Charging Infrastructure and Consumer Incentives Drive Cross-Country Disparities in Electric Vehicle Adoption

Shanjun Li Binglin Wang Muxi Yang Fan Zhang*

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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 electric vehicle sales across the world from 2013 to 2020. Our analysis shows that the highly uneven electric vehicle penetration across countries is partly driven by cross-country variation in buyer incentives and, to a much greater degree, by the availability of charging infrastructure. Investment in charging infrastructure is much more cost effective than consumer purchase subsidies in promoting electric vehicle adoption. The findings highlight the importance of expanding charging infrastructure in the next phase of wider electric vehicle diffusion.

Keywords: electric vehicles, consumer demand, incentives, charging infrastructure

JEL classification: L91, Q48, Q51

*Shanjun Li (sl2448@cornell.edu) is a Professor at the Dyson School of Applied Economics and Management, Cornell University and NBER; Binglin Wang (bw474@cornell.edu) is a PhD student at the Dyson School of Applied Economics and Management, Cornell University; Muxi Yang (my458@cornell.edu) is a PhD student at the Dyson School of Applied Economics and Management, Cornell University; Fan Zhang (fzhang1@worldbank.org) is a senior economist at the Chief Economist's Office of Infrastructure, World Bank. We thank Kezhou Miao, Se Ra Yun, and Hui Zhou for excellent data and research assistance.

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 to be a key pathway to reach carbon neutrality (Crabtree, 2019). Governments around the world offer a host of incentives including both financial and non-financial incentives to promote consumer adoption of electric vehicles (EVs). Global EV stocks reached 10 million in 2020 after a decade of growth that began with the introduction of the Chevrolet Volt and Nissan Leaf as the first mass-market EV models into the U.S. market in late 2010. The global EV market has shown significant growth in terms of both market size and market composition. Between 2013 and 2018, EV sales increased by over 50% each year. In 2019, the growth rate temporarily stalled but quickly regained strength; by 2020, EV sales around the world had reached nearly 3 million, representing a significant increase despite the COVID-19 pandemic (Figure 1 panel B). China was by far the largest EV market from 2016 to 2019, when it accounted for over half of global sales. In 2020, Europe overtook China to become the largest EV market. The diffusion of EVs needs to accelerate significantly worldwide to reach adoption goals set by many countries and regions (Figure S1).

Despite the rapid expansion of the global EV stock, diffusion of these vehicles has been highly uneven across countries. In Norway, which leads the world in EV adoption, the EV share of the new passenger vehicle market more than tripled, from 18% in 2015 to 67% in 2020 (Figure 1 panel A). Remarkable growth has also occurred in Sweden and the Netherlands, with the EV market shares reaching over 20% in both countries in 2020. In China, Spain, Canada, and the United States, EV shares of the new vehicle market are far smaller, ranging from 3% to 5% in 2020. These countries also have a diverse set of choices of EV models. In 2020, for example, more than 200 different EV models were available in China; by contrast, just roughly 50 models were available in Canada and the United States (Figure 1 panel C). See supplemental materials section A for discussion on heterogeneous preferences in vehicle attributes (Figure S3) and local brand dependence by region (Figure S4).

What drove the dramatic cross-country disparities in EV adoption during the first decade of EV diffusion? The spatial variation across countries points to key questions about the key market and policy drivers behind EV adoption. Previous studies have documented multiple economic and technological challenges in EV diffusion (Hardman and Tal, 2021), including the high upfront purchase cost of EVs (Krutilla and Graham, 2012; Adepetu and Keshav, 2017), limited driving range and model availability (Schneidereit et al., 2015), the lack of adequate charging infrastructure (Li et al., 2017; Taalbi and Nielsen, 2021; Berkeley et al., 2018; Wei et al., 2021), and the inherent and perceived uncertainty about this new technology (Carley et al., 2013; She et al., 2017). However, much focus has been placed on country-specific or region-specific analysis. Thus, many questions about EV global adoption remain unanswered. How much of EV diffusion is driven by markets and different types of policies? What policies are cost effective and applicable for countries that currently have low adoption rates, but have huge potential for future uptake? Understanding the determinants of EV diffusion from a cross-country perspective has important implications for the next phase of EV market development in addressing pressing climate change and local air pollution challenges.

This study aims to investigate the market growth and spatial disparity of EV diffusion based on what to our knowledge is the most comprehensive data complied on the global EV market. Our data include model-level EV sales by country, vehicle attributes, charging infrastructure, detailed EV policies, and demographic and socioeconomic variables by country from 2013 to 2020. Our analysis focuses on 13 countries with the highest EV sales. These countries account for 95% of total global EV sales during this period. We conduct regression analysis based on standard panel-data methods to establish the causal effects of various drivers. The model allows us to include a rich set of fixed effects to control for brand-level shocks and annual fluctuations in global demand. We address additional identification concerns by using multiple sets of instrumental variables carefully constructed to account for price endogeneity due to unobserved product attributes and simultaneity between EV demand and charging infrastructure. Based on regression estimates, we simulate EV market shares across countries under various policy scenarios, and we assess the cost effectiveness of key policies.

The analysis presents three key findings. First, charging infrastructure and consumer incentives are both effective in promoting EV adoption. Second, from the government investment perspective, charging infrastructure is more cost effective than consumer subsidies in promoting EV adoption. The government spending needed to induce one addition EV purchase is seven times higher when subsidizing consumer purchases than when expanding charging networks. Finally, the cross-country variation is driven by observed differences in the size of charging networks to a much larger extent than by differences in consumer incentives.

Key drivers of global EV adoption

We investigate two main policy drivers of EV demand: purchase incentives and availability of charging infrastructure. There are two well-known challenges to credibly identify their effects.

First, the post-incentive price of EVs might be endogenous, leading to a downward bias in the estimated effect of consumer incentives on EV adoption (Berry et al., 1995; Petrin, 2002). This can occur when unobserved product attributes (i.e., model quality or prestige) influence both vehicle price and consumers' purchase decisions. Second, simultaneity between consumer demand for EVs and investment decisions on charging facilities could bias the estimated effect of charging infrastructure (Li et al., 2017; Springel, 2021). To address price endogeneity, we construct a set of instrumental variables based on supplier-specific battery capacity and vehicle attributes for rival brands. To deal with simultaneity, we use the stock of heavy-duty EVs and construction labor costs adjusted for charging speed as the instrumental variables. (See the Methods section for details). We find that consumer subsidies and charging infrastructure both have positive and significant impacts on EV sales (shown in column (5) of Table 1 and discussed in detail in supplemental materials section B). Based on the coefficient estimates, a back-of-the-envelope calculation suggests that to increase EV sales by 10% requires either an increase in consumer subsidies of about \$3,000 per vehicle or a 12.2% increase in charging infrastructure. The results are robust under a series of alternative models (see supplemental materials Section D).

Next we investigate how country level socioeconomic variables affect the estimated price responsiveness. We interact post-incentive price with a set of different variables representing countries' key demographic indicators. Detailed regression results are presented in Table S3 and discussed in supplemental materials Section C. Consumers in countries with higher real income levels are less price sensitive, though the effect size is fairly small. Figure 2a provides a visualization of this pattern by plotting the estimated price coefficient for each country against countries' mean income levels. Consumers from higher income countries are less sensitive to price changes and EV incentives. Gasoline prices also influence the effectiveness of EV subsidies by inducing the substitution of gasoline vehicles with EVs. In countries with higher gasoline prices, EV demand is more inelastic with respect to EV purchase prices (Figure 2b). In addition, price elasticity also correlates with charging-network density measured by the number of chargers per square kilometer in urbanized areas. In countries with better charging networks, EV demand is less price elastic (Figure 2c), which suggests potential policy complementarity between subsidies for charging stations and subsidies for EV purchases.

We find evidence that expanding the charging network alleviates consumers' range anxiety. We extend the baseline regression model by interacting the charging-port variable with EVs' driving range and an indicator variable for plug-in hybrid EVs (PHEV) or battery EVs (BEV). The negative and significant coefficient for the interaction term with driving range variable suggests that charging ports have a larger effect on EV models with shorter ranges (Table S3). In addition, the availability of charging ports matters more for hybrids than battery EVs, possibly due to the fact that most hybrids have a shorter range and require more frequent charging than battery-powered EVs. In addition, we also find that a larger effect of expanding charging networks in countries with higher gasoline prices.

Cross-country variation in EV adoption

EV adoption is highly uneven across countries. In 2020, Norway had the highest EV market share, with EVs accounting for 67.4% of all new cars sold. By contrast, in Japan less than 1% of new cars sold are EVs. To explain the wide disparities in EV adoption rates among countries, we examine the roles of EV subsidies and the availability of charging infrastructure.

