Charging Uncertainty: Real-Time Charging Data and Electric Vehicle Adoption

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Abstract

The development of US electric vehicle charging infrastructure is poised to play a key role in the transition to electric vehicles (EVs), but chargers can only lead to increased EV adoption if drivers can reliably find chargers that are working and available when they need them. In this paper, we investigate the prevalence of real-time data reporting by DC fast chargers on six major US Interstates to a centralized repository and model the impacts of expanding access to real-time data to all near-highway DC fast chargers. On average, between March and August 2024, 34.5% of DC fast chargers within two miles of I-5, I-10, I-75, I-80, I-90, and I-95 provide their real-time status on PlugShare, a major charge-finding app, with gaps of up to Y miles in which no eligible charger provides real-time data. We incorporate the state of real-time data into a two-sided model of consumer vehicle choice and charging station buildout adapted from Cole et al. (2023) to predict that, by 2030, full real-time data reporting alone can increase the electric share of new vehicle sales by 1.0 percentage points, increase the size of the US light-duty EV fleet by 1.5%, and reduce carbon emissions by 2.8 million metric tons per year. If provision of real-time data is accompanied by improved charger uptime and driver confidence, the impact on the EV share of new vehicle sales grows to 6.8 percentage points, the impact on the EV fleet to 9.4%, and the impact on carbon emissions to 18.5 mmt.

1 Introduction

Achieving the stringent proposed Corporate Average Fuel Economy (CAFE) standards and Environmental Protection Agency (EPA) greenhouse gas emissions standards for US light-duty vehicles, as well as achieving broadly defined US climate goals, requires a substantial shift away from internal combustion (ICE) to electric (EV) light-duty vehicles by 2027.

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A key prerequisite to achieving this EV transition is the buildout of public EV charging infrastructure, according to the substantial literature estimating the impact of charging infrastructure on consumer vehicle choice (Springel (2021); Sommer and Vance (2021); Li et al. (2017); Zhou and Li (2018); Xing, Leard and Li (2021)), and according to Cole et al. (2023), who find that, on the margin, government spending on charging infrastructure is substantially more effective than spending on EV tax credits at incentivizing EV purchases.

However, the effectiveness of charging infrastructure for EV adoption in practice depends not only on the number of chargers on the road, but also on customers' beliefs about the reliability of chargers. Specifically, it is a potential car buyer's belief about charging reliability at the time of vehicle purchase that influences their decision to purchase an EV or not; for drivers who have never owned an EV before, these beliefs are formed through a variety of channels, including conversations with existing EV drivers and encounters with popular press articles about EV drivers' experiences.

The popular media narrative surrounding the EV charging experience is currently predominantly negative. Over the last several years, newspaper columnists[1], industry studies[2], and academic literature (Rempel et al., 2022) have documented EV drivers' frustration with charging infrastructure, both in terms of the number of chargers and in terms of their reliability. In particular, Rempel et al. (2022) document the many reasons drivers may fail to successfully charge at California's DC fast chargers (DCFC, also called Level-3 chargers): nonfunctioning screens, payment failures, charging cables too short for some EV models, etc. On top of these failed charges, insufficient charging infrastructure means that drivers may fail to charge simply because chargers are occupied.

One partial solution to these myriad types of charging failures is the reporting of real-time data on charger status to consumers. When we discuss real-time data, we mean data reported *in one centralized place* across charging providers (CPOs) which identifies the locations and types of EV charging stations along with whether they are currently working and currently available. While it is true that most CPOs provide data on their own chargers through a proprietary mobile app, this falls short of the benefits of centralized real-time data, since drivers cannot always cross-reference multiple apps to find working and available chargers while driving. These apps may also require subscriptions, which will become an increasing barrier to EV adoption as the market grows and prospective EV owners become more likely to have low to moderate incomes. For drivers accustomed to using a single mapping app to find gas stations along their driving routes, the lack of centralized searchable data on EV chargers may be a real barrier to EV adoption, especially as the longer time needed to refuel an EV and the possibility of unreliable EV chargers drive range anxiety that does not exist in the ICE context.

[1] https://www.wsj.com/tech/i-visited-over-120-ev-chargers-three-reasons-why-so-many-were-broken-7a5d3e45

[2] https://www.jdpower.com/cars/shopping-guides/lack-of-public-chargers-draining-ev-owner-satisfaction

In this paper, we focus specifically on the reporting of real-time data in centralized apps ("charging locators" or "locator apps") for DCFCs (which we define as chargers providing 50+ kW) on major U.S. highways. Consumers considering purchasing EVs often worry about range anxiety in their most extreme use cases: long road trips far from home, where they are likely to be unfamiliar with available charging infrastructure, and where running out of charge can be the most consequential. Good knowledge of highway fast charging and the availability of specific chargers plays a key role in mitigating that range anxiety and making EVs more accessible to the American public.

Charging firms, or charge point operators (CPOs) may not want to provide centralized real-time data, both for fear that competitors will use it to their advantage and because proprietary data is an inherently valuable part of their businesses (Veldkamp, 2023). The National Electric Vehicle Infrastructure (NEVI) program created by the 2021 Infrastructure Investment and Jobs Act (IIJA, also known as the Bipartisan Infrastructure Law) provides an example of a policy which mandates the reporting of real-time data for highway DCFCs, though its coverage is limited. Specifically, the policy requires "third-party data sharing" (i.e., data accessible to aggregators via an API) on "real-time status by port" and "real-time price to charge" at the plug level, for all NEVI-funded chargers – but imposes no requirements on non-NEVI chargers. If DCFC plugs cost $100,000 on average, however, NEVI can only possibly fund up to 65,000 DC-fast charging ports; compared to NREL's forecast[3] of 182,000 DCFCs by 2030, NEVI-funded chargers will always be in the minority.

Our goals in this paper are to 1) assess the current state of real-time data reporting for DCFCs on major highways, and 2) model the impacts of universally providing real-time data at those stations on the speed of the EV transition and the resulting carbon emissions. To document the state of real-time data today, we present results from repeated scraping of PlugShare[4], a major consumer-facing app and website providing locations of EV chargers worldwide, plus data including plug type, wattage, and (sometimes) real-time status of chargers. In particular, we document on six major US highways the fraction of DCFCs providing real-time data, the CPOs which do and do not provide real-time data to PlugShare, and locations where real-time data is particularly sparse. Most recently, across our six Interstate highways on August 18th, 2024, 34.4% of DCFC stations and 21.0% of plugs provided real-time data on PlugShare. Across our entire scraping interval from March to August of 2024, we find that 34.5% of DCFC stations and 19.3% of DCFC plugs on average report real-time data on PlugShare.

To model the impact of real-time data reporting on EV adoption, we modify the two-sided EV market model from Cole et al. (2023), which combines a discrete choice model for consumer adoption of EVs with an entry-exit model for charging station deployment. In our new version of the model, we incorporate in the consumer's utility function not only the total

[3]https://driveelectric.gov/files/2030-charging-network.pdf, page 26, table 6

[4]Google Maps and Apple Maps also provide real-time data on some DCFCs. We focus on PlugShare and present brief evidence that PlugShare reliably provides real-time data for a higher fraction of highway DCFCs than does Google Maps or Apple Maps.

number of DCFCs on US roads but also the consumer's beliefs about the fraction of those chargers which are working and available at any given time, which in turn depends on the fraction that provide real-time data. Using this modified model, we predict that universal real-time data provision alone increases the size of the light-duty EV fleet by 1.5% on average in 2030, and if that real-time data reporting results in improved charger uptime and consumer beliefs about charger reliability, the size of the light-duty EV fleet could instead increase by 9.4% on average.

This paper is organized as follows. In section 2, we describe our methodology for scraping PlugShare and present results documenting current patterns in the reporting of real-time data. In section 3, we describe a forthcoming survey documenting EV drivers' and potential buyers' beliefs about the reliability of DCFCs that do and do not report real-time data. Section 4 presents our modified model of the EV market and results of our simulations of various real-time data scenarios, and section 5 concludes.

2 The state of real-time data

In this section, we document the state of centralized real-time data for DC Fast chargers on six major US Interstate highways. We focus on DCFCs because slower Level-2 chargers require multiple-hour charging sessions so are impractical for long-distance road trips except at overnight stops; DCFCs, therefore, are key to alleviating consumers' range anxiety around long-distance travel. In particular, we present trends over time in real-time data provision for DCFCs on PlugShare.com, a major charger mapping application and website affiliated with EVgo. We collect data on six highways covering 13,538 miles in 40 states and 27.7% of the US Interstate system by distance: I-5, I-10, I-75, I80, I-90, and I-95. We also provide a brief comparison of PlugShare with real-time data reporting on Google Maps and Apple Maps, though we focus our attention on PlugShare as the best of the three.

2.1 Methodology

In February 2024, we identified location codes for all DCFC or Level-3 chargers, defined as plugs providing at least 50 kW, within a 2-mile driving distance of exits on the six Interstates mentioned above from PlugShare. Within major metro areas, defined as U.S. census incorporated places with a population of at least 100,000 and a population density of at least 2,500 people per square mile, we additionally require that chargers are within a 0.5-mile Euclidean distance from the end of the highway off-ramp to account for heavier traffic and therefore less convenient charger access in dense cities. We exclude chargers noted as restricted access, and we exclude chargers at dealerships except where specified otherwise.

Using the resulting location codes, we have repeatedly scraped from PlugShare.com data on whether each plug at the identified stations is available, in-use, or unavailable. We classify plugs listed as none of the three as not providing real-time data, and we classify plugs with real-time data as working as long as they are identified as either "available" or "in-use". We collect data at the plug level but present many of our results at the station level, where

we define a station as all plugs at a location ID which are rated to provide at least 50 kW (to distinguish from Level-2 chargers) and have the same charging provider. That is, one location can be counted as multiple stations in our analysis if it contains plugs provided by multiple different CPOs. In the results below, the full list of stations is updated only once, on July 22nd, 2024; any changes in the provision of real-time data before July 22nd or between July 22nd and August 18th are therefore the result of changing real-time data provision within the set of existing chargers.

2.2 Results: PlugShare

Table 1 summarizes data from the most recent PlugShare scrape on August 18th, 2024. Overall rates of real-time data reporting are provided at the station level for each highway individually and for the six highways in aggregate, where a station is defined as providing real-time data if at least one of its plugs provides real-time data at the time of scraping. Overall, real-time data is provided at 34.4% of stations, though this ranges from 26.1% on I-90 to 46.1% on I-5.

The second set of rows in the table provides these statistics for all stations except those provided by Tesla. Tesla is a major holdout in the provision of real-time data, but is not necessarily relevant to the decision process of non-Tesla drivers, as up to present, Tesla fast chargers have been available almost exclusively to Tesla vehicles. Excluding Tesla chargers brings the overall share of DCFC stations providing real-time data to 54.3%, with a range from 41.0% on I-90 to 63.9% on I-5.

Finally, the last two rows in Table 1 present results which exclude both Tesla and Electrify America, the other major holdout in providing real-time data. Electrify America chargers are available to non-Tesla drivers and the absence of central real-time data reporting, therefore, represents a major obstacle to full real-time data provision for drivers of all vehicle types. Excluding both Tesla and Electrify America brings the total share of stations providing real-time data to 70.2%, with a range of 54.7% on I-90 to 79.1% on I-80. Excluding these major holdouts substantially improves the perceived fraction of stations providing real-time data, but does so at the cost of reducing the number of stations overall by nearly 51% (1,212 total stations vs. 594 excluding Tesla and EA).

Appendix Table A.1 presents the same statistics at the plug-level rather than at the station level. The share of plugs providing real-time data is lower than the share of stations providing real-time data in the full population (21.0% vs. 34.4%) because Electrify America tends to have large stations, with a median of 8 plugs and a mode of 8 plugs – compared to a median 10 plugs (mode 8) for Tesla stations and median 4 (mode 4) for all other stations. Electrify American and Tesla also have much longer right tails in the distribution of station size; the largest EA station on our six highways has 21 plugs and the largest Tesla station has 84 plugs, whereas EVgo is the only other CPO operating any station with more than 12 plugs. The same pattern is true to a lesser extent when Tesla is excluded; 48.1% of plugs provide real-time data, vs. 54.3% of stations. By contrast, the share of plugs providing

Table 1: Real-time data provision on August 18th, 2024

	I-95	**I-5**	**I-10**	**I-75**	**I-80**	**I-90**	**Total**
Total Stations	284	280	161	144	186	157	1,212
% w/RT Data	**30.3%**	**46.1%**	**33.5%**	**31.3%**	**33.3%**	**26.1%**	**34.4%**
Non-Tesla Stations	158	202	101	89	118	100	768
% w/RT Data	**54.4%**	**63.9%**	**53.5%**	**50.6%**	**52.5%**	**41.0%**	**54.3%**
Excluding Tesla and EA	130	163	76	70	80	75	594
% w/RT Data	**66.2%**	**79.1%**	**71.1%**	**64.3%**	**77.5%**	**54.7%**	**70.2%**

data is higher than the proportion of stations providing real-time data when both Tesla and Electrify America are excluded (71.7% of plugs vs. 70.2% of stations) because the majority of large stations without real-time data have been excluded.

Whether an individual station provides real-time data is primarily a function of its CPO, though there are CPOs which provide real-time data at only some of their stations. A notable example is ChargePoint, whose stations are franchised and therefore vary in their real-time data reporting since the decision to share rests with the charger owner or site host. This is true even on ChargePoint's own mobile app, where some ChargePoint-branded DCFCs provide real-time data but others do not. Regional differences in the dominant charging providers in large part explain the variation in data availability across highways. Table 2 lists the top four providers of DC fast chargers (excluding chargers at dealerships) across our six highways as of July 22nd, 2024; the number of stations they provide; the percentage of those that report real-time data on PlugShare; the number of stations belonging to other CPOs; and the number of non-networked stations, which are neither associated with a specific CPO nor connected to the internet, so cannot supply real-time data.

