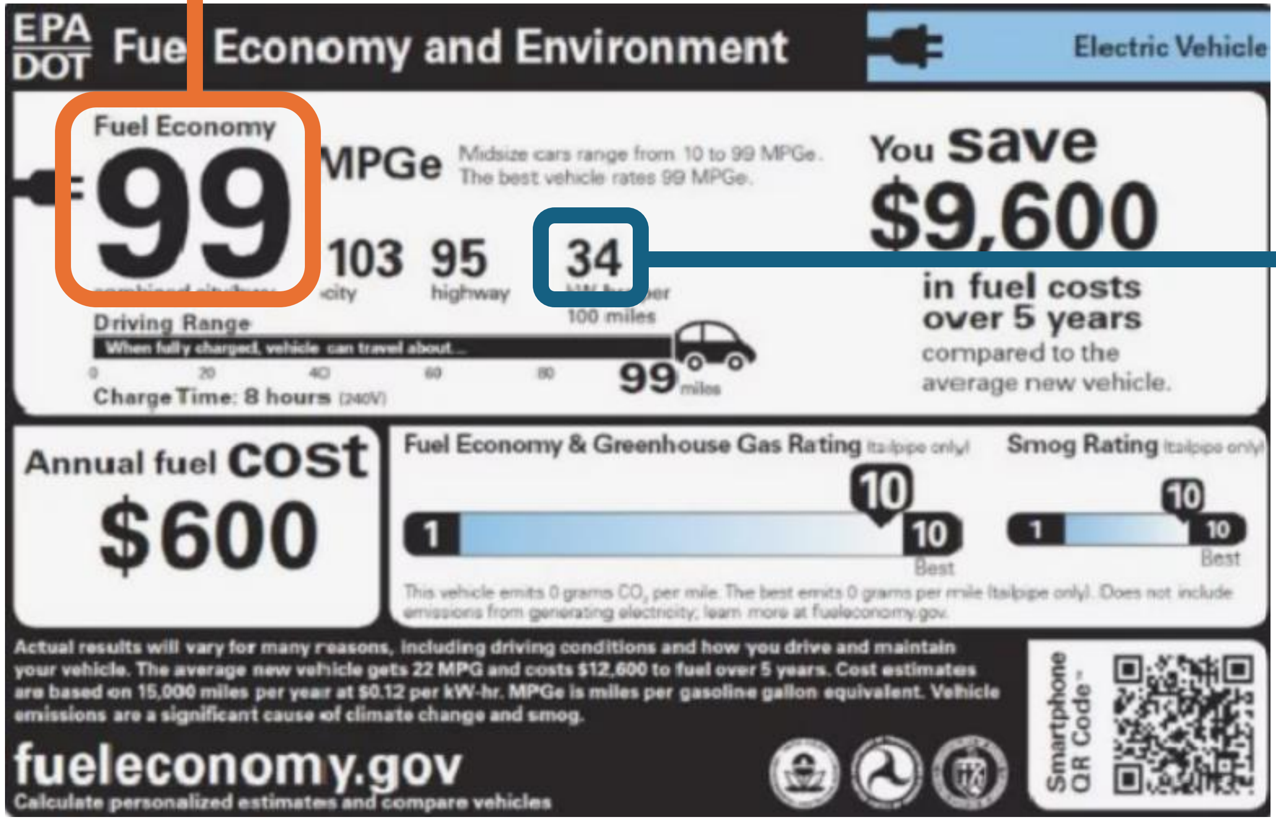
EV Monroney Label

Federal government has set fuel efficiency standards **since 1975**.

EPA **validates, classifies, and tests** (random) vehicles.

Label **provides mileage, efficiency, and fuel cost ranges** based on **vehicle class**

EPA Provides EV Mileage and Efficiency Metric



EPA reported efficiency ranges from a low of 0.8 miles/kWh to a high of 4.2 miles/kWh.

MPGe for EV based on 33.705 kWh/gallon conversion

Example: EPA rates this EV with an overall mileage of **99 MPGe**, and an efficiency value of **34 kWh/100 miles**.

Conversions:
99 MPGe/33.705 kWh/gallon =
2.94 Miles-per-kWh

2.94 Miles-per-kWh:
1/2.94 x 100-miles =
34 kWh-per-100 miles.

Higher efficiency = higher miles/kWh.

EV Efficiency

Options to define EV as efficiency measure

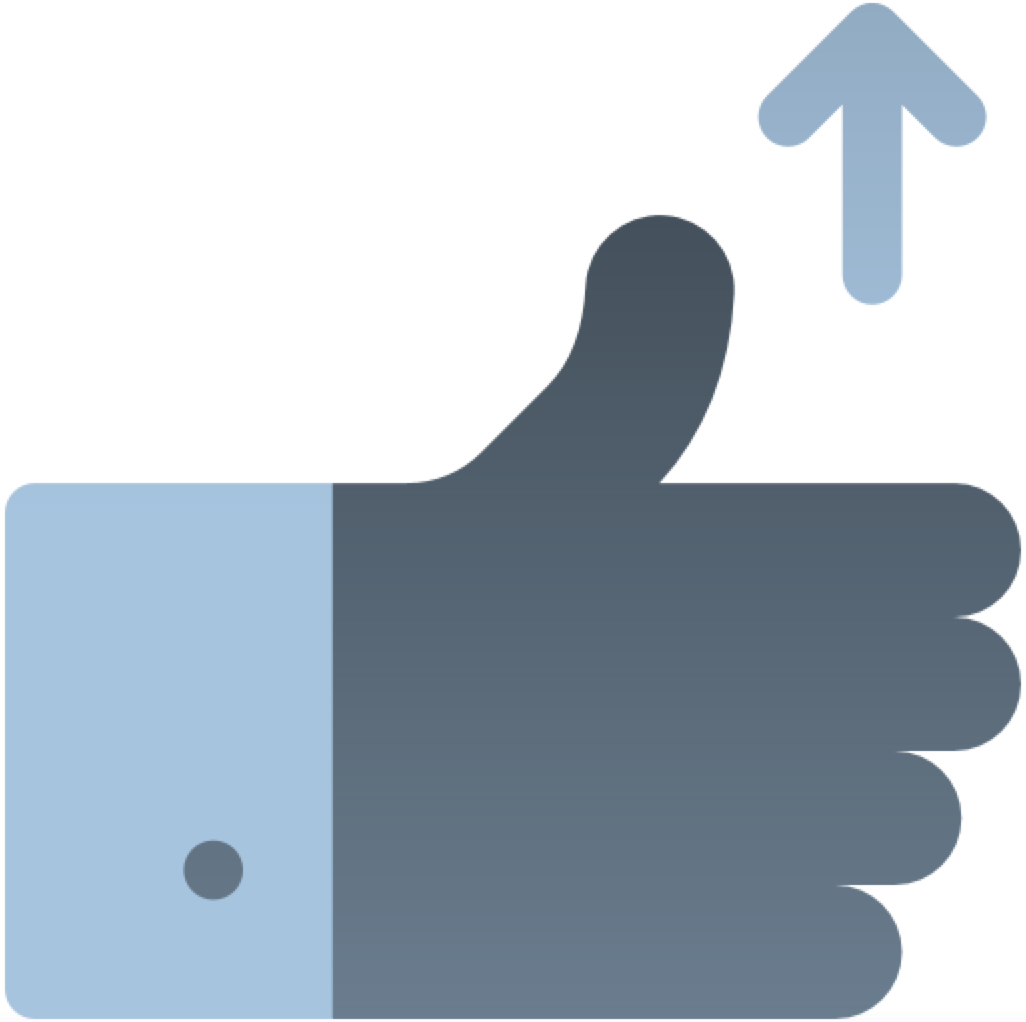
Option 1: Adopt EPA efficiency ratings

- The EPA efficiency rating by EV class used to define baseline consumption and select efficient vehicles
- Real-world driving data validates EPA rating values
- EVs in registration data aligns with EPA

