Effects on housing market of expanding electric vehicle charging stations in California

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Abstract: Vehicle electrification is critical to enabling countries to develop more sustainably. Wider electric vehicles (EVs) adoption relies on the deployment of EV charging stations (EVCSs). However, the local benefits associated with offering more charging opportunities to nearby residents remain unexplored. Here, we provide empirical evidence about the impacts of proximate EVCSs on housing prices in California. We apply a hedonic property value approach using the EVCS data combined with about 14 million housing transaction records during 1993-2021. Our results show that access to charging infrastructure can be capitalized into property values. The average price premium for houses with EVCSs within 1 km is about 3.3% (or $17,212) compared to homes without proximate EVCSs. The largest effect is a 5.8% increase for houses with EVCSs within 0.4-0.5 km compared to houses without proximate EVCSs. We find different results across neighborhoods with diverse socio-demographic characteristics. Proximity to EVCSs increases traffic flows by 0.3-0.5% and lowers PM2.5 emissions level by 1.3-2.2%. The increased property value after EVCS installation can incentivize the private real estate sector to expand the availability of charging services. More information on the housing price premium should be provided to facilitate the deployment of this sustainable infrastructure.

Introduction

Electrification of fossil fuel vehicles holds great potential to address social externalities such as emission reduction, mitigation of climate change, and energy security[1,2]. Since the transportation sector contributes to approximately 30% of the greenhouse gas emissions in the United States, transportation electrification plays an essential role in achieving a Net-Zero society[3]. However, vehicle electrification relies on the deployment of energy infrastructure, which is critical to overcoming the barriers to the wider adoption of light-duty electric vehicles (EVs)[3–5]. Investments in sustainable charging infrastructure have expanded rapidly in recent years in the United States. The Infrastructure Investment and Jobs Act was passed on Nov 15, 2021, with $7.5 billion to be invested in establishing a nationwide network of chargers, which would boost the development of clean transportation infrastructure.

Although existing EVs are mostly charged at home[6,7], public charging infrastructure is an essential part of the EV charging network. Here, we denote "public charging" as the charging infrastructure accessible to the public at all places besides home, (e.g., workplace, commercial buildings, utilities, and government buildings). There are typically three levels of public chargers, namely, level 1, level 2, and DC fast chargers. Many of the public charging infrastructures are commercial and drivers could pay by the hour (or kWh), or by subscription. Free chargers are sometimes also available at places such as shopping malls and hotels to their consumers.

Although we expect the potential prosperity of charging infrastructure, the benefits and costs of public EV charging infrastructure remain unexplored and debatable, which is important for policymaking on the future deployment of such infrastructure. On one hand, public chargers offer more charging opportunities for drivers without off-street parking and for longer travels. Public charging serves as a substitute for home-charging, potentially generating a positive amenity to nearby neighbors[8–10]. Public chargers help drivers replenish the depleted power[8,11], relieving the drivers' range anxiety (i.e., concerns about insufficient electricity to reach their destinations). Public chargers can potentially increase the share of EVs in the nearby road traffic and thus improve local air quality.

On the other hand, while some drivers hold generally positive attitudes toward public charging and support public investments in charging infrastructure, past studies have shown that many are unlikely to pay for public charging infrastructure[12–14]. Yet, no systematic research has been done on public perception toward public EV charging stations[14]. Additionally, negative repercussions from charging infrastructure could be influential, such as overloading of district distributional system, increased electric shocks, and risks of fires[11,15,16]. Some wireless chargers are even associated with hazardous exposure to magnetic fields[17]. Besides, charging stations can potentially attract more EV drivers, thus generating extra traffic. Therefore, it is important that we examine the public acceptance of charging infrastructure so that we can efficiently scale up the charging infrastructure in the future.

