# Effectiveness and Heterogeneous Effects of Purchase Grants for Electric Vehicles: Evidence from Germany*

Peter Haan† Adrián Santonja‡ Aleksandar Zaklan§

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This paper analyzes the effectiveness and heterogeneous effects of the German purchase grant program for electric mobility using granular registration data at the vehicle model level covering all of Germany. Pre/post estimations and difference-in-differences analyses exploiting the tiered structure of the subsidy system show that the purchase program led to a change in the composition of the German car market. It significantly increased the number of EV models available on the market and the number of purchases per EV model. We further show that the program caused an offsetting decrease in the number of combustion-engine vehicles purchased. The policy thus did not affect the overall number of cars. However, the extent of the program's environmental effectiveness is unclear.

**JEL codes:** Q54, Q58, H23, R48

**Keywords:** Decarbonizing road transport, electric mobility, purchase subsidies, policy effectiveness, distributional effects of climate policy

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†Free University Berlin, German Institute for Economic Research (DIW Berlin) and Berlin School of Economics

‡German Institute for Economic Research (DIW Berlin)

§German Institute for Economic Research (DIW Berlin) and Berlin School of Economics

# 1 Introduction

Decarbonizing transportation is an increasingly urgent goal of national and international climate policy, as the transport sector represents about one quarter of global greenhouse gas (GHG) emissions and lags behind other sectors with respect to abatement. Given the target of climate neutrality by mid-century increasingly accepted by policymakers worldwide, the transport sector must be largely decarbonized within the next three decades. Passenger cars represent the greatest share of GHG from transportation by far. Therefore, policies targeting emissions from cars are crucial planks in countries' climate policy packages. In recent years a policy mix has emerged, which on one hand penalizes emissions through carbon pricing while on the other hand directly stimulating demand for low-carbon vehicles, e.g. through consumer purchase grants. However, so far there exists only limited evidence about the effectiveness and in particular on heterogeneous effects of stimulation packages. Specifically, it is not clear if consumers use the subsidies as windfall gains and if the increase in demand for electrical vehicles is crowding out the demand for cars with a combustion engine. Moreover, it is important to understand the heterogeneous effects of the subsidy.

This paper analyzes the effectiveness and heterogeneous effects of the German purchase grant program for electric mobility, which provides consumer grants for the purchase of electric vehicles (EVs) of up to 9,000 euro per purchased vehicle.[1] Our analysis is of interest for several reasons. On the benefit side, purchase grants can be an effective way of stimulating the development of low-carbon segments of the car market. However, they may be ineffective if they are non-additional, i.e. if consumers would have bought the respective vehicles without the subsidy. Also due to adverse substitution effects their environmental benefits may be limited (e.g. Holland et al., 2016; Chen et al., 2021). Moreover, subsidies also transfer purchasing power from all taxpayers to persons willing and able to purchase a new car, and to suppliers of electric vehicles which has distributional implications. Subsidies to EVs are further likely

[1] This version of the paper draft focuses on the baseline effectiveness of the subsidy due to data constraints, and only on EVs. A special county-level dataset commissioned from the German Federal Motor Transport Authority will be available during spring of 2022, which contains a breakdown of monthly registrations by engine type for several years prior to 2019. It will additionally differentiate registrations according to privately or commercially owned vehicles. The richer dataset will thus allow for an analysis of several relevant dimensions of the purchase grant policy's heterogeneous effects in time for presentation at the conference.

to exhibit heterogeneous effects, e.g. in urban vs. rural areas. Drivers of such heterogeneity may partly be the greater availability of charging infrastructure in urban areas, a preference by rural drivers for the greater range of combustion vehicles compared to the current generation of EVs, or cultural factors.

Our main contributions are threefold: First, we estimate the impact of a subsidy program on EV uptake by focusing on careful identification of causal effects using a quasi-experimental design and highly granular vehicle registration data covering all of Germany, the most important car market in Europe. We also analyze the program's effect on combustion-based cars and whether it affected the overall number of cars. Second, we provide a detailed analysis of heterogeneous policy effects with respect to geography, vehicle ownership type (commercial vs. private) and over time.[2] In this way we contribute to disentangling the mechanism behind the average policy effect. Third, our setting with rapid progression from early adopters who may be less price sensitive, as in Li et al. (2017), to the mass market, as in Springel (2021), allows us to analyze the effect of subsidies on different segments of demand for EVs.

We focus on the effectiveness of the introduction of the purchase grant system in its current form, according to which EVs purchased after November 5, 2019 became eligible for subsidies of up to 6,000 euro per vehicle. The grant amount was increased a few months later, up to 9,000 euro per vehicle. Our analysis proceeds in two main steps. Using data on monthly registrations of new vehicles at the vehicle model level from the German Federal Motor Transport Authority (*Kraftfahrt-Bundesamt*), we first perform a pre/post analysis of the policy's impact. In a second step, similar to Chen et al. (2021) we exploit the tiered structure of the subsidy system for a difference-in-differences strategy, using highly priced EVs ineligible for subsidies as the main control group. We generically control for the concurrent development of charging infrastructure through the use of month-year fixed effects and for industrial production, a proxy for GDP at the monthly level.[3]

While purchase grants are targeted at EVs, they might also affect the demand for similarly priced

[2] Again, the analysis of heterogeneous effects will be available in time for the conference, once we receive the granular custom dataset, in spring 2022.

[3] Once the confidential county-level data are available, we will be able to delve more deeply into the importance of charging infrastructure. By mapping geo-coded charging stations to counties we will be able to identify counties with different levels of development with respect to charging infrastructure.

vehicles using internal combustion engines. Negative spillovers are expected to be especially salient for close substitutes, i.e. cars with different engine types but with otherwise comparable performance characteristics. Thus, using an analogous identification strategy, we evaluate the impact of the purchase grant on registrations of vehicles using internal combustion engine technology.