Option 2: Adopt EV attribute model

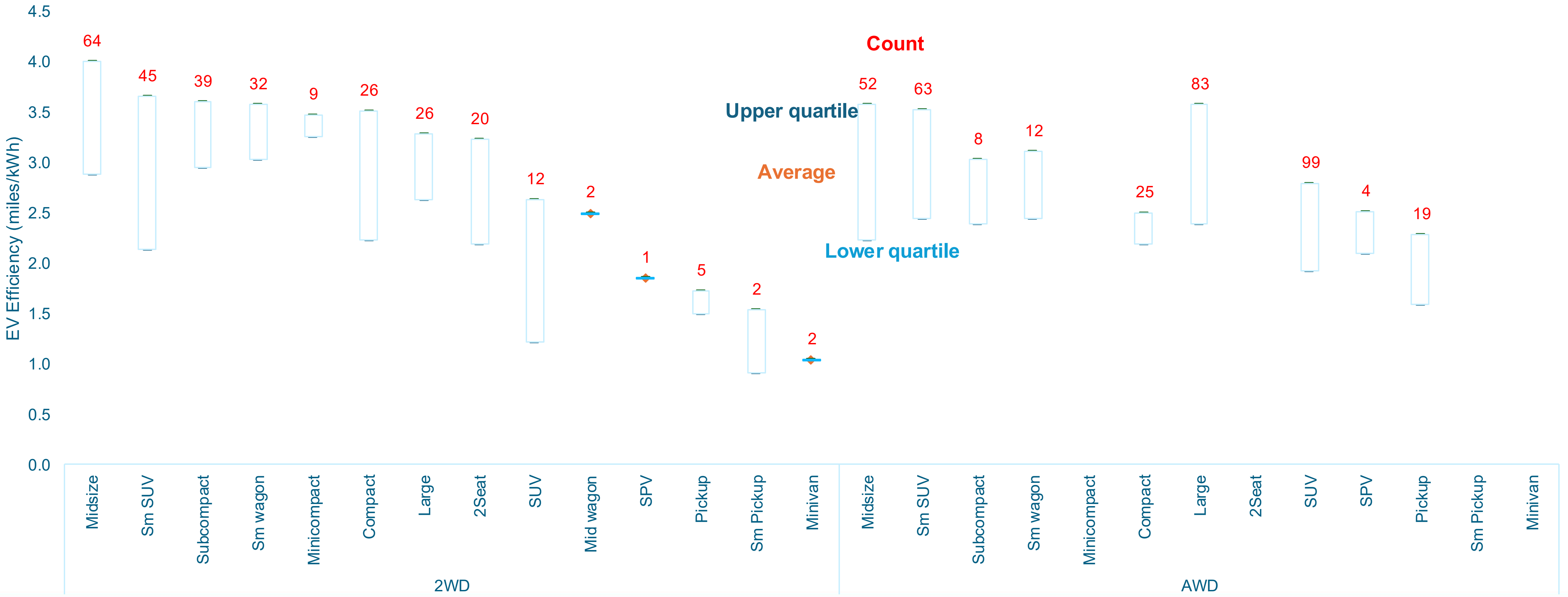
- EV attribute dataset used to “rate” cars by class, then define baseline consumption and select efficient vehicles.
- Must establish attribute/details of each EV– i.e., trim data
- EVs in registration data aligns with model

EPA efficiency rating advantages



EPA EV Counts and Interquartile Efficiency Ranges

Most classes/drive types with sufficient counts also have wide (> 20%) efficiency ranges.
Efficiency ranges and averages based on EPA data only, are not sales weighted!



Source: EPA ratings, 2020-2024 EVs

EPA Uses Comprehensive Test Procedures

Fuel Economy Testing: Automakers must follow specific test procedures and submit fuel economy data to EPA for all their models each year. EVs with fully charged battery driven continuously for each cycle, recording distance driven until battery depleted.

- **(A) Default two-cycle test (no HVAC operation):**
  - **(1) City; (2) Highway:**
- **(B) 3 additional optional cycles **:**
  - **(3) Aggressive/high speed; (4) Hot @ 95° F: HVAC cooling; (5) Cold @ 20° F: HVAC heating and defrost**

Real-world Adjustment Factor: **2-cycle test** ranges **adjusted downward by 30%** to account for real-world factors not represented in laboratory test procedures (HVAC, temperatures, and high speed/aggressive driving). **Optional 5-cycle process** receives "***more favorable***" adjustment factor.

EPA Validation: EPA lab (Ann Arbor, MI) uses dynamometer to validate randomly selected models each year.

***** Note: currently, only Tesla, Rivian, and Audi adopt the 5-cycle alternate***

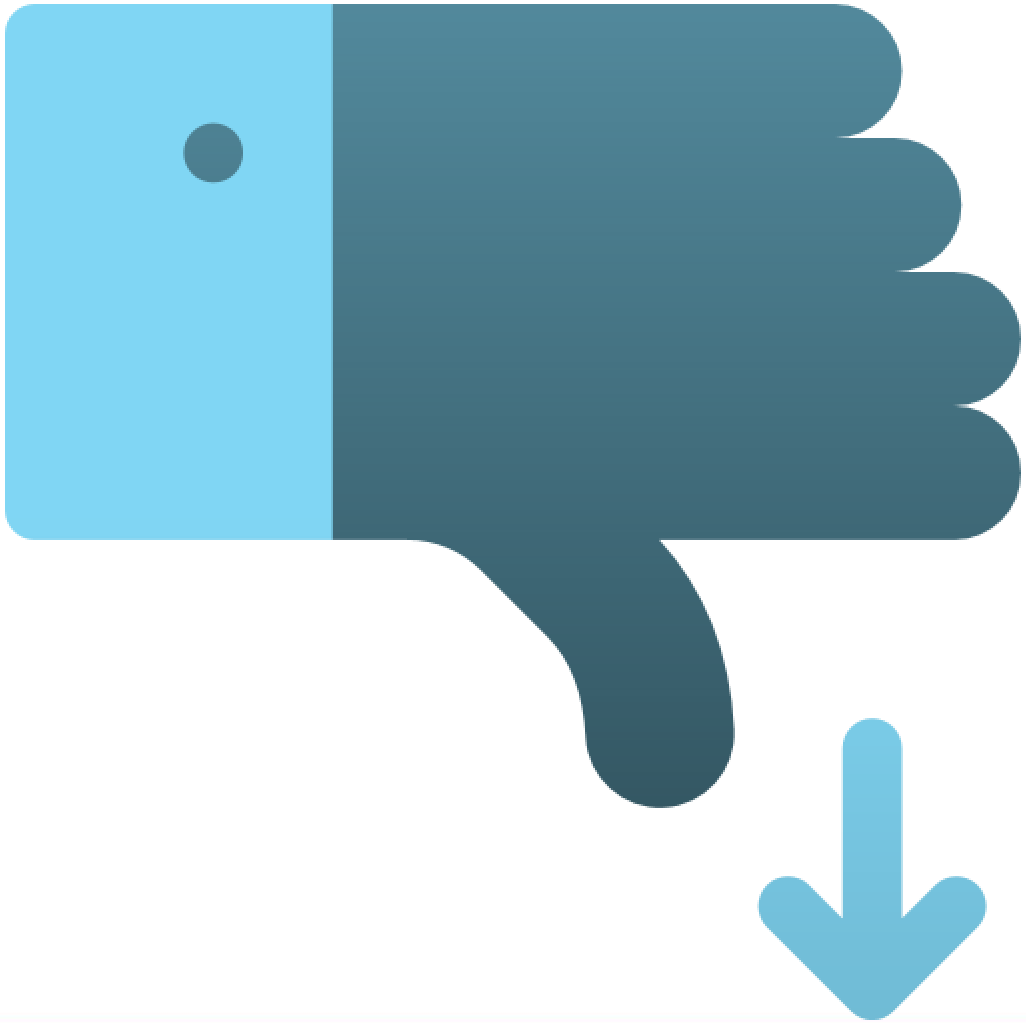
Example Per EV Unit Annual Savings based on EPA efficiency ratings

EPA derived per EV annual kWh savings range from 200 to over 1,000 kWh

Drive	Class	(A) EPA Avg EE (miles/kWh)	(B) EPA 90% (High) EE (miles/kwh)	(C) Avg Annual Miles	(D) = A x C Avg Annual kWh	(E) = B x C High EE kWh	(E - D) Annual Savings (kWh)
2WD	Compact	2.8	3.5	13,000	4,643	3,714	929
	SUV	2.2	2.6		5,909	5,000	909
	Sm SUV	3	3.7		4,333	3,514	820
	2Seat	2.8	3.2		4,643	4,063	580
	Large	2.9	3.3		4,483	3,939	543
	Midsize	3.5	4		3,714	3,250	464
	Subcompact	3.3	3.6		3,939	3,611	328
	Sm wagon	3.3	3.6		3,939	3,611	328
AWD	Midsize	2.8	3.6		4,643	3,611	1,032
	Pickup	2	2.3		6,500	5,652	848
	SUV	2.4	2.8		5,417	4,643	774
	Sm SUV	2.9	3.5		4,483	3,714	768
	Large	3	3.6		4,333	3,611	722
	Sm wagon	2.7	3.1		4,815	4,194	621
	Compact	2.4	2.5		5,417	5,200	217

Source: EPA, note, data are NOT sales weighted

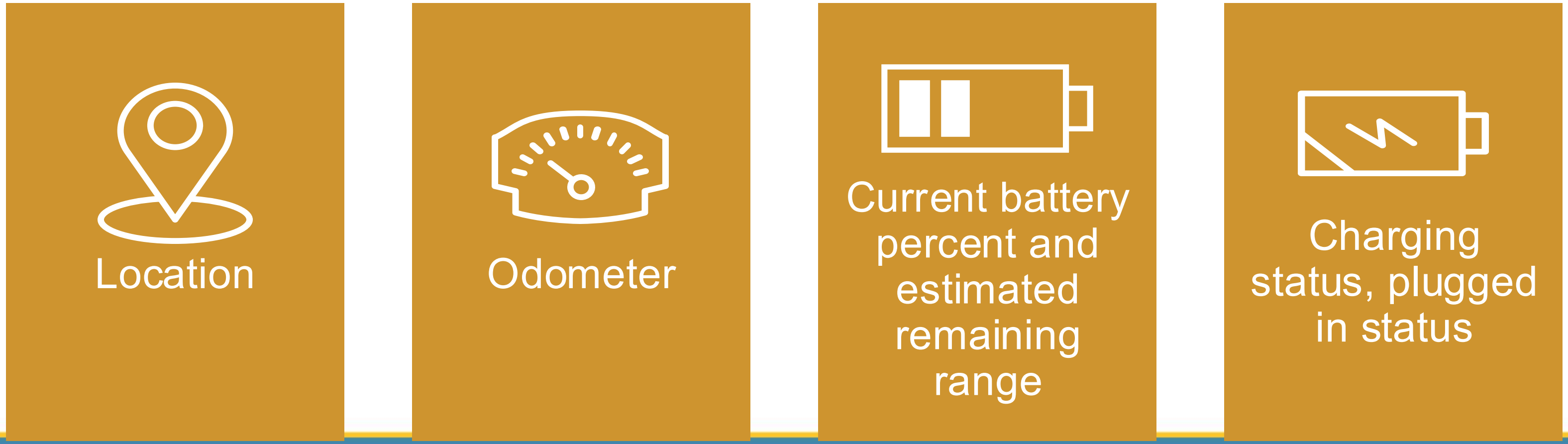
EPA efficiency rating shortcomings



Real-World Efficiency Based on EV Telematics Data

Apex used Rolling Energy Resources (RER) EV telematics data to examine real-world efficiency.