This study applies a reduced-form hedonic property value approach (Supplementary Note 1) where access to nearby EV charging infrastructure is capitalized into property values. By investigating the house prices paid by homebuyers, the hedonic approach measures the value of nonmarketed services/features. This hedonic approach has also been employed by burgeoning literature to evaluate transportation facilities or energy infrastructure. An overview of the literature implies that their effects can be simply categorized into positive effects, negative effects, or mixed effects. A positive price premium is reported for houses in the surrounding areas of transportation stations such as urban rail stations because of increased accessibility[18,19]. On the other hand, negative effects are observed for polluting energy infrastructure such as gas stations, which are found to decrease nearby housing values by 10%[20]. Similarly, fossil fuel development and gas leaks are shown to impose negative impacts on nearby houses and reduce house prices [21,22]. Moreover, a growing body of literature has also investigated the effects on housing market of renewable energy infrastructure[23–25], and they indicate a negative proximity effect given the negative externalities such as noise and visual impacts[23,25]. Importantly, some studies detect both positive accessibility improvement and negative environmental effects, for instance, for houses close to transport infrastructure[26,27]. Yet, no studies have specifically focused on the sustainable energy infrastructure of EV charging stations. This study fills this research gap by evaluating public charging infrastructure. By showing charging stations' effects on the housing market, it provides supporting evidence for future investments and helps to justify the spending on sustainable infrastructure.

Our paper provides empirical evidence on house sales price premiums induced by public EV charging stations (EVCSs) in California. We choose California to focus on because it is in the vanguard among all states in the US and also has the most developed public charging network. California has set the most aggressive goals in decarbonization of transportation compared to other states and pledged to end sales of new gasoline-fueled vehicles by 2035. Fig. 1 plots the spatial distribution of EVCSs at the zip-code zone level in California. Public charging stations are usually located at places such as hotel parking lots, car dealerships, office buildings, government buildings, and shopping centers (Supplementary Fig. 1). For our analysis, we use 14 million housing transactions records during 1993-2021 and combine that with public EVCS data (over 13,000 in California). We employ a hedonic DID (difference-in-differences) model under a quasi-experimental design. We find that EV charging stations have increased the house sales price and the largest sales price premium is 5.8% for houses that have proximate EVCSs within 0.4-0.5 km. This price premium implies that local residents perceive nearby public charging infrastructure positively. This positive spillover effects on the housing market can stimulate future investments in EVCSs from private real estate entrepreneurs.

Results

Varying price premium by distances

This study applies the two-way fixed effects model (or a generalized DID model). We exploit the temporal and cross-sectional variations in repeat sales data (i.e., houses sold at least twice, once before the treatment and once after the treatment, during our study period) to provide causal inference. The treatment group consists of houses with proximate EVCSs within 1 km while the control group includes those without proximate EVCSs. We use ten distance bins from 0 to 1 km with a 0.1 km increment. Our choices of the distance bins follow prior studies on transportation and renewable energy infrastructure[3,28], where they find most of the effects are limited to 1 km (Supplementary Note 2). During the DID analysis, we control for the unobserved building-specific, area-specific, and time-specific confounders (e.g., building square footage, housing market variation, and land costs). Details of the DID model can be found in the Methods section.

We find that proximity of EVCSs has increased house sales prices and the magnitudes of price premium vary across different distance bins (Fig. 2). Panel (a) plots the price premium based on the analysis that controls for building, year, and month-of-year fixed effects while panel (b) corresponds to the analysis controlling for the building, month-of-year, and county-by-year fixed effects. Panel (a) indicates a price premium of up to 8.2%, however; panel (b) shows on average, the price premium is 3.3% when the county-by-year fixed effects are included. Generally, the estimated price premiums in panel (b) become slightly smaller in magnitude than in panel (a). The largest price premium is 5.8% for houses located about 0.4-0.5 km from the charging stations (panel b). Our results suggest that households do value the proximity of charging infrastructure positively, which is captured as the price premiums. Interestingly, the houses closest to the EVCSs (with 200 meters) do not exhibit a price increase. This may be associated with concerns about magnetic radiation, noise, and other nuisance effects. This is in line with other studies that show negative impacts are more pronounced for houses closer to the transportation infrastructure and thus may cancel out the positive benefits brought by the stations[26,29]. The summary statistics of the variables in the analysis are presented in Supplementary Table 1. The detailed regression coefficients from the analysis are displayed in columns 1-2 in Supplementary Table 2 and the results including county-level covariates are listed in column 5.

The analysis based on the event study model is used to verify the parrel trend assumption. During the analysis, we obtain the coefficients before (leads) and after (lags) the installation of EVCSs at the zip-code zone level (Supplementary Fig. 2). We find that before the EVCS installation, the effects of EVCSs are not statistically different from zero, which confirms the parallel trend assumption between control and treated houses. After the installation, EVCSs start to show a positive impact although the magnitude fluctuates. This fluctuation is likely related to the uncontrolled seasonality of transactions. Further tests of assumptions are presented in Supplementary Note 3, and they help to verify the treatment effect homogeneity assumption and parallel trend assumption, indicating a high probability of passing the pre-test condition and low contamination from other periods.

