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CHARGING UNCERTAINTY:
REAL-TIME CHARGING DATA AND ELECTRIC VEHICLE ADOPTION

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ABSTRACT

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Abstract

Charging infrastructure is critical to electric vehicle (EV) adoption, but for chargers to be most useful, EV drivers need to know in real time where they are and whether they are working and available. We investigate the availability of real-time data from DC fast chargers on six major US Interstates and model the impacts of expanding access to real-time data to all DC fast chargers near highways. On average, between March and August 2024, 32.9% of DC fast charging stations adjacent to those six Interstates provided their real-time status on PlugShare, a major charge-finding app, with gaps of up to 1,308 mileswithout real-time data. Further, we survey potential car buyers and EV owners and find low credibility of currently-available real-time data. We incorporate this data into a two-sided model of consumer vehicle choice and charging station buildout adapted from Cole et al. (2023). If universal real-time data is accompanied by improved charger uptime and driver confidence in the accuracy of the real-time data, we predict that the EV share of new vehicle sales would grow by 8.0 percentage points in 2030, expanding the EV fleet by 13.2%, and reducing 2030 carbon emissions by 22.5 mmt, versus baseline projections for 2030.

1 Introduction

Electric vehicle (EV) adoption is crucial for curtailing U.S. greenhouse gas emissions from transportation in the coming years. Prior literature finds that car purchasers choosing between EVs and internal combustion engine (ICE) vehicles place great weight on the availability of charging infrastructure (Springel, 2021; Sommer and Vance, 2021; Li et al., 2017;

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Zhou and Li, 2018; Xing, Leard and Li, 2021). Whether charging infrastructure will spur EV adoption in practice, however, depends on consumers' beliefs about the reliability of those chargers – even more so because Americans tend to believe that EV charging stations are and will continue to be insufficient. A 2024 Pew Research Center survey[1] found that "56% of Americans are not too or not at all confident that the U.S. will build the necessary infrastructure to support large numbers of EVs." Given the perception that charging infrastructure is inadequate, the reliability and availability of existing chargers plays a potentially important role in drivers' decision to buy an EV or not.

The popular media narrative surrounding the EV charging experience is currently negative. Over the last several years, newspaper columnists[2], industry studies[3], and academic literature (Rempel et al., 2022; Asensio et al., 2020) have documented EV drivers' frustration with charging infrastructure, in terms of both the number of chargers and their reliability. In particular, Asensio et al. (2020) use supervised machine learning algorithms to classify reviews from 2011 to 2015 on a major EV charging locator app and report that nearly half of reviews represent negative charging experiences. 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 be unable to charge promptly simply because chargers are occupied and other EVs may be waiting[4].

In this paper, we assess real-time data on DC fast charging stations as a partial solution to the problem of station reliability and availability. Our goals are to 1) assess the current state of real-time data reporting for DCFCs on major highways, 2) document drivers' beliefs about charging reliability with and without real-time data, and 3) model the impacts of universal real-time data for public DCFCs on the speed of the EV transition and resulting carbon emissions.

When we discuss real-time data, we mean data reported *in one centralized app* across multiple charging providers (CPOs) that identifies the locations and types of EV charging stations and whether they are currently working and available. While most CPOs provide data on their own chargers through a proprietary mobile app, this falls short of the benefits of centralized real-time data for two reasons. First, cross-referencing apps puts substantial search burden on EV drivers: in our data scraping along six major interstates, we encountered 39 distinct CPOs. Second, unaccompanied EV drivers cannot safely search multiple apps

[1] https://www.pewresearch.org/short-reads/2024/06/27/about-3-in-10-americans-would-seriously-consider-buying-an-electric-vehicle/

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

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

[4] Searching for charging is costly even when charge attempts do not fail; Dorsey, Langer and McRae (2022) estimate that under the current distribution of charging infrastructure, searching and waiting for charging costs EV drivers without access to public charging the equivalent of $7,763 per driver per year in lost time.

to find working and available chargers while driving. These proprietary CPO apps may also require subscriptions, which will become an increasing barrier to EV adoption as the market grows–particularly the used EV market, in which prospective buyers are more likely to be low- and middle-income, and therefore more sensitive to subscription costs. For drivers accustomed to the ease of finding gas stations at rest stops and via prominent highway signs, the lack of centralized searchable data on EV chargers may be a real barrier to EV adoption. The difficulty of finding EV chargers, combined with the longer time needed to refuel an EV and the possibility of unreliable EV chargers, together exacerbate EV range anxiety.

We focus specifically on 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[5] in their most extreme use cases: long road trips far from home, where they are likely to be unfamiliar with local charging infrastructure, and where running out of charge can involve an expensive and time-consuming tow. Good knowledge of highway fast charging and the availability of specific chargers plays a key role in mitigating range anxiety and making EVs more accessible to the American public.

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 $5 billion National Electric Vehicle Infrastructure (NEVI) program created by the 2021 Infrastructure Investment and Jobs Act (IIJA, also known as the Bipartisan Infrastructure Law) mandates the reporting of real-time data for highway DCFCs it funds. Specifically, the program 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 fund up to 62,500 DC-fast charging ports with 20% state cost share; compared to NREL's forecast[6] of 182,000 DCFC ports by 2030, NEVI-funded chargers will always be in the minority[7].

Real-time data on chargers is available in mainstream general-purpose mapping apps like Apple Maps and Google Maps, and in specialized third-party charging locator apps like PlugShare. These apps report locations of EV chargers worldwide, and for some chargers at some times also report data on plug type, wattage, and real-time status. As we show, PlugShare has the best coverage of these three main apps. We therefore present results from repeated scraping of PlugShare; for six major U.S. highways, we report 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 18, 2024, 34.4% of DCFC stations and 18.6% of plugs on average reported real-time data on PlugShare.

[5] Range anxiety includes anxiety about charger reliability, search time, and congestion – not just the absolute number of chargers on the road.

[6] https://driveelectric.gov/files/2030-charging-network.pdf, page 36, table 6

[7] For comparison, there are about 160,000 gasoline stations in the United States. With a conservative estimate of 4 nozzles per station, this implies 640,000 gas nozzles in the country.

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 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.

To parameterize this model, we conduct a survey of current EV drivers and potential EV buyers to elicit their beliefs about charging reliability at highway DC fast chargers as a function of real-time data.[8] Overall, we find that drivers are pessimistic about the reliability of chargers. When presented with a charging station with real-time data reporting that at least one plug is working and available, respondents estimate that they can successfully charge at it less than two thirds of the time on average. Moreover, current EV drivers are *more* pessimistic than prospective buyers, predicting an average successful charge 59% of the time, compared to 65% of the time for prospective buyers. Nonetheless, real-time data is still useful: both prospective buyers and current drivers are even more pessimistic about charging reliability at stations without real-time data.

Using our modified model and parameters from our PlugShare scraping and our survey, we predict that universal real-time data provision alone increases the EV share of new car sales by 1.1 percentage points and the size of the light-duty EV fleet by 1.9% 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 13.2% on average and the EV share of new car sales by 8.0 percentage points. We also find that the impact of real-time data on the EV share of new LDV sales does not vary with the magnitude of IRA consumer EV tax credits, so real-time data is likely to matter even if current EV incentives are modified or removed.

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 present survey evidence on 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

[8]We do not ask survey respondents about the reliability of Level-2 chargers, which may differ from DC fast chargers, as we do not model uncertainty about their availability. Similarly, while there are many estimates of elasticities of EV demand to charging station buildout in the literature, none that we know of separately estimate the impacts of Level-2 and DC fast chargers on EV purchases.

require multiple-hour charging sessions so are impractical for long-distance road trips except at overnight stops. 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 most comprehensive 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, which we define as U.S. census incorporated places with a population of at least 100,000 and a population density of at least 2,750 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 slower travel to a charger than in less dense areas. 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 most of our results at the station level, where we define a station as all plugs at a PlugShare 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 22, 2024; any changes in the provision of real-time data before July 22 or between July 22 and August 18 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 18, 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 33.2% of stations, though this ranges from 23.3% on I-90 to 45.4% 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

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

	I-5	I-10	I-75	I-80	I-90	I-95	Total
Total Stations	350	187	150	214	189	336	1,426
% w/RT Data	**45.4%**	**31.6%**	**33.5%**	**30.0%**	**23.3%**	**28.6%**	**33.2%**
Non-Tesla Stations	248	116	91	133	111	188	887
% w/RT Data	**64.1%**	**50.9%**	**49.5%**	**53.4%**	**39.6%**	**51.1%**	**53.4%**
Excluding Tesla and EA	197	82	70	89	81	150	669
% w/RT Data	**80.7%**	**72.0%**	**64.3%**	**79.8%**	**54.3%**	**64.0%**	**70.9%**

necessarily relevant to the decision process of most non-Tesla drivers. Until earlier this year, Tesla fast chargers were available exclusively to Tesla vehicles. Tesla has recently begun opening chargers to EVs from certain automakers and, under an agreement with the White House, is required to make some chargers open to any EV by the end of the year[9]. Excluding Tesla chargers brings the overall share of DCFC stations providing real-time data to 53.4%, with a range from 39.6% on I-90 to 64.1% on I-5.

Finally, the last two rows in Table 1 present results which exclude both Tesla and Electrify America (EA), 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 70.9%, with a range of 54.3% on I-90 to 80.7% on I-5. 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 over 53% (1,426 total stations vs. 669 excluding Tesla and EA).

Appendix Table A1 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 (19.9% vs. 33.2%) because Tesla and Electrify America tend to have large stations. Tesla has a median station size of 10 plugs and a mode of 8

[9] In order to qualify for NEVI funding, which requires that chargers not be exclusive to a single brand of EV (https://www.politico.com/news/2023/02/15/tesla-chargers-public-electric-vehicles-00082875), Tesla has agreed with the White House to open at least 7,500 chargers to all non-Tesla EVs by the end of 2024 (https://www.whitehouse.gov/briefing-room/statements-releases/2023/02/15/fact-sheet-biden-harris-administration-announces-new-standards-and-major-progress-for-a-made-in-america-national-network-of-electric-vehicle-chargers/), both through upgrades to some of the existing charger network and construction of new chargers. Of these, at least 3,500 must be 150-kW Superchargers. Additionally, some automakers have made agreements with Tesla to allow all of their EVs access to any Tesla Supercharger upgraded to be compatible with non-Tesla EVs. Ford, Rivian, and GM EVs have technically received access, subject to buying adapters that are reportedly in inadequate supply and backordered (https://www.consumerreports.org/cars/hybrids-evs/tesla-superchargers-open-to-other-evs-what-to-know-a9262067544/).

plugs, and Electrify America has a median of 8 plugs and a mode of 8 plugs – compared to a median 4 (mode 4) plugs for all other stations. Electrify America 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 holds to a lesser extent when Tesla is excluded; 46.6% of plugs provide real-time data, vs. 54.3% of stations. By contrast, the share of plugs providing data is higher than the proportion of stations providing real-time data when both Tesla and Electrify America are excluded (72.6% of plugs vs. 70.9% 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 22, 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.

