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FUELING ALTERNATIVES: GAS STATION CHOICE AND THE IMPLICATIONS FOR ELECTRIC CHARGING

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ABSTRACT

This paper quantifies the value of electric vehicle (EV) charging networks and the marginal value of network speed and density. We estimate a model of gasoline drivers' refueling preferences and simulate how these potential future EV drivers value refueling time under counterfactual charging networks. Drivers value refueling time at $19.73/hour. EV adopters with home charging receive $675 per vehicle in benefits from avoiding travel to gas stations, whereas refueling travel and waiting time costs $7,763 for drivers using public charging. Increasing network charging speed yields three times greater time savings than a proportional increase in station density.

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Annual vehicle travel in the United States grew from 1.1 trillion total miles in 1971 to over 3.1 trillion miles in 2021 (Bureau of Transportation Statistics, 2023). The transportation sector is fueled overwhelmingly by the combustion of petroleum products which generate harmful tailpipe emissions, including local air pollutants that harm human health and carbon dioxide emissions that contribute to climate change (Holland et al., 2016). To address these externalities, policymakers have recently sought to encourage the transition from gasoline to electricity as the dominant transportation fuel. Yet such an energy transition would require large-scale investment in electric vehicle (EV) charging stations. Recognizing this, the 2021 *Infrastructure Investment and Jobs Act* and the 2022 *Inflation Reduction Act* provide grants and tax credits intended to expand the nationwide number of charging stations to 500,000 by 2030 (White House, 2023). While policymakers have prioritized building new chargers, few policies stipulate charger attributes—such as charging speed—that may be beneficial to drivers.

This paper studies drivers' value of EV charging infrastructure. We evaluate drivers' time costs of refueling an EV relative to a gasoline vehicle for both those with access to at-home charging and those relying on the network of public chargers. Moreover, we explore a key trade off inherent in EV charging network design: the *speed-density* trade off. That is, for a given infrastructure budget, how do drivers value a sparser network with faster chargers relative to a denser network with slower chargers?

Given currently deployed EV charging technology, most charging takes long enough that drivers using public chargers choose to recharge while they are at their destinations rather than waiting at the station for their vehicle to charge.[1] Drivers going about their daily routine will therefore value faster charging because it allows them to recharge more in the time that they would already spend at their destination. However, a denser charging network means that drivers' destinations are more likely to be close to a charging station, so that drivers do not need to travel as far from the charger to their destinations. Since charger costs increase proportionally with speed (Nicholas, 2019), empirical analysis is required to determine if the returns are higher from investing in network speed or network density. However, measuring the value of charging station density versus speed is difficult as it requires information on the distance from chargers to drivers' destinations, the time drivers spend at these destinations, and drivers' propensity to refuel on a given trip, which is partly determined by drivers' remaining fuel.

We leverage uniquely detailed data to understand drivers' refueling preferences and the implications of these preferences for EV adoption and charging network design. We observe second-by-second driving data in gasoline vehicles that includes information on drivers' routes, fuel tank level, fuel consumption, and gasoline refueling stops for a sample of drivers. These data provide

[1]The exception to this is for long road trips, where drivers will often need to refuel along the way to their destination. Charging speed will be critical in these settings.

insights into the trade offs that drivers face when refueling, including when to stop for fuel given their tank level and whether to drive out of their way for a lower fuel price, as well as the locations of trips and the time drivers spend at each destination. We focus on individuals driving gasoline vehicles rather than those driving EVs because EVs made up less than 1% of the overall U.S. vehicle fleet in 2021 (Energy Information Administration, 2023), suggesting that EV drivers are highly selected. By choosing EVs, these drivers reveal that they likely have relatively low recharging costs, either because they have access to charging at home or because their trips are located near existing charging infrastructure. Given that investments in EV charging infrastructure are aimed at increasing EV penetration and providing charging to *future* EV drivers, we argue that studying gasoline vehicle drivers is crucial for evaluating EV infrastructure policy.

We pair our detailed driving data with information on gasoline station prices and locations to estimate a model of drivers' refueling decisions. In our model, drivers make a discrete choice on each trip over whether to stop for fuel and, if they stop, which station to stop at. Drivers choose whether to stop based on their tank level and choose which station to stop at given the station characteristics such as price, brand, and excess travel distance from the driver's optimal route. The model captures fundamental features of drivers' refueling choice, including drivers' lack of perfect information. Specifically, our model recovers an estimate of how consumers form perceptions of stations' prices, which may differ from actual prices due to imperfect information. We allow drivers to be imperfectly informed about both the prices at a given station on a given day (e.g. Ho et al., 2017; Thakral and Tô, 2021) and the existence of stations that we do not observe the driver passing in our data (e.g. Abaluck and Adams-Prassl, 2021; Goeree, 2008). We identify drivers' disutility from having an emptier fuel tank from the propensity to make a refueling stop on trips with different starting tank levels. We infer drivers' value of travel time from their observed willingness to travel further from their routes in order to pay a lower expected gasoline price. Finally, we identify drivers' level of awareness about gas stations' current prices from a combination of information on which stations drivers pass and changes in each station's observed choice probability as its price diverges from its long-run average price.

Our refueling choice model generates three key findings. First, drivers are highly unlikely to stop for fuel when their tanks are over one-third full, but the likelihood of stopping increases steeply as the tank level falls below one-quarter. This means that there are a relatively limited number of trips on which drivers consider refueling, making the stations available on those trips particularly valuable. Second, drivers' station choices imply that they value time spent traveling to refuel at \$19.73/hour, or 63.6% of the median wage in our sample group,[2] which is only slightly

[2]Median wage rates come from the Bureau of Labor Statistics' Occupational Employment and Wage Statistics for May 2010. We calculate the median wage as the average Census-tract median wage where the drivers in our sample stop most frequently.

higher the estimate of 50% of the wage rate (White, 2016) used by the U.S. Department of Transportation. Third, we find that drivers respond about twice as much to each station's long-run average price than to its current price, which is consistent with consumers relying on average prices to form a belief about the price they would pay at a given station. Importantly, we show that ignoring imperfect information leads to severely biased estimates of the value of time.

Our estimates of drivers' refueling preferences allow us to investigate several questions pertinent to EV charging. We begin by calculating the value EV drivers obtain from avoiding time-consuming gasoline stops via recharging an EV at home. We find that drivers in our sample would save $675 in travel costs over the lifetime of driving an EV. This calculation highlights a modest benefit of switching to an EV for drivers with access to at-home charging.[3]

Yet many drivers do not have access to home charging (Ge et al., 2021), and therefore must rely on the public charging network to recharge an EV. To understand the value of different charging station network configurations for those drivers, we combine our driving data and refueling model estimates with data on EV charging station locations. This allows us to simulate when drivers would stop to recharge and how they would make trade offs between different charging stations on a given trip. In our baseline simulation, we assume that drivers can choose between waiting for their vehicles to charge and continuing to their destination on foot to minimize total excess time (including walking and/or waiting time). The time cost of refueling at a particular station on a given trip therefore depends on the combination of walking time and any waiting time the driver accrues beyond the observed time that they spend at their destination. Crucially, these EV charging simulations require several behavioral assumptions (e.g., drivers' preferences for walking versus waiting) and assumptions about the EV's technical attributes, such as its range, which determine how frequently the driver would need to refuel. We therefore conduct numerous robustness checks to understand how these assumptions influence the main results.

Our baseline simulations show that in 2022, relying on EV charging stations instead of gasoline stations would increase excess time spent refueling from 3.1 minutes to 34.6 minutes per stop. Specifically, gasoline vehicle drivers spend an average of 2.3 minutes driving to gas stations and 0.8 minutes waiting at gas stations, whereas EV drivers spend an average of 34.6 minutes walking round-trip to chargers and 1.2 minutes waiting at charging stations. Combined, refueling an EV with public chargers would entail $7,763 in increased time costs over the life of a vehicle. This implies that, based on refueling time alone, drivers who can charge at home would value an EV at up to $8,438 ($7,763+$675) more than drivers without home charging. This helps to explain why homeowners are substantially more likely to purchase EVs than renters (Davis, 2019), given that renters may be less likely to have access to dedicated off-street parking that would facilitate

[3]This value is in addition to any fuel cost savings coming from EVs' fuel efficiency relative to gasoline vehicles, but omits the cost of installing faster charging at home.

EV charging at home (Traut et al., 2013).

While our simulations suggest that EV drivers relying on the existing charging network would bear considerable refueling time costs, we also show that those costs have fallen markedly over time as the charging network has improved. Between 2012 and 2022, the number of charging stations in Michigan and Ohio increased over 14-fold from 149 in 2012 to 2,331 in 2022, with the share of direct-current (DC) fast charging stations increasing from 3% to 14%. We estimate that this increased station density and charging speed reduced the excess EV refueling time by 54.4% from 78.4 to 35.7 minutes per stop. Additionally, we show that if all of the 2022 charging stations were converted to DC-fast chargers, with 250 kW charge speed, this would further reduce driver's average refueling time by 51% to 18 minutes per stop. These simulations illustrate the benefits that charging infrastructure improvements can yield to EV drivers.

However, these results also raise an important policy question: is it more valuable to invest in faster chargers or additional chargers going forward? To analyze the speed-density trade off, we simulate excess refueling times across a range of potential network configuration that independently vary both charger speed and the number of chargers. Our simulations of alternative charging networks generate several striking results. First, for the majority of cases, EV drivers get more value from increasing network speed rather than network density. We estimate that the marginal value of increasing the speed of the current network is three times larger than the marginal value of increasing the number of charging stations in the current network (as of 2022). Relatedly, we find that when a social planner chooses between slower, but less expensive, "Level 2" chargers and the budget-equivalent number of faster "Level 3" chargers, drivers' refueling costs are minimized when the planner invests entirely in Level 3 chargers. When the planner uses the same budget to make a continuous choice between charger speed and charger density (as measured by stations per million population), we find that the efficient network in 2022 is 200% faster but about 70% less dense than the current observed network. Our robustness analyses show that the relative value of speed vs. density investments will depend on EVs' range. Charging speed becomes even more valuable relative to density as EV range improves.

Finally, we use our simulations to show which drivers would benefit the most from investments in charging network speed rather than density. We show that, within our data, EV drivers from lower-income Census tracts and those under 60 years old would benefit more than richer or older drivers if investments increased charging network speed rather than density. We further show that drivers that do not often spend more than eight hours at their destinations would obtain the largest benefit from increasing charger speeds.

This research contributes to four key strands of literature. First, we expand the literature that seeks to understand the value of electric vehicle charging infrastructure. Early work in this literature (e.g. Greaker and Heggedal, 2010) developed calibrated theory as to how EV adoption

and charging infrastructure evolve in tandem. Later work brought data to the same question while grappling with issues surrounding the identification of the relationship between charging stations and EV adoption when both could be driven by unobserved variables (e.g. Li, Jing, 2017; Li et al., 2017; Springel, 2021; Zhou and Li, 2018). Our work expands this literature by combining extremely detailed real world data on driver behavior, a model of driver preferences, and simulation of driver behavior given counterfactual charging networks that together allow us to understand the benefits of alternative infrastructure investment strategies.

Second, our model of driver decision-making extends the research on gasoline purchasing and the value of information. This literature has generally lacked information on driver's individual purchasing decisions, and so has instead used information on firms' pricing behavior to form inferences about drivers' behavior (e.g. Chandra and Tappata, 2011; Lewis, 2011; Yang and Ye, 2008). A smaller set of papers have used information on commuting patterns and gas station prices (and sometimes sales quantities) to measure drivers preferences more directly, (e.g. Houde, 2012; Levin et al., 2017; Pennerstorfer et al., 2020). Some researchers have also used the gasoline market to investigate broader economic concepts such as collusion (Byrne and De Roos, 2019; Lewis and Noel, 2011), household budgeting (Hastings and Shapiro, 2013), and information provision (Luco, 2019). We contribute to this literature by estimating drivers' preferences directly and using these preferences to better understand optimal stopping behavior, the role of imperfect information, and drivers' value of time.

Third, our analysis contributes to the broader literature on consumer search, especially in the context of imperfect information (e.g. De los Santos et al., 2012; Hortaçsu and Syverson, 2004; Larcom et al., 2017; Weitzman, 1978). Earlier work on the cost of imperfect information showed how consumers' misperceptions of product characteristics can reduce their welfare (Leggett, 2002; Liebman and Zeckhauser, 2004). Later work expanded this to include estimation of consumers' perceptions from their observed purchase decisions (Allcott and Taubinsky, 2015; Houde, 2018; Ito, 2014). Our data allow us to observe drivers' actual choices of when and where to stop for gasoline in a setting where they do not necessarily know the prices at stations in their choice set. By using the stations drivers pass to help understand information sets and estimating the weight that drivers place on current prices relative to long-run average prices, we are able to approach imperfect information in a unique way, even relative to earlier papers that investigate search in gasoline (e.g. Nishida and Remer, 2018). We can also quantify drivers' value of perfect information (e.g. Allcott, 2013; Houde, 2018; Leggett, 2002).

Finally, we expand the extensive literature that measures individuals' value of time by estimating drivers' value of time when making refueling decisions. The value of time is a critical input into cost-benefit analyses of transportation policy (Small et al., 2005; Wolff, 2014), such as fuel economy standards, highway infrastructure investment, and gasoline station zoning laws.

This literature has its roots in early empirical work such as Beesley (1965), but gained firm theoretical grounding with Oort (1969) which built on the broader work by Becker (1965). Work in this literature has recovered values of time from decisions over transportation modes (Lave, 1969), routes (Small et al., 2005), speeding behavior (Wolff, 2014), and rideshare choices (Buchholz et al., 2020; Goldszmidt et al., 2020). We provide what we believe is the first estimate of drivers' value of time from on-road refueling choices. Within this literature, the closest work to ours is Deacon and Sonstelie (1985) which uses a natural experiment that looks at drivers' willingness to wait in line at one gasoline station rather than pay a higher price without wait at another station. Our estimates are in line with both Deacon and Sonstelie (1985) and the more recent literature (e.g. Goldszmidt et al., 2020), which suggest that the Department of Transportation's current value of time—one-half of the wage rate—likely undervalues public investments and policies that provide time savings.

We begin our analysis by describing our data and providing descriptive evidence on drivers' refueling choices in Section II. We then discuss our empirical framework in Section III and present estimation results in Section IV. We investigate the value of charging network structure for drivers who both can and cannot charge at home in Section V. Section VI concludes.

II Data

Our analysis relies on data from three main sources: data on individual driver behavior (Sayer et al., 2010) which we use to identify fueling stops, data on the location and speed of EV charging stations over time (U.S. Department of Energy, 2022), and data on gasoline station locations and prices (Oil Price Information Service, 2012). In this section, we discuss each of these data sets in turn and provide descriptive evidence on both the characteristics of drivers' trips that will affect the value of EV charging networks and the variation in the data that allow us to recover drivers' preferences.

A IVBSS Experimental Data

We use driving data from the Integrated Vehicle-Based Safety Systems (IVBSS) study conducted by University of Michigan Transportation Research Institute (UMTRI) from April 2009 to May 2010 (Sayer et al., 2010). During this study, identical vehicles were provided to 105 drivers in southeast Michigan for approximately 40 days each.[4] The objective of the study was to observe

[4]There were 117 drivers who were provided a vehicle. However, several people were dropped from the sample due to non-compliance with the experimental guidelines (e.g. allowing others to use the vehicle). Three drivers had technical issues with their cameras that mean that we cannot observe fuel tank levels, so they are dropped from our sample.

driver responses to modern safety equipment including lane-departure and collision warning systems. The drivers used the vehicles as if they were their own (including purchasing their own gasoline, although the cars were given to the drivers with a full tank), and UMTRI collected high-frequency data on location, speed, and fuel use. Cameras in the vehicles captured video of the driver and the surrounding roadway.[5]

The top panel of Table 1 provides characteristics of drivers in the sample. UMTRI sent information about the experiment to a random subset of Michigan license holders with clean driving records living within a radius of approximately one hour's driving time from Ann Arbor. Of the drivers who expressed interest in the program, the final sample was stratified to contain equal numbers of men and women in three age categories: 20–30, 40–50, and 60–70, who drove above a minimum number of miles per day on average. The table shows that the average driver lived in a Census tract with median household income of approximately $64,000 per year (U.S. Census Bureau, 2010) which is above the median household income in Michigan of $54,379. However, there was substantial variation across drivers, with Census tract median household income ranging from below $20,000 to over $145,000.[6] Experimental participants drove 1,761 miles on average, equivalent to 51 miles per day (18,500 miles per year). In total, UMTRI collected data on 6,275 hours (224,700 miles) of driving.[7]

For each driver, these data include comprehensive, high-frequency information on vehicle operation and driver behavior. In particular, we observe information about the time and location of every driving trip during the experiment. We define a unique driving trip as beginning each time a driver turns on their vehicle and ending when the driver shuts the vehicle down. The on-board computers document the starting and ending latitude and longitude associated with each trip as well as detailed data within each trip regarding the vehicle location, speed, heading, fuel consumption, and more, which we use at the one-second level. We therefore know exactly which route each driver took between the trip starting and ending locations. Table 1 shows that the average driver completed nearly 200 trips.

We aggregate the high frequency data to obtain a trip-level data set on fuel consumption and other variables of interest. Table 1 provides details about the characteristics of trips in our sample. The median trip lasted 8.75 minutes (3.82 miles). Over half of trips lasted between 3 and 18 minutes, however some trips were substantially longer, which results in a right-skewed trip

[5]We use data on the driving and refueling behavior of gasoline vehicle drivers rather than EV drivers because of the fairly low adoption rates of EVs. In 2021, EVs comprised 0.8% of vehicles on the road in the U.S. (Energy Information Administration, 2023). Investments in charging infrastructure are long-lived, so it is important to look at potential future EV drivers (current gasoline vehicle drivers) rather than merely the selected early EV adopters.

[6]We do not know the home address of drivers, but define the location that each driver stops at most frequently as the driver's "home." Appendix Figure A.1 shows the distribution of the drivers' median Census tract income.

[7]Drivers were not compensated for their participation in the experiment other than through the use of the car and a nominal payment for completing baseline and endline surveys.

Table 1: Driving Data Summary Statistics

Driver Characteristics						
	N	Mean	SD	Pct25	Median	Pct75
Census Tract Median Income ($)	105	64541.87	27674.61	47132.00	61806.00	76905.00
Days With Vehicle	105	39.22	4.76	39.00	39.00	39.00
Total Driving Distance (Miles)	105	1819.10	840.78	1210.56	1704.76	2350.85
Total Driving Trips	105	187.12	77.95	136.00	177.00	230.00
Total Number of Refueling Stops	105	8.06	5.25	5.00	7.00	10.00
Refueling Stops Per Week	105	1.59	0.93	1.03	1.31	1.94
Has Home Garage {0,1}	105	0.73	0.44	0.00	1.00	1.00
Tract Single Family Home Share [0,1]	105	0.71	0.23	0.61	0.78	0.87
Tract Population Density (Pop./Mile^2)	105	2505.03	2134.77	697.20	2100.54	3598.25

Trip Characteristics						
	N	Mean	SD	Pct25	Median	Pct75
Trip Distance (miles)	19825	8.60	14.86	1.26	3.82	9.79
Trip Time (minutes)	19825	14.11	18.45	3.61	8.75	17.67
Trip Destination is Home (0,1)	19825	0.31	0.46	0.00	0.00	1.00
Weekend (0,1)	19825	0.26	0.44	0.00	0.00	1.00
Refueling Stop (0,1)	19825	0.04	0.20	0.00	0.00	0.00
Tank Level at Start of Trip (gallons)	19825	7.17	3.46	4.42	6.98	9.83

Time Between Trips (minutes)						
	N	Mean	SD	Pct25	Median	Pct75
Minutes at Destination (All Trips)	19825	287.02	664.26	16.55	72.50	314.63
Minutes at Destination (Trips to Home)	6077	629.19	821.05	87.15	484.96	891.04
Minutes at Destination (Away from Home)	13748	136.11	513.96	11.23	40.42	134.25
Longest Daily Stop at Home	3665	1000.33	923.62	624.92	834.58	1120.57
Longest Daily Stop Away from Home	3665	364.29	952.22	95.10	233.29	479.48

Notes: The top panel presents summary information about IVBSS drivers. The drivers were 50% male and 50% female. The drivers were approximately evenly distributed across three age groups: 20-30 years old, 40-50 years old, and 60-70 years old. The middle panel reports summary statistics across all trips in Michigan and Ohio made by all drivers during the experiment. The bottom panel reports summary statistics on the amount of time drivers spend at various destinations following trips. Pct25 and Pct75 are the 25th and 75th percentiles, respectively.

time distribution. We also see that 26% of trips occur on weekends, and 31% of trips end at the driver's home.

One variable not recorded by the monitoring equipment was the fuel tank level. The amount of fuel remaining in the tank is the major factor that determines whether a driver stops to refuel and how much gasoline they choose to purchase. We recovered an estimate of the fuel tank level using images from an in-car "over-the-shoulder" camera directed at the steering wheel and dashboard, combined with second-by-second fuel consumption data. We describe details of this procedure in Appendix B. We estimate that, on average, drivers begin each trip with about 7.17

gallons (39%) remaining in the tank.

Given our focus on EV infrastructure, the bottom panel of Table 1 lays out key information for understanding EV charging behavior: the distribution of time spent at the destination at the end of each trip. If a driver's daily routine includes many short stops at destinations, then there will not be many opportunities for the driver to receive a substantial charge from a slower charger. We see that across all trips, the median time spent at a destination is 72.5 minutes. However, longer stops mean that the average stop duration is over 4.5 hours. Stop durations are substantially longer when drivers stop at home. The median home stop lasts over 8 hours compared to only 40 minutes on trips away from home. Even if we only look at drivers' longest daily stop away from home, the median stop duration is under 4 hours. In this much time, a slower "Level 2" public charger would be able to supply a charge equivalent to at most 2.2 gallons of gasoline.

Figure 1a explores the distribution of stop durations by showing the share of trips on which the driver is at their destination long enough to receive a substantial charge as a function of the charger speed. We define a substantial charge as the electricity equivalent of the observed mean gasoline purchase in our data (8.4 gallons $\times$ 33.7 kWh/gallon $=$ 283 kWh).[8] We see that at the 2012 average charging speed of 20.69 kW, only about 5% of trips in our data end in stops long enough to get 283 kWh ($\sim$8.4 gallons) of electric charge. At a Level 3 charging speed of 80 kW, nearly 30% of trips end in a stop long enough to get a substantial charge. This shows that if there are charging stations near every destination, then increasing charging speed can substantially change the likelihood that a driver is at their destination long enough to get a substantial charge when their tank is low.

B Electric Vehicle Charging Infrastructure

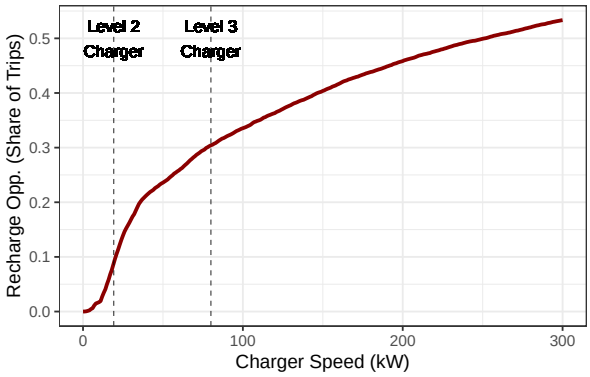
As in the rest of the country, public charging in Michigan and Ohio has expanded substantially in the last decade. Table 2 shows that the number of charging stations in Michigan and Ohio expanded over 15-fold from 149 stations in 2012 to 2,331 stations in 2022.[9] The share of DC fast chargers in the network also increased from 3% to 14%, although this increase only implies a 34.5% increase in the mean charger speed.

The combination of these two data sets allows us to assess the extent to which drivers' access to charging stations has improved over time. Figure 1b plots how the average walking time (at

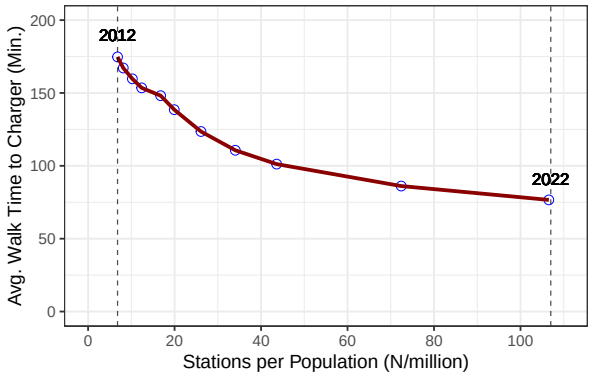
[8]Drivers in our preferred analysis sample (which only includes stations the driver otherwise passed in our data period) purchase 8.4 gallons on average. Across all stops, drivers purchase 8.49 gallons on average.