The expansion of the global EV market benefited from financial incentives such as direct rebates and tax credits or tax exemptions. Countries with higher financial incentives have a larger EV share in the passenger vehicle market in general (Figure S6a). Norway has the most aggressive incentives for EVs in the world, offering about $8,800 per vehicle on average from 2013 to 2020 (Figure 3a). The average EV incentive is around $6,000 in the United states while that in China is around $3,000.[1] In addition to financial incentives, there are a variety of non-financial incentives for EV purchases (Figure 3b). Many countries designate distinctive-looking green plates for EVs, allowing EVs to stand out and facilitating the implementation of free parking or privileges that allow drivers to use lanes reserved for high-occupancy vehicles. These non-financial policies reduce the ownership cost of EVs and bring non-monetary benefits that could encourage EV adoption.

There is also strong correlation between EV penetration and charging infrastructure at the country-year level (Figure S6b). We focus on electric vehicle supply equipment (EVSE), or charging ports. Since both EV sales and the number of charging ports grow over time, the ratio of EV stock to EVSE reflects the relative growth rate of the two (Figure 4 Panel A). A lower ratio represents higher availability of chargers. China and the Netherlands have the lowest ratios; Norway and the United States have higher ratios. [2] Another metric is the number

[1] Direct subsidies can be flat (as used in the UK), or based on range (as used in China), battery capacity (as used in the United States), or carbon emissions (as used in France). In addition to offering direct subsidies, governments may partially or fully exempt vehicle acquisition taxes and vehicle ownership taxes, as is often the case in Europe, where tiered vehicle taxes are often based on carbon emissions and key vehicle attributes such as weight, engine rating, and cylinder capacity.

[2] In China, the charging infrastructure has rapidly expanded in the recent years. Publicly accessible EVSE

charging ports (extent of EVSE) per thousand new car sales, including both EVs and gasoline vehicles. This reflects the charging availability for the total potential EV market in the country with 100% electrification of the new vehicle market. The Netherlands and Norway are far ahead of other countries in terms of charging availability (Figure 4 Panel B). The ability of charging infrastructure to meet EV demand depends not only on the number of charging ports but also the charging speed of the connectors.[3] In China, while the sales of EV models compatible with fast charging has been increasing drastically since 2013, the number of fast-charging ports has also grown significantly. Globally, by contrast, sales of fast-charging EV models have increased drastically in recent years, even though the share of fast-charging ports has remained relatively steady on average across countries in our sample (Figure 4 Panel C).

We simulate the counterfactual EV market shares by country based on regression estimates. To investigate the impact of EV incentives, 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.[4] Figure 5a compares these simulated EV market shares with the observed EV market shares in 2020. For the five countries that have above-average incentives, the simulated market share is lower than the observed market share. However, for the rest of the countries, increasing incentives to the world-average level would help them catch up to the market shares of leading countries.

We then examine how the charging infrastructure helps to explain cross-country differences in EV adoption. Again, we compare simulated and observed EV market shares, this time by charging-infrastructure level, which we define as the number of charging ports per thousand new cars sold. The simulation uses the average charging-infrastructure level in our sample as the basis for the comparison with actual levels across countries. Figure 5b presents the results. The charging infrastructure has a much larger impact on the simulated market shares compared to the purchase incentives. Norway and the Netherlands would see a decrease in EV market share under the simulated infrastructure scenario, while EV penetration would expand in all other countries. This highlights the importance of building up charging infrastructure in global EV

increased from 30,000 sites in 2013 to 800,000 sites in 2020.

[3]There are typically four levels of charging speed 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 the BMW i8 PHEV). Level 3 and Level 4 chargers use DC and are suitable for fast-charging EV models (primarily BEV models such as the 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 stations are an exception in that Tesla connectors are not compatible with those of other EV models.

[4]We assume that the induced new sales of EVs substitute for an estimate 50% of vehicles that rely on internal combustion engines. Our data do not include information on vehicles powered by internal combustion engines; therefore, our analysis cannot directly estimate the substitution.

diffusion.

In both cases, reducing the disparity in incentives or charging infrastructure would lead to more uniformly distributed EV penetrations across countries - though to a far greater degree via the infrastructure route. We find that removing the cross-country variation in purchase incentives reduces the differences in EV market shares by 17%. By contrast, removing cross-country variation in charging-infrastructure levels reduces the differences among countries' EV market shares by 69%.

Cost-effectiveness of EV policies

In this section, we assess the cost effectiveness of providing financial incentives and building charging infrastructure.

All 13 countries provide financial incentives for buying EVs. The average incentive from the central government is about $3,400 per vehicle, and can reach as high as $56,000 for certain models. From 2013 to 2020, the financial incentives in these countries totaled $43 billion. To understand the impact of financial incentives, Figure 6a shows the counterfactual sales that would have occurred if the subsidies had not been in place. The impact of financial incentives is based on the coefficient estimate in column (5) of Table 1. We compute the total number of EV car sales induced by the financial incentives by calculating the difference between the observed sales and the simulated sales that would have occurred absent the subsidies. We estimate that the financial incentives provided over the sample period account for 3.9 million cars sold in all these countries. Thus, the financial incentives for buyers from the central government explained 40% of EV sales overall.

An alternative strategy to promote EV diffusion is to expand the size of the charging network by subsidizing investments in charging stations. A larger charging network could facilitate EV adoption by alleviating consumers' anxiety about such vehicles' driving range. Based on the coefficient estimates in column (5) of Table 1, Figure 6a shows the counterfactual sales that would have occurred if the total number of charging ports had fallen by 50%. We estimate that the total number of sales induced by this policy is about 4.3 million vehicles, equivalent to about 43% of EV sales. To enable a fair comparison of sales impacts from purchase subsidies and charging infrastructure, Figure 6c depicts a scenario in which government spending on both policies is equal, with government spending $43 billion on consumer subsidies and $43 billion on buiding charging stations. This shows that the larger charging network that would result from this level of spending would lead to a 300% increase in EV sales in the sample period; by contrast the purchase subsidies result in 40% increase in sales. Therefore, investing in charging infrastructure has a much bigger, positive impact on EV sales than providing consumer purchase subsidies.

Next, we calculate the average government spending per induced sale as the ratio between the aggregated government spending and the induced sales under each policy. On average, inducing one additional electric vehicle through subsidies of consumer purchases would cost $10,872 in government spending. By contrast, the average government spending needed to induce additional sale through expanding charging infrastructure would cost only $1,587 . Thus, it is far more cost effective for governments to invest in expanding the charging network rather than providing purchase incentives. 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), the United States (Li et al., 2017), and Norway (Springel, 2021).[5]

Conclusion

This study provides a comprehensive analysis of the global diffusion of electric vehicles that has taken place since the technology was introduced to the mass market a decade ago. The analysis shows that investing in charging infrastructure is a more cost-effective way to promote EV adoption than providing consumer subsidies. This finding is consistent with previous findings from the literature based on data from individual countries. Our study sheds new light on the reasons for the significant variation in EV adoption across countries, even among those with similar socio-economic characteristics. Our analysis shows that differences in subsidy levels drive roughly 17% of the cross-country variation. By contrast, differences in charging network size account for 69% of variation in EV adoption. These findings underscore the importance of investing in charging infrastructure 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

[5] One important caveat is that the calculated average government spending per induced sale in this analysis applies only to central government incentives. Our data on incentives include only national-level subsidies and tax reductions. However, some countries also provide local subsidies. For example, in China local subsidies account for 22% of total subsidies on average. In the United States, rebates and tax credits are offered at the state level; for instance, California offers rebates and tax credits equivalent to 30% of the federal-level tax credit. Thus, the estimated impacts from incentives might be larger if all local incentives were available in the data.

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., 2017; Holland et al., 2016). Future research could use consumer-level data and richer models to better capture consumer choices among different EV and gasoline models, and to 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; it does not examine the supply-side responses such as product choices of automakers and part suppliers (e.g., battery manufactures). 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.

Methods

Data We collected and compiled seven major datasets on EV sales, vehicle attributes, incentives, charging infrastructure, and socioeconomic conditions for a set of countries with top EV sales from 2013 to 2020. The datasets include 13 countries: Austria, Canada, China, France, Germany, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, the United Kingdom, and the United States. These countries account for 95% of all EV sales worldwide. We merge these data into a panel data set of 3,980 observations at the level of vehicle model by country by year. Most developing countries are excluded from the sample due to extremely low EV penetration. More details on data collection and processing can be found in supplemental materials section F. Table S1 presents the summary statistics of the data.

Empirical framework We define a vehicle model as a brand-model combination (e.g., Tesla 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 the tax-inclusive price of a vehicle. S_{ckt} denotes the total subsidies that consumers are eligible to receive. The first term measures the actual acquisition cost (price minus subsidies). β_1 measures consumer sensitivity to the acquisition cost. The implicit assumption is that consumers respond similarly to the vehicle purchase price and to subsidies on a dollar-to-dollar basis. The assumption could be violated if the subsidies are not as salient as prices, or if 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 they are 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.[6]

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 include only consumer subsidies at the national level. Subsidies at the local level (e.g., from states or municipalities) are common but collecting them all for all these countries is impractical. 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 together.