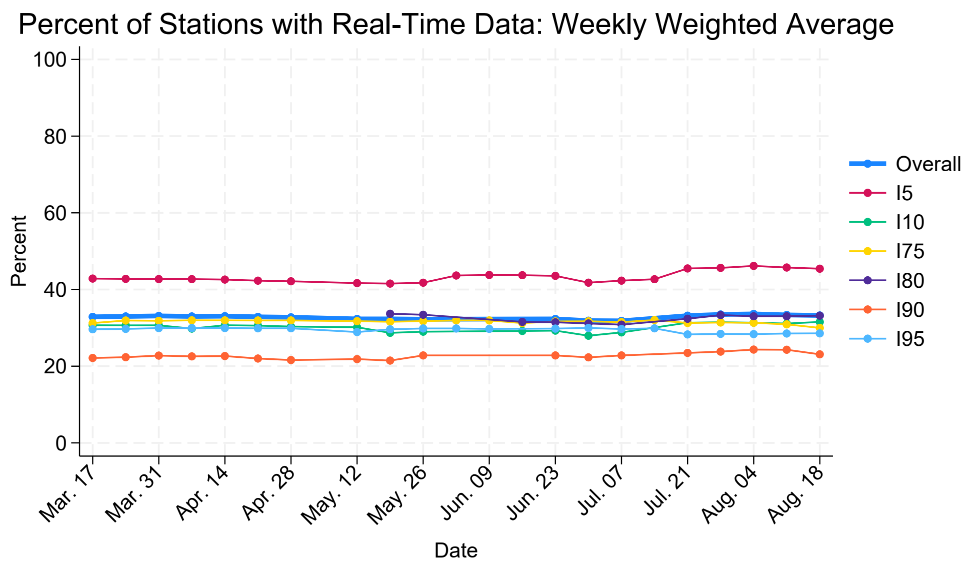
On every highway except I-90, the top four CPOs are (Tesla) Supercharger, Electrify America, EVgo, and ChargePoint (on I-90, EV Connect is the fourth largest provider, with 13 stations, and ChargePoint is 5th, with 8). Among these, Supercharger is always the largest provider and Electrify America is 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.

Not only is current reporting of real-time data for DCFCs is far from universal, but it is not meaningfully improving. On the six highways we study, it has not significantly improved over the period in which we have scraped data from PlugShare. In fact, Electrify America briefly 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-

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

		I-5	**I-10**	**I-75**	**I-80**	**I-90**	**I-95**	**Total**
Supercharger	Total Stations	102	71	59	81	78	148	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	42	26	16	24	15	36	159
	# w/RTD	40	25	16	24	15	35	155
	% w/RTD	**95%**	**96%**	**100%**	**100%**	**100%**	**97%**	**97%**
ChargePoint	Total Stations	52	14	26	24	8	40	164
	# w/RTD	49	12	25	23	8	39	156
	% w/RTD	**94%**	**86%**	**96%**	**96%**	**100%**	**98%**	**95%**
Non-networked	Total Stations	6	4	1	4	2	7	24
	# w/RTD	0	0	0	0	0	0	0
	% w/RTD	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**
Other	Total Stations	97	39	27	39	56	66	324
	# w/RTD	68	22	6	23	21	20	160
	% w/RTD	**70%**	**56%**	**22%**	**59%**	**38%**	**30%**	**49%**
Highway Total	Total Stations	349	188	150	216	189	335	1427
	# w/RTD	157	59	47	70	44	94	471
	% w/RTD	**45%**	**31%**	**31%**	**32%**	**23%**	**28%**	**33%**

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



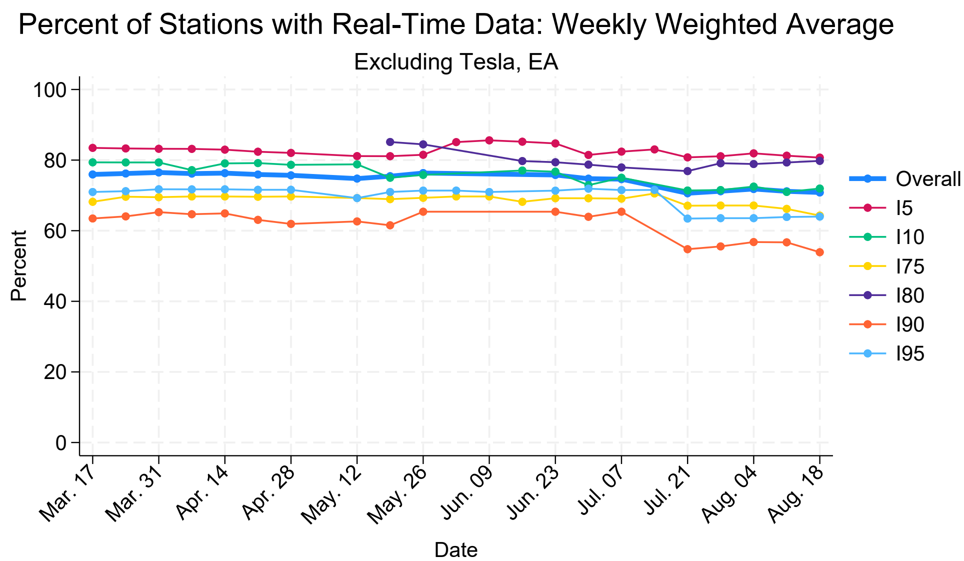
time data provision on our six highways are presented in Figure 1 (all CPOs), and Figure 2 (excluding Tesla and Electrify America). Appendix Figure A1 presents an analogue to Figure 1 but includes dealers. Each point on these graphs represents a weighted average of successful PlugShare scrapes within the relevant week[10].

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 22; any changes on July 22 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 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

[10] We only use data from scraping runs which successfully collected data on at least 95% of stations on the relevant highway. I-80 scrapes before May 21 did not meet the 95% threshold.

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



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.

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%

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

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

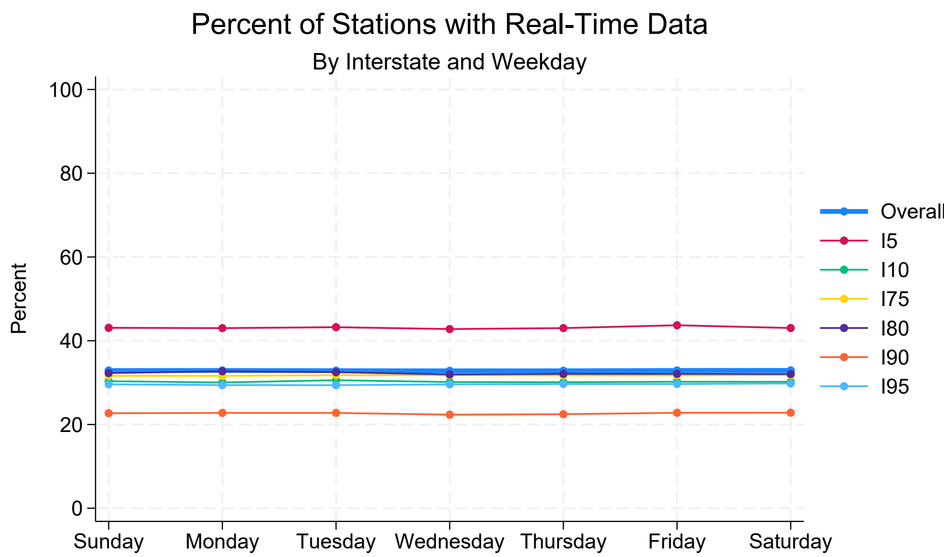


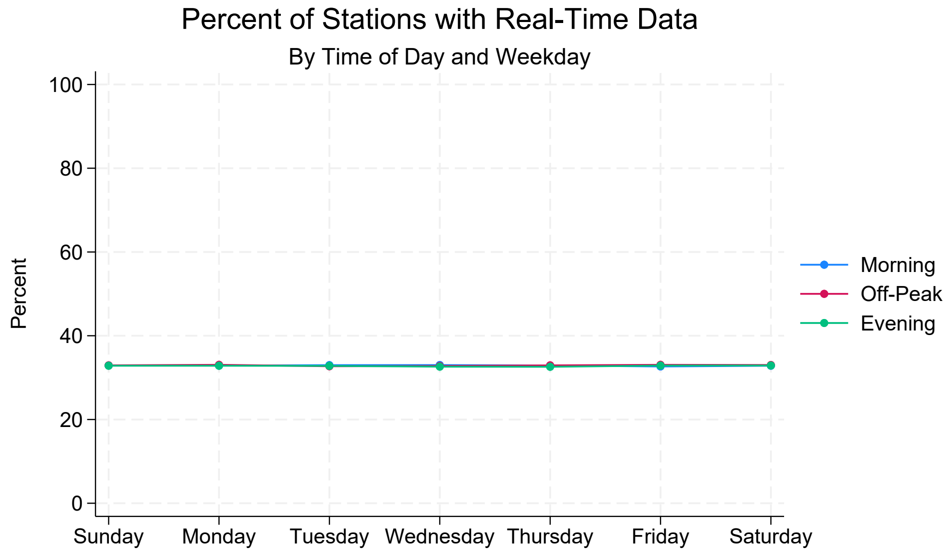
Table 4: Fraction of stations providing real-time data at at least one plug by data provider, excluding Tesla and Electrify America

	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%

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 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 for Apple Maps on I-95, where PlugShare provides real-time data for nearly eight times as many stations as does Apple. 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.

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



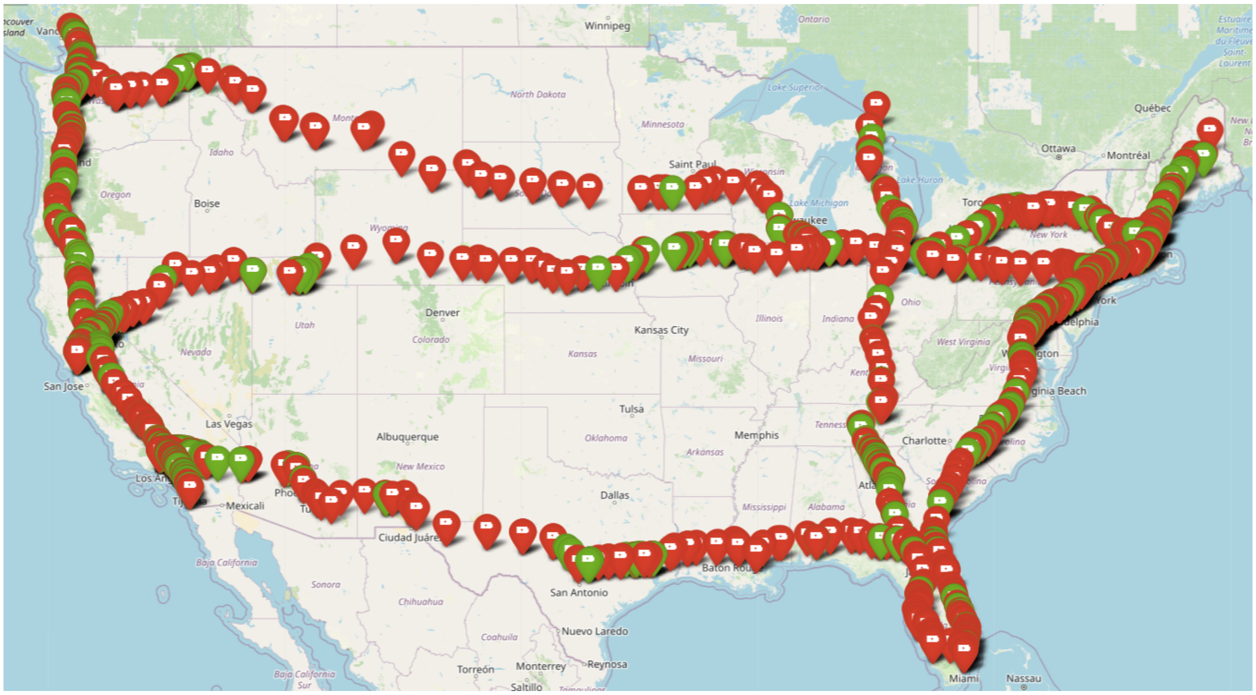
2.4 Results: Data Deserts

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. However, they obscure the regional variability in real-time data provision within those six highways. In Figure 5, we illustrate this regional variation by mapping all of the DC fast chargers on our six highways and whether they shared real-time data on PlugShare as of July 22, 2024. Stations in green provide real-time data on at least one plug, and stations in red do not provide any real-time data. The three cross-country highways (I-10, I-80, and I-90) not only have the lowest proportion of stations providing real-time data, but also the least uniform distribution of real-time data across space, leading to long stretches of highway with no access to real-time data on chargers.

