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The effect of changing registration taxes on electric vehicle adoption in Denmark

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ABSTRACT

Large-scale deployment of battery electric vehicles (BEVs) is strategically important for the transition toward a low-carbon economy. Denmark has traditionally stimulated BEV diffusion through a registration tax exemption that was lifted in 2016 and partially reintroduced in 2018. Exploiting car registration and detailed population data covering the period 2013–2019 and using Bayesian additive regression trees, this paper provides new evidence on (i) the effects of the changes in the registration tax on the adoption of BEVs in Denmark, (ii) the socioeconomic factors that influence BEV adoption, and (iii) the presence of freerider effects. The results suggest that the number of BEVs would have been higher had the tax exemption remained. Moreover, we detect heterogenous treatment effects that are larger the more likely a socioeconomic group is to purchase a BEV. Consequently, we expect that there are substantial freerider effects in the promotion of BEVs via the tax system.

1. Introduction

In the European Union, transportation is the only sector in which carbon emissions have increased in recent decades (EEA, 2019a; 2021).[1] Within the transport sector, road transport is the largest emitter of greenhouse gases, accounting for more than 70 % of all transport-related emissions (EEA, 2019b). The large-scale consumer uptake of battery electric vehicles (BEVs) is considered crucial in decarbonizing the transport sector and reducing dependence on fossil fuels (Rezvani et al., 2015; Tran et al., 2012). Therefore, many countries have stipulated policies to foster the market diffusion of BEVs (Baldursson et al., 2021; Cansino et al., 2018; van der Steen et al., 2015).

In numerous countries, policy makers have introduced some sort of purchase incentive (Hardman et al., 2017). For instance, point-of-sale grants reduce the purchase price of a vehicle by GBP 4,500 in the UK and by EUR 4,000 in Germany. Similarly, the US applies rebates that are given after the purchase of a BEV that range between USD 7,500 and 10,000. In the Scandinavian countries, owing to the high level of taxes on private vehicles, various taxation measures have been favored over subsidies to promote BEV adoption (Kester et al., 2018).

In this paper, we focus on Denmark and investigate the effect of Danish policy changes on BEV adoption. Specifically, in Denmark, the government granted a full exemption from the registration tax on BEVs that was lifted in 2016 and partially reestablished in 2018.

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[1] Preliminary estimates for 2020 indicate a decline in transport emissions due to decreased activity during the COVID-19 pandemic (EEA, 2021).

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We employ data spanning the period from 2013 to 2019 on a sample of more than 300,000 car owners using actual purchase information and apply Bayesian additive regression trees (BART). This nonparametric method is particularly appropriate to account for nonlinearities and high-dimensional interactions between variables, enabling us to more readily identify heterogeneous treatment effects (Hill, 2011).

Our main research question (i) is to descriptively investigate to what extent the changes in the registration tax influenced the adoption of BEVs in Denmark. In addition, we (ii) identify the socioeconomic determinants of BEV adoption and (iii) assess the presence of freerider effects that arise from the promotion of BEV uptake via the tax system.

We make three contributions to the literature. First, we contribute to a relatively scarce literature that assesses the impact of policies on BEV adoption using revealed preference data (e.g. Alberini and Bareit, 2019; Springel, 2021). Second, while previous studies that estimate the effect of policy interventions rely on stringent functional form assumptions, which reduce the predictive power of the model, we apply the BART method, which is an increasingly popular flexible machine learning method that is able to estimate heterogeneous treatment effects (Hill et al., 2020; Frondel et al., 2020; Hill, 2011). The BART algorithm consists of estimating a large number of regression trees, where each single subtree is a function of the assigned treatment and the observed confounding covariates. In the causal inference literature, the BART method has consistently outperformed a variety of other methods (Hill et al., 2020; Dorie et al., 2019). Third, we are the first to investigate Denmark, which provides an ideal setting to conduct our analysis, as at more than 100 % of the vehicle price, the registration tax is among the highest worldwide (OECD, 2020). In addition, renewable energy sources generate approximately 80 % of Danish electricity needs (IEA, 2020). This is a necessary condition for decarbonizing the transport sector as the reduction of greenhouse gas emissions possible with BEVs is strongly dependent on the type of generation used to charge batteries and cover additional electricity demand.