[9]We also can compare the existing gasoline station network to the EV charging station network. Table A.5 shows that, in 2022, there were an average 8.2 charging stations within a 5 minute drive of each trip. This is relative to 21.1 gas stations and 12.6 gas stations that the driver had previously passed. Moreover, on a typical trip, a driver could stop for gas within a one minute deviation of their route but the closest EV charger was located over four minutes away.

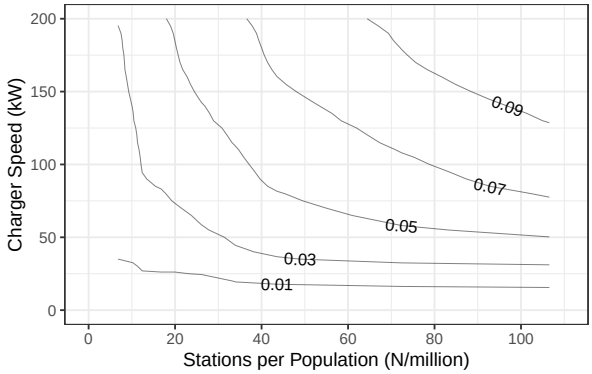
Figure 1: Trip, Destination, and EV Charging Network Characteristics



(a) Share of Trips with Sufficient Time at Destination for Charging



(b) Walk Time to Closest Charger By Charging Station Density



(c) Share of Trips with Viable Charging by Network Speed and Density

Notes: Figure 1a shows the share of trips on which an EV driver remains at their destination long enough to get a substantial charge (equivalent to the average gasoline purchase in our data, 8.4 gallons or 283 kWh) as a function of the station's charging speed. The vertical lines for Level 2 and Level 3 (Type 1) are the maximum charger speeds for each charger type as designated by SAE (2017). Figure 1b shows average round-trip walking time from a driver's destination to the closest charger as function of the number stations per million population. In Figure 1b, each blue dot represents the mean walk time given the location of stations for a specific year 2012-2022. The bottom plot shows the share of trips in which drivers have a "convenient" opportunity to refuel their EV as function of the number of charging locations and charger speed. We define a destination as having a "convenient" opportunity to refuel if: (1) the driver can walk round trip to the charging station in less than 30 minutes, and (2) the driver spends enough time at their destination to obtain a substantial charge without additional waiting time.

a speed of 3 miles per hour) from each trip destination to the nearest charger has evolved with station entry. Each blue circle in the figure represents one year of station data. We see that, given the 2012 charging network, drivers on an average trip would need to walk almost 3 hours round-trip (90 minutes each way) from the nearest charging station to their destination. This average walk time has fallen by more than 50% with observed station entry through 2022, but still stands at over 75 minutes. Notably, additional station entry reduced walk time substantially more in

Table 2: Public EV Charger Network in Michigan and Ohio Over Time

Year	Charging Stations	Stations/Pop. (N/million)	Fast Charger Share $[0, 1]$	Mean Charger Speed (kW)
2012	149	6.81	0.03	20.69
2015	271	12.39	0.05	22.10
2019	745	34.05	0.13	27.01
2022	2331	106.55	0.14	27.83

Notes: The number of total EV charging stations and the number of stations per capita are determined by each station's entry year in the DOE data. To calculate the share of stations that offer DC fast charging by year we code stations that offer both DC fast chargers and AC chargers based on their share of fast chargers (e.g. 0.5 if half the chargers at the station are fast chargers). The last column calculates the mean estimated charging speed across all stations in the network assuming each fast charger is 80 kW and all other chargers are 19.2 kW.

earlier years than more recently.

Of course, since Figure 1b presents the average walk time across all trips, it could be that station entry more recently has been closer to destinations where drivers are more likely to remain for extended periods. Figure 1c therefore shows the share of stops in our driving data that are both (1) within a 30 minute walk of a station and (2) have stop durations long enough for the driver to get a substantial charge, as a function of the charger speed and the observed station density. We see that at low station densities like those observed in 2012 (6.8 stations per million population), there are very few trips (less than 1% at contemporaneous charging speeds of 20.69kW) where charging would be relatively inexpensive in terms of walking and waiting times. Further, at these low station densities, increasing charging speed does not substantially increase the share of trips with easy charging access. On the other hand, the figure suggests that when the station density exceeds 90 stations per million population, increasing charging speed can substantially increase the share of trips on which charging is accessible.

C Refueling Choice, Gas Stations, and Prices

Evaluating EV refueling costs requires understanding drivers' value of time and their preferences for when to refuel, which we will estimate in our model of refueling choice. To do this, we match the vehicle locations from the IVBSS driving data to Oil Price Information Service (OPIS) data on gasoline stations to recover information on station locations, gasoline prices, and refueling choices during our driving sample window. The OPIS data contain the name, brand, address, approximate geographic coordinates, and daily gas prices for every gas station in Michigan and

Table 3: Summary of Refueling Stops

	N	Mean	SD	Pct25	Median	Pct75
Tank Level at Start of Trip (gallons)	828	3.07	2.13	1.49	2.57	4.29
Purchase Quantity (gallons)	828	8.49	3.74	5.39	8.50	11.85
Price Paid ($/gal.)	828	2.60	0.16	2.50	2.60	2.70
Weekend (0,1)	828	0.25	0.44	0.00	0.00	1.00
Station within 10 Miles of Home (0,1)	828	0.60	0.49	0.00	1.00	1.00
Passed Station Previously (0,1)	828	0.91	0.29	1.00	1.00	1.00
Excess Time (min)	828	2.40	3.09	0.49	1.22	3.09
Excess Distance (miles)	828	0.97	1.99	0.04	0.19	1.06

Notes: Summary statistics are reported across all refueling stops in Michigan and Ohio made by all drivers during the experiment. Pct25 and Pct75 are the 25th and 75th percentiles, respectively.

Ohio (Oil Price Information Service, 2012).[10] We supplemented this information using aerial photographs from an online mapping service to add the exact latitude and longitude of the gas pumps at each station. We find that drivers refueled an average of 8 times each during the experiment.[11]

Table 3 provides descriptive information for the 828 gas stops in Michigan and Ohio that we observe in the driving data. The mean quantity of gasoline in drivers' tanks at the start of trips on which they stop to refuel is just over 3 gallons and the mean quantity purchased at each stop is nearly eight and a half gallons.The mean price paid by drivers in the sample is $2.60 per gallon, with an interquartile range of $2.50 to $2.70. Drivers are equally likely to refuel during weekends relative to weekdays (weekends represent 25% of stops and 26% of trips). Drivers are more likely to stop at stations that they are likely to be familiar with: drivers pick stations located within 10 miles of their home 60% of the time and choose stations that they have previously passed during our sample period 91% of the time.[12]

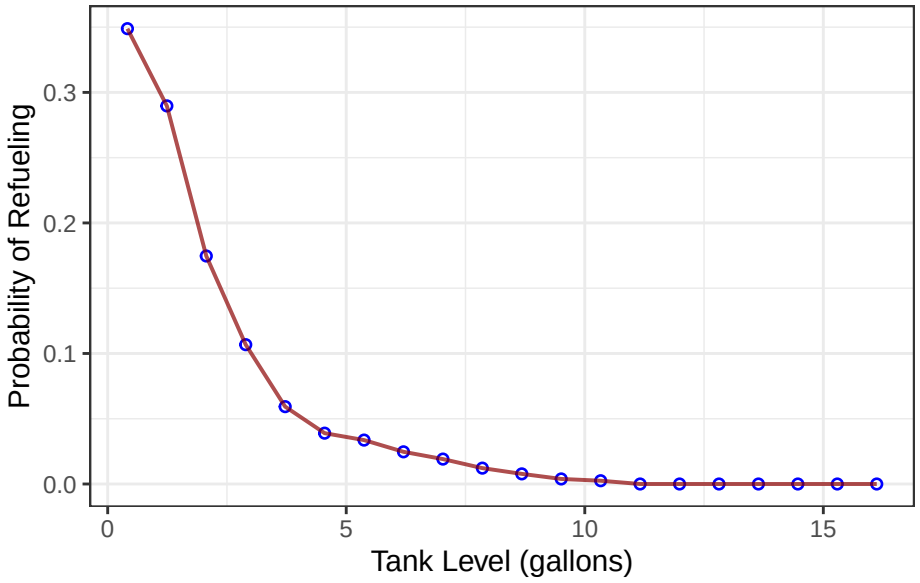
To understand how driver preferences affect the value of different EV charging network configurations, we will estimate a model that focuses on recovering drivers' preferences over when to stop for fuel and cost of delay caused by refueling. It is therefore critical that our data include

[10]The OPIS data only report the price for regular gasoline. The Honda Accords used for the experiment run on regular gasoline and we consider it unlikely that drivers used a different (and more expensive) gasoline grade given that they do not actually own the vehicles.

[11]Appendix B details how we identified precise gas station locations, used vehicle camera images to determine whether a vehicle was stopped at a gas pump, and recovered the gasoline purchase quantity for each stop. Appendix Figure A.2 shows the locations of the 828 gas stops in the data and Appendix Figure A.3 shows the date and price of the gas stops, as well as the average daily gas price across all stations in Michigan and Ohio. A small number of gas stops were identified in states other than Michigan and Ohio. These stops are excluded from our analysis due to the lack of price data.

[12]BP and Speedway were the most common brands choices with a 18% and 15% share of the gas purchases in our data, respectively. Appendix Table A.1 provides the share of stops at each brand in our data. Smaller regional brands and unbranded stations were chosen at 18% of stops.

Figure 2: Refueling Choice by Driver Tank Level



Notes: Drivers' likelihood of stopping to purchase gasoline as a function of the vehicles' tank level.

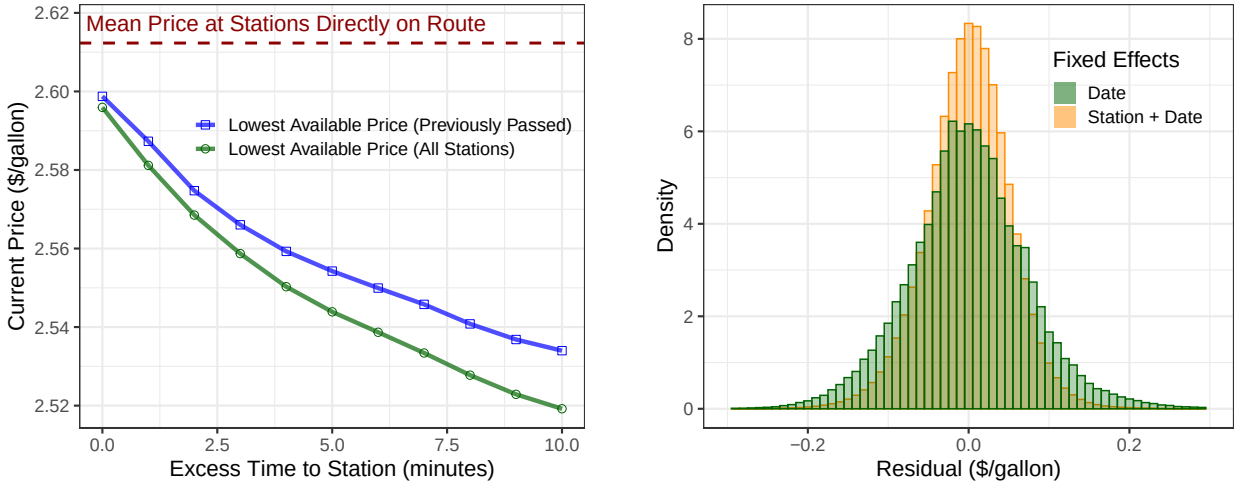
variation that we can use to recover these preferences. Figure 2 shows how the likelihood of stopping relates to the tank level at the start of the trip. Most drivers stop when their tanks are close to empty, with 75% of stops occurring when the vehicle's tank level is below a one-quarter full (4.6 gallons). On trips which drivers stop for fuel, the average starting tank level was just over 3 gallons. The likelihood of stopping will also depend upon the characteristics of the stations near each trip.

One of the most critical trade offs drivers face when deciding between gas stations is between the excess time to travel to a station and station characteristics such as price and brand. Figure A.5 visualizes a driver's choice among a set of gas stations near their route on a selected trip in our data. For each trip we calculate the excess time for the driver to travel from the trip starting location to each potential gas station and then to the trip ending location, relative to the most direct route between the trip starting and ending locations.[13]

Figure 3a demonstrates that driving farther from their route provides drivers improved options in terms of gasoline prices. In the left-side panel, the red dashed line shows the mean price a driver would pay at stations located within 15 seconds of their route. The green line with circles shows how the lowest price available (averaged over trips) changes with each incremental minute

[13]Suppose the trip originates at location A, proceeds to a gas station at location B, then continues on to location C. The excess time for the gas station stop at location B is the fastest time for the route A to B to C, less the fastest time for the direct route from A to C. Travel times between points were calculated using the Open Source Routing Machine (Luxen and Vetter, 2011) based on road network data for the U.S. Midwest (OpenStreetMap, 2022).

Figure 3: Variation in Gasoline Prices



(a) Price Frontier by Excess Time From Drivers' Route

(b) Residual Variation in Gas Prices Conditional on Date and Station

Notes: In the left panel, each point is the lowest available price offered (mean) by stations given the excess time it would take the driver to reach those station on a trip where the driver stops to purchase gas. The dashed line shows the mean price that a driver would pay among stations located within 15 seconds of their optimal route. The right panel plots two histograms. The green histogram plots the distribution of residuals from a regression of gas station prices on date fixed effects. The orange histogram shows the analogous distribution for a regression with both date and gas station fixed effects.

further away from the optimal route, and the blue line with squares shows the same information for stations the driver has previously passed in the data. A driver can find lower prices with each incremental minute of excess time both because: 1) stations located on more common routes can charge higher prices, and 2) drivers can access a larger set of stations with longer diversions so the expected minimum price available would fall even if price and excess time were not correlated. We see that the largest incremental saving opportunities occur within the first couple of minutes deviation from the route: a driver would save about $0.03/gallon at the lowest-priced station one minute away from their route relative to the average price available directly along their route. However, possible savings from driving further off route occur at a decreasing rate. In particular, a driver needs to travel an additional three minutes to save an additional $0.03/gallon (four total minutes to save $0.06/gallon total).

Figure 3b illustrates that there exists substantial variation in gasoline prices even after conditioning on day of sample and station means. The green histogram shows the residuals from a regression of station prices on date fixed effects. We see that the 95% confidence interval for these residuals within a given day spans 29.3 cents in our data, so there is the potential for drivers to pay much lower prices if they find the cheapest stations. However, it is theoretically possible that this could come from some stations always being cheaper than others. The orange histogram

therefore shows the residuals from a regression that includes both date and station fixed effects. There we find that the 95% confidence interval for a given station on a given day spans 20.7 cents. This means that, conditional on the day of the sample, knowing which station the driver will stop at only reduces the variation in the expected price by approximately 30%. This suggests that drivers would need to have very precise information on the price at a given station on a given day to be able to choose the lowest priced station. During the period of our analysis, sites like *gasbuddy.com* were in their infancy and were not widely known or used, so drivers were unlikely to be fully informed about prices at every station near their route. Importantly, our model will fail to capture drivers' value of stopping or excess travel time if we assume that drivers have more information than they actually possess. Therefore, our refueling model in the next section will relax the assumption that drivers are informed about the existence of all nearby stations and about each station's current price. Table 3 reveals that nearly 90% of refueling stops occur at stations that drivers passed previously, and we will use this information on passed stations to help identify the stations which drivers are likely to consider.

III Model of Refueling Choice

To understand drivers' preferences for refueling, we model their choices of whether to stop for fuel, where to stop, and the quantity of fuel to purchase. On a given trip $t = 1, ..., T$, each driver $i = 1, ...N$ has a choice of whether to stop at each of $k = 1, ..., K$ stations and the outside option of not stopping for gas, which we denote $k = 0$. The utility that each driver receives from stopping at a given station is given by:

$$U_{ikt} = \alpha \, \mathbb{E}_i[p_{ikt} \cdot q_{ikt} | Z_{ikt}] + \gamma \, \text{Excess Time}_{ikt} + X_k' \beta + \varepsilon_{ikt}, \tag{1}$$

where $\mathbb{E}_i[p_{ikt} \cdot q_{ikt} | Z_{ikt}]$ is driver i's expected total expenditure (with unit price p_{ikt} and quantity q_{ikt}) at station k on trip t. Throughout this section, the expectation operator $\mathbb{E}_i$ is taken over the driver's subjective distribution of stations' price and purchase quantity given observable information available at the start of the trip, Z_{ikt}. This information might include variables such as the quantity of fuel left in the driver's tank and the average price charged at each station, and we will refer to the subset of information that affects expected purchase quantities as Z^q_{ikt} and the (potentially overlapping) subset of information that affects expected purchase price as Z^p_{ikt}. The driver's utility also depends on several additional terms: Excess Time$_{ikt}$ is the additional travel

time to visit station k on trip t relative to not stopping for gas;[14] X_k is a vector of characteristics of the station k such as corporate brand; and ε_{ikt} is an idiosyncratic preference shock.

We normalize the utility the driver gets if they choose not to stop as $U_{i0t} = W'_{it}\delta + \varepsilon_{i0t}$, where W_{it} is a vector of characteristics of the trip and driver, including the amount of gasoline remaining in the fuel tank at the start of the trip, month-of-sample fixed effects, and (in some specifications) driver demographics.[15] We assume that the unobserved idiosyncratic preference shock in our model, ε_{ikt}, has a generalized extreme value distribution where ε_{ikt} may be correlated with ε_{ik^*t} ($k \neq k^*$, both greater than zero), while ε_{i0t} is uncorrelated with all other ε_{ikt}. This error structure generates the familiar nested logit model (Cardell, 1997) where all stations are in one nest, and we denote the nesting correlation parameter as $\lambda \in [0, 1]$.

In reality, the driver's decision is dynamic because the choice not to stop on trip t includes the option value of stopping on a future trip. While our model does not explicitly model dynamics, it is consistent with conditional choice probabilities (CCPs) of an underlying dynamic model such as Hendel and Nevo (2006). In particular, W_{it} includes a function of the fuel remaining in the tank, which is the critical state variable that would affect this option value and hence the CCPs.[16]

In our model each driver observes the information $Z_{ikt} = \{Z^p_{ikt}, Z^q_{ikt}\}$ at the start of the trip and uses these variables to form expectations over the price that they will pay and the quantity of fuel they will purchase at each station. We express each driver's expected total expenditure as the product of the expected purchase price and the expected purchase quantity:[17]

$$\mathbb{E}_i[p_{ikt} \cdot q_{ikt} | Z_{ikt}] = \underbrace{\left(\theta p_{ikt} + (1-\theta)\overline{p}_k\right)}_{\mathbb{E}_i\left[p_{ikt}|Z^p_{ikt}\right]} \cdot \underbrace{\left(Z^{q\prime}_{ikt}\phi\right)}_{\mathbb{E}_i\left[q_{ikt}|Z^q_{ikt}\right]}. \tag{2}$$

This expression shows that we use the current price at each station and the long-run average price to proxy for the information the driver uses to form expectations of the price they will pay ($Z^p_{ikt} = \{p_{ikt}, \overline{p}_k\}$). Given this formulation, we interpret θ as the relative weight placed on current

[14] Our calculation of the excess time out of the way to each station assumes that if the driver had made a different choice about where to stop for gasoline, they would still have traveled from the same starting location and would travel to the same destination after leaving the station. This rules out a scenario, for example, where a driver chooses to pick up coffee at a different coffee shop, depending on which gas station they stop at.

[15] This formulation of the utility of not stopping assumes that not stopping incurs a price expenditure of zero and a time driven out of the way of zero. Since we do not observe instances in the data where drivers run out of gas, we cannot recover the cost of running out of gas directly. Instead, we allow this cost to be embedded in the increased value of stopping for fuel as the tank level decreases.

[16] Because we model dynamics only through CCPs, our counterfactuals will assume that as the value of the refueling network changes, the option value of not stopping changes similarly. We conduct extensive robustness checks of our results to this assumption.

[17] Appendix C lays out the assumptions required to express expected expenditure as the product of expected price given Z^p_{ikt} and expected quantity given Z^q_{ikt}.

prices in drivers' expected price paid, leaving $1-\theta$ as the weight on information from long-run average prices at station k, $\overline{p}_k$.[18] Notably, this model nests the standard full information model. In particular, $\theta = 1$ implies that drivers place full weight on current prices, whereas $\theta = 0$ implies that drivers only respond to average prices. We assume that Z^q_{ikt} includes ExcessTime$_{ikt}$, W_{it} (fuel left in the tank and month-of-sample fixed effects), and X_k (primarily station brand fixed effects) so that if, for instance, a driver plans to purchase more fuel at a station far from their route, this expectation is properly incorporated into the expected fuel expenditure term.

Substituting Equation (2) into Equation (1), we can write the indirect utility function as:

$$U_{ikt} = \alpha\left(\theta p_{ikt} + (1-\theta)\overline{p}_k\right)\cdot\left(Z^{q\prime}_{ikt}\phi\right) + \gamma\text{ExcessTime}_{ikt} + X_k'\beta + \varepsilon_{ikt}. \tag{3}$$

We estimate Equation (3) in two steps. In the first step, we estimate $\widehat{\phi}$ by regressing purchase quantities on the variables in Z^q_{ikt}.[19] We estimate the remaining parameters (including the parameters in Equation (3) and the nesting parameter, λ) by pseudo maximum likelihood and bootstrap the standard errors to account for the two-step estimation process. Our two-step approach is similar in spirit to the common two-step approach for estimation of dynamic models (e.g. Hotz and Miller, 1993).

Identification: Identification of the expenditure coefficient α requires that (expected) expenditure is not correlated with the idiosyncratic preference shock, ε_{ikt}. This requires three underlying assumptions. The first is that any errors in drivers' expectations of the price that they will pay at a station or the quantity of fuel they will purchase are uncorrelated with each other and with the drivers' idiosyncratic preference shocks, ε_{ikt}, conditional on the Z_{ikt} variables. This assumption would be violated if, for instance, a driver prefers to stop at a station where they expect to purchase relatively more fuel, but this expectation is not captured in Z^q_{ikt}. Similarly, if a driver dislikes stopping at stations in a particular neighborhood and will only purchase a small amount

[18] Our formulation of $\mathbb{E}_i[p_{ikt}|Z^p_{ikt}]$ does not assume that drivers know the current price, but rather uses the current price to proxy for information that the driver may use to form this expectation, such as recent news coverage of gas prices, prices the driver has recently observed, or prices the driver observed at this station in the past.

[19] Table 3 shows that drivers purchase on average 8.5 gallons of fuel and have just over 3 gallons of fuel in their tank at the start of refueling trips. Since the vehicles in our data have 18.5-gallon tanks, this means that many drivers do not fill their tanks when they stop for gasoline. Yet we will find that drivers' search behavior indicates that they have fairly high values of time, which may suggest that there are behavioral forces that affect drivers' purchasing. For instance, Hastings and Shapiro (2013) show that drivers may use mental accounting (Thaler, 1985) when deciding whether to purchase regular or premium gasoline, by setting aside fixed budgets for gasoline (for instance always putting $20 of gas in the tank). However, Appendix Figure C.1 shows that we observe only small amounts of bunching around round dollar amounts, which suggests that this effect is not substantial. Alternatively, drivers may use rules of thumb around round quantity levels (Havranek and Sokolova, 2020; Lacetera et al., 2012) where they choose, for instance, to always purchase 10 gallons of gasoline when they stop. Appendix Figure C.1 again suggests that if this is occurring these rule-of-thumb quantities are likely different for different drivers. Given the variety of potential behavioral models of fuel purchasing, we will model purchase quantities flexibly and leave a full behavioral analysis of gasoline purchasing and the implications of such behavior for estimating drivers' value of time to future research.

of gas if they stop there, this would violate our assumption.[20] We therefore include every variable that is in Z^q_{ikt} directly in the utility function (e.g. in X_k or W_{it}) as well, so that variables that affect expected purchase quantity are allowed to directly affect *observable* station quality.

The second assumption required to identify α is an exclusion restriction: we assume that the variables that affect drivers' expectations of purchase quantities, Z^q_{ikt} and those that affect expectations of purchase price, Z^p_{ikt} are not identical. While it is possible that Z^p_{ikt} could be a proper subset of Z^q_{ikt} or vice versa, in practice we assume that the driver's tank level at the start of the trip does not affect the price the driver expects to pay at any station (conditional on the other variables) and that drivers are inelastic to the price at a given station on a given day, conditional on the Z^q_{ikt}. This is a weaker version of the assumption in Hastings and Shapiro (2013)—that purchase quantities are fully price inelastic—because it allows quantities to respond to variables like tank level, station brand, month-of-sample, and excess distance from the driver's route. We provide evidence for this assumption in Appendix Table A.4.