The results show that the purchase grant program was effective in increasing the sales of subsidized EVs. This total increase results as a combination of an increase in the number of EV models on the market (extensive margin) and an increase of the sales per model (intensive margin). Our estimates suggest that monthly EV registrations rose by 551 per subsidized model that was already on the market prior to the subsidy increase.[4] Our analysis of the registrations of cars running on combustion engines mirrors this result: registrations in this engine class are estimated to decrease by 569 sales per model for models with a listed price below 65.000 euro. Thus, overall the policy induced a shift from cars with a combustion engine to EVs, but did not lead to an overall increase in the number of cars.

A sizable literature focuses on the baseline effectiveness of subsidy schemes and finds that subsidies are an important determinant of EV uptake (e.g. Jenn et al., 2018; Clinton and Steinberg, 2019; Münzel et al., 2019; Azarafshar and Vermeulen, 2020). Fewer studies focus on delivering quasi-experimental evidence using granular data on vehicle uptake. The baseline analysis in our paper contributes to this stream of the literature, in the vein of Muehlegger and Rapson (2018), who analyze the effectiveness of an EV purchase program in California targeting low and middle-income buyers and Chen et al. (2021), who examine the impacts of a purchase program in China. We contribute by investigating the heterogeneity of policy effectiveness using a quasi-experimental strategy at a detailed regional level and for different classes of vehicle ownership, commercial and private. Moreover, we add to this literature by analyzing the effectiveness of purchasing subsidies in Europe's most important car market.

Our paper is also related to a literature studying the role of policy choices on decisions by players in the car market using a more structural approach. Li et al. (2017) address the indirect network effect on two sides of the EV market, charging infrastructure and EV adoption. This leads to a "chicken-and-egg"

[4] The conference version of the paper will also contain an analysis of the subsidy's effectiveness with respect to registrations of PHEVs, data on which is poor in the publicly available baseline dataset used for this version of the paper.

problem, where vehicle adoption depends on the availability of sufficient charging infrastructure, while investment in charging infrastructure becomes more attractive with a larger EV fleet. Based on data on the early stage of the U.S. EV market dominated by early adopters, Li et al. (2017) find that network effects play an important role for EV adoption and that supporting charging infrastructure would have been more effective than a consumer tax credit used to stimulate vehicle demand in their sample. Springel (2021) estimates a structural model of the car market featuring subsidies to both EV purchase and investment in charging stations using data from Norway and comes to a qualitatively similar conclusion in-sample, finding that both subsidy types are effective, with the latter more so. However, policy simulations show that the relative effectiveness of purchase grants vs. infrastructure subsidies can reverse in later stages of market development. Liu et al. (2021) confirm that investment in charging infrastructure played a larger role in EV adoption than direct purchase grants for China. Li (2019) focuses on the role of charging standards in the U.S. EV market and finds that introducing a unified standard increases consumer surplus and substantially increases vehicle sales, while manufacturer investment in charging infrastructure drops somewhat. In a somewhat distinct contribution, Remmy (2020) also estimates a structural model of the vehicle market, using data from Germany similar to the baseline data used in this version of the paper, and investigates the effects of subsidies on decisions of car manufacturers with respect to price and range of vehicles. We contribute to this literature through our analysis of effect heterogeneity. In particular, once the county-level data are available we will be able to assess to what extent the effectiveness of EV subsidies varies depending on the local availability of charging infrastructure. The relatively long time series dimension of our data also allows for an assessment of the effectiveness of the policy scheme on the EV market in two distinct stages, early adoption and transition to a mass market.

## 2 Background

Germany's federal government provides a package of support measures with the goal of establishing Germany as a lead market for electric mobility. A major component is the introduction of consumer grants for the purchase of battery-electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs).

The consumer purchase grant program was initiated in 2016, with vehicles newly registered after May 18, 2016 becoming eligible for subsidies (BMWi, 2016). Subsidies are shared by the federal government and by vehicle manufacturers. The government paid out 2,000 euro for the purchase of an EV and 1,500 euro for a PHEV conditional on the purchase receipt documenting a manufacturer rebate of equal extent. Vehicles with a listed price of up to 60,000 euro were eligible for the grant program. As the mandated manufacturer rebate is likely to interact with other purchase incentives offered by manufacturers, we consider the government amount as the baseline treatment intensity.[5] The initial grant program had a total budget of some 600 million euro (BMF, 2021).

The purchase program became progressively more ambitious starting in early 2020. In February 2020 both the government grant amount and manufacturer rebates increased by 50% for vehicles with a listed price of up to 40,000 euro, to 3,000 euro for EVs and 2,250 euro for PHEVs, for a total value of 6,000 and 4,500 euro, respectively. Cars newly registered after November 5, 2019 were eligible for the increased grants (BMWi, 2020a). For vehicles with a listed price between 40,000 and 65,000 euro, government grants and required manufacturer rebates increased by 25% each, to a total value of 5,000 euro for EVs and 3,750 euro for PHEVs. Moreover, the federal government extended the duration of purchase program (at the original grant level prior to 2019) until the end of 2025, with a total budget commitment of 2.09 billion euro for the period 2020-2023 (BMF, 2021). In June 2020 the amount of the government grant was doubled compared to the level set a few months earlier, while the manufacturer share remained unchanged (BMWi, 2020c), bringing the total grant amount up to 9,000 euro per EV for vehicles with listed prices below 40,000 euro and 7,500 euro for those with listed prices between 40,000 and 65,000. A further 2 billion euro was also added to the total budget of the program (BMF, 2021). In late 2020 the doubling of the government share was extended until 2025 (BMWi, 2020b). According to estimates in the grey literature, the current level of the subsidy is making EVs in the lower (below 40,000 euro) and middle (40,000 - 65,000 euro) market segments competitive with comparable internal combustion models, while highly priced EVs have already been competitive without receiving subsidies (Agora

[5] As transaction prices are not available to us, the extent to which the manufacturer rebate substituted for other rebates normally provided during the purchase negotiation is not clear.