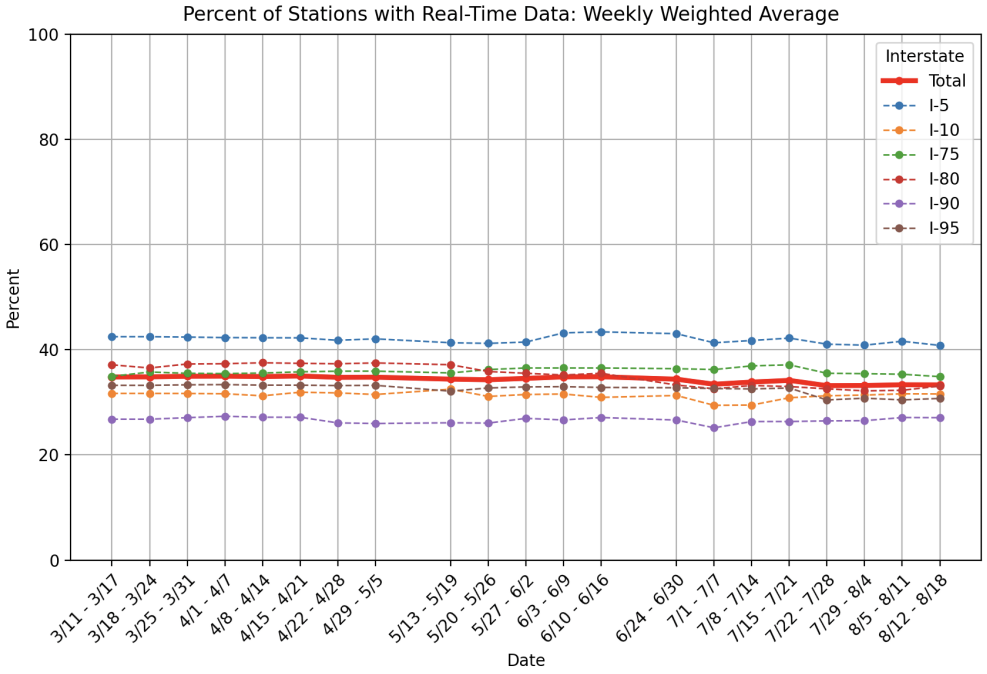
On every highway except I-90, the top four CPOs are (Tesla) Supercharger, Electrify America, EVgo, and ChargePoint (on I-90, EV Connect is the fourth largest provider, with 13 stations). Among these, Supercharger is always the largest provider and Electrify America is always in the top three; these two major CPOs never provide centralized real-time data. Supercharger and Electrify America together represent between 44% and 58% of stations along each of these six major Interstates. EVgo is the largest CPO providing near-universal real-time data on all six highways, and ChargePoint provides universal real-time information on I-90 and substantial real-time coverage (86%-96% of stations) on the other five highways. Outside of these four providers, the market is less concentrated, with EV Connect, Applegreen Electric, Rivian Adventure Network, and Shell Sky EV Technology each appearing in the top five on only one of the six highways, and EVCS appearing twice.

Current reporting of real-time data for DCFCs is far from universal. On the six highways we study, it has not significantly improved over the period in which we have scraped data

Table 2: Number and percent of stations providing real-time data on PlugShare by CPO on July 22nd, 2024

		I-95	**I-5**	**I-10**	**I-75**	**I-80**	**I-90**	**Total**
Supercharger	Total Stations	148	102	71	59	81	78	539
	# w/RTD	0	0	0	0	0	0	0
	% w/RTD	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**
Electrify America	Total Stations	38	50	34	21	44	30	217
	# w/RTD	0	0	0	0	0	0	0
	% w/RTD	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**
EVgo	Total Stations	36	42	26	16	24	15	159
	# w/RTD	36	40	25	16	24	15	156
	% w/RTD	**100%**	**95%**	**96%**	**100%**	**100%**	**100%**	**98%**
ChargePoint	Total Stations	40	52	14	26	24	8	164
	# w/RTD	39	49	12	25	23	8	156
	% w/RTD	**98%**	**94%**	**86%**	**96%**	**96%**	**100%**	**95%**
Non-networked	Total Stations	7	6	4	1	4	2	24
	# w/RTD	0	0	0	0	0	0	0
	% w/RTD	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**
Other	Total Stations	66	97	39	27	39	56	324
	# w/RTD	20	68	22	6	23	21	160
	% w/RTD	**30%**	**70%**	**56%**	**22%**	**59%**	**38%**	**49%**
Highway Total	Total Stations	335	349	188	150	216	189	1427
	# w/RTD	95	157	59	47	70	44	472
	% w/RTD	**28%**	**45%**	**31%**	**31%**	**32%**	**23%**	**33%**

Figure 1: Percent of stations reporting real-time data at at least one plug

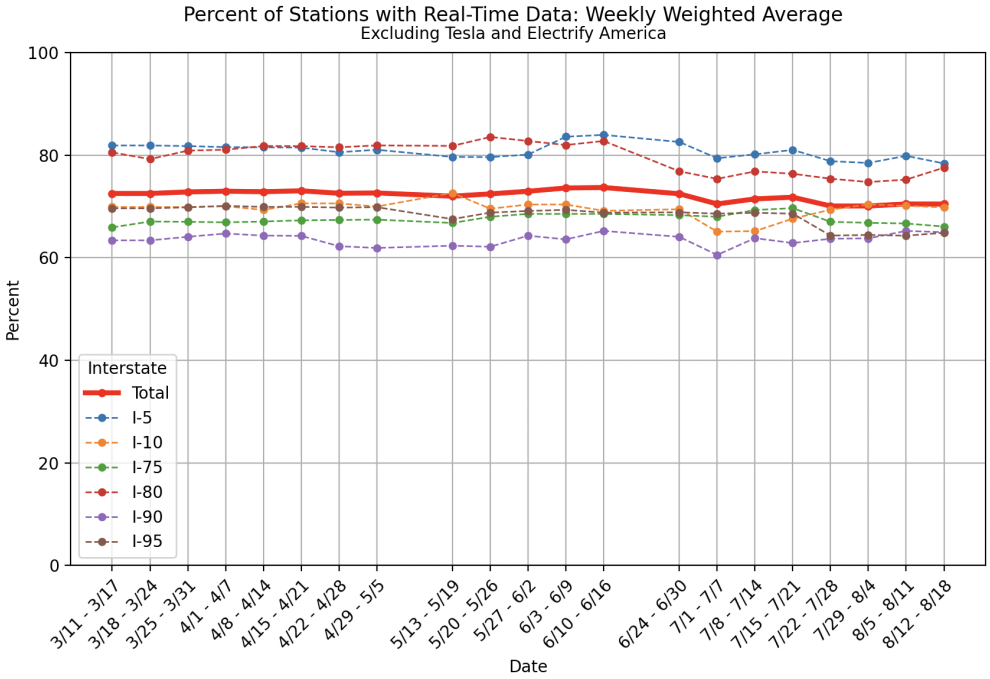


from PlugShare. In fact, Electrify America provided real-time information on PlugShare as of early fall 2023, but has since stopped and has not provided any real-time data for the duration of our scraping period. BP Pulse has begun to share real-time data on Plugshare during our scraping interval, but currently makes up only 0.77% of stations (11 stations) across our six highways. Overall trends in real-time data provision on our six highways are presented in Figure 1 (all CPOs), and Figure 2 (excluding Tesla and Electrify America). Appendix Figure 18 presents an analogue to Figure 1 but excludes dealers. Each point on these graphs represents a weighted average of successful PlugShare scrapes within the relevant week[5].

Across our six highways, the overall share of stations providing real-time data is relatively stable, with almost no heterogeneity in the trend across highways. We updated the list of stations once on July 22nd; any changes on July 22nd reflect the net effect of station entry/exit and changes in the composition of stations sharing real-time data, while any changes during the rest of the scraping period may be due to station exit but not entry (as a station whose listing on PlugShare has been removed will not appear in our scraping data) and therefore reflect primarily differences in the composition of stations sharing real-time data. Figure 2 shows somewhat less steady real-time data sharing when we exclude Tesla and Electrify America; this is unsurprising, since Tesla and EA make up such a large share of the total population of chargers on these highways. However, despite greater fluctuation week to week as compared to Figure 1, Figure 2 does not demonstrate a clear trend over time across highways. The prevalence of real-time data sharing is largely unchanged since

[5]Data before May 21st, 2024 does not include I-80 east of Chicago.

Figure 2: Percent of stations reporting real-time data at at least one plug, excluding Tesla and Electrify America



the beginning of our data collection in March, 2024.

To test for differences in real-time data availability within weeks, we regularly performed PlugShare scrapes on each day of the week and at three different times of day, based on the local time in the timezone of each station: 8 am ("morning rush"), 12 pm ("off-peak"), and 5:30 pm ("evening rush"). Figure 3 plots the average fraction of stations reporting real-time data for at least one plug by day of week and highway, and Figure 4 plots the average fraction of stations reporting real-time data for at least one plug by day of week and time of day. There are no discernible systematic differences in real-time data provision by weekday or by time of day.

2.3 Comparison with Google Maps and Apple Maps

In this section, we compare real-time data sharing on PlugShare with Apple Maps and Google Maps to validate our use of PlugShare as the most comprehensive source of real-time DCFC data. While PlugShare is the best of the three in terms of its coverage of real-time data, it is least accessible to the new EV driver, who likely already uses Google or Apple Maps for navigation.

To conduct our comparison with Google and Apple, we randomly sample 20% of stations from our list of highway DCFCs on PlugShare, then manually check whether each of these chargers provides real-time data on Google Maps and Apple Maps. We count a charger as providing real-time data on Google Maps or Apple Maps if it is present on the relevant

Figure 3: Average fraction of stations reporting real-time data at at least one charger by day of week

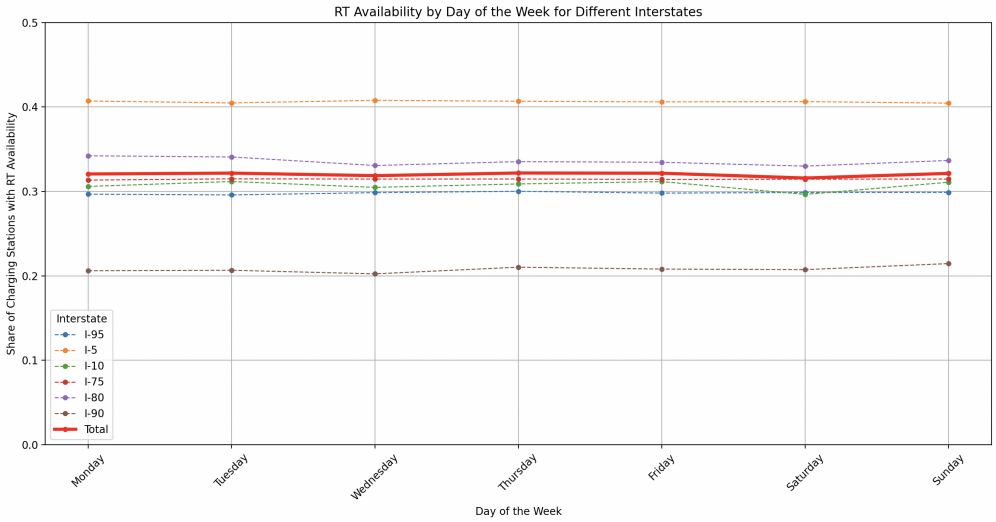


Figure 4: Average fraction of stations reporting real-time data at at least one charger by day of week and time of day

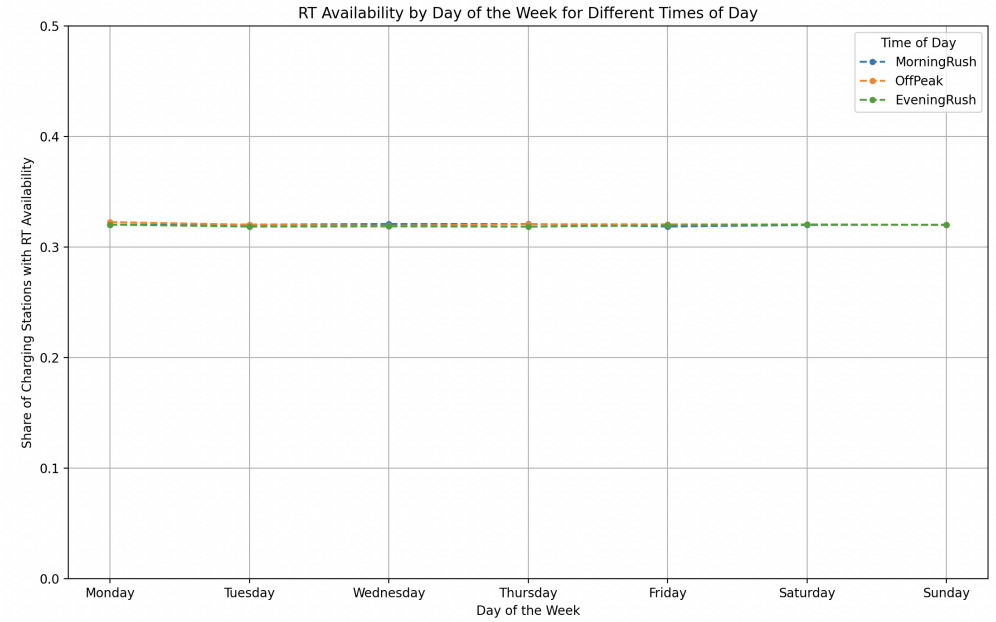


Table 3: Fraction of stations providing real-time data at at least one plug by data provider

	I-95	**I-5**	**I-10**	**I-75**	**I-80**	**I-90**	**Total**
PlugShare	28.6%	51.4%	18.9%	39.4%	37.2%	19.4%	35.3%
Google	28.6%	18.1%	13.5%	33.3%	20.9%	8.3%	19.7%
Apple	3.6%	18.1%	2.7%	18.2%	14.0%	8.3%	12.0%

Table 4: Fraction of stations providing real-time data at at least one plug by data provider, excluding Tesla and Electrify America

	I-95	**I-5**	**I-10**	**I-75**	**I-80**	**I-90**	**Total**
PlugShare	53.3%	78.7%	46.7%	92.9%	76.2%	50.0%	69.8%
Google	53.3%	27.7%	33.3%	78.6%	42.9%	23.8%	38.9%
Apple	6.7%	27.7%	6.7%	42.9%	23.8%	21.4%	23.0%

app and identifiable as the same charger as the sampled PlugShare charger *and* it provides real-time data for at least one plug. Stations which do not appear on Google or Apple are counted as not providing real-time data.

Table 3 presents the results for our 20% sample on Google, Apple, and PlugShare, and Table 4 presents results for the same sample excluding Tesla and EA chargers. PlugShare is better than either Google Maps or Apple maps across highways, whether or not Tesla and EA are included; only on I-95 is Google Maps as good as PlugShare within our 20% sample. The difference is starkest on I-95, where PlugShare provides real-time data for nearly eight times as many stations as does Apple Maps. Google Maps generally provides better real-time data than Apple Maps, excepting a few comparisons where the two are equivalent: I-5 with and without Tesla and EA, and I-90 with Tesla and EA.

2.4 Results: Data Deserts

The above results paint a broad picture of the state of real-time data provision along six major US highways and variation between those highways, but they obscure the regional variability in real-time data provision within these six highways. In this section, we focus on what we call "data deserts": long stretches of highway where no DC fast charger within two miles of the highway (0.5 miles in metro areas) provides real-time data on PlugShare. These dataless stretches can at times span distances longer than even the longest stated range of existing EV models, and therefore require meticulous advanced planning. Without cross-referencing the individual apps of charging providers within these deserts, drivers have no way of knowing whether a functioning charger exists over distances of several hundred

miles.

