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# The Global Diffusion of Electric Vehicles

## Lessons from the First Decade

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## Abstract

Electrifying the transportation sector is key to reaching the goal of carbon neutrality. This paper provides a comprehensive analysis of the diffusion of passenger electric vehicles based on detailed data on model-level electrical vehicle sales across the world from 2013 to 2020. The analysis shows that the highly uneven electrical vehicle penetration across countries is partly driven by cross-country variation in incentives and especially in the availability of charging infrastructure. Investment in charging infrastructure would have been much more cost-effective than consumer purchase subsidies in promoting electrical vehicle adoption. This finding highlights the importance of expanding charging infrastructure in the next phase of deeper electrical vehicle diffusion.


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Major economies in the world have pledged to become carbon neutral by 2060. Electrifying the transportation sector coupled with a cleaner electricity grid is considered a key pathway to reach carbon neutrality. The diffusion of electric vehicles (EVs) faces multiple economic and technological challenges including the high upfront purchase cost of EVs, limited driving range, the lack of adequate charging infrastructure, and the inherent and perceived uncertainty about this new technology (Krutilla and Graham, 2012; Carley et al., 2013; Li et al., 2017a). Despite these challenges, global EV sales reached 4.2 percent of the new vehicle market (or 3.2 million units) in 2020 after a decade of growth beginning from the introduction of the Chevrolet Volt and Nissan Leaf as the first mass-market EV models into the U.S. market in late 2010. Nevertheless, the diffusion process needs to accelerate significantly in order to reach the EV adoption goals set by many countries and regions (Figure 1).

What are the key market and policy drivers behind the spatial disparities of global EV diffusion? What are the important lessons from the first decade of the market growth? Understanding these questions has important implications for the next phase of development in the global EV market and for addressing pressing climate change and local air pollution challenges. This study aims to answer these questions based on, to our knowledge, the most comprehensive data ever complied on the global EV market including model-level EV sales by country, vehicle attributes, charging infrastructure, detailed EV policies, and demographic and socio-economic variables by country from 2013 to 2020. Our analysis focuses on 13 countries with the highest EV sales, accounting for 95% of total global EV sales during this period.

## Global EV Diffusion Patterns

After rapid growth in the past decade, the global EV stock reached 10 million in 2020. Between 2013 and 2018, the global EV market saw rapid expansion - sales increasing by over 50% each year. In 2019, the growth rate stalled temporally but quickly regained strength. By 2020, EV sales around the world reached nearly 3 million, representing a 38% increase from 2019 despite the COVID-19 pandemic. Figure 2 depicts the annual EV sales by country. China is by far the largest EV market during 2016 to 2019, accounting for about 40%-60% of global sales. In 2020, Europe overtook China and became the largest EV market, with a market share of 43%. Germany, United Kingdom, France, Norway, Netherlands, and Sweden all saw sizable growth in EV sales from 2018 to 2020, albeit the relatively low market share for each country. The global market share of EVs in the United States reduced from 47% in 2013 to 10% in 2020.

The strong growth of the EV market is in contrast to the recent decline of the overall passenger vehicle market. Nevertheless, the EV diffusion has been highly uneven across countries. Norway leads the world in EV adoption, where the EV share tripled from 18% in 2015 to 67% in 2020. Sweden and Netherlands also saw remarkable growth in the EV market share in the new vehicle market, reaching over 20% in 2020. For countries such as China, Spain, Canada and the United States, the EV share is smaller (3%-5% in 2020), but still represents significant growth over the years (Figure 3). Appendix figure S1 shows the map of the EV penetration rate in 2020 for all countries around the globe. On average, EVs have a stronger presence in richer countries: Northern Europe has generally higher EV shares while African and Asian countries have relatively low EV penetration. But it is not clear what explains the large differences among countries with similar socio-economic characteristics.

**Cross-country variation in EV choices** There is also considerable variation in the types of EVs purchased across regions. Figure 4 presents the average battery capacity, post incentive price, and vehicle size for battery EVs sold during 2013-2020 in four main regions in the estimation sample: China, Japan, Europe,[1] and North America.[2] We present the sample and sales-weighted averages in dark and light shades, respectively. Sales-weighted average battery capacity is generally higher than the sample average in all regions except Japan, indicating battery capacity is a key attribute that consumers select on. In particular, consumers in Europe and North America disproportionately prefer EVs with higher driving range. The sales-weighted average post-incentive price is lower than the sample average post incentive price in all regions, as expensive models tend to have lower market shares. Finally, in North America, the sales-weighted average size is slightly larger than the sample average, which may suggest that consumers prefer larger vehicles. Comparing across regions, EVs sold in North America have the largest sales-weighted average battery capacity. EVs sold in China have lower post incentive price, battery capacity, and size on average, likely driven by both consumer preferences and purchase subsidies based on driving range (Li et al., 2021). EV models in Europe and Japan tend to have higher prices than other markets.

From 2015 to 2020, the number of EV models increased from 90 to 370 in the world, reflecting the ever growing choices for consumers.[3] There appears to be strong preference towards local

[1] Norway, Sweden, Netherlands, Switzerland, Germany, France, United Kingdom, Austria, Spain.

[2] United States and Canada.

[3] Source: IEA Global EV Outlook 2021.

brands as documented for conventional gasoline vehicles in Coşar et al. (2018) and Barwick et al. (forthcoming). Figure 5 shows the top-5 brands in cumulative sales from 2013 to 2020 by region . Chinese brands including BYD, BJEV, and Chery dominates the EV market in China. Similarly, the majority of top-selling brands in Europe are European brands such as VW, BMW, Renault, and Mercedes. US-based brands are more popular in the US while Japanese brands are more popular in the rest of world, primarily Japan and the Republic of Korea. Tesla is the only brand appearing in the top-5 across all four regions.

**Charging infrastructure** Figure S5b plots the correlation between EV market shares and charging infrastructure at the country-year level. There is strong correlation between EV penetration and charging infrastructure. Figure 6 shows the EV stock per Electric Vehicle Supply Equipment (EVSE, or charging port) for each country in 2014 and 2020 separately with a lower ratio representing higher availability of chargers. The number of EVs supported at each EVSE is above 20 in Norway and Sweden. Canada and the United States also have a high ratio of above 15. In China and the rest of Europe, the ratio is below 10.[4] Since both EV sales and the number of EVSEs grow over time, the EV stock to EVSE ratio reflects the relative growth rate of the two. The ability of charging infrastructure to meet EV demand not only depends on the number of charging ports but also the charging level of the connectors.[5] Figure S3 shows that as the world-wide sales of fast charging EV models has increased drastically in recent years, the share of fast charging ports has remained relatively steady. The model-level variation in available charging ports is important in estimating the effect of charging infrastructure on EV demand.

**EV incentives** Among other factors, the expansion of the global EV market benefited from financial incentives such as direct rebates and tax credits or tax exemption. Direct subsidies can be flat (e.g. UK), range-based (China), battery capacity-based (US), or $CO_2$-based (e.g. France). BEVs typically are eligible for higher subsidies than PHEVs. In addition to direct subsidies, vehicle acquisition tax and vehicle ownership tax are often partially or fully exempted

[4]In China, the charging infrastructure has seen rapid development in the recent years – the number of publicly accessible EVSEs increased from 30,000 in 2013 to 800,000 in 2020.

[5]There are typically four charging levels available at public charging ports. Level 1 and Level 2 chargers use AC and are suitable for slow charging EV models (primarily PHEV models with low battery capacity such as BMW i8 PHEV). Level 3 and Level 4 chargers use DC and are suitable for fast charging EV models (primarily BEV models such as Nissan Leaf). Typically fast charging models can use all four levels of chargers while slow charging models can only use level 1 and 2 chargers. Tesla charging station is an exception in that its connectors are not compatible with other EV models.

in Europe, where the tiered vehicle tax is often based on carbon emissions and key vehicle attributes such as weight, engine rating, and cylinder capacity.

Norway has the most aggressive tax incentives for EVs in the world - all purchase and import taxes are waived for EVs. In fact, the net acquisition cost of EVs is comparable to gasoline vehicles in Norway. Although the central government has been gradually scaling back incentives from 2014 to 2018, Norway still remains as the country with the most generous EV incentive at about $8,800 per vehicle on average in the world. Figure 7a shows average incentive from 2013 to 2020 by country offered by central (or federal) governments. The average EV incentive is around $6,000 in the United states while that in China is around $3000. Switzerland and Canada only have regional incentives, thus the population weighted regional incentive is used in the study. Overall, sizable financial incentives are available in almost all major EV markets.

Figure S5a plots the relationship between EV market shares and average financial incentives at the country-year level. It shows that countries with higher financial incentives have a larger EV share in general. In addition to financial incentives, there are a variety of non-financial incentives for EV purchases. Many countries designated distinctive-looking green plates for EVs, allowing EVs to stand out on the road as well as facilitating the implementation of free parking or HOV lane privileges. These non-financial policies reduce the ownership cost of EVs and bring non-monetary benefits that could encourage EV adoption.

Lastly, we look at the role of changing country demographics in EV penetration. Figure S5c shows the correlation between the real income per capita and the EV market shares. Richer countries tend to have higher EV shares: A $10,000 increase in a country's real income growth is associated with a 2.2% increase in EV market shares. Other than income, other demographic variables, such as the rate of urbanization (shown in Figure S5d), do not exhibit a strong correlation with EV market shares. These correlation plots suggest that substantial variation in EV diffusion cannot be accounted for by the demographic variables. In the following, we use panel regression models to examine the role of various market and policy factors in the spatial and temporal patterns of EV diffusion.

# Methods

**Data** Our analysis is based on seven major data sets for 13 countries from 2013 to 2020: (1) model-level EV sales by country by year, (2) model-level vehicle attributes by country by year, (3) charging ports by charging speed by country by year, (4) model-level financial incentives for

EV buyers by country by year, (5) non-financial incentives including green plate, free parking, and HOV lane privilege for EVs by country by year, (6) sales of heavy-duty EVs by country by year, (7) unit labor cost index in construction sector by country by year, and (8) socio-economic variables by country by year. The 13 countries include Austria, Canada, China, France, Germany, Japan, Netherlands, Norway, Spain, Sweden, Switzerland, United Kingdom, and United States, accounting for 95% of world EV cumulative sales. Note that most developing countries are excluded from the sample due to extremely low EV penetration – for example 0.14% for India and 0.1% for Brazil in 2020. [6]

We merge these data into a panel data set of 3,980 observations at the level of vehicle model by country by year. Table 1 presents the summary statistics of the data.

**Empirical framework** We define a vehicle model as a brand-model combination (e.g., Telsa Model 3). Let $c$ index a country, $k$ index a model, and $t$ index a year. We specify the following baseline equation for the analysis:

$$ln(q_{ckt}) = \beta_1(P_{ckt} - S_{ckt}) + \beta_2 ln(N_{ckt}) + X'_{ckt}\alpha + \eta_{ck} + \delta_t + \varepsilon_{ckt} \tag{1}$$

where $q_{ckt}$ is the sales of EV model $k$ in country $c$ and year $t$. $P_{ckt}$ denotes tax-inclusive price of a vehicle. $S_{ckt}$ denotes the total subsidies that consumers are eligible for. The first term measures the actual acquisition cost (price minus subsidies) and $\beta_1$ measures consumer sensitivity to the acquisition cost. The implicit assumption is that consumers respond to vehicle purchase price and subsidies similarly on a dollar-to-dollar basis. The assumption could be violated if the subsidies are not as salient as prices or the pass-through of the subsidies is not complete (Busse et al., 2006; Chetty et al., 2009). National-level EV subsidies in our study are of considerable size and widely publicized. Recent research points to complete pass-through in consumer subsidies for alternative fuel vehicles (Sallee, 2011; Muehlegger and Rapson, 2018). Li et al. (2021) shows that consumers respond to EV prices and purchase subsidies similarly in China.[7]

From a practical standpoint, while it is possible to separately estimate consumer responses to prices and subsidies as in Li et al. (2021), our data only include consumer subsidies at the national

[6] In India, all most all electric vehicle ownership constitutes two-wheelers and three-wheelers, which are not the focus of this paper (Punditz (2021)). In Brazil, EV sales of popular EV brands (e.g. Nissan Leaf and Tesla Model 3) were less than 50 units in 2019. In the recent decade, even the gasoline vehicle per capita ownership in major developing countries is below that of major developed countries (Li et al. (2020)).