Our results suggest that on average abolishing the registration tax exemption (and setting it at 20 %) reduced the adoption of BEVs by 0.6 percentage points. Similarly, settling the registration tax at 20 % instead of applying a tax exemption for cars priced up to 400,000 DKK (approximately EUR 53,4000) lowered the uptake of BEVs by 1.7 percentage points. Therefore, had the tax exemption remained, the stock of electric cars in Denmark would have been notably higher. However, the average treatment effects of both models lie within posterior intervals that include zero. Allowing for heterogeneous treatment effects indicates that the policy changes had a particularly strong impact among men, middle-aged car owners, college graduates, car owners in the highest income quintile, and car owners living in metropolitan areas. By coupling these heterogeneous treatment effects with the probability of adopting an electric vehicle, we suggest that substantial freerider effects exist in the promotion of electric vehicles via the tax system.

The remainder of the paper is organized as follows. Section 2 provides an overview of the policies for electric vehicle diffusion in the EU and the Danish context and summarizes the literature on barriers to and policies for the penetration of electric vehicles. Section 3 describes the data and methods used. Section 4 provides the empirical results of the treatment effect estimates, the predictors of BEV adoption, and freerider effects. Section 5 summarizes and concludes the paper.

2. Background

2.1. Policy

Over the last decade, the European Commission has established a common framework of measures to drive the automotive market toward low-carbon options and higher fuel efficiency. Targeted support measures range from regulations setting CO_2 emission performance standards for new passenger cars (The European Parliament and the Council of the European Union, 2019) to directives establishing minimum requirements for creating the infrastructure for alternative fuels (The European Parliament and the Council of the European Union, 2014). These legal acts are an integral part of the EÚs vision to phase out internal combustion engine vehicles by 2030 and, more broadly, to achieve climate neutrality by 2050 (European Commission, 2018). Recently, the EU Green Deal has reinforced the ambition to decarbonize transportation by accelerating the roll-out of charging points and tightening CO_2 standards (European Commission, 2019). The guiding principle for these policies is that the increased penetration of electric mobility facilitates the integration of renewables into existing grids, which in turn reduces greenhouse gas emissions, dependence on energy imports, and energy intensity (European Commission, 2013; 2016).

Efforts to promote electric mobility at the EU level are complemented by national, regional, and local policies, which can take a variety of forms. For example, Germany, Ireland, Italy, Sweden, Norway, the UK, and other countries base their registration and/or annual circulation car tax on CO_2 emissions, engine power, or curb weight (Alberini and Hovarth, 2021; Yan, 2018; Wappelhorst et al., 2018; Vassileva and Campillo, 2017; Figenbaum et al., 2015). France, Sweden, Italy, and Switzerland have implemented a feebate/bonus-malus scheme, whereby low-emission cars benefit from a price reduction and the most polluting cars are subject to taxation (Alberini and Bareit, 2019; d'Haultfoeuille et al., 2014). Spain, the United Kingdom, Germany, Greece, Luxembourg, and other countries offer one-time purchase incentives or fiscal rebates, which can either be fixed or a function of the vehicle type or price (European Automobile Manufacturers Association, 2020; Münzel et al., 2019). Tax benefits and purchase incentives are often combined and apply once at the time of purchase, after purchase, or on a recurring basis. The extent of these benefits differs substantially across countries and, in some instances, within the same country. Other widespread benefits include access to high-occupancy-vehicle (HOV) lanes, waivers for parking and toll fees, incentives for developing charging infrastructure, and electricity price discounts (for a comprehensive policy overview, see Münzel et al., 2019; Rietmann and Lieven, 2019; and Cansino et al., 2018).

The Danish government used the tax system to grant a full exemption from the registration tax on electric passenger cars until the end of 2015. Given the high tax rate for newly registered passenger cars – 105 % of vehiclés value up to approximately DKK 81,700 (approximately EUR 10,950) and 180 % of the rest (excluding the 25 % VAT) until the end of 2015[2] – the tax exemption was considered a generous incentive. In 2016, concerns over fiscal revenues and resource allocation led the government to gradually phase-in the registration tax over a five-year period (20 % for 2016; 40 % for 2017; 65 % for 2018; 90 % for 2019; and 100 % for 2020). In addition, as of January 1, 2016, BEVs were no longer exempt from the weight-based tax[3] and green owner tax.[4] As a result of the new vehicle registration tax reform, BEV sales stagnated (Ministry of Taxation, 2017).