In this section, we focus these 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, which we call "data deserts". These dataless stretches can, at times, span distances longer than even the longest stated range of existing EV models, and therefore require meticulous advance 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. The cost of an error could be high: a tow to the next working fast charger (that is compatible with the driver's vehicle[11]) or hours at a Level-2

[11]Not all electric vehicles are compatible with all charging plugs. In addition to Tesla and non-Tesla vehicles following different charging standards and needing adapters to use each other's plugs (in the cases where non-Tesla vehicles are not explicitly excluded from using Tesla chargers), there is also variation in charging standards within non-Tesla vehicles. Most non-Tesla vehicles use J-1772 plugs for level-2 charging

Figure 5: Locations of chargers in our PlugShare scrape on July 22, 2024. Chargers in red supply no real-time data, and chargers in green share real-time data for at least one plug.



charger to gain enough charge to drive to the next working fast charger.

Table 3 presents data deserts on our six highways as of May 17, 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 Emlenton, PA. The state of data availability is worst on I-90; a single 1,308-mile desert between Post Falls, ID and Blue Earth, MN is immediately adjacent to another 293-mile data desert between Blue Earth, MN and Madison, WI.

and CCS1 for fast charging, but some US EVs, like the Nissan Leaf, use ChaDeMo plugs. While many DC fast chargers include both CCS1 and ChaDeMo plugs, some only include one or the other.

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

	Start Location	End Location	Length (mi)	# Stations	Tesla	EA	Other CPOs
I-10	Tucson, AZ	Deming, NM	209	4	2	2	0
	Deming, NM	Kerrville, TX	586	15	9	5	1
	Baytown, TX	Robertsdale, AL	466	17	10	4	3
	Robertsdale, AL	Tallahassee, FL	226	12	6	4	2
I-80	Truckee, CA	Lovelock, NV	148	7	4	3	0
	Lovelock, NV	Carlin, NV	153	3	1	2	0
	Coalville, UT	Kearney, NE	709	16	8	6	2
	Bettendorf, IA	Rolling Prairie, IN	221	12	6	2	4
	Perrysburg, OH	Emlenton, PA	209	9	5	3	1
	Emlenton, PA	Columbia, NJ	274	12	8	4	0
I-90	Post Falls, ID	Blue Earth, MN	1,308	38	23	8	7
	Blue Earth, MN	Madison, WI	293	11	5	1	5
I-95	Lynchburg, SC	Savannah, GA	145	8	7	1	0

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 charging station 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 reduced.

Appendix Table A2 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 A2 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 are 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[12].

3 Consumer attitudes 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 DCFCs 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.

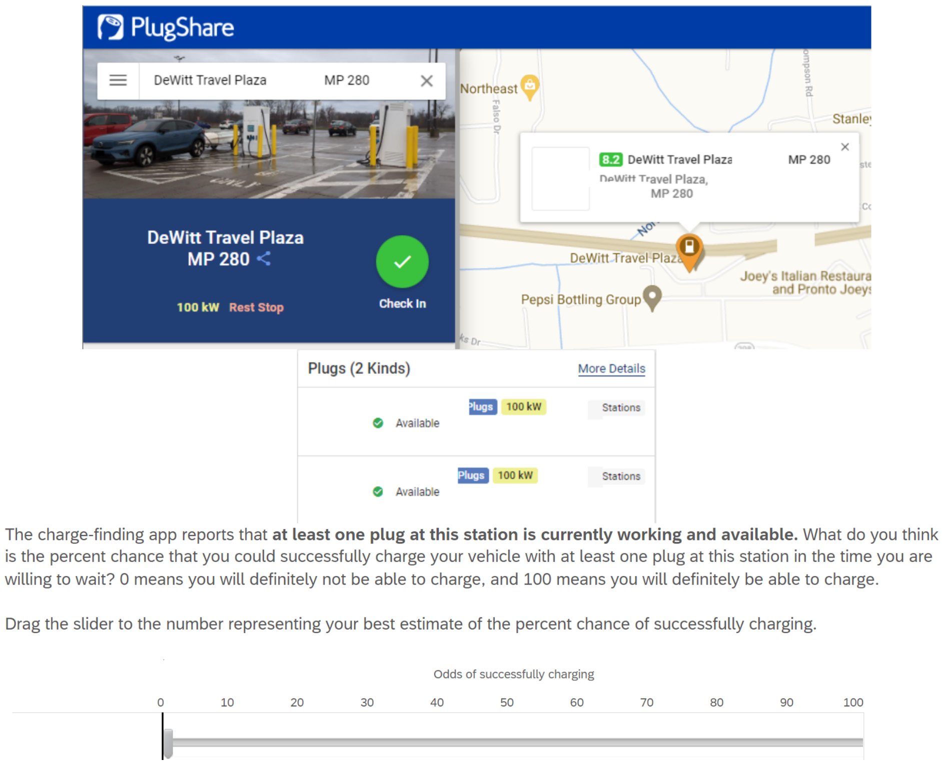
We conduct two surveys with the same questions but distinct samples: one of US-based current EV drivers and one of US-based non-EV drivers who expect to buy a new car soon. The current EV driver sample is comprised of members of the Electric Vehicle Association, a North American nonprofit working to accelerate 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 6 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. We 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 them to assess 1) a station with real-time data and at least one plug working and available, 2) a station with real-time data and at least one plug working but none available, and 3) a station 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 station without real-time data and an Electrify America station without real-time data, one third of respondents are asked to assess a station

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

Figure 6: Sample survey question



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 charger than at an 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 a charger identified as currently available. 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 7: Available chargers, occupied chargers, and chargers without real-time data: probability of successful charge by survey sample

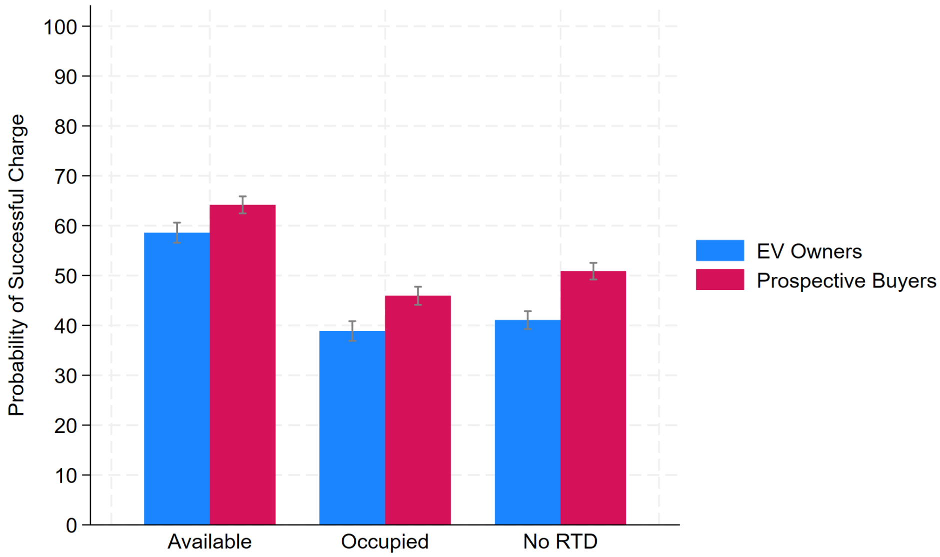
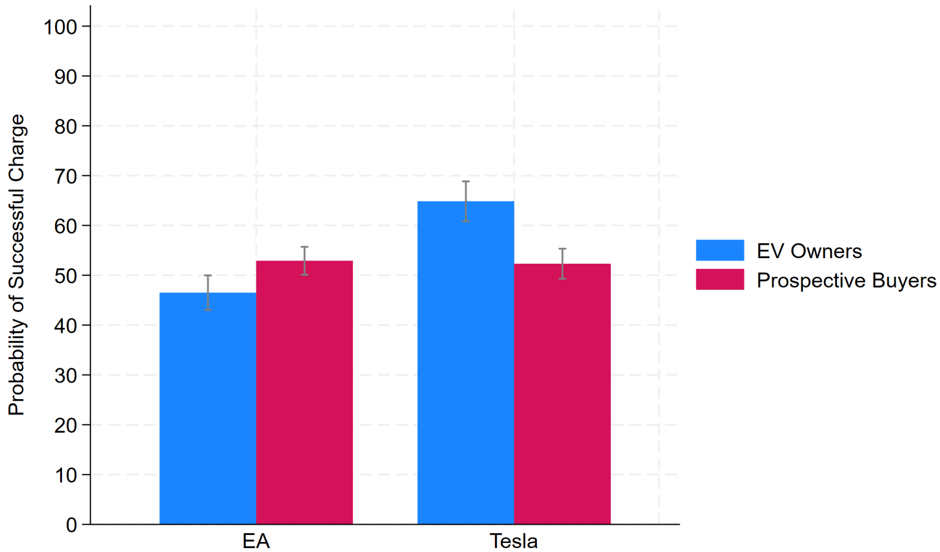


Figure 7 plots the average response and 95% confidence interval for the three main questions in our survey, split by survey sample. Perhaps most striking is the pessimism with which respondents view chargers that provide real-time data and are reported working and available. Prospective car buyers estimate that they can successfully charge at such a station 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).

We see two primary reasons why drivers may believe that a charger reported to be working and available may only provide a successful charge less than two-thirds of the time: congestion and overreporting of uptime. While we stipulate that the charger is available at the time the driver checks PlugShare, drivers are likely aware that other drivers may occupy any free chargers before they reach the station. Additionally, in their 2024 Annual Reliability Report, the company ChargerHelp reports that true uptime, or the actual fraction of attempted charges that prove successful, often falls short of reported uptime – which is what would be captured in real-time data. In particular, ChargerHelp finds that 15% of stations they test fail despite both the app and the physical station status reporting that the station is online and available (ChargerHelp, 2024). This can happen because chargers are physically blocked, network connections or payments fail, or cords are too short, among other reasons.