[7] We drop 2019-2020 data for China in our analysis due to the heterogeneous impact of the pandemic across countries, especially between China and other countries.

level. Subsidies at the local level (e.g., state or municipalities) are common but impractical to collect for all these countries. The measurement error in subsidies could lead to attenuation bias if we were to estimate the coefficients separately using OLS. Instead, we implement an IV strategy that deals with the endogeneity in the price variable and the measurement error in the subsidy variable altogether.

$N_{ckt}$ denotes the total number of fast or slow public charging ports that is available to model $k$ in country $c$ by the end of a given year. The coefficient on $\beta_2$ captures the (indirect) network effect of charging infrastructure on consumer adoption of EVs. $X_{ckt}$ is a vector of vehicle attributes including vehicle size and driving range of an elective vehicle. We also include a full set of country fixed effects, brand (e.g., Tesla) fixed effects and year fixed effects in equation (1). Country fixed effects control for time-invariant country-specific factors that influence EV demand. Brand fixed effects controls for the effect of unobserved time-invariant vehicle attributes such as brand loyalty. Year fixed effects control for common demand shocks, such as the changes in consumer awareness of the EV technology. In addition to the level of charging ports, the density of charging ports could also be an important factor. We focus on the level of charging ports here because there is no clear way to measure charging ports density, especially at the country level. One could consider weighting using country area or urbanized area. However, both measures do not have variation over time. With time fixed effects, weighting by these measures would not have impact on the regression results.

**Identification strategy** Our key parameters of interest are the $\beta$'s, which capture the effects of consumer subsidies and the availability of charging infrastructure. However, the price variable is subject to the concern of endogeneity even with the rich set of controls in (1). The first source is unobserved product attributes at the model level (e.g., quality or prestige) that could render vehicle prices endogenous. Previous literature on vehicle demand (e.g., Berry et al. (1995) and Petrin (2002)) has documented that failing to control for unobserved product attributes could lead to downward bias in the price coefficient estimates. The brand fixed effects included in (1) controls for unobserved vehicle attributes at the brand level as well as brand loyalty that do not vary across models for a given brand and over time. The remaining variation in prices and in observed attributes $X_{ckt}$ comes from the variation over time across models for the same brand across different countries. Nevertheless, the variation in unobserved attributes across models within the same brand and over time could still be correlated with vehicle price, likely leading to the downward bias in the price coefficient estimate.

The second source of endogeneity is the simultaneous nature of the relationship between consumer demand for EVs and investment decisions on charging infrastructure. The availability of charging facilities could help promote consumer adoption by alleviating concerns consumers have about the limited driving range of EVs. The importance of charging infrastructure in the early stage of EV diffusion has been shown in Li et al. (2017a), Zhou and Li (2018), Springel (2021), and Meunier and Ponssard (2020). At the same time, investors' decisions take into account current and future demand conditions. The simultaneity between consumer demand and charging infrastructure could result in $N_{ct}$ being endogenous, as shown in Corts (2010) (in the context of the U.S. flex-fuel vehicle market) and Li et al. (2017a) (in the EV market), respectively.

We address the two sources of endogeneity — unobserved product attributes and simultaneity — using the instrumental variable method. To address price endogeneity due to unobserved product attributes, we deploy two sets of IVs. We first construct a set of IVs based on battery capacity (kWh) interacting with supplier dummies. Battery is a key cost component of EV production. A larger battery with higher battery capacity is generally more costly to produce and install. The supplier dummies capture the cost difference across battery suppliers reflecting the fact that different battery suppliers that supply batteries for different EVs models could have different cost advantages. Note that the battery cost to manufactures might vary due to a range of factors such as production cost differences, bargaining power differences, or other mark-up differences. We do not take a stand on the reason for the source of cost differences, provided that they are uncorrelated with demand shocks. In addition, the identification is valid since conditioning on driving range (which is included in the regression as a control variable), passengers' purchase decisions should not be directly correlated with the size of the battery. The second set of IVs for price follows Berry et al. (1995) and include the number of EV models and attributes (battery capacity, size, and range) for both rival brands and own brand within the same car segment. The identification assumption behind the BLP IVs is that observed vehicle attributes are not correlated with unobserved ones, but firm pricing decisions would imply that the price of a given model would be affected by the attributes of other products in the market.

To address the endogeneity in the size of charging infrastructure (i.e., the number of charging ports) due to simultaneity, we use as IVs the stock (i.e., cumulative sales) of heavy-duty EVs (e.g., buses) and construction labor costs interacting with dummy variable for fast charging models. The identification assumption is that the heavy-duty EV stock reflects the underlying incentives for building up charging stations while it is unlikely to be correlated with concurrent demand

shocks for passenger EVs. While it is possible that some heavy-duty EVs might not share the same charging stations with passenger EVs, the construction and operation cost of charging infrastructure for heavy-duty EVs will spillover to those for passenger EVs, which suggests correlation between heavy-duty EV stock and passenger EV charging infrastructure. Similarly, the construct labor cost reflect supply side cost shocks which directly affects the construction of charging stations but unlikely to be correlated with demand side factors. The interaction with the fast charging model dummy allows for the effect to be potentially different for fast charging models and slow charging models.

It is possible that financial and non-financial incentives that we are interested in are correlated with unobserved demand shocks or other policies. We include time fixed effects to control for common demand shocks around the globe and country fixed effects to control for nation-specific shocks that do not vary over time. However, we acknowledge that these EV incentive policies could be endogenous if they are designed and implemented in response to time-varying and country-specific shocks.

# Regression Results

In this section we report the effects of key market drives for global EV diffusion based on the empirical framework described in the previous section.

**Parameter estimates** Table 2 reports the estimation results of the EV demand model from five specifications. We include in our regressions the cost of purchasing a new vehicle measured by price minus financial incentive, the number of available charging ports, driving range, vehicle size and an indicator for non-financial incentives. The first three columns report estimates from OLS, in which we add different sets of fixed effects to control for potential confounding factors. The last two columns are estimates using different instrumental variable strategies to address the price and charging station endogeneity aforementioned.

The regression in column (1) suffers from different sources of confounding factors which bias the price coefficient towards zero, although all the coefficients have intuitive signs. Column (2) adds brand (e.g., Tesla) fixed effects in order to control for brand-specific time-invariant confounders such as brand loyalty and unobserved car attributes (such as product quality) that are correlated with price while affecting sales. It also adds fuel type fixed effects (i.e., BEV or PHEV) to account for different consumer preferences for different fuel types. The price coefficient becomes more than doubled in magnitude suggesting that it is important to control for these

confounders at the brand level to get a correct inference on price sensitivity. The coefficient estimate on charging ports however remains nearly unchanged. This is because the identifying variation for charging station is largely at country-year level. [8] Column (3) includes country fixed effects and year fixed effects to further control for country-specific and time-invariant factors that could influence EV adoption as well as common annual demand shocks across countries. Although the coefficient estimates are similar in size, the standard error for charging station goes up significantly. This results from the fact that country fixed effects and year fixed effects remove a fair amount of variation in the charging port variable. We also note that the indicator variable for non-financial incentives becomes insignificant. These indicators are rough measures of the non-financial policy adoption at the country-year level which lacks year-to-year variation across countries and therefore are largely absorbed by country fixed effects and year fixed effects. OLS point estimates suggest: 1) a $1,000 decrease in the suggested retail price (or increase in the financial incentives) increases EV sales by 2.2%; 2) a 10% increase in the number of charging ports results in increases EV sales by 3.2%.

Column (4) addresses the price endogeneity problem by instrumenting prices with battery supplier IV and BLP IVs. This set of IVs strongly predict the prices as shown by the first stage F-statistics. The price coefficient becomes larger in magnitude from -0.019 to -0.027. This suggests that there might be other unobservables (e.g. brand-year specific demand shocks) that are not captured by fixed effects, The use of IVs help to overcome these remaining endogeneity concerns. In addition to the price instruments, to further account for the endogeneity of the charging networks, column (5) adds another set of IVs using heavy-duty EV stock and construction labor costs interacted with fast charging model dummy. The coefficient estimate on the charging ports more than doubled though 2SLS procedure leads to a larger standard error.

The coefficient estimates on range and vehicle size are intuitively signed. The coefficient estimate on non-financial incentives, though positive, is not significant in specifications after controlling for country and year fixed effects. This is partly due to the data limitation that we can only collect non-financial incentive policies (such as green plate, free parking etc.) up to country-level while many of these policies are implemented at local level (state or municipalities) which we do not observe.

Our preferred specification in column (5) suggests that (1) a $1,000 decrease in consumer prices (e.g., via an increase in subsidies) increases EV sales by 2.9%, and (2) a 10% growth in

[8] Note that the availability of charging ports (fast charger and slow charger) also depends on charging types (fast charging and slow charging) at the model level. This is why column (2) and column (3) have slightly different estimates for charging ports.

the number of charging ports increases EV sales by 8.2%. Based on the coefficient estimates, a back-of-the-envelope calculation suggests that in order to increase the EV sales by 10%, an increase of consumer subsidies by about $3,000 per vehicle subsidy or additional 12.2% more in charging infrastructure would be needed.

**Heterogeneity analysis** Table 3 presents regression results examining the heterogeneity of our baseline findings. We first look at how country level social-economic variables affect estimated price responsiveness. In column (1), we interact price with countries' real income level. The rationale is that consumers from higher income countries might be less sensitive to price changes and EV incentives. Figure 8a provides a visualization of this pattern by plotting the estimated price coefficient for each country against countries mean income level. The graphical pattern seems to suggest consumers in higher income countries are less price sensitive. Though the interaction term is significant at 90% level, the effect size is fairly small. In column (2), we interact the price variable with charging network density measured by number of chargers per urbanized area square kilometer. Figure 8c provides a visualization of this pattern. The estimated coefficient for the interaction term is positive and significant suggesting in countries with better charging network, consumers are more inelastic about EV price in their purchase. This also points to a policy complementarity between subsidies for charging stations and subsidies for EV purchases. Column (3) interacts price with country average gasoline price. Gasoline price affects EV purchase through inducing the substitution of gasoline cars towards EVs. The positive and significant coefficient for the interaction term suggests that in countries with a higher gasoline price, EV demand is more inelastic with respect to EV purchase price. Figure 8b indeed shows a consistent pattern. Column (4) adds an interaction term between price and population density to examine how commuting distance affects EV price sensitivity. We do not find any evidence.

We also look at how these demographic variables affect the impact of charging station. Column (5) shows that in countries with higher gasoline prices, the effect of building up charging stations on promoting EV sales is larger. We again do not find any interaction effect with respect to population density in column (6). Column (7) and (8) examines how the charging ports build-out alleviates consumers' range anxiety. To do this, we interact charging ports with EV's driving range and a dummy variable for PHEV. The negative and significant coefficient for the interaction term is in line with our intuition that charging ports tend to have a larger effect for EV models with shorter range. In addition, charging ports matter more for PHEV than BEVs. The reason might be due to the fact that most PHEVs have a shorter range than BEVs and therefore need to be constantly charged up.

