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

Omar Asensio, Elaine Buckberg, Cassandra Cole, Luke Heeney, Christopher Knittel, and James H. Stock*

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Abstract

The development of US electric vehicle charging infrastructure is poised to play a key role in the transition to electric vehicles (EVs), but chargers can only lead to increased EV adoption if drivers can reliably find chargers that are working and available when they need them. In this paper, we investigate the prevalence of real-time data reporting by DC fast chargers on six major US Interstates to a central app and model the impacts of expanding access to real-time data to all near-highway DC fast chargers. On average, between March and August 2024, 34.5% of DC fast charging stations within two miles of I-5, I-10, I-75, I-80, I-90, and I-95 provide their real-time status on PlugShare, a major charge-finding app. We find gaps of up to 1,308 miles in which no highway-adjacent fast charger provides real-time data. We incorporate the state of real-time data into a two-sided model of consumer vehicle choice and charging station buildout adapted from Cole et al. (2023). Real-time data can catalyze faster EV adoption by shining light on non-working chargers and alleviating range anxiety. We predict that universal real-time data alone has limited effect; by 2030, it could increase the electric share of new vehicle sales by 0.9 percentage points, increase the size of the US light-duty EV fleet by 1.8%, and reduce carbon emissions by 2.4 million metric tons per year. But if provision of real-time data is accompanied by improved charger uptime and driver confidence, our model predicts that the EV share of new vehicle sales would grow by 6.4 percentage points, expanding the EV fleet by 11.4%, and carbon emissions would be reduced 16.0 mmt.

*Asensio: Georgia Tech and HBS (email: asensio@pubpolicy.gatech.edu); Buckberg: Harvard University (email: elaine_buckberg@fas.harvard.edu); Cole: Harvard University (email: ccole@g.harvard.edu); Heeney: MIT (email: heeney@mit.edu); Knittel: MIT and NBER (email: knittel@mit.edu); Stock: Harvard University and NBER (email: james_stock@harvard.edu). We are thankful for excellent research assistance from Catherine Liang, Karina Chung, Lauren Hollis, and Joie Liu. This study was determined exempt from further IRB review under Harvard IRB protocol IRB24-0589.

1 Introduction

Achieving the stringent proposed Corporate Average Fuel Economy (CAFE) standards and Environmental Protection Agency (EPA) greenhouse gas emissions standards for US light-duty vehicles, as well as achieving broadly defined US climate goals, requires a substantial shift away from internal combustion (ICE) to electric (EV) light-duty vehicles by 2027. A key prerequisite to achieving this EV transition is the buildout of public EV charging infrastructure, according to the substantial literature estimating the impact of charging infrastructure on consumer vehicle choice (Springel (2021); Sommer and Vance (2021); Li et al. (2017); Zhou and Li (2018); Xing, Leard and Li (2021)), and according to Cole et al. (2023), who find that, on the margin, government spending on charging infrastructure is substantially more effective than spending on EV tax credits at incentivizing EV purchases.

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

The popular media narrative surrounding the EV charging experience is currently predominantly negative. Over the last several years, newspaper columnists[2], industry studies[3], and academic literature (Rempel et al., 2022; Asensio et al., 2020) have documented EV drivers' frustration with charging infrastructure, both in terms of the number of chargers and in terms of their reliability. In particular, Asensio et al. (2020) use supervised machine learning algorithms to classify reviews 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 charger promptly simply because chargers are occupied and other EVs may be waiting. Moreover, searching for charging is costly even when charge attempts do not fail; Dorsey, Langer and McRae (2022) estimate that under

[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

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.

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

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

Charging firms, or charge point operators (CPOs), may not want to provide centralized real-time data, both for fear that competitors will use it to their advantage and because proprietary data is an inherently valuable part of their businesses (Veldkamp, 2023). The National Electric Vehicle Infrastructure (NEVI) program created by the 2021 Infrastructure Investment and Jobs Act (IIJA, also known as the Bipartisan Infrastructure Law) provides an example of a policy which mandates the reporting of real-time data for highway DCFCs, though its coverage is limited. Specifically, the policy requires "third-party data sharing" (i.e., data accessible to aggregators via an API) on "real-time status by port" and "real-time price to charge" at the plug level, for all NEVI-funded chargers – but imposes no requirements on non-NEVI chargers. If DCFC plugs cost $100,000 on average, however, NEVI can only possibly fund up to 65,000 DC-fast charging ports; compared to NREL's forecast[4] of 182,000 DCFCs by 2030, NEVI-funded chargers will always be in the minority.

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

Our goals in this paper are to 1) assess the current state of real-time data reporting for DCFCs on major highways, and 2) model the impacts of universally providing real-time data at those stations on the speed of the EV transition and the resulting carbon emissions. To document the state of real-time data today, we present results from repeated scraping of PlugShare[5], a major consumer-facing app and website providing locations of EV chargers worldwide, plus data including plug type, wattage, and (sometimes) real-time status of chargers. 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 21.0% of plugs provided real-time data on PlugShare. Across our entire scraping interval from March to August of 2024, we find that 34.5% of DCFC stations and 19.3% of DCFC plugs on average report real-time data on PlugShare.

To model the impact of real-time data reporting on EV adoption, we modify the two-sided EV market model from Cole et al. (2023), which combines a discrete choice model for consumer adoption of EVs with an entry-exit model for charging station deployment. In our new version of the model, we incorporate in the consumer's utility function not only the total number of DCFCs on US roads but also the consumer's beliefs about the fraction of those chargers which are working and available at any given time, which in turn depends on the fraction that provide real-time data. Using this modified model, we predict that universal real-time data provision alone increases the size of the light-duty EV fleet by 1.8% 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 11.4% on average.

This paper is organized as follows. In section 2, we describe our methodology for scraping PlugShare and present results documenting current patterns in the reporting of real-time data. In section 3, we 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 require multiple-hour charging sessions so are impractical for long-distance road trips except at overnight stops; DCFCs, therefore, are key to alleviating consumers' range anxiety around long-distance travel. In particular, we present trends over time in real-time data provision for DCFCs on PlugShare.com, a major charger mapping application and website affiliated

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

with EVgo. We collect data on six highways covering 13,538 miles in 40 states and 27.7% of the US Interstate system by distance: I-5, I-10, I-75, I80, I-90, and I-95. We also provide a brief comparison of PlugShare with real-time data reporting on Google Maps and Apple Maps, though we focus our attention on PlugShare as the best of the three.

2.1 Methodology

In February 2024, we identified location codes for all DCFC or Level-3 chargers, defined as plugs providing at least 50 kW, within a 2-mile driving distance of exits on the six Interstates mentioned above from PlugShare. Within major metro areas, defined as U.S. census incorporated places with a population of at least 100,000 and a population density of at least 2,750 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 many of our results at the station level, where we define a station as all plugs at a location ID which are rated to provide at least 50 kW (to distinguish from Level-2 chargers) and have the same charging provider. That is, one location can be counted as multiple stations in our analysis if it contains plugs provided by multiple different CPOs. In the results below, the full list of stations is updated only once, on July 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 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

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%**

House, is required to make some chargers open to any EV by the end of the year[6]. 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 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

[6] 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/).

highways has 21 plugs and the largest Tesla station has 84 plugs, whereas EVgo is the only other CPO operating any station with more than 12 plugs. The same pattern is true to a lesser extent when Tesla is excluded; 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.

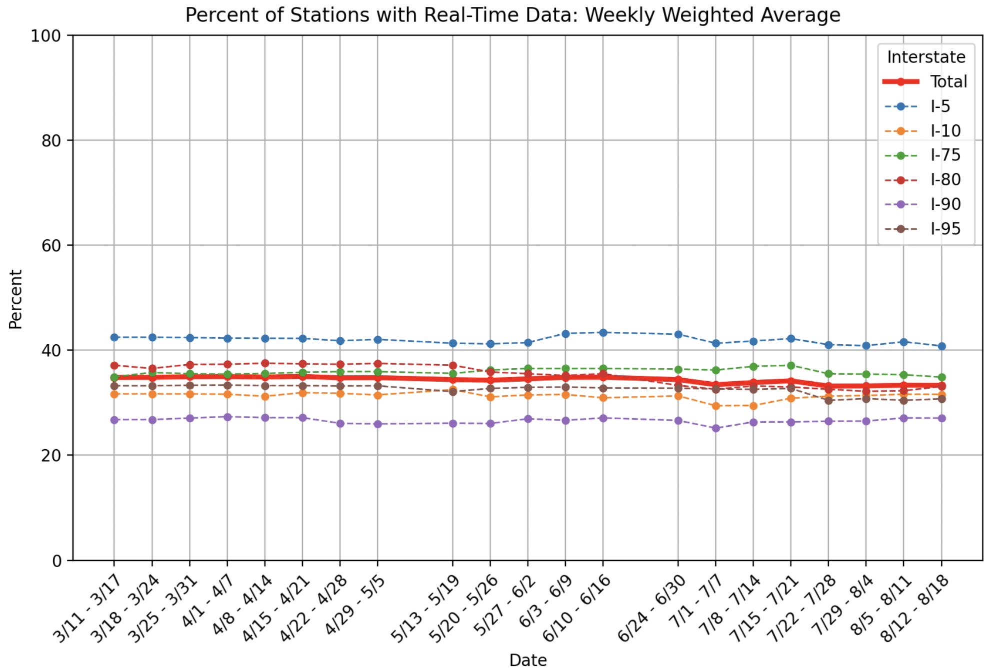
On every highway except I-90, the top four CPOs are (Tesla) Supercharger, Electrify America, EVgo, and ChargePoint (on I-90, EV Connect is the fourth largest provider, with 13 stations). Among these, Supercharger is always the largest provider and Electrify America is always in the top three; these two 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-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 excludes dealers. Each point on these graphs represents a weighted average of