The final assumption is that the variables that enter Z^p_{ikt}, current station price and long-run average station price, are not correlated with the unobservable quality of the station, conditional on ExcessTime_{ikt} and X_k. Since gasoline is generally a homogeneous product, this assumption largely requires that prices cannot be correlated with the quality of the gas station's non-gasoline characteristics such as its location or convenience store offerings. Our ability to observe each driver's excess time to reach each station on their current trip removes much of the driver-specific value of a station's location from unobservable station quality. To account for the correlation between price and station attributes such as the quality of the convenience store, we include gas station brand fixed effects in the utility function.[21]

The weight that drivers place on information related to current price, θ, is identified through within-station price variation over time. On days when a station sets price at its long-run average price, any $\theta \in [0, 1]$ implies the same choice probability, and so observations on those days can be used to identify α. Identification of θ separate from α comes from days where a station's price differs from its long-run average. If the station's market share is unchanged on these days (all else equal), then θ must be zero, but if market shares change substantially then θ must be positive.[22]

Identification of the remaining parameters follows standard arguments. Appendix C discusses

[20] We show that our results are robust to the inclusion of neighborhood demographics in both Z^q_{ikt} and X_k Appendix Table C.1.

[21] In robustness checks, we show that controlling for additional station characteristics does not change our results, which may suggest that there is little remaining correlation between station prices and unobservable quality after controlling for station location.

[22] The variation in average gas prices over time during our sample window is somewhat smaller than in other similarly-sized time-frames. While this is unlikely to bias our estimates of α or θ within our sample period, it is possible that drivers are more attentive to current prices (so θ is larger) or overall more expenditure-sensitive (so α is more negative) in periods when the variation in gas prices is more substantial.

the assumptions required for identification of our model in greater detail.

IV Model Estimation Results

We first present the results of our refueling choice model, and then use our estimates to calculate drivers' implied value of time and their potential gains from improved information about gas stations and current prices. We then explore heterogeneity in driver preferences and the robustness of our results to changes in the model specification and underlying assumptions.

A Model Estimates

We report the estimates from the first step purchase quantity regression, $q_{ikt} = Z_{ikt}^{q\prime}\phi + \eta_{ikt}^{q}$, in Table 4. In these regressions, we specify the expected purchase quantity as a quadratic function of the drivers' tank level at the start of trip. Further, we allow drivers' expected purchase quantity to depend on gas station brands, the month-year of the stop, and the excess time required for the driver to reach the station. In our preferred choice model specification, we restrict each drivers' choice set to include only stations that the driver previously passed during the IVBSS experiment, so we estimate our first step regression on only these observations in Column (2). This requires dropping just under 10% of gas stops in which drivers refueled at a station they had not previously passed.[23]

Column (2) of Table 4 shows that the expected purchase quantity increases by nearly half a gallon for each one-gallon reduction in the driver's initial tank level. The intercept implies that drivers' expected purchase quantity at an unbranded station (or small brand) is approximately 10 gallons if their tank is empty at the start of the trip. We find that most gas brands are not associated with a statistically significant change in expected purchase quantity—notable exceptions are BP, Mobil, Marathon and Sunoco which are associated with lower expected purchase quantities relative to unbranded stations. Appendix Table A.4 shows that—conditional on the controls—these refueling quantities are not correlated with the current price at the station. This supports our exclusion restriction that drivers are choosing refueling quantities largely independent of current prices at each station.

Table 5 presents estimates for several specifications of our indirect utility model. Namely, Column (1) of Table 5 shows results for a specification where we assume drivers are fully informed. In particular, we assume that drivers are aware of all gas stations within a 20-minute deviation from their optimal route and we assume that drivers are fully informed about current prices at

[23] There are slightly fewer stops in the first step regression because of observations where we could not identify the purchase quantity because we did not observe a fuel gauge reading between two refueling stops.

Table 4: Purchase Quantity Regressions

	Purchase Quantity (Gallons)	
	(1)	(2)
Intercept	9.828	9.991
	(1.025)	(1.088)
Tank Level (gallons)	-0.2958	-0.4287
	(0.1866)	(0.2000)
Tank Level (gallons^2)	-0.0186	-0.0065
	(0.0202)	(0.0224)
Observations	828	751
R^2	0.16299	0.18249
Model # (Table 5)	1,3	2,4
Choice Set	All	Passed
Station Brand Fixed Effects	Y	Y
Month-Year Fixed Effects	Y	Y
Excess Time Control	Y	Y

Notes: The dependent variable is the imputed purchase quantity associated with each observed refueling stop. The intercept represents the purchase quantity at zero tank level for small brands and unbranded stations. We use these regression estimates to predict expected purchase quantity conditional on stopping. We use these predictions to calculate the expected expenditure for the choice models presented in Table 5. We use predictions from Column (1) for Models 1 and 3 in Table 5, and predictions from Column (2) for Models 2 and 4 in Table 5.

all stations in their choice set. Columns (2) through (4) of Table 5 show results for specifications that relax these full-information assumptions.

In Column (2), we account for the possibility of limited consideration sets (e.g. Abaluck and Adams-Prassl, 2021; Goeree, 2008) by restricting the choice set to include only stations that we observe the driver previously passing in our data. In Column (3), drivers' price perceptions vary with either the current price or the long-run average price (or both). Our preferred specification in Column (4) allows for imperfect price information and restricts the consideration set to previously passed stations. In all of the specifications, we control for gas station brand and month-year fixed effects (interacted with the decision to stop).

The top panel of Table 5 demonstrates how the value of not stopping to refuel depends on the amount of fuel remaining in the tank. We see that not stopping is more valuable when the driver has more fuel remaining in the tank. Appendix Figure A.4 shows the empirical probability of stopping as a function of tank level along with our predicted probability of stopping using the model estimates and shows that the model predicts this pattern very well.

The second panel of Table 5 reports the parameters that determine the station choice conditional on stopping. For the specifications that allow for imperfect price information, we estimate

Table 5: Driver Preference Estimates

	Full Price Information		Imperfect Price Information	
	(1)	(2)	(3)	(4)
Value of Not Stopping				
1[No Stop] × Constant	-4.856	-5.406	-10.792	-12.472
	(0.635)	(0.753)	(1.480)	(1.290)
1[No Stop] × Tank Level (gallons)	0.932	1.037	1.102	1.325
	(0.040)	(0.046)	(0.060)	(0.060)
1[No Stop] × Tank Level (gallons^2)	-0.005	-0.013	0.006	-0.008
	(0.003)	(0.003)	(0.004)	(0.003)
Station Choice				
α - Expected Expenditure ($)	-0.243	-0.251	-0.464	-0.511
	(0.025)	(0.030)	(0.057)	(0.049)
θ - Weight on Current Price			0.355	0.313
			(0.057)	(0.057)
γ - Excess Time (minutes)	-0.255	-0.206	-0.227	-0.168
	(0.019)	(0.016)	(0.026)	(0.016)
Nesting Parameter				
λ	0.570	0.557	0.568	0.557
	(0.034)	(0.034)	(0.055)	(0.032)
Choice Set	All	Passed	All	Passed
Station Brand Fixed Effects	Y	Y	Y	Y
Month-Year Fixed Effects	Y	Y	Y	Y
Number of Stops	848	771	848	771
Number of Trips	19825	19588	19825	19588
Observations	2285082	834208	2285082	834208
McFadden R^2	0.312	0.282	0.314	0.285
	Implied Value of Time ($/hour)			
	63.04	49.11	29.33	19.73
	(8.83)	(7.45)	(4.46)	(2.95)

Notes: This table reports pseudo maximum likelihood estimates of driver preferences. The expected purchase quantities are predicted from the regressions in Table 4. The full information model assumes drivers know current gas prices at each station and the imperfect information models allow drivers' price perception to be a weighted average of current price and station average price. λ is the nested logit correlation parameter. Choice Set = "All" indicates that all stations with 20 minutes of the driver's route are included in the choice set. Choice Set = "Passed" means stations that the driver has previously passed that are within 20 minutes of the route are included in the choice set. Bootstrapped standard errors are reported in parentheses. The implied value of time (per hour) is calculated as $60 \cdot \frac{\gamma}{\alpha}$.

that drivers place a lower weight on current prices (31%-36%) relative to long-run average prices when forming price perceptions. In other words, drivers respond about twice as much to long-run variation in prices across stations compared to day-to-day variation in station-level prices. For all specifications, both the price and the excess time coefficients have the expected sign and are statistically significant. That is, more expensive stations and stations further from the driver's route are less likely to be chosen.

The gas brand coefficients (not reported) show that Costco stations are the most likely to be chosen after controlling for price and location. Whereas, Marathon and Sunoco are the least likely to be chosen conditional on price and location. Appendix Table A.3 provides robustness results for each column of Table 5 without brand fixed effects. Interestingly, we find that the estimated expenditure coefficients are substantially smaller in magnitude after we control for gas brand fixed effects (see Appendix Table A.3). Typically, we would expect brand controls to increase the magnitude of the expenditure coefficient if brand quality is positively correlated with price. However in the gasoline market, high quality firms may set lower gas prices as a "loss leader" strategy to attract customers to visit their convenience stores or grocery stores.[24] The estimates presented in Table 5 and Table A.3 therefore suggest that the bias from potential price endogeneity is less problematic compared to the bias caused by misspecification of consumer information in this setting. However, to the extent that price is still correlated with unobservables, we expect our estimates would be more likely to overstate the magnitude of the expenditure coefficient due to the apparent negative correlation between price and station quality. Thus, our model should provide a conservative estimate of drivers' value of time which we discuss in the next subsection.

B Value of Time

Our model allows us to obtain estimates of drivers' *value of time* (VOT), which allows us to value time savings for alternative EV charging network configurations in the next section. Intuitively, the VOT is determined by the marginal rate at which drivers trade off time savings—by selecting more conveniently located stations—and expected dollar savings at the pump. Specifically, we calculate the VOT as follows:

$$\text{VOT} = 60 \times \frac{d\,\mathbb{E}_i[p_{ikt} \cdot q_{ikt}]}{d\text{ExcessTime}_{kt}} = 60 \times \frac{\partial U_{ijt}/\partial \text{ExcessTime}_{kt}}{\partial U_{ijt}/\partial\,\mathbb{E}_i[p_{ikt} \cdot q_{ikt}]} = 60 \times \frac{\gamma}{\alpha}. \tag{4}$$

[24] Some of these brands offer discount cards or promotions bundled with supermarket purchases. As a result, the price paid by some drivers may be less than the list price in our OPIS data. This could also explain why these brands are preferred after controlling for (list) price and location. We do not observe which customers have discount cards in our data. Additionally, while we do not observe whether stations are full- or self-service, a newspaper article from 2009 quotes the president of the Michigan Petroleum Association as estimating that there were only 20 stations in Michigan offering full-service gas at the time (Chandler, 2009).

Here, we multiply by 60 to convert the value of time from dollars per minute to dollars per hour. The bottom panel of Table 5 presents our value of time estimates for each specification. The first specification, in which we assume drivers consider all stations and know all stations' current prices, implies a relatively high VOT of $63 per hour.

Our VOT estimate falls substantially to $49/hour after we allow for drivers to consider only the set of stations that they have previously passed (Column (2)). Similarly, our VOT estimate declines to $29/hour when we let drivers be imperfectly informed about current gas station prices (Column (3)) but consider all stations. Our preferred VOT estimate of $19.73 per hour in Column (4) allows for imperfect station and price information. Comparing the VOT in Column (1) to the last three columns of Table 5 makes clear the importance of modeling imperfect information. In particular, our θ estimates imply that drivers respond more to long-run price differences across stations than short-run price differences. Intuitively, if drivers are not aware of changes in current prices, we will see relatively little substitution towards stations that reduce prices on any specific day. Thus, we would understate drivers' willingness to drive further to save on gas expenditures if we assume that they know all of these (current) prices at all stations.

Our preferred estimate of drivers' VOT is very close to the recent estimates by Goldszmidt et al. (2020) of $19.38 per hour in the context of ridesharing decisions and the VOT used by U.S. government agencies, which ranges from 33% to 50% of the wage rate.[25] Our VOT estimate of $19.73 per hour amounts to 63.6% of the median household income for the Census tracts in which our drivers live.[26]

Appendix D provides evidence on heterogeneity in our results across demographic groups and robustness of our results to alternative specifications. We find that younger drivers, women, and drivers from high income Census tracts all have statistically significantly higher values of time than other drivers. We show that our key takeaways are robust to alternative (1) controls for gas price changes over time, (2) assumptions about drivers' choice sets, (3) assumptions about how drivers form average price expectations, and (4) controls for characteristics of the neighborhoods surrounding stations.

C Value of Information

We have shown that drivers have imperfect information about gasoline prices when choosing where to refuel and that this imperfect information affects our estimate of drivers' value of time. It would be possible for drivers to acquire more information about station prices, for instance, by

[25]For example, the Environmental Protection Agency uses a VOT of 33% of the wage (Cesario, 1976), and the Department of Transportation use a VOT of 50% of the wage rate (Small et al., 2005; White, 2016). For our sample, US government guidelines would imply a VOT between $10.21 and $15.47 per hour.

[26]To calculate median wages, we first take the average of median Census-tract incomes where the drivers live. Then we follow the the U.S. DOT (White, 2016) and divide annual income by 2,010 hours worked per year.

driving to potential stations to check the current price and searching for the best price (Diamond, 1971; Stigler, 1961). However, we see little evidence of this in the driving data. This raises the question of how much value drivers would place on complete information in the gasoline market, or what the returns to an individual searching for more information on station locations and prices would be.

We measure the welfare effects of changing drivers' information using a similar framework to Leggett (2002), Allcott (2013), and Houde (2018). Under this framework, drivers choose a refueling station based on imperfect *perceptions* about stations' prices, but then their ex-post utility depends on the *actual* price they pay when they arrive at their chosen station. Thus, better information about current prices can increase ex-post utility through changing station choices, and therefore, the actual price paid for fuel. Appendix C.3 provides further details about our calculation of the value of information.

Table 6: Value of Information

	Δ Consumer Surplus vs. Baseline ($)	
	Per Gallon	Per Stop
Current Prices Known, Choice Set = Passed Stations	0.005	0.045
Imperfect Price Info, Choice Set = All Stations	0.011	0.094
Current Prices Known, Choice Set = All Stations	0.017	0.144

Notes: Each cell shows the normalized change in consumer surplus (CS) from a change in drivers' information about current prices and/or nearby stations. We calculate the change in CS relative to the baseline case where drivers only consider previously passed stations and are imperfectly informed about current prices. In the baseline case, station price expectations are a function of $\hat{\theta}$. We first calculate the expected change in CS for each trip in the data. We then sum the expected change in CS across all trips. Finally, in each column, we divide the aggregate change in CS by the total gallons purchased, and total stops, respectively.

Table 6 shows the change in consumer surplus if drivers became fully informed about current prices relative to the baseline case where drivers perceive prices as a weighted sum of current price and long-run average price, with the weights determined by $\widehat{\theta}$. In the first row, we restrict the choice set to previously passed stations and show that learning current prices for previously passed stations would only slightly improve consumer surplus by 4.5¢ per refueling stop (0.5¢ per gallon purchased). In the second row, we calculate the change in consumer surplus from adding all gas stations within 20 minutes of drivers' routes to their choice sets, holding constant drivers' imperfect perceptions of prices. We find that adding these stations to the choice set increases consumer welfare by 9.4¢ per stop (1.1¢ per gallon purchased). Finally, the last row presents the gains from both informing drivers about all nearby stations and about current prices at all these stations. In this case, the consumer welfare benefits remain small in magnitude—14.4¢ per gas

stop or 1.7¢ per gallon purchased.[27]

Why do consumers benefit so little from better information? Our model estimates indicate that drivers place a high value on their time, which means they strongly prefer to avoid traveling far from their routes to refuel. Figure 3a shows that on an average trip, drivers could save roughly \$0.34 (\$0.04/gal. $\times$ 8.4 gallons purchased) by finding the cheapest station within two minutes of their route relative to stopping at a random station directly on their route. However, if the cheap station is located two minutes away from the route, the time cost associated with visiting the cheapest station would be \$0.66 (\$19.73/hour $\times$ $\frac{2}{60}$ hours). Thus, most drivers are unlikely to make substantially different station choices when they learn about new stations or about current prices.[28]

V Implications for Electric Vehicle Charging

Our model estimates allow us to analyze the value of the electric vehicle charging network and the impact of investments in improving network speed and density. We begin by assessing the time costs associated with EV charging given the existing network. We consider the value gained by EV drivers who can charge at home versus the cost borne by those who rely on the EV charging network instead of gasoline stations. We then investigate alternative charging station networks to understand the relative value of investing in charging speed and density.

A The Value of Electric Vehicle Charging

For many households, purchasing an EV can provide added convenience by allowing drivers to refuel at home instead of traveling to fueling stations. In particular, drivers with access to a garage or carport with electric charging can plug in their EV when they arrive at home and charge the vehicle overnight. By allowing drivers to charge at home, EVs effectively reduce the time cost that drivers spend visiting fueling stations in a gasoline-powered car.

[27] Our value of information results assume that stations do not update their pricing decisions in the counterfactuals. Thus, our calculation is more appropriate for assessing the benefits of offering a single driver or a small set of drivers additional information about prices or nearby stations. Luco (2019) and Byrne and De Roos (2019) show that price disclosure can increase prices by facilitating collusion, which suggests that our estimates could yield an upper-bound on the consumer welfare benefits of large-scale price disclosure policies.

[28] Appendix Figure A.6 provides additional intuition about the channels behind our value of information estimates by plotting the change in consumer surplus from adding incremental stations to drivers' choice sets relative to the baseline. Drivers' baseline choice sets include 37 previously passed stations that lie within 20 minutes of their route on average. In the figure, we plot how consumer surplus per gas stop changes as we sequentially add unpassed stations into the choice sets, starting with stations that are nearest to drivers' routes. The figure confirms that drivers benefit the most from learning current prices at stations very close to their route, which allows them to reduce fuel expenditures without significantly increasing travel time.

We use our VOT estimates along with our data on driver refueling behavior to calculate the gains from avoiding travel to gasoline stations over the lifetime of an EV. Assuming that EVs are driven similarly to gasoline vehicles over time, and applying our preferred value of time estimate of $19.73/hour, we find that drivers who refuel at home save $675 over the lifespan of their vehicles.[29] The first row of Table 7 shows that drivers spend an average of 2.27 minutes of additional driving time per gasoline stop and 0.84 minutes waiting at the pump. Thus, $492.70 (72%) of the time value from home charging comes from avoiding driving time to gas stations, and the remaining $182.30 (18%) is from avoiding waiting time at the gas pump.

These calculations highlight an important benefit of switching to an EV for drivers that have access to home charging. However, there are several important caveats to take into account when interpreting the results. In particular, this calculation does not include the cost of installing a Level 2 home charger, which would be necessary for drivers to receive a fast enough charge at home to complete their daily driving. Even for households with a garage or other location to charge at home, installing a Level 2 home charger costs an average of $1,800 even without substantial electrical work (Borlaug et al., 2020), which means that the average driver in our sample should not switch to an EV based on the refueling time savings alone.

Our calculations also abstract from any benefits that consumers may obtain from visiting gas station convenience stores. Further, these calculations do not account for potential welfare consequences of having to recharge an EV on longer road trips, which would reduce the benefit of not needing to stop at gas stations. Finally, the baseline time savings estimate masks substantial heterogeneity in the potential time savings across drivers. Importantly, aggregate time savings will depend on how much each individual drives and refuels their vehicle and their individual value of time. For example, we observe some drivers who stop for gasoline upwards of five times per week which would imply aggregate time savings of over $2,500 over the lifespan of an EV.

Cost of Public Charging: Of course, there are many drivers who do not have access to home charging (Traut et al., 2013) and would therefore need to refuel using the public charging network, which is slower and less-dense than the gasoline station network. Understanding the cost of charging for these drivers is complicated by the fact that drivers will optimally choose when and where to recharge their vehicles. We therefore use our model estimates plus additional assumptions about driver behavior to simulate drivers' optimal decisions and estimate the refueling

[29] The precise calculation is: Value of Time Saved $= \sum_{t=0}^{25} \frac{1}{(1+r)^t} \times M_t \times \frac{\text{Gas Stops}}{\text{Mile}} \times \frac{\text{Excess Time}}{\text{Gas Stop}} \times \text{VOT}$, where r is the annual discount rate, which we assume to be 0.05, and M_t is the survival-weighted mileage driven in year t of the vehicle's life given by Lu (2006). We calculate this value of time saved separately for cars and light trucks following Lu (2006) and then assume a 70% market share of light trucks based on their share in April 2019 (U.S. Bureau of Economic Analysis, 2023a,b). We calculate the number of gasoline stops per mile and the refueling time per gasoline stop from our data. The waiting time to pump gasoline is based on the average fill quantity in our data and a pump rate of 10 gallons per minute, which is the maximum speed given Environmental Protection Agency regulations.

time cost of switching to an EV for drivers without home charging.

The first set of assumptions required for this simulation surround the characteristics of the charging network. We assume that drivers are aware of all charging stations, that the charging network speed, density, and EV station locations are identical to what we observe in 2022, and that the price of charging and brand characteristics are identical across stations.[30] Differences across stations may allow drivers to offset some of the disutility from driving further out of the way for lower prices or better station attributes. However, the assumption of homogeneous stations allows us to focus on excess time as the primary determinant of station choice.

The second set of assumptions relate to drivers' routing, purchasing, and optimal stopping behavior. We assume that drivers do not change their routes (origins or destinations) as a result of driving an EV,[31] and that when they stop they charge enough to drive the same amount of mileage as the average gasoline stop.[32] We further calibrate the base option value of not stopping on each trip (the constant in the decision to stop equation) so that drivers stop as often as in the data. This imposes that the mean difference between the value of not stopping and the inclusive value of stopping is unchanged in counterfactual refueling networks. Intuitively, this means that if the average station network the driver faces on this trip gets substantially worse, then their expectation of the average network quality on future trips is also substantially lower. One interpretation of this set of assumptions is that the range of an EV is the same as the range of the observed gasoline vehicles, although other interpretations are also possible.[33] We conduct extensive sensitivity checks of these assumptions, which would capture EVs with different ranges or drivers who are more or less anxious about having low battery levels.

The third set of assumptions surrounds how drivers decide what to do while their vehicles charge. Drivers have the option to *wait* at each station for their vehicle to charge or leave their car and *walk* to their destination (and back) at a pace of three miles per hour. We assume that drivers will stay at their destination for the same amount of time as observed in the data. If drivers choose to walk, they may still bear some waiting time if the necessary charging time exceeds the total walking time plus the time spent at the destination. We assume that drivers

[30] We see charging price information for only a subset of stations and some drivers receive discounts at certain charging stations, so we abstract from price variation. Since charging station brands differ from gasoline brands, we do not know the relative value of different brands, so we cannot allow this to vary in our simulations.

[31] This assumption rules out that drivers change their routes to better accommodate EV charging, for instance by visiting a different grocery store or restaurant with an EV charger nearby. These adjustments may mitigate the costs of a limited EV charging network, but they are also costly to drivers in ways that we can not measure.

[32] Drivers in our analysis data purchase 8.4 gallons of gasoline on the average refueling stop, which will allow them to drive an average of 221 additional miles. We use the Environmental Protection Agency's (EPA's) assumption that one gallon of gasoline is equivalent to 33.7 kWh of charge to calculate that drivers will stop for 283 kWh of charge at each stop (e.g. https://www.fueleconomy.gov/feg/topten.jsp).

[33] While this assumption is strong for the early EVs, it appears to increasingly reasonable. The reported range of vehicles in our data was 444 miles. The current Tesla Model 3 has a range of 263 miles (with a long range version getting 353 miles), and the Model S has a range of 405 miles.

choose whether to *walk* or *wait* to minimize the total excess time spent refueling—the sum of waiting time, walking time, and the excess time to drive to the station.[34] This means that drivers will choose to walk to their destination if the destination is close to the chosen station or the time spent at the destination is long relative to the charging time. We further assume that the disutility from walking is the same as the disutility from waiting. We explore how changing drivers' relative preference for walking versus waiting affects the key results.

Lastly, we assume that there is no congestion at charging stations in our simulations.[35] This implies that drivers would have immediate access to any of the charging stations nearby their routes.[36]

Given these assumptions and our empirical model estimates, we reconstruct each driver's refueling choice set for each trip with the locations of EV charging stations within a 20-minute driving deviation from the driver's optimal route and proceed by simulating drivers charging decisions.[37] We find that EV drivers without home charging would spend substantially more time on refueling than if they owned a gasoline vehicle. As shown in Table 7, with 2022 charging locations and average speeds, the average charging stop adds 35.8 extra minutes of driving, walking, and/or waiting time relative to only 3.1 excess minutes for a gasoline stop. Over the course of a vehicle's lifetime, our VOT estimates imply that excess refueling time costs for EVs are $7,763 in 2022 compared to $675 for gas vehicles. The slow speed of existing EV chargers contributes to this high time cost. The average charger speed in 2022 was 27.8 kW, which means that it would take over 600 minutes to get 283 kWh of electricity (equivalent to 8.4 gallons of gasoline). Thus drivers almost always leave their vehicles and walk to their destinations, with 34.6 minutes of walking per charging stop. The total excess time per stop would only drop to 19.9 minutes if all chargers were replaced with Tesla DC Superchargers. However, DC fast chargers are substantially more expensive than slower chargers: a 250 kW DC supercharger would cost approximately 10 times as much as a 25 kW charger (Nicholas, 2019).