We adopt an instrumental variable approach as one way to further relieve the concerns on the endogeneity. We use EV adoption as an instrumental variable (IV) for EVCS installation after controlling for household income. The results indicate that EVCS installation can increase house prices at the zip code level by around \$12,181, equivalent to a 1.9% increase from the average prices (Supplementary Table 3). The smaller magnitude observed here could be due to that zip-code level data can hide some variation at individual house levels.

Meanwhile, we additionally match the treated houses (with proximate EVCSs) to control houses (without proximate EVCSs) to check robustness. The control houses have similar characteristics, are in the same county, and are transacted in the same year as the treated houses. Only the matched samples are included in the regression analysis (Supplementary Fig. 3). During the matching procedure, the sample size decreases as some treated houses cannot be matched with untreated ones, or some fail to meet the matching criteria. We estimate the proximity effects within 1 km without differentiating them by distance as the trimmed sample is not sufficiently large. We find an average house sales price premium of 4.1% (Supplementary Table 4), which is close to our former results.

Heterogeneity of price premium

The price premium from charging stations is heterogeneous across socioeconomic characteristics. We examine how price premium varies with respect to several key socioeconomic factors at the county level, including income per capita, race, and environmental awareness. Note that the examination here is not meant to be causal but to explore how price premium is influenced by different socioeconomics. We employ a flexible semiparametric approach for fixed effects panel data[30–32]. This approach has the advantage of estimating heterogeneity by allowing for linearity in some variables and non-linearity in others.

The results (Fig. 3) show that higher-income residents (panel a) are significantly more likely to pay a higher premium for houses near public EVCSs potentially because they are wealthier and could afford a higher price. Counties with slightly higher rates of non-white residents are also more likely to pay a higher premium, *ceteris paribus* (panel b). Interestingly, people in areas with lower EV market shares are willing to pay a higher price (panel c), likely because they value public charging more when EVs are fewer and concomitant infrastructure is still at the early deployment stages. The price premium tends to decrease as the marginal utility from more charging infrastructure also decreases. In addition, people with higher environmental awareness seem to have a higher premium (panel d). However, the price premium seems to decrease when environmental awareness continues to grow. This may be because some people with a very high level of awareness may prefer other more convenient and greener charging technologies such as in-home charging or solar charging[33,34]. Moreover, our heterogeneity analysis also indicates that more dynamic housing markets (e.g., higher house price growth and income growth) are associated with higher price premiums (panels e & f) (More supportive regression analysis in Supplementary Note 4).

Changes in traffic and air quality

We also run additional analyses to explore how air pollution (PM2.5) and traffic flows change after the installation of EVCSs. The analyses on traffic flows and air quality can also assist in explaining some of the estimated impacts on housing prices. We merge our datasets further with data on traffic flows and air pollution, which are collected from monitoring stations near highways in California. Our results show that the installation of charging stations increases the annual traffic by 0.3% and increases the peak month traffic by 0.5% (Table 1). Peak hour traffic does not see an increase probably because charging does not usually happen during daily traffic peak hours. Meanwhile, air quality is slightly improved by 1.3%-2.2%, indicating environmental benefits from sustainable infrastructure in the surrounding areas. Better air quality helps to explain the observed positive proximity effects. However, it is also true that increased traffic flows mean congestion, noise, and other disamenities, but this effect is constrained to houses in the immediate vicinity. They help explain why the houses usually very close to stations (i.e., within 300 meters) are more negatively impacted by increased traffic [29,35] and they enjoy no net price premium. Note that increased traffic and better air quality happen concurrently because more EVs are attracted, which increases traffic flows while not deteriorating air quality.

In addition, we also added the changes in business patterns into our analysis. This analysis does not only use business change as a proxy of traffic, which confirms the former results, but also helps address potential endogeneity issues (changes in businesses lead to new EVCS installation as well as changes in property values). Business patterns here cover various business types including shopping malls, grocery stores, manufacturing, hotels, food, and services. We use business establishments at the zip-code level to capture business changes. Our results (Fig. 4) are consistent with the previous results (Fig. 2), though the average magnitude becomes slightly larger by approximately 1%. The largest price premium is 7.1% for houses with EVCSs in 0.5-0.6 km. Price premium is observed for houses located closer than 0.1 km to EVCSs, which implies that the negative impacts of being adjacent to EVCSs, as observed in Fig. 2, are very likely due to negative externalities (e.g., being noisy) associated with new businesses. The coefficients are displayed in column 3 in Supplementary Table 2.