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

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

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



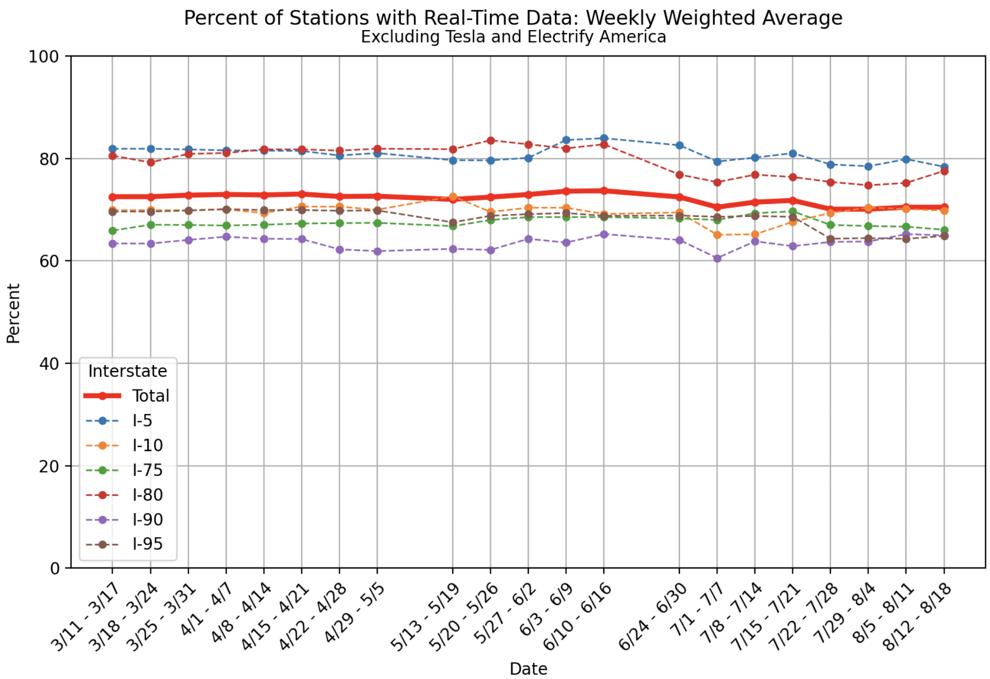
successful PlugShare scrapes within the relevant week[7].

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 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.

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

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



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 at at least one charger by day of week

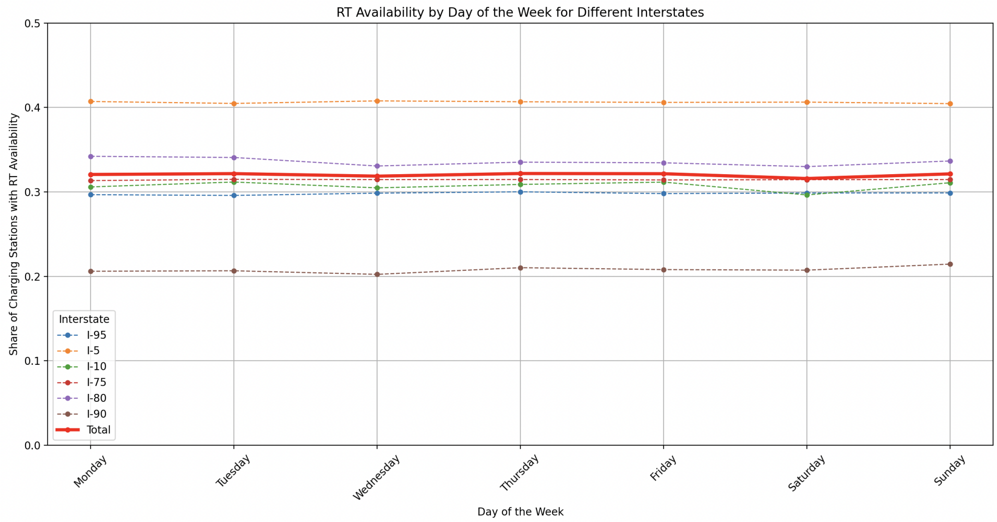


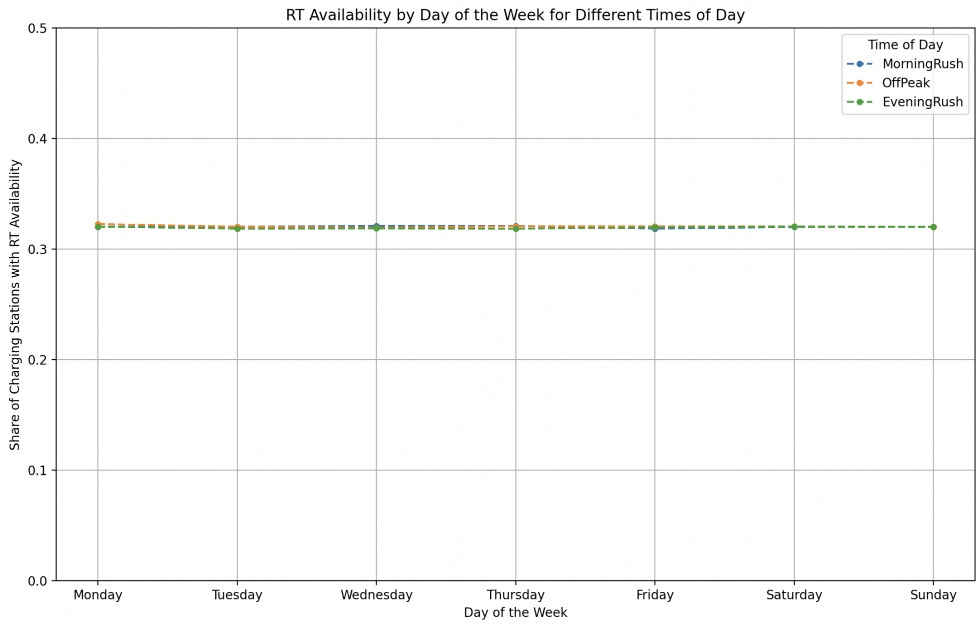
Table 4: Fraction of stations providing real-time data at at least one plug by data provider, excluding Tesla and Electrify America

	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 on I-95, where PlugShare provides real-time data for nearly eight times as many stations as does Apple Maps. Google Maps generally provides better real-time data than Apple Maps, excepting a few comparisons where the two are equivalent: I-5 with and without Tesla and EA, and I-90 with Tesla and EA.

Figure 4: Average fraction of stations reporting real-time data at 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 this section, we focus on what we call "data deserts": long stretches of highway where no DC fast charger within two miles of the highway (0.5 miles in metro areas) provides real-time data on PlugShare. These dataless stretches can, at times, span distances longer than even the longest stated range of existing EV models, and therefore require meticulous 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[8]) or hours at a Level-2 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

[8]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 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.

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 (where the single ChargePoint station providing real-time data is under repair as of June 4, 2024) is immediately adjacent to another 293-mile data desert between Blue Earth, MN and Madison, WI.

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

	Start Location	**End Location**	**Length (mi)**	**# Stations**	**Tesla**	**EA**	**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[9].

3 Consumer attitutes towards real-time data

Charging infrastructure buildout and policies meant to incentivize it can only spur EV adoption if consumers considering buying EVs trust that chargers work and are likely to be accessible and available when needed. To understand the extent to which charging reliability is salient to potential EV buyers and the potential impact of providing better charging information on adoption, we have conducted two consumer surveys eliciting beliefs about the subjective probability of successfully charging at 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.