Figure 8: Tesla and EA stations without real-time data: probability of successful charge by survey sample



Figures 8 through 10 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 stations without real-time data (t=1.16), whereas EV drivers surprisingly consider rural stations 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 10-plug stations with no real-time data than at 4-plug stations with no real-time data.

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 11 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 outside the Tesla network of stations (for which Tesla owners get real-time data through their vehicles), and therefore also little experience charging 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 on PlugShare data significantly more reliable than EA stations without real-time data (t=14.41), non-Tesla drivers do not distinguish between the two

Figure 9: Urban and rural stations without real-time data: probability of successful charge by survey sample

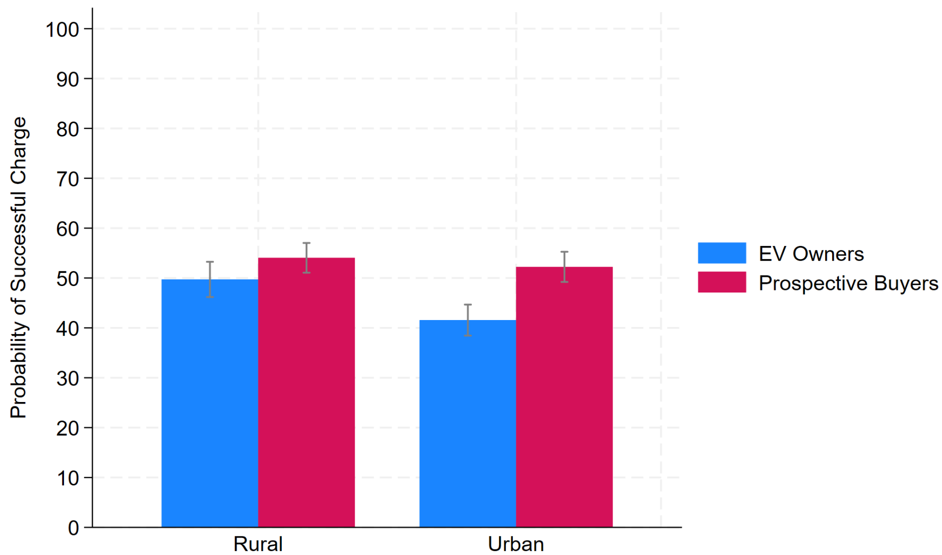


Figure 10: 4-plug and 10-plug stations without real-time data: probability of successful charge by survey sample

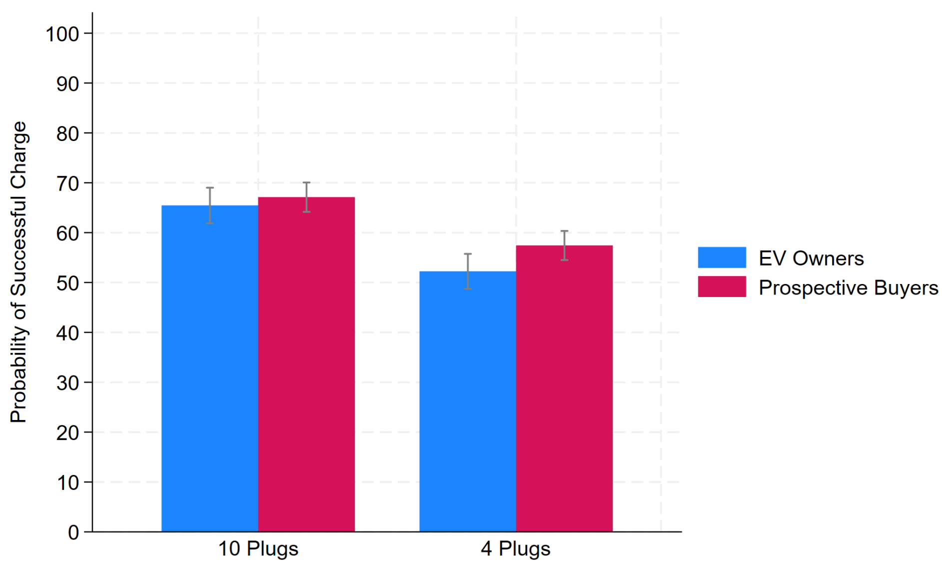
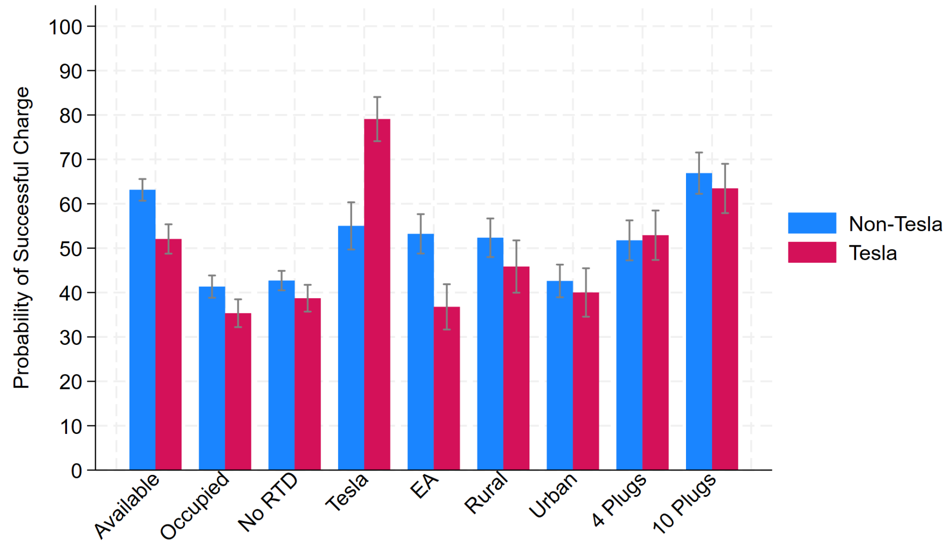


Figure 11: Survey results for Tesla owners vs. non-Tesla EV owners



(t=0.65).

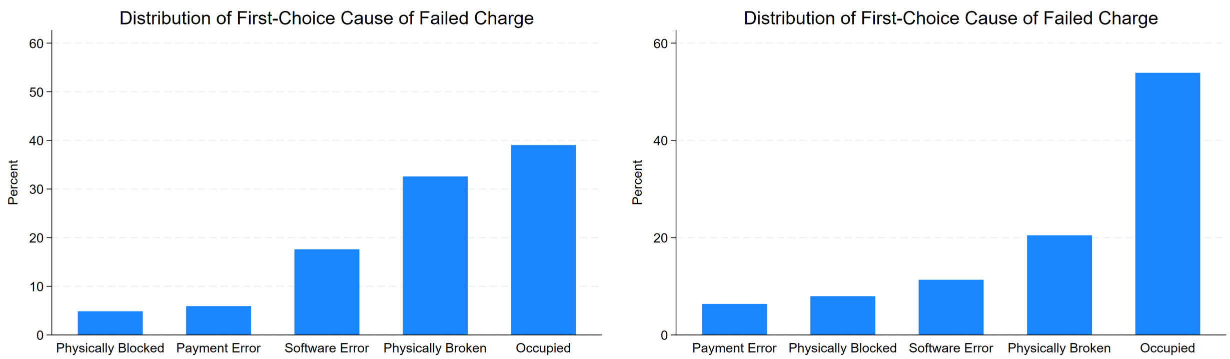
In addition to the main survey questions on specific hypothetical chargers, we ask two additional questions to better understand drivers' beliefs and preferences about chargers without real-time data.

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 12 shows the distribution of first-choice 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. However, prospective buyers who do not already drive an EV are disproportionately likely to expect a charger to be occupied, whereas EV owners are comparatively more likely to expect a charger to be physically broken. The most common issue, chargers being occupied, would be diminished by the reporting of real-time data; drivers could choose not to visit chargers which were listed as occupied, searching instead for a charger that was currently available. Appendix Figure A2 shows the full distribution of the rankings of the five options for each of the two groups.

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 station in 15 miles without real-time data, and a station 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

Figure 12: Distribution of first-choice reason for failed charging at hypothetical station without real-time data

(a) EV Owners (b) Prospective Buyers



each respondent. Figure 13 plots the fraction of respondents choosing to drive directly to the second station (currently available with real-time data) for each of our two samples, by their randomized distance to the second station. The 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.

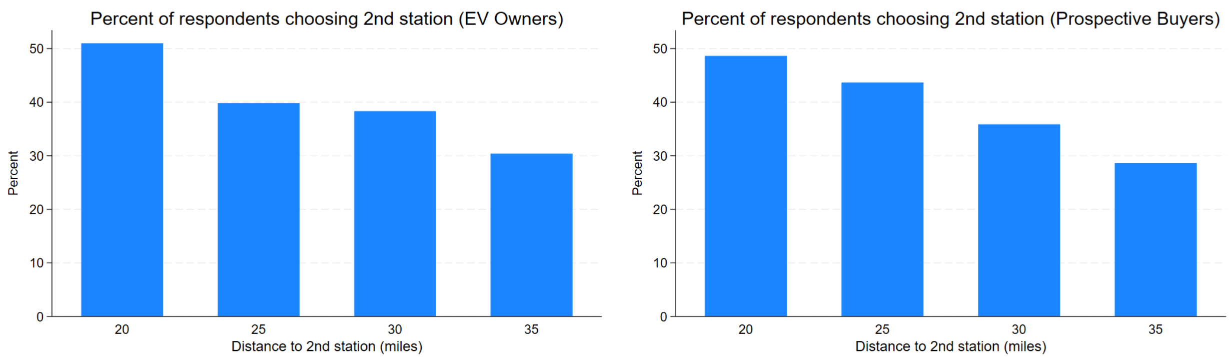
Overall, our survey responses indicate that, while real-time data does not fully solve the problem of charger reliability – given that respondents only expect to be able to successfully charge at stations marked available 58.6% or 64.6% of the time – it has the potential to go a long way in improving 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) demonstrates that subsidizing charging infrastructure is more effective on the margin than directly subsidizing EV purchases, but takes as given the elasticities of EV demand to the size of the charging network estimated in prior literature. Since 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.

Figure 13: Fraction of respondents choosing to bypass first station (without RTD) by distance to second station (working and available)

(a) EV Owners (b) Prospective Buyers



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_{jt} 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. This captures current federal EV policy as of October 2024.

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, following the standard federal budgeting convention.

Considerable uncertainty surrounds the future of these tax credits. One possibility is that all the tax credits will continue as created in the IRA, that increasingly many vehicles and buyers will qualify for the full $7,500 tax credit and that, for those consumers and vehicles that do not qualify, more take advantage of the leasing loophole by which commercial vehicles (leasing fleets) qualify for the tax credit. Further, the used EV tax credit may boost used EV prices, and the tax credits may be fully passed through to the consumer. At the other end, some or all of the EV tax credits could be repealed as soon as 2025. Given this uncertainty, we undertake a sensitivity analysis of the impact of real-time data under a range of EV price subsidies.