N_{ckt} denotes the total number of fast or slow public charging ports available to model k in country c by the end of a given year. The coefficient on β_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 control for 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. The density of charging ports could matter in a different way from the number of the charging ports. One could consider weighting using country area or urbanized area. However, because these measures do not have variation over time, with time fixed effects, the regression results would not be affected by these weighting.

Identification strategy Our key parameters of interest are the β's, which capture the effects of consumer subsidies and the availability of charging infrastructure. However, the price variable and the charging ports variable are subject to the concern of endogeneity, even with the rich set of controls in (1).

We address the two sources of endogeneity — unobserved product attributes and simultaneity — using the instrumental variable (IV) method. To address price endogeneity due to unobserved

[6] We drop the 2020 data for China in our analysis due to the impact of COVID-19.

product attributes, we deploy two sets of IVs. We first construct a set of IVs based on battery capacity (kWh) interacting with supplier dummies. Batteries are a key cost component of EV production. A larger battery with higher capacity is generally more costly to produce and install. The supplier dummies capture the cost difference across battery suppliers reflecting the fact that different suppliers of batteries for different EV models could have different cost advantages.[7] Therefore, the interaction terms between battery capacity and battery suppliers are good predictors for vehicle price. Furthermore, the identification is valid because by conditioning on driving range (which is included in the regression as a control variable), factors that affect passengers' purchase decisions should not be directly correlated with the size of the battery. The second set of price instruments is standard in the literature which follows Berry et al. (1995). It includes 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 Berry-Levinsohn-Pakes style IVs is that observed vehicle attributes are not correlated with unobserved ones, while firm pricing decisions would imply that the price of a given model would be affected by the attributes of other products in the market making them good exogenous predictors for vehicle prices.

The charging infrastructure variable (i.e., the number of charging ports) could be endogenous because unobserved demand shocks might be correlated with the size of the charging network through affecting charging station investment decisions which is known as the simultaneity problem (Corts, 2010; Li et al., 2017). The availability of charging facilities could help promote consumer adoption by alleviating concerns consumers have about the limited driving range of EVs. At the same time, investors' decisions on charging infrastructure take into account current and future demand conditions. To address this endogeneity, we use as IVs the stock (i.e., cumulative sales) of heavy-duty EVs (e.g., buses) and construction labor costs interacting with dummy variables for fast charging models. The identification assumption is that the heavy-duty EV stock reflects the underlying incentives for building up charging stations, but 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 - suggesting a correlation between heavy-duty EV stock and passenger EV charging infrastructure. Similarly, the construction labor costs reflect supply-side cost shocks,

[7] Note that the battery cost to manufactures might vary due to a range of factors such as production cost differences, bargaining power differences, and 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.

which directly affect the construction of charging stations but are unlikely to be correlated with demand-side factors. The interaction with the fast-charging model dummies allows for the effect to be potentially different for fast-charging models and slow-charging models.

Data availability

The data except the proprietary sales data that supports the plots and tables in the manuscript are available at https://doi.org/10.7910/DVN/KDFTAY.

Code availability

Codes for the analysis are available at https://doi.org/10.7910/DVN/KDFTAY.

Author contribution

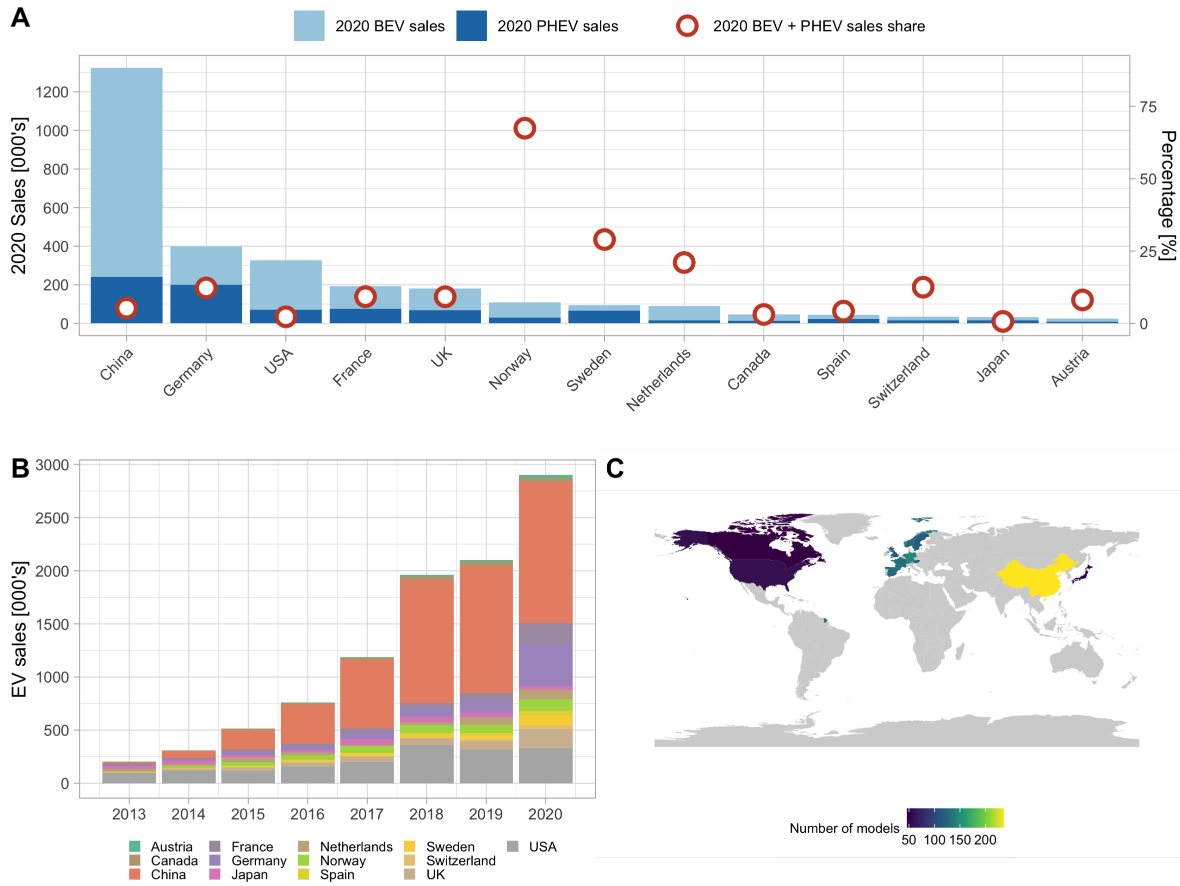
S.L. conceived and designed the project and guided the analysis process. B.W. and M.Y. collected data and performed the analysis. S.L., B.W., and M.Y. wrote the manuscript. F.Z. provided data, reviewed the results, and revised the manuscript.

Competing interests

The authors declare no competing interests.

Figures and Tables

Figure 1: EV Sales Volume, Market Share, and Model Diversity



Notes: **Panel A** shows sales of battery EVs compared to plug-in hybrid EVs (left primary axis and blue bars) The secondary (right) axis (and the red circles) shows the market share of EVs by country in 2020. **Panel B** shows annual EV sales by country from 2013 to 2020. Both plug-in hybrid EVs and battery EVs are included. **Panel C** is a map indicating the number of unique EV models by country (in our sample) in 2020.