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

Figure 5: Sample survey question

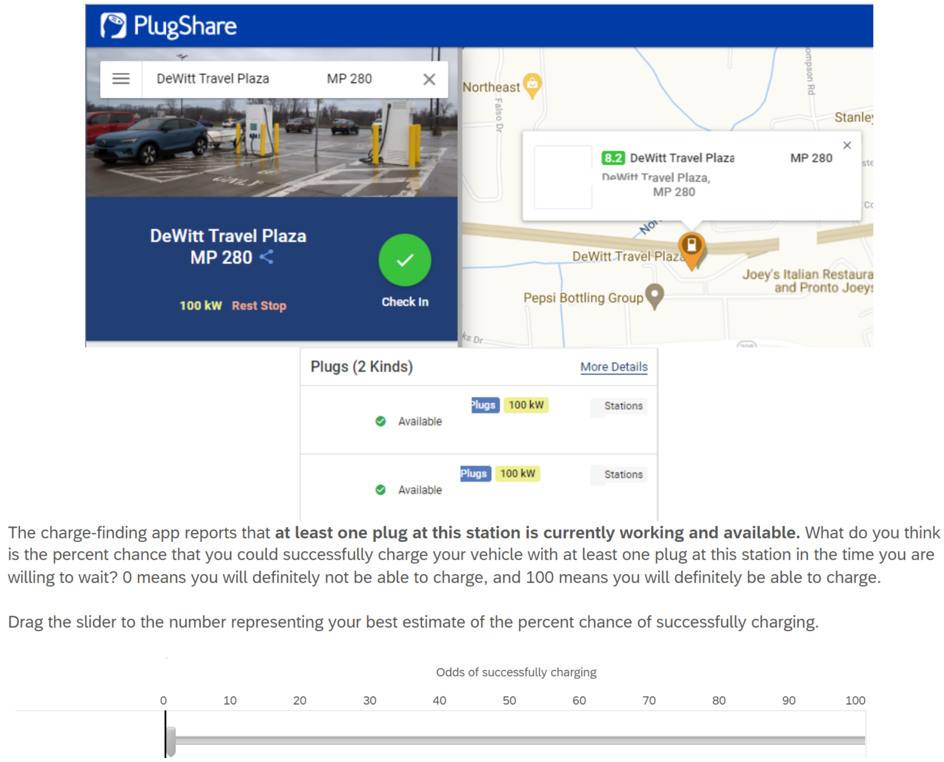


Figure 5 presents an example of the main questions in our survey. We ask respondents to imagine that the chargers we ask about are all within 200 miles of their home, within 2 miles of a US Interstate, and compatible with their vehicle. We then present a censored image of an example station on PlugShare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

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

We received 1,006 completed survey responses from prospective car buyers via Dynata and 814 completed survey responses from current EV drivers via EVA. Among these, we drop survey responses submitted in under 2 minutes on the basis that they were likely not completed carefully; the median survey duration is 3.9 minutes for Dynata respondents (mean 11.5) and 6.3 minutes for EVA respondents (mean 15.5), who are likely to be more invested in the subject matter than Dynata's panel of prospective car buyers. This leaves us with 908 responses from prospective car buyers and 813 from current EV drivers. Other characteristics of responses could potentially indicate carelessness; 33.0% of Dynata respondents and 19.9% of EVA respondents report a higher likelihood of successful charging at an unavailable 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 6 plots the average response and 95% confidence interval for the three main questions in our survey, split by survey sample. Perhaps most striking is the pessimism with which respondents view chargers that provide real-time data and are reported working and available; prospective car buyers estimate that they can successfully charge at such a station 64.6% of the time, and current EV drivers estimate that they can successfully charge at such a station only 58.6% of the time. Also striking is the fact that EV owners are statistically significantly *more pessimistic* than prospective buyers in all three scenarios. The order of the rankings is the same for both groups: available stations (64.6% for prospective buyers and 58.6% for EV drivers) are considered more reliable than stations without real-time data (52.4% for prospective buyers and 41.1% for EV drivers) which are in turn more reliable than occupied chargers (47.9% for prospective buyers and 39.0% for EV drivers).

Figures 7 through 9 show the average percent chance of successfully charging at stations without real-time data by CPO, location, and size. By CPO, EV drivers believe they are statistically significantly more likely (t=7.79) to be able to charge at a Tesla charger without real-time data than at an EA charger without real-time data, whereas prospective buyers do not distinguish between the two (t=0.74). In fact, Tesla chargers without real-time data are the only type of charger we present at which current EV drivers are more optimistic than prospective buyers. Prospective buyers also cannot distinguish between urban and rural chargers without real-time data (t=1.16), whereas EV drivers surprisingly consider rural chargers significantly more reliable than urban chargers (t=6.61). Finally and unsurprisingly, both EV drivers (t=9.14) and prospective buyers (t=7.42) consider themselves significantly more likely to be able to successfully charge at 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 10 plots results for our nine main survey questions, splitting the sample of EV owners into Tesla and non-Tesla owners. In general, whenever a CPO is not specified, non-Tesla drivers are more optimistic about charging than

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

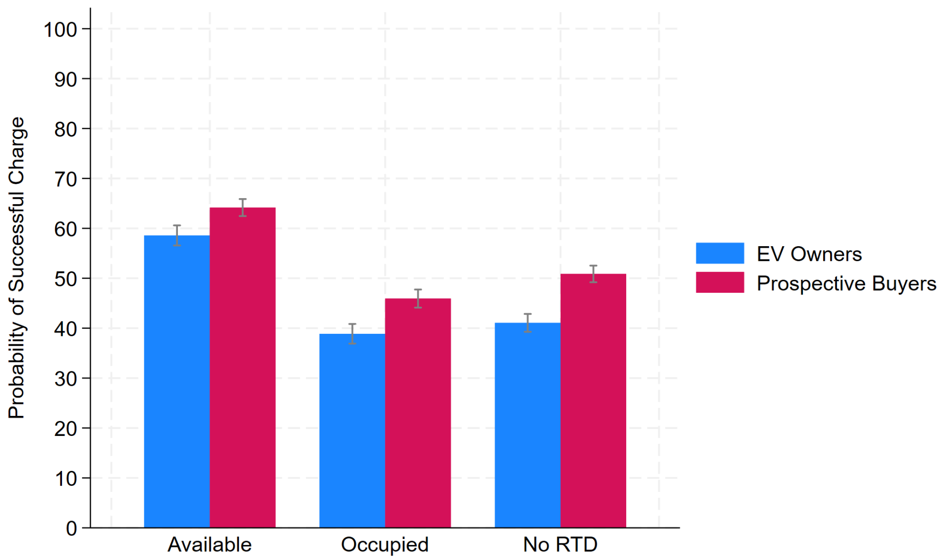


Figure 7: Tesla and EA chargers without real-time data: probability of successful charge by survey sample

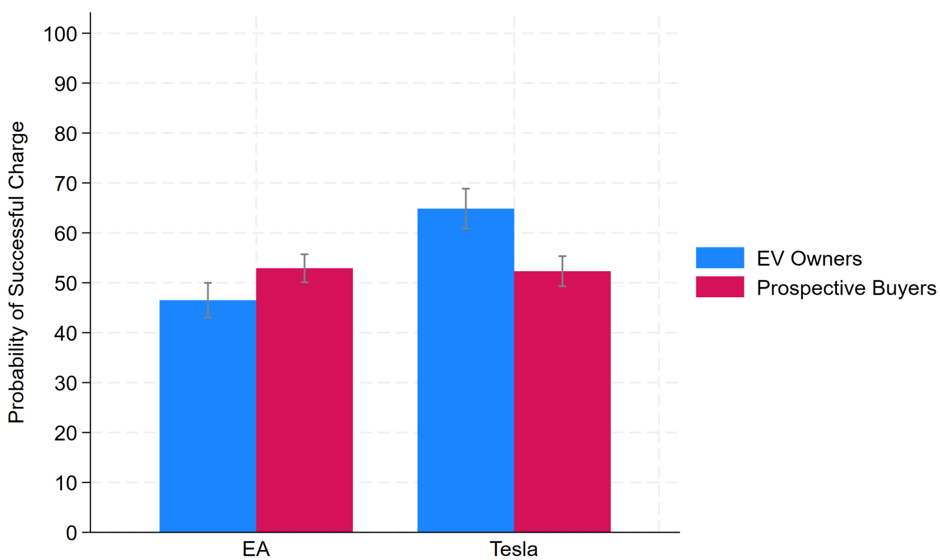


Figure 8: Urban and rural chargers without real-time data: probability of successful charge by survey sample

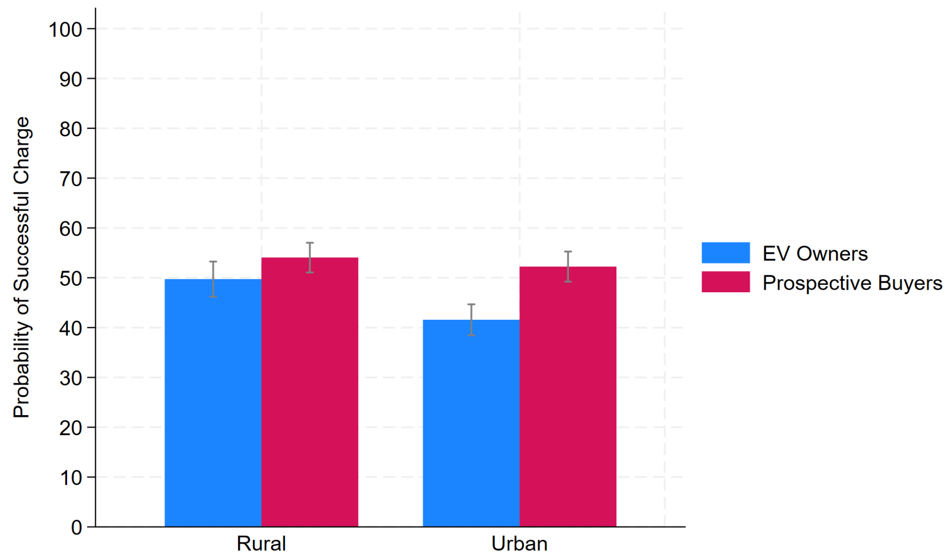


Figure 9: 4-plug and 10-plug chargers without real-time data: probability of successful charge by survey sample