The last two columns investigate whether consumer price sensitivity and the impact of charging infrastructure change over time. To do this, we first define an indicator variable "1(*Post* 2016)" which takes on value 1 for the later period of our study. We then interact this dummy variable with price and charging port variables. We do not find consumers to be more or less price sensitive over time and the impact of charging infrastructure remains similar. The individual coefficients are also plotted separately in Figure S4.

**Alternative specifications and robustness checks** We examine several alternative model specifications and the robustness of our findings. Similar to the demand equation that we estimated in Equation 1, we use $log(s_{ckt}) - log(s_{0kt})$ as the dependent variable where $s_{ckt}$ is the market share of EV model $k$ in country $c$ year $t$ and $s_{0kt}$ is the share of consumers who do not purchase an EV. This specification has the advantage of being theoretically consistent with an underlying utility maximization framework where it can still be conveniently estimated linearly (Berry, 1994). Table S1 shows the estimation results of the logit demand model. This framework gives implied own price elasticity by $\hat{\beta}_p \times p_k \times (1 - s_k)$. The coefficient estimates are largely in line with our baseline estimates. We then estimate an alternative specification using the logarithm of price as a robustness check. Table S2 shows the results. The implied price elasticities are comparable with the original specification and charging station coefficient estimates are largely the same.

# Policy Analysis

In this section, we assess the cost-effectiveness of two major policies in promoting global EV diffusion: (1) providing financial incentives for EV purchase and ownership, and (2) building charging infrastructure.

First, we use estimates of the global EV demand model to simulate the counterfactual EV sales under each policy scenario. The difference between the counterfactual sales and the observed sales represents the policy induced sales. Second, we calculate the aggregate government spending required for each policy scenario. Finally, we calculate the average government spending per induced EV sale. We first present the simulated induced sales and assess the cross-country differences, and then compare the cost-effectiveness of the three policies.

## The Role of Policies in EV Sales

All 13 countries provide EV buyers financial incentives and the average incentive from the central government is about $3,400 per vehicle, and can reach as high as $56,000 for certain models. The total financial incentives amounted to $43 billion from 2013 to 2020 in these countries. To understand the impact of financial incentives, Figure 9a shows the counterfactual sales by removing the subsidies based on the coefficient estimates in column (5) of Table 2. The total induced sales (difference in the observed sales and the simulated sales) for the entire sample period is 3.9 million. Overall, the financial incentives from the central government explained 40% of EV sales.

An alternative strategy to promote EV diffusion is to expand the size of charging network by subsidizing charging station investment. A larger charging network could facilitate EV adoption through alleviating consumers' range anxiety. Based on the coefficient estimates in column (6) of Table 2, Figure 9a shows the counterfactual sales from a 50% reduction in the total number of charging ports. The total induced sales is about 4.3 million units, equivalent to about 43% of EV sales. To enable a fair comparison of sales impacts from purchase subsidies and charging infrastructure, Figure 9c depicts the EV sales where the same amount of government spending as consumer subsidies ($43 billion) is used to build charging stations, leading to a 2.7-fold increase in the number of charging ports. The large charging network would lead to a three-fold increase in EV sales in the sample period, relative to the 40% increase from purchase subsidies. Therefore, investing in charging infrastructure has a bigger impact on EV sales than providing consumer purchase subsidies.

## Cross-Country Differences

A salient pattern observed around the globe is that EV adoption is highly uneven across countries. In 2020, Norway has the highest EV market share of 67.4% among all countries, while Japan only has less than 1% EVs among all new cars sold on the market. In this exercise, we try to examine the role of EV policies, such as EV subsidy and charging infrastructure investment, in explaining cross-country disparity in EV adoption.

To investigate the impact of EV incentives (including direct consumer subsidies and tax credits etc.), we simulate the EV market shares across countries in 2020 by changing EV subsidies per vehicle for all countries to the average level in the sample.[9] The simulated EV market shares

[9] We assume the induced new EV sales substitute 50% of the ICE vehicles. Our data does not include ICE

across countries are shown in Figure 10a in comparison to observed EV market shares in 2020. For the five countries that have above-average incentives, the simulated market share would be lower than the observed market shares. However, for the the rest of the countries, increasing incentives to the world average level would help them catch up in market shares with the leading countries.

The accessibility of charging infrastructure is also highly uneven across countries. We then examine how the charging infrastructure helps to explain cross-country differences in EV adoption. Figure 10b presents simulated EV market shares assuming charging infrastructure level measured by the number of charging ports per thousand new cars sold to be at the sample average. The simulation results show a much larger impact compared to the incentive case. Norway and Netherlands would see a decrease in EV market share, while EV penetration would deepen in all other countries. This highlights the importance of building up charging infrastructure in global EV diffusion.

In both cases, reducing the disparity incentive or charging infrastructure would lead to more uniformly distributed EV penetrations across countries. The dispersion of market shares is reduced by about 17% and 69% after removing the cross-country variation in incentive levels and charging infrastructure, respectively.

## Cost-Effectiveness Comparison

We calculate the average government spending per induced sale as the ratio between the aggregated government spending and the induced sales under each policy. For illustration purpose, we compare the induced cost and average government spending per induced sale under scenarios with no incentive and no charging station.[10] The aggregated government spending from financial incentives is calculated based on incentive levels and sales in the data. The aggregated government spending of installing charging ports is calculated based on the number fast and slow charging ports in the data and the construction cost for each type of charging port.[11]

On average, to induce one unit of EV sale, it would cost $10,872 in terms of government

vehicles and therefore our analysis cannot directly estimate the substitution.

[10] We simulate sales by reducing the number of charging ports to one instead of zero, since our model uses the logarithm scale of charging ports.

[11] China, US, and European countries have different slower charger construction and fast charger construction cost that we account for in the aggregate construction cost. China: $1,449 (slow AC) and $14,493 (fast DC); US ad Canada: $5,440 (slow AC) and $81,818 (fast DC); Europe and Japan: $7,273 (slow AC) and $173,580 (fast DC). Cost estimates are from Nicholas (2019) and Mathieu (September 2018).

spending via consumer purchase subsidies. In contrast, the average government spending needed is only $1,587 by installing charging infrastructure to induce one additional sale. That is, it is more cost-effective for governments to invest in expanding the charging network rather than providing purchase incentives for EVs. Governments can subsidize the private sector and share the investment cost for charging network construction. This is qualitatively consistent with previous findings in China (Li et al., 2021), US (Li et al., 2017a), and Norway (Springel, 2021). One important caveat is that the calculated average government spending per induced sale in this analysis only applies to central government incentives. Our data on incentives only include national-level subsidies or tax reduction, but local subsidies account for 22% of total subsidies on average in China while US states such as California offer rebates or tax credits equivalent to 30% of the federal-level tax credit. The estimated impact from incentives might be larger if all local incentives were available in the data.

# Conclusion

This study provides a comprehensive analysis of global EV diffusion during the first decade of the technology being introduced to the mass market. The analysis shows that investing in charging infrastructure is more cost-effective than providing consumer subsidies in promoting EV adoption, consistent with the finding from the literature based on data from individual countries. More importantly, this study allows us to understand the significant variation in EV adoption across countries, even among those with similar socio-economic characteristics. Our analysis shows that 17% of the cross-country variation is driven by observed differences in subsidy levels and 69% by differences in charging network size. These findings highlight the importance of investing in charging infrastructure in order to further electrify the transportation sector in the next decade.

We conclude with a discussion on the limitations of our study and directions for future research. First, our data do not include gasoline models and do not allow us to examine the substitution pattern between EVs and different gasoline models, a crucial element in evaluating the environmental impacts (e.g., avoided carbon emissions) of the new technology (Li et al., 2017b; Holland et al., 2016). Future research could rely on consumer-level data and richer models to better capture consumer choices among different EV and gasoline models and provide additional insights on the environmental and welfare impacts of different market and policy drivers of EV demand. Second, this study focuses on demand-side policies that directly affect

consumer EV adoption and does not examine the supply-side responses such as product choices of automakers and part (e.g., battery) suppliers. Future research could examine these supply-side responses as well as the impacts of supply-side policies such as R&D subsidies and production subsidies that also affect the transition to an electrified transportation system.

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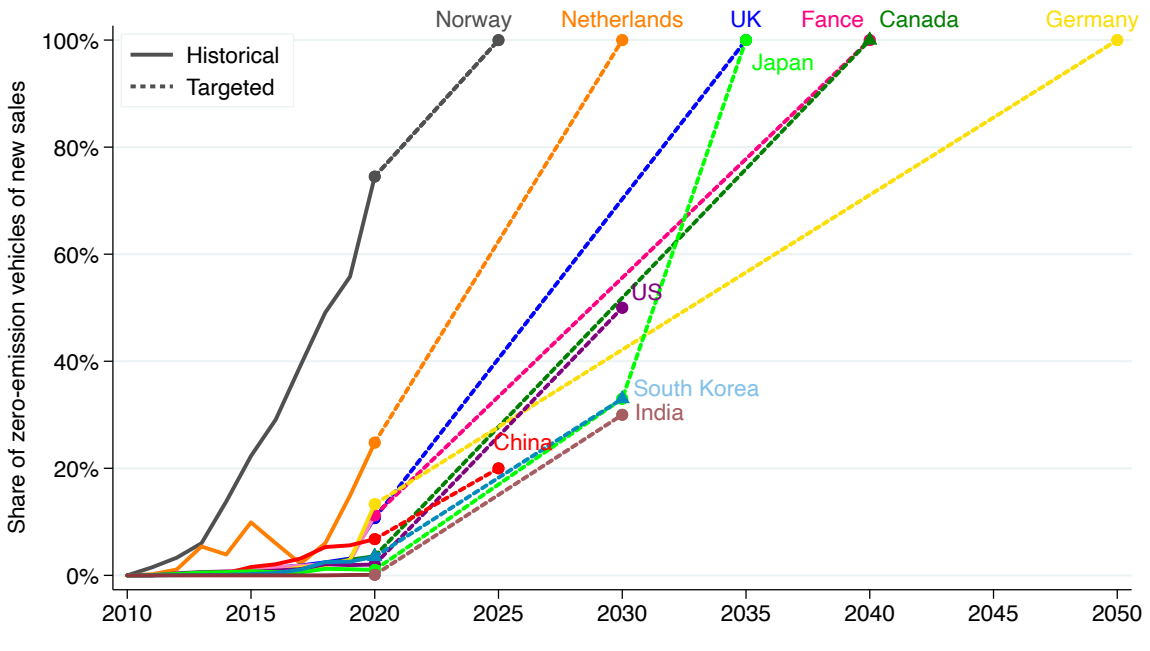
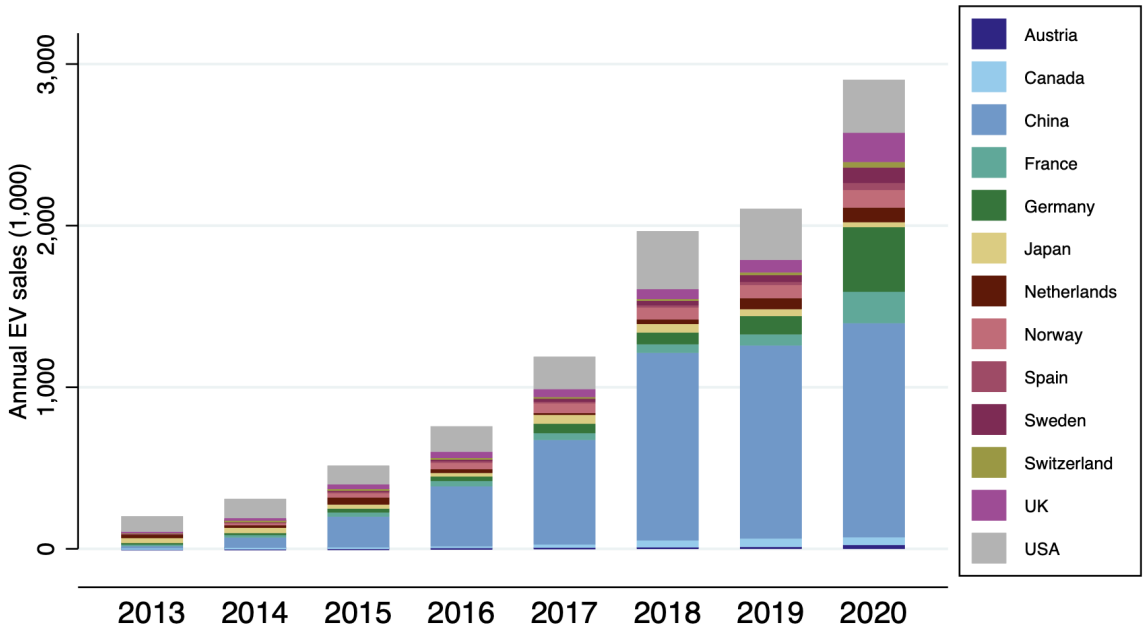
# Figures and Tables