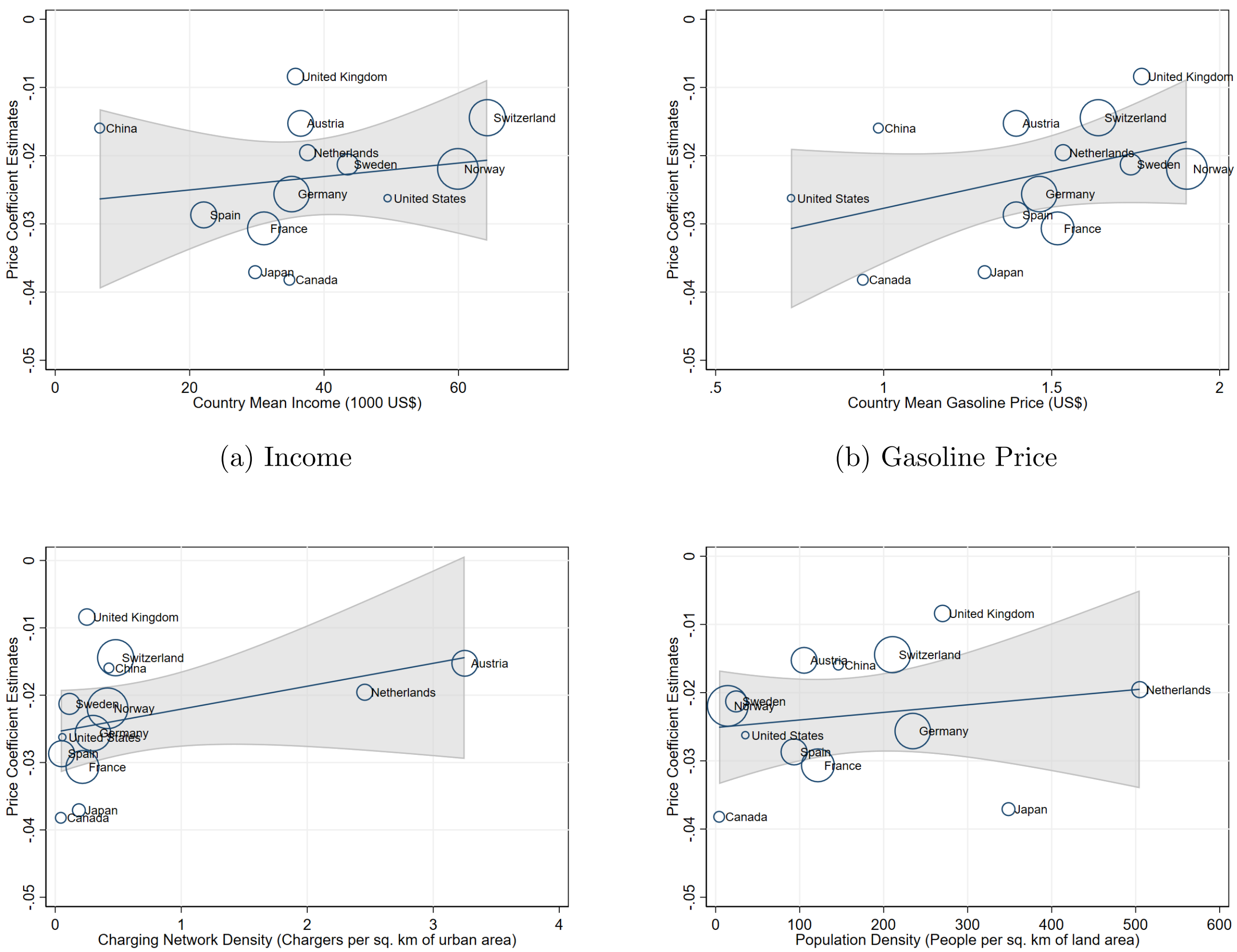
Table 1: Estimation Results for EV Demand

	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) $\times$ 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 COVID-19. The dependent variable is log(sales). The *Price - Incentive* variable is constructed from the tax-inclusive price minus the total incentive received. Column (4) shows 2SLS estimates using two sets of instruments for consumer prices: the first set of IVs is the battery-supplier dummies interacted with battery capacity; the second set is the Berry-Levinsohn-Pakes style IVs including the number of models, model size, battery capacity, and range for both own and rival brands. Column (5) adds additional 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 are reported in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 2: Price-sensitivity Heterogeneity across Countries



(a) Income

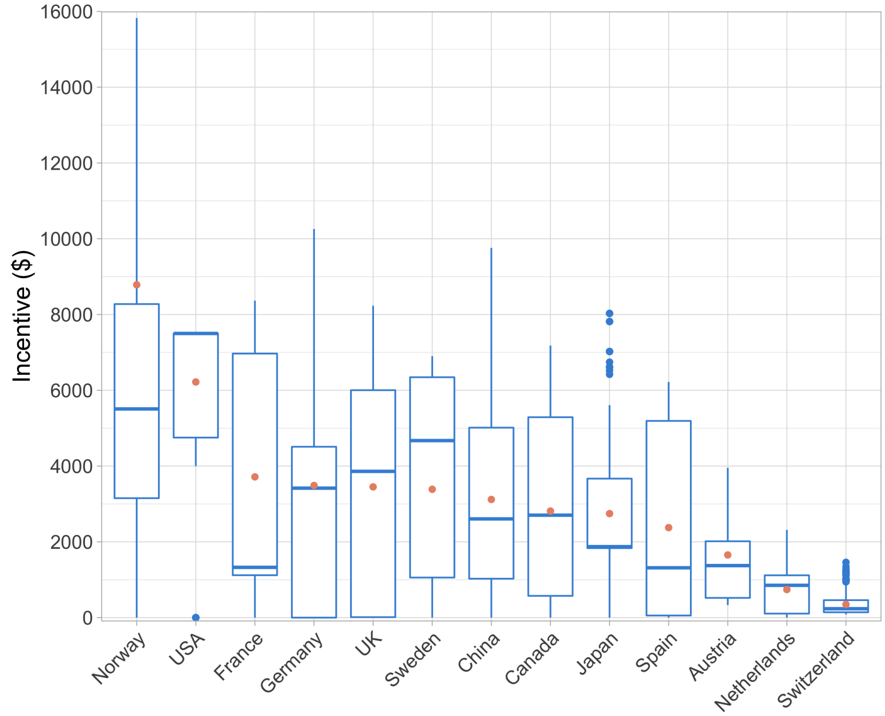
(b) Gasoline Price

(c) Charging Network Density

(d) Population Density

Notes: The Y-axis shows 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 3: Summary of Financial and Non-financial EV Incentives



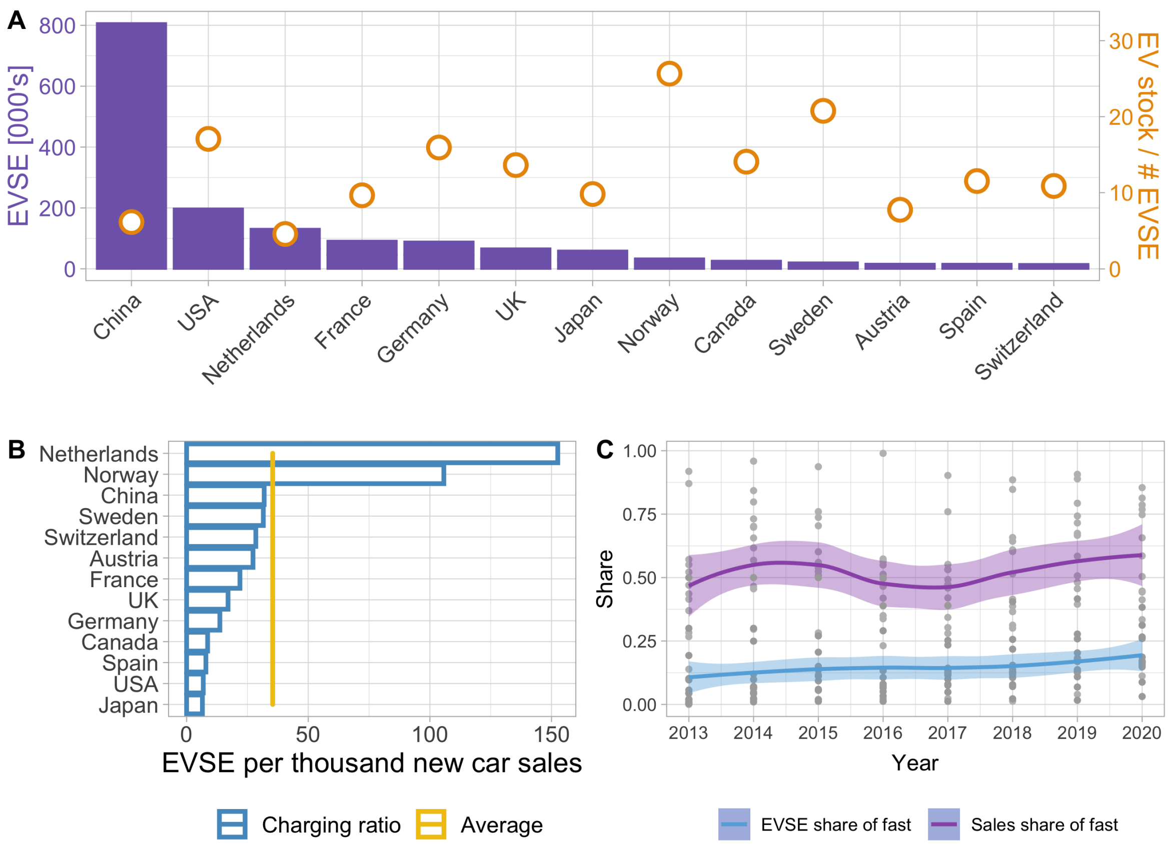
(a) Average EV Financial Incentives by Country

	Austria	France	Germany	Netherlands	Norway	Spain	Sweden	Switzerland	UK	China	Japan	Canada	US
Consumer subsidy	●					●	●		●	●	●	○	
Acquisition tax discount	●	●	●	●	●								●
Ownership tax discount	●		●	●		●	●	○	●				
Free parking	○	○	○	○	●	○			○	○			○
HOV lane		○	○	○	●	○	○		○	○	○	○	○
Green plate	○		○		●	○				○		○	○