Differentiating effects

First, we differentiate price premiums between housing types. Different home types dictate different home charging availability, translating to different perceived price premiums. Typically, home charging is more available for single-family houses with off-street parking while multi-family houses or apartments usually have limited capability of home charging. We would expect people in multi-family houses (i.e., townhouses, cluster homes, condominiums, row houses) have a higher price premium for public EVCSs. Our results support this expectation and we find that people in multi-family houses do have a higher willingness to pay for EVCSs. Especially, people in apartments/condominiums are willing to pay 1.6%-3.8% more than their single-family counterparts (Supplementary Table 5).

Second, we differentiate chargers close to highways from those farther away as highway proximity may be influential. We define highway proximity as being within 200 meters of highways. Information on highway segmentation is from the Department of Transportation in California. Our data include 3,311 or 25% of EVCSs located near highway segments. The results indicate that (Supplementary Fig. 4) houses located fewer than 300 meters away from highway chargers experience negative impacts due to noise and other disamenities[29,35]. This is consistent with previous findings, which show that disamenities of highways are dominating within 0.2 miles (or around 300 meters)[36]. The largest housing premium is around 5% and happens for houses around 0.5-0.7 km away from chargers.

Third, we break down the price premium into two types of charging networks: exclusive network and non-exclusive network. The exclusive network is only accessible to certain brands of EVs and the non-exclusive network is generally accessible to all vehicles and requires no special adapters. Our results show that exclusive EVCSs have a lower housing premium at 1.0%-3.6% compared to the non-exclusive ones (Supplementary Table 6). This finding highlights the significance of providing more accessible chargers, which are associated with a higher price premium.

Discussion

This study estimates how proximity to EVCSs is capitalized into property values. We find that houses with proximate EVCSs have an average price premium of 3.3% or $17,212 (calculated by the mean housing price multiplied by the average premium). The average housing price premium is calculated to be larger than the costs of levels 1 & 2 EVCSs while lower than DC fast chargers.

On average, the total infrastructure costs and installation costs are around $2,800 for level 1 chargers, $10,500 for level 2 chargers, and $53,300 for fast chargers (Supplementary Table 7). The average price premium is much larger than the cost of level 1 or level 2 chargers probably because there are also other accompanying transaction costs such as cognitive costs and information searching costs[31,37]. The transaction costs[6] are high as EV owners generally have low awareness of charging stations[6,38] and they also need to search for and compare information on the locations and availability of chargers, which takes nontrivial time and efforts. New drivers will need to gain knowledge of power levels, plug types, charging time, etc. Especially, they need to know how to get access, which could require registration, subscription, or other credentials. The high transaction costs also explain why our results differ from the contingent valuation results, which show people are unwilling to pay an extra fee for public charging[14].

Since decision-making is usually based on aggregated-level estimation, we also show aggregated benefits and costs at the zip-code level. The benefits are estimated as the total price premiums of affected houses (within 1 km proximity of EVCSs). The costs are infrastructure, installation, and operating costs of all EVCSs in that zip-code zone. Our estimation suggests that the aggregated cost-benefit comparison differs across the types of chargers. Level 1 chargers see benefits higher than the costs while the opposite is true for level 2 and DC fast chargers. The aggregated costs are about $7.9 billion higher than the benefits if all chargers are level 2 and the gap can be even higher for DC fast chargers. Note that this simple comparison does not account for elements such as environmental benefits, which a more holistic cost-benefit assessment should take into account.