Verkehrswende, 2021).

In this preliminary version of the paper we consider the effects of the introduction of the tiered subsidy system for which cars purchased from November 2019 onward became eligible. We do not separately analyze the increase in treatment intensity in June 2020, and due to data constraints we currently cannot analyze the effectiveness of the initial introduction of subsidies in 2016. Once the county-level data is available the analysis will include all three policy changes.

In addition to purchase grants, the government also supports electric mobility in additional ways. One major point of intervention is support for the installation of charging infrastructure, a requirement for the viability of EVs. Stations for rapid charging are of particular interest, as due to the high charging speed they represent the closest substitute for traditional gas stations. The government is also deploying its own purchasing power, by setting a target that 20% of its vehicle fleet shall consist of EVs. As government agencies are not eligible for subsidies, government purchases generate additional demand for EVs without crowding out demand for subsidies from other market players, while depressing demand for vehicles with internal combustion engines. Moreover, owners of EVs receive further privileges, such as freedom from the federal vehicle tax for 10 years for each vehicle, tax incentives for charging vehicles at their owners' work location and privileged parking spaces.

# 3 Data

## 3.1 Data sources

The main data source used in this paper is a confidential dataset from the German Federal Motor Transport Authority (*Kraftfahrt-Bundesamt*) at the vehicle model level, e.g. Renault Zoe or Volkswagen ID.3. It contains the monthly number of newly registered vehicles in German counties. While this includes both cars newly purchased in Germany and cars brought into Germany from abroad, we consider the data to be an excellent proxy of newly purchased vehicles in Germany shortly prior to the registration date. The full dataset that will be used in the conference version of the paper spans the period January 2015 - spring 2022. It further distinguishes registrations by engine type, i.e. different classes of internal-combustion engines like gasoline or diesel, plug-in hybrid engines or battery electric vehicles. Additionally, registrations are distinguished by ownership type, i.e. whether a vehicle is commercially or privately owned.

This version of the draft uses publicly available registrations data, which record registrations at the national level and the engine type, with no information on ownership type available. Moreover, the time series dimension is shorter than in the full dataset, for 2017-2021, as information on the engine type with respect to EVs is only available starting in 2017.

We map registrations of vehicle models into the subsidy policy framework using data on listed prices for each model from ADAC (*Allgemeiner Deutscher Automobil-Club*), the German motoring association, and government data on EV models eligible for purchase subsidies from the German Federal Office for Economic Affairs and Export Control (*Bundesamt für Wirtschaft und Ausfuhrkontrolle*).

Geo-coded data on charging stations is obtained from the register of charging stations published by the German Federal Network Agency *Bundesnetzagentur*, the electricity regulator. Data on industrial production is from the German statistical office.

### 3.2 Descriptive overview

Before we turn to the econometric analysis we first provide descriptive evidence about the effect of the reform. Table 1 contains a breakdown in vehicle registrations before and after the implementation of the reform, different categories of vehicles and different sample definitions. Table 1, top panel, shows registrations prior to the introduction of the current system of subsidies, for which EVs purchased after November 5, 2019 became eligible. Table 1, bottom panel, focuses on registrations after the current policy framework went into effect.

We distinguish three ways of coding our data at the vehicle model level. The first two columns of Table 1 shows registrations when defining the data as a balanced sample containing all vehicle models available for sale at some point during the sample period. If models are unavailable prior to a certain point in time,

Table 1: Vehicle registration and models, by model price segment and engine type

| | **Balanced** | | **Unbalanced** | | **Cond. Pre/Post** | |
|---|---|---|---|---|---|---|
| | Mean | # Models | Mean | # Models | Mean | # Models |
| **Pre** | | | | | | |
| All | 659 | 420 | 871 | 363 | 970 | 304 |
| ICE | 781 | 350 | 920 | 332 | 1028 | 278 |
| ICE < €65k | 898 | 295 | 1044 | 283 | 1169 | 236 |
| ICE > €65k | 153 | 55 | 195 | 49 | 218 | 42 |
| EV | 46 | 70 | 158 | 31 | 171 | 26 |
| EV < €40k | 56 | 52 | 178 | 22 | 194 | 18 |
| EV €40-65k | 11 | 13 | 67 | 7 | 74 | 6 |
| EV > €65k | 38 | 5 | 96 | 2 | 96 | 2 |
| **Post** | | | | | | |
| All | 443 | 420 | 605 | 365 | 640 | 304 |
| ICE | 476 | 350 | 634 | 300 | 652 | 278 |
| ICE < €65k | 547 | 295 | 732 | 252 | 750 | 236 |
| ICE > €65k | 97 | 55 | 124 | 48 | 131 | 42 |
| EV | 276 | 70 | 433 | 65 | 509 | 26 |
| EV < €40k | 338 | 52 | 525 | 48 | 656 | 18 |
| EV €40-65k | 105 | 13 | 172 | 12 | 205 | 6 |
| EV > €65k | 86 | 5 | 131 | 5 | 43 | 2 |