Comparing the time cost of using public charging to the time savings (relative to a gasoline vehicle) of charging at home demonstrates the value of home charging for drivers who have already decided to purchase an EV. Since the benefits of a Level 2 home charger accrue over time,

[34] Appendix E.1 discusses the EV charging excess time variable and the EV charging simulations in more detail.

[35] We assume that drivers also do not experience congestion at gasoline stations in our data, even though there may be waiting for a free pump at some locations, notably Costco gas stations. To the extent that congestion is present across stations within a brand, this would be captured by our brand fixed effects.

[36] Ignoring capacity constraints is perhaps more reasonable in this context of evaluating the network speed vs. density trade off because the choice between fewer fast chargers and a higher quantity of slow chargers will not necessarily alter the total charging capacity of the network. For example, one 100 kW fast charger could charge 10 vehicles back-to-back and achieve the same result as ten vehicles charging simultaneously at ten separate 10 kW AC chargers.

[37] There are some trips on which drivers do not have an EV charging station within a 20 minute drive of their route. We assume that drivers do not have the opportunity to charge on these trips.

Table 7: Refueling Times by Technology Type

Type	Technological Refuel Time (Min.)	Excess Time Per Refuel				Walk Share $[0, 1]$	Time Cost Per Stop ($)	Vehicle Lifetime Time Cost ($)
		Walk (Min.)	Wait (Min.)	Drive (Min.)	Total (Min.)			
Gas								
Pump	0.84	2.27	0.00	0.84	3.11	0.00	1.02	675
Electric (2012)								
Mean Charger Speed	822.75	0.37	74.27	3.78	78.42	1.00	25.79	17,013
All Tesla Supercharger	68.10	1.26	23.89	14.04	39.20	0.83	12.89	8,504
Electric (2022)								
Mean Charger Speed	611.64	-0.00	34.59	1.19	35.78	1.00	11.77	7,763
All Tesla Supercharger	68.10	0.03	17.97	1.89	19.89	0.99	6.54	4,316

Notes: For the "Gas Pump" technology type, we assume drivers consider only previously passed gasoline stations. For the "Electric" types, we assume that drivers consider all electric charging stations within a 20-minute drive and that all stations feature the same charging technology and prices. The technological refuel time column indicates the minutes needed to refuel based on the average refueling quantity in our estimation sample (8.4 gallons, equivalent to 283 kWh). We assume a technological refuel time of 10 gallons per minute for gas stations. The mean electric charger speed was 20.7 kW in 2012 and 27.8 kW in 2022, and we specified a 250 kW charger speed for the Tesla Supercharger simulations. The density of the charging station network in 2012 was 6.8 per million residents versus 106.6 per million residents in 2022. The excess time columns indicate the average amount of added time to refuel based on the station locations, refueling technology, and driver preference estimates. The walk share column indicates the fraction of refueling stops where it is time-minimizing for drivers to park at the charging station and walk to their destination. The average time cost per stop is calculated based on the baseline VOT estimate from Section IV. The total time cost is the discounted expected time cost aggregated over a vehicle's lifetime.

but the costs are paid up front, our estimates imply that consumers with an EV would install home charging as long as their annual discount factor is above 0.214 (for a $1,000 charger) or 0.625 (for a $2,000 charger). These discount factors are far below the levels of discounting reported in the literature (Busse et al., 2013; De Groote and Verboven, 2019; Myers, 2019), suggesting that conditional on purchasing an EV and having a location to charge at home, drivers will very likely want to install a Level 2 charger at home.

Although EV refueling time costs are large, Table 7 further shows that excess refueling times for EVs fell substantially between 2012 and 2022. Over that period, excess refueling time fell by over 50%, from 78.4 minutes to 35.8 minutes per refueling stop, due to the growing number of stations and the availability of fast chargers.

B Charging Speed Versus Density Trade Off

These results raise the key question of how future investment in the EV charging network is likely to further lower these costs, and how increasing network speed and density benefits EV

drivers. To understand these trade offs, we use a stylized model that casts the charging network investment problem through the lens of a social planner who seeks a charging network that minimizes the representative driver's refueling time cost subject to a budget constraint.[38] The planner can choose to build additional stations, N, or upgrade the speed, S of chargers in the network. Drivers' refueling time, τ, is a decreasing function of both N and S. Thus, the planner's investment problem can be written formally as:

$$\begin{aligned} \min_{N,S} \quad & \tau(N,S) \\ \text{s.t.} \quad & \kappa \cdot N \cdot S \leq \overline{B}. \end{aligned} \tag{5}$$

Here, $\overline{B}$ is the planner's budget to spend on charging infrastructure, and we have made explicit the assumption that capital costs are proportional to the total network power capacity ($N \cdot S$). Therefore, the κ parameter is the fixed cost of increasing the power capacity of the network.[39]

Solving the planner's problem yields the following simple optimality condition:

$$\frac{\partial \tau}{\partial N} \cdot \frac{N}{\tau} = \frac{\partial \tau}{\partial S} \cdot \frac{S}{\tau} \quad \Rightarrow \quad \varepsilon_N = \varepsilon_S. \tag{6}$$

Intuitively, the most efficient charging network for a given level of spending must satisfy the condition that the elasticity of time savings from adding additional stations ε_N should be equal to the elasticity of time saving from increasing the charging speed of the network ε_S.

Notably, the solution does not depend on κ, so we can trace out the efficient network configuration without any further assumptions on the fixed cost structure. To solve for the efficient charging network configuration, we only need to obtain estimates ε_N and ε_S. To do this, we use the EV refueling choice model discussed in Section A to evaluate the excess refueling times—the $\tau(N,S)$ function—at a grid of different values of S and N. Specifically, we solve for the mean excess refueling time in each year between 2012-2022 which provides substantial variation in the number of stations as many new EV charging stations were entering the market over this time period. At each of these station densities, we solve for the average excess time per refueling stop across different assumed charger speeds ranging from 15 kW to 300 kW. In total, we solve the model across 220 (11×20) different possible $\{N,S\}$ network combinations.[40] We then

[38] We model the planner as having a choice of station speed and density, but not station locations for two reasons. First, optimizing station locations using our data would likely minimize costs to drivers in our data without considering costs to the broader set of drivers. Second, we do not observe zoning laws or electric grid attributes that may affect whether a given location could feasibly host a charging station.

[39] Proportionality implies that installing three 50 kW chargers would cost approximately the same as installing one 150 kW charger. Since the installed cost of building faster chargers may actually be slightly less than proportional to the installed cost of slower chargers, this biases us towards finding a greater value for charging station density relative to charging speed.

[40] This approach assumes that stations enter the network in the order we observe them entering in practice.

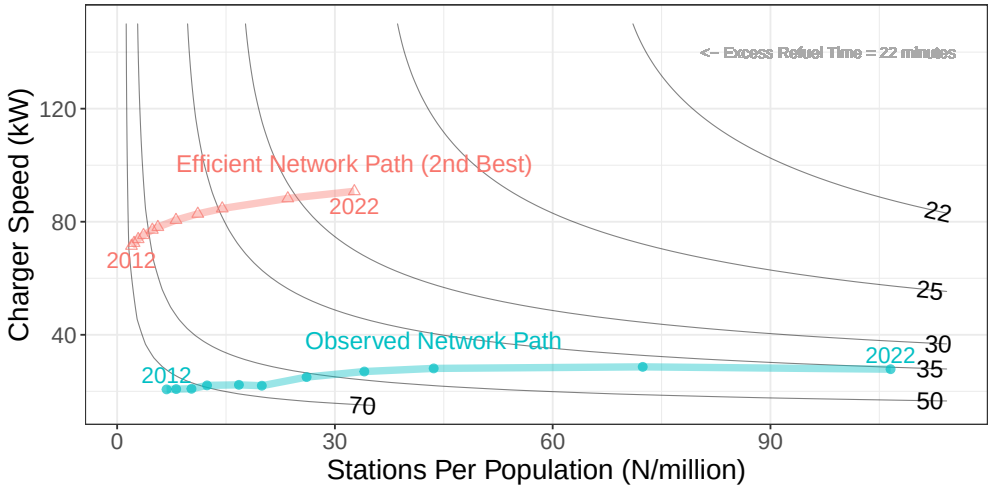
approximate $\tau(N, S)$ with a flexible trans-log functional form estimated across the grid points, i:

$$\log(\overline{\text{Excess Refuel Time}_i}) = \beta_0 + \beta_1 \log(N_i) + \beta_2 \log(S_i) + \beta_3 \log^2(N_i) + \beta_4 \log^2(S_i) + \beta_5 \log(N_i) \times \log(S_i) + \varepsilon_i. \tag{7}$$

Here, the dependent variable is the logarithm of the mean excess refuel time per stop for simulation grid point i. We use the approximation of $\tau(N, S)$ in two ways. First, by differentiating Equation (7), we can calculate the elasticities of excess refueling time with respect to both N and S, ε_N and ε_S. Second, given the calculated cumulative charging network budgets in each year, we can find the most efficient (e.g. excess time minimizing) way to allocate that budget between the total number of chargers and the speed of those chargers.

The regression results from our main specification of $\tau(N, S)$ are shown in the Column (2) of Appendix Table E.1.[41] We can see that the regression functions provide an excellent fit with an R^2 of 0.987. The coefficient estimates indicate that refueling times are decreasing at a decreasing rate in both N and S.

Figure 4: Excess Refuel Time Contour Map as a Function of Station Density and Charger Speed



Notes: The thin grey lines show contours representing the estimated excess refueling time per EV refueling stop across different counterfactual combinations of station density (stations per population) and charging speed of the network (kW). The lower blue line plots the evolution of the observed EV charging network density and speed from 2012 to 2022. The red line shows combination of charger density and speed that would minimize drivers' excess refueling time, while holding the total capital cost of the network fixed in each year. Appendix Figure A.7 shows an illustration of the budget constraint for 2022.

Figure 4 presents charging networks with different potential average charging speed (on the vertical axis) and the number of charging stations (on the horizontal axis, represented as stations

[41] Column (1) shows the results using a simpler Cobb-Douglas functional form.

per million people). The grey contour lines show combinations of network speed and density with equal mean excess refueling time per stop, where networks to the top right require less excess time per stop. The observed network investment path is represented by teal circles and shows that investment between 2012 to 2022 largely focused on increasing network density rather than speed. The efficient network path (red triangles) given the same expenditure (as determined by Equation (6)) is nearly 1/3 the density of the observed network, but 3 times faster on average. The efficient charging network results in an average excess refueling time of only 27.95 minutes rather than 35.8 minutes with the observed network.

The first two panels of Table 8 show how our results would change if EV drivers stopped more or less frequently than gasoline drivers, whether because of different EV ranges, different charge quantities, or driver range anxiety. The top panel presents these results given the charging network in 2012 and the second panel replicates this exercise for the 2022 network. The second row of each of these panels shows our baseline results in that year. With the 2012 network, each charging stop cost drivers over 78 minutes of excess time. The elasticity of this result with respect to investments in station density (ε_N) is -0.29, whereas the elasticity with respect to charging speed (ε_S) is -0.72, implying that the return to additional investment in charging speed is 2.45 times greater than a proportional investment in the number of stations. If EV drivers stop for fuel half as frequently as gasoline drivers, the total time per refueling stop would increase slightly to 79.25 minutes, and the ratio of the return to an investment in speed relative to density increases to 5.46. The top panel of Table 8 shows that more frequent refueling substantially increases the time cost per refueling stop as drivers walk to a greater share of their destinations, but the baseline result—that investments in speed provide a higher benefit in terms of reduced time than investments in density—is repeated regardless of what we assume about the frequency of refueling in 2012.

Robustness: Our result that investments in charging network speed yield higher returns than investments in network density relies on a few key assumptions. In Table 8 we show how our results would change based on different assumptions about the frequency EV drivers stop for charging and driver preferences over walking versus waiting.

The second panel of Table 8 shows that this result continues to hold in 2022 regardless of whether we increase or decrease the rate at which EV drivers stop for fuel by 50% relative to gasoline drivers. However, we do find that there is a range of stopping frequencies for which this result is reversed: if EV drivers in 2022 stop between 2 and 5 times more often than gasoline vehicle drivers, then the elasticity of excess time with respect to density is larger (in absolute value) than the elasticity with respect to network speed. Yet, when drivers refuel their EV 10 times more frequently than gasoline, the result reverses again and increasing speed is again more valuable than increasing density.

Why do investments in network density reduce excess time more than investments in network

Table 8: Refueling Frequency and Excess Time Elasticity with Respect to Speed and Density

	Excess Time Per Refuel (Normalized)							
	Drive (Min.)	Walk (Min.)	Wait (Min.)	Total (Min.)	Walk Share [0, 1]	ε_N	ε_S	Vehicle Lifetime Time Cost ($)
2012 Network								
50% Fewer Refuel Stops than Gas	0.21	62.57	16.46	79.25	1.00	-0.30	-1.64	17,192
Baseline - Gas Refueling Frequency	0.37	74.27	3.78	78.42	1.00	-0.29	-0.72	17,013
50% More Refuel Stops than Gas	0.42	100.20	3.23	103.85	1.00	-0.31	-0.51	22,530
2X More Refuel Stops than Gas	0.90	136.12	6.17	143.19	1.00	-0.33	-0.34	31,065
5X More Refuel Stops than Gas	3.16	345.51	62.87	411.55	0.99	-0.25	-0.34	89,284
10X More Refuel Stops than Gas	52.03	224.50	475.19	751.71	0.46	-0.12	-0.69	163,082
2022 Network								
50% Fewer Refuel Stops than Gas	-0.01	20.31	0.50	20.80	1.00	-0.20	-1.37	4,511
Baseline - Gas Refueling Frequency	-0.00	34.59	1.19	35.78	1.00	-0.20	-0.60	7,763
50% More Refuel Stops than Gas	0.02	48.53	1.02	49.57	1.00	-0.23	-0.35	10,753
2X More Refuel Stops than Gas	0.06	63.93	2.45	66.44	1.00	-0.26	-0.14	14,414
5X More Refuel Stops than Gas	0.15	172.04	19.25	191.44	1.00	-0.22	-0.16	41,532
10X More Refuel Stops than Gas	23.29	195.20	220.04	438.53	0.69	-0.11	-0.59	95,137
Refueling Preference								
Walk or Wait to Minimize Time	-0.00	34.59	1.19	35.78	1.00	-0.20	-0.60	7,763
Always Walk to Destination	-0.00	34.59	1.19	35.78	1.00	-0.22	-0.54	7,763
Always Wait at Charger	5.41	0.00	611.64	617.05	0.00	0.00	-1.00	133,866
Value of Waiting Time								
50% Less than Travel Time	-0.01	32.88	5.78	38.65	1.00	-0.26	-0.37	7,759
75% Less than Travel Time	-0.01	30.59	15.91	46.49	1.00	-0.23	-0.11	7,497
90% Less than Travel Time	2.27	12.94	292.06	260.99	0.59	-0.08	-0.58	9,637

Notes: Excess refueling times and the elasticity of excess time with respect to changes in the network speed and density. Across the columns refueling times and elasticities are evaluated for the 2012 and 2022 observed network speed and density in the top two panels. In our baseline simulation (Row 2 of the second panel) drivers are assumed to refuel EVs at the same frequency (i.e. number of stops per week). In other rows of the first two panels, we show how the results change if drivers were to change the frequency they refuel an EV relative to a gas vehicle. The excess time variable is normalized so that it represents the total number of additional minutes the driver takes to refuel the average refueling quantity in our estimation sample (8.4 gallons, equivalent to 283 kWh). In the third and fourth panels, we show how our results change when we change drivers' preferences over walking and waiting time.

speed when drivers are stopping 2-5 times more frequently than with gasoline vehicles? At this refueling frequency, drivers are getting less charge at each stop, so the share of trips on which they can get a sufficient charge is higher than in our baseline. The statistics in Table 8 on the excess time per refuel (Columns 2-5) show that if drivers in 2022 refuel their EVs 2-5 times more than their gasoline cars, then each charge still takes 1-3 hours. In these cases, drivers would still predominately choose to leave their EV and walk to their destination, and this walking cost would be incurred frequently. Investments in density can therefore reduce walk times more effectively than investments in speed can increase the share of trips on which drivers are able to stop. On the other hand, when EV drivers stop 10 times more frequently than gas vehicle drivers, they obtain so little charge on each stop that they wait for their vehicle to charge on 31% of stops (rather than

walk), so investments in network speed again become particularly valuable. In the extreme case where charging speed was fast enough that drivers could get a full charge nearly instantaneously, investments in density would again become valuable, because they would decrease driving time to stations. However, at that point, EV refueling would look very similar to current gasoline refueling, and may not require policy intervention to spur charging infrastructure investment.

The third panel of Table 8 examines how our 2022 network results depend on whether EV drivers always walk to their destinations or always wait at the station (rather than optimizing across this margin as in our baseline estimates). The charging network in 2022 features relatively slow charging speeds (28 kW) so drivers find that walking from the charging station to the destination is time-minimizing approximately 100% of the time. This means that our results are almost completely unchanged if we assume that drivers always walk to their final destination. Alternatively, if drivers always wait at the charger for their vehicle to charge, then drivers are spending over 10 hours on each charge (only a small percentage of which comes from extra travel time to the charger), and the return to investments in charging speed completely overwhelm the return to investments in charging density.

The bottom panel of Table 8 shows our results under different assumptions about value of waiting time. We show that if drivers value waiting less than driving and walking (perhaps because they can complete other tasks while their vehicle charges) then drivers are more likely to wait at the charger, and the total excess time from recharging will increase. Our result that investments in charging network speed are more valuable than those in network density holds when drivers value waiting 50% or 90% less than walking and driving, but flips when drivers value waiting 75% less than walking or driving. In this range, drivers still generally choose to walk to their destinations, but they choose to recharge on trips with shorter durations at their destinations, which increases waiting time. The value of increasing station density to decrease walking time is therefore high, but shortening waiting times by increasing station speed is not particularly valued by drivers.

Finally, our results could be dependent upon different assumptions about drivers' value of time. Because our simulations assume that all charging stations have equal prices, changing drivers' value of time affects EVs' lifetime refueling time costs, but not drivers' optimization across which stations to choose and whether to wait at the station or walk to their destination. This means that increasing all drivers' value of time by a fixed percentage will increase the vehicle lifetime time cost in the right-most column of Table 8 proportionally, but will not change the relative value of investing in charging network speed or density. Thus, while drivers' value of time is critical for their decision whether to purchase an EV rather than a gasoline vehicle and is important for the optimal level of investment in the charging network, it does not affect the efficient allocation of a fixed budget to improving network speed relative to density.

Overall, these analyses show that our key result that the return to investments in charging network speed are more valuable than investments in charging network density is extremely robust to alternative assumptions. We find that there is a small range of EV recharging frequencies in 2022 that would make investments in charging network density more valuable than proportional investments in network speed. This suggests that the long-standing pattern of substantial investments in network density rather than network speed may not have reduced EV drivers' recharging time costs as much as relatively more investment in network speed would have.

Level 2 versus Level 3 chargers: Much of the current policy discussion has focused on the question of whether investment should focus on "Level 2" or "Level 3" chargers. Level 2 chargers are relatively slower (19.2 kW or less) and provide under 50 miles of charge per hour, whereas Level 3 chargers (over 50 kW) can deliver over 150 miles on an hour of charge.[42] To shed light on this question, we conduct an alternative version of our speed-density analysis where we solve the social planner's budgeting problem for the efficient number of total charging stations and the efficient share of Level 3 stations (versus Level 2). One complication of solving this problem is that we must determine in which locations the Level 3 chargers would be located in our simulations as the share of Level 3 chargers expands. We address this issue by using a machine learning algorithm trained on nearby states to predict the likelihood that each observed charging station (in 2022) in Michigan and Ohio would be Level 3. We then assume that the planner will start with the stations most likely to be Level 3 (according to the ML prediction) when increasing the share of Level 3 stations.[43] Appendix E.3 presents a more detailed exposition of the version of the planner's problem with only two discrete charger speeds and explains more about how we implement these simulations.

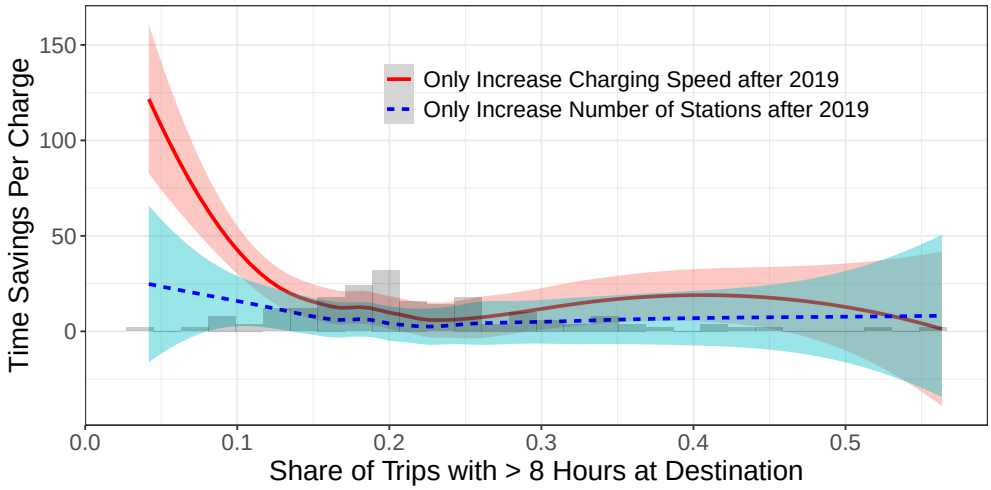
We find overwhelming evidence that, given a level of infrastructure spending, investing in Level 3 chargers reduces excess travel time more than investing in Level 2 chargers. In fact, when we assume that Level 2 chargers are 10 kW, we find that the planner's most efficient choice would be to invest the entire budget in Level 3 chargers, regardless of whether the Level 3 chargers are 80 kW, 150 kW, or 250 kW. In fact, we find that the planner would only split the budget between Level 2 and Level 3 chargers if we assume that the Level 2 charger technology was above 20 kW—which exceeds the Society of Automotive Engineers range of 6.2 to 19.2 kW for Level 2 chargers. We take these results as overwhelming evidence that investment in Level 3 charging reduces

[42] According to Nicholas (2019), a Level 2 charger costs $3,127 in hardware and $2,745 in installation costs, for a total cost of $5,872. A 150 kW Level 3 charger costs $21,401 in hardware and $26,964 in installation costs, for a total cost of $58,492. A 350 kW Level 3 charger costs $140,000 in hardware and $39,097 in installation costs, for a total cost of $179,097. These costs do not include the cost of upgrading nearby electricity grid transformers, which may be necessary for the higher power chargers.

[43] We perform this ML approach because exploring the universe of potential charging station locations and modeling the electricity grid to understand which locations could feasibly install Level 3 chargers would necessitate substantial additional modeling and assumptions.

excess refueling times by more than investment in Level 2 charging for the drivers and trips in our sample.

Figure 5: Heterogeneity in Time Savings from Increasing Speed and Density of Network



Notes: The underlying histogram shows the density of drivers for each share of trips with more than eight hours at the destination. The red solid line shows the excess time reduction across these individuals if all investments in charging infrastructure between 2019 and 2022 had increased network speed. The blue dotted line shows the same information if the investments between 2019 and 2022 had only increased density.

Heterogeneity: While we have found substantial evidence that investing in EV charging network speed yields higher returns than investing in network density, our data also allow us to understand *who* benefits from investments in speed relative to density. The blue line in Figure 4 shows that nearly all investment between 2019 and 2022 went to increasing the density of the network. To investigate heterogeneity in the benefits of speed versus density investments we consider two counterfactuals. In the first counterfactual, we assume that all of the network budget between 2019 and 2022 is spent on increasing the number of stations (similar to the observed pattern). In the second counterfactual, we assume that the full budget between 2019 and 2022 is spent on increasing the speed of chargers. We then compare how different drivers benefit from these density versus speed improvements.

Figure 5 shows the decrease in travel time if the entire infrastructure investment budget had been spent on increasing network speed (red, solid line) or network density (blue, dotted line), differentially for drivers with different shares of stops that are longer than 8 hours (time at destination at the end of each trip). For nearly all drivers, the gains from increasing charging speed are higher than the gains from increasing charging station density. Drivers with a small share of stops less than 8 hours see the largest benefits from either charging network expansion, but also

the largest differential benefit from investments in charging speed rather than density. These are the drivers for whom faster chargers would provide more opportunities to receive a substantial charge.