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.

In addition to these modifications, we calibrate the drift parameter ψ_{jt} in consumer tastes for EVs so that the average EV share of new car sales in 2030 under the IRA and IIJA is 48.0%, matching Bloomberg New Energy Finance's projection for 2030 EV penetration under current policy. This is somewhat below the 57.7% penetration in 2030 forecast in Cole et al. (2023), and above the potential scenarios the EPA calculates for meeting its final LDV greenhouse gas emissions rule[13] (31%, 37%, or 44% in each of three scenarios depending on the distribution of ICE, hybrid electric vehicles, and plug-in hybrid electric vehicles making up the rest of the fleet).

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:

[13] https://www.govinfo.gov/content/pkg/FR-2024-04-18/pdf/2024-06214.pdf

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

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:

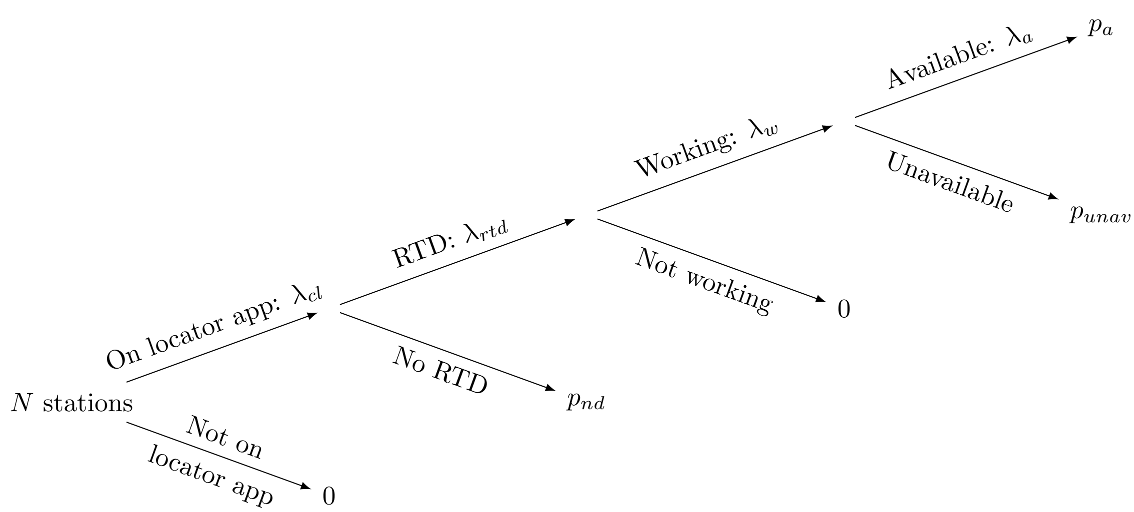
$$s_{jt} = \frac{exp(\bar{u}_{jt})}{1 + exp(\bar{u}_{jt})}$$

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. Figure 14 shows the classification of chargers by data availability and status alongside the conditional probabilities we parameterize to define μ. Moving from left to right on the decision tree, we begin with N DC fast stations. These appear on a charging locator app with probability λ_{cl}. We assume that drivers cannot successfully charge at stations that are not on locator apps, as they cannot learn about them except by word of mouth. Chargers on locator apps provide real-time data with probability λ_{rtd}; consumers can successfully charge at stations without real-time data with probability p_{nd}. Chargers providing real-time data have at least one plug working with probability λ_w; we assume that consumers cannot successfully charge at stations that provide real-time data but have no working plugs. Finally, chargers that are working have at least one plug available with probability λ_a; the probability of a successful charge at one of these stations is p_a, and the probability of a successful charge at a station which is working but has no available plugs (so the driver would expect to need to wait to charge) is given by p_{unav}.

Figure 14: Possible real-time data scenarios and corresponding parameters



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 6 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.

Table 6: 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

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. Recent research on the value of data to firms and the role of data in the economy is summarized in Farboodi and Veldkamp (2023), where data is unique compared to other kinds of capital in that it is accumulated as a byproduct of production (e.g. through learning about consumer demand) and feeds back into the profits of future production (e.g. by applying those lessons about consumer demand). A key feature of the data economy which informs the choice of CPOs to share or not share real-time data is that while data is non-rival–two firms can simultaneously use the same piece of data–the value to a firm of any given piece of data may decrease when other firms also have access to that data. Thus while data in and of itself is not problematic for competition between firms, firms can use data asymmetry to win customers away from other firms (Farboodi and Veldkamp (2023), Farboodi and Veldkamp (2021)). As modeled in Farboodi and Veldkamp (2021), firms can sell data δ to other firms, but that comes at a cost $\iota\delta$ to the selling firm, corresponding to the reduction in value of the data once multiple firms can access it. In the case of CPOs, providing freely accessible real-time data both incurs the cost $\iota\delta$ for each additional firm that can access the data *and* deprives the original CPO of the opportunity to sell that data for revenue.

While these are undoubtedly key forces in understanding why CPOs are reticent to supply publicly accessible real-time data, our goal in this paper is to model the impact of exogenously changing the fraction of stations providing real-time data on EV adoption. We therefore 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), $\pi_t(N_t, Q_t) = (exp(\kappa)/(N_t))^{\frac{1}{\gamma}} Q_t$ (suppressing $l3$ subscripts for convenience), 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:

$$\pi_t = \lambda_{cl}\lambda_w(exp(\kappa)/(N_t))^{\frac{1}{\gamma}}Q_t$$

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:

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

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 and the discounted cost of building next period. This yields the following supply equation for level-3 chargers:

$$ln(N_t) = \kappa + \gamma ln(\lambda_{cl}\lambda_w) + \gamma ln(Q_t) - \gamma ln(\tilde{C}_t)$$

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 Scenario 1, the share of DCFCs providing real-time data (λ_{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 Scenario 2, 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 97% between 2024 and 2029. This scenario corresponds to one in which charger reliability improves to match the 97% 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 Scenario 3, in addition to the changes in λ_{rtd} and λ_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.

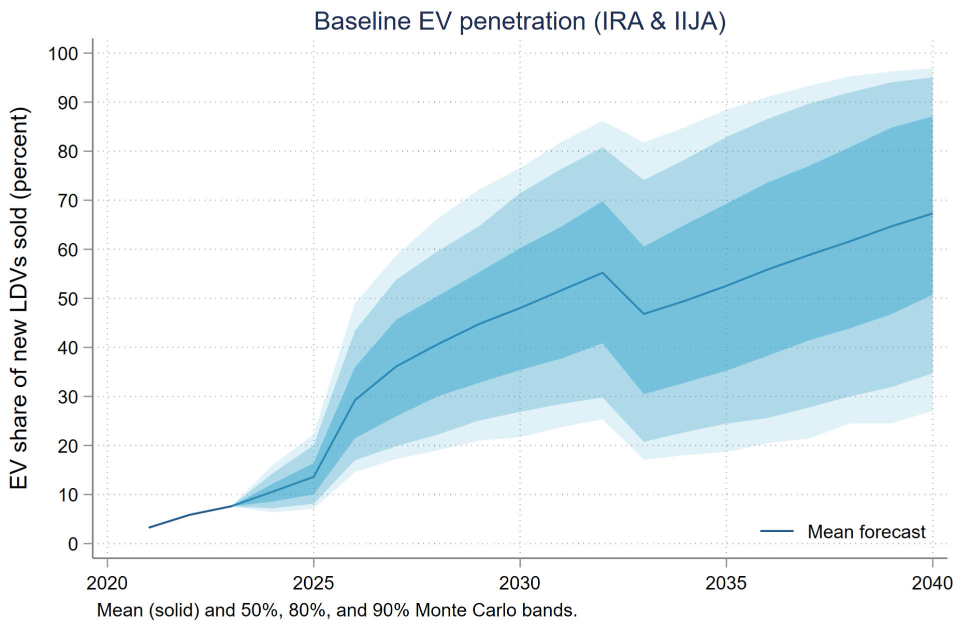
Scenarios 2 and 3 are plausible but far-from-certain outcomes of Scenario 1 and current policy. With the provision of real-time data, CPOs will have the incentive to invest in improving charger uptime because their downtime is more visible to consumers. Moreover, the NEVI mandate of 97% uptime may increase uptime overall, either because a high proportion of chargers with real-time data are funded by NEVI, or because CPOs who need to maintain their NEVI-funded chargers may improve maintenance of their non-NEVI-funded chargers. Scenario 3, in which driver trust in real-time data improves, may come about because CPOs learn to provide *better* real-time data as they provide *more* real-time data.

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 1, 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 15 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 48.0% of new cars in 2030 will be electric in the baseline IIJA+IRA scenario, with a 90% Monte Carlo band of 21.7% to 76.5%. The drop in EVs as a share of new car sales in 2033 corresponds to the expiration of the IRA's tax credits (both for vehicles and for charging stations) at the end of 2032, resulting in 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.

Figure 15: Main estimate and uncertainty for baseline EV share of new car sales under IRA & IIJA with no change in RTD reporting



We find that universal real-time data alone has limited effects, but our model predicts a substantial acceleration in EV adoption if real-time data leads to higher DCFC uptime and alleviates range anxiety. Table 7 presents values for the EV share of new car sales under our three simulated scenarios in the key years of 2025 to 2030. In scenario 1, all stations provide real-time data by 2029. Real-time data alone produces only a modest increase in EV penetration of up to 1.1 percentage point by 2030. In Scenario 3, increases in real-time data and uptime lead to full driver confidence in real-time data, yielding a more powerful 8.0 percentage point increase in EV over the same period. In effect, scenario 3 accelerates EV adoption by more than a year by the end of the decade, achieving in 2029 an EV share of new car sales of 52.8%, higher than the share achieved in 2030 (48.0%) in the baseline.

Figure 16 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 97% 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 97% uptime as well as 100% consumer confidence in real-time data by 2029.