In April 2017, to alleviate the impasse and revitalize the BEV market, the government decided to maintain the registration tax at 20 % of the full registration tax rate until 2020 and introduced a deduction based on battery capacity (DKK 1,700 – approximately EUR 228 – per kWh of battery capacity up to and including 45 kWh). However, a freeze on the BEV registration tax phase-in was followed by a reduction in the registration tax on all cars in October 2017, which reduced the cost competitiveness of BEVs. In late 2018, Parliament passed a bill exempting BEVs priced at up to DKK 400,000 (approximately EUR 53,400) from the registration tax in 2019 and 2020 (Ministry of Taxation, 2018; OECD, 2019).[5]

In December 2019, in its National Energy and Climate Plan (Denmark's Integrated NECP, 2019) submitted to the European Commission, Denmark set out a ban on new fossil-fueled cars as of 2030. In September 2020, the Commission for a Transition to Green Passenger Cars proposed an increase in the fuel tax and a more gradual increase in the registration tax by 2030 for BEVs, which was planned to be 65 % for 2021, 90 % for 2022, and 100 % for 2023 (Commission for a Transition to Green Passenger Cars, 2020). Other policies implemented in recent years include fiscal rebates on private charging infrastructure in 2016 and 2017 (Ministry of Finance, 2018), tax rebates on electricity bills (Ministry of Taxation, 2019), partial or full exemption from parking fees in some municipalities, and waivers for tolls (OECD, 2019). Table 1 summarizes the main policies targeting BEVs in Denmark from 2013 to 2019. The policies are grouped into three periods following the changes in the registration tax.

2.2. Literature review

Our research is based on a growing body of literature assessing the barriers to and drivers of the penetration of electric vehicles. In their review, Coffman et al. (2017) group the barriers into internal and external as well as policy-related factors. Internal factors encompass higher cost, longer charging time, and lower driving range (Bobeteh and Matties, 2018; Nazari et al., 2018; Liao et al., 2017; Langbroek et al., 2016; Hackbarth and Madlener, 2013; Ziegler, 2012; Axsen et al., 2009). The external factors include relative fuel prices (e.g., Gallagher and Muehlegger, 2011) and the availability of charging infrastructure (e.g., Egnér and Trosvik, 2018). As most policies that were implemented by governments worldwide are in place to overcome these barriers posed by internal and external factors, they represent an ideal setting to study the barriers to the uptake of electric vehicles.

Cansino et al. (2018) apply this distinction to the EU-28 and report that financial incentives include taxes (e.g., registration fees and vehicle ownership taxes) and direct subsidies. France, for instance, provides an incentive of 5,000 EUR when a car is purchased that does not emit more than 60 g CO_2/km. These financial measures directly address the internal factor of higher cost. Another large set of policies is intended to improve public infrastructure and thus overcome external barriers. For instance, low emission zones in the Netherlands restrict access to environmentally friendly vehicles, and many countries provide free parking for electric vehicles.

Despite the lack of evidence on the effect of public infrastructure on the uptake of electric cars in China (Sovacool et al., 2019) and Canada (Miele et al., 2020), a number of studies based on stated preferences (see e.g., Bobeth and Matties, 2018; Nazari et al., 2018; Liao et al., 2017; Hackbarth and Madlener, 2013; Ziegler, 2012), report that a lack of charging infrastructure is a major barrier to the uptake of electric vehicles. For instance, Patt et al. (2019), Achtnicht et al. (2012), and Lebeau et al. (2012) find that increasing charging infrastructure density would substantially increase the share of electric vehicles. Moreover, Langbroek et al. (2016) use a stated-choice experiment with policy incentives and find that free parking or access to bus lanes are efficient alternatives to subsidies.

Studies using revealed preference data generally concur with these findings. For instance, Li et al. (2017) and Narassimhan and

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[2] For further details, see the website of the Danish tax authority: https://skat.dk/SKAT.aspx?oId=8686.

[3] The weight-based tax is calculated on the basis of the vehicle's weight. The heavier the vehicle, the higher the vehicle weight tax. In 2015, the weight-based tax ranged from DKK 930 semi-annually (approximately EUR 125) for passenger cars with total permissible weight (TPW) of up to 600 kg and DKK 3,710 (approximately EUR 498) semi-annually for passenger cars with a TPW of up to 2,000 kg (for more details, see European Automobile Manufacture Association, 2015 https://www.acea.auto/files/ACEA-Tax-Guide-2015.pdf; OECD, 2020).