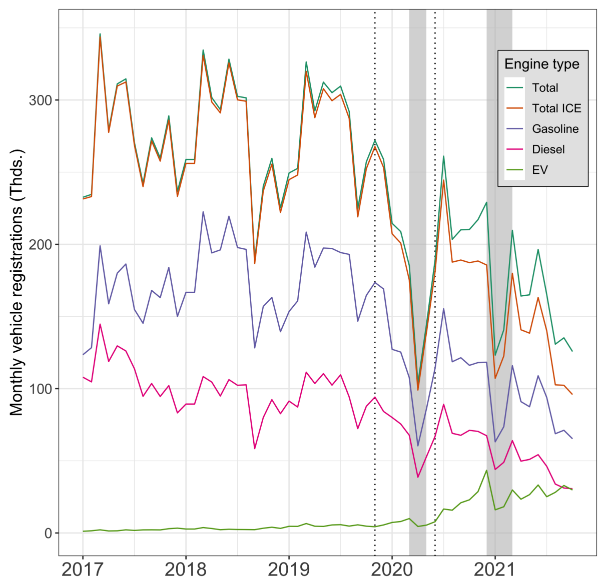
Sources: German Federal Motor Transport Authority, ADAC, BAFA, own calculations.
Notes: Columns 1 and 2 show data for a balanced sample in which observations when a vehicle model was not available on the market are coded as zeros. Columns 3 and 4 contain data on the same sample as in columns 1 and 2, with the difference that observations for periods in which models were not available on the market are coded as missings. Columns 5 and 6 contain a sample of models available on the market at least one semester prior to November 2019 and one semester after November 2019.

their registration numbers are coded as zeroes. This is why the column showing the number of models for the balanced sample section of Table 1 indicates the same number of models both before and after the subsidy increase. The two middle columns of Table 1 presents an unbalanced panel of vehicle models, i.e. prior to being available in the market models are coded as missings instead of as zeroes. Finally, the last two columns are based on a subsample of the unbalanced sample, as it only includes models that were on sale for at least one period before and after November 2019.

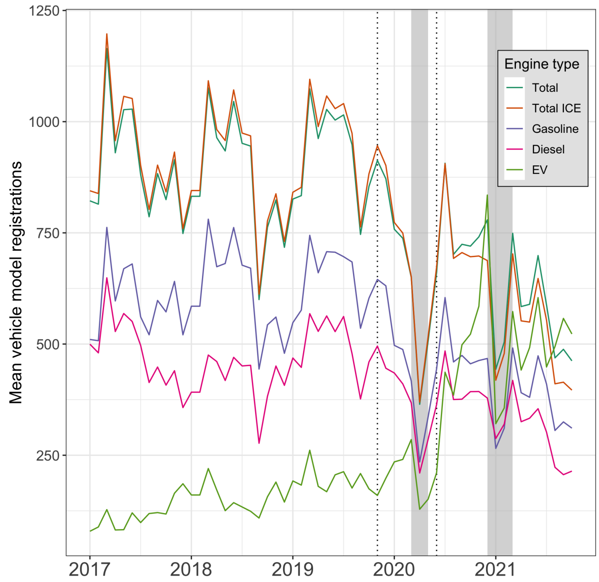
We observe a clear rise in the number of EV models available on the market during the post-policy phase, with the number of models with listed prices below 40,000 euro increasing from 22 to 48, models with prices between 40,000 and 65,000 euro rising from 7 to 12 and those more expensive than 65,000 euro going from 2 to 5 models. The number of EV registrations per model also went up strongly, from an average of 158 registrations per month during the pre-policy phase to 433 during the post-policy phase. The rise in EV uptake is driven by the lower market segment, with an increase in monthly average registrations of EVs per model from 178 pre-November-2019 to 525 in the segment under 40,000 Euro. The same qualitative patterns are observed when looking at the balanced sample, only moderated due to the inclusion of models which were not yet available in the market. The opposite trend emerges for vehicles with internal combustion engines. The average number of monthly registrations per model decreases across market segments and overall, for both the unbalanced and balanced samples. Again, the effect is moderated for the balanced sample through the inclusion of zeroes for periods when the model was not available for purchase. When focusing on the sample conditioned on sales before and after November 2019, it is important to notice that this sample now only includes 26 EV models, as opposed to the 65 models available after Nov 2019 in the unbalanced sample. In addition, the increase in EV vehicle sales per model is stronger in this conditional sample than in the unbalanced sample, increasing from 171 to 509 rather than from 158 to 433.

Figure 1 provides further supporting evidence about the effect of the reform. Figure 1a shows that at the beginning of our sample period, in early 2017, almost all vehicles in Germany were based on internal combustion engine (ICE) technology: The lines indicating total registrations and total ICE registrations overlap almost perfectly. Gradually a wedge opens between these two aggregates and widens especially after the introduction of maximum subsidies, for which vehicles purchased after June 4, 2020 were eligible. We also observe synchronized drops in registrations which affects all engine types during the two lockdown periods due to Covid-19. A contrary patterns emerges when we consider EV registrations compared to total registrations and other engine classes: Amongst all categories, only EVs present an upward trend. The latter keep increasing or are stable.

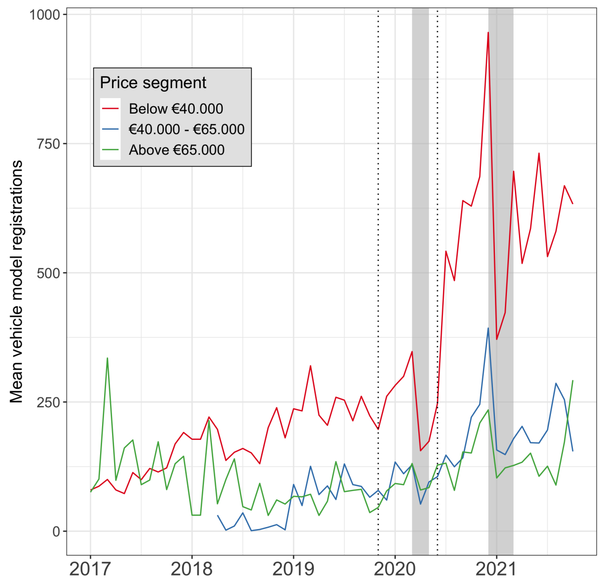
Figure 1b confirms this development at the model level. For EVs, the number of registrations per model increases rapidly, with the EV engine type rising from having the lowest average number of registrations per model until mid-2020 to having the highest by the fall of 2021. As shown in Figure 1c, this increase is primarily driven by lower-priced EVs, whose registration numbers have roughly quadrupled