Table 9: Heterogeneity in Simulated EV Refueling Times

	VOT ($)	Share of Trips $\geq$ 8 Hours at Destination	2019 Share Destinations $\leq$ 30 Min. Walk to Charger	2019 Excess Time (Min.)	Δ_N Increase Only N After 2019 (Min.)	Δ_S Increase Only S After 2019 (Min.)	$\Delta_S - \Delta_N$ (Min.)	Value Per Stop ($)
Income								
Low Income (Q1)	18.15	0.16	0.03	57.49	-9.22	-17.25	-8.03	2.43
Mid. Income (Q2-Q4)	14.44	0.21	0.08	41.01	-2.72	-12.18	-9.46	2.28
High Income (Q5)	22.33	0.22	0.12	49.89	-9.65	-13.91	-4.26	1.58
Age								
Age $<$ 60	21.01	0.20	0.08	43.09	-6.59	-15.38	-8.80	3.08
Age $\geq$ 60	16.01	0.20	0.04	35.55	-1.71	-7.53	-5.82	1.55
Gender								
Male	17.08	0.19	0.08	41.91	-4.68	-13.55	-8.87	2.53
Female	22.99	0.21	0.06	46.01	-6.72	-13.48	-6.76	2.59
Garage								
No Garage	15.99	0.18	0.07	46.74	-8.19	-16.46	-8.26	2.20
Has Home Garage	20.63	0.21	0.07	42.78	-5.00	-13.25	-8.26	2.84

Notes: This table uses estimates of the VOT and preferences separately by demographics as described in Appendix Section D and Table D.1. We then simulate the EV refueling choices for each demographic group allowing preferences, driving locations, and destinations to vary. Column (4) shows the mean excess recharging time for each group based on the 2019 observed charging network. Columns (5) and (6) show the counterfactual change in mean excess time if all of the charging station expenditures from 2019 to 2022 was spent on increasing the number of stations (N) and increasing charger speed (S), respectively. Column (7) shows the difference between the two counterfactuals and the last column quantifies the per stop value that each group of drivers would obtain from investing in speed relative to density.

Finally, Table 9 provides initial evidence on the distributional consequences of investing in EV charging network speed versus density across driver demographics. Namely, we use our heterogeneous model results in Appendix Table D.1 to understand the value of the EV charging network and the marginal value of investments in network speed and density for drivers with different demographic characteristics. We find that investments in network speed are particularly valuable for low-income drivers and those under age 60. For low-income drivers, this is because they are less likely than other groups to be at their destination for more than 8 hours and their destinations are generally farther from the nearest charger. For younger drivers, this is largely because their high value of time makes the time savings from speed investments particularly valuable. We do not see substantial differences in the benefits of investments in speed relative to density depending on the driver's gender or whether the driver's home has a garage.

Given our small sample sizes, we suggest interpreting these distributional results with caution. However, our main results, which show that the time benefit of refueling an EV is $675 for households with home charging while the time cost of refueling an EV is $7,763 for house-

holds that must recharge at the public charging network, already suggest that the benefits of EV subsidies will be skewed toward richer households with access to private garages to facilitate charging.

VI Conclusion

In this paper we seek to understand the trade offs involved in investments in electric vehicle charging infrastructure. We use unique data on drivers' behavior to better understand the value of investing in increasing the charging network speed and density, and find substantial evidence that, at the current network configuration, the return to investing in charging station speed is higher than the return to investing in charging station density. This result is robust to a wide range of assumptions, with investments in network density being more valuable than investments in speed only when drivers stop for fuel two to five times more frequently with EVs than they do with gasoline vehicles. Given that modern EVs have ranges that are approaching those of gasoline vehicles, this scenario seems unlikely to be the outcome moving forward.

Our EV refueling results rely on a number of key assumptions. We assume that drivers do not encounter congestion at chargers that could increase time costs even more and change the return to investments in charging speed. To the extent that certain charging stations experience congestion, technologies that allow vehicles to plug in and then automatically switch which vehicle is being charged would allow drivers to leave their vehicle at a station rather than waiting for a charger to become free.

We also assume that drivers do not change their driving behavior when driving an EV rather than a gasoline vehicle. It is possible that destinations where drivers spend some time such as malls, movie theaters, and restaurants may use EV charging as a way to encourage EV drivers to stop there rather than at rivals' locations. If these drivers view these destinations as close substitutes for the destinations they are currently visiting, this may reduce the cost of EV charging.

While we document that gasoline vehicle drivers have incomplete information when choosing between gas stations—but that the value of complete information for any individual would be low—we assume that EV drivers have complete information about the location of charging stations and pay the same price at every station. It is possible that the sparse nature of the charging station network would mean that EV drivers would collect more information about the location of and pricing at charging stations than gasoline vehicle drivers do. Large-scale charging networks, which have vehicle and phone applications that let drivers observe all of their locations, may help to reduce the cost of this information acquisition, thereby increasing EV adoption and demand for charging stations. Yet there is still substantial variation in pricing across stations, including legal mandates that require stations to price by the minute rather than by the kilowatt-hour in

some states, which may mean that EV drivers' information acquisition costs further affect the cost of EV charging.

In this paper we do not consider the optimal *location* of EV charging stations, but rather assume that the current charging station locations were the ones that were available for EV stations. Future research could delve into the question of EV charging station location, including understanding the set of potential locations for extremely high-speed chargers and the potential for investments in electricity grid infrastructure to facilitate more widespread adoption of these chargers. Relatedly, research on the incentives of charging station owners and what policy tools may be most effective at encouraging the most valuable types of entry seems valuable. While some researchers are beginning to investigate these questions (e.g. Dimanchev et al., 2023), many important dimensions remain under-explored.

Finally, given that our sample of drivers is fairly small, we cannot make strong conclusions about the distributional implications of different types of investments in charging infrastructure. Given the policy incentives available for these investments, understanding which drivers are most likely to benefit from investments in charging infrastructure speed, location, and density is critical for developing equitable policy.

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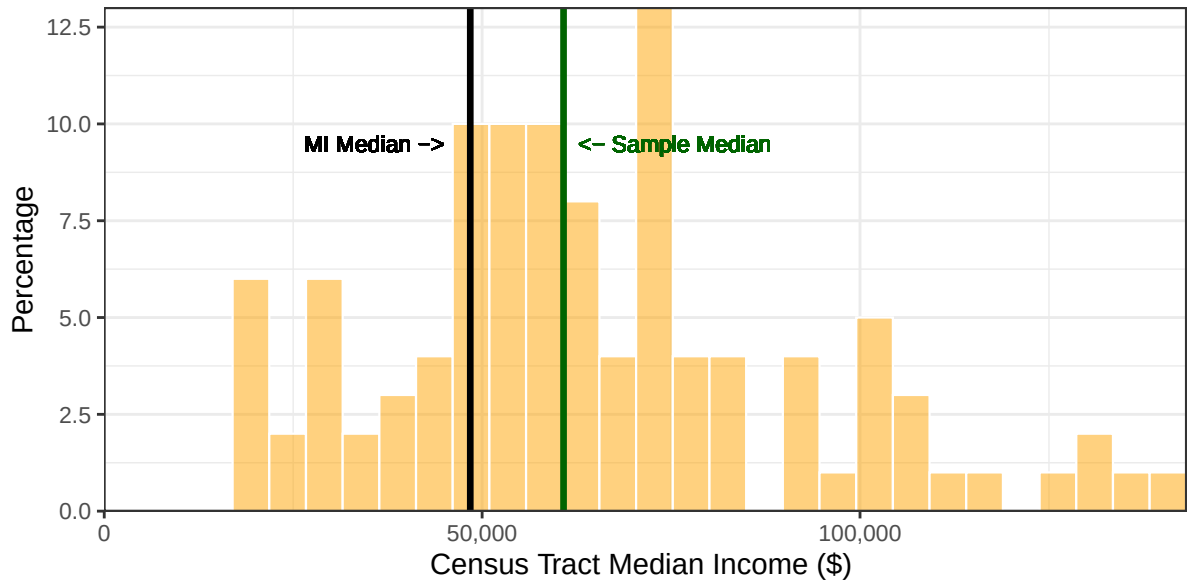
Online Appendix

Title: Fueling Alternatives: Gas Station Choice and the Implications for Electric Charging

Authors: Jackson Dorsey, Ashley Langer, and Shaun McRae

A Additional Tables & Figures Referenced in Main Paper

Figure A.1: Driver Income Distribution



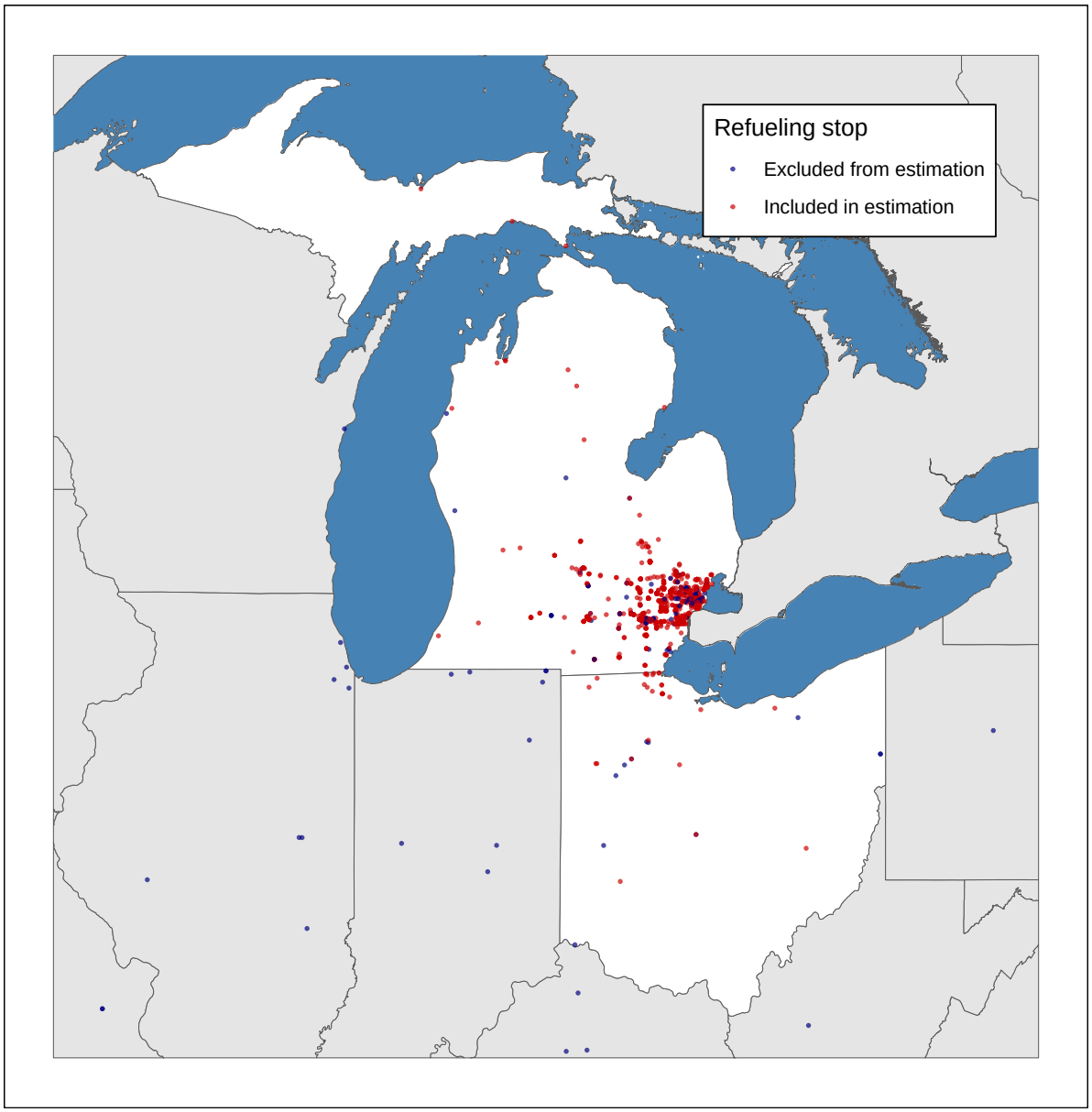
Notes: Distribution of drivers' income based on the Census tract in the 2010 American Community Survey.

Table A.1: Station Brand Choice Shares

Brand	Choice Share (%)
BP	17.69
Citgo	5.07
Costco	2.71
Marathon	12.38
Meijer	6.25
Mobil	8.61
Other	18.40
Shell	5.90
Speedway	14.86
Sunoco	8.14

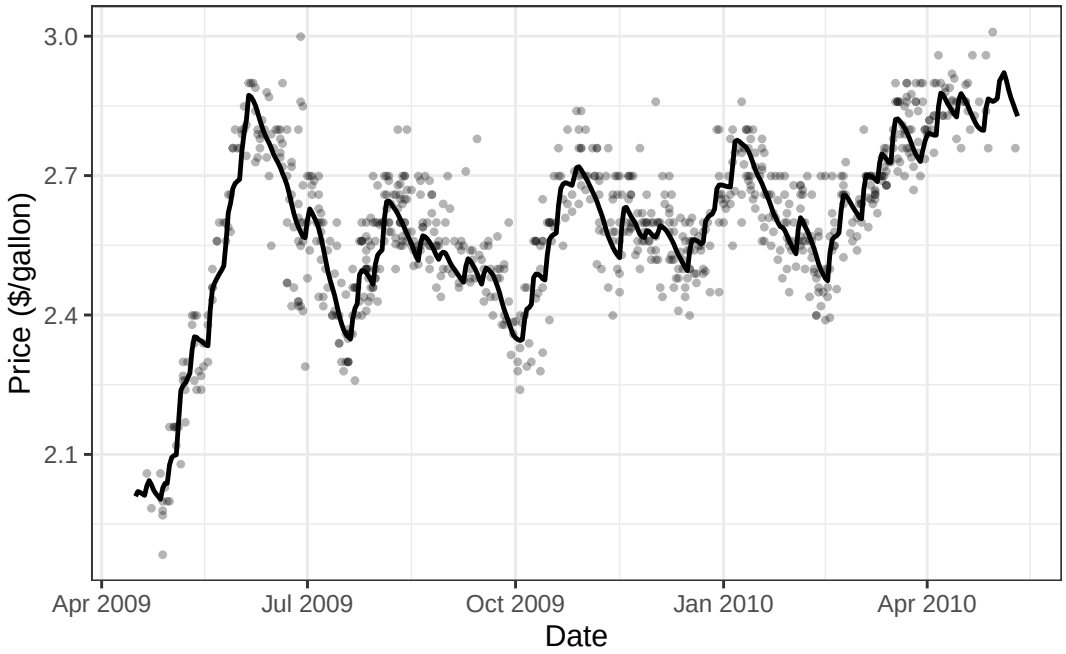
Notes: Empirical choice shares across all refueling stops made by all drivers during the experiment.

Figure A.2: Map of Observed Refueling Locations



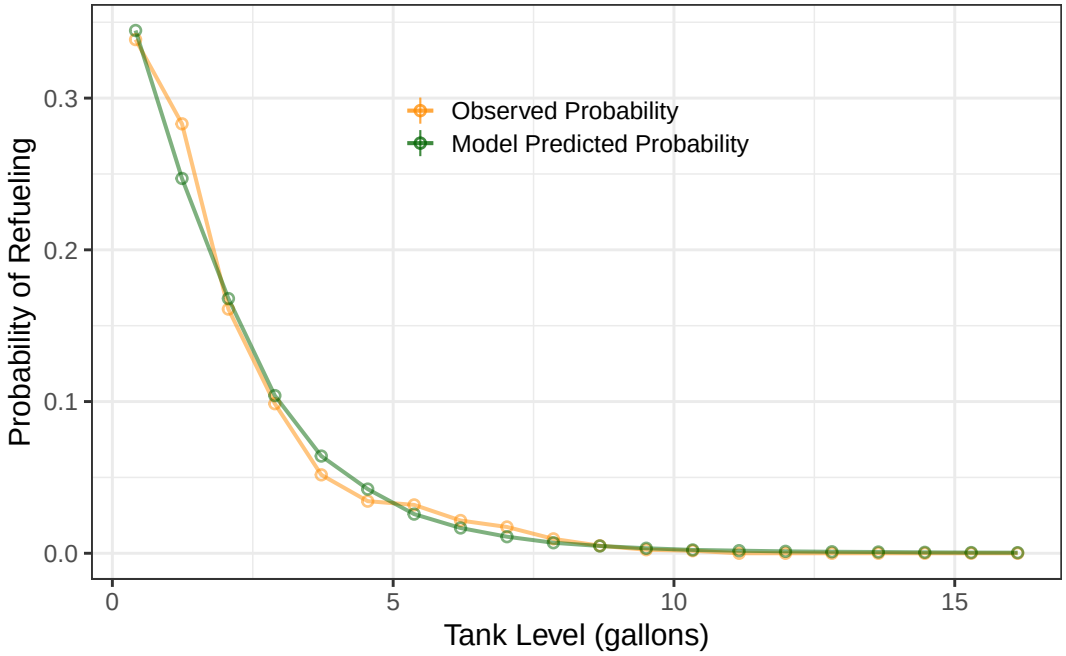
Notes: Each point is a refueling stop that we identified using vehicle locations and the in-car cameras. The red points are the refueling stops that are included in the estimation dataset. Reasons for excluding a stop from estimation include missing price information, missing location data at the start or end of the trip, and missing information on tank levels. Our OPIS price data only covers Michigan and Ohio, so all stops outside of those states are excluded from the estimation data. Background map data is from U.S. Census Bureau (2018), Esri (2019) and Government of Canada (2016).

Figure A.3: Average gasoline price and observed purchase price through sample period



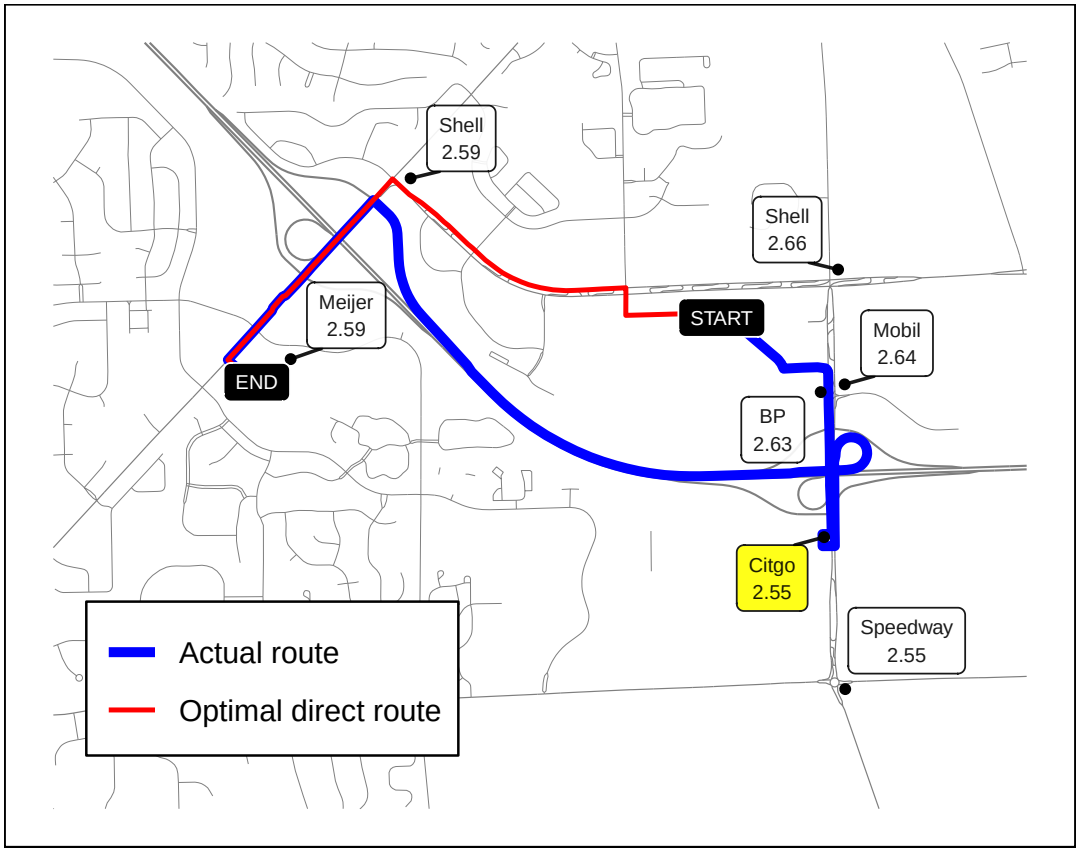
Notes: The black line shows the daily average gasoline price in MI and OH from the OPIS data. Each dot represents the date and price associated with one of the refueling stops that we identify. Posted prices exhibit greater variation within a period.

Figure A.4: Probability of Stopping by Tank Level Model Fit



Notes: The orange circles show the empirical probability of stopping by trip starting tank level in the data. The green circles show the model fit of these probabilities using our baseline specification.

Figure A.5: Example Trip Route including Nearby Refueling Options



Notes: The red line shows the optimal direct route from origin to destination for a trip taken by a driver in Ann Arbor, MI. The blue line shows the route taken by the driver to stop at the Citgo station. Each point shows the location of gas stations near the driver's route along with the prices on the day of the trip.

Table A.2: Comparison of Non-Passed and Passed Stations

	Not Passed (N=121790)		Passed (N=52601)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	Std. Error
Excess Time (minutes)	11.37	5.18	8.50	5.82	-2.87	0.03
Current Price ($/gallon)	2.59	0.17	2.62	0.15	0.03	0.00

Notes: The table compares prices and excess time for all previously passed and not previously passed stations. The sample includes all potential stations that are within a 20 minute deviation from a trip.

Table A.3: Driver Preference Estimates - Impact of Station Brand

	Full Price Information				Imperfect Price Information			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Value of Not Stopping								
1[No Stop] × Constant	-5.862	-4.856	-6.394	-5.406	-12.302	-10.792	-12.472	-12.472
	(0.703)	(0.802)	(0.746)	(0.860)	(1.219)	(1.463)	(1.625)	(1.625)
1[No Stop] × Tank Level	0.976	0.932	1.102	1.037	1.163	1.102	1.325	1.325
	(0.057)	(0.058)	(0.065)	(0.068)	(0.065)	(0.069)	(0.090)	(0.090)
1[No Stop] × (Tank Level)^2	-0.002	-0.005	-0.011	-0.013	0.008	0.006	-0.008	-0.008
	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
Station Choice								
α - Expected Expenditure ($)	-0.323	-0.243	-0.335	-0.251	-0.574	-0.464	-0.511	-0.511
	(0.031)	(0.033)	(0.033)	(0.035)	(0.051)	(0.057)	(0.062)	(0.062)
θ - Weight on Current Price					0.336	0.355	0.313	0.313
					(0.060)	(0.081)	(0.076)	(0.076)
γ - Excess Time (minutes)	-0.192	-0.255	-0.139	-0.206	-0.154	-0.227	-0.168	-0.168
	(0.018)	(0.019)	(0.017)	(0.019)	(0.016)	(0.018)	(0.018)	(0.018)
Nesting Parameter								
λ	0.507	0.570	0.480	0.557	0.518	0.568	0.557	0.557
	(0.035)	(0.036)	(0.041)	(0.042)	(0.034)	(0.035)	(0.041)	(0.041)
Choice Set	All	All	Passed	Passed	All	All	Passed	Passed
Station Brand Fixed Effects	N	Y	N	Y	N	Y	N	Y
Number of Stops	848	848	771	771	848	848	771	771
Number of Trips	19825	19825	19588	19588	19825	19825	19588	19588
Observations	2285082	2285082	834208	834208	2285082	2285082	834208	834208
McFadden R^2	0.299	0.312	0.269	0.282	0.303	0.410	0.274	0.285
	Implied Value of Time ($/hour)							
	35.65	63.04	24.83	49.11	16.13	29.33	9.51	19.73
	(4.92)	(10.38)	(3.99)	(8.74)	(2.26)	(4.58)	(1.80)	(3.45)

Notes: Table reports pseudo maximum likelihood estimates of driver preferences. The expected purchase quantities are predicted from the regressions in Table 4. The full information models assume drivers know current gas prices at each station and the imperfect information models allow drivers' price perception to be a weighted average of current price and station average price. λ is the nested logit correlation parameter. In models with brand fixed effects, the constant in the decision to stop represents small brand and unbranded stations. Choice Set = "All" indicates that all stations within 20 minutes of the driver's route are included in the choice set. Choice Set = "Passed" means stations that the driver has previously passed that are within 20 minutes of the route are included in the choice set. MLE standard errors are reported in parentheses. The implied value of time (per hour) is calculated as $60 \cdot \frac{\gamma}{\alpha}$.