Figure 1: Zero-emission Vehicle Market Shares and Targets



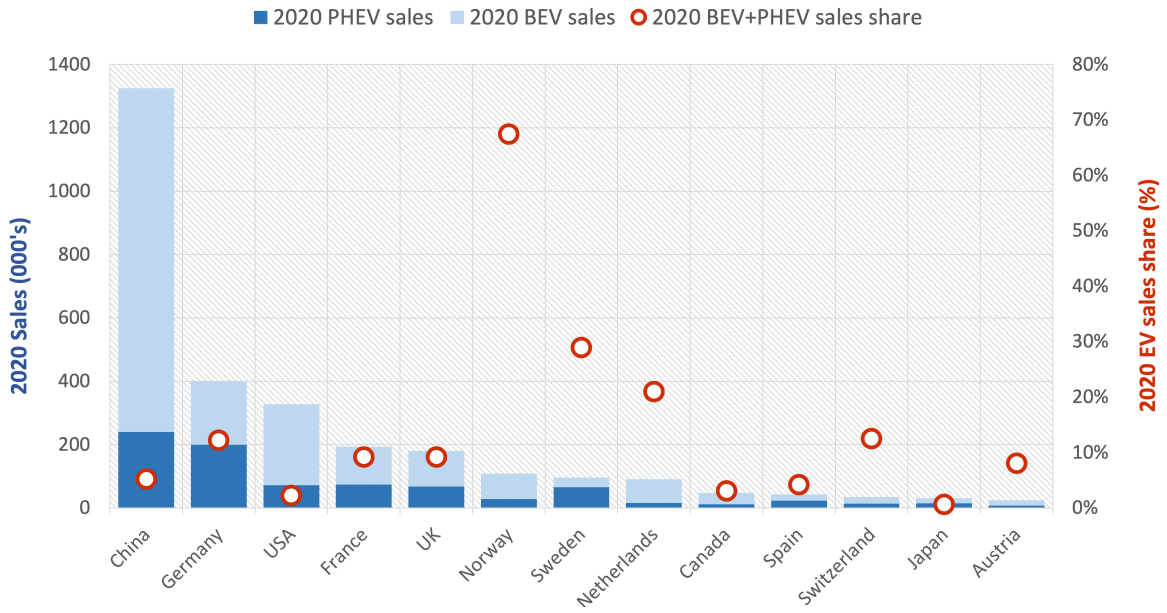

*Notes*: The market shares in 2020 and targets of zero emission vehicle (ZEV) in major EV countries. ZEVs include EVs and hydrogen vehicles.

Figure 2: Annual EV sales by country



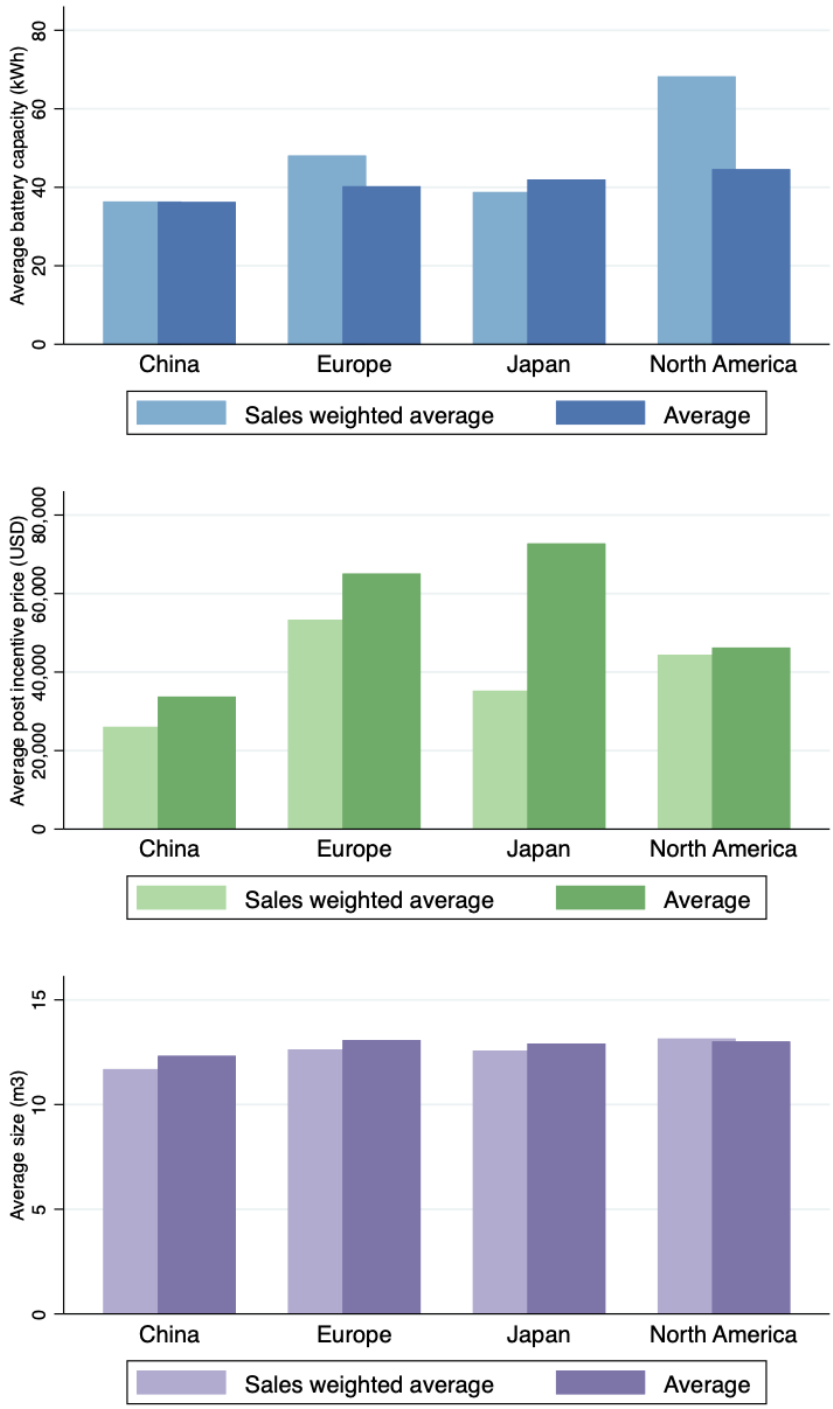

*Notes*: Annual EV sales by country from 2013 to 2020. Both plug-in Hybrid EVs and Battery EVs are included.

Figure 3: EV sales and market share by country in 2020



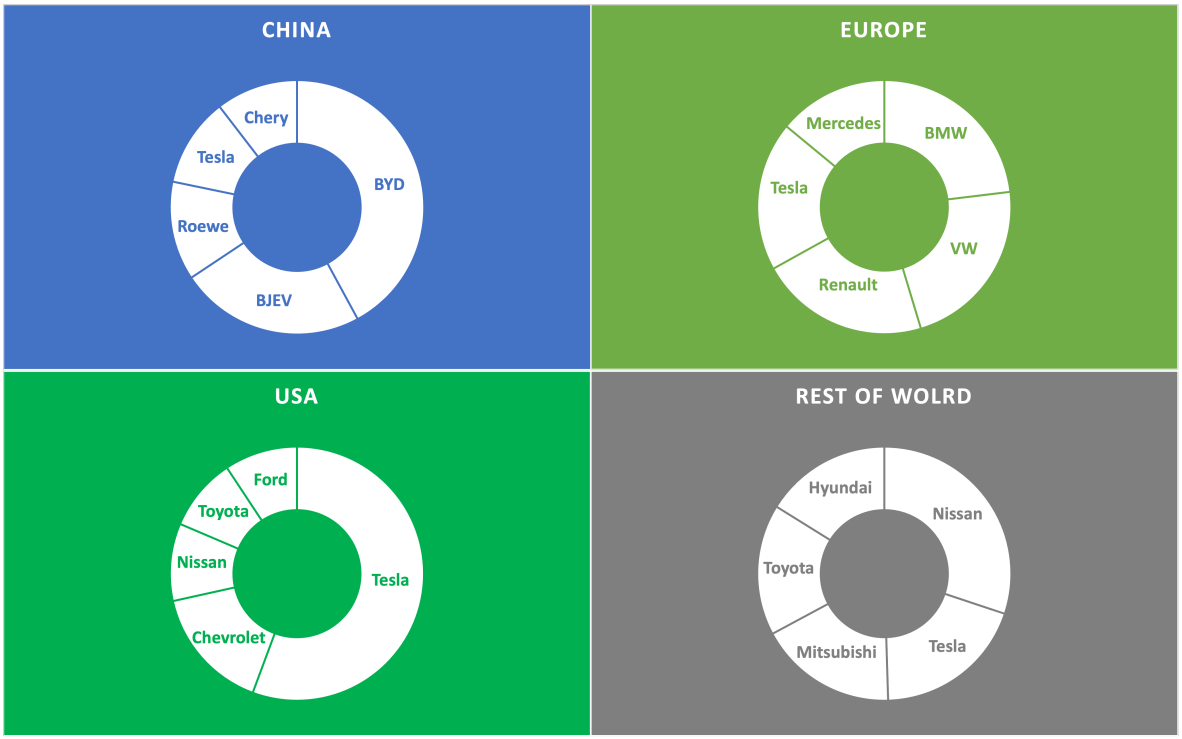

*Notes*: Sales of battery EVs versus Plug-in Hybrid EVs (primary axis) and market share of EVs by country (secondary axis) in 2020.