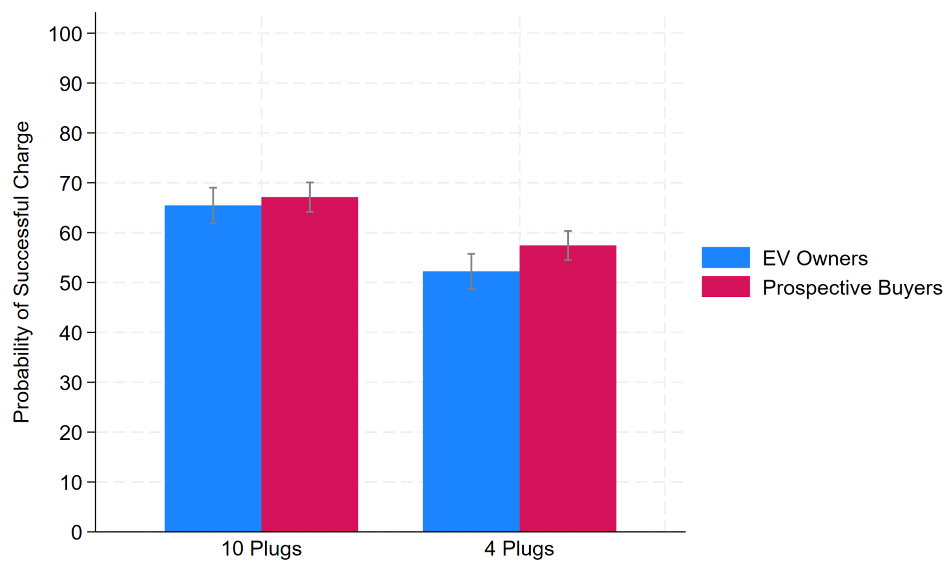
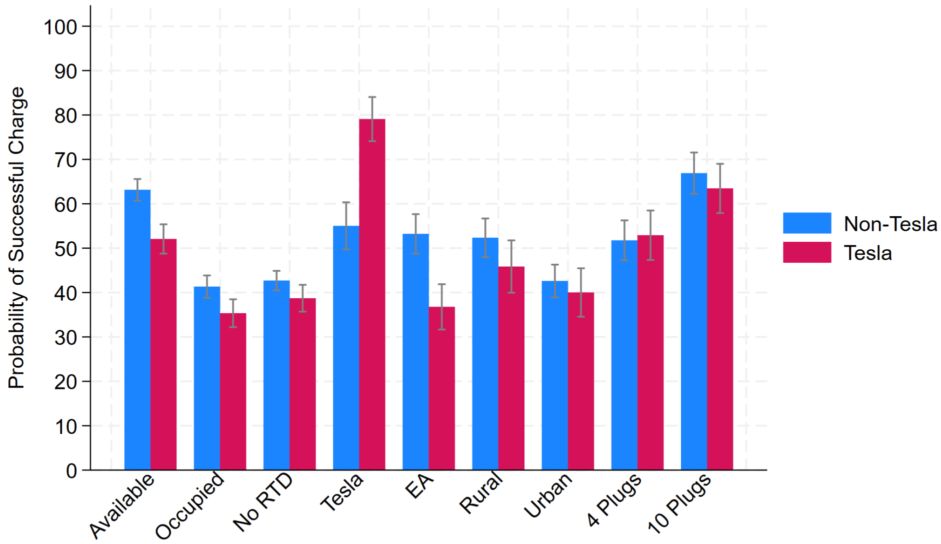


Figure 10: Survey results for Tesla owners vs. non-Tesla EV owners



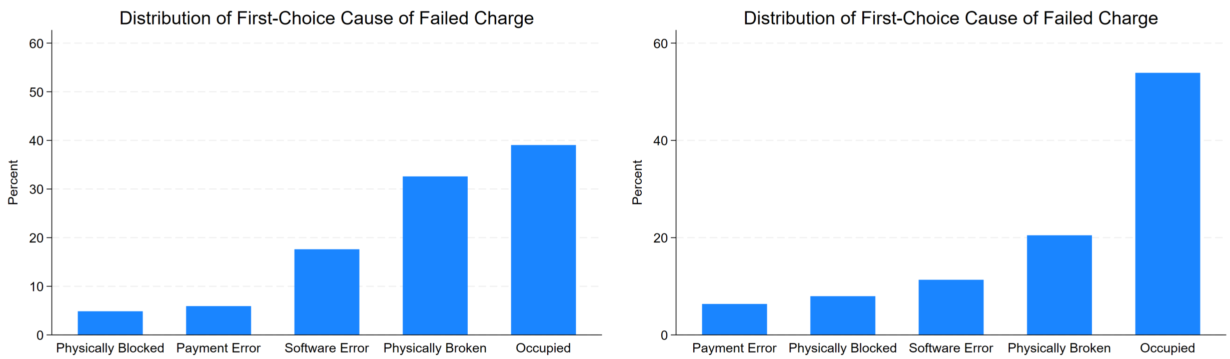
Tesla drivers – perhaps because the Tesla network is large enough that Tesla drivers may have little experience charging outside the Tesla network of stations (for which Tesla owners get real-time data through their vehicles), and therefore also little experience charging at stations without real-time 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 (t=0.65).

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

First, we ask respondents to imagine that they are driving on an Interstate and considering stopping at a DCFC without real-time data, then to rank the potential problems which might prevent them from successfully charging at such a station. Figure 11 shows the distribution of 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, 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.

Figure 11: Distribution of first-choice reason for failed charging at hypothetical station without real-time data

(a) EV Owners (b) Prospective Buyers



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 charger in 15 miles without real-time data, and a charger in N miles which reports having at least one plug working and available, where N is randomized to equal 20, 25, 30, or 35 miles for each respondent. Figure 12 plots the fraction of respondents choosing to drive directly to the second 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.

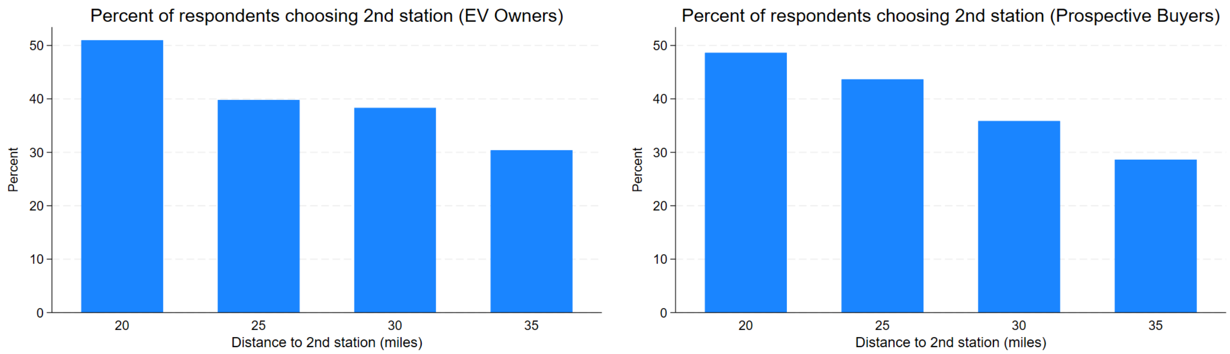
Overall, our survey responses indicate that, while real-time data does not fully solve the problem of charger reliability – given that respondents only expect to be able to successfully charge at stations marked available 58.6% or 64.6% of the time – it has the potential to go a long way in improving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

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

(a) EV Owners (b) Prospective Buyers



as given the elasticities of EV demand to the size of the charging network estimated in prior literature. 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.

4.1 Base model from Cole et al. (2023)

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

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

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

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

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

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

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

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

4.2 Modifications: Parameters and calibration

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

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

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

There is, however, considerable uncertainty in the actual implementation of these tax credits in the longer term. Currently, relatively few vehicle models qualify for these tax credits, but more are likely to in the future, especially with onshoring of production, and tariffs on Chinese-produced EVs are likely to drive more consumers to purchase US-made vehicles. Additionally, there is currently a leasing loophole by which consumers may be able to accrue some benefits of the tax credits for vehicles that do not otherwise qualify; leased vehicles are currently counted as commercial vehicles, which are not subject to the same income, price, and origin restrictions as the consumer tax credits, so the leasing company can qualify for the tax credits and choose whether to pass some or all of them on to the consumer through a lower price. The leasing loophole could be close before the expiration of the credits. Given these various sources of uncertainty, the net effect of which is hard to quantify, we present results on the impact of real-time data not only under the main IRA specification but also for varying magnitudes of the tax credit effectively delivered to consumers.

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

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

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

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[10] (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

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

chargers in the consumer utility function by a Bernoulli random variable representing the probability that a randomly chosen charger can provide a successful charge at any given point in time. We then calculate consumers' expected utility from an EV relative to an ICE before aggregating to obtain the EV share of new sales for each vehicle class.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

4.4 Parameterization of μ and σ

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

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

This yields the following expression for μ:

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

.

Table 7: Parameter and sources for parameterizing μ

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

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

4.5 Modifications: Charging Firms

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

A full treatment of real-time data sharing would explicitly model the value of data to firms and allow firms to set the fraction of chargers providing real-time data as a choice variable. 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), $\pi_t(N_t, Q_t) = (exp(\kappa)/(N_t))^{\frac{1}{\gamma}} Q_t$ (supressing $l3$ 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 the first, 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 the second scenario, in addition to the increase in λ_{rtd}, the share of stations with real-time data at which at least one plug reports working (λ_w) grows linearly to 95% between 2024 and 2029. This scenario corresponds to one in which charger reliability improves to match the 95% uptime requirement set forth by NEVI. We do not explicitly model the mechanism by which this improvement occurs, but it could take place either because of similar requirements for other DCFC stations or because providing universal real-time data shines light on failing chargers and incentivizes CPOs to take steps to improve quality.