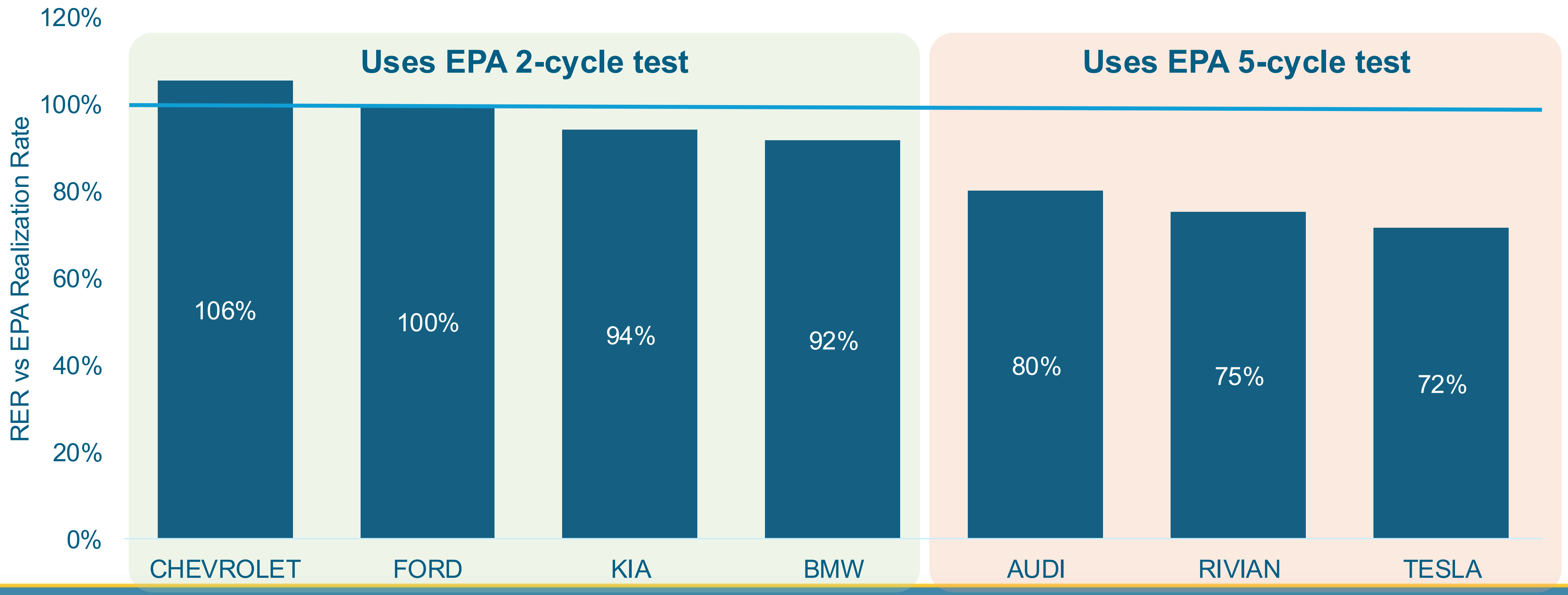
- RER captures EV telematics data at regular intervals for over 6,000 EVs
- Odometer reading, battery State of Charge (SOC)** and capacity as inputs, calculated energy (kWh) & demand (kW)
- Calculated EV efficiency is ratio of **miles driven** divided by **kWh consumed on a monthly basis**
- **Compared RER actual EV efficiency relative to EPA rated efficiency (i.e., realization rate)**



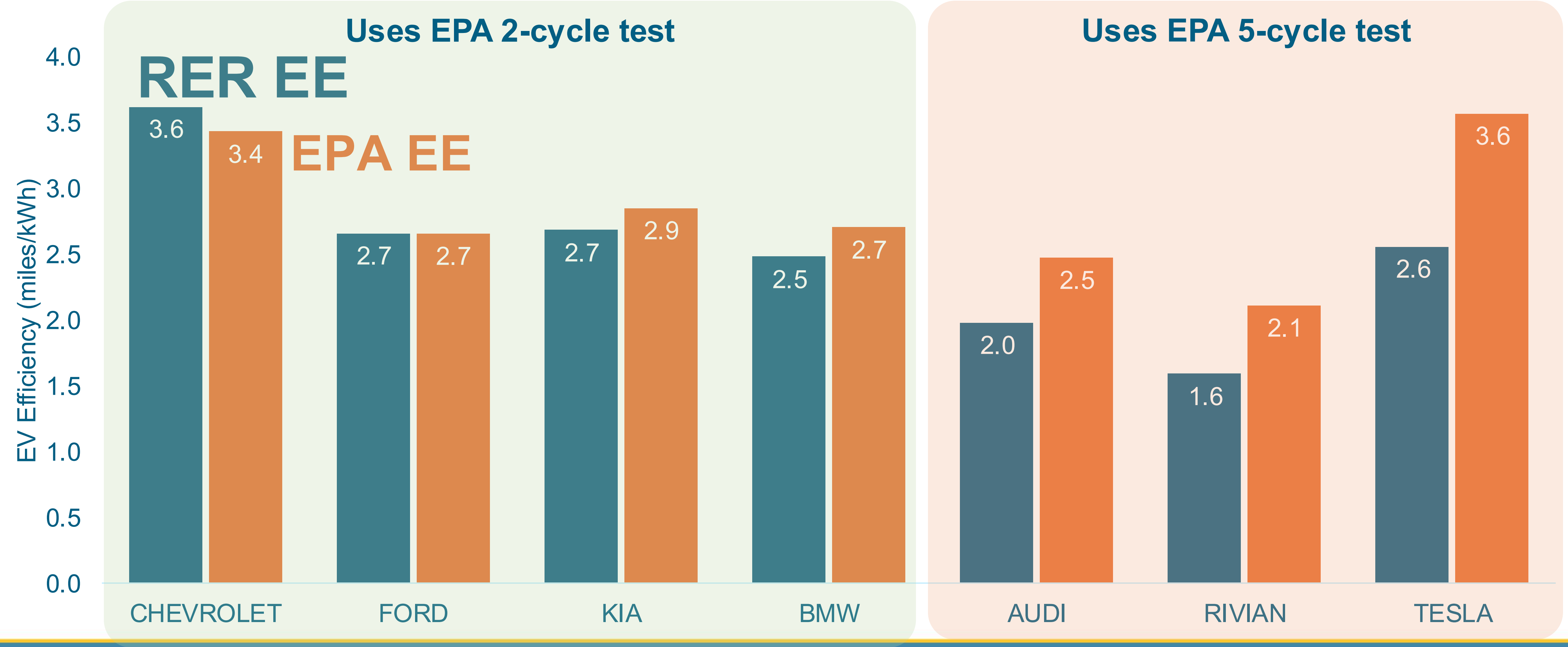
Battery State of Charge (SOC) is percentage charge remaining (i.e., EV "fuel gauge")

Real-World EV EE Is Different Than EPA Rated EE

EPA EV efficiency is a reasonable proxy for real-world efficiency for some mfgs: Only Chevy and Ford meet or exceed EPA rated efficiency