Figure 4: Key vehicle attributes by region



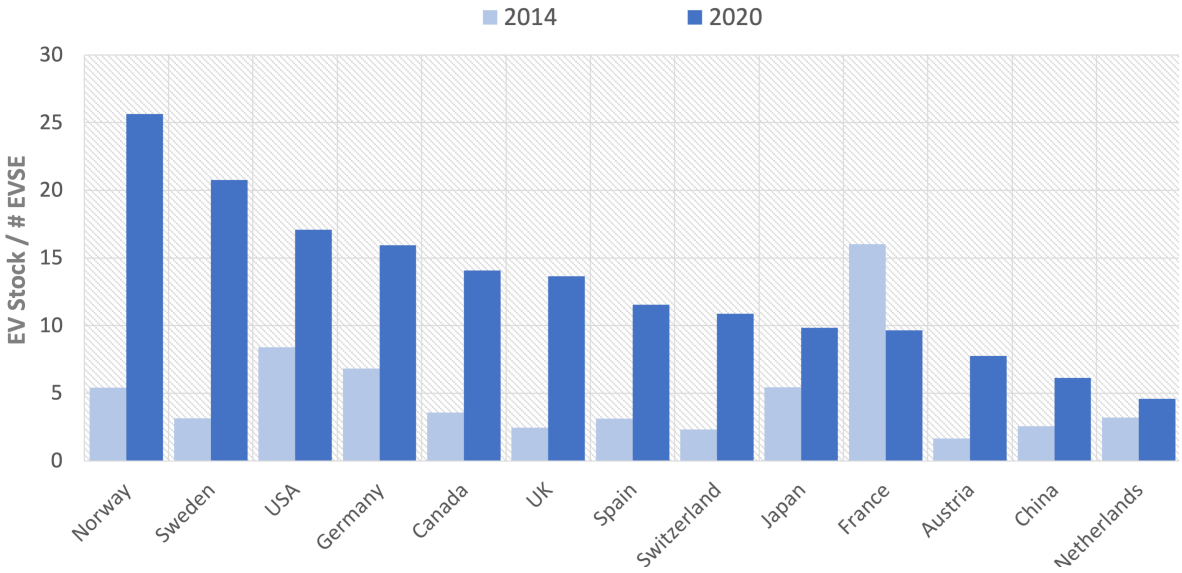

*Notes*: Average (dark shade) and sales weighted average (light shade) of vehicle attributes in terms of battery capacity, retail price, and vehicle size (length×weight×height) from 2013 to 2020 by region. The average battery capacity is shown for **BEV models** in each region while the average price and size is calculated for all models in each region.

Figure 5: Top-selling brands by region



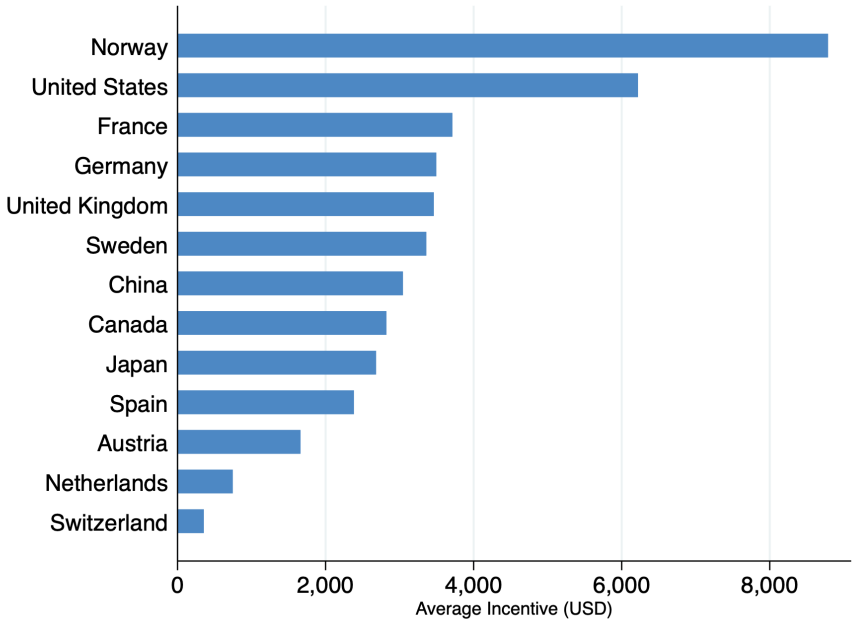

*Notes*: Brands ranking top 5 in terms of aggregate EV sales from 2013 to 2020 in China (top left), Europe (top right), USA (lower left), and Rest of World (lower right).

Figure 6: EV stock to EVSE ratio




*Notes*: This figure shows, for each country, the ratio between the EV stock (cumulative EV sales from 2013 to a given end year) and the number of charging ports available at a given end year. The ratio using 2014 as the end year are shown in light blue and the ratio using 2020 as the end year are shown in dark blue.

Figure 7: Summary of financial and non-financial EV incentives



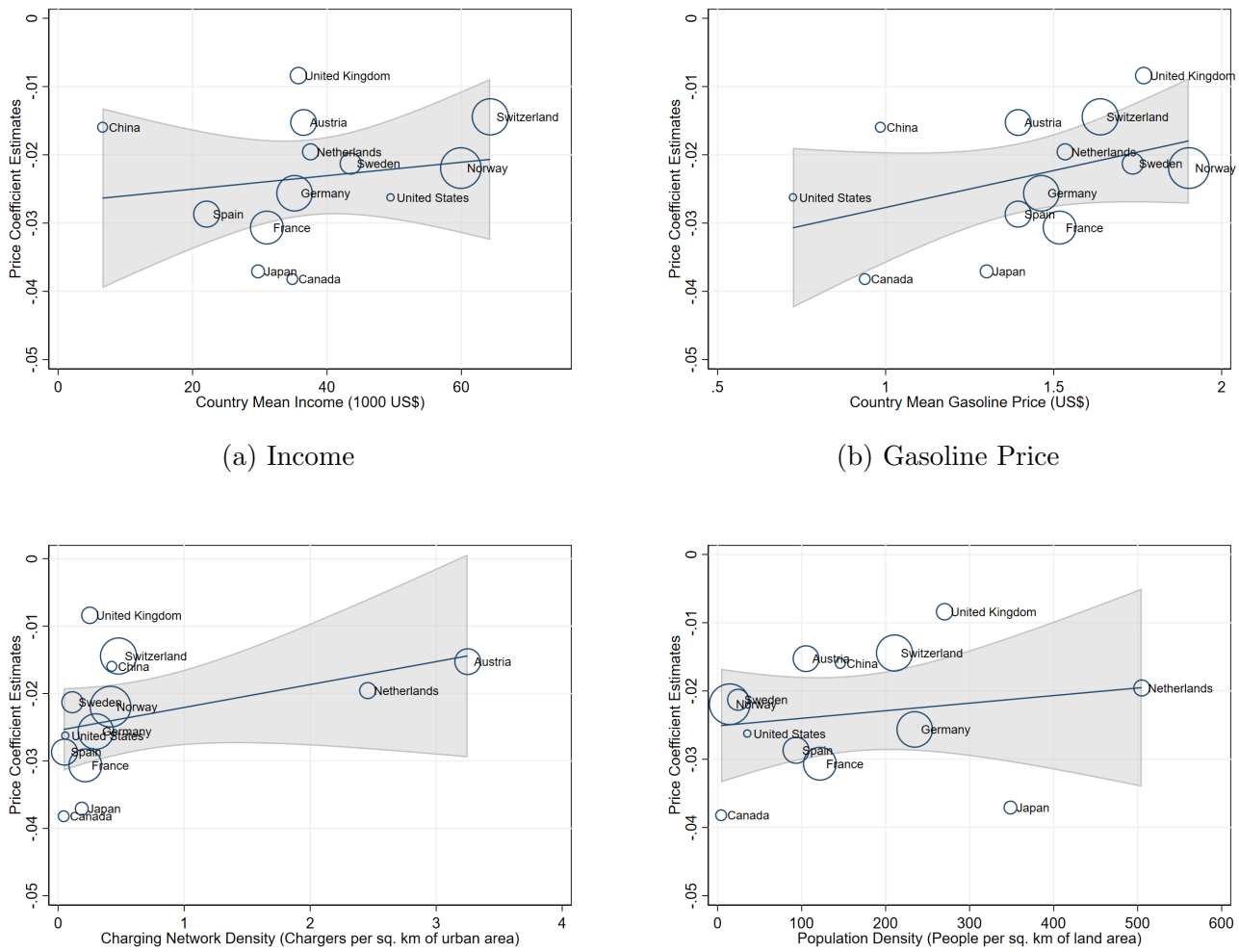

(a) Average EV financial incentives by country

| | Austria | France | Germany | Netherlands | Norway | Spain | Sweden | Switzerland | UK | China | Japan | Canada | US |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Consumer subsidy | ● | | | | | ● | ● | | ● | ● | ● | ○[1] | |
| Acquisition tax discount | ● | ● | ● | ● | ●[2] | | | | | | | | ● |
| Ownership tax discount | ● | | ● | ● | | ● | ● | ○[3] | ● | | | | |
| Free parking | ○ | ○[4] | ○ | ○ | ●[5] | ○ | | | ○ | ○ | | | ○ |
| HOV lane | | ○ | ○ | ○ | ● | ○ | ○ | | ○ | ○ | ○ | ○ | ○ |
| Green plate | ○ | | ○ | | ● | ○ | | | [6] | ○ | | ○ | ○[7] |

(b) EV policies by country

*Notes*: Summary of EV policies. Panel (a) shows the average national-level incentive from 2013 to 2020 by country. Generally local or regional incentives are not included, except for Switzerland and Canada, which didn't have central incentives in our sample period. Panel (b) shows the the whether financial or non-financial policies exist at the national or regional level. Dot (hallow) circle indicates national (regional) policies. Dark (light) blue shade indicates policies that were implemented prior to (after) 2017.

Figure 8: Price Sensitivity Heterogeneity across Countries




(a) Income

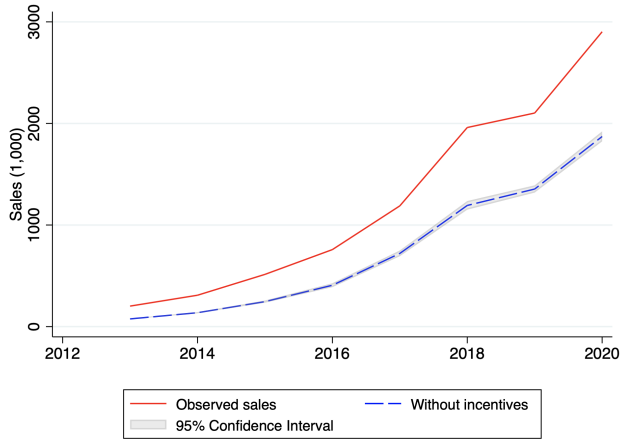
(b) Gasoline Price

(c) Charging Network Density

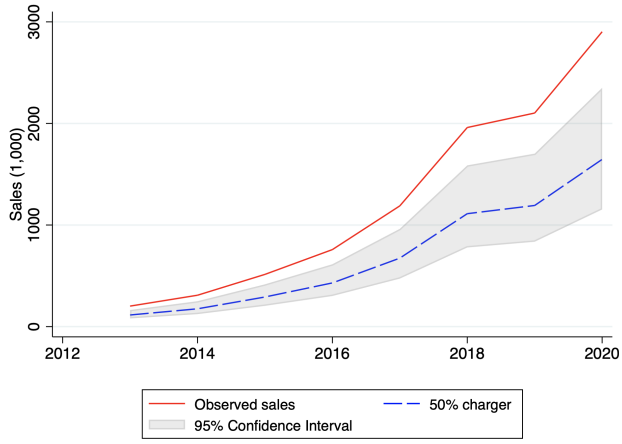
(d) Population Density

*Notes*: Y-axis is the price coefficient estimates. Each point on the graph is a country. The size of the point represents the inverse of the standard error of the price coefficient estimates. The blue solid line is the linear fit of the points on the graph.