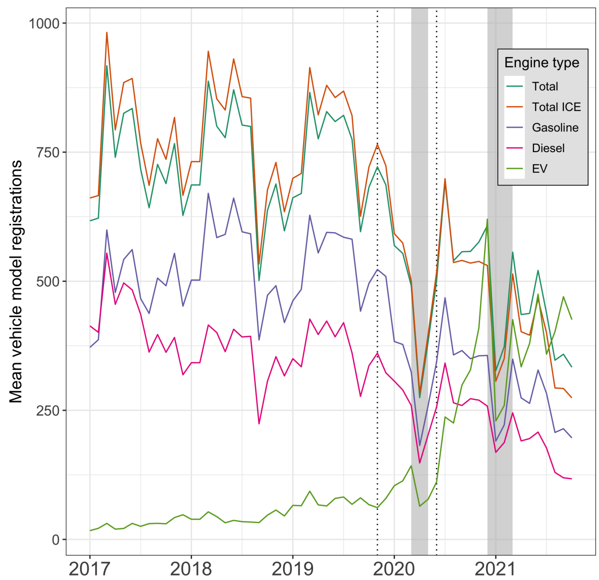

**(a)** Aggregate registrations, by engine type




**(b)** Mean registrations per vehicle model, by engine type




**(c)** Mean EV model registrations, by price segment




**(d)** Mean registrations per vehicle model, by engine type

Figure 1: Number of Registrations, by engine type and price segment

Sources: German Federal Motor Transport Authority, ADAC, BAFA, own calculations.
Note: The panels are based on monthly vehicle registration data from January 2017 until October 2021. The first dotted line indicates the introduction of the tiered subsidy system, with EVs purchased after November 5, 2019 eligible. The second dotted line shows the eligibility cutoff for maximum government subsidies, for vehicles purchased after June 4, 2020. Grey shaded areas indicate periods of lockdown due to Covid-19. Panel (b) and (c) are based on the sample conditional on market presence, Panel (d) is based on the balanced sample.

from below 250 monthly registrations per model on average to almost 1,000 at the onset of the second period of Covid-19-related lockdown in late 2020. Even after some regression from this peak, monthly registrations remained at more than 600 per model. While mid-priced and highly priced registrations also increased, this was less pronounced than for the cheaper models. Finally, Figure 1d shows virtually identical evolution patterns as Figure 1b, but is based on the balanced sample and therefore presents lower average sales per model.

# 4 Research design

## 4.1 Identification

The goal of the regression analysis in this paper is to identify the effect of purchase subsidies on purchases of eligible EVs. We proceed in two steps. First, we estimate a simple pre/post linear model only using data for eligible EVs. In this model we account for time varying variables. This allows for a first assessment of the policy's effectiveness by comparing EV sales prior to and after the policy's start. However, a causal interpretation relies on the assumption that time trends are captured by the observable time varying variables. Second we use an event study DID strategy exploiting the tiered structure of the subsidy system. In more detail, similar to Chen et al. (2021) we use vehicles with listed prices above 65,000 euro, which are ineligible for purchase subsidies, as the control group. Including buyers of ineligible EVs allows us to net out observables common to all EV buyers. Most importantly, it is plausible that buyers of EVs, irrespective of the price segment, have similar expectations regarding the development of the EV market in the future, such as effects of government policy on the re-sale value of vehicles, and regarding climate policy in general.

As relative prices of EVs and combustion-based cars change due to the policy intervention, the policy effect spills over into the market for comparable vehicles powered by combustion engines. It is therefore important to study the effect of the subsidy for EVs on the demand for combustion engine cars as well. For the analysis of the policy's effect on the market for combustion engine cars we use the same strategy.

First, we estimate how the demand changes over time before and after the policy intervention. Then we use the DID estimator with more expensive vehicles powered by internal combustion engines as the control group.

Moreover, it is important to account for the two-sided nature of the EV market, where EV purchases and the charging network interact (e.g. Li et al., 2017; Springel, 2021). The data used in this preliminary version of the paper lacks geographical granularity, so we use time fixed effects to generically control for the concurrent development of the charging infrastructure. Once the county-level data are available we will be able to exploit the geographical dispersion of charging stations to disentangle the purchase subsidy effect from the charging infrastructure effect, e.g. by comparing EV purchases in counties with good and poor coverage of charging stations.

Finally, in our setting national and European climate policy with respect to the EV market overlaps. Starting in early 2020, EU-level $CO_2$ regulation imposes fleet-level carbon intensity limits on manufacturers. European policy is likely to mostly affect the supply decision by car manufacturers with respect to EVs, as firms have an incentive to bring new EV models to the market to reduce their fleet-wide $CO_2$ intensity. Our analysis therefore estimates both extensive - i.e. the likelihood that a model enters the market - and intensive margin effects - i.e. sales per model - of the German purchase grant policy. We acknowledge that the extensive margin estimates are likely to be affected by EU policy. Our estimates of the intensive margin therefore provide a lower bound estimate of the total effectiveness of the subsidy system.