Table A.4: Purchase Quantity Regression - Evidence for Exclusion of Current Prices

	Purchase Quantity (gallons)				
	(1)	(2)	(3)	(4)	(5)
Tank Level	-0.429	-0.449	-0.415	-0.423	0.212
	(0.203)	(0.203)	(0.200)	(0.201)	(0.157)
(Tank Level)^2	-0.002	-0.0009	-0.008	-0.007	-0.064
	(0.023)	(0.023)	(0.022)	(0.022)	(0.018)
Current Price ($/gallon)		-1.50		-0.849	-1.02
		(0.785)		(1.19)	(0.914)
Driver's Mean Purchase (gallons)					0.978
					(0.033)
Observations	751	751	751	751	751
R^2	0.121	0.125	0.185	0.186	0.563
Choice Set	Passed	Passed	Passed	Passed	Passed
Station Brand FEs	Y	Y	Y	Y	Y
Excess Time Control	Y	Y	Y	Y	Y
Month-Year FEs	N	N	Y	Y	Y

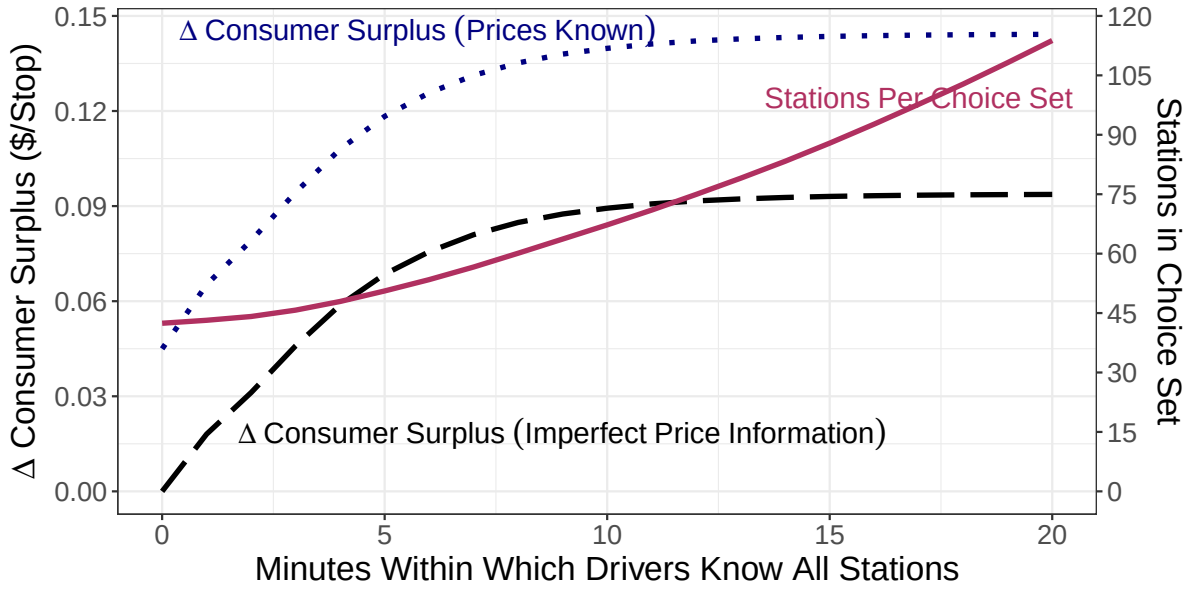
Notes: The dependent variable is the imputed purchase quantity associated with each observed refueling stop. The regressions estimates are used to predict expected purchase quantity conditional on stopping for each trip conditional on initial tank level (gallons). The regression in Column (3) is used to predict expected purchase quantity for the baseline model in Table 5.

Table A.5: Driver Access to Gasoline Station Network vs. Electric Charging Station Network

	Gas (All)	Gas (Passed)	Electric (All)
Stations within 5 Minutes of Route	20.99	12.62	8.19
Closest Station (minutes)	0.99	1.12	4.10

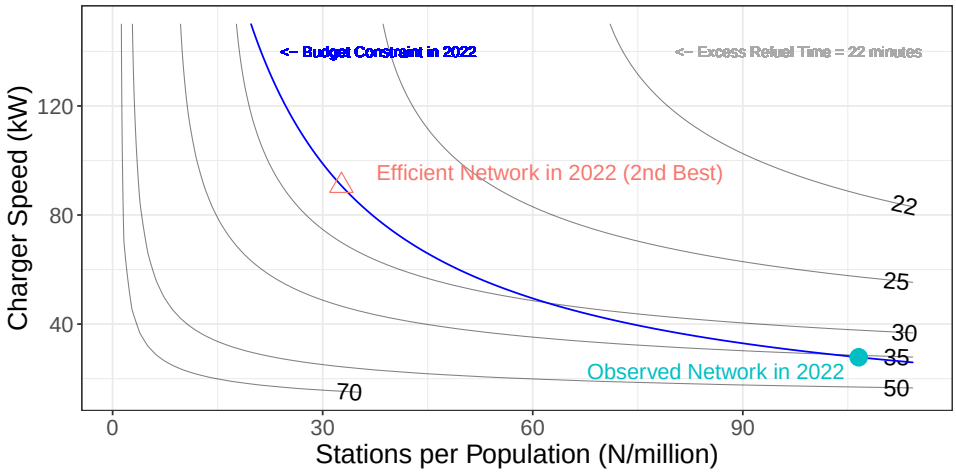
Notes: Column (1) includes all gas stations in OPIS and Column (2) only counts the stations that each driver has previously passed. Column (3) summarizes all public electric chargers in 2022 based on DOE data. The first row reports the average number of stations located within five minutes deviation from a driver's route, across all trips in our data. The second row shows that average time to the closest station relative to driver's routes across all trips in the data.

Figure A.6: Consumer Surplus Gains from Adding Stations to Choice Set



Notes: The solid maroon line plots the average number of stations available to drivers if all the previously unpassed stations within X minutes of the drivers' optimal route were added to the choice set. The dashed black line shows the change in consumer surplus in dollars per gas stop from adding additional (unpassed) stations to the choice set, assuming that drivers remain imperfectly informed about current gas prices, relative to the baseline case where only passed stations are in the choice set. The dotted blue line shows the change in consumer surplus in dollars per gas stop if drivers were perfectly informed about current prices and additional unpassed stations are added to the choice set, relative to the baseline case with only passed stations in the choice set and imperfect information about current prices.

Figure A.7: Excess Refuel Time Contour Map as a Function of Station Density and Charger Speed with Budget Constraint



Notes: The thin grey lines show contours representing the estimated excess refueling time per EV refueling stop across different counterfactual combinations of station density (number of stations) and charging speed of the network (kW). The excess refueling time for each counterfactual network configuration is determined by the location of charging stations relative to drivers routes and behavioral assumptions that are described in Section 4. The blue line plots the available budget set based on the number of stations and average charge speed of the observed 2022 network.

B Data Construction

In this section, we describe the procedure for constructing our dataset of gasoline refueling stops, including the station location and purchase quantity. This procedure relied on the following multimodal data from the IVBSS experiment (Sayer et al., 2010):

- second-by-second latitude and longitude of the vehicle
- second-by-second gasoline consumption of the vehicle
- left-side camera video feed
- over-the-shoulder camera video feed showing the dashboard (from which we extracted images at a five-minute frequency)

Unfortunately, the onboard computers used in the IVBSS experiment did not record the fuel tank level, so we were not able to calculate the fuel purchase quantities directly.

We combined the above IVBSS data with the latitude and longitude of the gas stations in Michigan and Ohio (Oil Price Information Service, 2012). For all of the stations in southeast Michigan, we confirmed the location of each station using aerial photographs from an online mapping service. We adjusted these locations when necessary to correspond to the exact latitude and longitude of the gas pumps at each station.

Our procedure for constructing the refueling stop dataset is as follows:

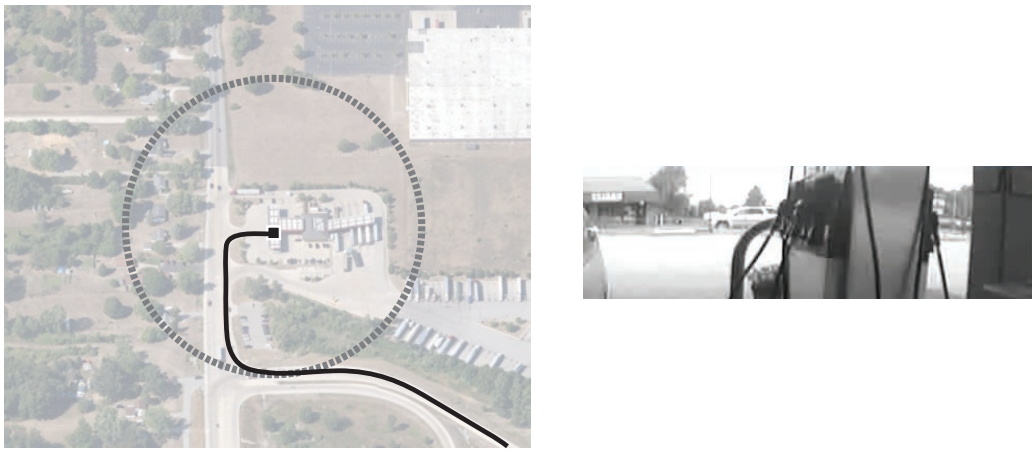
1. We coded every vehicle stop within a 200-meter radius of a gas pump as a potential refueling stop (left panel of Figure B.1). Because some of these stops may have been for reasons other than purchasing gasoline, we then checked the left-side video images during all of these potential stops (right panel). If the camera showed that the vehicle was stopped beside a gas pump, the stop was coded as a refueling stop.

2. We extracted a sample of cabin photos from the over-the-shoulder video feed at a five-minute frequency. From the cabin photos, we cropped a 30x25 pixel rectangle at the fuel gauge location on the dashboard. Based on an analysis of the pixels in this rectangle, we classified the image into one of four types: good, underexposed, overexposed, and low contrast. The image was rescaled and smoothed.

3. We then uploaded the "good" gauge photos to Amazon S3 for classification by Mechanical Turk workers (Dorsey et al., 2013). The Mechanical Turk workers completed a series of tasks. Each task consisted of the classification of three fuel gauge photos. The gauge level classifications ranged from 0 (empty) to 8 (full), with a value of 9 corresponding to an illegible gauge level. At least three workers classified each photo.

4. We calculated the gauge level associated with each five-minute interval (*i.e.* each photo) as the mean gauge classification (across the Amazon Turk workers) between 0 and 8.

Figure B.1: Procedure for identifying gas station stops



Notes: All vehicle stops within a 200-meter radius of gasoline station pumps were considered as possible refueling stops (left image). Images from the driver's side camera were used to confirm that the car was stopped at a gas pump (right image).

5. We combined the five-minute observations of the fuel gauge level with the second-by-second data on gasoline consumption in milliliters. We used the gasoline consumption data to calculate the cumulative fuel consumption between each trip start-point, end-point, refueling event, or five-minute fuel gauge image.

6. To recover the fuel tank levels, we estimated a regression of the cumulative fuel consumption on (i) a quadratic in the fuel gauge level between 0 and 8, and (ii) driver-by-refueling-event fixed effects. From this regression, the driver-by-refueling-event fixed effects correspond to the initial fuel tank level at the start of each refueling event.

7. We combined the initial fuel tank level after each refueling event with the incremental fuel consumption data to calculate the fuel tank level at each second in the data.

8. For some trips and drivers, the imputed fuel tank levels were physically impossible: either greater than the tank capacity of 17.2 gallons, or less than zero. This necessarily implied that we had missed a refueling stop in step (1) of our procedure. In these cases, we used a combination of the fuel gauge photos and the latitude and longitude data to search for the time and location of the missing refueling stop. These stops may not have been identified in (1) because: (i) the stop was outside of Michigan and Ohio, (ii) the station was outside of southeast Michigan and had incorrect coordinates in the OPIS data, (iii) there was a GPS fault in the vehicle and the location was not recorded before and after the refueling stops, (iv) the refueling occurred at a station that was missing from the OPIS data, or (v) the vehicle was left running while refueling so the stop did not occur at the end of a trip. For those cases in which we were not able to identify the exact station where the driver stopped, we still coded the stop as a refueling event to be

able to recover the tank levels. However, without the gasoline prices, we were unable to include these stops in our estimation.

9. We inferred the fuel purchase quantity associated with each refueling event as the change in fuel tank level (in gallons) before and after a refueling event. For imputed purchase quantities of less than two gallons, we went back to the fuel gauge images and confirmed that there was a visible increase in the gauge level after the refueling stop. We deleted potential refueling events with no visible gauge increase. These were likely due to a driver parking beside a gas pump, entering the shop or bathroom, but not purchasing gasoline.

10. We compared the imputed tank levels to the mean gauge level classifications from the Mechanical Turk workers in (4). Where there was a large discrepancy between the two values, we reviewed the fuel gauge images and, in many cases, manually corrected the Mechanical Turk reports.

11. After adding or deleting refueling stops as discussed in (8) and (9), and correcting the reported fuel gauge levels in (10), we repeated the above steps from (5) to (10). We continued this process until there were no imputed fuel tank levels above 17.2 or below 0 gallons, and all refueling stops had a visible increase in the fuel gauge level. This process gave us our final dataset of refueling stops and purchase quantities.

C Details on Station Choice Model

This appendix section provides details on our empirical model. Section C.1 goes through the identification arguments for our model in detail. Section C.2 provides the form of the quasi-maximum likelihood estimator. Section C.3 explains how we calculate the value of information from our model.

C.1 Identification

Identification of our model rests upon a series of assumptions that we outline here. First, recall that each driver forms expectations about the price that they will pay at each station and the quantity of gasoline that they will purchase at the start of each trip. Using this information, drivers choose whether to stop and at which station to stop. We express prices and quantities as the sum of drivers' expectations and prediction errors:

$$p_{ikt} \equiv \mathbb{E}_i[p_{ikt}|Z_{ikt}] + \eta^p_{ikt} \tag{C.1}$$

$$q_{ikt} \equiv \mathbb{E}_i[q_{ikt}|Z_{ikt}] + \eta^q_{ikt}. \tag{C.2}$$

In this formulation, Z_{ikt} are observable characteristics of the driver, trip, and station, such as the driver's tank level at the start of the trip, the long-run average price at each station, and the station brand. We take $\mathbb{E}_i[p_{ikt}|Z_{ikt}]$ and $\mathbb{E}_i[q_{ikt}|Z_{ikt}]$ to be the driver i's (subjective) expected purchase price and quantity given the information they have at the start of the trip. Further, η^p_{ikt} and η^q_{ikt} represent mean-zero unobserved shocks to prices and quantities, respectively, that are not explained by Z_{ikt}.

Given these definitions, the expected fuel expenditure at station k on trip t conditional on variables the driver uses at the start of the trip to form expectations is:

$$\mathbb{E}_i\Big[(\mathbb{E}_i[p_{ikt}|Z_{ikt}] + \eta^p_{ikt}) \cdot (\mathbb{E}_i[q_{ikt}|Z_{ikt}] + \eta^q_{ikt})\Big|Z_{ikt}\Big]. \tag{C.3}$$

Plugging this function into the utility function from Equation (1) in the text, we get:

$$\begin{aligned} U_{ikt} = \alpha\mathbb{E}_i\Big[(\mathbb{E}_i[p_{ikt}|Z_{ikt}] + \eta^p_{ikt}) \cdot (\mathbb{E}_i[q_{ikt}|Z_{ikt}] + \eta^q_{ikt})\Big|Z_{ikt}\Big] \\ +\gamma\text{Excess Time}_{ikt} + X_k'\beta + \varepsilon_{ikt}, \end{aligned} \tag{C.4}$$

where, as in the main text, X_k is a vector of characteristics of the station k such as corporate brand. Also, recall, that the value of not stopping on trip is given by:

$$U_{i0t} = W_{it}'\delta + \varepsilon_{i0t}, \tag{C.5}$$

where W_{it} includes variables—such as tank level—that impact the value of not stopping to

refuel for driver i on trip t.

To identify the model, we begin by making an assumption about the relationship between the shocks to purchase price and quantity, η^p_{ikt} and η^q_{ikt}, and the driver's expected purchase price and expected quantity conditional on Z_{ikt}:

Assumption 1 *Unexpected shocks to the quantity of gasoline that a driver purchases at any given station, η^q_{ikt}, are independent of the driver's expected purchase price, $\mathbb{E}_i[p_{ikt}|Z_{ikt}]$, and the shocks to the driver's expected purchase price, η^p_{ikt}, given the information the driver has at the start of the trip, Z_{ikt}:*

$$\mathbb{E}_i[p_{ikt}|Z_{ikt}] \perp\!\!\!\perp \eta^q_{ikt}|Z_{ikt},$$
$$\textit{and } \eta^p_{ikt} \perp\!\!\!\perp \eta^q_{ikt}|Z_{ikt}.$$

Similarly, unexpected shocks to the prices at any given station, η^p_{ikt} are independent of the driver's expected purchase quantity, $\mathbb{E}_i[q_{ikt}|Z_{ikt}]$ given the information the driver has at the start of the trip, Z_{ikt}

$$\mathbb{E}_i[q_{ikt}|Z_{ikt}] \perp\!\!\!\perp \eta^p_{ikt}|Z_{ikt}.$$

This assumption ensures that the expectations over the gasoline price and purchase quantity that the driver has at the start of their trip are uncorrelated with the shocks that they receive to both purchase price and quantity when they arrive at the station to make the purchase (and that those shocks are also uncorrelated with each other). In practice, the strongest component of this assumption is that that drivers' fuel purchases are inelastic with respect to the price shock, η^p_{ikt}, conditional on Z_{ikt}. One interpretation of this is that drivers decide on their fuel purchase quantity before observing the actual price at the station. This is a weaker version of the assumption in Hastings and Shapiro (2013) that drivers are completely price inelastic when purchasing gasoline, since we do allow the driver's purchase quantity to respond to variables like the station brand, the quantity of fuel in their tank, and month-year fixed effects via the conditioning on Z_{ikt}. We see in Columns (2), (4), and (5) of Appendix Table A.4 that the station's current price is not a statistically significant predictor of observed purchase quantities conditional on the variables we assume the driver uses to predict purchase quantities. This lends support to the assumption that the η^p_{ikt} that the driver observes when they reach the station does not substantially affect the quantity of fuel purchased.

Assumption 1 allows us to rewrite the driver's expected gas expenditure at station k on trip t as:

$$\underbrace{\mathbb{E}_i[p_{ikt} \cdot q_{ikt}|Z_{ikt}]}_{\text{Expected Fuel Expenditure}} = \underbrace{\mathbb{E}_i[p_{ikt}|Z_{ikt}]}_{\text{Expected Price}} \cdot \underbrace{\mathbb{E}_i[q_{ikt}|Z_{ikt}]}_{\text{Expected Purchase Quantity}}, \tag{C.6}$$

which we can plug back into the utility function, Equation C.4 to write utility as:

$$U_{ikt} = \alpha \mathbb{E}_i[p_{ikt}|Z_{ikt}] \cdot \mathbb{E}_i[q_{ikt}|Z_{ikt}] + \gamma \text{Excess Time}_{ikt} + X_k'\beta + \varepsilon_{ikt}. \tag{C.7}$$

The above equation makes clear that our empirical approach will require variation in the price drivers expect to pay independent of the quantity they expect to purchase. This requires an additional assumption. To explain the assumption, we first define $Z^p_{ikt} \subseteq Z_{ikt}$ and $Z^q_{ikt} \subseteq Z_{ikt}$, which are the information that the driver uses to form expectations over purchase price and quantity, respectively. Using this notation, we impose the following assumption:

Assumption 2 *The information the driver uses to form expectations over the purchase quantity at the beginning of a trip, Z^q_{ikt}, is not identical to the information the driver uses to form expectations over the purchase price, Z^p_{ikt}. Further, p_{ikt} is independent of Z^q_{ikt} given Z^p_{ikt} and q_{ikt} is independent of Z^p_{ikt} given Z^q_{ikt},*

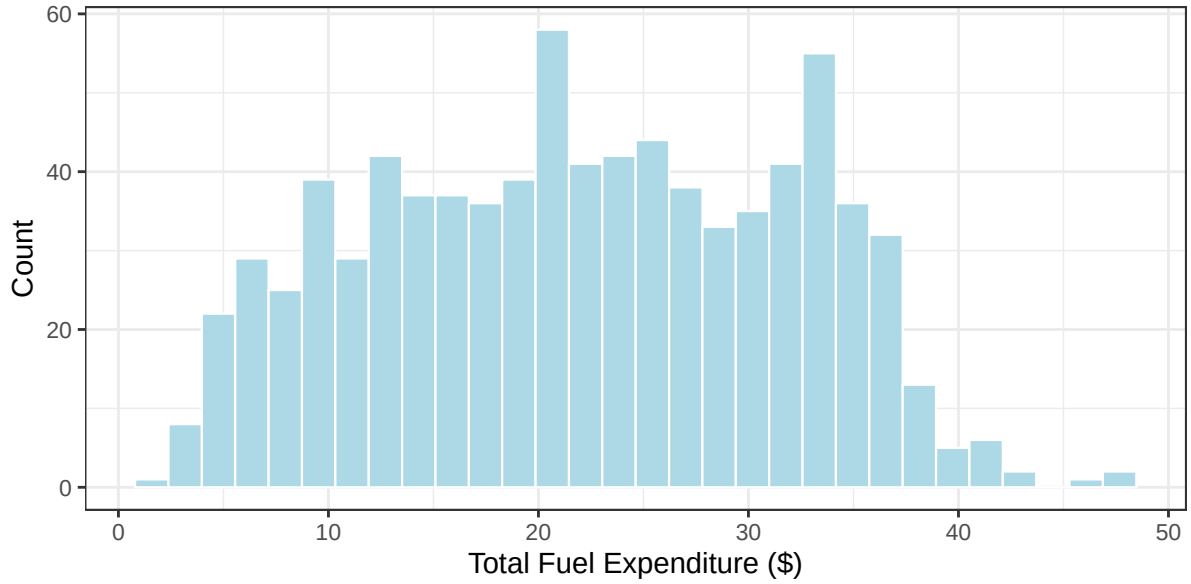
$$Z^p_{ikt} \subseteq Z_{ikt} \text{ and } Z^q_{ikt} \subseteq Z_{ikt} \text{ such that } Z^p_{ikt} \neq Z^q_{ikt},$$
$$\text{and } \mathbb{E}_i[p_{ikt}|Z^p_{ikt}] = \mathbb{E}_i[p_{ikt}|Z_{ikt}], \text{ and } \mathbb{E}_i[q_{ikt}|Z^q_{ikt}] = \mathbb{E}_i[q_{ikt}|Z_{ikt}].$$

Assumption 2 is an exclusion restriction: it must be the case that there are some variables that are associated with the expected purchase quantity or the expected purchase price, but not both. In addition, the assumption implies that drivers' expectations of purchase prices are only based on the information in Z^p_{ikt} and not the other information in Z_{ikt}, and their expectations of purchase price are based only on the information in Z^q_{ikt} and not other information in Z_{ikt}.

In theory, we could allow, for instance, for Z^p to be a proper subset of Z^q so that all variables in Z^p are included in Z^q. However, we found that there was not sufficient variation in the data to precisely estimate the model parameters under this formulation. Therefore, we specify Z^p_{ikt} and Z^q_{ikt} as completely distinct sets of variables. Specifically, we specify that stations' current prices and stations' long-run average prices affect the price the driver expects to pay but not the quantity of fuel that the driver expects to purchase, conditional on Z^q_{ikt}. Here we are again relying on the evidence in Table A.4 that prices do not significantly affect expected purchase quantities conditional on the driver's tank level, the station's brand, ExcessTime_{ikt}, and the month-year fixed effects. Relatedly, we assume that the driver's tank level, the station's brand, ExcessTime_{ikt}, and the month-year fixed effects are not affecting the price the driver expects to pay, conditional on the station's long-run average price and the station's current station price.

Another concern might be that drivers' expectations about their purchase quantity could be correlated with the actual price at the station if drivers budget a fixed dollar amount for gasoline (*e.g.* \$20). In this case, the expected purchase quantity would be mechanically related to the realized price at the station where the driver chooses to refuel in violation of Assumptions 1 and 2. To provide evidence that this type of budgeting is not an important determinant

Figure C.1: Distribution of Total Fuel Expenditure



Notes: The graphic shows a histogram of total fuel expenditure in dollars across all refueling stops in our sample. Total expenditure is calculated as the current price (in $ per gallon) at the driver's selected station multiplied by the implied purchase quantity (gallons) for the trip. Our procedure for recovering purchase quantities is described in the appendix.

of purchase quantities, Figure C.1 plots a histogram of the implied fuel expenditure across all refueling stops and shows that there is only weak evidence of a discrete jump in expenditure at any specific dollar amount.[46]

Assumption 2 allows us to rewrite Equation (C.7) as:

$$U_{ikt} = \alpha \mathbb{E}_i[p_{ikt}|Z^p_{ikt}] \cdot \mathbb{E}_i[q_{ikt}|Z^q_{ikt}] + \gamma \text{Excess Time}_{ikt} + X_k'\beta + \varepsilon_{ikt}. \tag{C.8}$$

This equation illustrates how our estimation approach, where we estimate $\mathbb{E}_i[q_{ikt}|Z^q_{ikt}] = (Z^q_{ikt})'\phi$ in a first-stage, builds off of Assumptions 1 and 2.