This study observes the net positive effects of EVCSs, which may occur through the following channels: (1) More charging opportunities for drivers without off-street parking (Hardman et al., 2018). There are close to 20% of residents living in multi-family houses and nearby public charging is critical for these residents. (2) Public chargers serve as substitutes for home chargers due to higher charging speeds[39,40]. Public chargers are useful in cases when home chargers fail to function, or drivers need fast charging immediately. A study also shows that free DC fast charging may lead charging to shift from home to public chargers[39]. (3) Nearby public chargers help family visitors and friends to fulfill their charging needs during visits. It is reported that public charging infrastructure is needed for at least 3-8% of EV journeys[41]. The possibility of families and friends traveling to places with EVCSs makes houses there more attractive. (4) There are other benefits such as better local air quality and higher overall living quality in neighborhoods with EVCSs. EVCS access acts as a signal of the overall quality or other characteristics. With all these possible channels, consumers with EVs or with the intention to purchase EVs are more willing to pay a higher price for houses with nearby public charging stations. Note that this study focuses on estimating the net average effects of EVCSs and we call for further research that could detangle these effects and sort these channels out. Negative effects such as radiation and noise also appear and are more likely to be a concern for houses located too close to stations. Moreover, our study shows that the effects of EVCS are heterogeneous among different characteristics such as environmental awareness, and more examination of these influencing factors could further contribute to studies in this strand.

One of the policy implications is that the price premium could help the policymakers to convince the real estate sector to deliver more charging. The increased property value due to charging access gives the local building sector more incentives while attracting tenants and addressing charging demand. Co-financing between the private sector and the government should be encouraged, especially when installation costs are high. This co-financing could improve public welfare while reducing the investment risk for the private sector. In addition, collaborative efforts between the private sector and the government are also needed to reduce transaction costs and improve the quality of charging service. Providing more accessible information and facilitating easier access reduces the searching costs and cognitive costs associated with EVCSs.

While the private sector is incentivized to provide more charging services, policymakers should also make sure that there is equitable public distribution in the disadvantaged communities. California has a leading EV market, which is expected to have more affordable EV modes and a rising number of used EVs in the future[42,43]. This tendency will make charging infrastructure more critical for the low- and middle-income communities. In addition, our study finds that the more non-white neighborhoods have a higher price premium for public charging, which provides one more justification for the EVCS installation in the disadvantaged communities. These under-resourced communities are disproportionally impacted by environmental problems already and the EV owners there may be more likely to demand public charging. Insufficient provision of sustainable infrastructure for the underprivileged neighborhoods will further jeopardize the environment and energy equality and justice in these places. It is also unneglectable that infrastructure provision in disadvantaged communities should avoid unintended gentrification in the longer term as more public infrastructure supply may increase the attractiveness of some communities, which possibly accelerates gentrification[44].

Besides fulfilling the need for charging, we show that EVCSs could also enhance social welfare by reducing air pollution and thus saving abatement costs. Our study indicates a maximum of 2.2% decrease in local PM2.5 emissions, which corresponds to daily abatement costs of $79,200, supposing the daily air pollution emissions from vehicles are 30 tons[45], and the average reduction cost is $12,000 per ton[46]. This externality is worth more if considering the health and economic benefits from better air quality[47]. Failing to consider the co-benefits would cause an under-evaluation of the welfare gains from sustainable energy infrastructure.

Some caveats and limitations exist in our study. Probably, we still fail to capture all the contemporaneous changes and neighborhood changes[48] that coincide with the construction of EVCSs. Contamination from these changes may remain and possibly bias our estimates. Their effects may be captured and attributable to our estimates. In that case, our estimates can be considered as an upper bound of the true effects. Moreover, it is possible that waterbed effects exist[49], meaning the relocation of residents closest to EVCSs causes the popularity of houses at further places. If the waterbed effects are large, then the effect induced by EVCSs at farther distances, for instance, at 0.5 km is overestimated. Our estimation can be treated as mixed effects. Our main findings still hold given that the aggregate price premium for houses within 1 km proximity is positive. Additionally, this study focuses on the situation in California, which has the highest number of EVs, charging stations, and residents in multi-family buildings in the US. The magnitudes of response to EVCSs in other states or in other countries could be different. Future market-specific studies in other regions will be essential.

Methods

Data

We obtain EVCS data from the U.S. Department of Energy's Alternative Fuels Data Center. This database contains the most complete data on EV charging station data. A range of station attributes such as locations (e.g., longitudes, latitudes), installation dates, access type (public vs. private), and nearby facility type (e.g., hotels, parking) are available in this dataset. There are altogether 13,644 charging stations in California by August 2021.

Individual housing transaction data is provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX). The ZTRAX dataset was used to support a large number of valuable academic studies [(e.g., 31,50)]. The dataset provides data on house sales prices, locations, translation dates, etc. It also includes property-level building attributes such as the number of rooms, square footage, land values, and year built. There are approximately 14 million housing transactions in California from 1993 to 2021. We match the houses with nearby public charging stations based on their longitudes and latitudes.