Table 3 presents data deserts on our six highways as of May 17th, 2024. We document data deserts of 145 miles or longer on four of our six highways: I-10, I-80, I-90, and I-95. Table 3 presents the details of the full set of deserts including their start and end locations, their lengths, and how many of the stations in the deserts are owned by Tesla and EA. We find 13 data deserts in total, with four on I-10, six on I-80, two on I-90, and one on I-95; we find no deserts of 145 miles or longer on I-5 or I-75. Four of the sixteen deserts are over 300 miles long, longer than the stated range of many current EV models: Deming, NM to Kerrville, TX (586 miles) and Baytown, TX to Robertsdale, AL (466 miles) on I-10; Coalville, UT to Kearney, NE (709 miles) on I-80; and Post Falls, ID to Blue Earth, MN (1,308 miles) on I-90. Moreover, several of these deserts are adjacent; on the 795 miles of I-10 between chargers in Tucson, AZ and Kerrville, TX, the only intermediate chargers with real-time data are in Deming, NM. On I-80, the 148-mile Truckee, CA to Lovelock, NV data desert is immediately adjacent to another 153-mile data desert to Carlin, NV, and between Perrysburg, OH and COlumbia, NJ, the only chargers with real-time data are in Columbia, NJ. The state of data availability without is worst on I-90; a single 1,308-mile desert between Post Falls, ID and Blue Earth, MN (where the single ChargePoint station providing real-time data is under repair as of June 4th, 2024) is immediately adjacent to another 293-mile data desert between Blue Earth, MN and Madison, WI.

Table 5: Data deserts of at least 145 miles, excluding dealerships

	Start Location	**End Location**	**Length (mi)**	**Stations**	**Tesla**	**EA**
I-10	Tucson, AZ	Deming, NM	209	4	2	2
	Deming, NM	Kerrville, TX	586	15	9	5
	Baytown, TX	Robertsdale, AL	466	17	20	4
	Robertsdale, AL	Tallahassee, FL	226	12	6	4
I-80	Truckee, CA	Lovelock, NV	148	7	4	3
	Lovelock, NV	Carlin, NV	153	3	1	2
	Coalville, UT	Kearney, NE	709	16	8	6
	Bettendorf, IA	Rolling Prairie, IN	221	12	6	2
	Perrysburg, OH	Emlenton, PA	209	9	5	3
	Emlenton, PA	Columbia, NJ	274	12	8	4
I-90	Post Falls, ID	Blue Earth, MN	1,308	38	23	8
	Blue Earth, MN	Madison, WI	293	11	5	1
I-95	Lynchburg, SC	Savannah, GA	145	8	7	1

For non-Tesla drivers, opportunities to charge in these deserts are sparse even at stations without real-time data. Excluding Tesla Superchargers, there is, on average, a DC fast charger every 81.8 miles on I-90 between Post Falls, ID and Blue Earth, MN, and every 78.8 miles on I-80 between Coalville, UT and Kearney, NE. This leaves little freedom for repeated failed charging attempts, especially in cold weather conditions when EV ranges are limited.

Appendix Table 12 presents data deserts on our six highways including chargers at dealerships. With the exception of I-95, the overall picture of data deserts improves significantly in this context; the 13 data deserts documented in Table 5 are broken into 16 shorter data deserts. However, some chargers at dealerships may be restricted only to their own customers or to certain hours of the day, so the improved state of charging data presented in Table 12 may not reflect the reality of publicly available charging.

It should be emphasized that these data deserts are not *charging* deserts; even on the 1,308 miles of I-90 between Post Falls and Blue Earth, publicly accessible DCFCs are available within two miles of the highway on average every 34 miles. Thus, the major problem documented is not that there is insufficient charging for highway drivers in these parts of the country (though this may also be the case), but rather that there is insufficient *information* about that charging to guarantee these trips will be feasible and ease range anxiety.

It should also be noted that, in recent months, the state of data deserts has improved marginally on our six highways. Most significantly, what is now a 201-mile data desert between Tallahassee, FL and Pensacola, FL was in early April, 2024 a 385-mile desert between Jacksonville, FL and Daphne, AL. The addition of a ChargePoint charger providing real-time data at a Genesis dealership in Pensacola and an EVConnect charger in Tallahassee, FL have substantially shortened the distances drivers have to travel in the southeastern US without real-time information on DCFC availability. The existence of these data deserts may continue to lessen as NEVI chargers requiring real-time data reporting a rolled out throughout less EV-ready areas of the United States, but progress on this front has been slow; by late March, 2024, only 7 NEVI stations with 38 plugs had opened to the public in Hawaii, Pennsylvania, Ohio, and New York[6].

3 Consumer attitutes towards real-time data

Charging infrastructure buildout and policies meant to incentivize it can only spur EV adoption if consumers considering buying EVs trust that chargers work and are likely to be accessible and available when needed. To understand the extent to which charging reliability is salient to potential EV buyers and the potential impact of providing better charging information on adoption, we have conducted two consumer surveys eliciting beliefs about the subjective probability of successfully charging at DCFC with and without real-time data on US highways. These survey results serve to document beliefs about charging reliability among current EV drivers and potential buyers, and to feed into our modeling of the impact of improved real-time data provision on EV adoption described in Section 4.

We conduct two surveys with the same questions but distinct samples: one of US-based current EV drivers and one of US-based non-EV drivers who expect to buy a new car soon. The current EV driver sample is comprised of members of the Electric Vehicle Association,

[6] https://www.washingtonpost.com/climate-solutions/2024/03/28/ev-charging-stations-slow-rollout/

a North American nonprofit working towards accelerating the adoption of EVs. We acquire an age- and gender-balanced panel of US-based non-EV drivers likely to buy a new car in the next 1-2 years through the survey firm Dynata.

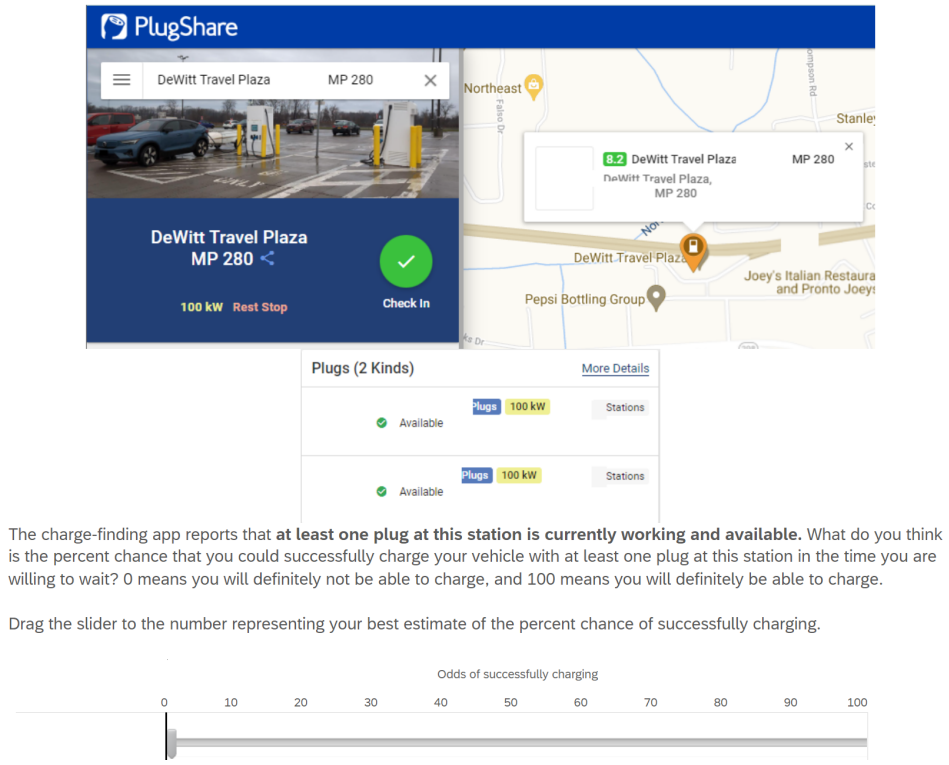
Figure 5 presents an example of the main questions in our survey. We ask respondents to imagine that the chargers we ask about are all within 200 miles of their home, within 2 miles of a US Interstate, and compatible with their vehicle. We then present a censored image of an example station on PlugShare (removing details like the charger's location, user ratings, and number and availability of plugs), alongside key details of the hypothetical station and ask the respondent to estimate the probability of successfully charging at that station. All respondents receive three variations of this question in a random order, asking to assess 1) a charger with real-time data and at least one plug working and available, 2) a charger with real-time data and at least one plug working but none available, and 3) a charger without real-time data.

To understand heterogeneity in expectations about different categories of chargers, we randomize respondents into three groups and ask an additional two questions. One third of respondents are asked to assess a Tesla charger without real-time data and an Electrify America charger without real-time data, one third of respondents are asked to assess a station with 4 plugs and no real-time data and a station with 10 plugs and no real-time data, and the final third are asked to assess a station in a rural area with no real-time data and a station in an urban area with no real-time data.

We received 1,006 completed survey responses from prospective car buyers via Dynata and 814 completed survey responses from current EV drivers via EVA. Among these, we drop survey responses submitted in under 2 minutes on the basis that they were likely not completed carefully; the median survey duration is 3.9 minutes for Dynata respondents (mean 11.5) and 6.3 minutes for EVA respondents (mean 15.5), who are likely to be more invested in the subject matter than Dynata's panel of prospective car buyers. This leaves us with 908 responses from prospective car buyers and 813 from current EV drivers. Other characteristics of responses could potentially indicate carelessness; 33.0% of Dynata respondents and 19.9% of EVA respondents report a higher likelihood of successful charging at an unavailable than available charger, and 33.1% of Dynata respondents and 20.4% of EVA respondents report a higher likelihood of successful charging at a charger without real-time data than at an available charger. However, we do not drop these responses, as they are plausibly rational; drivers may know that an occupied charger cannot possibly be physically blocked or broken in some way that does not register in real-time data, and drivers may believe that the CPOs that do not provide centralized real-time data are generally more reliable than the CPOs that do.

Figure 6 plots the average response and 95% confidence interval for the three main questions in our survey, split by survey sample. Perhaps most striking is the pessimism with which respondents view chargers that provide real-time data and are reported working and available; prospective car buyers estimate that they can successfully charge at such a station

Figure 5: Sample survey question



64.6% of the time, and current EV drivers estimate that they can successfully charge at such a station only 58.6% of the time. Also striking is the fact that EV owners are statistically significantly *more pessimistic* than prospective buyers in all three scenarios. The order of the rankings is the same for both groups: available stations (64.6% for prospective buyers and 58.6% for EV drivers) are considered more reliable than stations without real-time data (52.4% for prospective buyers and 41.1% for EV drivers) which are in turn more reliable than occupied chargers (47.9% for prospective buyers and 39.0% for EV drivers).

Figures 7 through 9 show the average percent chance of successfully charging at stations without real-time data by CPO, location, and size. By CPO, EV drivers believe they are statistically significantly more likely (t=7.79) to be able to charge at a Tesla charger without real-time data than at an EA charger without real-time data, whereas prospective buyers do not distinguish between the two (t=0.74). In fact, Tesla chargers without real-time data are the only type of charger we present at which current EV drivers are more optimistic than prospective buyers. Prospective buyers also cannot distinguish between urban and rural chargers without real-time data (t=1.16), whereas EV drivers surprisingly consider rural chargers significantly more reliable than urban chargers (t=6.61). Finally and unsurprisingly, both EV drivers (t=9.14) and prospective buyers (t=7.42) consider themselves significantly more likely to be able to successfully charge at stations with no real-time data and 10 plugs than stations with no real-time data and 4 plugs.

Figure 6: Available chargers, occupied chargers, and chargers without real-time data: probability of successful charge by survey sample

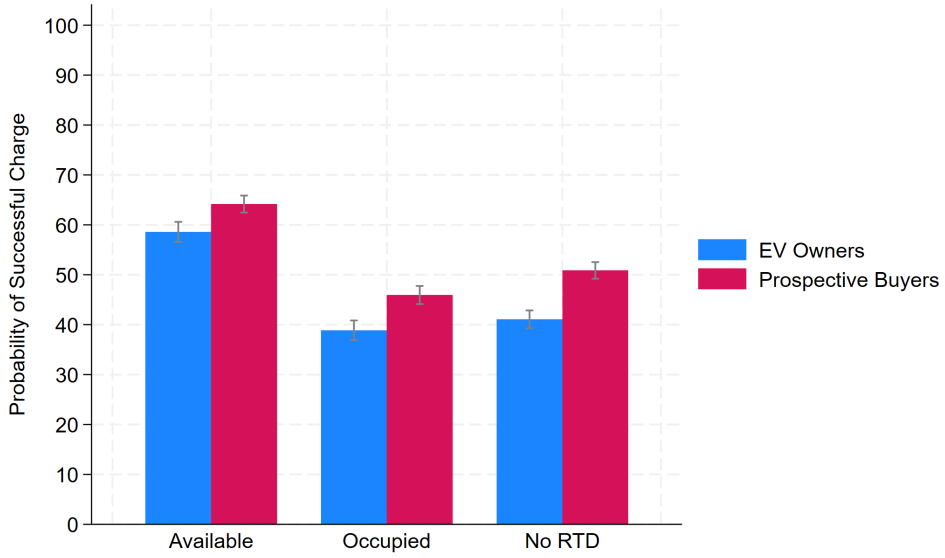


Figure 7: Tesla and EA chargers without real-time data: probability of successful charge by survey sample

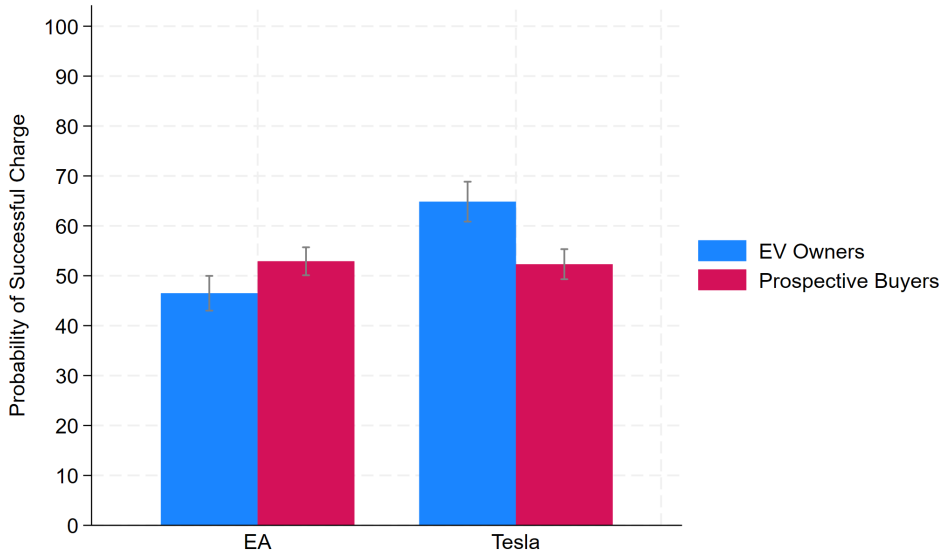


Figure 8: Urban and rural chargers without real-time data: probability of successful charge by survey sample