Table 7: Impact of RTD scenarios on EV share of new vehicle sales, 2025-2030

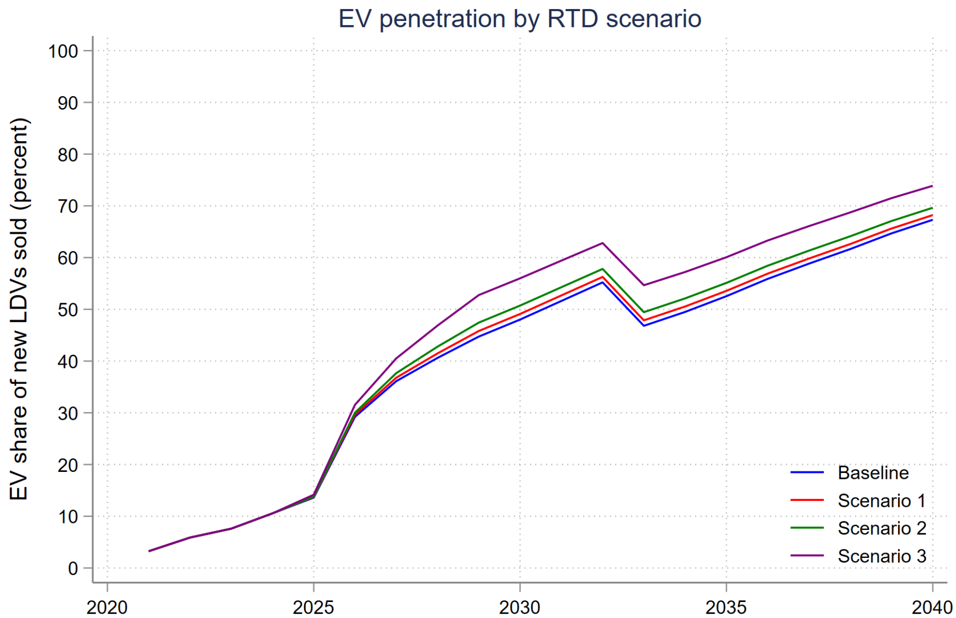
	Baseline	All stations provide RTD		… and 97% uptime		… and full driver confidence in RTD	
			ppt over baseline		ppt over baseline		ppts over baseline
2025	13.6%	13.7%	0.12	13.8%	0.19	14.2%	0.56
2026	29.2%	29.6%	0.41	30.0%	0.79	31.5%	2.31
2027	36.1%	36.8%	0.67	37.7%	1.55	40.5%	4.41
2028	40.6%	41.5%	0.87	42.8%	2.17	46.8%	6.24
2029	44.7%	45.8%	1.08	47.4%	2.70	52.8%	8.02
2030	48.0%	49.1%	1.08	50.7%	2.71	56.0%	7.97

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 97% 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 792 highway runs, the average fraction of stations with real-time data at which at least one plug is reported working is 88.2%. 44 highway scraping runs (5.52%) already meet or exceed the 97% uptime requirement from NEVI at the station level.

Appendix figures A3 through A5 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, we further simulate the model with the effective tax credit set at \$0, \$2,000, \$4,000, \$6,000, \$8,000, and \$10,000 (where a credit of \$0 represents the removal of all IRA tax credits for personal EVs, and values above \$7,500 account for the used vehicle tax credit the consumer may accrue upon reselling their vehicle). Figure 17 plots the percentage point increase from real-time data in each of our three scenarios for each possible effective tax credit. Across our three scenarios, the size of the effective tax credit makes very little difference in the magnitude of the impact of real-time data.

Figure 16: EV share of new sales over time by RTD scenario

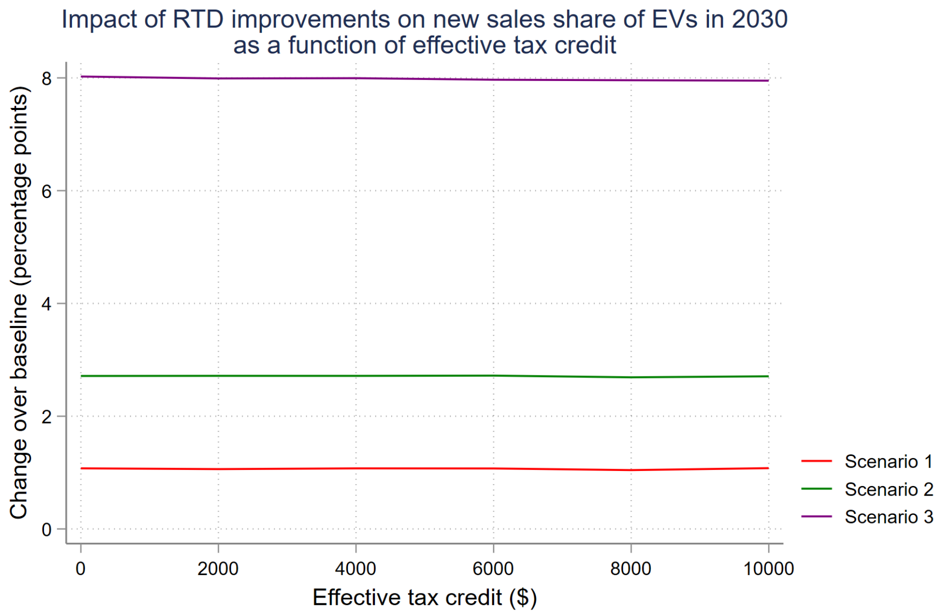


4.8 Results: EV fleet size

The total number of EVs on the road under each of our scenarios is a variable of particular interest 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 8 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 1.9%, scenario 2 by 4.5%, and scenario 3 by 13.2%. This over-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 feeds back into the consumer choice side of the model, further expediting the transition to EVs.

Figure 18 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 A6 through A8 present uncertainty around these projections.

Figure 17: Change in EV share of new car sales in 2030 over IRA & IIJA baseline by effective consumer tax credit



4.9 Results: Carbon emissions

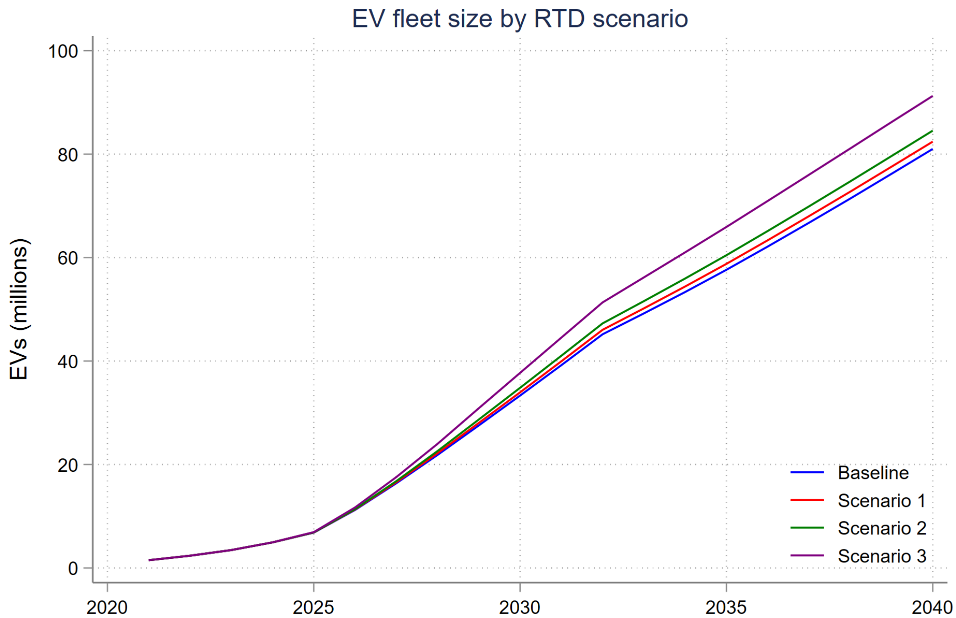
Figure 19 presents changes in yearly carbon emissions from the light-duty vehicle fleet relative to the IRA and IIJA baseline for each of our three real-time data scenarios[14], measured in millions of metric tons. As in Cole et al. (2023), our projections for carbon intensity of the power sector are based on Stock and Stuart (2021). Table 8 presents the same information

[14]Note that we only model the purchase decision between EVs and ICE vehicles. Another margin on which real-time data can effect carbon emissions is by influencing the driving decisions of households with vehicles of both types; with better real-time data, households may choose to take their EV on long road trips instead of their ICE.

Table 8: Impact of RTD scenarios on EV fleet size (millions), 2025-2030

	Baseline	All stations provide RTD		. . . and 97% uptime		. . . and full driver confidence in RTD	
			ppt over baseline		ppt over baseline		ppts over baseline
2025	6.83	6.86	0.31%	6.87	0.46%	6.93	1.38%
2026	11.21	11.30	0.79%	11.37	1.46%	11.69	4.28%
2027	16.37	16.57	1.19%	16.79	2.52%	17.56	7.25%
2028	21.85	22.18	1.49%	22.60	3.41%	24.00	9.81%
2029	27.56	28.04	1.74%	28.70	4.14%	30.88	12.05%
2030	33.33	33.95	1.87%	34.83	4.51%	37.71	13.17%

Figure 18: EV fleet size over time by RTD scenario



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 3.1 million metric tons. Scenario 2, which additionally requires 97% uptime at all highway DCFCs, reduces emissions by 7.6 million metric tons. Finally, scenario 3, which additionally requires improved confidence in real-time data by consumers, reduces carbon emissions in 2030 by 22.5 million metric tons on average. By 2040, scenario 1 reduces cumulative carbon emissions by 63.5 mmt over time relative to the baseline, scenario 2 by 158.2 mmt, and scenario 3 by 469.0 mmt relative to carbon emissions from light-duty vehicles over the same time period in the IRA and IIJA baseline.

As a point of reference, in Cole et al. (2023), the combined provisions of the IRA and IIJA are predicted to reduce carbon emissions in 2030 by 80 mmt on average. Therefore, improving real-time data, uptime, and consumer confidence in the data can reduce carbon emissions by up to an additional 28.1%, 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.

Appendix figures A9 through A11 present uncertainty around these projections.

Figure 19: Emissions reductions (mmt) relative to IIJA & IRA baseline

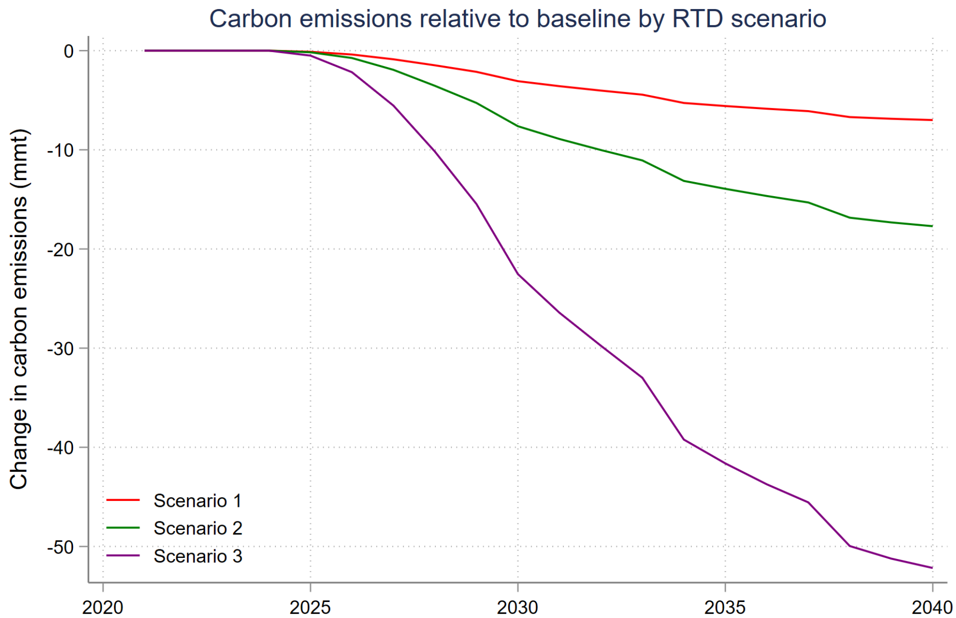


Table 9: Emissions reductions relative to IIJA & IRA baseline (mmt)

	All stations provide RTD	... and 97% uptime	... and full driver confidence
2025	-0.1	-0.2	-0.5
2026	-0.4	-0.7	-2.2
2027	-0.9	-1.9	-5.5
2028	-1.5	-3.5	-10.2
2029	-2.1	-5.3	-15.5
2030	-3.1	-7.6	-22.5

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.