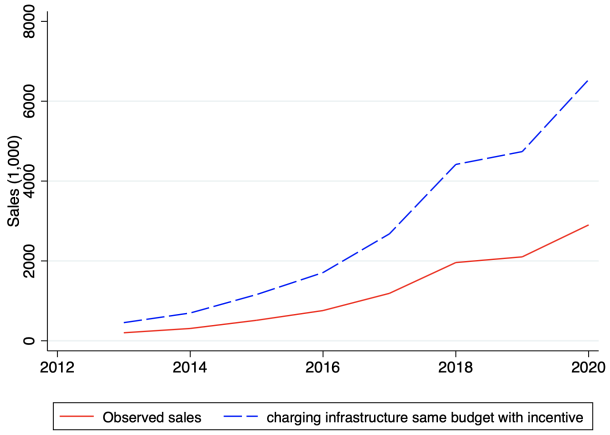
Figure 9: Counterfactual sales under alternative policy scenarios




(a) Simulation without financial incentives (or 100% reduction in incentive)



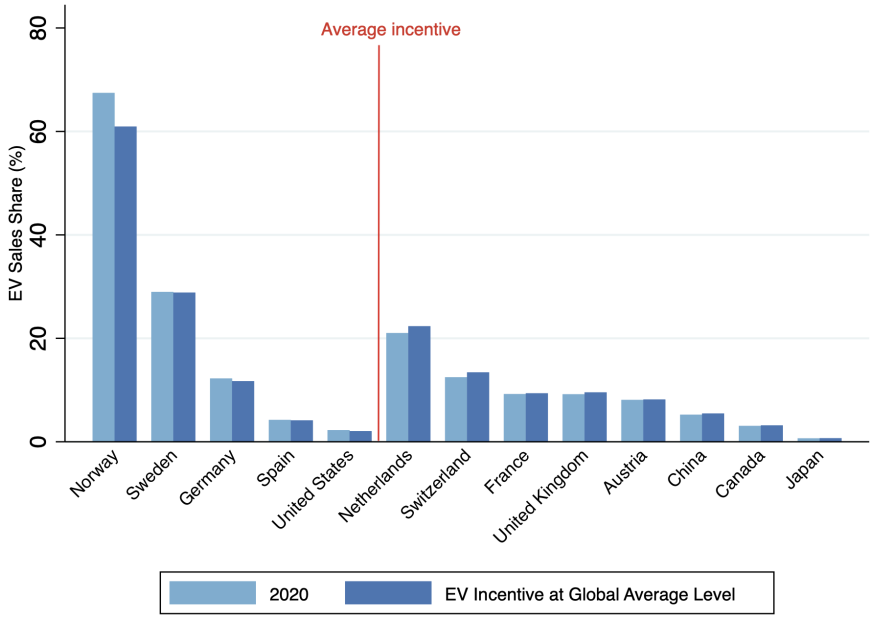

(b) Simulation with 50% reduction in charging ports



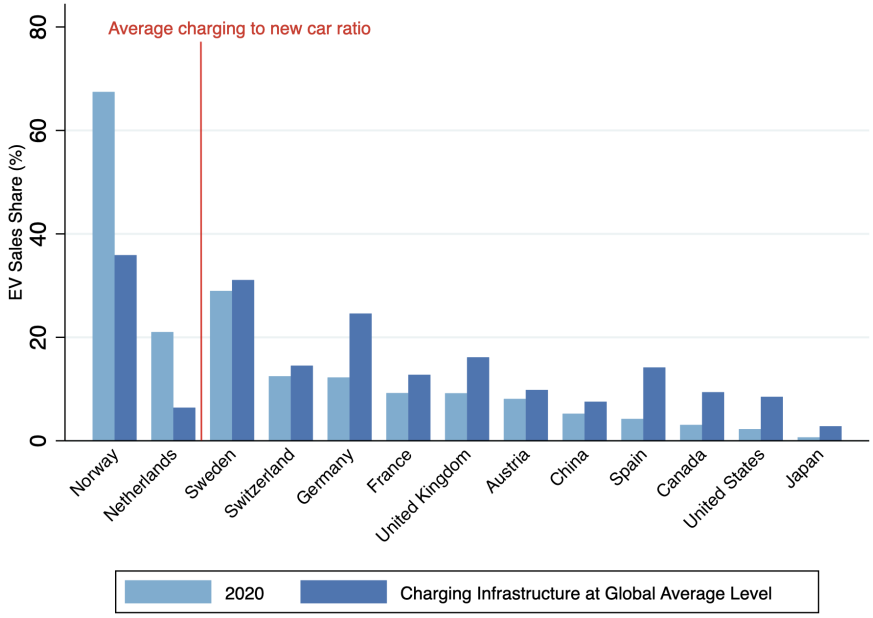

(c) Simulation with charging infrastructure having the same government budget as incentive

*Notes*: This figure shows point estimates and 95% confidence interval of the annual counterfactual sales without financial incentives (a), with 50% reduction in charging ports (b),and with charging infrastructure having the same government budget as consumer incentives (c). Overall EV incentives contributed to 40% of EV sales. A 50% decrease in number of charging ports would lead to a reduction of 43% in EV sales.

Figure 10: Simulated EV Market Shares across Countries




(a) Incentive simulation




(b) Charging infrastructure simulation

*Notes*: This figure plots EV market shares in 2020 in comparison to simulated EV market shares assuming all countries' incentive (a) and charging ports (b) are at sample average level and new EV sales substitute 50% of ICE vehicles. The red line indicates the sample average of incentives (a) and sample average of ratio of charging ports/new vehicle (b) in 2020. Countries to left of the red line have above average incentives or charging ports ratio. In each panel, the countries are ranked by descending observed 2020 market share (light blue bar) within the above average group (left of the red line) and the below average group (right of the red line).

Table 1: Summary Statistics

| | Mean | Standard Deviation | Min. | Max. |
|---|---|---|---|---|
| Annual sales | 1833.3 | 6811.6 | 1.0 | 164357.0 |
| Price - Incentive (1,000 USD) | 59.0 | 37.3 | 1.7 | 200.7 |
| MSRP (1,000 USD) | 62.4 | 36.6 | 6.9 | 202.1 |
| Incentive (1,000 USD) | 3.4 | 3.8 | 0.0 | 56.3 |
| Number of EV chargers (1,000) | 34958.2 | 60925.6 | 600.0 | 515908.0 |
| Battery capacity (kWh) | 25.7 | 21.2 | 4.4 | 100.0 |
| Range (miles) | 103.5 | 98.4 | 0.7 | 706.5 |
| Vehicle size (m3) | 13.0 | 2.8 | 6.3 | 26.7 |
| Engine Horsepower | 194.1 | 103.7 | 11.8 | 761.0 |
| Indicator of Non-financial Incentives | 0.7 | 0.5 | 0.0 | 1.0 |
| Heavy-duty EV Stock | 810.7 | 2557.5 | 0.0 | 10588.2 |

*Notes:* The unit of observation is country-year by model. The number of observations is 4,528. The data are from 2013 to 2020 for 13 countries. Price is MSRP (manufacturer suggested retail price) plus taxes.

Table 2: Estimation Results for EV Demand

| | OLS | OLS | OLS | IV | IV |
|---|---|---|---|---|---|
| Price - Incentive (1,000 USD) | -0.010*** | -0.022*** | -0.019*** | -0.027*** | -0.029*** |
| | (0.001) | (0.001) | (0.002) | (0.005) | (0.005) |
| Log Charging Ports | 0.451*** | 0.475*** | 0.317** | 0.290** | 0.818* |
| | (0.072) | (0.066) | (0.149) | (0.145) | (0.462) |
| Range (miles) | 0.005*** | 0.004*** | 0.008*** | 0.008*** | 0.008*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| 1(PHEV) × Range | 0.019*** | -0.012** | 0.006 | 0.003 | 0.003 |
| | (0.003) | (0.005) | (0.006) | (0.007) | (0.007) |
| Vehicle size (m3) | -0.040** | -0.012 | -0.017 | 0.007 | 0.013 |
| | (0.017) | (0.015) | (0.014) | (0.021) | (0.021) |
| Indicator of Non-financial Incentives | 0.479*** | 0.521*** | 0.223 | 0.219 | 0.096 |
| | (0.167) | (0.141) | (0.148) | (0.149) | (0.180) |
| Brand FE | | ✓ | ✓ | ✓ | ✓ |
| Fuel Type FE | | ✓ | ✓ | ✓ | ✓ |
| Country FE | | | ✓ | ✓ | ✓ |
| Year FE | | | ✓ | ✓ | ✓ |
| First Stage F-stats for Price | | | | 54.67 | 77.00 |
| First Stage F-stats for Charging Station | | | | | 36.34 |
| Underidentification Test | | | | 62.60 | 77.22 |
| Weak Identification Test | | | | 31.85 | 22.47 |
| Overidentification Test | | | | 55.14 | 62.14 |
| Observations | 4528 | 4528 | 4528 | 4528 | 4528 |

*Notes:* The regressions are based on data for 13 countries from 2013 to 2020. Observations for China in 2020 are excluded due to the impact of COVID19. The dependent variable is log(sales). *Price - Incentive* variable is constructed from tax inclusive price subtracting total incentive received. Column (4) shows 2SLS estimates using instruments for consumer prices using the battery supplier dummy interacted with battery capacity as well as BLP instruments including the number of models and models' size, battery capacity, and range for both own brand and rival brands. Column (5) in addition instruments for the number of charging ports using heavy duty EV stock, construction labor costs, and their interactions. Standard errors are clustered at the country by year level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Heterogeneity Analysis

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Price - Incentive (1,000 USD) | -0.033*** | -0.030*** | -0.036*** | -0.032*** | -0.025*** | -0.029*** | -0.037*** | -0.035*** | -0.031*** | -0.029*** |
| | (0.007) | (0.005) | (0.009) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.006) | (0.005) |
| × Income (10k USD) | 0.002* | | | | | | | | | |
| | (0.001) | | | | | | | | | |
| × Charger Denisty (per Sq. km) | | 0.003*** | | | | | | | | |
| | | (0.001) | | | | | | | | |
| × Gasoline Price (USD) | | | 0.009* | | | | | | | |
| | | | (0.005) | | | | | | | |
| × Population Denisty (100 ppl per Sq. km) | | | | 0.001 | | | | | | |
| | | | | (0.001) | | | | | | |
| × 1(Post 2016) | | | | | | | | | 0.002 | |
| | | | | | | | | | (0.003) | |
| Log Charging Ports | 1.024** | 0.703 | 0.865** | 0.706 | 0.045 | 0.441 | 1.368*** | 0.392 | 0.922* | 0.846 |
| | (0.432) | (0.435) | (0.418) | (0.448) | (0.448) | (0.408) | (0.466) | (0.499) | (0.473) | (0.543) |
| × Gasoline Price (USD) | | | | | 0.667** | | | | | |
| | | | | | (0.313) | | | | | |
| × Population Denisty (100 ppl per Sq. km) | | | | | | 0.049 | | | | |
| | | | | | | (0.083) | | | | |
| × Range | | | | | | | -0.002*** | | | |
| | | | | | | | (0.000) | | | |
| × 1(PHEV) | | | | | | | | 0.446** | | |
| | | | | | | | | (0.188) | | |
| × 1(Post 2016) | | | | | | | | | | -0.068 |
| | | | | | | | | | | (0.115) |
| Range (miles) | 0.008*** | 0.008*** | 0.008*** | 0.008*** | 0.008*** | 0.008*** | 0.028*** | 0.010*** | 0.008*** | 0.008*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.005) | (0.002) | (0.001) | (0.001) |
| 1(PHEV) × Range | 0.004 | 0.003 | 0.004 | 0.002 | 0.003 | 0.002 | -0.008 | -0.008 | 0.002 | 0.002 |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.006) | (0.007) | (0.006) | (0.008) | (0.007) | (0.007) |
| Vehicle size (m3) | 0.006 | 0.009 | -0.005 | 0.014 | 0.002 | 0.014 | 0.029 | 0.025 | 0.016 | 0.014 |
| | (0.019) | (0.021) | (0.018) | (0.020) | (0.020) | (0.021) | (0.022) | (0.022) | (0.019) | (0.021) |
| Indicator of Non-financial Incentives | 0.059 | 0.124 | 0.088 | 0.122 | 0.079 | 0.192 | 0.052 | 0.142 | 0.070 | 0.090 |
| | (0.189) | (0.174) | (0.179) | (0.178) | (0.198) | (0.173) | (0.200) | (0.178) | (0.186) | (0.191) |
| Brand FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Fuel Type FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 4528 | 4528 | 4528 | 4528 | 4528 | 4528 | 4528 | 4528 | 4528 | 4528 |