Real-World EV EE Is Different Than EPA Rated EE



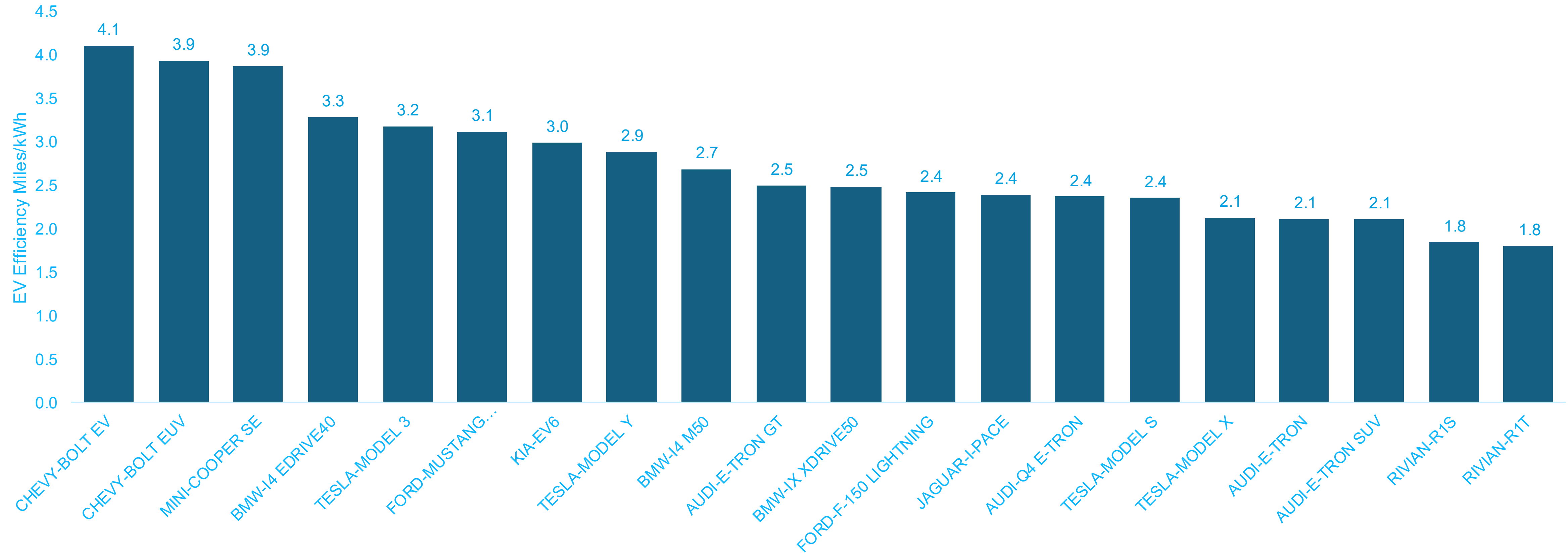
Source: Apex Analytics/Rolling Energy Resources and EPA

Tesla Models All Showed Low EV Efficiency Realization Rates

Tesla has largest market share and had lowest realization rate vs EPA rated efficiency

Wide range of real-world EV efficiency

Real world EV efficiency ranged from a high of 4 to a low of 1.8 miles/kWh



Only vehicles with more than five models in analysis dataset included in this figure

What Explains the Difference in EPA vs Real-World?

- Overstatement of range
  - Confirmed by published reports of overstated range estimates (~26%)
- Use of 5 cycle test
  - We cannot quantify, at this point, the magnitude of difference this may explain. Access to 2-cycle test results with default 30% adjustment factor could help validate
- Imperfect model matching
  - Cannot “perfectly” match model/trims between sources, especially for Tesla and to lesser extent Audi. Likely accounts for a quarter or third of the difference
- Driver behavior

$\neq$

Other Model Specific, Climate, and Variable Conditions

Winter Pre-Heating

Dog Mode

Greenhouse Effect

EV Efficiency Options

Option 2: Adopt EV attribute model.

- **Raises more questions than it answers.**
  - **Low explanatory power of EV efficiency. Modeling real-world and EPA EV efficiency showed physical vehicle attributes and weather explain approximately one-quarter of EV efficiency variance.**
  - **Inclusion of vehicle make (mfg) improves EPA model explanatory power but NOT real-world model.**

Can We Model EV Efficiency as a Function of EV Attributes?

We tested EV attribute models based on TWO different EV efficiency ratings

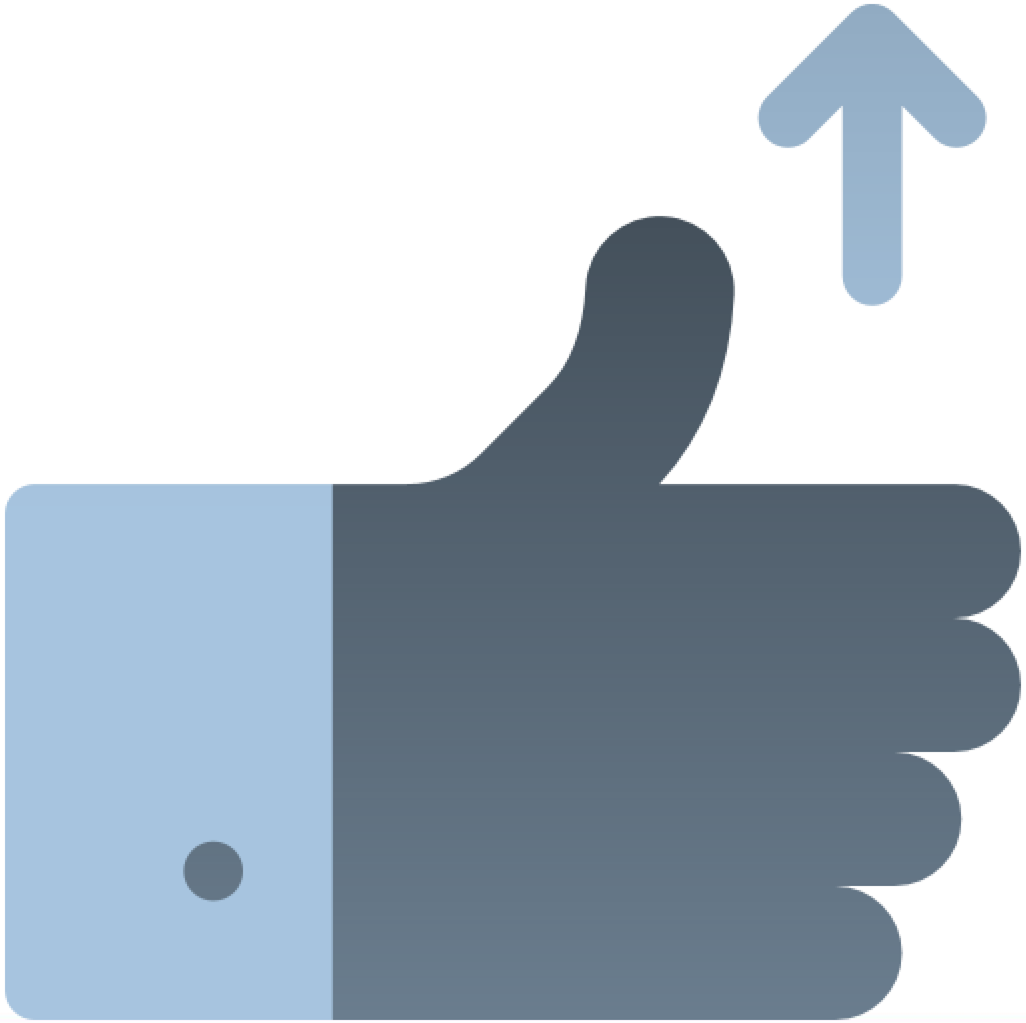
EV Regression 1: Real-world Data (RER)

- $RER\ EV\ Efficiency_i = \beta_0 + \beta_1 * Vehicle\ Class + \beta_2 * Temperature + \beta_3 * Battery\ Capacity + \beta_4 * Vehicle\ weight + \beta_5 * Drivetype + \beta_6 * VehicleAge$

EV Regression 2: EPA Data

- $EPA\ EV\ Efficiency_i = \beta_0 + \beta_1 * Vehicle\ Class + \beta_2 Battery\ Power + \beta_3 * Vehicle\ weight + \beta_4 * Drivetype + \beta_5 * Model_{year} + \beta_5 * Drag$