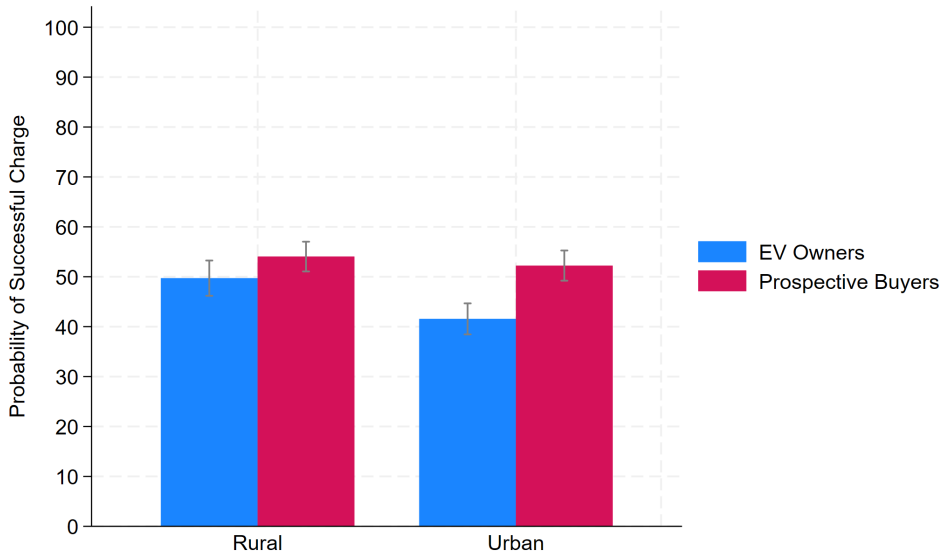


Figure 9: 4-plug and 10-plug chargers without real-time data: probability of successful charge by survey sample

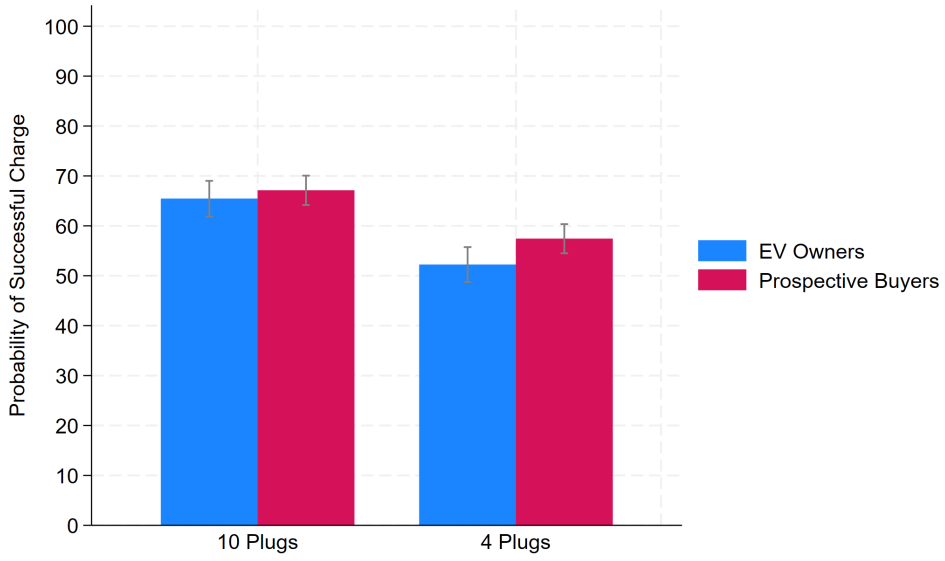
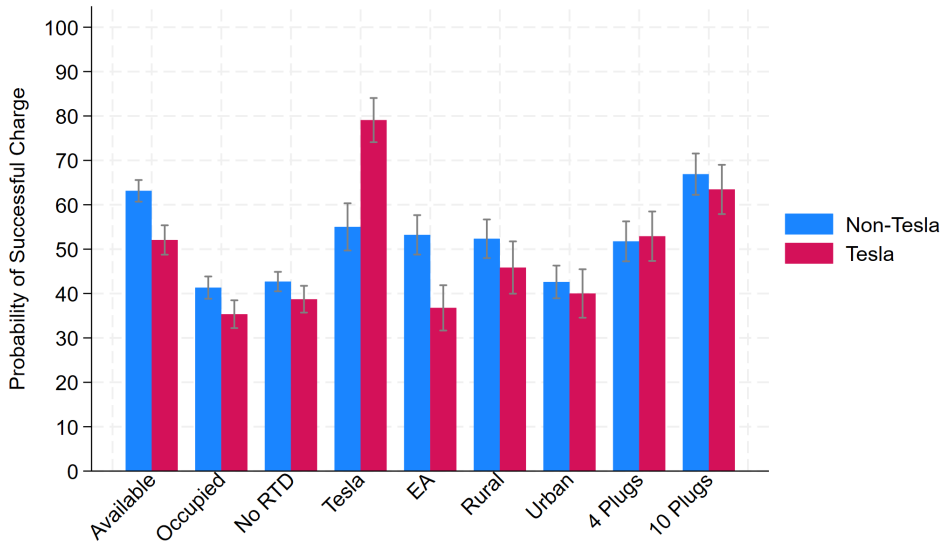


Figure 10: Survey results for Tesla owners vs. non-Tesla EV owners



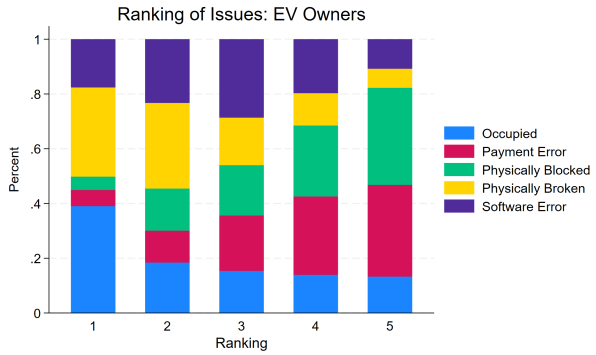
There is substantial variation in answers within the sample of EV owners based on whether they primarily drive a Tesla or non-Tesla EV. Figure 10 plots results for our nine main survey questions, splitting the sample of EV owners into Tesla and non-Tesla owners. In general, whenever a CPO is not specified, non-Tesla drivers are more optimistic about charging than Tesla drivers – perhaps because the Tesla network is large enough that Tesla drivers may have little experience charging at non-Tesla stations (and therefore also at stations without real-time data). The one striking exception is at Tesla stations without real-time data, where Tesla drivers are far and away more likely to believe they can successfully charge (79.3%) than are non-Tesla drivers (55.0%). Moreover, while Tesla drivers consider Tesla stations without real-time data significantly more reliable than EA stations without real-time data (t=14.41), non-Tesla drivers do not distinguish between the two (t=0.65).

In addition to the main survey questions on specific hypothetical chargers, we ask two additional questions to better understand drivers' beliefs and preferences about chargers without real-time data.

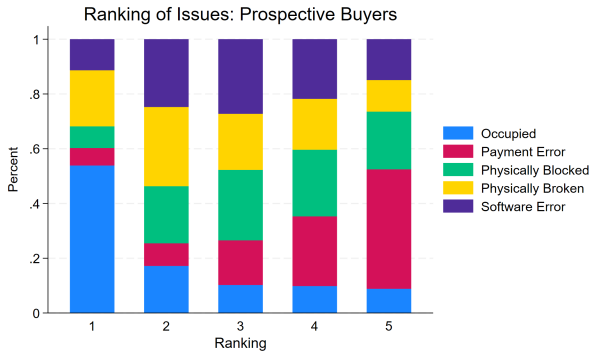
First, we ask respondents to imagine that they are driving on an Interstate and considering stopping at a DCFC without real-time data, then to rank the potential problems which might prevent them from successfully charging at such a station. Figure 11 shows the distribution of responses for EV owners and for prospective buyers. For both groups, the highest-ranked potential issue is that the charger is occupied, followed by the charger being physically broken. Physically blocked chargers and payment errors are ranked lowest on average by both groups. In general, the patterns in responses are similar between the two groups, but EV owners are more likely to expect a charger to be physically broken than occupied, relative to prospective buyers who do not already drive an EV. The most common issue, chargers being occupied, would be diminished by the reporting of real-time data; drivers could choose

Figure 11: Distribution of rankings of reasons for failed charging at hypothetical station without real-time data

(a) EV Owners



(b) Prospective Buyers



not to visit chargers which were listed as occupied, searching instead for a charger that was currently available.

Finally, as a measure of the risk tradeoff between visiting stations without real-time data and waiting longer to charge, we ask respondents to imagine that they are driving on the highway and need to charge in the next 60 miles; we offer the choice of stopping at a charger in 15 miles without real-time data, and and a charger in N miles which reports having at least one plug working and available, where N is randomized to equal 20, 25, 30, or 35 miles for each respondent. Figure 12 plots the fraction of respondents choosing to drive directly to the second (currently available) station for each of our two samples, by their randomized distance to the second station. Willingness to bypass the first station is remarkably similar between current EV owners and prospective buyers. While the fraction of drivers willing to bypass the first station falls as the second station moves farther away, approximately 30% of respondents in both groups value real-time data sufficiently to drive directly to the second station even at its maximum distance of 35 miles.

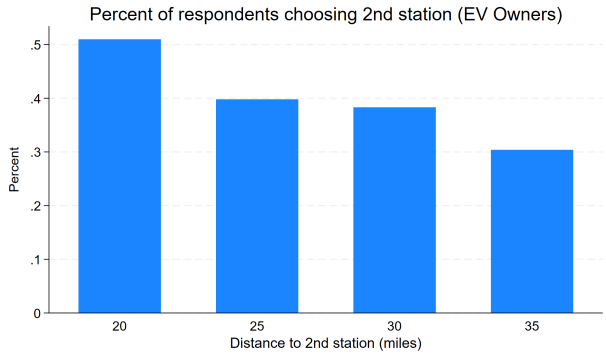
Overall, our survey responses indicate that, while real-time data does not fully solve the problem of charger reliability – given that respondents only expect to be able to successfully charge at stations marked available 58.6% or 64.6% of the time – it has the potential to go a long way in improving driver confidence in chargers by allowing them to avoid broken and occupied stations in favor of ones at which they are more likely to successfully charge.

4 Model: Impact of Real-Time Data on EV Adoption

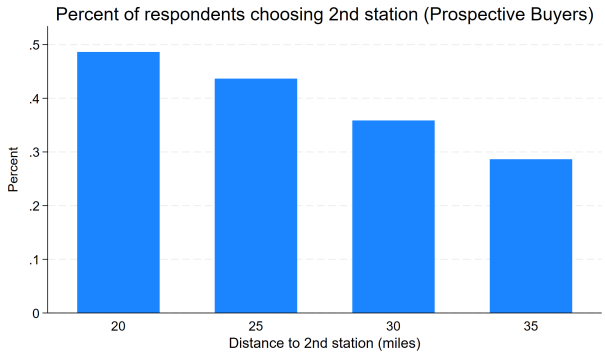
Previous modeling by Cole et al. (2023) which demonstrates that subsidizing charging infrastructure is more effective on the margin than directly subsidizing EV purchases takes

Figure 12: Fraction of respondents choosing to bypass first station (without RTD) by distance to second station (working and available)

(a) EV Owners



(b) Prospective Buyers



as given the elasticities of EV demand to the size of the charging network estimated in prior literature. These prior studies most frequently use data from early adopters or other countries, however, their estimated elasticities may not accurately reflect the true impact of charger buildout on EV adoption in the current US EV landscape. As such, we modify the model of electric vehicle demand and charging station supply from Cole et al. (2023) to account for consumer beliefs and uncertainty regarding charging availability.

4.1 Base model from Cole et al. (2023)

In this section we briefly summarize key equations from the existing model of EV demand and charging supply before detailing our modifications. See Cole et al. (2023) for the full details of the model.

Consumer i chooses between an electric and internal combustion engine version of their preferred vehicle type by maximizing utility, with utility from an EV relative to an ICE in vehicle class j (sedans vs. SUVs and light trucks) given by:

$$u_{ijt} = \alpha_j + \beta_p ln(P_{jt}) + \beta_2 ln(N_{t,l2}/Q_{t-1}) + \beta_3 ln(N_{t,l3}) + \psi_{jt} + \varepsilon_{ijt} = \bar{u}_j t + \varepsilon_{ijt}$$

where $P_j t$ is the price ratio of EVs to ICEs, $N_{t,l2}$ and $N_{t,l3}$ are the stocks of available Level-2 and Level-3 chargers, Q_{t-1} is the stock of EVs on the road in the prior period, ψ_{jt} captures the evolution of preferences for EVs vs. ICEs, and ε_{ijt} is an idiosyncratic taste shock with an i.i.d. Type-1 extreme value distribution. This yields the following expression for the EV share of new car sales in class j at time t:

$$s_{jt} = \frac{exp(\bar{u}_{jt})}{1 + exp(\bar{u}_{jt})}$$

Charging firms make an entry/exit decision in the charging market by equating the benefit of waiting to enter with the cost of waiting to enter. This yields the charging station supply curve:

$$ln(N_{t,k}) = \kappa_k + \gamma ln(Q_t) - \gamma ln(\tilde{C}_{t-k})$$

where κ is a constant, $N_{t,k}$ and Q_t are defined as above, and $\tilde{C}_{t,k} = C_{t,k} - \frac{1}{1+r}C_{t+1,k}$ is a function of costs of building a charger in the current and next period.

4.2 Modifications: Parameters and calibration

We take as our baseline the benchmark IIJA and IRA scenario from Cole et al. (2023) with minor modifications to reflect the reality of IRA and IIJA implementation and other recent policy changes.

The original IRA/IIJA benchmark scenario from Cole et al. (2023) assumes that $5 billion in NEVI funds will go to DCFC construction as an 80% subsidy from 2023 until the budget is exhausted, and that the IRA provides a 30% subsidy to all charging infrastructure (DCFC and level-2) from 2023 to 2032. We modify the NEVI budget to be awarded beginning in 2025 instead of 2023 to reflect the slow rollout of the program.