## 4.2 Empirical model

More formally, we estimate a pre/post model for affected EVs. We analyze both extensive margin effects, i.e. the change in the likelihood that a model enters the market due to the subsidy policy, and intensive margin effects, i.e. the policy's effect on the number of vehicles purchased per model:

$$y_{it} = \sum_{j=-m}^{q} \delta_j T_{iz,z=0+j} + X_t'\beta + \lambda_t + \varepsilon_{it}, \tag{1}$$

In our analysis of extensive margin effects we run a linear probability model, where $y_{it}$ is a binary variable capturing if a vehicle model is available on the market. In the intensive margin estimation, $y_{it}$ records the number of registrations of vehicle model $i$ in month $t$. $\delta_j$ is the coefficient of interest, the point estimate on pre/post indicator $T_{iz}$, which tracks periods relative to the start of the post-treatment period, on November 5, 2019.[6] We estimate $\delta_j$ at the semi-annual frequency, with $\delta_0$ being the coefficient in the first post-treatment semester, and $\delta_m$ and $\delta_q$ the earliest pre-treatment and latest post-treatment semester, respectively. Our current dataset contains four pre-treatment semesters and four post-treatment semesters.[7] Estimates of $\delta_j$ for the pre-treatment periods capture anticipation effects, while $\delta_j$ in the post-treatment period estimate the policy's effectiveness. We further control for industrial production, a proxy for GDP at monthly frequency, and month fixed effects and time fixed effecs, $\lambda_t$. Standard errors are clustered at the manufacturer level.

In a second step, we estimate intensive margin effects with a DID event study model:

$$y_{it} = \sum_{j=-m}^{q} \rho_j D_{iz,z=0+j} + \alpha_i + \lambda_t + \varepsilon_{it}, \tag{2}$$

$y_{it}$ in Equation (2) is the number of registrations of vehicle model $i$ in month $t$, while $\rho_j$ are estimates of the coefficient on the policy dummy, the interaction of treatment status and a dummy indicating the start of the post-treatment period, $D_{iz}$. We estimate $\rho_j$ at the semi-annual frequency, with $\rho_j$ being defined analogously to $\delta_j$ in Equation (1). Point estimates of $\rho_j$ for the pre-treatment periods serve as a test of the parallel trends assumption, while estimates of $\rho_j$ in the post-treatment period capture the policy's effectiveness while also allowing for an assessment of its persistence. We now include individual fixed effects at the vehicle model level, $\alpha_i$, and time fixed effects, $\lambda_t$. We use time fixed effects to generically control for the concurrent development of the charging infrastructure and any other year-month shock.[8] As in Equation (1), standard errors are clustered at the manufacturer level.

[6] Once the final dataset is available, we will be able to evaluate the very beginning of the purchase grant program, in 2016.

[7] The final dataset will have four more pre-treatment semesters, as it starts in 2015, and one additional post-treatment semester.

[8] This strategy of accounting for charging infrastructure investment is preliminary. Once the county-level data are available, we will be able to exploit geographical dispersion of charging stations to disentangle these two effects more precisely.

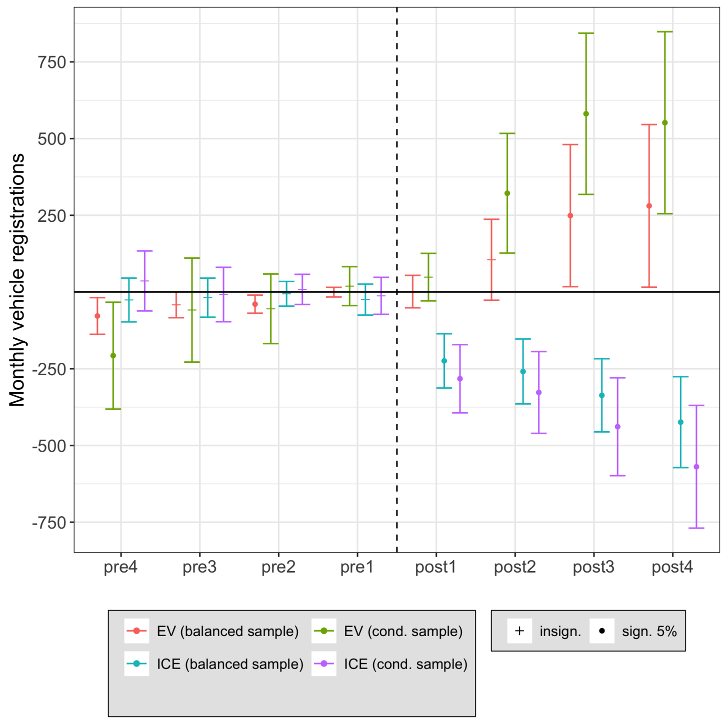



Figure 2: Difference-in-difference results for EV and ICE sales per model

## 5 Results

This section presents the main results of the paper, both on the extensive and intensive margins. Figure 2 presents our DID results in a graphical manner for EVs and ICEs and both the balanced and conditional pre/post samples (see Table 1). It encapsulates the main result of this paper: The EV subsidy changes relative prices of EVs and ICEs and causes demand effects that change the overall composition of the German car market. Demand for EVs increases strongly, while demand for ICEs decreases in a corresponding manner. Moreover, parallel trends to the respective control group hold relatively well before the subsidy increase. Finally, for both outcomes the effects are always larger for the conditional pre/post sample (Table 1, last two columns) .