(b) EV Policies by Country

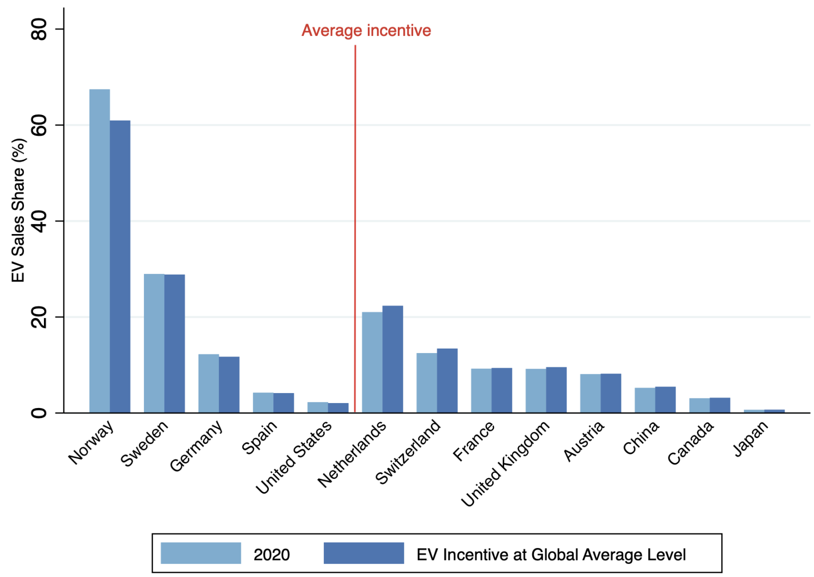
Notes: Summary of EV policies. **Panel (a)** shows the dispersion of national-level incentives for each country. Data are at the country-year-model level. The lower and upper hinges of the boxes represent the first and third quantiles. The upper whisker corresponds to $min(max(x), Q3 + 1.5IQR)$. The lower whisker extends to $max(min(x), Q1 - 1.5IQR)$. $IQR = Q3 - Q1$, or equivalently the length of the box. In the boxes, the blue line shows the median and the orange dot indicates the mean. Blue dots outside the boxes represent the outliers for each country. For Norway, 13% of data are defined as outliers using the calculation above; these data are omitted from the figure for visualization convenience. Generally, local or regional incentives are not included. However, Switzerland and Canada are exceptions because they did not have central incentives in our sample period. **Panel (b)** shows whether financial or non-financial policies exist at the national or regional level. The black dots indicate national policies. The hallow dots indicate regional policies. Dark blue shading indicates policies that were implemented prior to 2017. Light blue shading indicates that policies were implemented after 2017.

Figure 4: Summary of Charging Infrastructure by Country

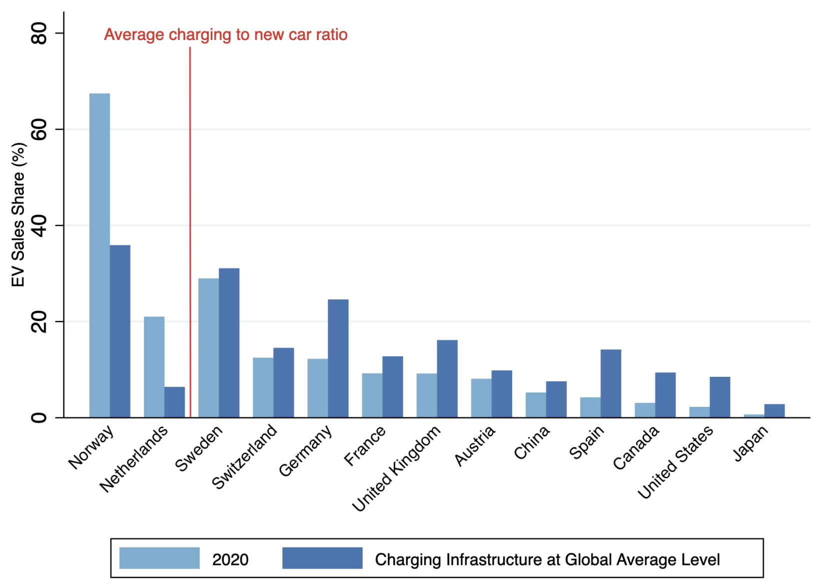


Notes: **Panel A** shows number of charging ports in 2020 by country on the primary axis with purple bars. It shows the ratio between the EV stocks (cumulative EV sales from 2013 to 2020) and the number of charging ports available in 2020 on the secondary axis with yellow circles. **Panel B** shows a measure of the extent of electric vehicle supply equipment (EVSE) per thousand new car sales in 2020 by country (blue bar). The yellow line shows the average level across countries. **Panel C** shows the average share and dispersion of the shares of the sales of fast-charging models among all EV models (purple) and the share of fast-charging ports among all charging ports by year (blue).

Figure 5: Simulated EV Market Shares across Countries



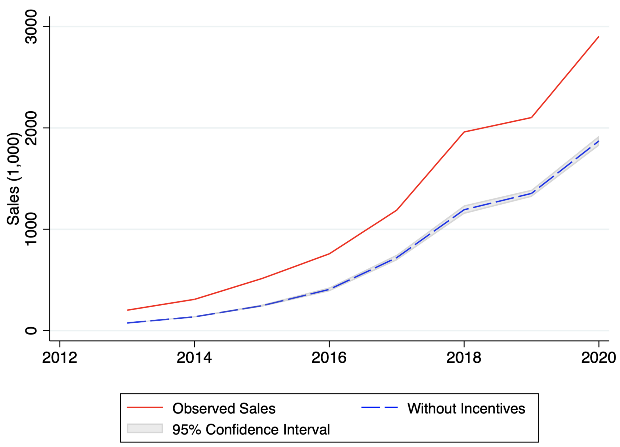
(a) Incentive Simulation



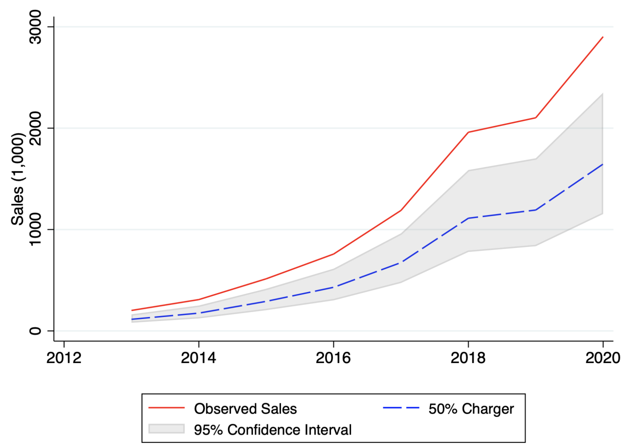
(b) Charging Infrastructure Simulation

Notes: This figure plots EV market shares in 2020 in comparison to simulated EV market shares assuming that the buyer incentives **(Panel a)** and charging ports **(Panel b)** of all countries are at the average level of the sample, and that new EV sales substitute 50% of vehicles powered by internal combustion engines. The red line indicates the sample average of incentives (panel a) and sample average of the ratio of charging ports to new vehicles (Panel b) in 2020. Countries to left of the red line have above-average incentives or above-average charging port ratios. In each panel, we first group countries by above (left of the red line) and blow (right of the red line) global average incentive (panel a) and charging infrastructure (panel b). The countries are then ranked by descending observed 2020 market share (light blue bar) within each group.

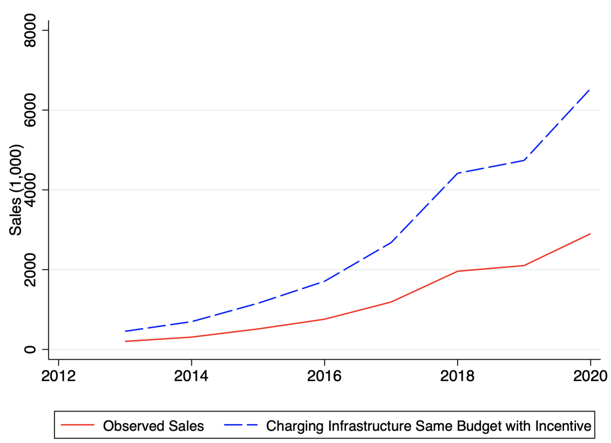
Figure 6: Counterfactual Sales Under Alternative Policy Scenarios



(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 **(Panel a)**, with 50% reduction in charging ports **(Panel b)**, and with charging infrastructure having the same government budget as consumer incentives **(Panel 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.

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Supplementary Information

A Cross-country Variation in EV Choices

There is also considerable variation in the types of EVs purchased across regions. Figure S3 presents the average battery capacity, post-incentive price, and vehicle size for battery EVs sold during the 2013-2020 period in four main regions in the estimation sample: China, Japan, Europe,[8] and North America.[9] We present the sample and sales-weighted averages in red and blue, respectively. Sales-weighted average battery capacity is generally higher than the sample average in all regions except Japan, indicating that battery capacity is a key attribute in consumers' choices. In particular, consumers in Europe and North America disproportionately prefer EVs with a higher driving range. The sales-weighted average post-incentive price is lower than the sample average post-incentive price in all regions because 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 a lower post-incentive price, battery capacity, and size on average; this is 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 those in other markets.