Identified Factors Influencing EV Efficiency

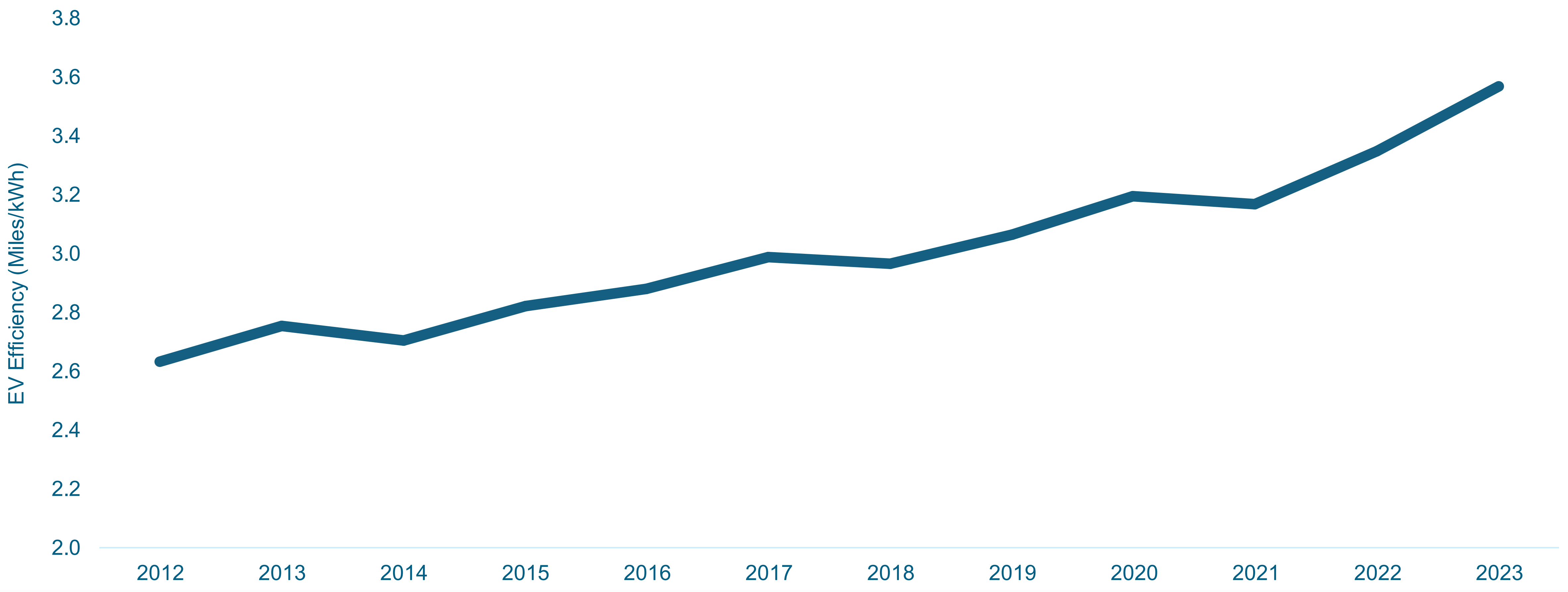


Attributes Impacting Vehicle EE and Availability for Modeling

Attribute Group	Attribute	RER Data	EPA Data	VIN Data	Units	Impact on EE	In Model	Notes
Fixed (Physical)	Make (mfg)	●	●	●		Var	Both	
	Model	●	●	●		Var	Both	
	Trim	◐	◐	◐		Var		“Other engine info” in VIN. Embedded in model name in EPA.
	Group/Type/Class	○	●	○		Var	Both	VIN class (“body type”) is inconsistent with EPA class
	Battery capacity	●	○	○	kWh	+	RER	RER battery used as proxy for trim (i.e., std vs performance models)
	Motor power (peak)	○	●	○	kW	+	EPA	
	Regenerative braking	○	○	○		+	N/A	No source
	Drag coefficient (cd)	○	○	○	Cd	-	Both	Requires online search
	Vehicle weight	○	○	○	Lbs	-	Both	Requires online search
	Vehicle age	●	●	●	Years	-	Both	Age in RER reflects both “technological” EE improvements with newer models and battery degradation, while age in the EPA model reflects “technological” EE improvements only.
	Wheel size	○	◐**	○	Inches	-	EPA	Embedded in model name for limited group of models in EPA, only reported starting in 2021+
	Drive type (AWD vs 2WD)	●	●	●	Binary	-	Both	Only attribute available in all sources
Variable (Behavioral)	Acceleration/Braking/ Speeding	○	◐	○		-	RER	EPA only partially accounts for this and applies 30% adjustment factor
Variable (Geographical)	City vs highway	○	◐	○		**+ City, - Hwy**	Both	
	Terrain	○	○	○		Var	RER	
	Weather	●	◐	○	HDD/ CDD	- Cold/Hot	Both	
Variable (Other)	Tires (pressure)	○	○	○	PSI	+	RER	

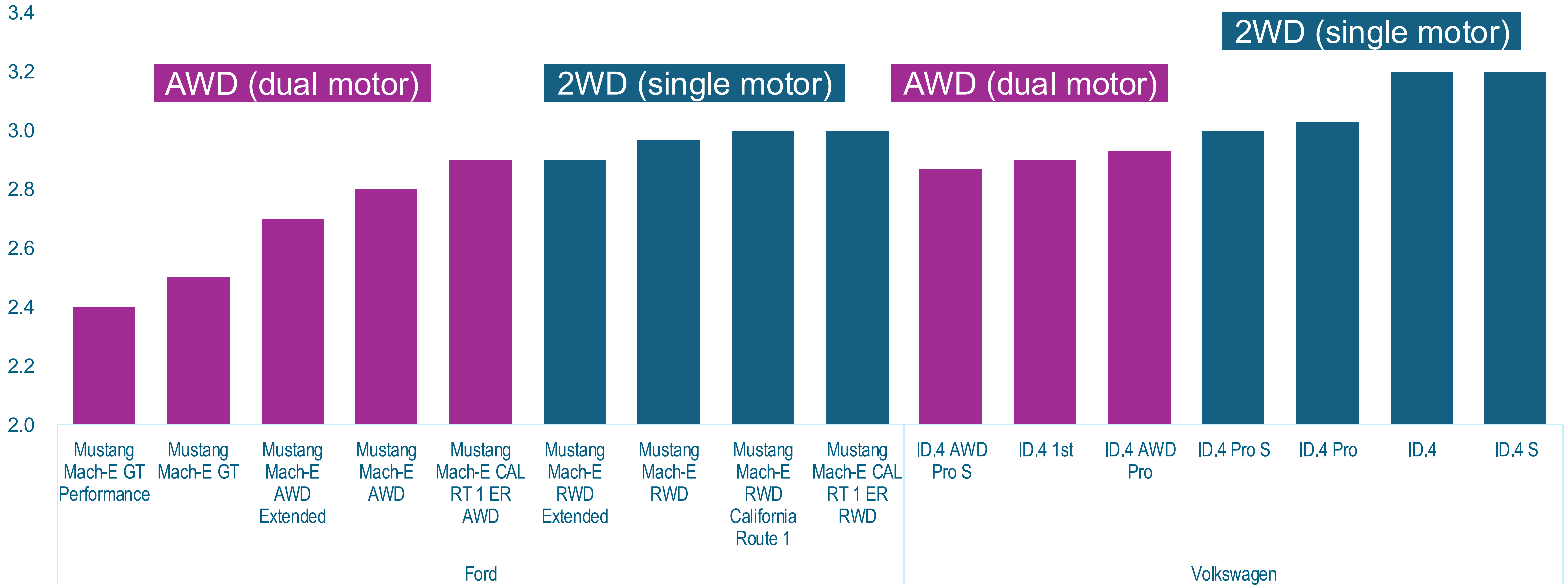
Older EV Models Are Less Efficient (EPA Estimates)

All else equal, EV age negatively impacts EE. Tesla Model S example below



AWD EVs Are Less Efficient Than 2WD (EPA Estimates)

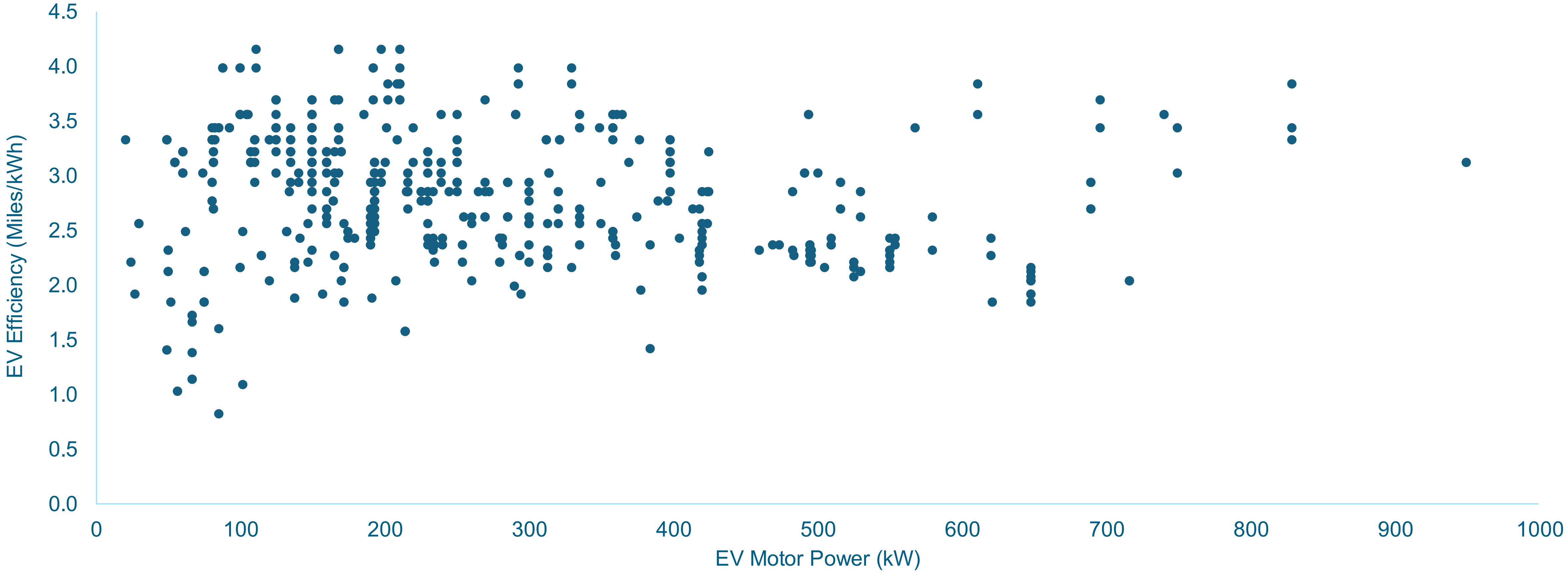
Efficiency range across trim/models is highly influenced by AWD (single vs dual motor)



Source: EPA efficiency ratings

EV Motor Power Significant but Weak Relationship With EV Efficiency (EPA)