The last step to identify α is to make the standard identification assumption that the expected expenditures conditional on Z^p_{ikt} and Z^q_{ikt} are not correlated with the unobservable quality of the station. We formalize the final identification assumption as follows:

Assumption 3 *The unobservable match quality shocks, ε_{ikt} are independent of the expected purchase quantity and price and the shocks to purchase quantity and price, conditional on the observable characteristics X_k, and W_{it}*

$$\mathbb{E}_i[p_{ikt}|Z^p_{ikt}], \eta^p_{ikt} \perp\!\!\!\perp \varepsilon_{ikt}|X_k, W_{it} \quad \forall i$$
$$\textit{and} \quad \mathbb{E}_i[q_{ikt}|Z^p_{ikt}], \eta^q_{ikt} \perp\!\!\!\perp \varepsilon_{ikt}|X_k, W_{it} \quad \forall i.$$

[46] There is a small increase in the likelihood of expenditure around $20, but this increase would imply that only very small percentage of refueling stops are affected by this type of budgeting. There are also similarly-sized increases in expenditures at other, non-round expenditures.

There are two potential concerns with this assumption. The first is that stations with high unobservable quality, ε_{ikt}, also have higher prices. This is the most common identification issue in many discrete logit settings (e.g. Berry et al., 1995). Our inclusion of station brand fixed effects in utility helps increase the plausibility of this assumption. However, it is still possible that this specification does not fully control for variation in station quality within a given brand. In theory we could include station fixed effects to control for station-level quality, but we do not have enough drivers or trips in practice to identify these station fixed effects. Table C.1 provides further evidence in support of this assumption by showing that our results are remarkably robust to controlling for characteristics of the neighborhood where each station is located, including census tract median income and population density.

The second concern is that anything that increases the driver's expected expenditure, $\mathbb{E}_i[p_{ikt}|Z^p_{ikt}] \cdot \mathbb{E}_i[q_{ikt}|Z^q_{ikt}]$ via the expected purchase quantity, $\mathbb{E}_i[q_{ikt}|Z_{ikt}]$, will also likely increase the driver's utility of stopping on this trip by increasing the amount of fuel that the driver will have in the tank after the stop.[47] For example, when a driver's tank level is close to empty, their expected purchase quantity is likely to be high which will tend to increase utility. On the other hand, expected expenditure will also be higher which will tend to decrease utility. To help alleviate this concern, we include every variable in Z^q_{ikt} as controls in the utility function (in either X_k or W_{it}) so that they are not captured by the ε_{ikt}'s. Assumption 3 further rules out, for instance, that a driver will form particularly high expectations of purchase quantity (and therefore expected expenditure) at a station that they prefer, thereby biasing the estimate of α.

Finally, our model imposes an implicit assumption that drivers are not engaging in a sequential search for gas stations. This assumption is supported by the fact that gas prices that drivers observed recently are uncorrelated with the decision to stop to refuel, conditional on tank level. A sequential model of search would have drivers stopping more often if they have recently seen prices that are above the current price (De los Santos et al., 2012; Diamond, 1971).

C.2 Estimation

We estimate the utility model using the two-step estimator discussed in the main text. We estimate the first step regression of purchase quantities on Z^q_{ikt} via ordinary least squares. We then insert the estimated coefficients, $\widehat{\phi}$ in a nested logit quasi likelihood function that we estimate in a second step. Note that there are only two nests in our model, one for all stations, and a second for the choice not to stop at a station on this trip. We label the nesting parameter for the station nest λ_k and the nesting parameter for the choice not to stop is λ_0, which we

[47] In particular, $\mathbb{E}_i[q_{ikt}|Z_{ikt}]$ may be correlated with the value of not stopping, $U_{i0t} = W'_{it}\delta + \varepsilon_{i0t}$.

Table C.1: Driver Preference Estimates - Station Neighborhood Controls

	(1)	(2)	(3)	(4)
Value of Not Stopping				
1[No Stop] × Constant	-12.472	-12.646	-14.673	-15.393
	(1.625)	(1.635)	(1.881)	(1.961)
1[No Stop] × Tank Level	1.325	1.347	1.388	1.42
	(0.090)	(0.091)	(0.096)	(0.099)
1[No Stop] × (Tank Level)^2	-0.008	-0.007	-0.007	-0.009
	(0.006)	(0.006)	(0.006)	(0.006)
Station Choice				
α - Expected Expenditure ($)	-0.511	-0.542	-0.569	-0.583
	(0.062)	(0.065)	(0.070)	(0.071)
θ - Weight on Current Price	0.313	0.312	0.285	0.286
	(0.076)	(0.072)	(0.072)	(0.070)
γ - Excess Time (minutes)	-0.168	-0.171	-0.197	-0.191
	(0.018)	(0.018)	(0.018)	(0.018)
Station Census Tract Median Income ($)		0.096		-0.052
		(0.014)		(0.015)
Station Census Tract Population Density (Pop/Mile^2)			-0.473	-0.505
			(0.054)	(0.058)
Nesting Parameter				
λ	0.557	0.569	0.627	0.627
	(0.041)	(0.041)	(0.044)	(0.044)
Choice Set	Passed	Passed	Passed	Passed
Station Brand Fixed Effects	Y	Y	Y	Y
Month-Year Fixed Effects	Y	Y	Y	Y
Number of Stops	771	771	771	771
Number of Trips	19588	19588	19588	19588
Observations	834208	834208	834208	834208
McFadden R^2	0.285	0.286	0.287	0.288
	Implied Value of Time ($/hour)			
	19.73	18.96	20.82	19.71
	(3.45)	(3.19)	(3.43)	(3.28)

Notes: Table reports pseudo maximum likelihood estimates of driver preferences. The expected purchase quantities are predicted from the regressions in Table 4. Each column shows how estimates change if we add controls for the characteristics for the station's neighborhood. In particular, we add controls for the median household income ($10,000s) and population density (100 inhabitants per square mile) of each station's Census tract according to data from the 2010 American Community Survey. Coefficient standard errors are reported in parentheses. The implied value of time is calculated as $60 \cdot \frac{\gamma}{\alpha}$ and standard errors are reported in parentheses.

normalize to one. The quasi log-likelihood function is therefore:

$$\mathcal{QLL} = \sum_{i=1}^{N}\sum_{t=1}^{T}\sum_{k=0}^{K} \log\left(\frac{\exp(V_{ikt}(\widehat{\phi})/\lambda_k)(\sum_{j\in B_k}\exp(V_{ijt}(\widehat{\phi})/\lambda_k))^{\lambda_k-1}}{1+(\sum_{j=1}^{K}\exp(V_{ijt}(\widehat{\phi})/\lambda_k))^{\lambda_k}}\right)\mathbb{1}\{i \text{ chose } k \text{ on } t\} \tag{C.9}$$

where B_k refers to the nest for choice k, $V_{i0t} = W_{it}'\delta$ for the choice not to stop, and

$$V_{ikt}(\widehat{\phi}) = \alpha\big(\theta p_{ikt} + (1-\theta)\overline{p}_k\big)\cdot\big((Z_{ikt}^q)'\widehat{\phi}\big) + \gamma\text{ExcessTime}_{ikt} + X_k'\beta$$

for the choice to stop at each station $k = 1, \ldots, K$.

C.3 Value of Information

In Section 4.3, we measure the welfare effects of changing drivers' information, assuming consumers make purchase decisions based on imperfect *perceptions* about product attributes, and then ex-post utility depends on *actual* product attributes. Specifically, we compare the welfare difference between these two scenarios, $s \in \{0, 1\}$, where the driver perceives the expenditure to refuel at station j as P_j^{0*} if $s = 0$ and as P_j^{1*} if $s = 1$. We calculate the expected change in consumer surplus for driver i on trip t between scenario 1 and scenario 0 as:

$$\begin{aligned}\Delta CS = &-\frac{1}{\alpha}\left[\ln\Big(1+\Big(\sum_{j\in C^1}\exp(\frac{V_j^{1*}}{\lambda})\Big)^{\lambda}\Big) - \ln\Big(1+\Big(\sum_{k\in C^0}\exp(\frac{V_k^{0*}}{\lambda})\Big)^{\lambda}\Big)\right] \\ &-\Big(\sum_{j\in C^1}\pi_j^{1*}(P_j - P_j^{1*}) - \sum_{k\in C^0}\pi_k^{0*}(P_k - P_k^{0*})\Big),\end{aligned} \tag{C.10}$$

where for scenario s, C^s is the choice set, P_j^{s*} is the perceived price at station j, P_j is the actual price at station j, V_j^{s*} is the perceived utility from choosing j, π_j^{s*} is the probability of choosing station j, and λ is the nesting parameter for the station nest. The actual prices at each station are held fixed across the two choice scenarios. The first line of Equation (C.10) is analogous to the standard formula for a change in consumer surplus for the nested logit model (Small and Rosen, 1981), given drivers' ex-ante *perceived* consumer surplus. The second line adjusts consumer surplus to account for the fact that actual prices paid may differ from consumer perceptions.

D Estimation Heterogeneity and Robustness Analysis

The disaggregate nature of our data allows us to further explore the heterogeneity in preferences across different types of drivers in our sample and across different types of trips. Table D.1 shows the results for specifications that allow the expenditure coefficient, α, the weight on current prices, θ, and the disutility from excess time, γ, to vary by age, gender, and Census tract income. Additionally, we allow for heterogeneity in price sensitivity across the time of trip (weekday versus weekend) and whether the driver's home has a garage.[48]

We find evidence of substantial heterogeneity in expenditure sensitivity across age groups. For ease of interpretation, we report the average marginal effects of belonging to each demographic group on the value of time in Table D.2. We find that a driver being in the oldest age category (age 60-70) is associated with a \$5/hour (25%) reduction in the value of time. This is in keeping with the literature on consumption in other settings (e.g. Aguiar and Hurst, 2005) that suggests that retirees may not change their consumption levels, but may engage in time-intensive approaches to reducing costs such as driving farther for less expensive gas or engaging in time-intensive search. Women's implied value of time is nearly \$6/hour (30%) higher than men's. In addition, we see that drivers from high-income Census tracts have a \$7.35/hour (37%) higher value of time compared to drivers in middle-income Census tracts. Lastly, having a home garage is associated with a \$4.65 increase in the value of time. Overall, the heterogeneity estimates—although sometimes statistically imprecise—are generally in line with demographic patterns in value of time that we would expect.

Having established our baseline and heterogeneity analyses, we also perform a series of robustness checks to support the validity of our value of time estimates. Table D.3 shows that our baseline value of time estimates are not particularly sensitive to removing month-by-year fixed effects and controlling instead for either the daily average price across all stations or the driver's mean purchase quantity in the value of not stopping. Table D.4 further shows that our value of time estimates are not sensitive to alternative assumptions about drivers' choice sets, such as only considering stations near home or that have been passed recently (within 7 or 14 days). Since each of these specifications further reduce the number of stops in the data, we maintain the specification with all stations previously passed in the data as the baseline choice set.

Table D.5 shows the impact of alternative specifications of stations' average prices based on shorter durations rather than the average price over our entire data period. We see that estimates of stations' average price based on shorter periods (week, month, quarter, or half-year) all yield somewhat larger weights on current price and higher implied values of time. This is what we would expect if these measures were only noisy estimates of the true long-run

[48] For the "purchase quantity regressions" we fit a flexible function that interacts both tank level and tank level squared with dummy variables for each of the demographic groups or trip types (*e.g.* weekend). We identify whether a driver's home has a garage by looking at images from an online mapping service near the location where the driver most frequently stops.

Table D.1: Heterogeneous Preferences

	(1)	(2)	(3)	(4)	(5)
Expected Expenditure					
α (Constant)	−0.511	−0.516	−0.533	−0.504	−0.563
	(0.062)	(0.063)	(0.066)	(0.063)	(0.066)
× 1[Age 60-70]	0.065				
	(0.017)				
× 1[Female]		0.015			
		(0.015)			
× 1[Low Income (Q1)]			−0.103		
			(0.020)		
× 1[High Income (Q5)]			−0.045		
			(0.021)		
× 1[Weekend]				−0.024	
				(0.017)	
× 1[Has Home Garage]					0.054
					(0.018)
Weight on Current Price					
θ (Constant)	0.393	0.243	0.207	0.322	0.364
	(0.085)	(0.084)	(0.079)	(0.083)	(0.137)
× 1[Age 60-70]	−0.299				
	(0.129)				
× 1[Female]		0.141			
		(0.125)			
× 1[Low Income (Q1)]			0.394		
			(0.153)		
× 1[High Income (Q5)]			0.097		
			(0.118)		
× 1[Weekend]				−0.031	
				(0.121)	
× 1[Has Home Garage]					−0.069
					(0.137)
Excess Time					
γ (Constant)	−0.179	−0.147	−0.128	−0.169	−0.150
	(0.019)	(0.018)	(0.017)	(0.019)	(0.022)
× 1[Age 60-70]	0.060				
	(0.019)				
× 1[Female]		−0.045			
		(0.020)			
× 1[Low Income (Q1)]			−0.064		
			(0.024)		
× 1[High Income (Q5)]			−0.087		
			(0.028)		
× 1[Weekend]				0.007	
				(0.022)	
× 1[Has Home Garage]					−0.025
					(0.020)
Nesting Parameter					
λ	0.536	0.552	0.552	0.557	0.576
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
Choice Set	Passed	Passed	Passed	Passed	Passed
Station Brand Fixed Effects	Y	Y	Y	Y	Y
Month-Year Fixed Effects	Y	Y	Y	Y	Y
Number of Stops	771	771	771	771	771
Number of Trips	19588	19588	19588	19588	19588
Observations	834208	834208	834208	834208	834208

Notes: Table reports psuedo maximum likelihood estimates of driver preferences. Standard errors are reported in parentheses. The choice set for each specification includes stations that the driver has previously passed before that are within 20 minutes of the route. First stage expected purchase quantity and the value of not stopping regressions both also include demographics.

average price drivers use to form beliefs about station prices. While these alternative models provide a similar fit to the data (similar McFadden R-squared), we chose the baseline specification that would provide the most conservative estimate of the value of time. The differences

Table D.2: Average Marginal Effects on Value of Time ($/Hour)

1[Age 60-70]	1[Female]	1[Low Income (Q1)]	1[High Income (Q5)]	1[Weekend]	1[Has Home Garage]
-5.00	5.91	3.48	7.35	-1.67	4.65
(2.63)	(2.64)	(2.51)	(3.06)	(2.70)	(2.56)

Notes: Table reports the average marginal effect on the value of time. The marginal effects corresponds to the estimates in Column (5) of Table D.1. Delta method standard errors are reported in parentheses.

in the value of time between the quarter, half-year, and full sample average price specifications (which vary from $19.73/hour to $27.65/hour but are not statistically different from each other) do raise the possibility that drivers may be using information that is related to, but not precisely, the long-run average price as we specify it. Overall, we find evidence across robustness checks that drivers are not *only* using the current prices at stations to choose where to stop for fuel, but instead are forming expectations of station prices based on both current and lagged information. Our preferred specification approximates this lagged information with the average price at each station over our full time period, but future work with larger data sets and variation explicitly related to expectation setting may be able to better specify the form of these expectations.

Finally, Table C.1 in Appendix Section C shows that controlling for additional characteristics of the neighborhoods surrounding stations, such as the Census tract median income or population density, does not substantially affect our value of time estimates. This provides reassurance that our price sensitivity estimates are not affected by unobservable station quality attributes such as neighborhood safety.

Table D.3: Driver Preference Estimates - Market Prices and Heterogeneous Quantities

height	(1)	(2)	(3)	(4)
Value of Not Stopping				
1[No Stop] × Constant	−12.256	−16.857	−12.472	0.205
	(1.593)	(2.552)	(1.625)	(0.185)
1[No Stop] × Tank Level	1.229	1.275	1.325	0.439
	(0.086)	(0.089)	(0.090)	(0.062)
1[No Stop] × (Tank Level)^2	−0.012	−0.012	−0.008	0.059
	(0.006)	(0.006)	(0.006)	(0.011)
1[No Stop] × Daily Average Price ($/gallon)		1.439		
		(0.533)		
1[No Stop] × Driver's Mean Purchase (gallons)				−1.147
				(0.146)
Station Choice				
α - Expected Expenditure ($)	−0.471	−0.500	−0.511	−0.455
	(0.058)	(0.061)	(0.062)	(0.056)
θ - Weight on Current Price	0.180	0.385	0.313	0.162
	(0.061)	(0.096)	(0.076)	(0.059)
γ - Excess Time (minutes)	−0.183	−0.173	−0.168	−0.113
	(0.017)	(0.017)	(0.018)	(0.020)
Nesting Parameter				
λ	0.529	0.534	0.557	0.538
	(0.040)	(0.039)	(0.041)	(0.040)
Choice Set	Passed	Passed	Passed	Passed
Station Brand Fixed Effects	Y	Y	Y	Y
Month-Year Fixed Effects	N	N	Y	N
Number of Stops	771	771	771	771
Number of Trips	19588	19588	19588	19588
Observations	834208	834208	834208	834208
McFadden R^2	0.280	0.280	0.285	0.280
	Implied Value of Time ($/hour)			
	23.33	20.76	19.73	14.93
	(3.70)	(3.43)	(3.45)	(3.87)

Notes: Table reports pseudo maximum likelihood estimates of driver preferences. Coefficient standard errors are reported in parentheses. The implied value of time is calculated as $60 \cdot \frac{\gamma}{\alpha}$ and standard errors are reported in parentheses.

E EV Refueling Choice Model and Counterfactuals

This appendix provides additional details on our EV charging simulation. Section E.1 explains the assumptions underlying the simulation in more detail. Section E.2 expands on the implementation of our simulation model. Section E.3 presents the version of our simple theoretical model that allows the social planner to make a discrete choice between Level 2 and Level 3 charging for each station rather than continuously choosing the speed of the charging network.

E.1 Assumptions Underpinning EV Station Choice Simulation

Excess Refueling Time

When making their EV refueling decision, we allow drivers to either (1) drive to the charg-

Table D.4: Driver Preference Estimates - Varying Specification of Driver Choice Sets

	(1)	(2)	(3)	(4)	(5)
Value of Not Stopping					
1[No Stop] × Constant	-12.472	-8.761	-8.445	-12.7	-12.48
	(1.625)	(1.720)	(1.867)	(1.660)	(1.704)
1[No Stop] × Tank Level	1.325	1.485	1.257	1.335	1.333
	(0.090)	(0.144)	(0.116)	(0.092)	(0.094)
1[No Stop] × (Tank Level)^2	-0.008	-0.021	-0.007	-0.008	-0.011
	(0.006)	(0.008)	(0.009)	(0.006)	(0.006)
Station Choice					
α - Expected Expenditure ($)	-0.511	-0.421	-0.407	-0.520	-0.512
	(0.062)	(0.074)	(0.082)	(0.064)	(0.066)
θ - Weight on Current Price	0.313	0.448	0.386	0.305	0.276
	(0.076)	(0.115)	(0.125)	(0.075)	(0.079)
γ - Excess Time (minutes)	-0.168	-0.142	-0.095	-0.153	-0.147
	(0.018)	(0.021)	(0.023)	(0.018)	(0.018)
Nesting Parameter					
λ	0.557	0.440	0.421	0.560	0.572
	(0.041)	(0.049)	(0.054)	(0.042)	(0.043)
Choice Set	Passed Ever	Home $\leq$ 10 mi. & Passed	Home $\leq$ 5 mi. & Passed	Passed $\leq$ 14 days	Passed $\leq$ 7 days
Station Brand Fixed Effects	Y	Y	Y	Y	Y
Month-Year Fixed Effects	Y	Y	Y	Y	Y
Number of Stops	771	475	383	751	718
Number of Trips	19588	14343	11350	19557	19503
Observations	834208	605680	459354	727205	600454
McFadden R^2	0.285	0.301	0.300	0.279	0.271
	Implied Value of Time ($/hour)				
	19.73	20.26	13.98	17.63	17.19
	(3.45)	(4.73)	(5.15)	(3.36)	(3.52)

Notes: Table reports pseudo maximum likelihood estimates of driver preferences. The expected purchase quantities are predicted from the regressions in Table 4. Each column shows results varying our specification of drivers' choice set. Column (1) shows our base specification where all stations that the driver has previously passed that are within 20 minutes of the route are included in the choice set. Columns (2) and (3) also set the choice set to stations that the driver has previously passed that are within 20 minutes, but further restrict the sample to only trips that started within 10 miles and 5 miles of the driver's home, respectively. Columns (4) and (5) restrict the choice sets to only stations within 20 minutes of the route and that the driver has passed within the last 14 days or 7 days, respectively. Coefficient standard errors are reported in parentheses. The implied value of time is calculated as $60 \cdot \frac{\gamma}{\alpha}$ and standard errors are reported in parentheses.

Table D.5: Driver Preference Estimates - Varying Specification of $\overline{P}$

	(1)	(2)	(3)	(4)	(5)	(6)
Value of Not Stopping						
1[No Stop] × Constant	-12.256	-12.472	-6.029	-7.087	-8.795	-8.448
	(1.593)	(1.625)	(0.936)	(1.054)	(1.224)	(1.246)
1[No Stop] × Tank Level	1.229	1.325	1.067	1.118	1.21	1.188
	(0.086)	(0.090)	(0.070)	(0.075)	(0.082)	(0.082)
1[No Stop] × (Tank Level)^2	-0.012	-0.008	-0.012	-0.011	-0.011	-0.011
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Station Choice						
α - Expected Expenditure ($)	-0.471	-0.511	-0.279	-0.329	-0.408	-0.394
	(0.058)	(0.062)	(0.039)	(0.045)	(0.054)	(0.055)
θ - Weight on Current Price	0.180	0.313	0.536	0.555	0.390	0.452
	(0.061)	(0.076)	(0.255)	(0.130)	(0.105)	(0.110)
γ - Excess Time (minutes)	-0.183	-0.168	-0.198	-0.188	-0.177	-0.181
	(0.017)	(0.018)	(0.020)	(0.019)	(0.019)	(0.019)
Nesting Parameter						
λ	0.529	0.557	0.547	0.540	0.541	0.546
	(0.040)	(0.041)	(0.043)	(0.043)	(0.041)	(0.042)
Choice Set	Passed	Passed	Passed	Passed	Passed	Passed
Station Brand Fixed Effects	Y	Y	Y	Y	Y	Y
Month-Year Fixed Effects	N	Y	Y	Y	Y	Y
$\overline{P}$	Full Sample	Full Sample	Week	Month	Quarter	Half-Year
Number of Stops	771	771	771	771	771	771
Number of Trips	19588	19588	19588	19588	19588	19588
Observations	834208	834208	834208	834208	834208	834208
McFadden R^2	0.280	0.285	0.282	0.283	0.283	0.283
	Implied Value of Time ($/hour)					
	23.33	19.73	42.50	34.23	26.03	27.65
	(3.70)	(3.45)	(7.90)	(6.51)	(4.83)	(5.33)

Notes: Table reports pseudo maximum likelihood estimates of driver preferences. The expected purchase quantities are predicted from the regressions in Table 4. Each column shows how estimates change if we specify a different measure of average price ($\overline{P}$) entering the drivers expectations. Column (1) is our base specification that sets $\overline{P}$ as the station's average price over the entire sample, Columns (3-6) set $\overline{P}$ as the mean price at the station over the last week, month, quarter, and half year, respectively, where the moving average window is truncated if the observation is at the beginning of the data period and such that there are not sufficient previous days in the data set. Choice Set = "All" indicates that all stations with 20 minutes of the driver's route are included in the choice set. Choice Set = "Passed" means stations that the driver has previously passed that are within 20 minutes of the route are included in the choice set. Coefficient standard errors are reported in parentheses. The implied value of time is calculated as $60 \cdot \frac{\gamma}{\alpha}$ and standard errors are reported in parentheses.

ing station and wait for their vehicle to recharge or (2) park their vehicle at the charging station and walk to their destination. For each station, we assume that drivers would choose to "walk" or "wait" to minimize the excess time spent refueling.

We define excess time refueling as the additional time that a driver would spend if they choose to refuel on a given trip compared to if they were instead to travel directly from their trip's origin to destination on the optimal route plus the time spent at the destination. We include the time spent at the destination because drivers can recharge their vehicle while they are visiting a destination. For example, a driver that spends many hours at work could park and charge their EV at a station during the work day.