From 2015 to 2020, the number of EV models available worldwide increased from 90 to 370, reflecting ever-growing choices for consumers.[10] There appears to be a strong preference for local brands, as documented for conventional gasoline vehicles in Coşar et al. (2018) and Barwick et al. (2021). Figure S4 shows the top-five brands in cumulative sales from 2013 to 2020 by region. Chinese brands including BYD, BJEV, and Chery dominate the EV market in China. Similarly, the majority of top-selling brands in Europe are European brands such as VW, BMW, Renault, and Mercedes. U.S.-based brands are more popular in the United States. Japanese brands are more popular in Japan and the Republic of Korea. Tesla is the only brand appearing in the top-five across all four regions.

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

[9]Canada and the United States.

[10]Source: International Energy Agency (IEA) Global EV Outlook 2021.

B Regression Parameter Estimates

Table 1 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 incentives), 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 regressions, 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 price and charging station endogeneity.

The regression in column (1) suffers from different sources of confounding factors that bias the price coefficient toward 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 and affect 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 more than doubles 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. [11] 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 is 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 increases EV sales by 8.2%.

Column (4) addresses the price endogeneity problem by instrumenting prices with battery supplier IVs and Berry-Levinsohn-Pakes style IVs. This set of IVs strongly predicts prices, as

[11] 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.

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. 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 doubles though the 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 (e.g., green plates, free parking, etc.) up to the country level, while many of these policies are implemented at the local level (state or municipality policies), 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 the number of charging ports increases EV sales by 8.2%. Based on the coefficient estimates, a back-of-the-envelope calculation suggests that increase the EV sales by 10% would require an increase of consumer subsidies by about $3,000 per vehicle subsidy or a 12.2% increase in charging infrastructure.

C Heterogeneity

Table S3 presents regression results examining the heterogeneity of our baseline findings. In column (1), we interact price with countries' real income levels. The rationale is that consumers from higher-income countries might be less sensitive to price changes and EV incentives. Figure 2a provides a visualization of this pattern by plotting the estimated price coefficient for each country against countries' mean income levels. The graphical pattern seems to suggest consumers in higher income countries are less price sensitive. Though the interaction term is significant at the 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 2c provides a visualization of this pattern. The estimated coefficient for the interaction term is positive and significant, suggesting that in countries with better charging networks, consumers are more inelastic about EV price in their purchase. This also points to a potential policy complementarity between subsidies for charging stations and subsidies for EV purchases, consistent with the policy simulation results for the U.S. in Cole et al. (2021). Column (3) interacts the purchase price variable with country-average gasoline prices. Gasoline prices affect EV purchases through inducing the substitution of gasoline cars with 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 2b 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 of an effect.

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). Columns (7) and (8) examine how building out the network of charging ports alleviates consumers' range anxiety. To do this, we interact charging ports with EVs' driving range and a dummy variable for PHEVs. 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 ranges. In addition, charging ports matter more for PHEVs than BEVs. The reason might be due to the fact that most PHEVs have a shorter range than BEVs and therefore need more frequent charging.

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 of one for the later period of our study. We then interact this dummy variable with price and charging-port variables. We do not find that consumers are more or less price sensitive over time; we find that the impact of charging infrastructure remains similar. The individual coefficients are also plotted separately in Figure S5.

D Alternative Specifications and Robustness Checks

We examine several alternative model specifications and the robustness of our findings. Using an approach similar to the one we employed in estimating the demand equation 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 advantages of being theoretically consistent with an underlying utility-maximization framework and of still being conveniently estimated linearly (Berry, 1994). Table S2 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 S4 shows the results. The implied price elasticities are comparable with the original specification and charging station coefficient estimates are largely the same.

E Policy Analysis

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. We then compare the cost-effectiveness of the three policies.

Next, 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.[12] 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.[13]

F Data Appendix

We construct the estimation sample on 13 countries using data from five major sources: 1) EV sales and heavy-duty EV sales purchased from EV-volumes database, 2) vehicle attributes purchased from IHS/Polk, 3) financial and non-financial incentives collected by the authors, 4) number of charging ports from the IEA Global EV Outlook, 5) the unit labor cost index in the construction sector from OECD, and 6) socio-economic data from the World Bank. The 13 countries are Austria, Canada, China, France, Germany, Japan, the Netherlands, Norway, Spain,

[12]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.

[13]China, the United States, and European countries have very different construction costs for slow- and fast-charger facilities. We account for these differences in the aggregate construction costs. Costs estimates are as follows: for China, \$1,449 for slow AC and \$14,493 for fast DC; for the United States and Canada, \$5,440 for slow AC and \$81,818 for fast DC; and for Europe and Japan, \$7,273 for slow AC and \$173,580 for fast DC. Cost estimates are from Nicholas (2019) and Mathieu (2018).

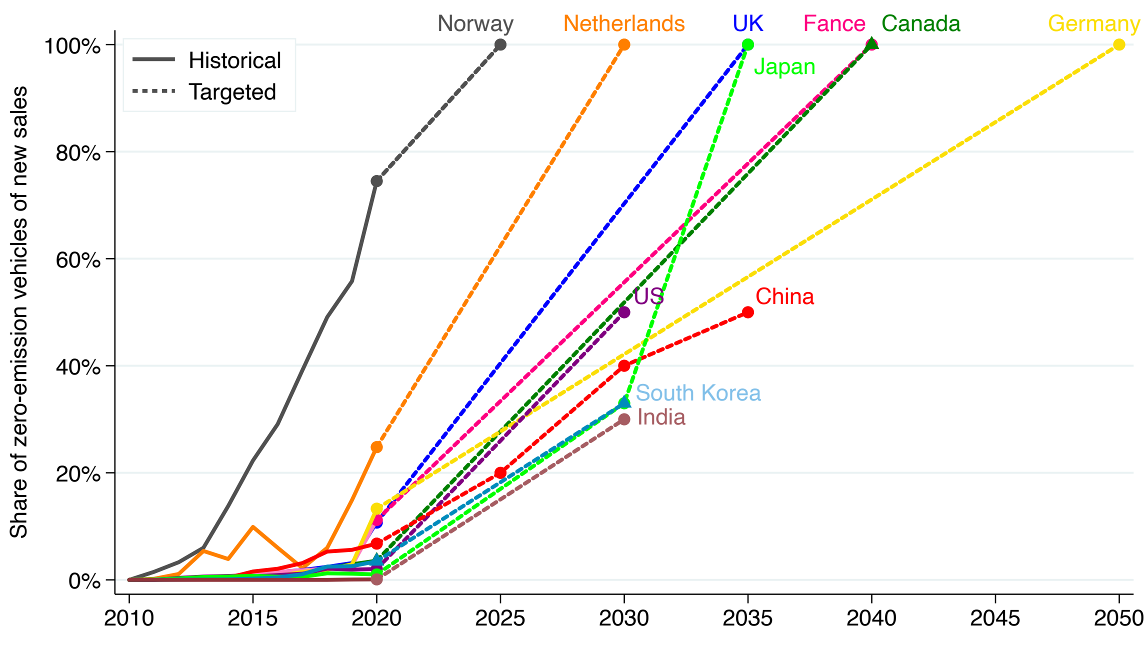
Sweden, Switzerland, the United Kingdom, and the United States, accounting for 95% of world EV cumulative sales. Note that most developing countries are excluded from the sample due to extremely low EV penetration – for example 0.14% for India and 0.1% for Brazil in 2020. In India, almost all electric vehicles sold are 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. Per capita ownership of vehicles in general (including those powered by internal combustion engines) in major developing countries over the past decade has been below that of major developed countries (Li et al. (2020)).

The financial incentives are collected and calculated at the country, year, and model levels. 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 subsidies, acquisition tax credits and ownership tax credits (Figure 3b). 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. In 2019, the government began offering a central subsidy that depends on both driving range and battery capacity. In 2020, the government stopped offering this central subsidy for models with price above 300,000 RMB. In the United States, consumers receive a federal income tax credit calculated based on battery capacity. Japan provides a direct consumer subsidy at the model-year level. Because Canada, to our knowledge, does not have central subsidies, we use a population-weighted average of provincial-level, 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 consist of consumer subsidies and/or acquisition or ownership tax deductions. Because Switzerland, to our knowledge, does not have central subsidies, we use the population-weighted average of metropolitan area tax credits offered by Zurich, 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 taxes for vehicles typically depend on CO_2 emissions; full or partial deduction of these taxes applies to electric vehicles. In addition, vehicle taxes sometimes also vary by PHEV/BEV type, curb weight, and engine power. We refer to the ACEA tax guide to calculate the vehicle taxes and deductions for each country in each year.