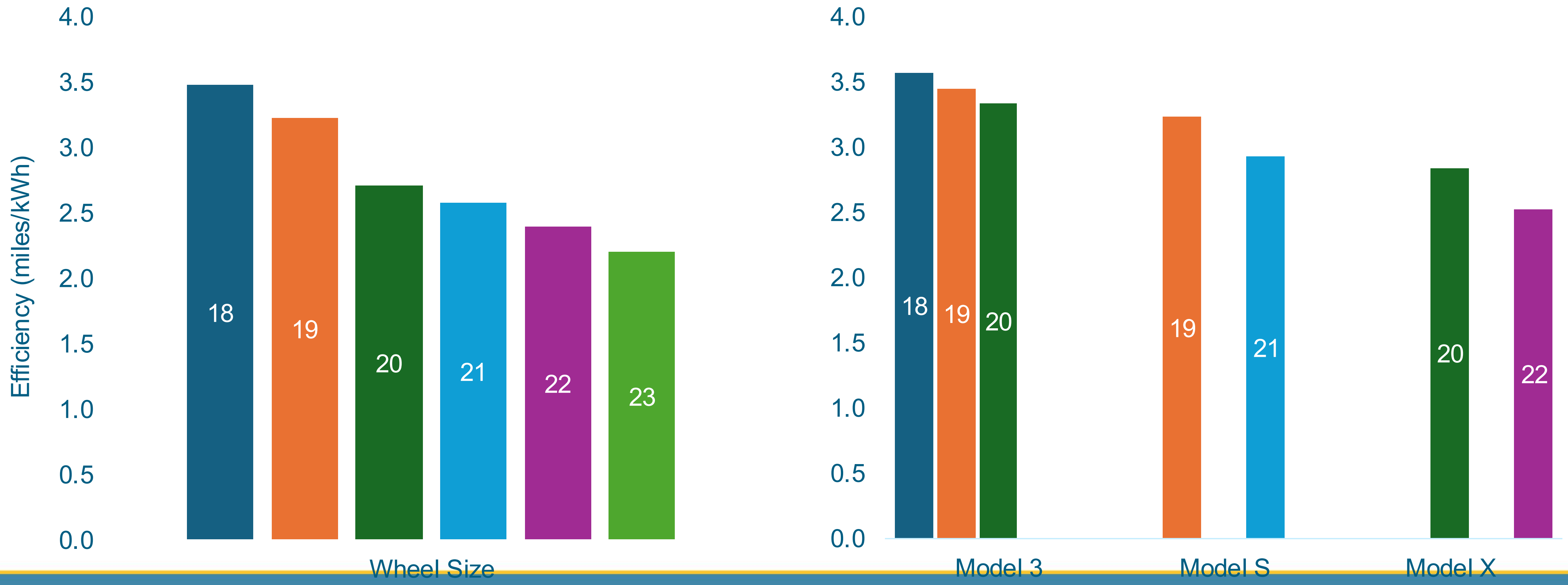
Weak relationship between EPA Motor Power and EPA Efficiency



Source: EPA efficiency ratings

Larger Wheels Negatively Impacts EV Efficiency (EPA Estimates)

Efficiency range across trim/models is highly influenced by wheel size, even when isolating to the same vehicle model (Tesla example below)

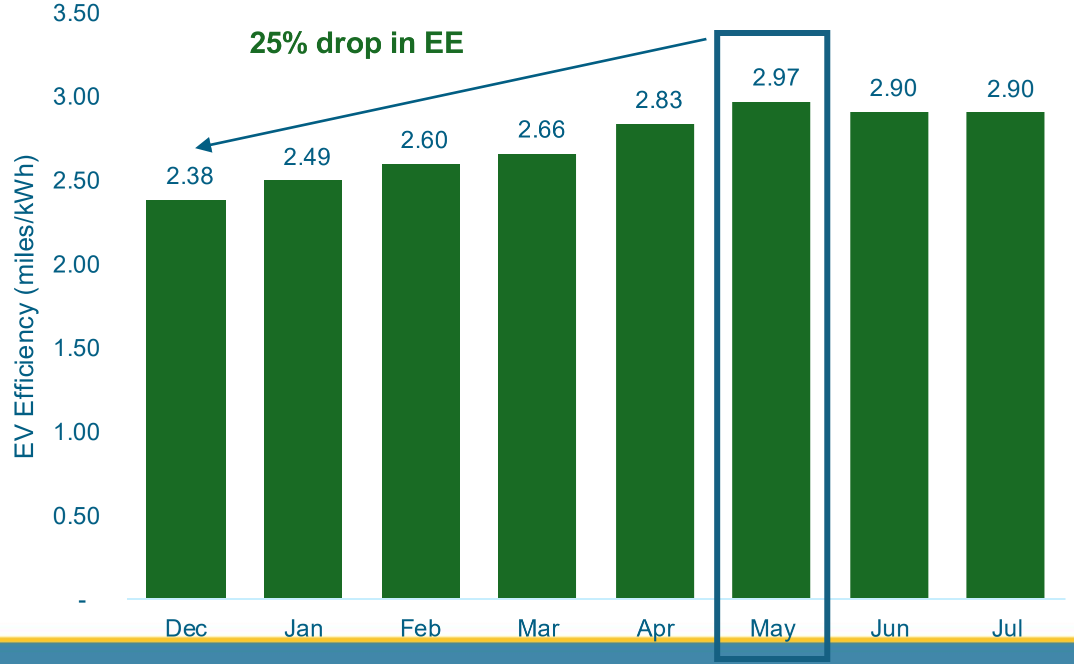


Source: EPA efficiency ratings

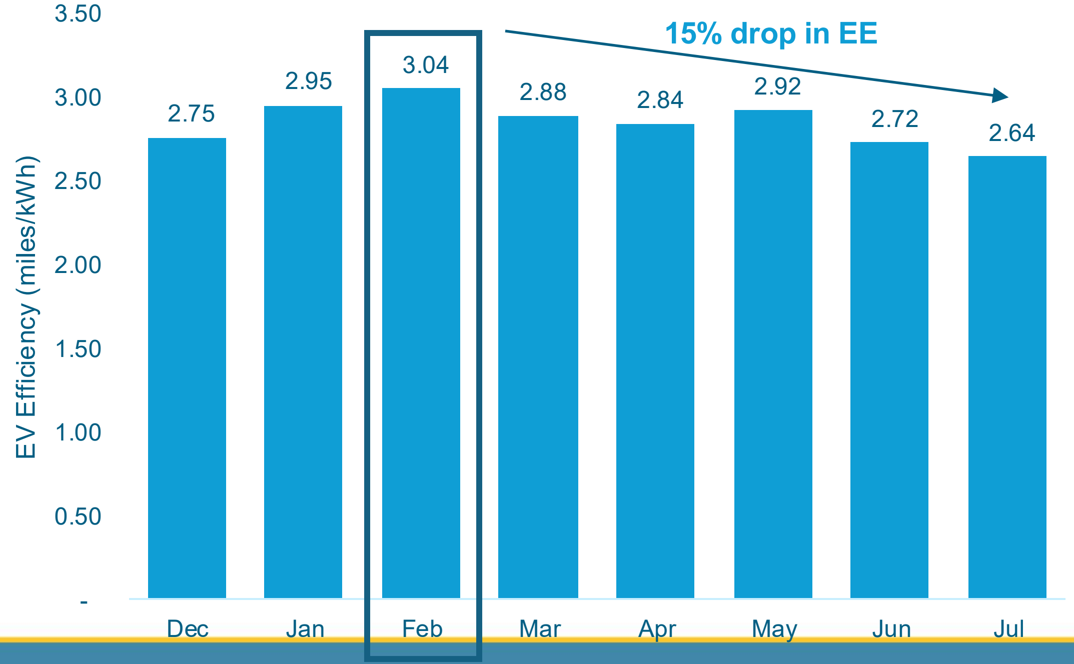
Weather Matters, especially COLD

- **EV efficiency peaks** in temperate months: shoulder months in **colder climates**, winter months in **hotter climates**.
  - EV efficiency varies between peak EE/lowest EE periods:
    - **25% in colder climates and 15% in warmer climates.**