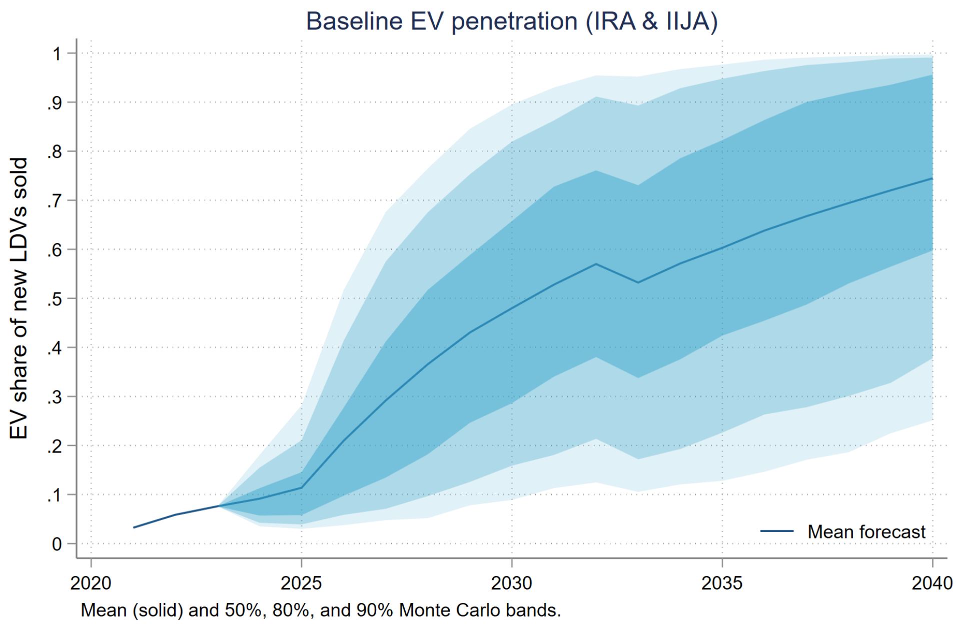
In the final scenario, in addition to the changes in λ_{rtd} and λ_w, consumers' belief that a charger which says it is working and available is actually working and available ($p_r td$) grows linearly to 100% between 2024 and 2029. This represents a best-case scenario, in which improvements in both 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.

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 13 presents our projection of EV adoption under the IRA & IIJA baseline; specifically, this figure plots the fraction of new car sales which are EVs over time under our benchmark definition of the IIJA and IRA as described in section 4.2. On average, our simulations predict that 48.0% of new cars in 2030 will be electric in the baseline IIJA+IRA scenario, with a 90% Monte Carlo band of 8.91% to 90.0%. 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 13: Main estimate and uncertainty for baseline EV share of new car sales under IRA & IIJA with no change in RTD reporting



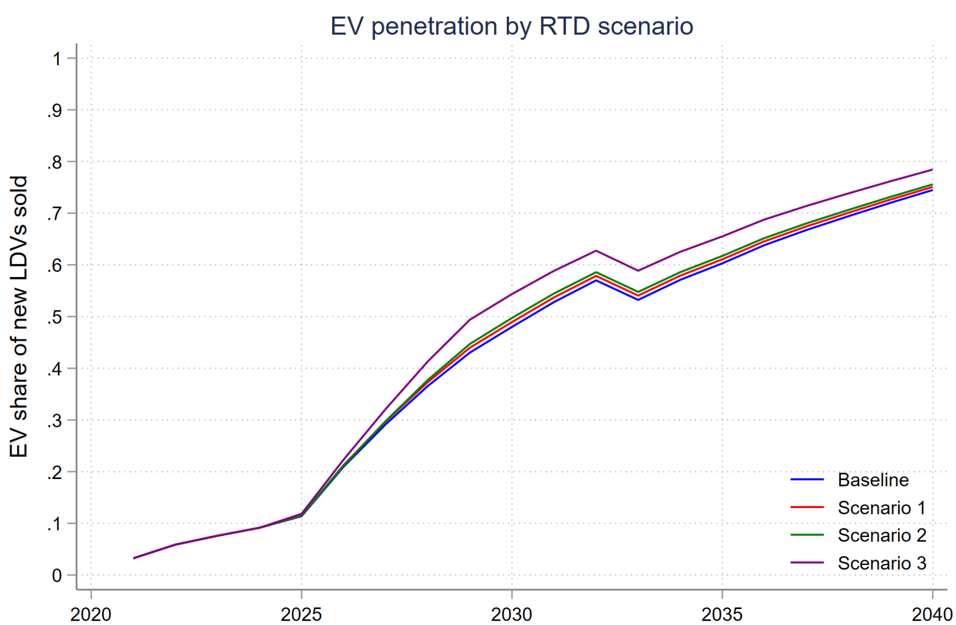
We find that universal real-time data alone has limited effects, but our model predicts a substantial acceleration in EV adoption if real-time data leads to higher DCFC uptime and alleviates range anxiety. Table 8 presents values for the EV share of new car sales under our three simulated scenarios in 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 0.9 percentage points 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 6.4 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 49.4%, higher than the share achieved in 2030 (48.0%) in the baseline.

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

	Baseline	All stations provide RTD		... and 95% uptime		... and full driver confidence in RTD	
			ppt over baseline		ppt over baseline		ppts over baseline
2025	11.4%	11.5%	0.10%	11.52%	0.15%	11.8%	0.46%
2026	21.0%	21.3%	0.32%	21.17%	0.20%	22.3%	1.37%
2027	29.2%	29.7%	0.55%	29.80%	0.64%	32.1%	2.96%
2028	36.6%	37.3%	0.76%	37.75%	1.18%	41.3%	4.76%
2029	43.0%	44.0%	0.94%	44.71%	1.67%	49.4%	6.36%
2030	48.0%	48.9%	0.94%	49.72%	1.73%	54.4%	6.36%

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

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

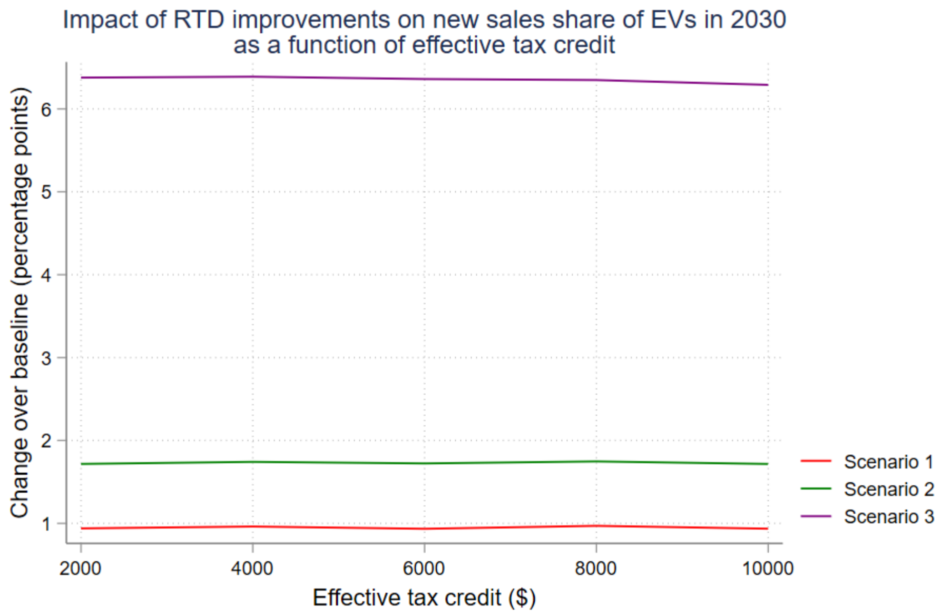


The largest increase in the EV share comes from improving consumer confidence in stations that claim to be working and available (scenario 2 to scenario 3). The shift from the baseline to scenario 1, which improves real-time data provision to 100%, has limited impact because survey respondents' subjective probabilities of being able to successfully charge at a working and available station are pessimistic. The shift from scenario 1 to scenario 2, which improves uptime to 95% for stations with real-time data, has a relatively small impact largely because uptime measured at the station-level is fairly good on average at stations providing real-time data; across our 792 highway runs, the average fraction of stations with real-time data at which at least one plug is reported working is 88.2%. 71 highway scraping runs (8.96%) already meet or exceed the 95% 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, I further simulate the model with the effective tax credit set at $2,000, $4,000, $6,000, $8,000, and $10,000 (where values above $7,500 account for the used vehicle tax credit the consumer may accrue upon reselling their vehicle). Figure 15 plots the percentage point increase from real-time data in each of our three scenarios for each possible effective tax credit. 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 15: Change in EV share of new car sales in 2030 over IRA & IIJA baseline by effective consumer tax credit



4.8 Results: EV fleet size

The total number of EVs on the road under each of our scenarios is a variable of 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 9 presents EV fleet size and percentage increases over the baseline for each scenario in the key years of 2025 through 2030. In 2030, scenario 1 increases the total size of the EV fleet by 1.8%, scenario 2 by 2.9%, and scenario 3 by 11.4%. 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 16 plots our estimates of the number of EVs on US roads in millions from 2021 to 2040 under our baseline and each real-time data scenario. As in the case of the EV sales share of new light-duty vehicles, the largest increase in EV fleet size is generated by moving from scenario 2 to scenario 3 (improving consumer confidence in real-time data reporting). Appendix figures A6 through A8 present uncertainty around these projections.