Tables 2 - 4 provide further detail to Figure 2 and our separate estimates of extensive margin effects. Table 2 starts by presenting extensive margin results for EV models with listed prices below 65.000 euro based on the balanced sample presented in Table 1, first two columns. We therefore estimate Equation (1) on a 0/1 outcome variable indicating whether a model $i$ was available on the market in month $t$. Note that the baseline time period is the semester prior to the subsidy increase in November 2019, and all the shown estimates are semester estimates to be interpreted with respect to the baseline semester. Table 2, Column 1, shows that the likelihood of a particular EV model being for sale on the market was already gradually increasing prior to the subsidy increase, but does so even more strongly after the subsidy increase (post1-post4 estimates). By the end of our sample period, the probability of an EV model below 65.000 euro to be for sale on the market was 42 percentage points higher than in the semester prior to November 2019. While Table 2, Column 2 adds the industrial production index as covariate and month of the year fixed effects, results remain virtually unchanged. In essence, these results confirm within a regression framework the descriptive increase in EV models already seen in Table 1.

Table 2: Results for EV model market presence

| | (1) LM | (2) LM with covs |
|---|---|---|
| pre4 | -0.15*** | -0.14*** |
| | (0.03) | (0.03) |
| pre3 | -0.15*** | -0.11** |
| | (0.03) | (0.05) |
| pre2 | -0.12*** | -0.12*** |
| | (0.03) | (0.03) |
| pre1 | -0.05 | -0.01 |
| | (0.03) | (0.05) |
| post1 | 0.06* | 0.09* |
| | (0.03) | (0.05) |
| post2 | 0.18*** | 0.18*** |
| | (0.03) | (0.04) |
| post3 | 0.35*** | 0.38*** |
| | (0.03) | (0.05) |
| post4 | 0.42*** | 0.42*** |
| | (0.03) | (0.04) |
| Model FE | No | No |
| Month FE | No | Yes |
| Adjusted $R^2$ | 0.1628 | 0.1615 |
| N | 3770 | 3770 |

$p<0.01$*** $p<0.05$** $p<0.1$*

Notes: Columns 1 contains results from a linear pre/post estimation, as in Equation (1). Column 2 additionally controls for industrial production and month fixed effects. All columns use a balanced sample, where periods in which models were unavailable are coded as zero. Robust standard errors clustered at the manufacturer level in parentheses. $p<0.01$*** $p<0.05$** $p<0.1$*

Regarding the intensive margin (sales per vehicle model), Table 3 presents our main estimates for the effect of the subsidy on treated EV models. This table presents results for two main approaches. The first three columns are based on the balanced sample (first two columns in Table 1), while the last three columns are based on the conditional pre/post sample restricted to models that were available for sale both prior and after November 2019 (last two columns in Table 1). For each approach, we present results for i) Equation (1) without covariates and fixed effects, ii) Equation (1) with the industrial production index as covariate and month of the year fixed effects and iii) the difference-in-difference specification presented in Equation (2).

Table 3: Results for EV registrations

| | Balanced sample | | | Presence pre/post Nov 2019 | | |
|---|---|---|---|---|---|---|
| | (1) LM | (2) LM with covs | (3) DID | (4) LM | (5) LM with covs | (6) DID |
| pre4 | -53.38** | -65.91** | -77.98** | -91.28 | -108.89 | -207.27** |
| | (26.29) | (30.24) | (30.49) | (71.15) | (83.81) | (88.78) |
| pre3 | -32.39 | -66.68 | -41.69* | 10.90 | -30.35 | -58.58 |
| | (29.39) | (46.62) | (21.41) | (81.66) | (139.67) | (86.45) |
| pre2 | -40.39 | -60.74** | -39.49** | -64.77 | -106.98 | -54.67 |
| | (29.39) | (30.89) | (15.09) | (76.15) | (79.52) | (57.78) |
| pre1 | -8.10 | -32.10 | -0.37 | 6.40 | -14.73 | 19.23 |
| | (29.39) | (45.46) | (8) | (71.3) | (131.29) | (32.33) |
| post1 | 20.61 | 33.64 | 1.45 | 39.82 | 89.72 | 48.57 |
| | (29.39) | (45.52) | (26.97) | (68.74) | (130.34) | (39.46) |
| post2 | 146.95*** | 193.33*** | 105.18 | 298.77*** | 389.05*** | 321.91*** |
| | (29.39) | (36.65) | (67.26) | (68.86) | (87.37) | (99.5) |
| post3 | 323.82*** | 326.09*** | 249.02** | 565.62*** | 593.79*** | 580.85*** |
| | (29.39) | (44.8) | (118.18) | (70.56) | (129.97) | (134.06) |
| post4 | 364.89*** | 391.00*** | 280.72** | 492.54*** | 543.75*** | 551.75*** |
| | (29.39) | (31.85) | (135.19) | (71.77) | (77.75) | (151.29) |
| Model FE | No | No | Yes | No | No | Yes |
| Month FE | No | Yes | No | No | Yes | No |
| Year-Month FE | No | No | Yes | No | No | Yes |
| Adjusted $R^2$ | 0.1168 | 0.1189 | -0.0241 | 0.1335 | 0.1354 | -0.0469 |
| N | 3770 | 3770 | 4060 | 1112 | 1112 | 1223 |

Notes: Columns 1 and 4 contain results from a linear pre/post estimation, as in Equation (1). Columns 2 and 4 additionally control for industrial production and month fixed effects. Columns 3 and 6 show estimates from a DID regression using EVs with listed prices of more than 65,000 euro as the control group, as in Equation (2). Columns 1-3 are based on a balanced sample, where periods in which models were unavailable are coded as zero. Columns 4-6 use a subsample of models with at least one non-zero observation before and after the policy's introduction. Robust standard errors clustered at the manufacturer level in parentheses. p<0.01*** p<0.05** p<0.1*

In all cases, estimates for semesters prior to the subsidy increase are small, negative and mostly insignificant. Estimates after the subsidy increase are positive, mostly significant and gradually become larger over time, which we interpret as evidence for the additional causal effect of the second subsidy increase in summer 2020. If the estimates of the simple linear models with covariates were to be interpreted causally, they would imply an increase of 391 additional sales per model (Table 3, Column 2) by the end of our sample period in the balanced sample and and analogous 543 increase (Table 3, Column 5) in the conditional pre/post sample. The difference between these two estimates can be likely attributed to the fact that, by construction, the conditional pre/post sample is restricted to established and therefore probably well-known EV models that might therefore present a larger treatment effect. However, this simple model cannot account for counterfactual trends, in our case the evolution of EV sales of models below 65.000 euro in the absence of the subsidy. In order to account for this development, we use untreated, expensive (i.e. above 65.000 euro) EV models as a control group in Table 3, Columns 3 and 6. This reduces the size of the estimate when compared to Columns 2 and 5, as the difference-in-difference estimates now take into account the increase in sales of untreated EV models.