*Notes:* The regressions are based on data for 13 countries from 2013 to 2020. Observations for China in 2020 are excluded due to the impact of COVID19. The dependent variable is log(sales). Coefficient estimates are based on preferred specification in baseline results column (5) 2SLS estimates using battery supplier and BLP instruments for consumer faced prices and using heavy duty EV stock and construction labor costs for charging ports. Charger density is measured by the number of chargers per square kilometer urbanzied area. Standard errors are clustered at the country by year level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# Supplementary Information

## A Data Appendix

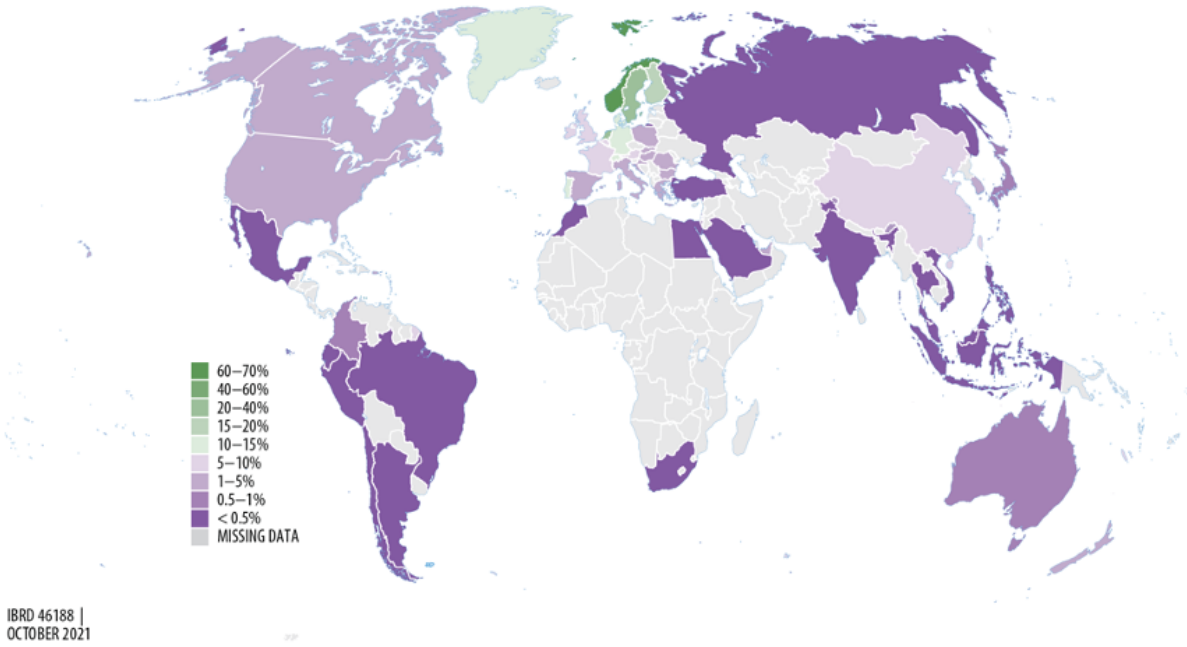
We construct the estimation sample using data from five major sources: 1) EV sales and heavy-duty EV sales purchased from EV-volume; 2) vehicle attributes purchased from IHS/Polk and Taobao; 3) financial and non-financial incentives collected by the authors; 4) number of charging ports from the IEA Global EV Outlook; 5) unit labor cost index in construction sector from OECD; and 6) socio-economic data from the World Bank.

The financial incentives are collected and calculated at the country, year, model level. For consistency across countries, we only consider central/ federal EV incentives or subsidies. The financial incentive can be offered in a variety of forms, including direct consumer subsidy, acquisition tax credit or ownership tax credit (Figure 7b). For China, we use the range-based calculation method in Table 2 of Li et al. (2021). The range-based subsidy is year-specific from 2013 to 2018. Starting 2019, central subsidy depends on both driving range and battery capacity. Further, the central subsidy is canceled for models with price above 300,000 RMB in 2020. For the US, consumers receive a federal income tax credit calculated based on battery capacity. Japan's incentive is provided as direct consumer subsidies at the model-year level. Canada does not have central subsidies to our knowledge, instead we use population weighted average of provincial direct subsidies offered by British Columbia, Quebec, and Ontario.

For European countries, the financial incentives are collected primarily from the European Automobile Manufacturers Association's (ACEA) guide on purchase and tax incentives for electric vehicles. The financial incentives consists of consumer subsidy and/or acquisition or ownership tax deduction. Switzerland does not have central subsidies to our knowledge, instead we use the population weighted average of metropolitan area tax credits offered by Zuric, Lausanne, Basel, Bern, and Geneva. Each province has its own tax credit determined by cylinder capacity or weight. For the rest of European countries in the sample, acquisition or ownership tax for vehicles are typically $CO_2$-dependent and full or partial deduction of these taxes applies to electric vehicles. In addition to $CO_2$, vehicle taxes sometimes also varies by PHEV/BEV type, curb weight, and engine power. We refer to the ACEA tax guide to calculate the vehicle tax and deductions for each country in each year.

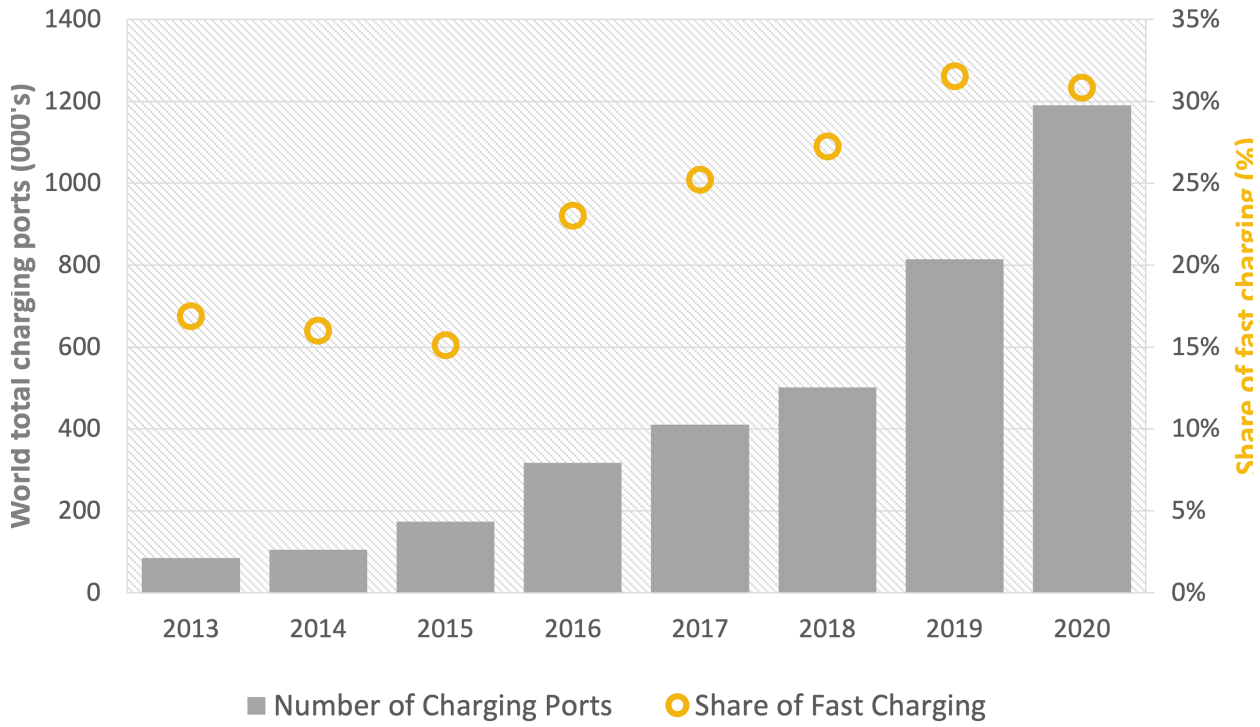
# B Additional Figures

Figure S1: EV share in new vehicle market in 2020



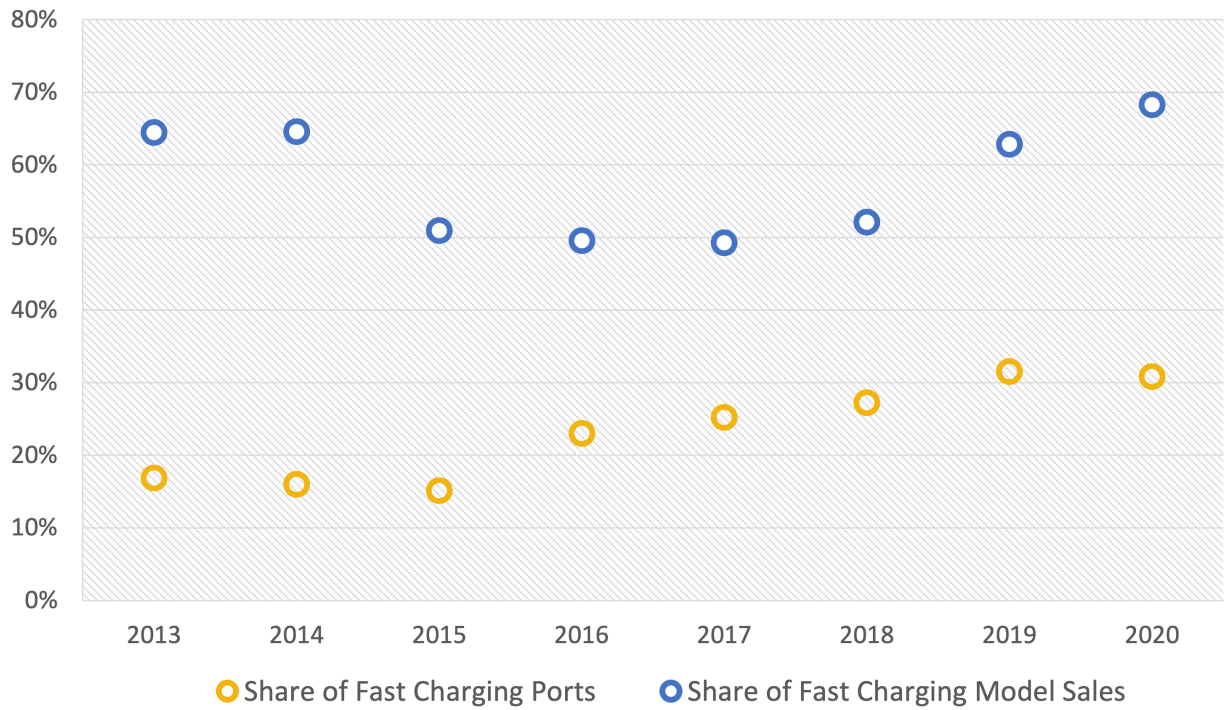

*Notes*: Share of EV sales in the new vehicle market by country in 2020. Norway leads EV penetration at 67%. Sweden and Netherlands's 2020 EV market share is over 20%. All countries with EV market share above 10% are in Europe. China, US, and Canada's EV penetration is around 3-5%. Countries in Asia and Africa generally had lower EV penetration.