Colder New England climate

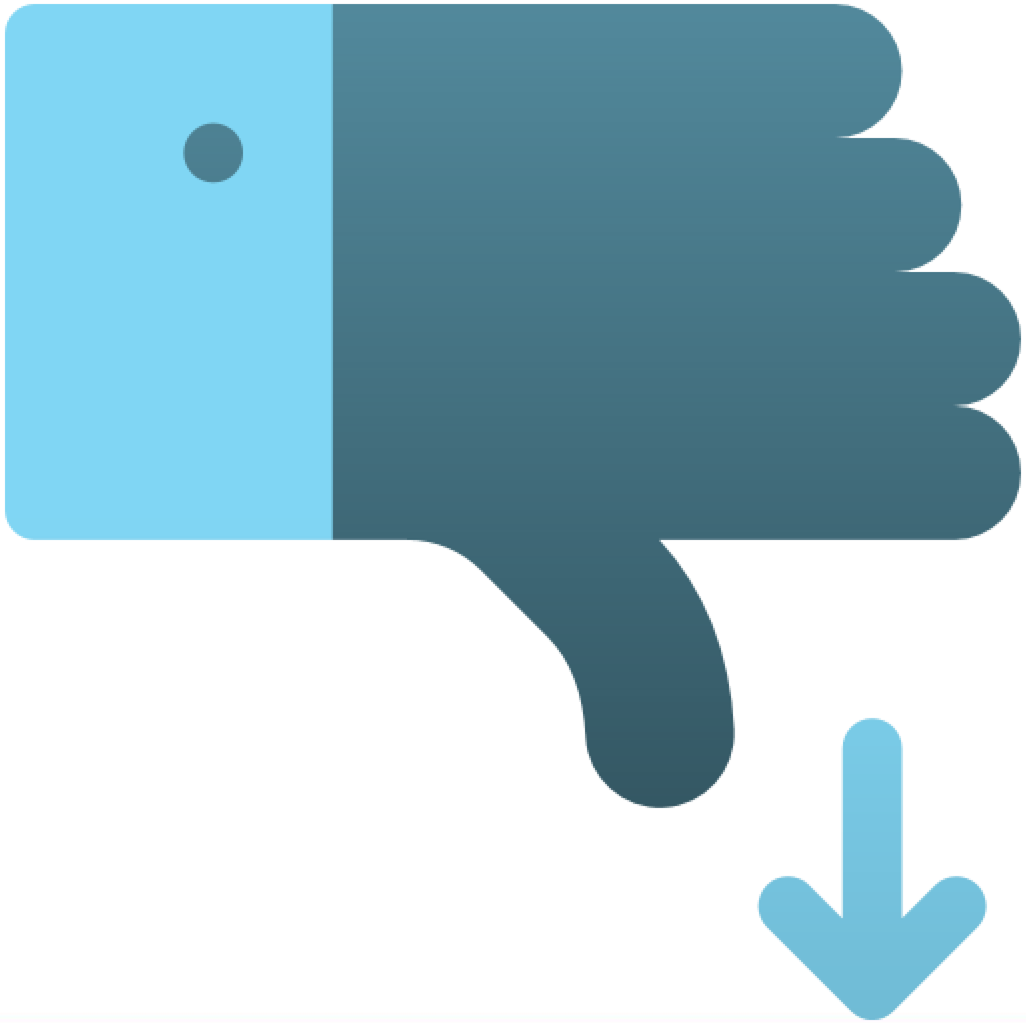


Warmer southern climate



Source: Apex Analytics/Rolling Energy Resources

Weak Explanatory Power of all Models



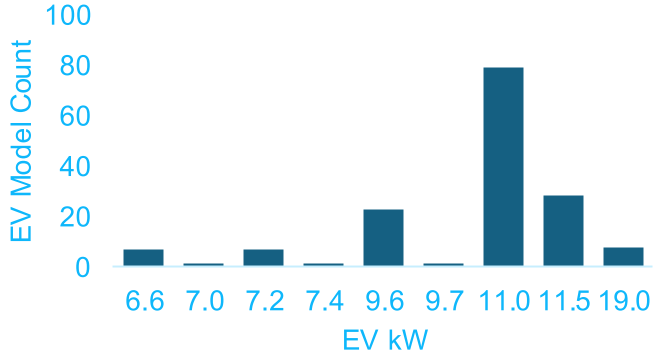
What We Learned From Regressions

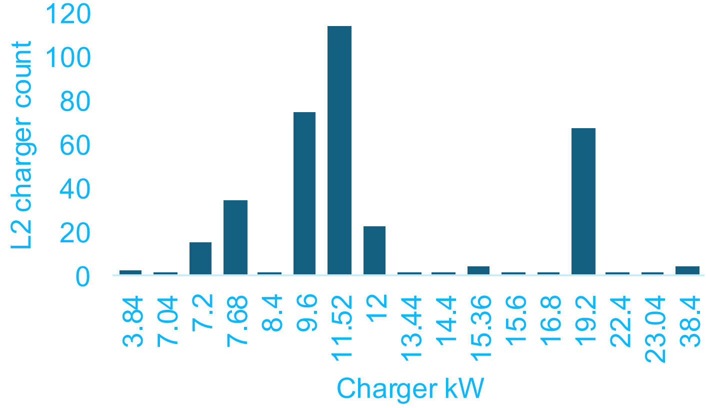
- **Low explanatory power**: Drive type, vehicle age, battery capacity (RER) or motor power (EPA), and weather (RER) significant attributes but STILL explain only a minority of variance in real-world EV efficiency
- **Stable results**: EV attribute regressions relatively stable regardless of additional attributes
  - Inclusion of EV Make (mfg) only improved explanatory power of EPA regression
    - *This likely reflects the disconnect between EPA rated and real-world efficiency!*
  - Weather attributes were significant, but has marginal improvement in overall explanatory power
- **Missing attributes**: Could not include wheel size in regressions given inability to match between sources and lack of consistent assignment in EPA data.

EV Load Management

EV Loads Depend on Various Factors

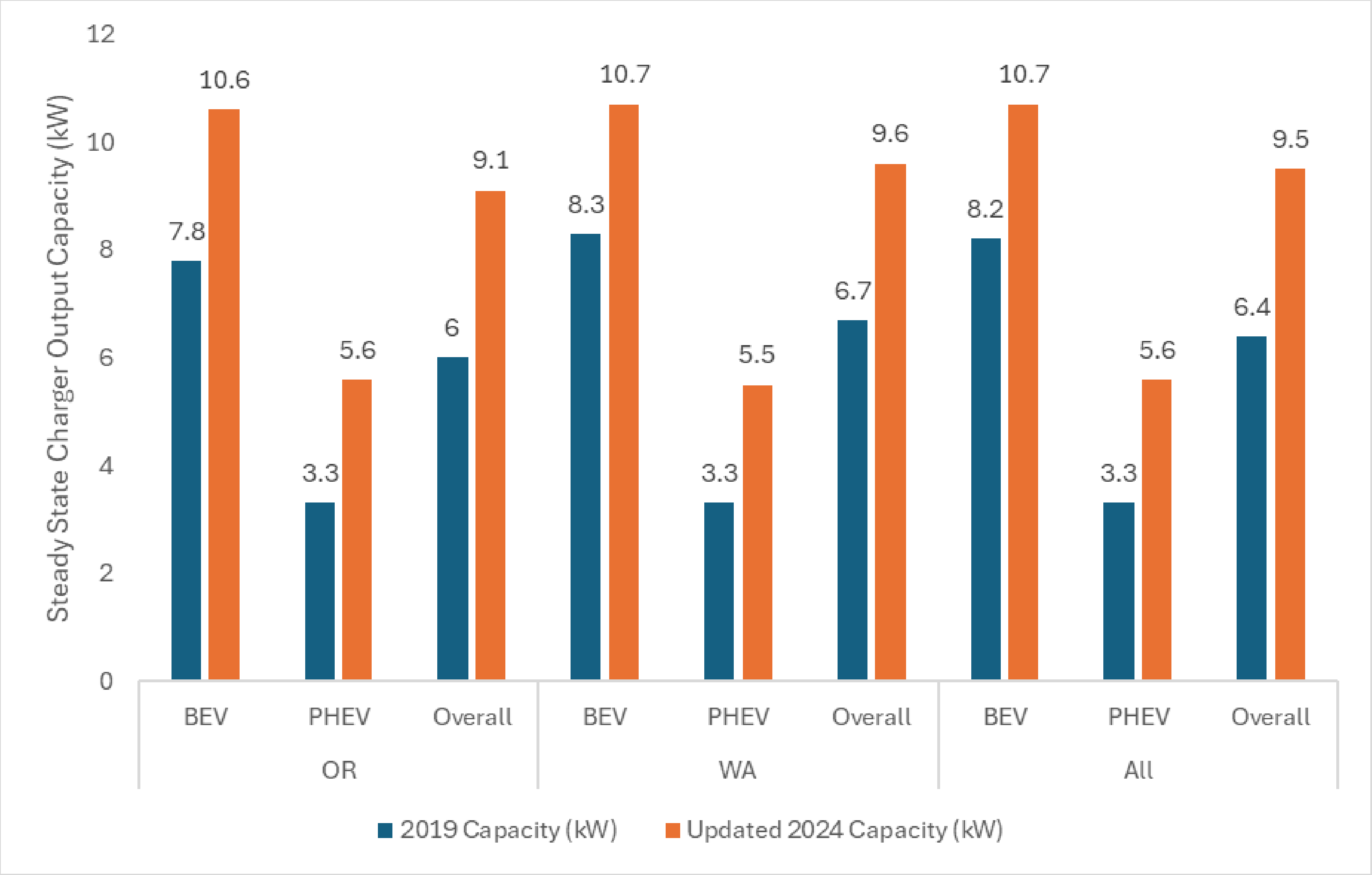
- Residential EV load varies based on:
  - EV battery rated acceptance
  - Charger type (Level 1 or 2) saturations.
  - If we assume Level 2 home charger, load also depends on:
    - Hardwired vs plug-in connection
    - The L2 charger rated max output power (kW)
    - The amperage of the panel circuit
    - Throttling (if battery is below 20 or above 80%)
  - Other: battery age, temperature