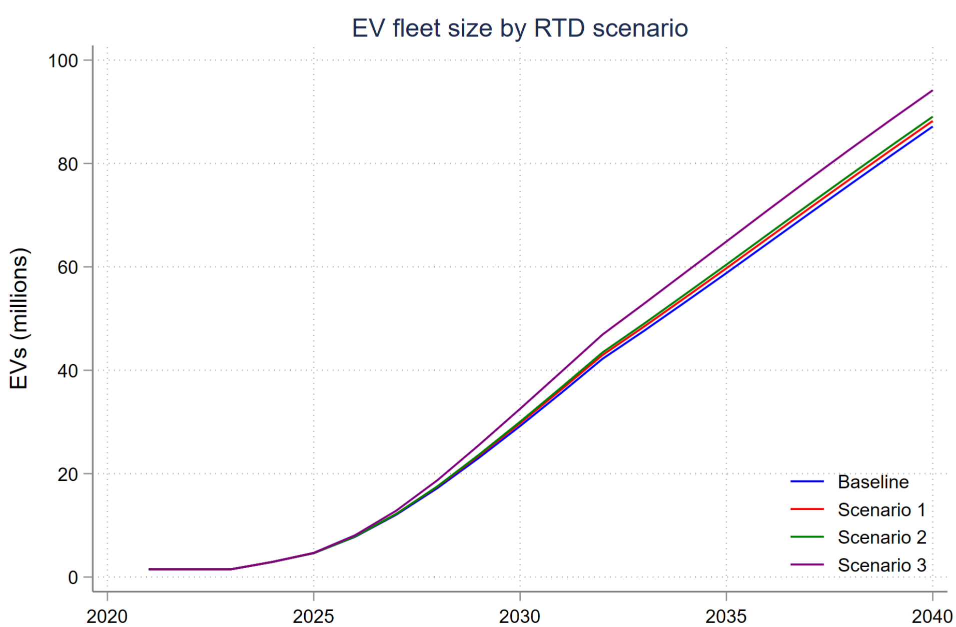
4.9 Results: Carbon emissions

Figure 17 presents changes in yearly carbon emissions from the light-duty vehicle fleet relative to the IRA and IIJA baseline for each of our three real-time data scenarios, measured

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

	Baseline	All stations provide RTD		... and 95% uptime		... and full driver confidence in RTD	
			ppt over baseline		ppt over baseline		ppts over baseline
2025	4.61	4.63	0.39%	4.63	0.54%	4.69	1.71%
2026	7.77	7.84	0.91%	7.83	0.74%	8.08	3.93%
2027	12.05	12.21	1.30%	12.21	1.34%	12.84	6.49%
2028	17.22	17.49	1.58%	17.57	2.02%	18.75	8.85%
2029	23.04	23.45	1.78%	23.64	2.61%	25.51	10.73%
2030	29.20	29.73	1.83%	30.04	2.89%	32.53	11.43%

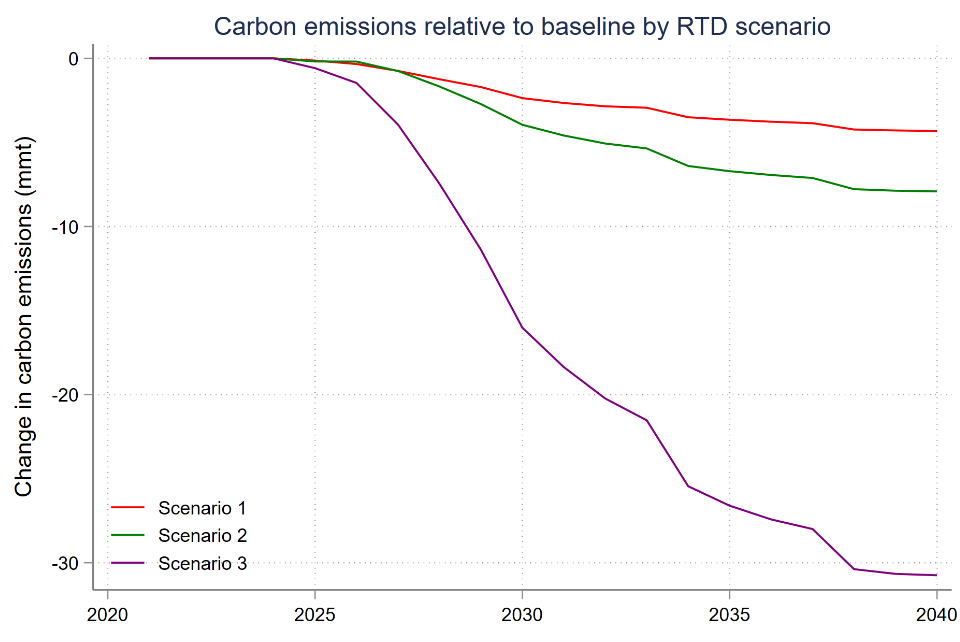
Figure 16: EV fleet size over time by RTD scenario



in millions of metric tons. As in Cole et al. (2023), our projections for carbon intensity of the power sector are based on Stock and Stuart (2021). Table 8 presents the same information in table form for the key years of 2025 to 2030. In 2030, providing real-time data at all highway DCFCs reduces carbon emissions, on average, by 2.4 million metric tons. Scenario 2, which additionally requires 95% uptime at all highway DCFCs, reduces emissions by 4.0 million metric tons. Finally, scenario 3, which additionally requires improved confidence in real-time data by consumers, reduces carbon emissions in 2030 by 16.0 million metric tons on average. By 2040, scenario 1 reduces cumulative carbon emissions by 42.6 mmt over time relative to the baseline, scenario 2 by 75.2 mmt, and scenario 3 by 300.2 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 20.0%, on average, relative to the carbon emissions reductions projected to be achieved under the IRA and IIJA without these improvements. Moreover, compared to the $451 billion in government expenditures for the IRA and IIJA estimated in Cole et al. (2023), mandating real-time data would be comparatively costless to the government as it would be a regulatory policy rather than a fiscal one.

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



Appendix figures A9 through A11 present uncertainty around these projections.

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

	All stations provide RTD	... and 95% uptime	... and full driver confidence
2025	-0.1	-0.2	-0.6
2026	-0.3	-0.2	-1.5
2027	-0.7	-0.8	-3.9
2028	-1.2	-1.7	-7.5
2029	-1.7	-2.7	-11.4
2030	-2.4	-4.0	-16.0

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 0.9 percentage point, increasing the size of the overall electric light-duty vehicle fleet by 1.8%, and reducing carbon emissions from US light-duty vehicles in 2030 by 2.4 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 6.4 percentage points in 2030, the size of the EV LDV fleet can increase by 11.4%, and carbon emissions in 2030 can decrease by 16.0 million metric tons. The drop in carbon emissions equals one fifth 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 at at least one plug, excluding dealerships

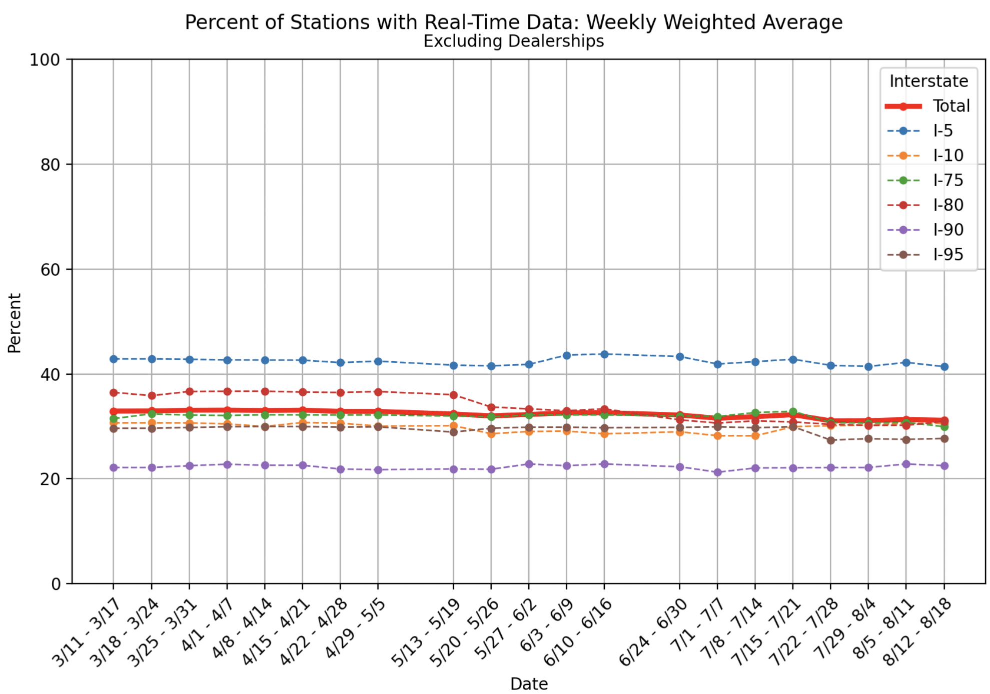
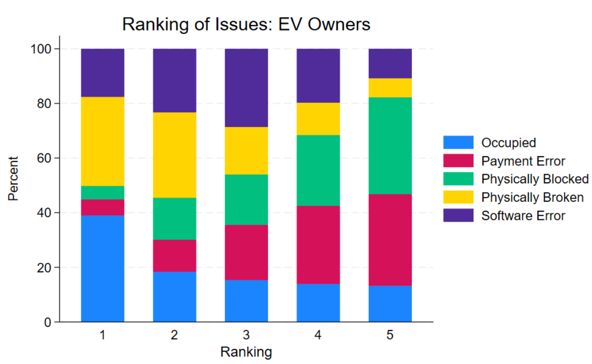