[4] The green owner tax denotes the annual tax calculated on the vehicle's fuel consumption. Gasoline vehicles face annual taxes ranging from 620 DKK, approximately EUR 83 (if exceeding 20 km/l) to 21,660 DKK, approximately EUR 2,900 (below 4.5 km/l). Diesel vehicle taxes range from 260 DKK, approximately EUR 35 (above 32 km/l) to 32,200 DKK, approximately EUR 4,330 (below 5.1 km/l). Diesel cars without a specific filter pay an extra DKK 1,000, approximately EUR 134. All diesel cars, including electric ones, pay an equalization tax. Battery electric vehicles (BEVs) avoid this tax if their energy consumption per kilometer exceeds the upper limit, paying instead a fixed minimum tax based on their energy use. The electricity consumption (Wh) per kilometer of the vehicles is converted into number of kilometers per liter of gasoline. The conversion of energy consumption measured in Wh/km to gasoline consumption per 100 km is achieved by dividing the energy consumption by a conversion factor of 91.25. For further details on the green owner tax, see https://skat.dk/skat.aspx?oid=2234535.

[5] For the sake of comparison, the cheapest Tesla Model 3 had a street price of DKK 374,000 in 2019 (approximately EUR 50,000) and accounted for approximately a quarter of all new electric vehicle registrations in 2019, followed by other electrified models from Hyundai, Nissan, and Renault that had a street price below DKK 400,000 (Hall et al., 2020).

Table 1
The main policies implemented during 2013–2019 targeting BEVs.

	Period 1(1.1.2013 – 31.12.2015)	Period 2(1.1.2016 – 31.12.2018)	Period 3(1.1.2019 – 31.12.2019)
Policy instrument	● Registration tax exemption ● Others: o Weight tax and green owner tax exemption o Tax rebates on the electricity bill	● Registration tax at 20 % of the full registration tax rate ● Others: ● Weight tax and green owner tax ● Fiscal rebates on private charging infrastructure ● Tax deduction based on battery capacity	● Registration tax exemption for BEVs priced at up to DKK 400,000 ● Others: ● Local incentives (e.g., waiver on tolls, exemption from parking fees)

Johnson (2018) analyze data from the US and identify a positive effect of adding charging infrastructure on BEV uptake. Similarly, Zhang et al. (2016), Springel (2021), Javid and Nejat (2017), and Sommer and Vance (2021) provide additional supporting evidence for Norway, California, and Germany, respectively. Despite its importance for the uptake of electric vehicles, there is limited evidence on the importance of policies for the penetration of electric vehicles or more pro-environmental cars in general. Compiling panel data on 32 countries, Münzel et al. (2019) analyze the impact of policies, such as the promotion of charging infrastructure. Using comprehensive data from Norway, Springel (2021) establishes a positive link between electric vehicle adoption and subsidies for both the purchase of a BEV and for charging infrastructure. Using stated preference data, Haustein et al. (2021) find that respondents who intend to buy a BEV but are waiting for more policy support are particularly likely to express uncertainty about such support. Based on survey data from Norway, Bjerkan et al. (2016) show that tax exemptions are critical incentives for promoting the ownership of electric vehicles for more than 80 % of respondents, while exemptions from tolls and bus lane access are also important factors.

Analyzing London's congestion charge, Morton et al. (2017) demonstrate that it is an effective strategy for promoting the adoption of electric vehicles, as these vehicles are exempted. Based on observed data on the Swedish green car rebate, Huse and Lacinda (2013) estimate a structural model and report that it decreased CO_2 emissions by approximately half a million tons, yielding an implicit carbon price of $109. This is at the lower end of the range provided by Li et al. (2013) and close to the estimate of Beresteanu and Li (2011), who use data from the US market. d'Haultfoeuille et al. (2014) analyze the French market and find that a bonus-malus system has positive impacts on the sales of environmentally friendly cars and a reduction in emissions. In Switzerland, Alberini and Bareit (2019) find that a bonus-malus system has varying effects on the adoption of lower-emission vehicles across cantons; imposing a malus on cars with high CO_2 emission rates reduced the sales of such cars (the opposite was true for a bonus). This effect, however, is small and comes at a high cost, suggesting limited potential for vehicle registration policies.