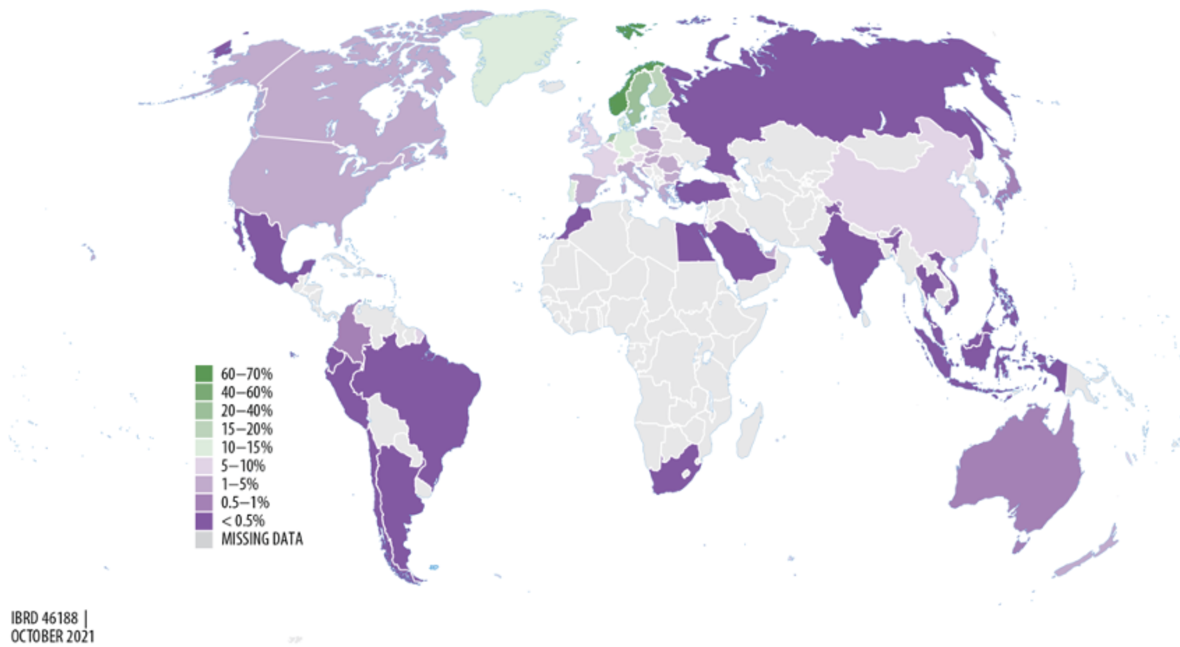
G Additional Figures and Tables

Figure S1: Zero-emission Vehicle Market Shares and Targets



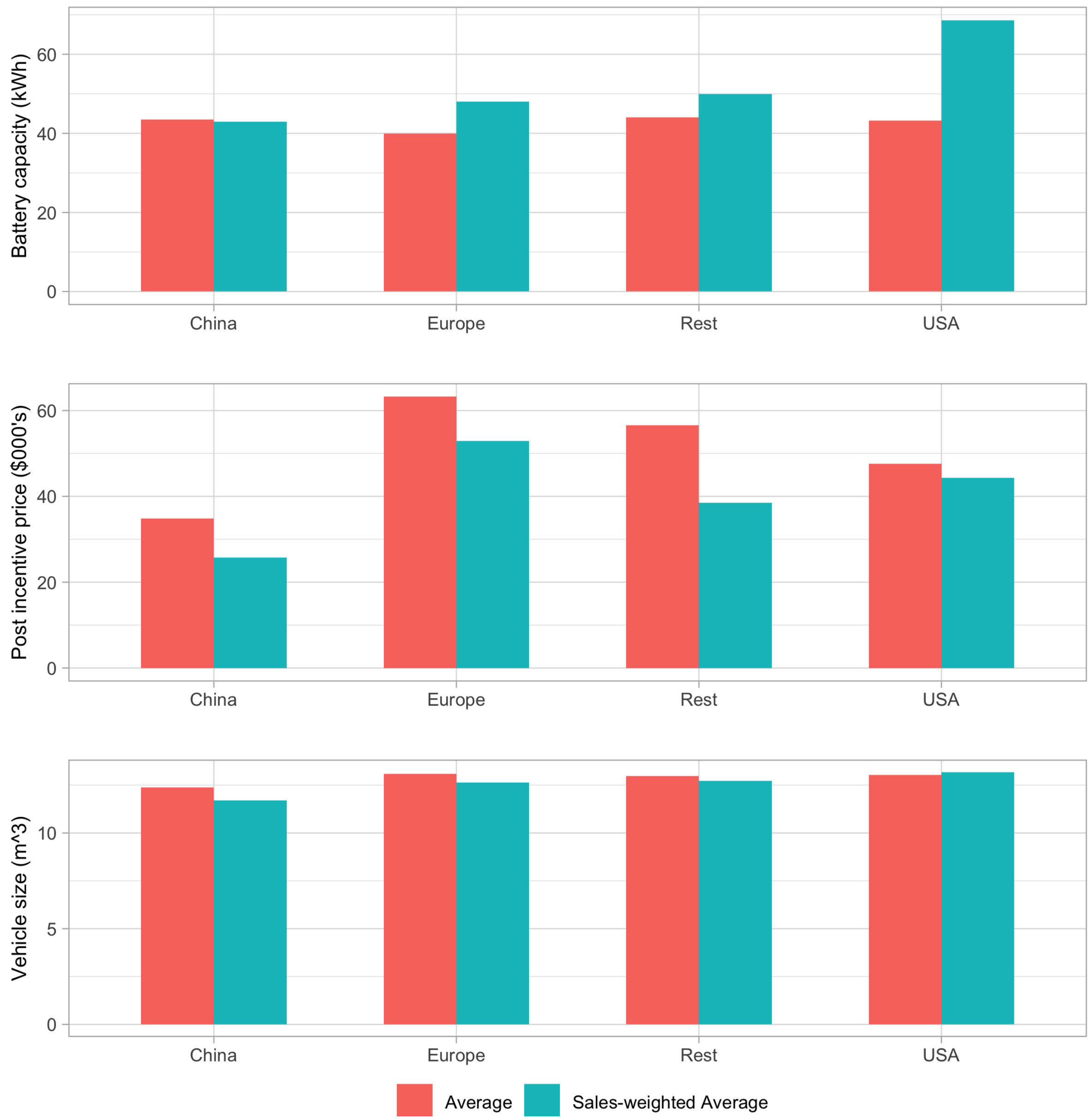
Notes: The market shares in 2020 and targets of zero-emission vehicles (ZEVs) in countries with major EV markets. ZEVs include EVs and hydrogen vehicles.

Figure S2: EV Shares of New Vehicle Markets in 2020



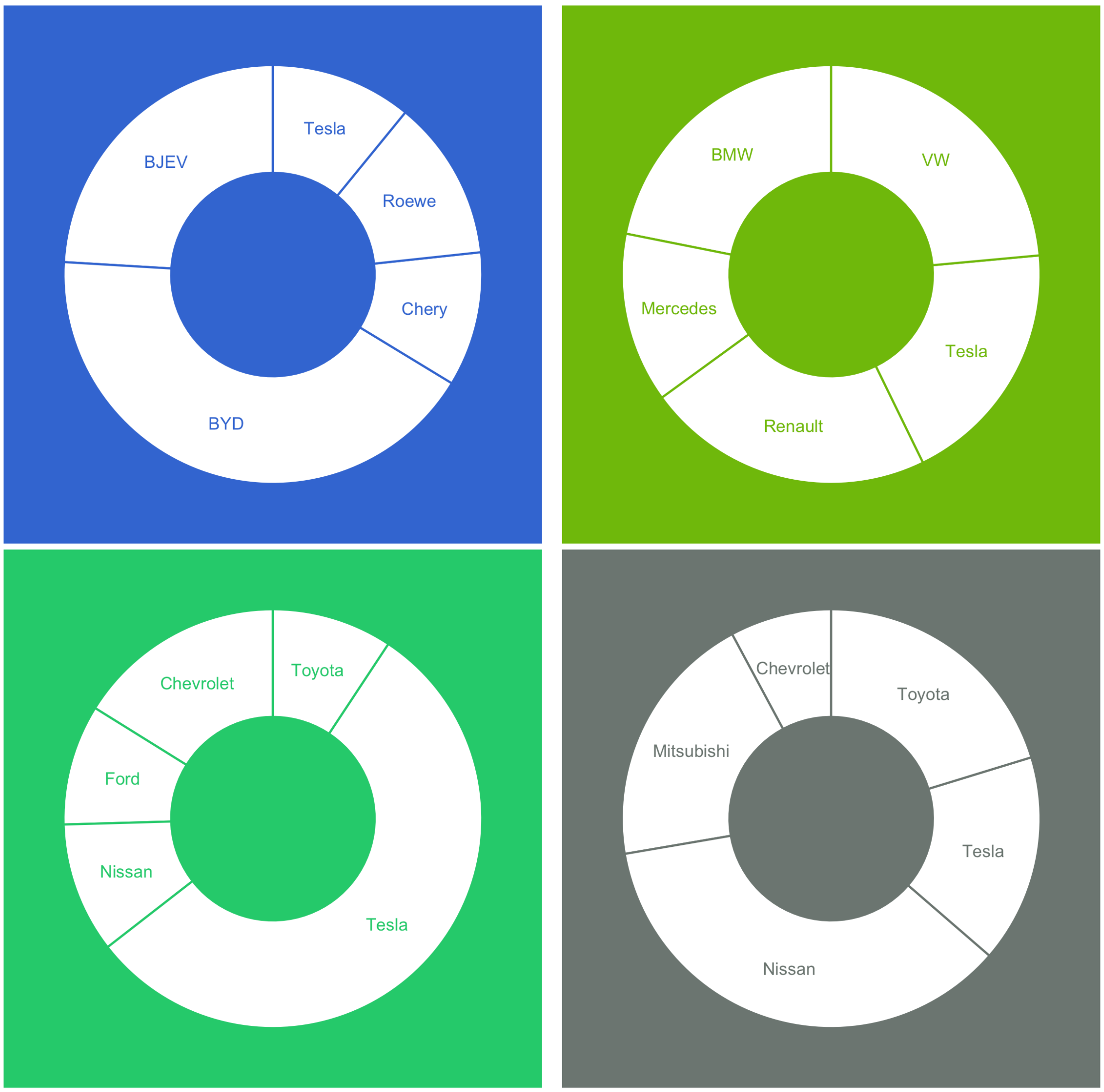
Notes: The map shows the shares of EV sales in new vehicle markets across countries in 2020. Norway leads EV penetration, with EVs representing 67% of all new cars sold. The EV market shares in Sweden and the Netherlands exceed 20%. All countries with EV market shares above 10% are in Europe. EVs account for 3% to 5% of all new vehicles sold in Canada, China, and the United States. Countries in Asia and Africa generally had lower EV penetration.