Table A2: Data deserts of at least 145 miles, including dealerships

	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

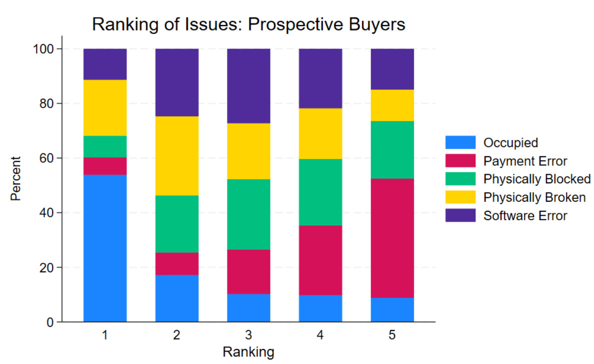


Figure A3: Uncertainty around impact of RTD reporting on EV sales share, scenario 1

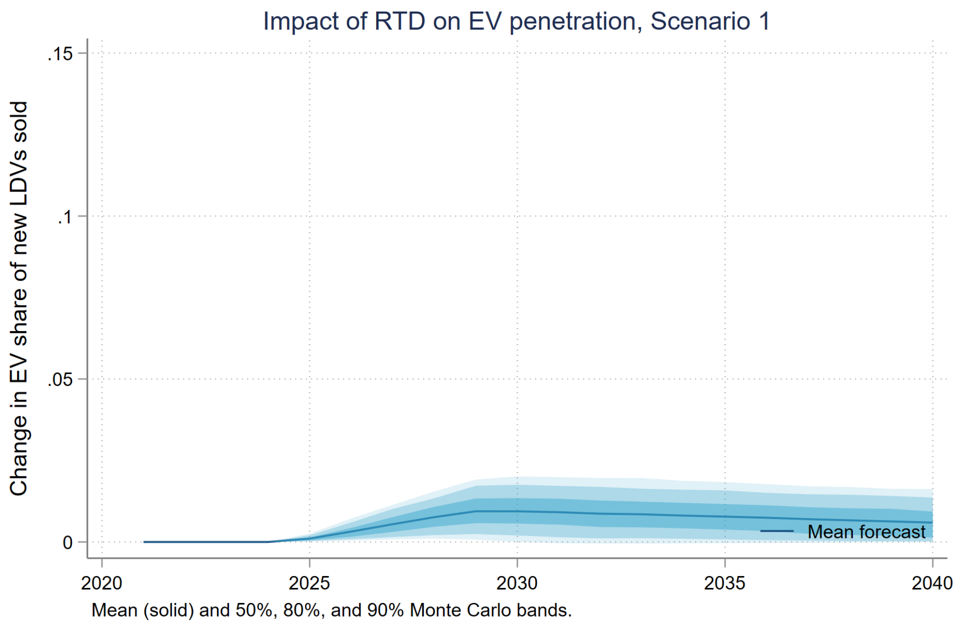


Figure A4: Uncertainty around impact of RTD reporting on EV sales share, scenario 2

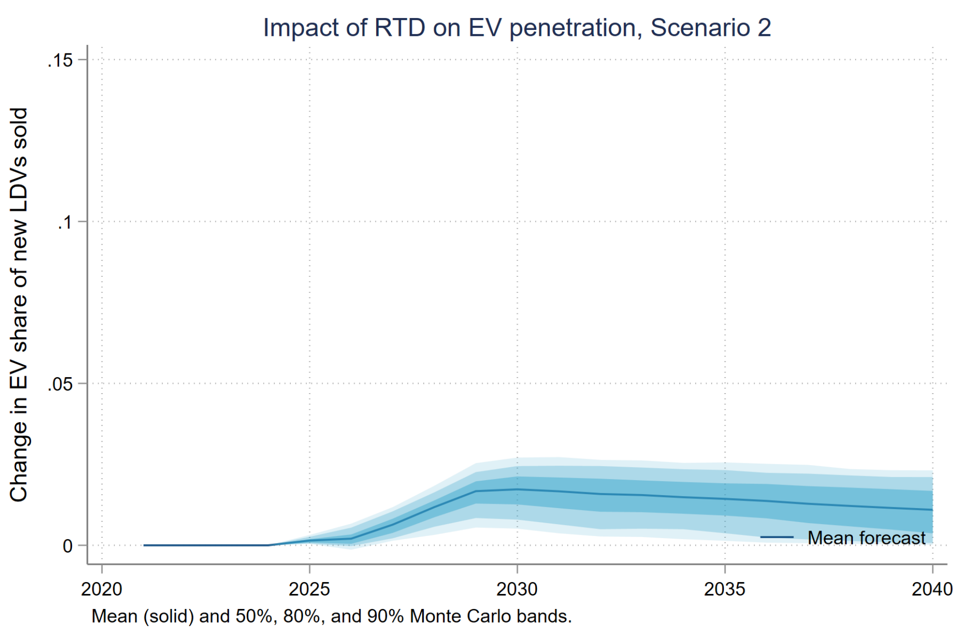


Figure A5: Uncertainty around impact of RTD reporting on EV sales share, scenario 3