Universal real-time data has little impact on EV adoption through information alone, but if it also shines light on non-working chargers, it can lead to higher charger uptime and increased consumer confidence in the EV charger data–in effect, alleviating range anxiety. We find that universal real-time data reporting alone, without any consequent improvement in uptime or consumer beliefs, has limited effects, raising the EV sales share of new light-duty vehicles in 2030 by 1.1 percentage points, increasing the size of the overall electric light-duty vehicle fleet by 1.9%, and reducing carbon emissions from US light-duty vehicles in 2030 by 3.1 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, however, the EV sales share can instead increase by 8.0 percentage points in 2030, the size of the EV LDV fleet can increase by 13.2%, and carbon emissions in 2030 can decrease by 22.5 million metric tons. The drop in carbon emissions amounts to more than one fourth of the carbon emissions reductions achieved in 2030 by the combined EV provisions of the IRA and IIJA in Cole et al. (2023), yet can be achieved at no fiscal cost, in contrast to the combined $451 billion fiscal bill for the IRA and IIJA EV provisions predicted in Cole et al. (2023).

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 A1: Real-time data provision on August 18, 2024 at the plug level

	I-5	I-10	I-75	I-80	I-90	I-95	Total
Total Plugs	3,119	1,820	1,200	1,642	1,333	2,653	11,767
w/RT Data	**26.4%**	**16.8%**	**17.3%**	**22.1%**	**13.0%**	**17.7%**	**19.9%**
Non-Tesla Plugs	1,415	698	506	766	574	1,059	5,018
w/RT Data	**58.1%**	**43.7%**	**41.1%**	**47.3%**	**30.1%**	**44.2%**	**46.6%**
Excluding Tesla and EA	985	423	331	423	339	720	3,221
w/RT Data	**83.5%**	**72.1%**	**62.8%**	**85.6%**	**51.0%**	**65.0%**	**72.6%**

Figure A1: Percent of stations reporting real-time data for at least one plug, including dealerships

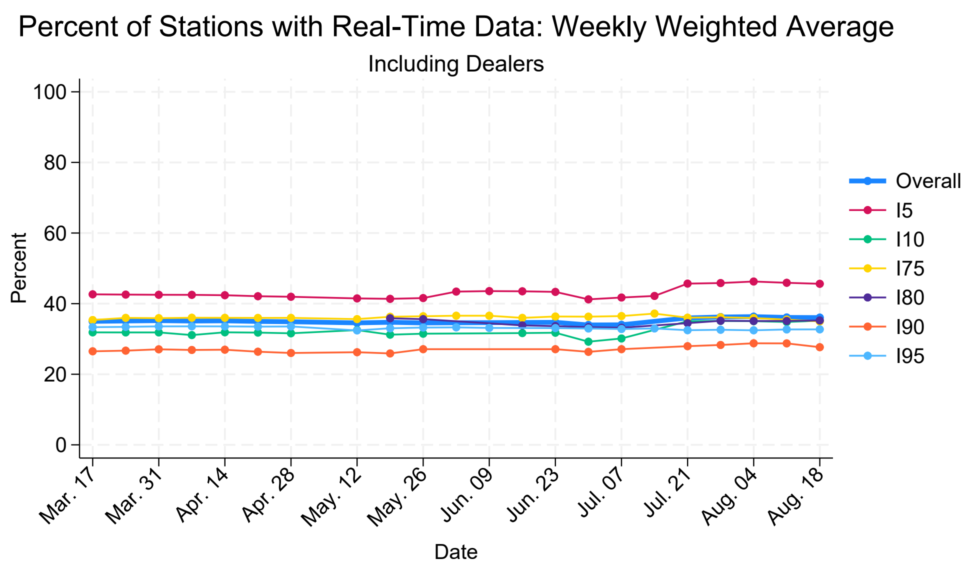
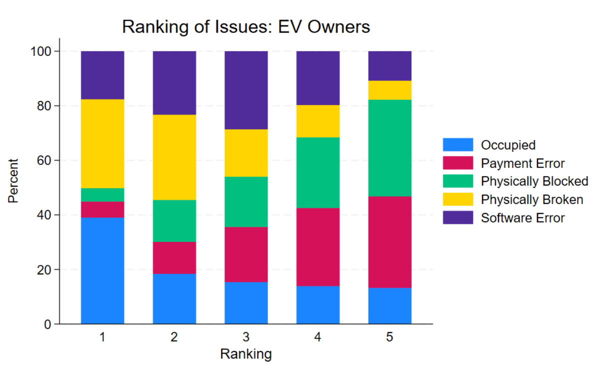


Table A2: Data deserts of at least 145 miles, including dealerships

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

Figure A2: Full distribution of reasons for failed charging at hypothetical station without real-time data

(a) EV Owners



(b) Prospective Buyers

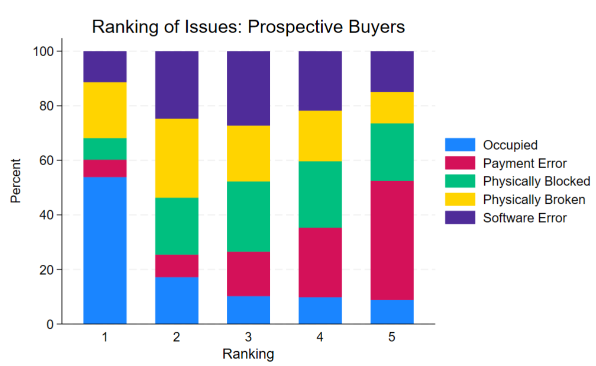


Figure A3: Uncertainty around impact of RTD reporting on EV sales share, scenario 1

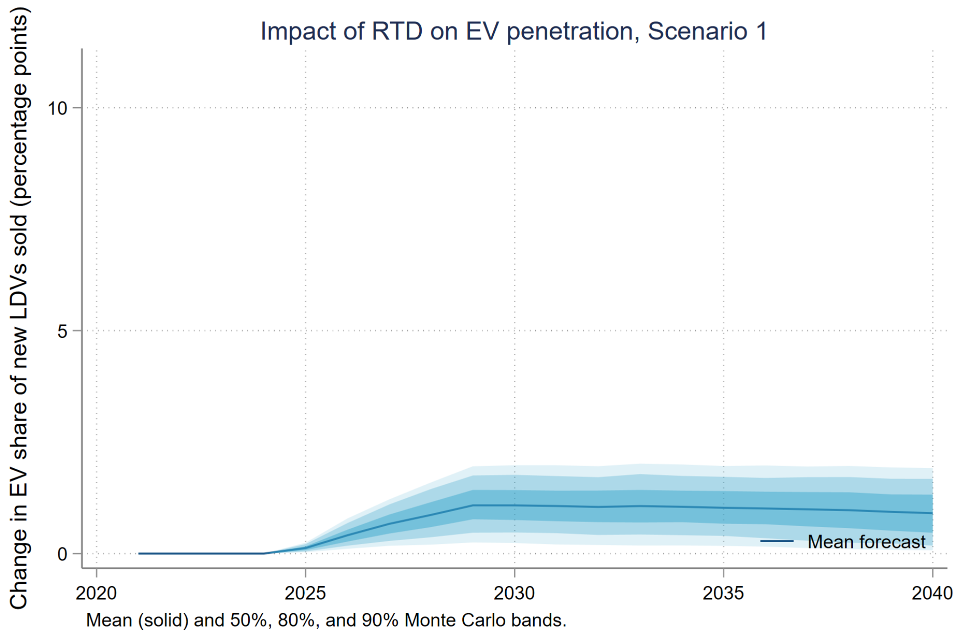


Figure A4: Uncertainty around impact of RTD reporting on EV sales share, scenario 2

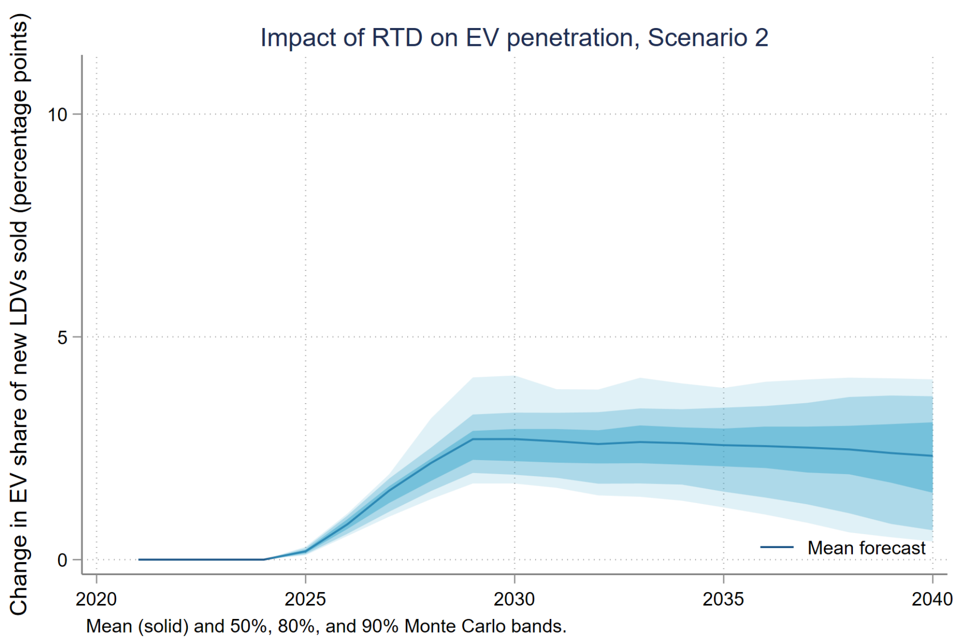


Figure A5: Uncertainty around impact of RTD reporting on EV sales share, scenario 3