In addition to investigating the mere uptake of cleaner cars, some scholars attempt to estimate freerider effects from financial incentives. For instance, Chandra et al. (2011) estimate that 26 % of all hybrid sales after the introduction of a tax rebate in Canada can be attributed to it. While this is a desirable result from an environmental perspective, it also emphasizes that there is a large freerider effect. Similar freerider effects are reported by Borenstein and Davis (2016) and Huse and Lucinda (2014). Complementing this line of evidence, Muehlegger and Rapson (2018) show that purchase subsidies for low- and middle-income households have a very limited effect on BEV adoption. This renders tax rebates and other financial instruments relatively inefficient (Yan, 2018).

We add to the literature by using a comprehensive real-world dataset that includes all newly registered vehicles in Denmark between 2013 and 2019 (N = 326,382). During our study period, we observe several policy changes that we exploit for our analysis. We can thereby contribute to descriptively answering the question of how successful policy is in steering customers toward more sustainable purchase decisions of cars and freerider effects. Moreover, using detailed microdata, we can directly control for many socioeconomic characteristics, while most papers are based on registration data only (e.g., Morton et al., 2017; Huse and Lacinda, 2013; Chandra et al., 2010), coupled with survey data (e.g., d'Haultefoeuille et al., 2014) or macro data (e.g., Münzel et al., 2018).

3. Data and methods

3.1. Data

For our analysis, we use car register and population-based register data on 326,382 Danish car owners covering the period from January 1, 2013, to December 31, 2019, provided by Statistics Denmark.[6]

The car register contains detailed data for each time a car is registered (i.e., new cars and after a change in owner), including

[6] The link between the car register and population-based register data is possible because all people living in Denmark are assigned a unique identification number, Det Centrale Person Register (CPR), which public authorities use to store personal information. Access to deidentified microdata is granted only to Danish research environments through a flexible and secure server at Statistics Denmark. Access is available from the desktop of any researcher, subject to both the researcher and the project being approved (Statistics Denmark, 2014; 2017).

information on the date of the first registration, fuel type, ownership, and usership of the vehicle. Since we are interested in investigating BEV adoption conditional on policy changes and socioeconomic characteristics of car owners, the analysis is restricted to owners who are also users of the vehicle.[7] In addition, we exclude all company-owned cars from the data. The selected population-based register data include information on gender, age, education, household disposable income, household size, working status, marital status, and residence. Finally, we collected average yearly gasoline and electricity prices from Drivkraft Danmark[8] and Eurostat (Eurostat, 2020), respectively.

Table 2 provides the descriptive statistics of the full dataset used in our analysis and divides it by treatment period as specified in Table 1. Over the full period, we observe 326,382 purchases of cars, of which 3,216 (roughly 1 %) are fully electric. Overall, the large majority (72 %) of all cars are registered by men, and roughly two-thirds of cars are registered by owners aged 51 or above. Furthermore, approximately 35 % of all car owners have a tertiary education. We have detailed information about yearly household disposable income, but for our analysis, we divide it into five quintiles. Finally, using data on the residence of households, we group them according to the population of the town in which they live. Approximately one-third of car owners live in rural areas that have fewer than 50,000 inhabitants, and approximately 15 % live in metropolitan areas with more than 1,000,000 inhabitants, which is akin to the capital region of Copenhagen.

We observe that the characteristics of car owners change slightly over the period we observe. For instance, in Period 3, at 46 %, the share of car owners who are aged 62 or over is approximately ten percentage points higher than in Period 1. Most other characteristics vary to a smaller extent. Regarding our dependent variable, we detect the lowest share of electric cars in Period 2, i.e., when tax exemptions were abolished (0.4 %), and it is highest in Period 3 after they were reintroduced (4.9 %). However, not only is the share highest in Period 3 but also the absolute number of electric cars purchased exceeds the purchases in Periods 1 and 2 despite the much shorter time frame.

The full sample (2013–2019) is also compared to the whole population of Denmark. The sample of car owners, which includes all owners of newly registered cars in Denmark over the period analysed, is not representative for the whole population in terms of the characteristics analysed. This is because a substantial portion of Danes relies on alternative modes of transportation, such as biking and public transit (particularly in urban areas like Copenhagen). Moreover, within Europe, Denmark has a high rate of urbanization, such that access to public transportation can be more convenient and cost-effective compared to owning a car.