Both Cole et al. (2023) and our main specification of our updated version of the model assume that the IRA's electric vehicle tax credits will, on average, yield $6,410 to the vehicle buyer and cost the government $6,872. In reality, the IRA provides two $3,750 tax credits to a new vehicle buyer (for a possible total of $7,500) and a $4,000 credit to a used vehicle buyer, both with restrictions based on the characteristics of the buyer and the car. Two key empirical questions remain regarding 1) what fraction of cars qualify for each of these credits, and 2) whether the credits accrue to the buyer or to the seller through changes in the EV price. Our specification corresponds to the original new EV buyer accruing, on average, one of the two $3,750 credits in the IRA plus a $4,000 credit four years later upon selling their used vehicle, both of which are adjusted downward to account for the proportion of individuals we expect to qualify. The resulting $6,410 to the buyer reflects the discounting of the $4,000 to present-day dollars, whereas the government expenditure of $6,872 is undiscounted.

There is, however, considerable uncertainty in the actual implementation of these tax credits in the longer term. Currently relatively few vehicle models qualify for these tax credits, but more are likely to in the future especially with onshoring of production, and tariffs on Chinese-produced EVs are likely to drive more consumers to purchase US-made vehicles. Additionally, there is currently a leasing loophole by which consumers may be able to accrue some benefits of the tax credits for vehicles that do not otherwise qualify; leased vehicles are currently counted as commercial vehicles, which are not subject to the same income, price, and origin restrictions as the consumer tax credits, so the leasing company can qualify for the tax credits and choose whether to pass some or all of them on to the consumer through a lower price. The leasing loophole could be close before the expiration

of the credits. Given these various sources of uncertainty, the net effect of which is hard to quantify, we present results on the impact of real-time data not only under the main IRA specification but also for varying magnitudes of the tax credit effectively delivered to consumers.

We further modify the original model to account for updated corporate average fuel economy (CAFE) standards and petroleum-equivalent fuel economy (PEF) values. In contrast to the model in Cole et al. (2023), we allow the proliferation of EVs to loosen CAFE standards for ICE vehicles by calculating a weighted average fuel economy across the two groups rather than requiring that ICE vehicles alone meet increasingly stringent CAFE standards.

Specifically, we calculate a time-varying approximate fuel economy in miles-per-gallon-equivalent for electric cars and light trucks by applying the PEF values established in the Department of Energy's 2024 rule to the 2023 Chevy Bolt and the 2023 Ford F-150 lightning. PEF values decline over time, so for the purpose of calculating CAFE standard compliance, this yields a fuel economy of approximately 293 mpge for cars and 167 mpge for light trucks through 2026, and 93 mpge for cars and 59 mpge for light trucks in 2030 and beyond. In each year of our model, we use this mpg equivalent value combined with the previous year's EV share of new sales to back out the fuel economy for ICE vehicles which exactly meets the CAFE standard for each of cars and light trucks. We additionally assume that fuel economy within an ICE vehicle class never declines from one year to the next, an assumption which becomes important as a growing share of EVs makes the effective CAFE standard for ICE vehicles less and less stringent.

In our calculations of carbon emissions and fuel costs, we scale the reported fuel economy of both ICE vehicles and EVs downward to account for real-world road conditions and the impact of temperatures on batteries.

With these modifications in place, our baseline (without IRA or IIJA) prediction of the EV share of new car sales in 2030 is 38.5%, relative to 36.6% in Cole et al. (2023), and our baseline prediction for the EV share of new car sales in 2030 with the IRA and IIJA is 60.2%, contrasted with 57.7% in Cole et al.et al (2023). While our estimates for EV penetration under the IRA and IIJA are somewhat higher than those elsewhere in the literature, our conclusions regarding the effectiveness of real-time data are drawn not from the level of EV penetration in 2030 but from the change relative to this baseline.

4.3 Modifications: Consumer charging experience

While the original model from Cole et al. (2023) takes into account the total number of chargers on the road, potential EV drivers may know that not all chargers are working or available all of the time, and that real-time information on which chargers are working or available is not always provided. We account for this by scaling the number of level-3 chargers in the consumer utility function by a Bernoulli random variable representing the probability that a randomly chosen charger can provide a successful charge at any given

point in time. We then calculate consumers' expected utility from an EV relative to an ICE before aggregating to obtain the EV share of new sales for each vehicle class.

Specifically, expected utility to consumer i in vehicle class j at time t from owning an EV is:

$$U_{ijt} = E[P_{EV,t}^{\beta_p}(\mu_t N_{t,l3})^{\beta_{l3}}(N_{t,l2}/Q_{t-1})^{\beta_{l2}} e^{\psi_{jt,EV}} e^{\varepsilon_{ijt,EV}}]$$

where μ_t is the Bernoulli random variable measuring consumer perceptions of the reliability of the DC fast charging network, and (deterministic) utility from owning an ICE vehicle is:

$$U_{ijt,ICE} = P_{ICE,t}^{\beta_P} e^{\psi_{ICE,t}} e^{\varepsilon_{ICE,ijt}}$$

Therefore consumer i will choose to purchase an EV as long as:

$$E[P_{EV,t}^{\beta_p}(\mu_t N_{t,l3})^{\beta_{l3}}(N_{t,l2}/Q_{t-1})^{\beta_{l2}} e^{\psi_{jt,EV}} e^{\varepsilon_{ijt,EV}}] \geq P_{ICE,t}^{\beta_P} e^{\psi_{ICE,t}} e^{\varepsilon_{ICE,ijt}}$$

$$\Leftrightarrow P_{jt}^{\beta_p} e^{\psi_{jt}} e^{\varepsilon_{ijt}} (N_{t,l2}/Q_{t-1})^{\beta_{l2}} E[(\mu_t N_{t,l3})^{\beta_{l3}}] \geq 1$$

where $P_{jt} = P_{jt,EV}/P_{jt,ICE}$, $\psi_{jt} = \psi_{jt,EV} - \psi_{jt,ICE}$, and $\varepsilon_{ijt} = \varepsilon_{ijt,EV} - \varepsilon_{ijt,ICE}$. To approximate $E[(\mu_t N_{t,l3})^{\beta_{l3}}]$, rewrite (dropping subscripts for now) as $E[(\bar{\mu}N + \mu N - \bar{\mu}N)^{\beta}]$, where $\bar{\mu}$ is the expectation of the Bernoulli random variable μ and N is the constant (from the point of view of the new vehicle buyer) number of DC fast charging stations on the road. Take a second-order Taylor expansion:

$$E[(\mu N)^{\beta}] = E[(\bar{\mu}N + \mu N - \bar{\mu}N)^{\beta}]$$

$$\approx E[(\bar{\mu}N)^{\beta} + \beta(\bar{\mu}N)^{\beta-1}(\mu N - \bar{\mu}N) + \frac{\beta(\beta-1)(\bar{\mu}N)^{\beta-2}}{2}(\mu N - \bar{\mu}N)^2$$

$$= (\bar{\mu}N)^{\beta} + \frac{\beta(\beta-1)(\bar{\mu}N)^{\beta-2}}{2}\sigma^2 N^2$$

where σ^2 is the variance of μ, given by $\mu(1-\mu)$, and therefore $\sigma^2 N^2$ is the variance of μN. Combining this with the consumer's decision rule and taking logs yields that the consumer will purchase an EV whenever:

$$\beta_p ln(P_{jt}) + \beta_{l2}(N_{t,l2}/Q_{t-1}) + ln((\bar{\mu}N)^{\beta} + \frac{\beta(\beta-1)(\bar{\mu}N)^{\beta-2}}{2}\sigma^2 N^2) + \psi_{jt} + \varepsilon_{ijt} \geq 0$$

Rewriting this into an individual component ε_{ijt} and a population component $\bar{u}_{jt} = \beta_p ln(P_{jt}) + \beta_{l2}(N_{t,l2}/Q_{t-1}) + ln((\bar{\mu}N)^{\beta} + \frac{\beta(\beta-1)(\bar{\mu}N)^{\beta-2}}{2}\sigma^2 N^2) + \psi_{jt}$ yields a standard logit formula for the share of new vehicles in class j which are EVs at time t:

$$s_{jt} = \frac{exp(\bar{u}_{jt})}{1 + exp(\bar{u}_{jt})}$$

Table 6: Possible real-time data scenarios and corresponding parameters

Is the charger on a locator app?	Does at least one plug at the charger provide real-time data?	Is at least one plug at the charger reported working?	Is at least one plug at the charger reported	Can a driver successffully charge?
Yes: λ_{cl}	Yes: λ_{rtd}	Yes: λ_w	Yes: λ_{avail}	p_{rtd}
			No: $1-\lambda_{avail}$	p_{unav}
		No: $1-\lambda_w$	No: 1	0
	No: $1-\lambda_{rtd}$	No: 1	No: 1	p_{nd}
No: $1-\lambda_{cl}$	No: 1	No: 1	No: 1	0

4.4 Parameterization of μ and σ

To parameterize μ (and by extension $\sigma^2 = \mu(1-\mu)$), we segment the population of N DC fast chargers by whether they appear on a charging locator, whether they provide real-time data, whether they have at least one working plug, and whether they have at least one available plug. We parameterize the fraction of chargers falling into each of these groups using data scraped from PlugShare. We then calibrate the subjective probability that a user can successfully charge at a station in each group based on the results of our consumer surveys.

Specifically, μ represents the probability of successfully charging at a randomly chosen charging station. Table 6 shows the classification of chargers by data availability and status alongside the conditional probabilities we parameterize to define μ, with expressions in each column representing probabilities of being in a given row conditional on all columns to the left. Row 1 represents chargers which provide real-time data on a charging locator and have at least one plug working and available; p_{rtd} gives the probability of a successful charge at one of these stations. Row 2 represents chargers which provide real-time data on a charging locator and have at least one plug working and none available; p_unav gives the probability of being able to charge at one of these stations, with the assumption that there may be a delay between accessing the information and arriving at the station, or that drivers may wait for a plug to become free. Row 3 represents chargers with real-time data at which no plug is working; we assume drivers cannot successfully charge at these stations. Row 4 represents chargers on charging locators but without real-time data; p_nd gives the probability of successfully charging at one of these stations. Row 5 represents chargers which do not appear on any charging locator; we assume drivers cannot successfully charge at these stations, as they cannot learn about them except by word of mouth. Combinations of parameters which cannot exist in reality (e.g. chargers which do not report real-time data but do report that one plug is working) are excluded from the table.

This yields the following expression for μ:

$$\mu = \lambda_{cl}(\lambda_{rtd}(\lambda_w(\lambda_{avail}p_{rtd} + (1-\lambda_{avail})p_{unav}))) + (1-\lambda_{rtd})p_{nd})$$

.

Table 7: Parameter and sources for parameterizing μ

Parameter	Source	Value
λ_{cl}	Authors' judgment	0.98
λ_{rtd}	PlugShare scraping	Drawn from distribution of Plugshare results
λ_{w}	PlugShare Scraping	Drawn from distribution of PlugShare results
λ_{avail}	PlugShare scraping	Drawn from distribution of PlugShare results
p_{rtd}	Survey	Drawn from distribution of survey results
p_{unav}	Survey	Drawn from distribution of survey results
p_{nd}	Survey	Drawn from distribution of survey results

Table 7 lists the parameters in the above expression alongside the data sources we use to calibrate them.

4.5 Modifications: Charging Firms

The lack of full reliability of charging stations means that not all chargers can be used at all times, affecting firms' profits and therefore altering their entry and exit decisions.

A full treatment of real-time data sharing would explicitly model the value of data to firms and allow firms to set the fraction of chargers providing real-time data as a choice variable. As our goal is to model the impact of exogenously changing the fraction of stations providing real-time data on EV adoption, we abstract away from firms' choices to provide real-time data and maintain stations and instead allow firms only to make an entry/exit decision.

Let the profit function given in Cole et al. (2023), $\pi^{t,l3}(N_{t,l3}, Q_t) = (exp(\kappa_l 3)/(N_{t,l3}))^{\frac{1}{\gamma}} Q_t$, be the profit for a DC fast charger that provides real-time data and is working. We consider a representative charging firm whose profit is the expected profit across the distribution of chargers that do and do not provide real-time data and are or are not working. That is, the representative firm's profit for DC fast chargers would be:

$$\pi_t = \lambda_{cl}(\lambda_{rtd}(\lambda_w \pi_{rtd,w} + (1-\lambda_w)\pi_{rtd,nw}) + (1-\lambda_{rtd})(\lambda_{w|nd}\pi_{nd,w} + (1-\lambda_{w|nd})\pi_{nd,nw})) + (1-\lambda_{cl})\pi_{ncl}$$

where, in addition to the parameters defined above, $\pi_{rtd,w}$ is the profit for a working station with real-time data, $\pi_{rtd,nw}$ is the profit for a station with real-time data that is out of service, $\lambda_{w|nd}$ is the probability that a charger is working conditional on having no real-time data, $\pi_{nd,w}$ is the profit for a station that has no real-time data and is working, $\pi_{nd,nw}$ is the profit for a station without real-time data that is out of service, and π_{ncl} is the profit for a station not found on a charging locator.

Three key assumptions allow us to simplify this profit function: 1) stations which are out of service or not on a charging locator deliver no profit; 2) the probability that a station without real-time data is working is the same as the probability that a station with real-time data is working, and 3) the profit from a station without real-time data that is working is

the same as the profit from a station with real-time data that is working. We cannot verify assumption (2) because all of our data on what percent of stations work at any given time comes from scraping data on only those stations that provide real-time data on PlugShare. (3) provides an important avenue for future work; estimating consumer choice of charging stations, rather than just the impact of charging stations on vehicle choice, would inform these profit functions and therefore more accurately model charging firms' choices. With these three assumptions and the functional form from Cole et al. (2023), the profit function for the representative charging firm becomes:

$$\pi_t = \lambda_{cl}\lambda_w(exp(\kappa_l 3)/(N_{t,l3}))^{\frac{1}{\gamma}}Q_t$$

Then, as in the original model, firms choose to build charging stations until they are indifferent between entering in the current period and the next:

$$\pi_{t,l3}(N_{t,l3}, Q_t) = C_{t,l3} - \frac{1}{1+r}C_{t+1,l3}$$

That is, per-charger profits π in this period as a function of the stock of chargers N and EVs on the road Q are equal to the difference between costs of building a charger this period, $C_{t,l3}$ and the discounted cost of building next period. This yields the following supply equation for level-3 chargers:

$$ln(N_{t,l3}) = \kappa_{l3} + \gamma ln(\lambda_{cl}\lambda_w) + \gamma ln(Q_t) - \gamma ln(\tilde{C}_{t,l3})$$

The supply of level-2 stations is unchanged from Cole et al. (2023).