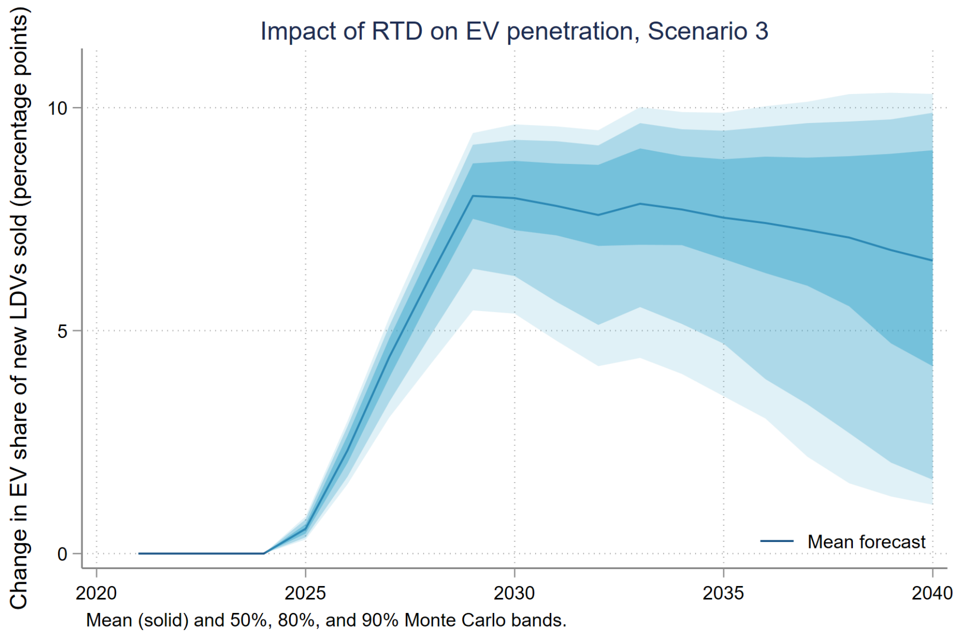


Figure A6: Uncertainty around impact of RTD reporting on EV fleet, scenario 1

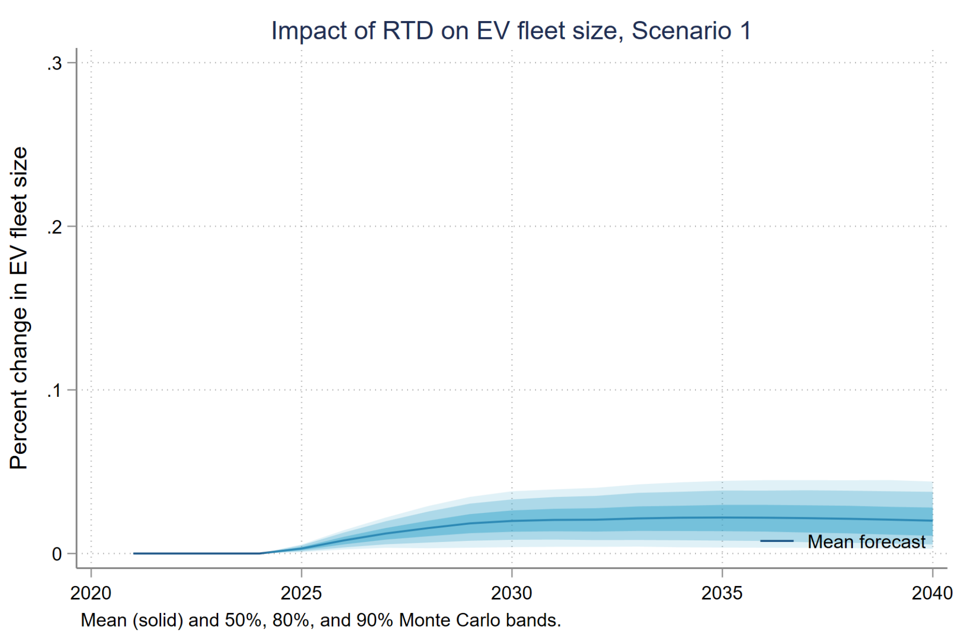


Figure A7: Uncertainty around impact of RTD reporting on EV fleet, scenario 2

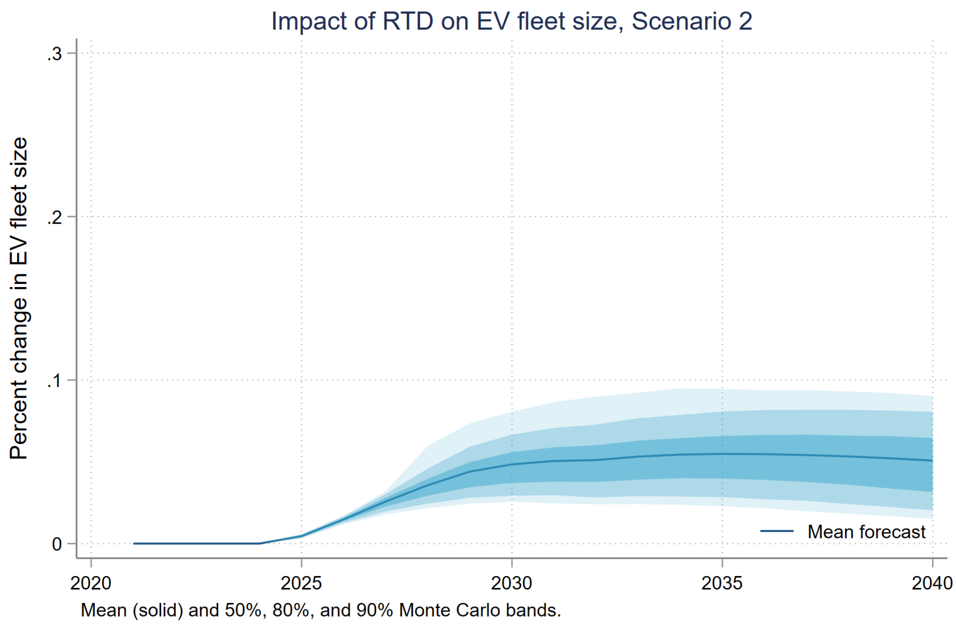


Figure A8: Uncertainty around impact of RTD reporting on EV fleet, scenario 3

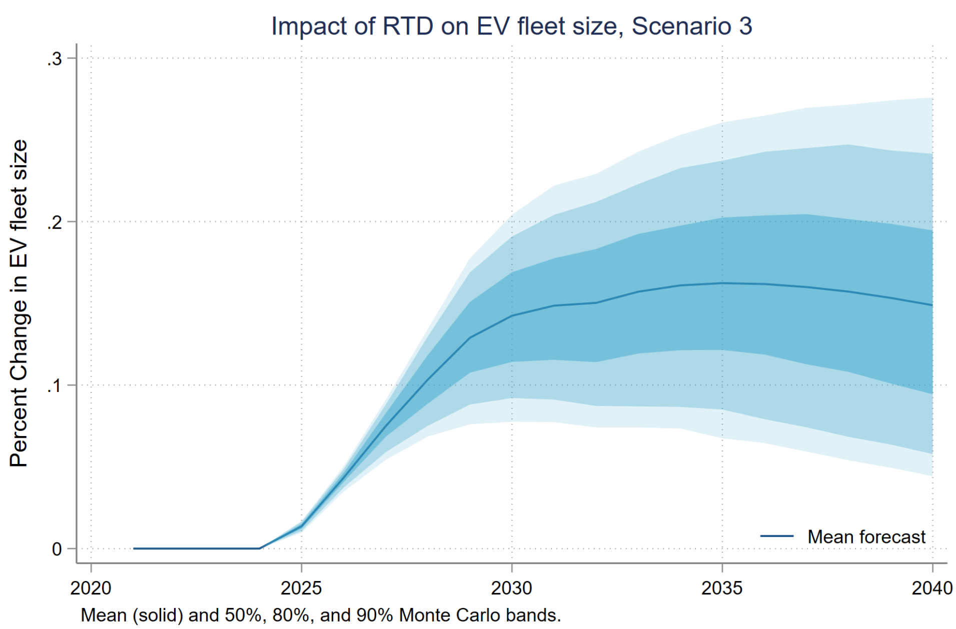


Figure A9: Uncertainty around impact of RTD reporting on carbon emissions, scenario 1

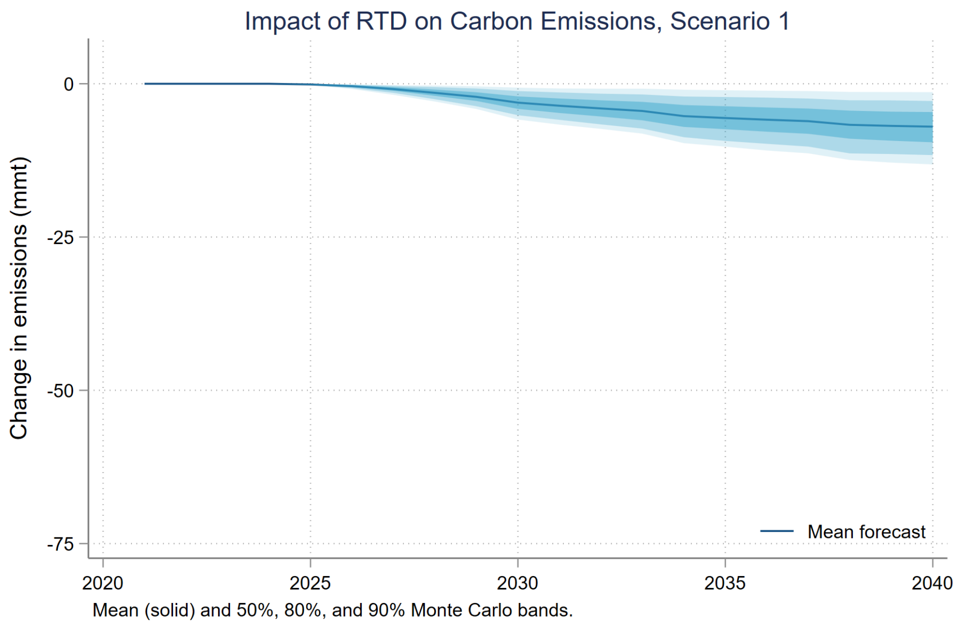


Figure A10: Uncertainty around impact of RTD reporting on carbon emissions, scenario 2

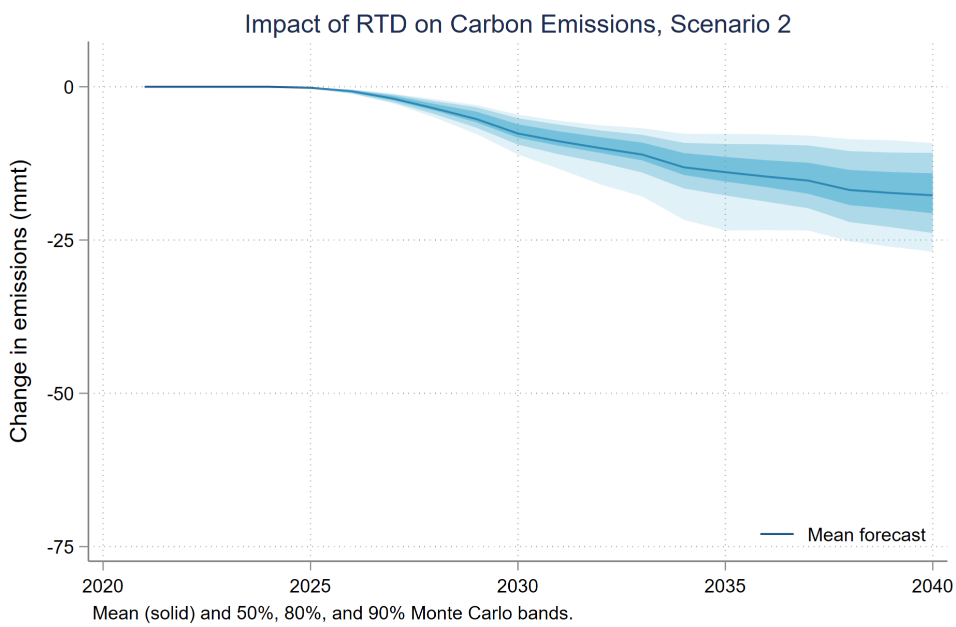


Figure A11: Uncertainty around impact of RTD reporting on carbon emissions, scenario 3