Regarding the effect on the sales of ICE models, we focus on the intensive margin, as the change in the number of ICE models over time is less pronounced than for the case of EV models. Table 4 presents the results on the sale of ICE vehicles for the conditional pre/post sample (i.e. the analogous results to the right panel of Table 3). Again, we observe small and mostly insignificant results before the treatment implementation, which turn negative and significant after November 2019. In an analogous approach to the one for EVs, the control group in 4, Column 3 is composed of ICE models with a listed price of more than 65.000 euro. Estimates for this specification imply that the sales per model for ICE models were reduced by 569 due to the subsidy implementation by the end of our sample period.

# 6 Conclusion

This paper analyzes the effectiveness and heterogeneous effects of the German purchase grant program for electric mobility with respect to the uptake of electric vehicles (EVs).[9] Our analysis contributes to the literature in three main ways: First, we provide quasi-experimental evidence on causal effects of the subsidy policy using highly granular vehicle registration data covering all of Germany, the largest

[9] The analysis of heterogeneity will be added in time for the conference version once the granular county-level data is available during the spring of 2022. This version of the draft focuses on the baseline effectiveness of the subsidy using registrations at the Germany level.

Table 4: Results for ICE registrations (conditional presence pre/post Nov 2019)

| | (1)<br>LM | (2)<br>LM with covs | (3)<br>DID |
|---|---|---|---|
| pre4 | 76.59 | -20.08 | 36.11 |
| | (52.75) | (60.75) | (49.86) |
| pre3 | 37.18 | -169.81* | -8.15 |
| | (58.46) | (94.96) | (45.24) |
| pre2 | 9.39 | -107.29* | 8.61 |
| | (58.22) | (61.22) | (25.03) |
| pre1 | -38.29 | -187.11** | -12.38 |
| | (57.96) | (92.33) | (30.75) |
| post1 | -290.91*** | -230.99** | -282.50*** |
| | (58.13) | (92.7) | (56.7) |
| post2 | -323.05*** | -59.86 | -327.23*** |
| | (58.59) | (73.38) | (68.01) |
| post3 | -441.58*** | -440.58*** | -438.89*** |
| | (59.3) | (92.03) | (81.36) |
| post4 | -548.65*** | -402.61*** | -569.36*** |
| | (60.16) | (64.93) | (102.05) |
| Model FE | No | No | Yes |
| Month FE | No | Yes | No |
| Year-Month FE | No | No | Yes |
| Adjusted $R^2$ | 0.0193 | 0.0253 | -0.0082 |
| N | 12667 | 12667 | 14939 |

Notes: Columns 1 contains results from a linear pre/post estimation, as in Equation (1). Column 2 additionally controls for industrial production and month fixed effects. Column 3 shows estimates from a DID regression using ICEs with listed prices of more than 65,000 euro as the control group, as in Equation (2). All columns use a subsample of models with at least one non-zero observation before and after the policy's introduction. Robust standard errors clustered at the manufacturer level in parentheses. p<0.01*** p<0.05** p<0.1*

car market in Europe. Second, our analysis of heterogeneous policy effects – exploiting variation in geography, vehicle ownership type and time – contributes to disentangling the mechanism behind the average policy effect. Third, our setting features rapid progression from early adopters to the mass market, which allows us to analyze the effect of subsidies on different segments of demand for EVs.

Our analysis proceeds in two steps. First, we run a pre/post analysis of the policy's impact for eligible EVs only. We consider extensive margin effects, i.e. effects of the policy on the likelihood that a vehicle model enters the market, and intensive margin effects, i.e. effects of the policy on the number of purchases per vehicle model. Second, we exploit the tiered structure of the subsidy system for a difference-in-differences (DID) strategy, using highly priced EVs ineligible for subsidies as the control group. We generically control for the concurrent development of charging infrastructure through the use of time fixed effects.[10] We conduct an analogous DID analysis for vehicles running on combustion engines.

Results with respect to the extensive margin suggest that the subsidy program increased the number of models available for purchase. However, we interpret this result with care, as a concurrent policy at the EU level targeting fleet-level $CO_2$ intensity likely also affected the extensive margin. With respect to the intensive margin, our results show that the purchase grant program caused a large increase in the uptake of EVs. Our analysis of the policy's effect on combustion engine vehicles shows an almost offsetting decrease of vehicle sales in this engine class, suggesting that the subsidy changed the composition of the overall car market rather than increasing overall car sales.

One limitation of this analysis is that it only considers effects of the EV subsidy on the car market without conducting a full cost-benefit analysis, including an analysis of environmental effectiveness. While the subsidy program was very effective at increasing demand for EVs, further analysis must determine the extent to which this was also beneficial in terms of abatament, both of greenhouse gas and local air pollution.[11]

[10] When the county-level data are available we will focus more strongly on the role of charging infrastructure.

[11] The conference version of the paper will include an analysis of the program's environmental effectiveness, at least as a back-of-the envelope calculation.

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