4.6 Simulations

We simulate three main scenarios for the impact of real-time data provision on EV adoption. In the first, the share of DCFCs providing real-time data increases ($\lambda + rtd$) increases linearly to 100% between 2024 and 2029, thereby influencing consumer choices purely through information provision, without any changes in charger reliability or beliefs.

In the second scenario, in addition to the increase in λ_{rtd}, the share of stations with real-time data at which at least one plug reports working (λ_w) grows linearly to 95% between 2024 and 2029. This scenario corresponds to one in which charger reliability improves to match the 95% uptime requirement set forth by NEVI. We do not explicitly model the mechanism by which this improvement occurs, but it could take place either because of similar requirements for other DCFC stations or because providing universal real-time data shines light on failing chargers and incentivizes CPOs to take steps to improve quality.

In the final scenario, in addition to the changes in rtd and w, consumers' belief that a charger which says it is working and available is actually working and available ($p_r td$) grows linearly to 100% between 2024 and 2029. This represents a best case scenario, in which improvements in both real-time data provision and charger reliability lead consumers to trust real-time data and therefore have more confidence in their ability to reliably charge.

As in Cole et al. (2023), we produce our results through Monte Carlo simulation with 1000 draws to account for uncertainty around our model parameters. In addition to the uncertainty in demand and supply parameters accounted for in the original model, we incorporate uncertainty around the state of real-time data and charger availability by drawing from the full distribution of our PlugShare scrapes since Fall 2023. Specifically, in each Monte Carlo iteration, we draw one single highway run (e.g. I-95 at 8am on April 1st, 2024), from which we compute each of the λ parameters used to calculate μ. Intuitively, we want to sample μ in a way that preserves the real-world correlations between the components that make up μ (the various λ parameters). For example, it may be the case that areas of the country with better real-time data provision also tend to have more congested EV chargers; by sampling individual highway runs, rather than pooling all of our charger data together to sample from, we preserve this real-world heterogeneity in drivers' charging experiences. We draw p_{rtd}, p_{unav}, and p_{nd} each from a normal distribution whose expectation is the relevant mean from the simulated survey and whose variance is the sample variance of that mean.

4.7 Results: EV Share of New LDV Sales

Figure 13 presents our projection of EV adoption under the IRA & IIJA baseline; specifically, this figure plots the fraction of new car sales which are EVs over time under our benchmark definition of the IIJA and IRA as described in section 4.2. On average, our simulations predict that 59.5% of new cars in 2030 will be electric in the baseline IIJA+IRA scenario, with a 90% Monte Carlo band of 20.3% to 93.1%. The drop in EVs as a share of new car sales in 2033 corresponds to our implementation of the IRA's tax credits (both for vehicles and for charging stations) as concluding in 2032, so that there is an effective increase in the relative price of EVs in 2033. Note that our focus in this paper is on policy impacts over and above the baseline from real-time data reporting, not on the precise prediction of the baseline itself.

Table 8 presents values for the EV share of new car sales under our three simulated scenarios in the key years of 2025 to 2030. Scenario 1 (all stations provide real-time data by 2029) increases EV penetration by up to 1.0 percentage points by 2030; scenario 3 (increases in real-time data and uptime lead to full driver confidence in real-time data) increases EV penetration by 6.8 percentage points over the same period. In effect, scenario 3 accelerates EV adoption by more than a year by the end of the decade, achieving in 2028 an EV share of new car sales of 55.6%, between the shares achieved in 2029 (55.1%) and 2030 (59.5%) in the baseline.

Figure 13: Main estimate and uncertainty for baseline EV share of new car sales under IRA & IIJA with no change in RTD reporting

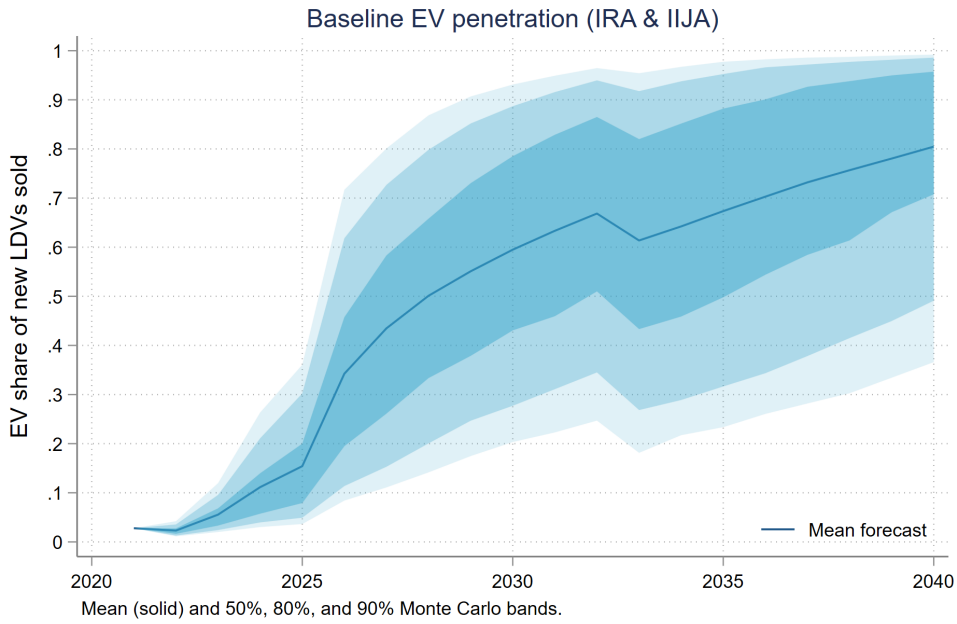
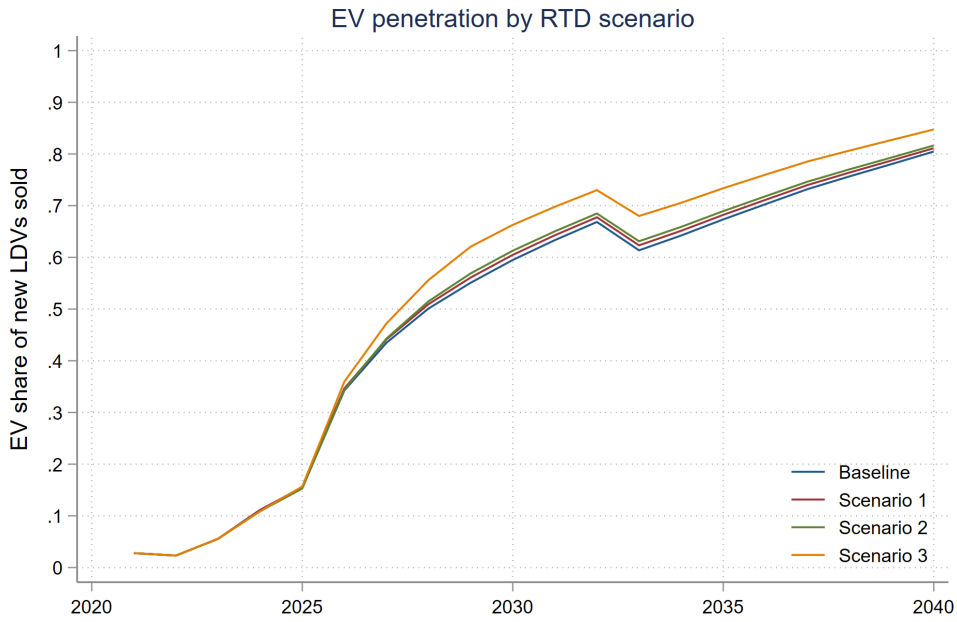


Table 8: Impacts of RTD scenarios on EV share of new vehicle sales, 2025-2030

	Baseline	All stations provide RTD		... and 95% uptime		... and full driver confidence in RTD	
			ppt over baseline		ppt over baseline		ppts over baseline
2025	15.4%	15.5%	0.12%	15.28%	-0.14%	15.7%	0.26%
2026	34.2%	34.6%	0.40%	34.38%	0.13%	36.0%	1.71%
2027	43.5%	44.1%	0.65%	44.30%	0.81%	47.2%	3.74%
2028	50.1%	51.0%	0.84%	51.51%	1.40%	55.6%	5.52%
2029	55.1%	56.1%	1.01%	56.90%	1.81%	62.1%	6.98%
2030	59.5%	60.5%	0.99%	61.28%	1.79%	66.3%	6.79%

Figure 14 presents average EV penetration under the baseline and each of our three real-time data scenarios. As a reminder, scenario 1 represents the shift to 100% real-time data provision without any change in the reliability of chargers that provide real-time data or in consumers' beliefs in the accuracy of real-time data. Scenario 2 represents the shift to both 100% real-time data provision and the shift to 95% uptime for stations with real-time data, but consumer beliefs about the accuracy of data do not change. Finally, scenario 3 is the most optimistic scenario, with 100% real-time data reporting and 95% uptime as well as 100% consumer confidence in real-time data by 2029.

Figure 14: EV share of new sales over time by RTD scenario



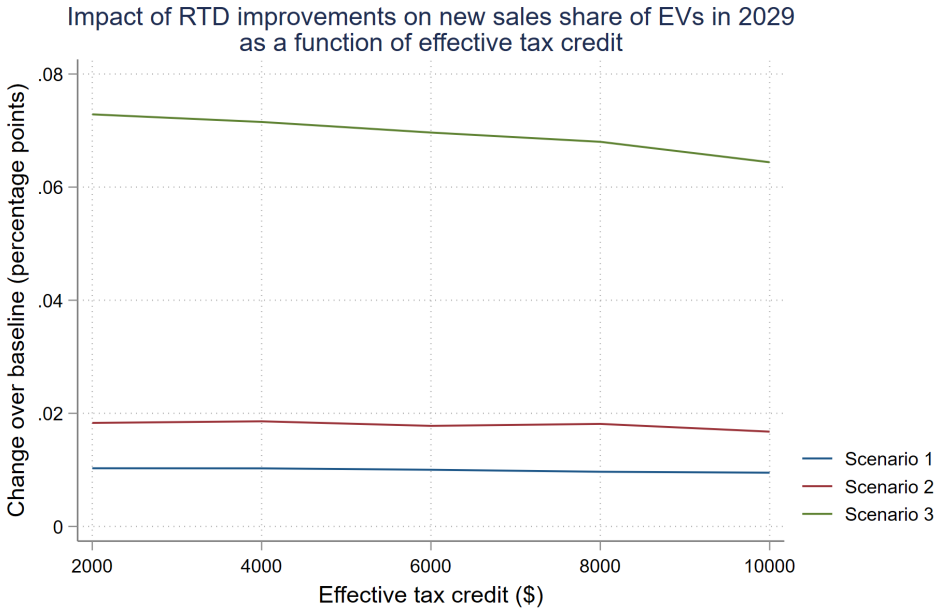
The largest increase in the EV share comes from improving consumer confidence in stations that claim to be working and available (scenario 2 to scenario 3). The shift from the baseline to scenario 1, which improves real-time data provision to 100%, has limited impact because survey respondents' subjective probabilities of being able to successfully charge at a working and available station are pessimistic. The shift from scenario 1 to scenario 2, which improves uptime to 95% for stations with real-time data, has a relatively small impact largely because uptime measured at the station-level is fairly good on average at stations providing real-time data; across our 714 highway runs, the average fraction of stations with real-time data at which at least one plug is reported working is 88.4%. 74 highway scraping runs (10.4%) already meet or exceed the 95% uptime requirement from NEVI at the station level.

Appendix figures 19 through 21 present uncertainty around the impacts relative to baseline of each of these three scenarios; specifically, we plot the mean change over baseline as well as 50%, 80%, and 90% Monte Carlo bands for each of the three scenarios. Uncertainty in these estimates comes from both variation in the state of real-time data across draws and from variation in the baseline; in simulations where baseline EV penetration under the IRA and IIJA is extremely high to begin with, there is little room for improved real-time data to spur further adoption.

To account for uncertainty in the true long-term tax credit consumers will benefit from, I further simulate the model with the effective tax credit set at $2,000, $4,000, $6,000, $8,000, and $10,000 (where values above $7,500 account for the used vehicle tax credit the consumer may accrue upon reselling their vehicle). Figure 15 plots the percentage point increase from real-time data in each of our three scenarios for each possible effective tax credit. In scenarios

1 and 2, the size of the effective tax credit makes very little difference in the magnitude of the impact of real-time data. In scenario 3, there is a slight decline in the effectiveness of real-time data as the effective tax credit increases, since lower prices experienced by the consumer make changes in the effective number of charging stations on the road less significant.

Figure 15: Change in EV share of new car sales in 2029 over IRA & IIJA baseline by effective consumer tax credit



4.8 Results: EV fleet size

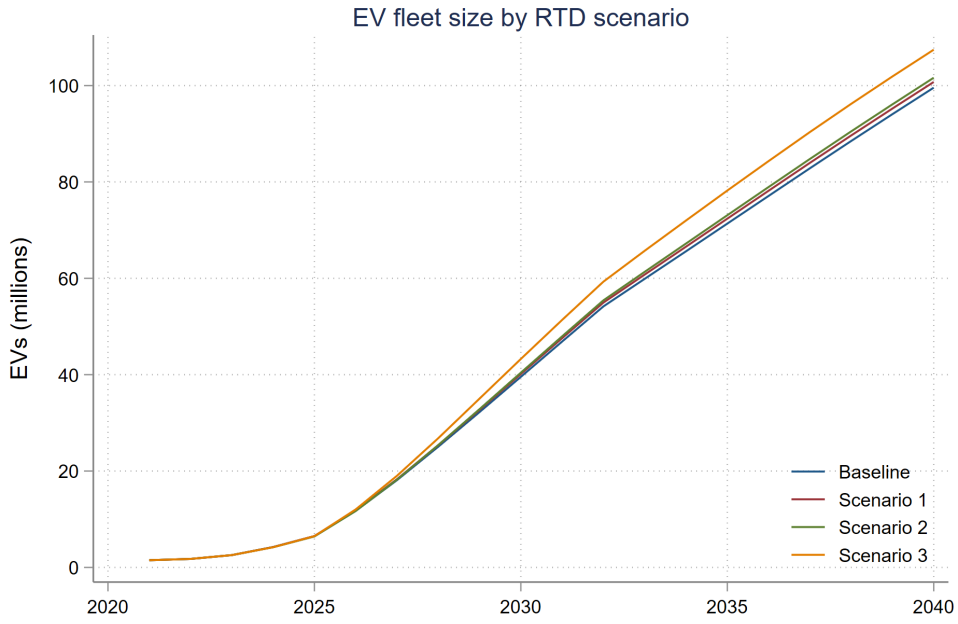
The total number of EVs on the road under each of our scenarios is a variable of interest especially for CPOs, for whom it represents their total addressable market. Note that we hold total annual light-duty vehicle sales fixed at 17 million, consistent with long-run trends in LDV sales in the US. We calculate the number of EVs on the road each year by applying a depreciation rate of 1/11.5 to the existing stock of EVs and adding our projected new EV sales. Table 9 presents EV fleet size and percentage increases over the baseline for each scenario in the key years of 2025 through 2030. In 2030, scenario 1 increases the total size of the EV fleet by 1.5%, scenario 2 by 2.2%, and scenario 3 by 9.4%. This near-10% increase in the number of EVs on the road in 2030 induces CPOs to build more chargers to serve the larger EV fleet, and thereby feed back into the consumer choice side of the model, further expediting the transition to EVs.