Data on population density and personal income per capita are retrieved from the Bureau of Economic Analysis, US Department of Commerce[51]. The sales shares of EVs are obtained from California Energy Commission[52]. Electricity prices are obtained at the state level from EIA[53]. Data on environmental awareness, measured by the percentage of residents that believe global warming is happening, is obtained from the Yale Program on Climate Change Communication[54]. Traffic flow data (2013-2020) and PM2.5 (2015-2020) data are collected at monitoring sites in the California highway system from dot.ca.gov[55]. The number of business establishments at the zip-code level is obtained from the U.S. Census Bureau[56].

Empirical strategies

EVCSs are not randomly located and are affected by factors such as population, income, land costs, and surrounding environment[57,58]. These factors may make some areas more prone to have EVCSs while also having higher house prices (Supplementary Table 8). This corresponds to the concern of self-selection (or sorting of houses). Other contemporaneous changes may also happen together with EVCS construction, such as new shopping malls and other local amenities. In this study, we apply the following strategies to address the endogeneity. Firstly, we use hedonic two-way fixed effects (or hedonic DID) under a quasi-experiment design. We take advantage of our panel data and exploit temporal and cross-sectional variations. This approach can help mitigate the omitted variable biases and establish a causal relationship. Secondly, we adopt an event study analysis to show comparable trends before the treatment and subsequentially argue that the estimated positive effects are due to treatment effects. Thirdly, to further address the endogenous biases, we adopt an instrumental variable approach at the zip-code level, using EV adoption as an instrumental variable (IV) after controlling for income. Finally, we use a cross-sectional hedonic model combined with a matching approach to construct a more comparable control group based on a rich set of observables. Moreover, we have also considered the impact of other contemporaneous changes such as business patterns to check the robustness of our estimations. Below we illustrate our empirical strategies in more detail.

Difference-in-differences

A two-way fixed effects model (or generalized DID model) with repeat sales data enables us to take advantage of our panel data. The houses with and without proximate EVCSs could be very different, and property fixed effects can capture these structural differences so that we can focus on comparing the sales of the same houses and avoid comparing houses of different characteristics. However, one concern of using a subset sample with multiple sales is that these properties may share different characteristics than the general houses, which may create some bias in the estimation. To address this concern, we compared the housing characteristics in the repeat sale sample with a full sample. The summary statistics indicate that the two samples exhibit very similar characteristics such as year built, number of stories, number of bedrooms, and number of rooms, though houses with repeat sales have slightly higher land values compared to those in the full sample (Supplementary Table 9). This similarity indicates relatively the bias from using a repeat sales sample is minimal in our context. We have also added a cross-sectional hedonic analysis, which includes all the sales (repeat sales and non-repeat sales). The two-way fixed effects model is specified as follows,

$$InY_{it} = \beta_{1,b} \sum_{b}^{10} Vicinity_{itb} * Post_{itb} + \beta_2 Post_{it} + \boldsymbol{X}'_{ct}\boldsymbol{\sigma} + \varphi_c * \omega_y + u_i + \gamma_y + \theta_m + \varepsilon_{it} \text{ (1),}$$

where $\ln Y_{it}$ is the natural logarithm of the sales price of house i at day t. Prices are adjusted with inflation rates and are converted into 2021 dollars. $Vicinity_{itb}$ is the treatment variable and equals 1 if a house has an EVCS within a distance bin b, and 0 otherwise. $Post_{it}$ equals 1 if it is after EVCS construction completion, and 0 otherwise. We apply ten distance bins from 0 to 1 km with a 0.1 km increment. u_i controls individual house fixed effects, capturing all time-invariant and building-specific characteristics. $\boldsymbol{X}'_{it}$ is a vector of covariates such as income levels and population. $\varphi_c * \omega_y$ represents county-by-year fixed effects, capturing unobservable features in changing county attributes, such as changes in the housing market, land costs, building codes, population, and relevant local policies. γ_y and θ_m include year fixed effects and month-of-year fixed effects. ε_{it} is an idiosyncratic error term. We cluster our standard errors at the zip code level, allowing for correlations between observations of the same zip code areas. We also test the validity of two-way fixed effects based on the methods from De Chaisemartin et al.[59,60] Our fixed-effects estimates are relatively robust to heterogeneous timing and constant treatment effect hypotheses and our evaluation provides suggestive evidence in favor of our assumption and findings (Supplementary Table 10).