The calculation of excess time refuel time for each EV station on each trip entails several steps:

1. Determine the drivers' refuel quantities conditional on stopping.

    - In our estimation sample, drivers purchase an average of 8.4 gallons which is equivalent to 283 kWh of electricity. Thus, on our baseline counterfactual we assume that drivers would refill their EV with an equivalent amount of "fuel" as we observe the drivers refueling in the gasoline market. However, we also show how the results would change if drivers decided to refill their EV more frequently with smaller quantities.
    - In our main set of counterfactuals, we assume that EV drivers stop for fuel at the same rate as drivers of gasoline vehicles. One interpretation of this assumption is that EVs have the same range as gasoline vehicles, but any interpretation that maintains the relationship between the continuation value (value of not stopping) and the value of stopping at any of the stations would lead to this frequency of stopping. This assumption allows us to better isolate the effects of the charging station network on excess refueling time. However, a limitation is that current EVs may have shorter range than gasoline vehicles, or drivers may feel more uncomfortable with low battery charge than they do with low fuel tank level. Moreover, because EVs refuel at a much slower rate than gasoline vehicles, drivers may choose to refuel EVs more (or less) frequently with smaller (larger) quantities. We run several alternative specifications that vary the assumed frequency and quantities that drivers would refuel their EV. These results are in Table 8.

2. Calculate the technological time required for the driver to refuel.

    - The time required to refill is determined by the assumed speed of the charging technology. For example, a 121 kW charger would take over two hours to charge 283 kWh of electricity.

3. Calculate the excess time associated associated with the driver's two possible refueling options: (1) "wait" and (2) "walk".

- For the "wait" option the total excess refueling time is equal to the sum of the excess driving time to travel to the station plus the technological charging time (from Step 2). The excess drive time is calculated in the same way as we calculate excess travel time for gasoline stations (see Section 2).
- For the "walk" method, excess time is calculated as follows:
  (a) Determine the amount of time that the driver spends at the final destination.
  (b) Calculate the time it would take the driver to walk round-trip from the refueling station to the destination assuming a walking speed of 3 miles per hour.
  (c) Determine how much "additional" waiting time, if any, is needed to complete the charging cycle. Here, we compare the technological refuel time with the sum of the time spent at the destination and the round-trip walking time from the station. If the technological refuel time exceeds the sum, then additional waiting time is added to the total excess refueling time.
    – For instance, suppose a driver requires three hours of technological charging time to achieve the refuel quantity established in Step 1. Further, suppose that the driver spends 2 hours at the destination and it takes 20 minutes to walk to and from the charging station. In this case, 40 minutes of waiting time is added to the total excess time for the "walk" method.
  (d) Calculate the net driving time to drive from the origin to the charging station instead of the origin to the destination.
    – Note that this net driving time could be negative if the station is closer to the origin than the destination.
  (e) The total excess time for the "walk" option is:
  Total Excess Time = Added Walk Time (b) + Added Wait Time (c) + Net Drive Time (d)

4. The excess time for each station on each trip is determined by the option (walk or wait) with the lowest total excess time.

- In our main set of counterfactuals, we assume that drivers always choose the time-minimizing option whenever they decide to wait at a charging station or to park at the station and walk to their destination. In practice, drivers may have explicit preferences for either walking or waiting when recharging their EV. Therefore, we also solve the counterfactuals under two alternative assumptions: (1) drivers prefer to always walk and (2) drivers prefer to always wait. We also present additional results for scenarios in which drivers value waiting time differently than they value walking time. These results are in Table 8.

Example

As an example, suppose a driver is traveling from origin A to destination C and is considering stopping at station B. The driver has two options: (1) they can wait at station B—this option adds five minutes of driving time to visit station B, or (2) they can leave their car at station B and walk to destination C—this option saves two minutes of total driving time but adds 32 minutes of round-trip walking time. The vehicle will take one hour to recharge and the driver plans to spend 20 minutes at destination C. If the driver waits at the station for the vehicle to charge, they will add 65 minutes of excess time to refuel—five minutes of added driving time plus 60 minutes of waiting time. On the other hand, if they choose to park and walk to the destination they would add only 40 minutes of excess refueling time—two fewer minutes of driving time, 32 minutes of added walking time, and 10 minutes of waiting time. Thus, we specify that the excess time associated with recharging at station B is 40 minutes.

Driver Refueling Choice

Once we have computed each driver's excess refueling time for each station, we simulate drivers' refueling choices. In this step of the simulation, we further assume that EV charging stations have homogeneous prices and brand qualities. This assumption allows us to isolate the impact of changes in the density of charging stations and speed of the charging stations on excess refueling time. In practice, we would expect that charging stations with more convenient locations might charge higher prices. If stations with better locations were to charge higher prices that would lead us to underestimate expected EV refueling times. However, given that the EV network is relatively sparse and that drivers have a high value of time, we do not expect that price heterogeneity would lead to substantial changes in station choices.

To carry out the simulations, we also need to ensure that our model predicts enough charging events so that drivers would obtain a sufficient amount of charge to cover the mileage that we observe in the driving data. To achieve this, we start with an initial guess for the intercept in the value of not stopping equation. We then iterate the EV refueling simulations with different levels of the intercept in the value of not stopping equation until we find an intercept value such that the expected number of EV charging events predicted by the model is equal to the total number of gasoline refueling event observed in the driving data. In robustness checks in which we assume the EV refueling frequency differs from the gasoline refueling frequency, we accordingly solve for an intercept in the value-of-not-stopping equation that would predict the desired EV refueling frequency.

E.2 EV Counterfactual Simulations Implementation Details

As discussed in Section 5.2, we use our model of drivers' behavior, combined with a range of different potential EV charging network configurations, to understand the value to drivers of improving network speed relative to density. We calculate the excess refueling time for each EV station located within a 20-minute drive of each trip in our data and use our refueling choice model outlined in Section 3 to predict which charging stations drivers would choose

and the expected time cost associated with those refueling choices. We repeat this simulation for 220 different combinations of EV charging station speed and density, with charger speeds ranging from 15kW to 300kW and for the locations of chargers in each year between 2012 and 2022. We then regress these excess times on a flexible translog functional form of charging network speed and density to understand the expected marginal effect of changing network speed or density on drivers' excess time per stop. This approach mimics the approach in Gowrisankaran et al. (2023) and Butters et al. (2021) where firms form expectations of profits based on a profit surface across model states.

Table E.1: Translog Regression Fit of Excess Refuel Time Surface

	Log(Excess Refuel Time)	
	(1)	(2)
Intercept	6.246***	10.09***
	(0.0783)	(0.1930)
Log(N)	-0.2349***	-0.4840***
	(0.0096)	(0.0493)
Log(S)	-0.2726***	-1.732***
	(0.0103)	(0.0384)
Log^2(S)		0.1615***
		(0.0035)
Log^2(N)		0.0170***
		(0.0036)
Log(N) × Log(S)		0.0070*
		(0.0037)
Observations	220	220
R^2	0.85574	0.98698
Adjusted R^2	0.85441	0.98667

Notes: Table reports regression estimates of excess refueling time (per stop) on the number of stations (N) and the charger speed of the network. We use 99 different combinations of stations (N) and kW charger speed (S) to fit the regressions. Our preferred specification, Column (2), is used to evaluate the elasticity of excess refueling time with respect to changes in the number of stations (N) and changes to the charging speed (S) of the network.

Table E.1 presents the results of this regression both with and without higher order interactions of network speed (S) and density (N). We see that including squared terms and interactions improves the model fit substantially, with an R^2 of 0.987 in our preferred specification (Column (2)). In both models, increasing speed or density will decrease excess time, and the squared terms and interaction are all positive in Column (2). We use derivatives based on this regression to understand the elasticity of excess time with respect to network speed and density.

E.3 Model of Public Charging Investment - Discrete

This appendix recasts the social planner's problem in Section 5.2 as a discrete choice between faster, more expensive chargers and slower, cheaper chargers. This setting more precisely replicates a planner choosing between installing Level 2 and Level 3 chargers.

Consider a planner that chooses a charging network design to minimize drivers' time costs subject to a budget constraint. The planner can invest in two types of charging technologies—fast chargers (e.g., direct-current chargers) and standard chargers (e.g., alternating-current chargers). The two technologies differ in their power capacity (kW), which determines the recharging rate and the time required to recharge an EV's battery. The power capacity of a fast charger is ρ_F, whereas the power capacity of a standard charger is ρ_S. As such, the planner chooses the number of stations to build, N, and the share of stations that are fast chargers, $S_F \in [0, 1]$. The share of fast chargers implicitly defines the average charging rate (i.e., speed) of the network, $\overline{R}$. Drivers' refueling time, τ, is a decreasing function of both the N and S_F. However, increasing either N or S_F will raise the capital cost of the network. For simplicity, we abstract away from modeling the exact locations of the charging stations and begin by assuming that each additional fast charger and standard charger would be evenly distributed spatially throughout the network. Thus, the planner's investment problem can be written formally as follows:

$$\begin{aligned} \min_{N, S_F} \quad & \tau(N, S_F) \\ \text{s.t.} \quad & \kappa \cdot N \cdot \overline{R} \leq B, \\ & 0 \leq S_F \leq 1, \\ & \overline{R} = S_F \cdot \rho_F + (1 - S_F)\rho_S \end{aligned} \tag{E.1}$$

Here, the first constraint imposes that the total capital cost of the network ($\kappa \cdot N \cdot \overline{R}$) must be weakly less than the budget available to the planner to spend on charging infrastructure, B. The functional form for capital costs is motivated by Nicholas (2019), whose estimates show that capital costs are roughly proportional to the total power capacity ($N \cdot \overline{R}$) of the network. For example, installing four 20 kW standard chargers would cost approximately the same as installing one 80 kW fast charger. Therefore, the κ parameter represents the fixed cost of increasing the power capacity of the network. The second constraint imposes that the share of fast chargers is bounded between zero and one. Finally, the third constraint defines the relationship between the share of fast chargers, S_F, and the average charge speed of the network, $\overline{R}$, which determines the capital cost of the network.

To clarify the exposition of the optimal solution, we recast the planner's problem as a choice of the number of stations, N, and the average charge speed, $\overline{R}$, noting that there is a one-to-one mapping between $\overline{R}$ and S_F, as shown in the last line of E.1. The refueling time function is monotonically decreasing in both arguments, so the planner would choose to use the entire budget. Thus, the following Lagrangian characterizes the solution to the planner's

problem:

$$\begin{aligned}\mathcal{L}(N, \overline{R}, \lambda, \mu_1, \mu_2) = \tau(N, \overline{R}) + \lambda_1(\kappa \cdot N \cdot \overline{R} - B) \\ +\mu_1 \cdot (\tfrac{\overline{R}-\rho_s}{\rho_F-\rho_s}) + \mu_2(\tfrac{\overline{R}-\rho_s}{\rho_F-\rho_s} - 1).\end{aligned} \tag{E.2}$$

Above, λ represents the shadow cost of relaxing the budget constraint, and μ_1 and μ_2 represent the Lagrangian multiplier associated with the constraints that the share of fast chargers ($S_F = \frac{\overline{R}-\rho_s}{\rho_F-\rho_s}$) must be weakly greater than zero and weakly less than one.

Broadly, the solution to the planner's problem can be separated into three possible cases: (1) an interior solution in which the optimal share of fast chargers lies between zero and one, (2) a corner solution in which the optimal share of fast chargers equals zero, and (3) a corner solution in which the optimal share of fast chargers equals one. Below, we derive the Karush–Kuhn–Tucker (KKT) conditions for an optimal solution to the problem.

Case 1: Interior solution

The KKT conditions for an interior solution where the share of fast chargers ($S_F = \frac{\overline{R}-\rho_s}{\rho_F-\rho_s}$) lies between zero and one are as follows:

$$\frac{\partial \tau}{\partial \overline{R}} = \lambda \cdot \kappa \cdot N, \tag{E.3}$$

$$\frac{\partial \tau}{\partial N} = \lambda \cdot \kappa \cdot \overline{R}, \tag{E.4}$$

$$\kappa \cdot N \cdot \overline{R} = B. \tag{E.5}$$

Rearranging the first two conditions we can derive the following simple optimality condition:

$$\tfrac{\partial \tau}{\partial N} \cdot \tfrac{N}{\tau} = \tfrac{\partial \tau}{\partial \overline{R}} \cdot \tfrac{\overline{R}}{\tau} \quad \Rightarrow \quad \varepsilon_N = \varepsilon_{\overline{R}}. \tag{E.6}$$

Intuitively, the most efficient charging network for a given level of spending must satisfy the condition that the elasticity of time savings from adding additional stations ε_N should be equal to the elasticity of time-saving from increasing the charging speed of the network $\varepsilon_{\overline{R}}$.

Case 2: Corner solution with no fast chargers

The KKT condition for the case where no fast chargers are built is shown below.

$$\varepsilon_N > \varepsilon_{\overline{R}} \tag{E.7}$$

$$\kappa \cdot N \cdot \overline{R} = B \tag{E.8}$$

In order for it to be optimal to build only standard chargers and build no fast chargers, condition E.7 states that the elasticity of time-savings from increasing the number of stations must be strictly greater than the elasticity of time-savings from increasing the average speed of the network.

Case 3: Corner solution with all fast chargers

The KKT condition for the case where only fast chargers are built are as follows:

$$\varepsilon_N < \varepsilon_{\overline{R}}, \tag{E.9}$$

$$\kappa \cdot N \cdot \overline{R} = B. \tag{E.10}$$

Analogous to Case 2, it is optimal to spend the entire budget on fast chargers if the elasticity of time-savings from increasing the number of stations must be strictly less than the elasticity of time-savings from increasing the average speed of the network.

Discrete Model Implementation

When implementing the simulation where the social planner chooses a share of charging stations to be Level 3 rather than Level 2, the largest difference from our baseline simulation with continuous charging network speed choice is that we need to take a stand on *which* stations would be Level 3 rather than Level 2 if the social planner chooses an interior solution. To do this, we train a machine learning model of Level 3 charging using data on the characteristics of charger locations for chargers in Michigan and Ohio and 8 nearby states: Illinois, Indiana, Kentucky, Minnesota, New York, Pennsylvania, West Virginia, and Wisconsin. These characteristics included: (i) housing and demographic characteristics at a census tract level (U.S. Census Bureau, 2012), (ii) the straight-line distance from the EV charger to the nearest primary road in 2010 (U.S. Census Bureau, 2010a) and 2021 (U.S. Census Bureau, 2021), and (iii) the number of businesses by primary NAICS code in the census block and census tract of the charger (Data Axle, 2010; U.S. Census Bureau, 2010b). We use logistic lasso and importance sampled learning ensemble (ISLE) as suggested in Hara et al. (2021) for prediction tasks for tabular data. We follow the hyperparameter tuning and model evaluation in Hara et al. (2021). Training and test sets are divided randomly by station-level (training, 75%; test, 25%). The best algorithm is the ISLE with subsampling ratio 0.5 and learning rate 0.1 when evaluated by the area under the receiver operating characteristic curve (AUC, 0.802). The ISLE with subsampling ratio 0.5 and learning rate 0.1 is also known as a standard hyperparameter specification for stochastic gradient boosting machine (Friedman, 2002). We then applied the best algorithm to predict Level 3 charger installation probabilities for each EV charging station in Michigan and Ohio. We also calculate Shapley Additive explanation (SHAP, Lundberg

and Lee, 2017) values ease interpretability of the model.

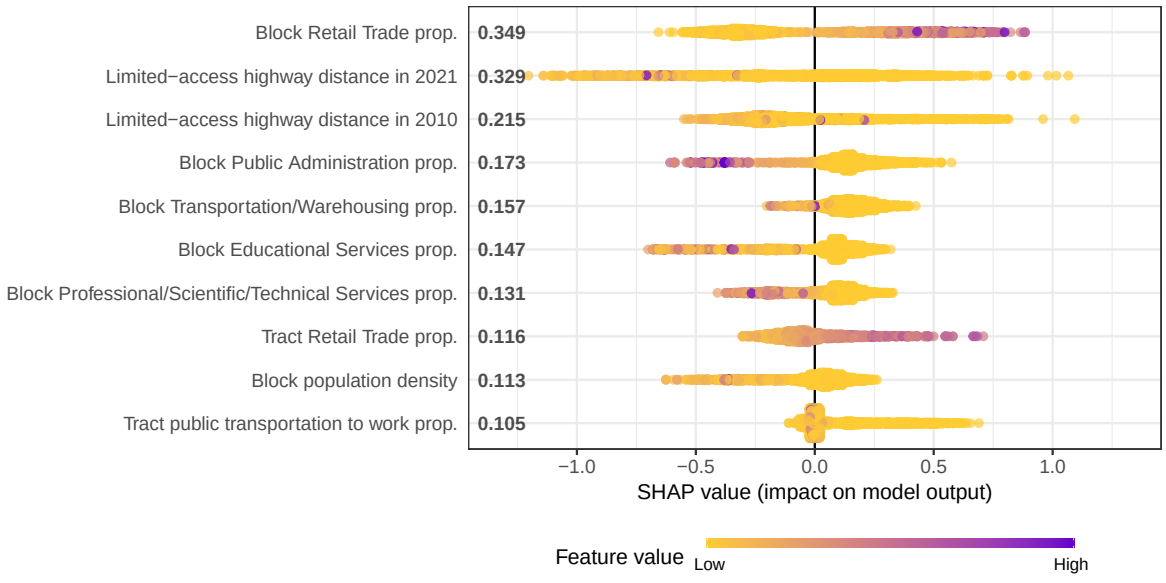
After predicting the probability of each charger in Michigan and Ohio being Level 3, we order chargers by this predicted probability and then assume that the social planner will make chargers Level 3 in this order (from highest probability to lowest probability). Thus, if the social planner chooses 25% of charging stations to be Level 3, then the 25% of stations with the highest probability of being Level 3 as predicted in our model will be Level 3 and the remainder will be Level 2.

Given this ordering of stations, we assume that Level 3 chargers charge at 80 kW and Level 2 chargers charge at 10 kW,[49] and then conduct robustness checks with faster Level 3 charging speeds. We proceed with solving the social planner's optimization in the same way that we did with the continuous choice case: We solve for drivers' excess time given a grid of 121 potential combinations of Level 3 charger share $\{0, 0.1, 0.2...1\}$ and station density (year 2012-2022). We then fit a flexible functional form through these excess time estimations to predict the excess time for any potential combination of Level 3 share and station density.

Discrete Model Results

We present some illustrative results of our machine learning model before turning to the social planner's solution to the discrete optimization problem.

Figure E.1: Impact of Local Characteristics on Level 3 Chargers



Notes: The figure shows the SHAP values for the ten most important variables for explaining whether a given charger is Level 3 rather than Level 2 in Minnesota, Wisconsin, Illinois, Indiana, Kentucky, West Virginia, New York, and Pennsylvania. We plot low feature values plotted in yellow and high feature values plotted in purple.

[49] The U.S. Department of Transportation defines Level 2 chargers as being 7-19 kW and Level 3 chargers as being 50-350 kW (https://www.transportation.gov/rural/ev/toolkit/ev-basics/charging-speeds).

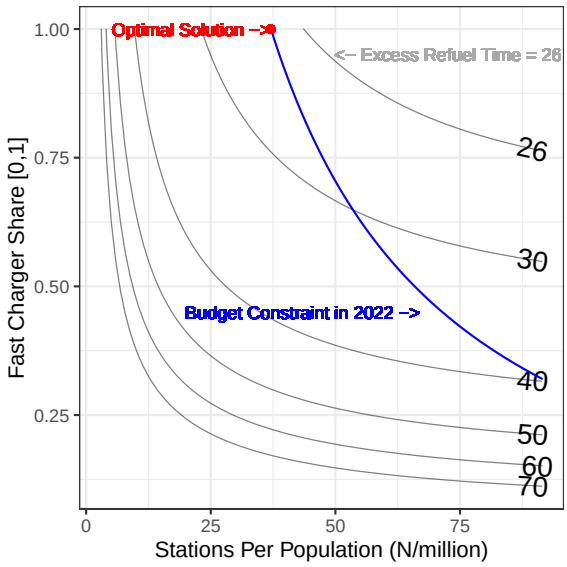
Figure E.1 displays the ten most important variables in explaining whether a given charger is Level 3 rather than Level 2. For the top variable, Census block retail trade proportion, we see the yellow dots concentrated below 0 SHAP value and the purple dots concentrated above 0. This means that if the EV charging station's Census block retail trade proportion is high, the predicted probability of having Level 3 EV chargers increases. On the flip side, it also means that if the EV charging station's Census block retail trade proportion is low, the predicted probability of having Level 3 EV chargers decreases. In contrast, for the bottom variable, the proportion of people who uses public transportation to work in the Census tract, we see the yellow dots concentrated above 0 SHAP value but not many dots below 0. This means that if the EV charging station's Census tract public transportation to work proportion is high, the predicted probability of having Level 3 EV chargers is lower, all else equal. However, the flip side is not true in this case. The predicted probability of having Level 3 EV chargers does not increase when the EV charging station's Census tract public transportation to work proportion is low. The indices on the left are the average absolute values of these SHAP values, which is called global impact in (Lundberg et al., 2018). So, for example, if we average over the absolute values of the plotted dots for the top variable, Census block retail trade proportion, we get 0.349. We include the ten variables with the highest global impact in the order of their global impact in the figure.

Figure E.2 presents information analogous to Figure A.7 in the text, showing the excess time contour lines in grey and the social planner's budget constraint in blue for the discrete social planner's problem in 2022. Panel E.2a shows the solution to the problem if the Level 3 charger technology is assumed to be 80 kW. We see that the excess time-minimizing solution is a corner solution to allocate 100% of charging stations as Level 3.

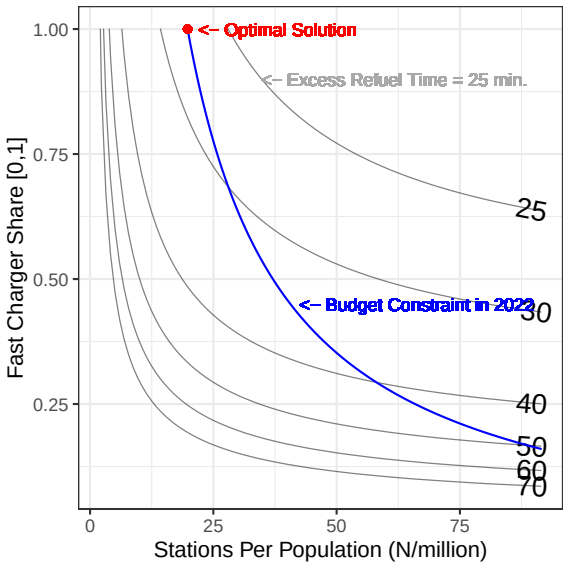
Figure E.2b and E.2c show that this result–that the social planner would choose to make 100% of stations Level 3–holds across a variety of potential charging speeds for Level 3 chargers. In fact, we found that the social planner would only allocate less than 100% of chargers to Level 3 if we assume that Level 2 chargers are faster than the SAE maximum charge rate for Level 2 chargers of 20 kW.

We take this as substantial support for the baseline result in the paper that investments in charging station speed substantially outperform investments in charging station density in terms of reducing EV drivers' excess time spent refueling. Because these results always find the corner solution–that the social planner would invest 100% of their budget in Level 3 charging–we focus our primary analysis in the main text on the social planner's continuous choice over charging station speed rather than the discrete choice between Level 2 and Level 3 charging.

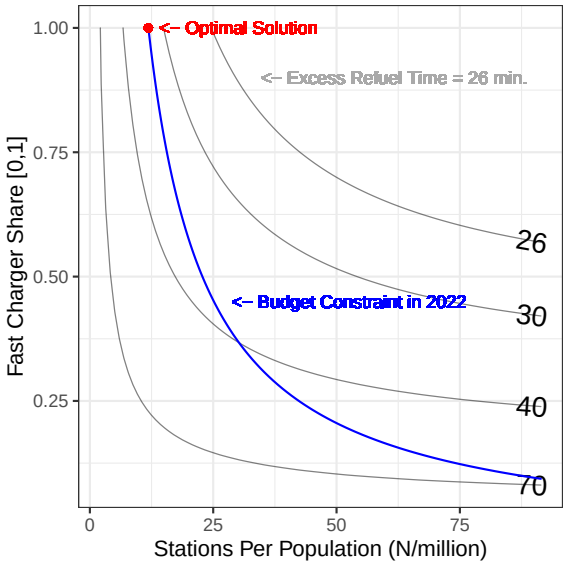
Figure E.2: Discrete Charger Model Solutions in 2022



(a) Level 2 = 10 kW, Level 3 = 80 kW



(b) Level 2 = 10 kW, Level 3 = 150 kW



(c) Level 2 = 10 kW, Level 3 = 250kW

Notes: The thin grey lines show contours representing the estimated excess refueling time per EV refueling stop across different counterfactual combinations of station density (number of stations) and the share of fast chargers. For these simulations we assume the Level 3 fast chargers have a rate of either 80 kW (a), 150 kW (b), or 250 kW (c). We assume that Level 2 chargers would charge at a rate of 10 kW.

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