Figure 16 plots our estimates of the number of EVs on US roads in millions from 2021 to 2040 under our baseline and each real-time data scenario. As in the case of the EV sales share of new light-duty vehicles, the largest increase in EV fleet size is generated by moving from scenario 2 to scenario 3 (improving consumer confidence in real-time data reporting). Appendix figures 22 through 24 present uncertainty around these projections.

Table 9: Impact of RTD scenarios on EV fleet size (millions), 2025-2030

	Baseline	All stations provide RTD		... and 95% uptime		... and full driver confidence in RTD	
			ppt over baseline		ppt over baseline		ppts over baseline
2025	6.48	6.51	0.32%	6.42	-0.96%	6.49	0.08%
2026	11.74	11.83	0.74%	11.71	-0.30%	12.04	2.52%
2027	18.11	18.30	1.05%	18.22	0.59%	19.02	5.00%
2028	25.06	25.37	1.26%	25.39	1.34%	26.82	7.04%
2029	32.24	32.70	1.43%	32.86	1.90%	35.04	8.67%
2030	39.55	40.14	1.49%	40.42	2.18%	43.26	9.37%

Figure 16: EV fleet size over time by RTD scenario

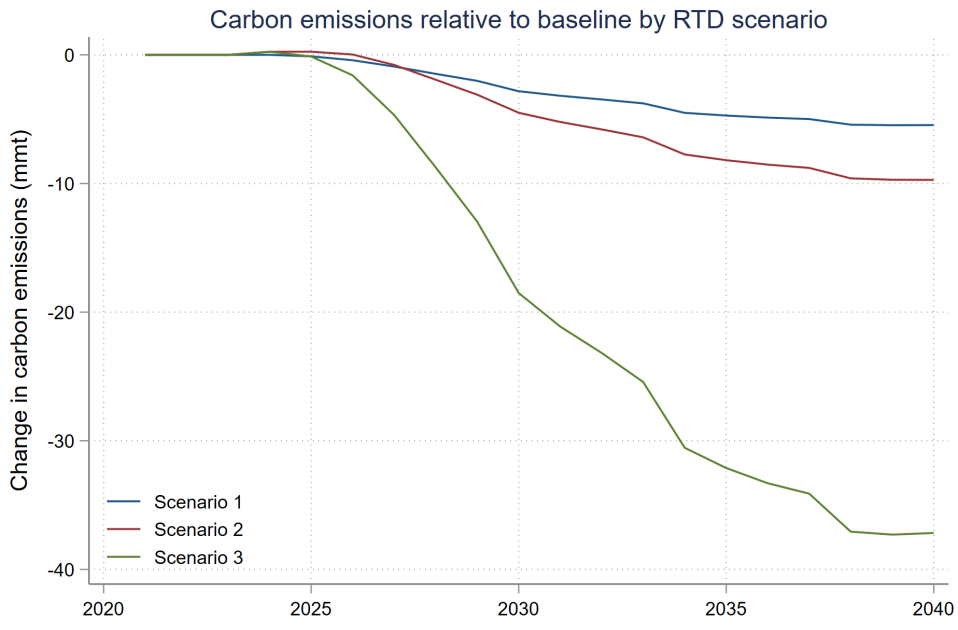


4.9 Results: Carbon emissions

Figure 8 presents changes in yearly carbon emissions from the light-duty vehicle fleet relative to the IRA and IIJA baseline for each of our three real-time data scenarios, measured in millions of metric tons. As in Cole et al. (2023), our projections for carbon intensity of the power sector are based on Stock and Stuart (2021). Table 8 presents the same information in table form for the key years of 2025 to 2030. In 2030, providing real-time data at all highway DCFCs reduces carbon emissions, on average, by 2.8 million metric tons. Scenario 2, which additionally requires 95% uptime at all highway DCFCs, reduces emissions by 4.5 million metric tons. Finally, scenario 3, which additionally requires improved confidence in real-time data by consumers, reduces carbon emissions in 2030 by 18.5 million metric tons on average.

As a point of reference, under our updated CAFE standard assumptions, the IRA and IIJA reduce carbon emissions in 2030 by 67.8 mmt on average. Therefore, improving real-time data, uptime, and consumer confidence in the data can reduce carbon emissions by up to an additional 27.3%, on average, relative to the carbon emissions reductions projected to be achieved under the IRA and IIJA without these improvements. Moreover, compared to the $451 billion in government expenditures for the IRA and IIJA estimated in Cole et al. (2023), mandating real-time data would be comparatively costless to the government as it would be a regulatory policy rather than a fiscal one.

Figure 17: Emissions reductions (mmt) relative to IIJA & IRA baseline



Appendix figures 25 through 27 present uncertainty around these projections.

Table 10: Emissions reductions relative to IIJA & IRA baseline (mmt)

	All stations provide RTD	... and 95% uptime	... and full driver confidence
2025	-0.1	0.2	-0.1
2026	-0.4	0.0	-1.6
2027	-0.9	-0.8	-4.7
2028	-1.5	-1.9	-8.7
2029	-2.0	-3.1	-13.0
2030	-2.8	-4.5	-18.5

5 Conclusion

Prior research shows that, dollar for dollar, US government spending on charging infrastructure is more impactful than spending on direct EV subsidies Cole et al. (2023). As the US government continues to incentivize EV adoption to facilitate the transition to EVs and achieve US climate goals, it is essential that spending on public EV charging infrastructure translates not only into more chargers, but into chargers that are reliable and visible to consumers. In this paper, we document that the current state of real-time information on charger availability is poor, and we argue that providing real-time data on the status of highway-adjacent DC-fast chargers is a key step towards instilling charging confidence in consumers, slowing the flow of negative news coverage of the EV driver's charging experience, and removing at least some of the specter of range anxiety – all in the service of ultimately inducing consumers to shift more quickly from ICE vehicles to EVs.

We find that universal real-time data reporting alone, without any consequent improvement in uptime or consumer beliefs, can increase the EV sales share of new light-duty vehicles in 2030 by 1.0 percentage point, increase the size of the overall electric light-duty vehicle fleet by 1.5%, and reduce carbon emissions from US light-duty vehicles in 2030 by 2.8 million metric tons. If improved real-time data reporting in turn leads to higher uptime for chargers and increased consumer confidence in the reliability of the real-time data, the EV sales share can instead increase by 6.8 percentage points in 2030, the size of the EV LDV fleet can increase by 9.4%, and carbon emissions in 2030 can decrease by 18.5 million metric tons, nearly one third of the carbon emissions reductions achieved in 2030 by the combined EV provisions of the IRA and IIJA. The additional emissions reduction can be achieved with no fiscal cost, in contrast to the combined $451 billion fiscal bill for the new IRA and IIJA EV provisions.

Of course, it may be the case that these benefits are slower to materialize than our model predicts. Given the low current proportion of EV drivers, prospective buyers may not know to look at sites like PlugShare to understand the availability of real-time data and its role in charging success. However, as the proportion of drivers who already have EVs grows so that prospective buyers learn more by word-of-mouth, and as real-time data leads to fewer sensational news stories on negative charging experiences, there is a clear path for the reporting of real-time data to influence the decisions of prospective EV buyers.

Potential policy options for implementing the reporting of real-time data include mandates, data reporting requirements for state-funded chargers like those put forth by NEVI, and disclosure requirements as consumer protection law; each has its own challenges and benefits. At the same time, it may be the case that the projected growth in the EV market due to real-time data reporting alone may be enough to incentivize key holdout CPOs to begin to provide real-time data for their own benefit.

Another element of real-time data reporting by DCFCs, which is required by NEVI but not addressed here, is the reporting of real-time pricing information. Like real-time status information, real-time pricing may currently be available on proprietary CPO apps, but is not universally available on PlugShare. Also, like real-time status information, real-time pricing may be able to speed the transition to EVs by easing prospective buyers' fears about predatory or surge pricing, especially in areas where chargers are sparse. We leave these questions for future research.

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6 Appendix

Table 11: Real-time data provision on August 18th, 2024 at the plug level

	I-95	I-5	I-10	I-75	I-80	I-90	Total
Total Plugs	2261	2457	1552	1138	1370	1070	9,848
w/RT Data	**18.7%**	**28.3%**	**18.0%**	**18.3%**	**22.3%**	**14.3%**	**21.0%**
Non-Tesla Plugs	880	1144	594	496	656	519	4289
w/RT Data	**48.1%**	**60.8%**	**47.0%**	**41.9%**	**46.5%**	**29.5%**	**48.1%**
Excluding Tesla and EA	619	849	393	335	365	318	2879
w/RT Data	**68.3%**	**82.0%**	**71.0%**	**62.1%**	**83.6%**	**48.1%**	**71.7%**

Figure 18: Percent of stations reporting real-time data at at least one plug, excluding dealerships

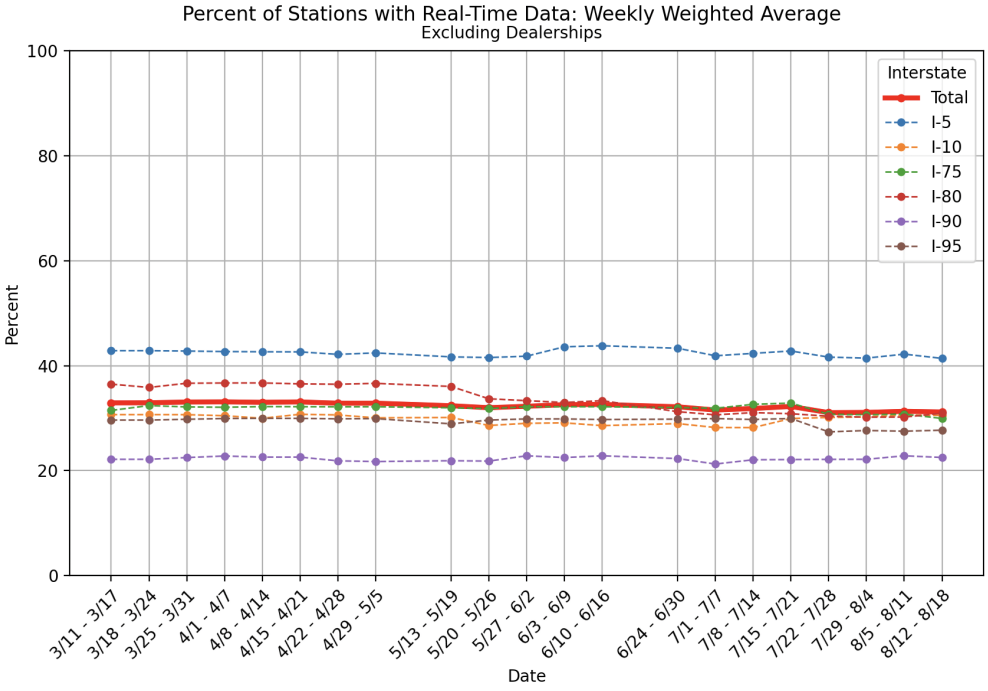


Table 12: Data deserts of at least 145 miles, including dealerships

	Start Location	End Location	Length (mi)	# Stations	Tesla	EA
I-10	Tucson, AZ	Deming, NM	209	4	2	2
	El Paso, TX	Kerrville, TX	481	11	6	5
	Beaumont, TX	Gulfport, MS	315	18	9	4
	Pensacola, FL	Tallahassee, FL	201	12	5	4
I-80	Truckee, CA	Lovelock, NV	148	7	4	3
	Lovelock, NV	Carlin, NV	153	3	1	2
	Coalville, UT	Laramie, WY	353	7	4	3
	Cheyenne, WY	Kearney, NE	318	9	4	3
	Bettendorf, IA	Lansing, IL	168	4	2	2
	Emlenton, PA	Bloomsburg, PA	195	6	4	2
I-90	Coeur d'Alene, ID	Missoula, MT	164	8	5	0
	Missoula, MT	Bozeman, MT	207	4	2	2
	Bozeman, MT	Sheridan, WY	271	7	4	1
	Sheridan, WY	Spearfish, SD	199	5	3	1
	Spearfish, SD	Mitchell, SD	322	10	4	3
I-95	Lynchburg, SC	Savannah, GA	145	8	7	1

Figure 19: Uncertainty around impact of RTD reporting on EV sales share, scenario 1

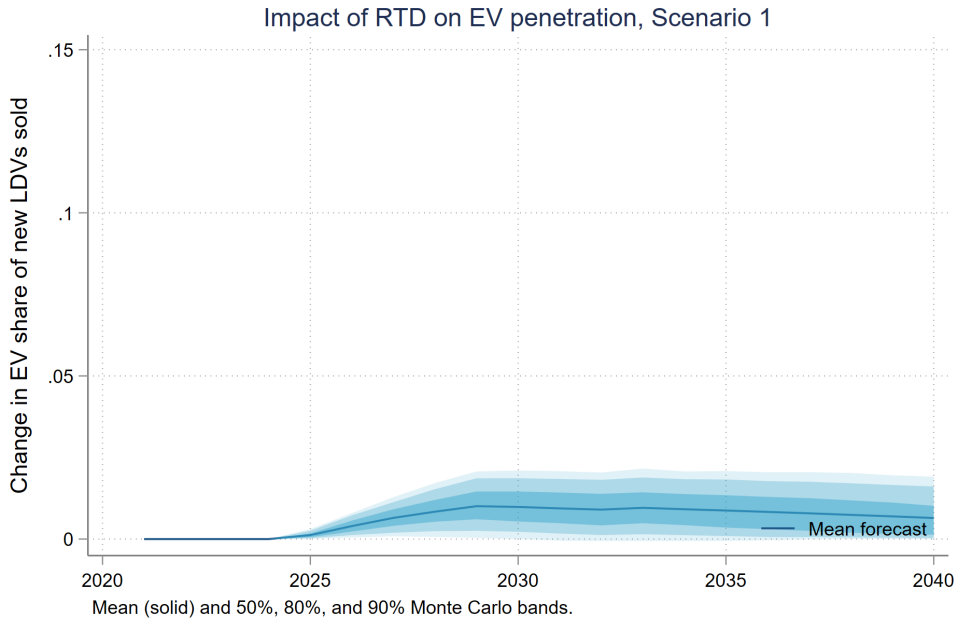


Figure 20: Uncertainty around impact of RTD reporting on EV sales share, scenario 2