Heterogeneity of the price premium

To examine the heterogeneity of the price premium, a flexible semiparametric approach using the partially linear varying coefficient fixed effects panel data is employed. The model is specified as follows:

$$InY_{it} = D_{it} \times g(U_{it}) + \boldsymbol{X}'_{it}\boldsymbol{\theta} + u_i + \boldsymbol{\gamma}_{\boldsymbol{ym}} + \varepsilon_{it} \text{ (2),}$$

where Y_{it} is the price of house i at time t. D_{it} is the treatment variable with a functional coefficient $g(U_{it})$ and U_{it} is a continuous variable to be examined for heterogeneity. $\boldsymbol{X}'_{it}$ is a vector of covariates such as population density and electricity prices. u_i denotes individual fixed effects, $\boldsymbol{\gamma_{ym}}$ includes year fixed effects and month-of-year fixed effects.

Event study analysis and matching

To test the plausibility of the parallel trend assumption between the houses with proximate EVCSs and those without, we conduct an event study analysis. If two groups of houses share a parallel trend, there is no systematic difference between them or the difference between two groups is constant over time, which helps justify the validity of our two-way fixed effects analysis. The event study model is specified as follows:

$$LogY_{it} = \alpha + \sum_{j=2}^{J} \beta_j (Lag\ j)_{it} + \sum_{k=1}^{K} \gamma_k (Lead\ k)_{it} + \rho_i + \mu_m + \delta_{cy} + \varepsilon_{it} \text{ (3)},$$

where Y_{it} is the average sales prices at the zip-code zone *i* at month *t*. *J* and *K* represent lags and leads, indicating the number of months away from the installation of EVCSs. The baseline omitted case is the first lag where *j*=1. We collapse the data at the zip code zone × monthly level so that we have observations each month to support such analysis (not possible with individual houses). The zip code zones with EVCSs installations are coded as treated and others are coded as control. ρ_i, μ_m, and δ_{cy} are zip code fixed effects, monthly fixed effects, and county-by-year fixed effects, respectively. ε_{it} is the error term.

The DID analysis exploits the intertemporal price variation for houses that are only sold repeatedly. To reduce the bias caused by using such a subsample, a matching approach is applied using cross-sectional data of all sales. To mitigate omitted variable biases, we apply the nearest-neighbor propensity score matching (PSM)[31,61] to make the houses with proximate EVCSs comparable to those without EVCSs conditional on observed building and socio-demographic characteristics. We first apply an exact match to control for some unobserved geographical and temporal variables (county and transaction year). Then, the PSM technique is used to find alternative control houses for all treated houses. The covariates for the matching procedure include year built, number of stories, number of bedrooms, number of rooms, land value, square footage, and income per capita, population, and number of EVs in the area. After PSM, we run an ordinary least squares model and regress the log of housing price on the treatment variable and building and sociodemographic covariates. Summary statistics of treated and control houses are displayed in Supplementary Table 11.

Instrumental variable approach

We also tried to adopt an instrumental variable approach, using EV adoption as an instrumental variable (IV) for the number of EVCSs while controlling for income. This analysis is done at the zip-code level due to data availability. The IV of EV adoption has a direct impact on the installation of EVCSs[57], but should not directly impact housing prices after controlling for household income. Using EV adoption as an instrument captures the variation in EVCS installation exogenous to housing prices, which could lead to an unbiased estimation of the EVCS coefficient.

$$EVCS_{zt} = \gamma_1 EV_{zt} + \omega_t + u_z + \varepsilon_{zt} \text{ (4)},$$

$Y_{zt} = \delta_1 EVCS_{zt} + \delta_2 Income_{zt} + \sigma_t + \gamma_z + \epsilon_{zt}$ (5),

Where $EVCS_{zt}$ is the total number of EV charging stations for zip code area *z* at year *t*, Y_{zt} is the average housing prices (in \$2021). δ_1 translates the EVCS access into an effect on house price. EV_{zt} is the number of EVs (including both PEV and BEV) and $Income_{zt}$ is the average family income. ω_t and σ_t are year fixed effects, and u_z and γ_z are zip code fixed effects.