Figure S3: Key Vehicle Attributes by Region



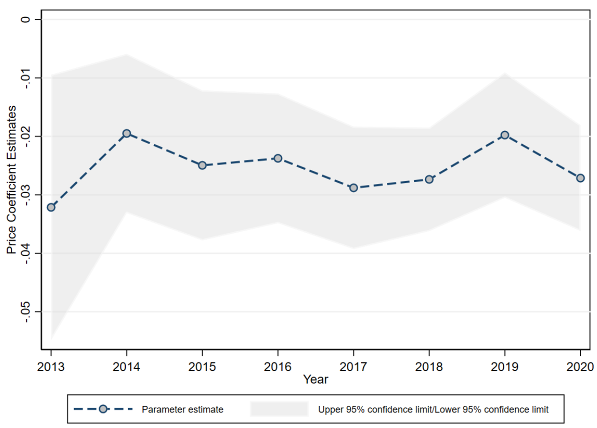
Notes: The average (red) and sales-weighted average (blue) of vehicle attributes are shown for battery capacity (**upper panel**), retail price (**middle panel**), and vehicle size (length×weight×height) (**lower panel**) from 2013 to 2020 by region. The average battery capacity is shown for **BEV models** in each region. Average price and size are calculated for all models in each region.

Figure S4: Top-selling Brands by Region

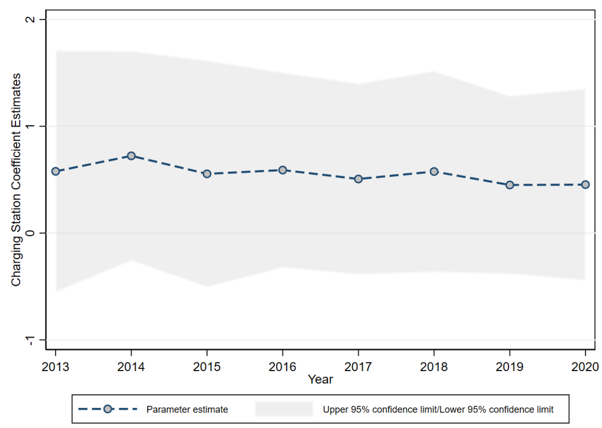


Notes: Brands ranking in the top five in terms of aggregate EV sales from 2013 to 2020 in China (**upper left**), Europe (**upper right**), United States (**lower left**), and the rest of world (**lower right**).

Figure S5: Heterogeneity over Time



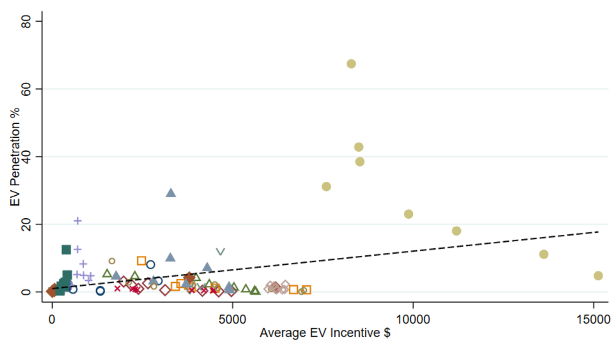
(a) Price Coefficient



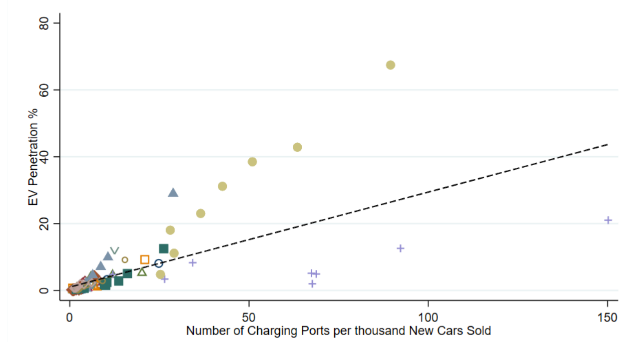
(b) Charging-station Coefficient

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

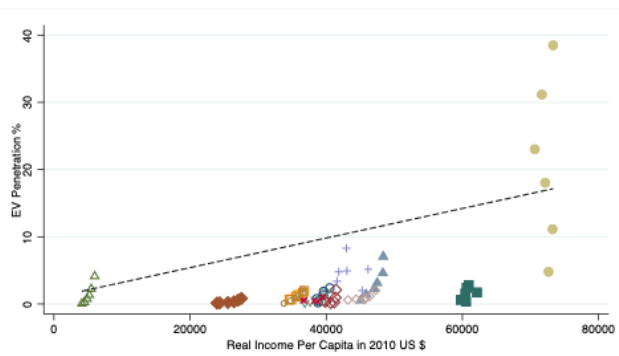
Figure S6: Correlation between EV Penetration and EV Purchase Incentives, Charging Infrastructure, and Country Demographics



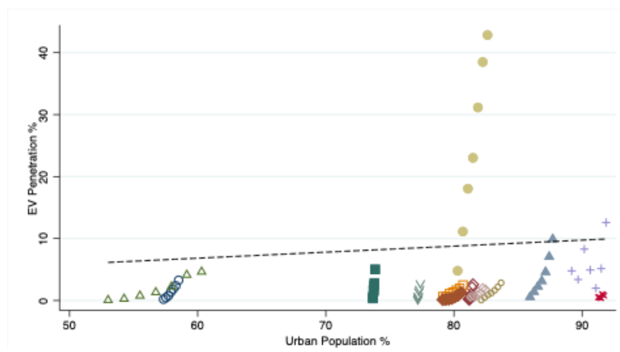
(a) EV Market Shares and Financial Incentives



(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 share of BEVs and PHEVs (combined) as a fraction of the total number of new vehicles sold. Each point on the graph is a country-year combination. The dashed line is the linear fit of the points on the graph.

Table S1: 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 the manufactture's uggested retail price (MSRP) plus taxes.

Table S2: 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 COVID-19. The dependent variable is the logit share in the logit demand model. The *Price - Incentive* variable is constructed from the tax-inclusive price minus the total incentive received. Column (4) shows 2SLS estimates using two sets of instruments for consumer prices: the first set of IVs is the battery-supplier dummies interacted with battery capacity; the second set is the Berry-Levinsohn-Pakes style IVs including the number of models, model size, battery capacity, and range for both own and rival brands. Column (5) adds additional 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 are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S3: 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 COVID-19. The dependent variable is log(sales). Coefficient estimates are based on the preferred specification in the column (5) of Table 1 which performs 2SLS estimation using battery supplier and Berry-Levinsohn-Pakes style IVs for consumer faced prices and using heavy-duty EV stock and construction labor costs as instruments for the charging-port variable. Charger density is measured by the number of chargers per square kilometer in urbanized areas. Standard errors are clustered at the country by year level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S4: 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) $\times$ 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 COVID-19. The dependent variable is log(sales). The *Price - Incentive* variable is constructed from the tax-inclusive price minus the total incentive received. Column (4) shows 2SLS estimates using two sets of instruments for consumer prices: the first set of IVs is the battery-supplier dummies interacted with battery capacity; the second set is the Berry-Levinsohn-Pakes style IVs including the number of models, model size, battery capacity, and range for both own and rival brands. Column (5) adds additional 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 are reported in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$