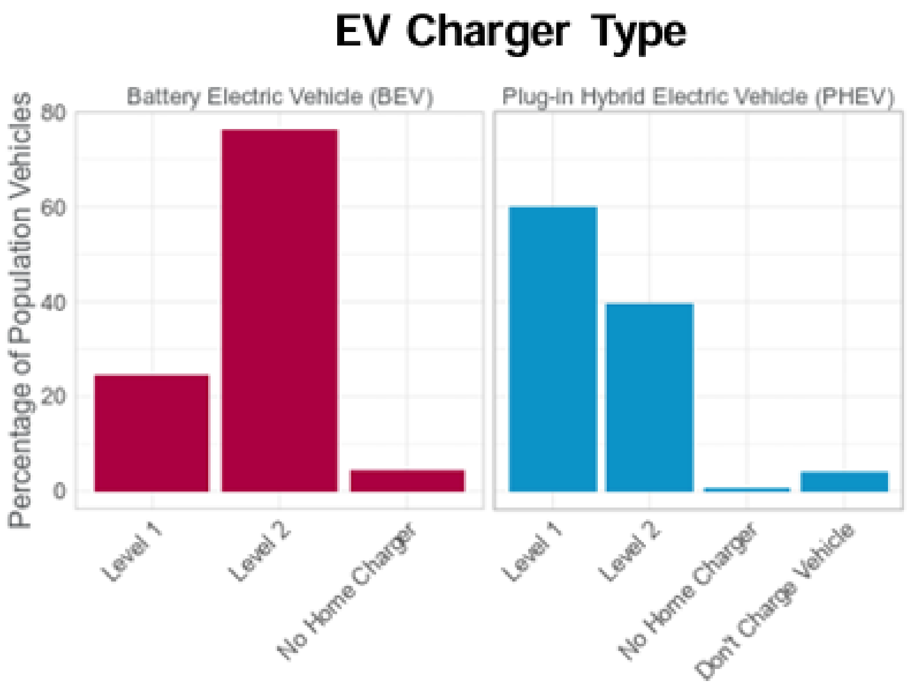
Average EV Battery kW Values in PNW

- Average EV battery acceptance rate now about 50% higher (from 6.4 kW to 9.5 kW) than estimated in 2019
- Increase driven by battery power levels (e.g., more models over 10 kW)



Charger Level

- Especially important for PHEVs (more L1 chargers)
- Example from the MA Baseline Study (2023) below

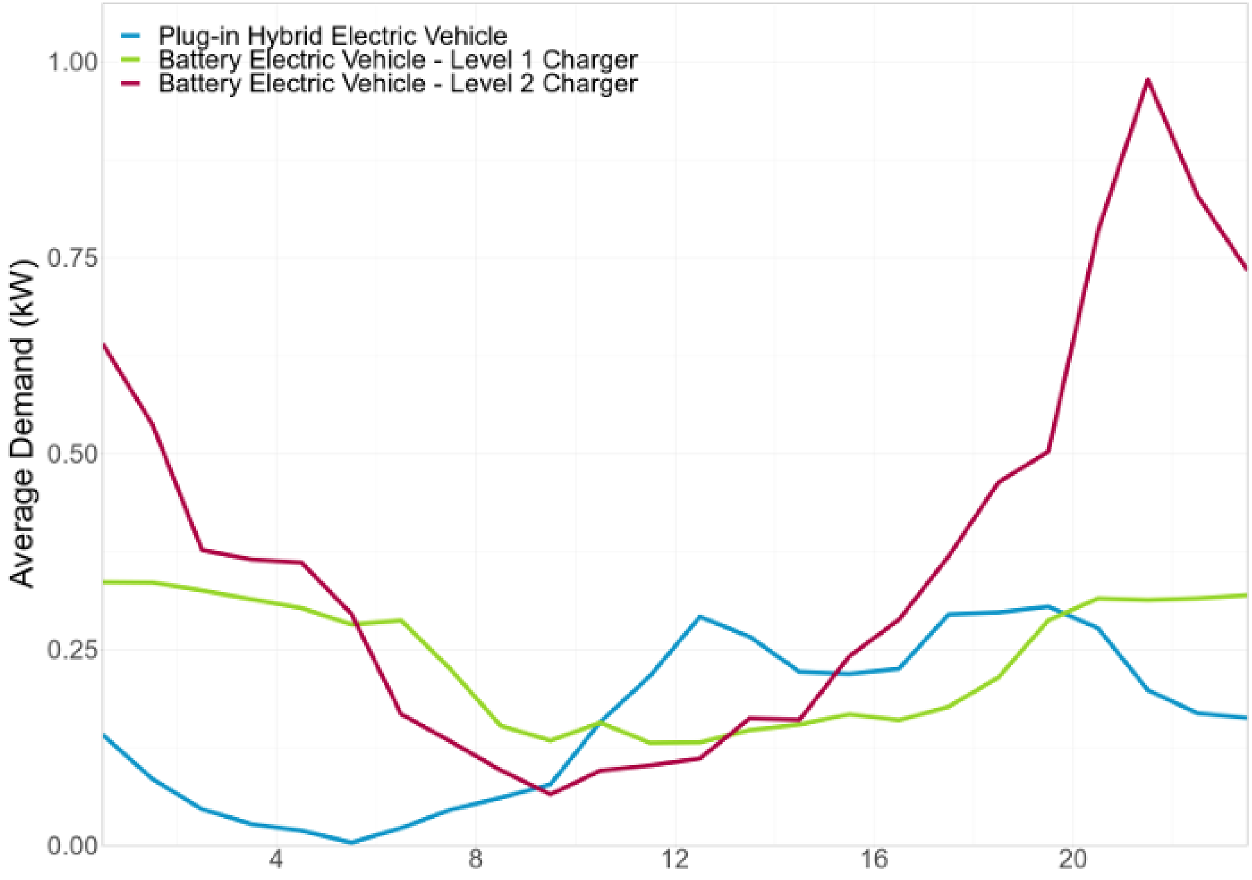


Most BEV owners have a level 2 charger (240V), while most PHEV owners have a level 1 charger (120 V). About 5% of BEV owners and 2% of PHEV owners do not own a home charger. About 5% of PHEV owners do not charge their vehicle.

L2 chargers can be either hardwired (higher max @ 19.2 kW) or plug-in (max @ 9.6 kW)

Load Shapes

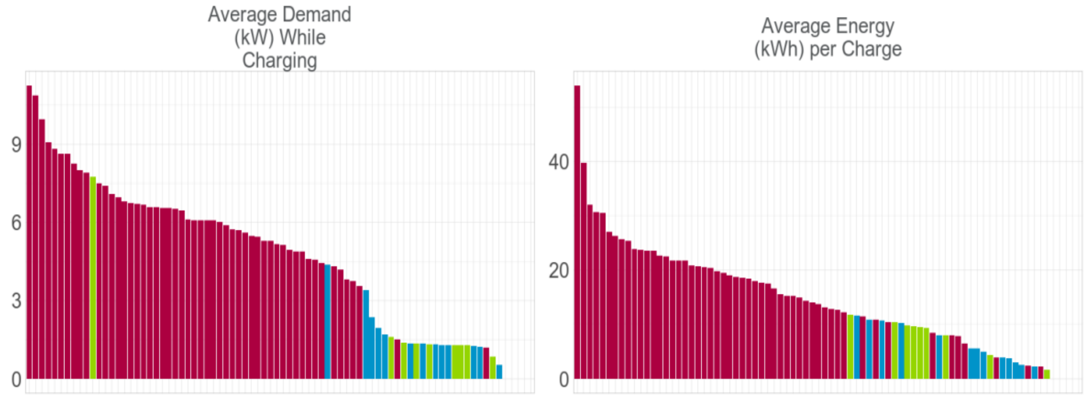
- Coincidence factors can be as low as 10-15% (i.e., the % of cars charging during peak periods)
- This substantially reduces the technical to the achievable potential. (i.e., even at peak the average kW draw - including cars that are not charging - is only about 1kW)
- Data from MA Baseline Study is a good example



Actual Charging Demand

- Data is challenging to capture
- Example below from MA Baseline Study and Rolling Energy Resources (training slides)

Figure 3-73. EV Charge Session Distributions – Per Home



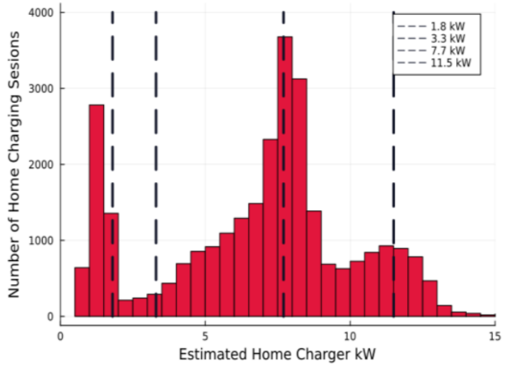
Distribution of kW Draw at the Meter

ROLLING ENERGY RESOURCES

APEX ANALYTICS

Charging session average kW draw at the meter:

- Vertical lines for common charger kW values
- Not exactly on lines due to tapering and differing losses through the transformer; and,
- There is also a lack of granularity in the data which can vary estimates by up to 1.5 kW for shorter charges
- Estimated by 30-minute (or less) pings based largely on change in battery charge, and battery capacity
- F-150 can charge at 19kW.



Key Takeaways From Real-World Program Data

- EV loads are highly flexible
  - Participants have high compliance with program requirements
- Behavioral and active load control can have similar efficacy switching customers to off-peak
- Hybrid programs may have diminished savings from active control
  - The behavior portion has already shifted the majority of the load
  - Caution: EV programs designed with L2 incentives, TOU rates, and then expect kW from managed charging will be disappointed!
- Fixed or variable incentives are both effective

Behavioral programs can shift load but can lead to timer peaks
Active load control may be needed to balance EV charging

Questions?
Thank you!

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