Other associated changes

To examine whether there are changes in air pollution (PM2.5) and traffic flows after the EVCS installation, the following model is applied:

$InT_{it} = \beta_2 Post_{it} + \boldsymbol{X'_{it}\theta} + \varphi_c * \omega_m + u_i + \gamma_y + \theta_m + \varepsilon_{ict}$ (6),

where T_{it} is the traffic volume (counts of vehicles) or air pollution near closest EVCSs (about 5-minute drive or 8 km) for the house *i* at time *t*. $Post_{it}$ equals 1 if it is after EVCS installation, and 0 otherwise. $\boldsymbol{X'_{it}}$ controls for covariates such as precipitation and temperatures. All the other variables share the same definitions as equation (1). A series of time fixed effects control for time-varying factors such as vehicle emission regulations. The traffic flows T_{it} has three measures—the annual, peak month, and peak hour traffic volumes. In this part of the analysis, control houses without proximate EVCSs are not included.

Data availability

Property transaction data is obtained from Zillow through the Zillow Transaction and Assessment Database (ZTRAX). We are restricted by a non-disclosure agreement and cannot share the Zillow data publicly, but information about the accessibility of this database can be found at https://www.zillow.com/research/ztrax/. While new applications are not accepted due to Zillow access policy change, aggregating data from other entities may produce similar transaction data. Other data used for this study are all retrieved from publicly available sources and the sources for each variable can be found in the Data section in Methods. The final compiled datasets (excluding the data from Zillow) and source data can be found on GitHub at https://github.com/jingliang727/evcs_housing_2022

Code availability

All data processing and analysis are conducted in Stata (15.1) and R (4.1.2). The custom code is available on GitHub at https://github.com/jingliang727/evcs_housing_2022

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Author contributions

All the authors conceived the paper, designed the paper, and planned the analysis. J.L. conducted the analysis and drafted the paper. Y.Q., P.L., P.H, and D.M. offered revision comments and edited the paper.

Competing interests

The authors declare no competing interests.

Tables

Table 1 Impact of EVCSs on traffic flows and air pollution

	Annual ADT		Peak month ADT		Peak hour ADT		PM 2.5	
Post EVCS installation	-0.000 (0.026)	0.003* (0.002)	0.003 (0.002)	0.005*** (0.002)	-0.008*** (0.002)	-0.002 (0.002)	-0.013*** (0.003)	-0.022*** (0.003)
Year fixed effects	Yes	No	Yes	No	Yes	No	Yes	No
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-by-year fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
N	2,740,269	2,740,203	2,740,269	2,740,203	2,740,269	2,740,203	1,972,308	1,972,308
R2	0.015	0.113	0.012	0.111	0.014	0.121	0.015	0.067

Notes: ADT: average daily traffic.

Figure Legends/Captions

Fig. 1 Distribution of EVCSs in California

Notes: The dots indicate EV charging stations installed at different years. Different zip codes are shaded by levels of average housing prices and darker orange colors indicate higher prices.

Fig. 2 Impacts of vicinity to EVCSs on housing prices

Notes: The dependent variable is the log of housing prices. Each panel is from one regression. The centers of the error bars are the values of the coefficients, which represent point estimates from the regressions and indicate the average effects of EVCSs. Their 95% confidence intervals are plotted vertically. Standard errors are clustered at the zip code level. For both regressions, the total number of observations is 13.8 million each. The number of houses with proximate EVCSs within 1 km is 1.36 million and that without is 2.56 million. Panel (a) is with individual, year, and month-of-year fixed effects, and panel (b) is with individual, county-by-year, and month-of-year fixed effects.

Fig. 3 Heterogeneity of the price premium
Notes: Each panel is a single regression at the county-year level, using a partially linear functional-coefficient panel-data model. The centers of the error bands represent the semiparametric estimation of the average effects at each value of the variable on the X-axis based on the model. The grey shaded areas denote 95% confidence intervals. Panel (a), income per capita; panel (b), share of the white; panel (c), share of EV sales; panel (d), environmental awareness; panel (e), annual income growth rate; panel (f), house price inflation.

Fig. 4 Impacts of vicinity to EVCS on housing prices, adding business pattern as a control variable
Notes: The dependent variable is the log of housing prices. The centers of the error bars are the values of the coefficients, which represent point estimates from the regressions and indicate the average effects of EVCSs. Their 95% confidence intervals are plotted vertically. The total number of observations is 8.7 million. The number of houses with proximate EVCSs (within 1 km) is 1.10 million and that without EVCSs is 1.86 million. Standard errors are clustered at the zip code level.

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