3.2. Method

To analyze our research question of whether policy changes have affected the uptake of BEVs, we use the BART method. This method has been implemented in several domains, such as health (Bleich et al., 2014), finance (Pierdzioch et al., 2016), and environmental sciences (Zhang et al., 2020), but has received little attention in the energy economics and policy literature. The original formulation of the BART model by Chipman et al., (2010 has been further extended by Hill (2011), Dorie et al. (2019), and Hill et al. (2020) to a wide range of applications for causal inference. Its main virtue is its ability to account for nonlinearities and interactions between variables, enabling us to more readily identify heterogeneous treatment effects (Hill, 2011; Frondel et al., 2020; Hill et al., 2020).

To estimate the causal effect of the registration tax on BEV adoption, the data are divided into three periods (see Table 1) following the change in the registration tax (and other policies): Period 1 spans from January 1, 2013, to December 31, 2015 (registration tax exemption), Period 2 spans from January 1, 2016, to December 31, 2018 (registration tax at 20 % of the full registration tax rate), and Period 3 spans from January 1, 2019, to December 31, 2019 (registration tax exemption for BEVs priced at up to DKK 400,000, approximately EUR 53,400). We define our treatment as a general increase in the tax, which results in one treatment period (Period 2) and two control periods. Contrasting Period 1 with Period 2 yields the treatment effect from full tax exemption to a registration tax of 20 % of the full registration tax for cars with an internal combustion engine. In turn, contrasting Period 3 with Period 2 yields gives the treatment effect from tax exemption for lower priced vehicles compared to a registration tax of 20 %.

The BART algorithm consists of a 'sum-of-tree' and a regularization prior. The model estimates the outcome of interest (Y) as follows (see Fig. 1 for an illustration):

$$Y = g(z, x; T_1, M_1) + g(z, x; T_2, M_2) + \ldots + g(z, x; T_m, M_m) + \varepsilon \tag{1}$$

where each $g\ (T_j, M_j)$ represents a single subtree model and $\varepsilon \sim \mathrm{N}\ (0, \sigma^2)$. T denotes a binary tree that consists of a set of decision rules (e.g., $x_1 < 0.9$) and a set of terminal nodes, and M(e.g., $(\mu_{h1}, \mu_{h2,}\mu_{h3})'$) denotes a set of parameter values for each terminal node. Then, $Y = f\ (z, x) + \varepsilon$ with $(z, x) = \sum g(z, x;\ T_j, M_j)$. The BART method fits the joint function $f\ (z, x)$, where z denotes the assigned treatment, and x denotes the observed confounding covariates, which is then used to draw from the posterior predictive distribution for both $y\ (1) = f\ (x, 1)$ and $y\ (0) = f\ (x, 0)$ (Hill, 2011; Dorie et al., 2019).

[7] There are various possible reasons for why an owner of a car is not its user. The most common reason is that the vehicle is owned by a leasing company and leased to another user. The user can be a private person or a company. In 2019, 45% of total newly registered cars were leased: private leasing accounted for about 21% of newly registered passenger cars in households, while 78% of newly registered passenger cars in industries were leased (https://www.statistikbanken.dk/bil55). As we are interested in identifying the determinants of adopting an electric car among private owners, we restrict our sample to individuals who own and use the car.

[8] https://www.drivkraftdanmark.dk/priser-og-forbrug/.

Table 2
Descriptive statistics.