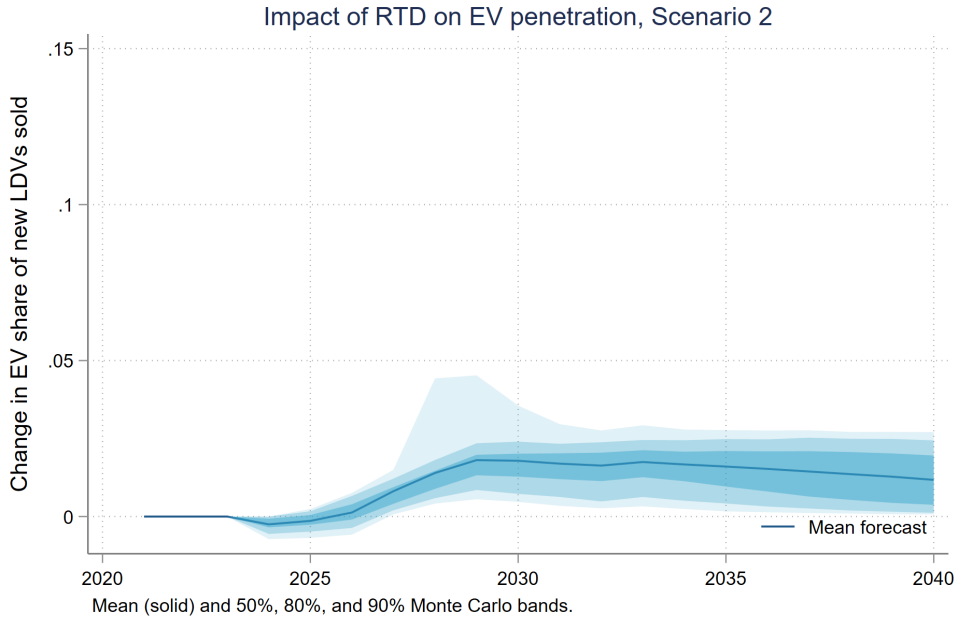


Figure 21: Uncertainty around impact of RTD reporting on EV sales share, scenario 3

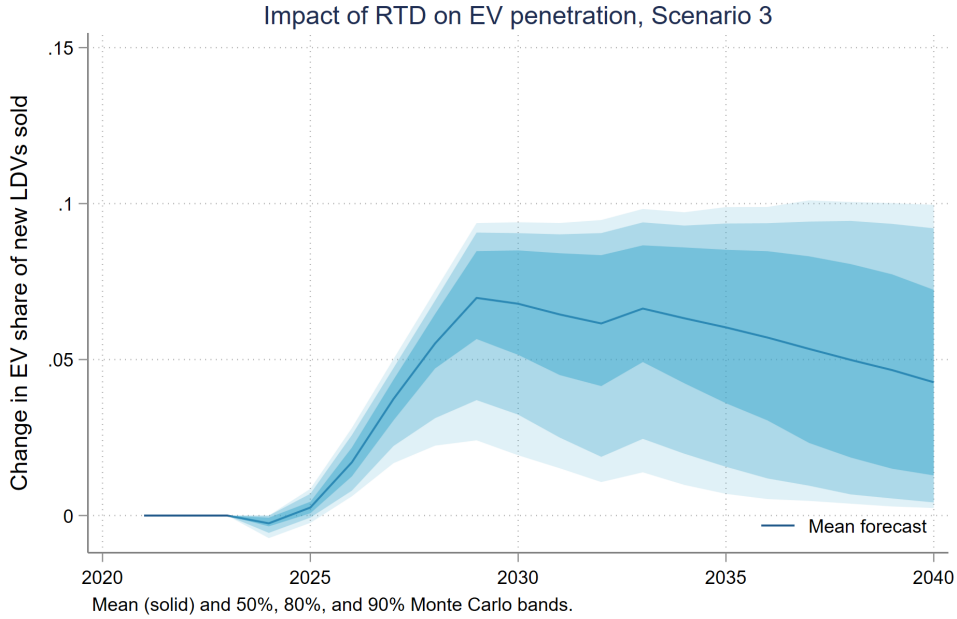


Figure 22: Uncertainty around impact of RTD reporting on EV fleet, scenario 1

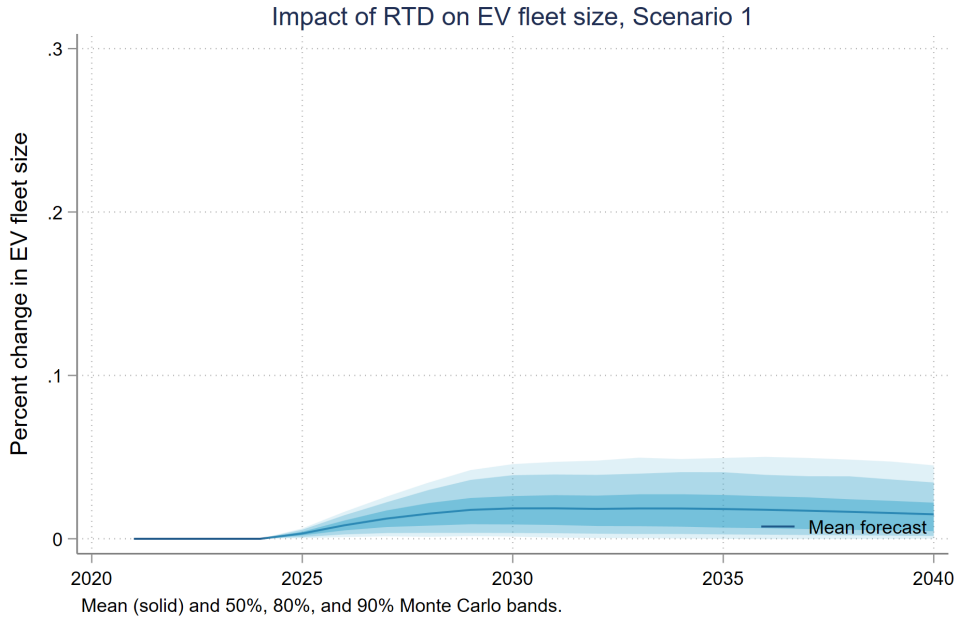


Figure 23: Uncertainty around impact of RTD reporting on EV fleet, scenario 2

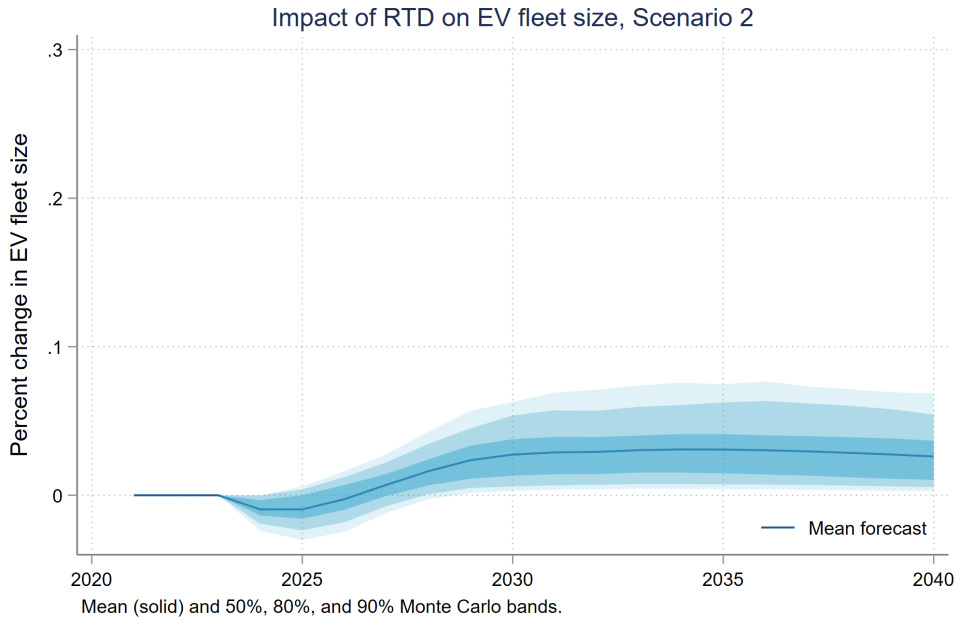


Figure 24: Uncertainty around impact of RTD reporting on EV fleet, scenario 3

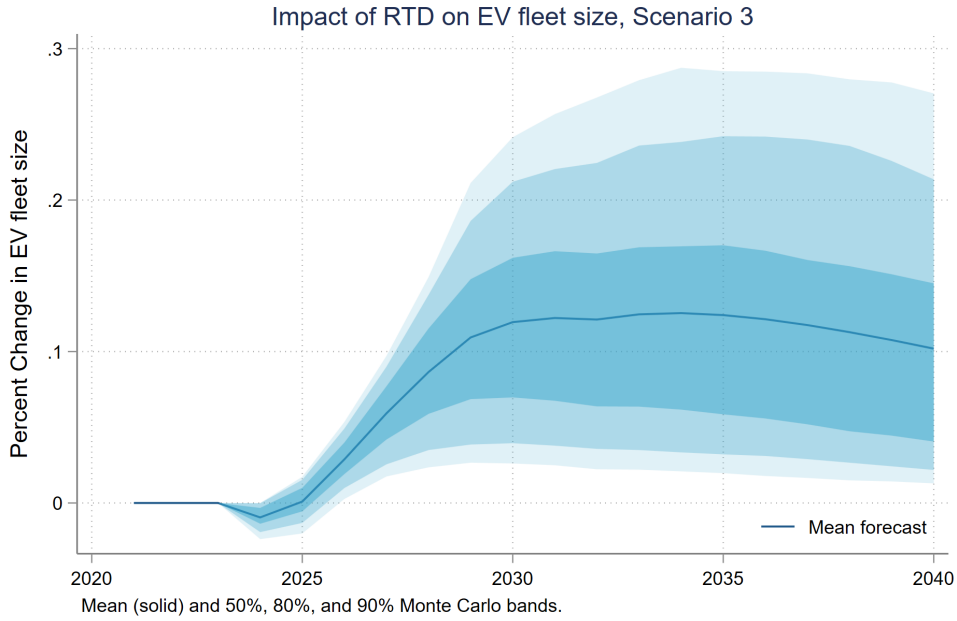


Figure 25: Uncertainty around impact of RTD reporting on carbon emissions, scenario 1

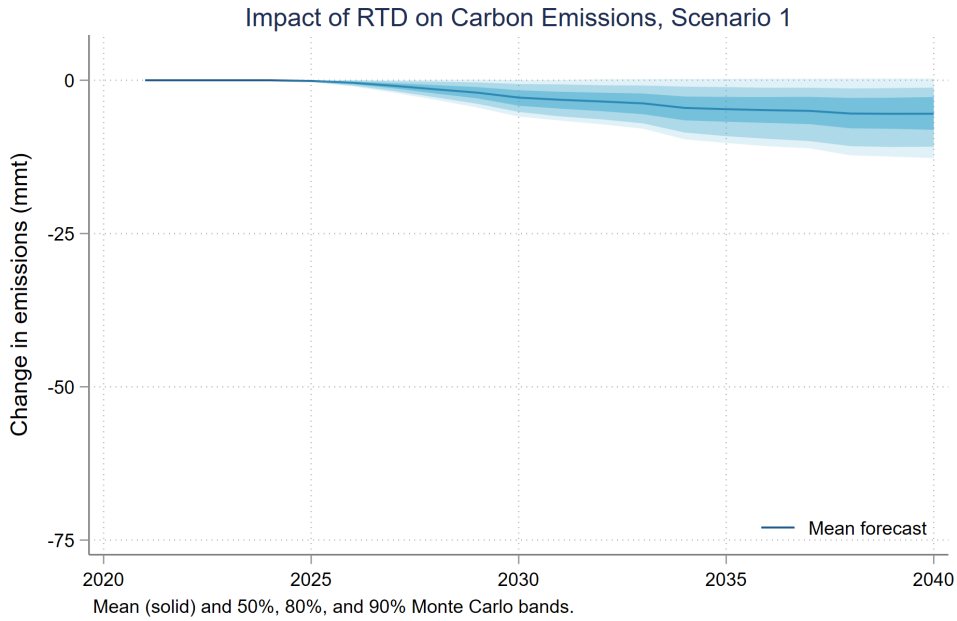


Figure 26: Uncertainty around impact of RTD reporting on carbon emissions, scenario 2

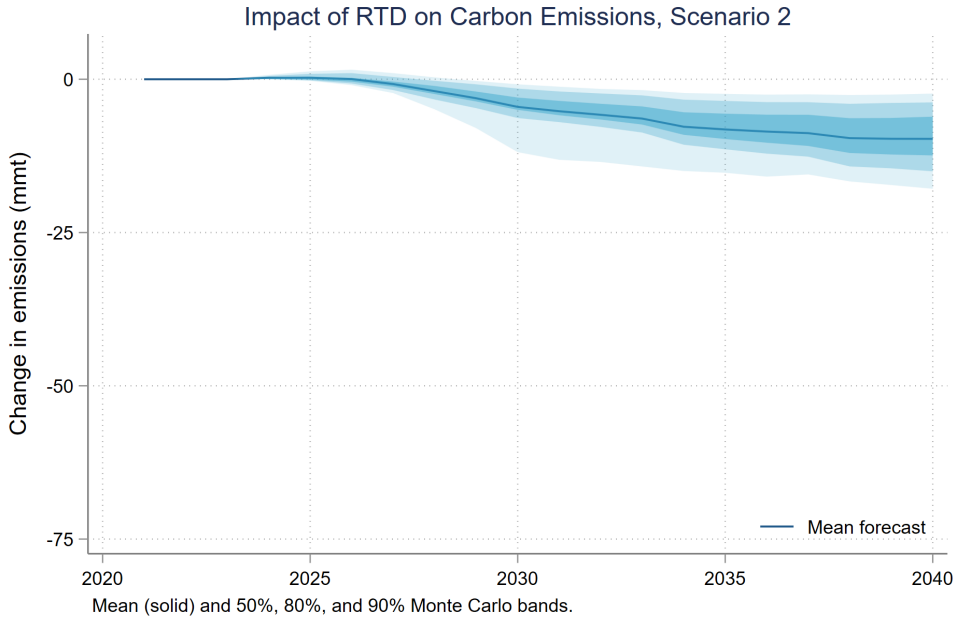


Figure 27: Uncertainty around impact of RTD reporting on carbon emissions, scenario 3