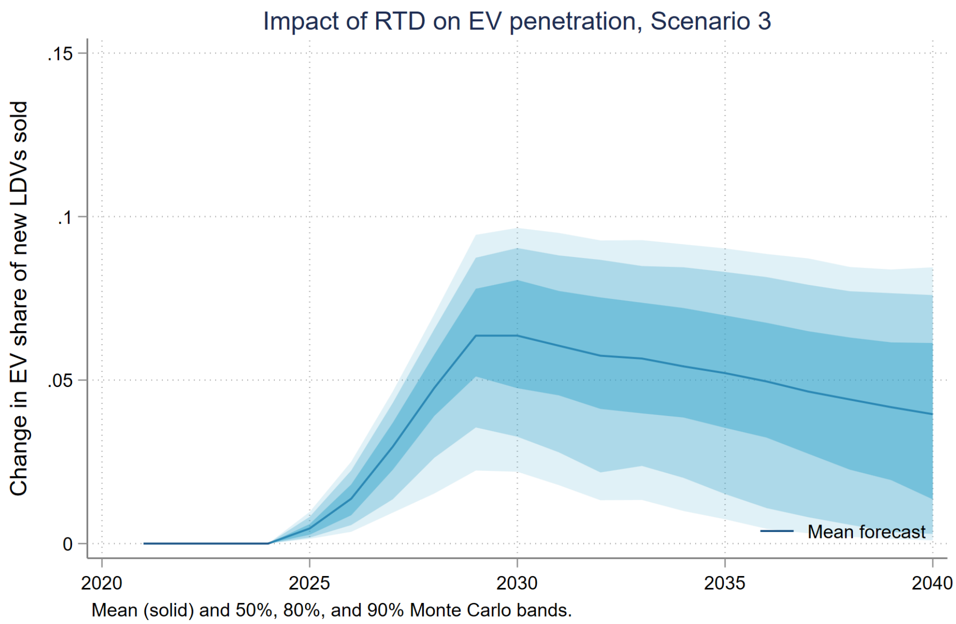


Figure A6: Uncertainty around impact of RTD reporting on EV fleet, scenario 1

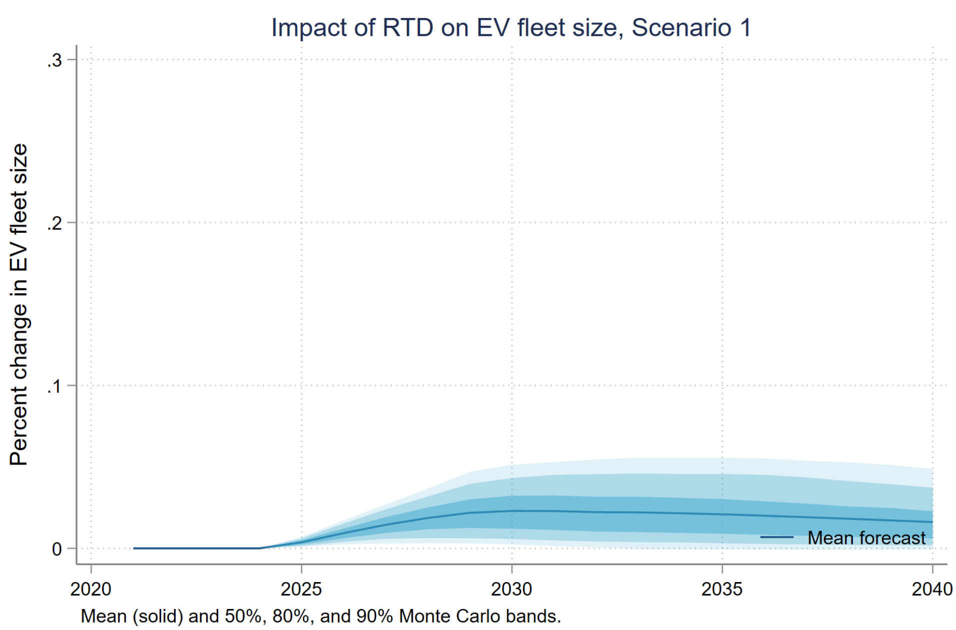


Figure A7: Uncertainty around impact of RTD reporting on EV fleet, scenario 2

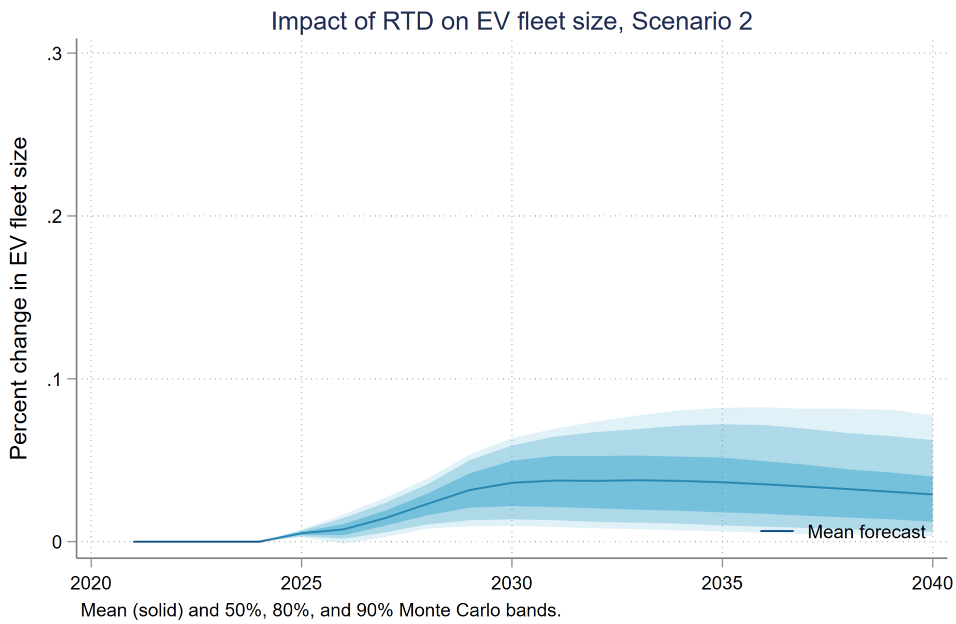


Figure A8: Uncertainty around impact of RTD reporting on EV fleet, scenario 3

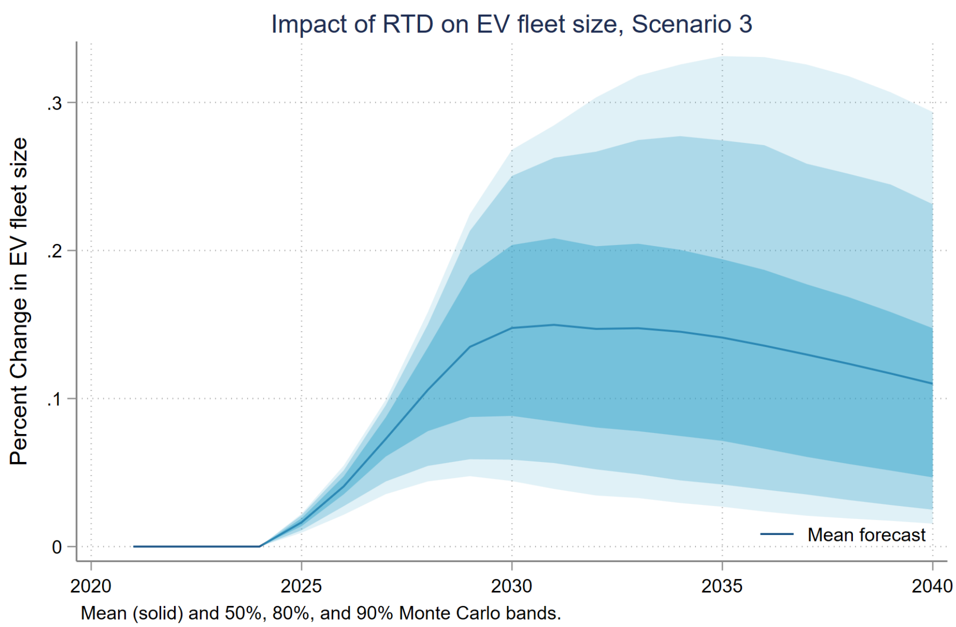


Figure A9: Uncertainty around impact of RTD reporting on carbon emissions, scenario 1

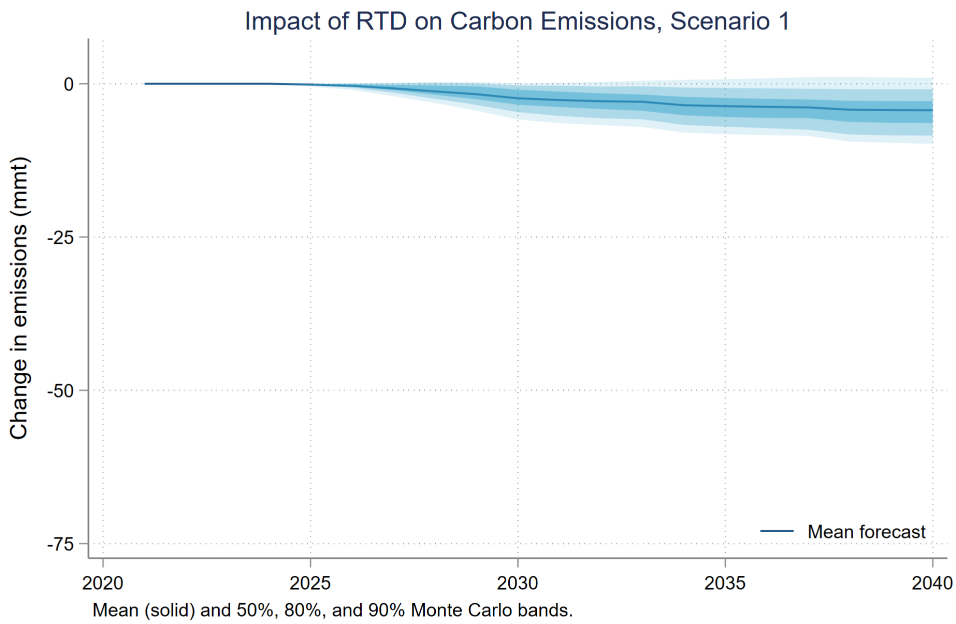


Figure A10: Uncertainty around impact of RTD reporting on carbon emissions, scenario 2

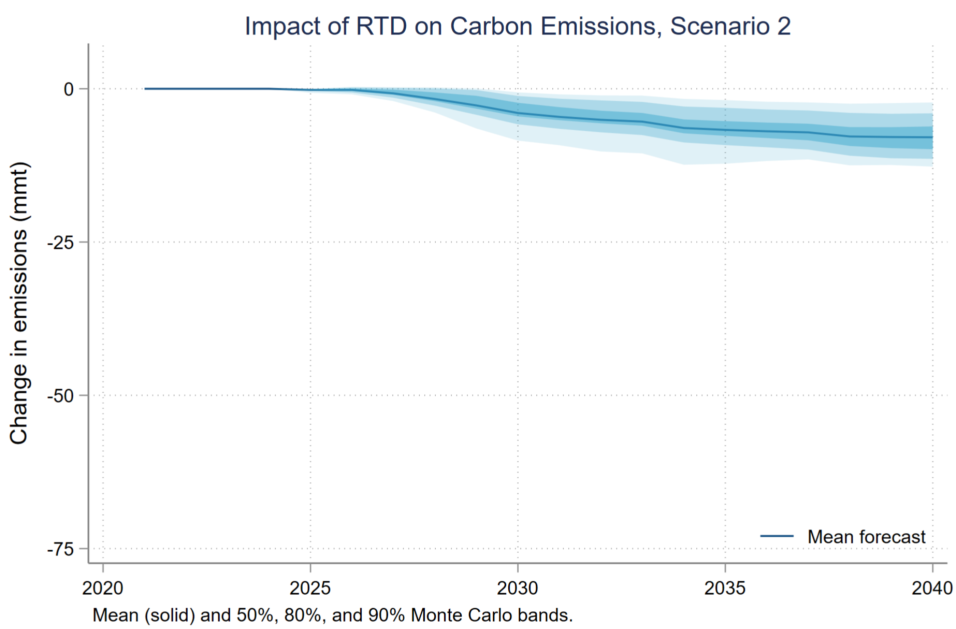


Figure A11: Uncertainty around impact of RTD reporting on carbon emissions, scenario 3