Figure S2: Total number of EVSE



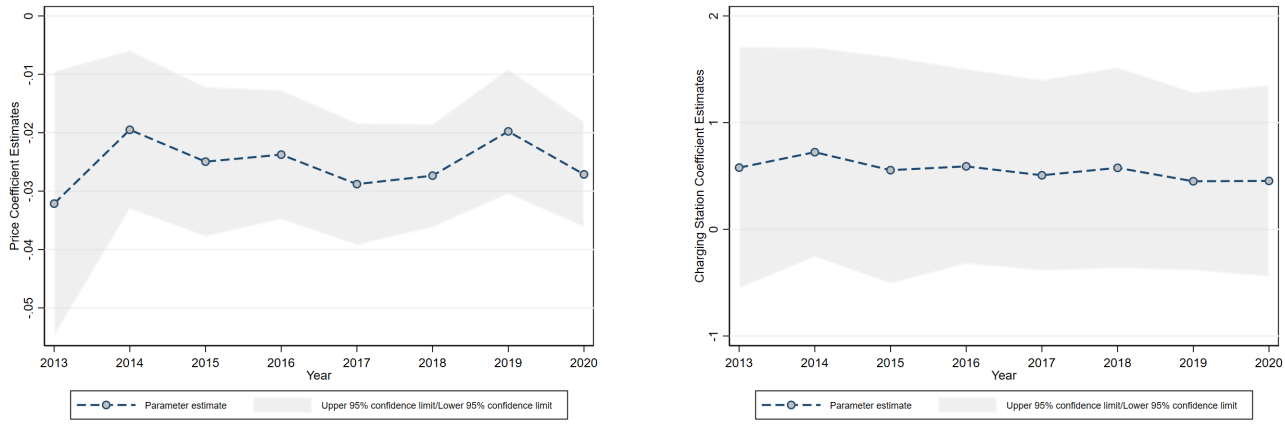

*Notes*: This figure shows the aggregated number of charging ports by year (primary axis) and share of fast charging ports by year (secondary axis).

Figure S3: Share of fast charging EV sales and share of fast charging charger




*Notes*: This figure shows the sales share of fast charging EV models and the share of fast charging chargers (number of fast chargers/total number of chargers) for all countries in the sample.

Figure S4: Heterogeneity over Time

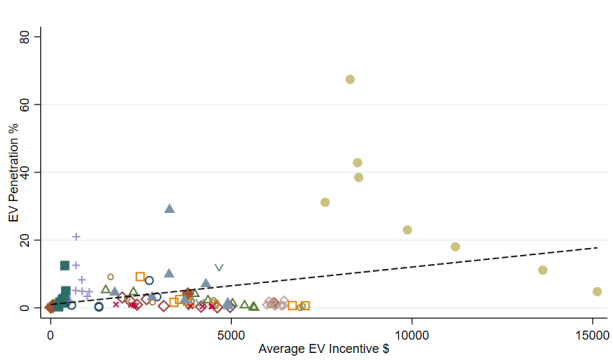



(a) Price Coefficient

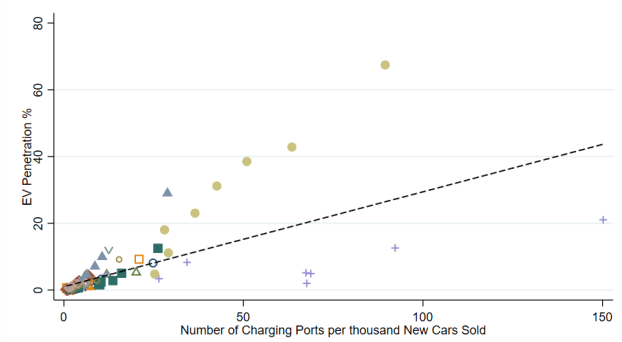
(b) Charging Station Coefficient

*Notes*: Y-axis is the coefficient estimates. Each point on the graph is a year. The grey area represents the 95% confidence interval for the coefficient estiamtes.

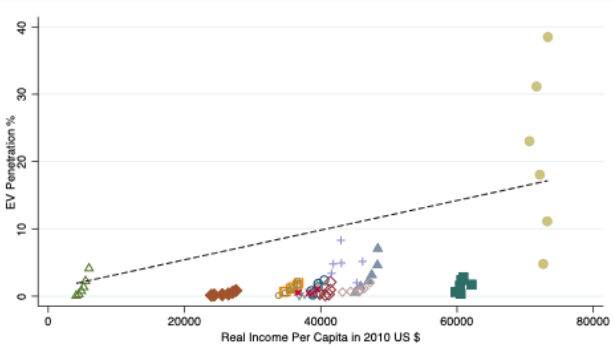
Figure S5: Correlation between EV penetration and EV incentive, charging infrastructure, country demographics



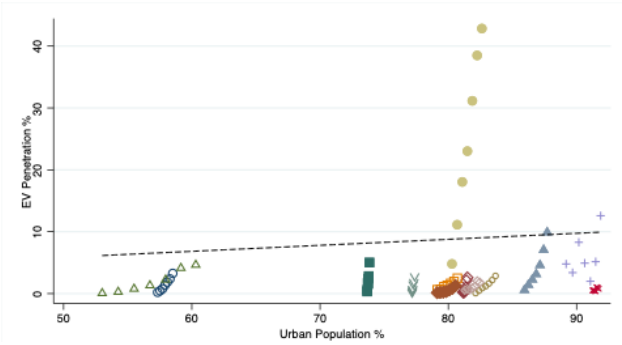

(a) EV Market Shares and Financial Incentives




(b) EV Market Shares and Charging Infrastructure




(c) EV Market Shares and Real Income




(d) EV Market Shares and Urbanization


*Notes*: EV penetration is defined as the total market shares of BEV and PHEV as a fraction of the total number of vehicles sold. Each point on the graph is a country-year combination. The dash line is the linear fit of the points on the graph.

# C Additional Tables

Table S1: Estimation Results for Logit Demand Model

| | OLS | OLS | OLS | IV | IV |
|---|---|---|---|---|---|
| Price - Incentive (1,000 USD) | -0.007*** | -0.019*** | -0.019*** | -0.027*** | -0.029*** |
| | (0.002) | (0.002) | (0.002) | (0.005) | (0.005) |
| Log Charging Ports | -0.393*** | -0.226* | 0.261* | 0.233 | 0.790* |
| | (0.125) | (0.114) | (0.152) | (0.150) | (0.460) |
| Range (miles) | 0.005*** | 0.008*** | 0.008*** | 0.008*** | 0.008*** |
| | (0.001) | (0.003) | (0.001) | (0.001) | (0.001) |
| 1(PHEV) × Range | 0.019*** | -0.006 | 0.006 | 0.003 | 0.003 |
| | (0.005) | (0.007) | (0.006) | (0.007) | (0.007) |
| Vehicle size (m3) | 0.002 | 0.018 | -0.018 | 0.007 | 0.013 |
| | (0.017) | (0.019) | (0.014) | (0.021) | (0.021) |
| Indicator of Non-financial Incentives | 0.378 | 0.219 | 0.177 | 0.173 | 0.043 |
| | (0.285) | (0.267) | (0.148) | (0.149) | (0.182) |
| Brand FE | | ✓ | ✓ | ✓ | ✓ |
| Fuel Type FE | | ✓ | ✓ | ✓ | ✓ |
| Country FE | | | ✓ | ✓ | ✓ |
| Year FE | | | ✓ | ✓ | ✓ |
| First Stage F-stats for Price | | | | 54.67 | 77.00 |
| First Stage F-stats for Charging Station | | | | | 36.34 |
| Underidentification Test | | | | 62.60 | 77.22 |
| Weak Identification Test | | | | 31.85 | 22.47 |
| Overidentification Test | | | | 55.16 | 62.93 |
| Observations | 4528 | 4528 | 4528 | 4528 | 4528 |

*Notes:* The regressions are based on data for 13 countries from 2013 to 2020. Observations for China in 2020 are excluded due to the impact of COVID19. The dependent variable is the logit share in logit demand model. *Price - Incentive* variable is constructed from tax inclusive price subtracting total incentive received. Column (4) shows 2SLS estimates using instruments for consumer prices using the battery supplier dummy interacted with battery capacity as well as BLP instruments including the number of models and models' size, battery capacity, and range for both own brand and rival brands. Column (5) in addition instruments for the number of charging ports using heavy duty EV stock, construction labor costs, and their interactions. Standard errors are clustered at the country by year level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S2: Robustness Check with Different Price Specification

| | OLS | OLS | OLS | IV | IV |
|---|---|---|---|---|---|
| Log(Price - Incentive) | -0.666*** | -1.561*** | -1.464*** | -1.132*** | -1.182*** |
| | (0.080) | (0.150) | (0.140) | (0.398) | (0.388) |
| Log Charging Ports | 0.423*** | 0.454*** | 0.232 | 0.266* | 0.907** |
| | (0.073) | (0.065) | (0.145) | (0.144) | (0.443) |
| Range (miles) | 0.006*** | 0.006*** | 0.009*** | 0.009*** | 0.009*** |
| | (0.001) | (0.002) | (0.001) | (0.002) | (0.001) |
| 1(PHEV) × Range | 0.021*** | -0.011** | 0.007 | 0.008 | 0.008 |
| | (0.004) | (0.005) | (0.006) | (0.007) | (0.007) |
| Vehicle size (m3) | -0.025 | 0.020 | 0.015 | -0.005 | -0.002 |
| | (0.017) | (0.016) | (0.015) | (0.025) | (0.025) |
| Indicator of Non-financial Incentives | 0.483*** | 0.470*** | 0.216 | 0.219 | 0.070 |
| | (0.159) | (0.137) | (0.147) | (0.147) | (0.186) |
| Brand FE | | ✓ | ✓ | ✓ | ✓ |
| Fuel Type FE | | ✓ | ✓ | ✓ | ✓ |
| Country FE | | | ✓ | ✓ | ✓ |
| Year FE | | | ✓ | ✓ | ✓ |
| First Stage F-stats for Price | | | | 105.23 | 121.44 |
| First Stage F-stats for Charging Station | | | | | 36.34 |
| Underidentification Test | | | | 53.38 | 62.30 |
| Weak Identification Test | | | | 36.49 | 24.08 |
| Overidentification Test | | | | 58.89 | 66.87 |
| Observations | 4528 | 4528 | 4528 | 4528 | 4528 |

*Notes:* The regressions are based on data for 13 countries from 2013 to 2020. Observations for China in 2020 are excluded due to the impact of COVID19. The dependent variable is log(sales). *Price - Incentive* variable is constructed from tax inclusive price subtracting total incentive received. Column (4) shows 2SLS estimates using instruments for consumer prices using the battery supplier dummy interacted with battery capacity as well as BLP instruments including the number of models and models' size, battery capacity, and range for both own brand and rival brands. Column (5) in addition instruments for the number of charging ports using heavy duty EV stock, construction labor costs, and their interactions. Standard errors are clustered at the country by year level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$