	Full sample (2013–2019)		Population (2013–2019)	Period 1 (2013–2015) Control I		Period 2 (2016–2018) Treatment		Period 3(2019) Control II	
Variables	**N**	**Mean**	**Mean**	**N**	**Mean**	**N**	**Mean**	**N**	**Mean**
Car owners									
Non-battery electric vehicle (“non-BEV”)	323,166	99 %	–	169,254	99.3 %	124,577	99.6 %	29,335	95.1 %
Battery electric vehicle (“BEV”)	3,216	1 %	–	1,158	0.7 %	556	0.4 %	1,502	4.9 %
(Ln) Electricity price (“El_pr”)	326,382	−1.188	–	170,412	−1.192	125,133	−1.176	30,837	−1.209
(Ln) Gasoline price (“Gas_pr”)	326,382	0.484	–	170,412	0.508	125,133	0.443	30,837	0.513
Gender									
Male (“Gend_M”)	233,403	71.5 %	49.3 %	120,686	70.8 %	90,311	72.2 %	22,406	72.7 %
Female (“Gend_F”)	92,979	28.5 %	50.7 %	49,726	29.2 %	34,822	27.8 %	8,431	27.3 %
Age									
18–28 (“Age_18_28”)	2,801	0.9 %	16.3 %	1,987	1.2 %	718	0.6 %	96	0.3 %
29–39 (“Age_29_39”)	30,653	9.4 %	15.9 %	18,753	11 %	10,249	8.2 %	1,651	5.3 %
40–50 (“Age_40_50”)	74,841	22.9 %	19.4 %	41,116	24.1 %	27,646	22.1 %	6,079	19.7 %
51–61 (“Age_51_61”)	92,971	28.5 %	19 %	47,989	28.2 %	36,176	28.9 %	8,806	28.6 %
$\geq$ 62 (“Age_62_more”)	125,116	38.3 %	29.4 %	60,567	35.5 %	50,344	40.2 %	14,205	46.1 %
Education									
Primary (“Edu_pri”)	62,060	19 %	31.4 %	33,025	19.4 %	23,308	18.6 %	5,727	18.6 %
Secondary (“Edu_sec”)	150,352	46.1 %	40.2 %	78,389	46 %	57,795	46.2 %	14,168	45.9 %
Tertiary (“Edu_ter”)	113,970	34.9 %	28.4 %	58,998	34.6 %	44,030	35.2 %	10,942	35.5 %
Household size									
1 member (“HH_size_1”)	58,286	17.9 %	29 %	30,346	17.8 %	21,830	17.4 %	6,110	19.8 %
2 members (“HH_size_2”)	156,647	48 %	37.1 %	79,417	46.6 %	61,158	48.9 %	16,072	52.1 %
3 members (“HH_size_3”)	40,264	12.3 %	13.2 %	22,655	13.3 %	14,630	11.7 %	2,979	9.7 %
4 members (“HH_size_4”)	52,897	16.2 %	14.7 %	28,512	16.7 %	20,243	16.2 %	4,142	13.4 %
$\geq$ 5 members (“HH_size_5_more”)	18,288	5.6 %	5.9 %	9,482	5.6 %	7,272	5.8 %	1,534	5 %
Household disposable income									
Lowest 20 % (“HH_inc_Low”) DKK < 298,427	63,570	19.5 %	22.1 %	34,390	20.2 %	23,326	18.6 %	5,854	19 %
Quintile 2 (“HH_inc_Q_2”)DKK 288,570 – 420,692	64,923	19.9 %	19.5 %	33,921	19.9 %	24,780	19.8 %	6,222	20.2 %
Quintile 3 (“HH_inc_Q_3”) DKK 405,875—561,722	65,418	20 %	19.6 %	33,444	19.6 %	25,837	20.7 %	6,137	19.9 %
Quintile 4 (“HH_inc_Q_4”)DKK 512,521 – 725,726	65,754	20.1 %	20 %	33,936	19.9 %	25,733	20.6 %	6,085	19.7 %
Highest 20 % (“HH_inc_High”) DKK > 638,135	66,717	20.4 %	18.8 %	34,721	20.4 %	25,457	20.3 %	6,539	21.2 %
Working status									
Worker (skilled/unskilled) (“Work_S_Work”)	95,896	29.4 %	27.1 %	51,038	29.9 %	36,597	29.2 %	8,261	26.8 %
Self-employed (“Work_S_Self”)	16,466	5 %	4.3 %	8,765	5.1 %	6,160	4.9 %	1,541	5 %
Routine nonmanual (“Work_S_Rout”)	45,769	14 %	12.9 %	25,202	14.8 %	16,715	13.4 %	3,852	12.5 %
Manager (“Work_S_Man”)	59,121	18.1 %	14.1 %	31,368	18.4 %	22,482	18 %	5,271	17.1 %
Outside workforce (“Work_S_Out”)	109,130	33.4 %	41.5 %	54,039	31.7 %	43,179	34.5 %	11,912	38.6 %
Marital status									
Married/Living with a partner (“Mar_S_Mar”)	232,103	71.1 %	49 %	120,077	70.5 %	90,023	71.9 %	22,003	71.3 %
Separated/divorced/widowed (“Mar_S_Sep”)	45,606	14 %	17 %	24,638	14.4 %	16,556	13.2 %	4,412	14.3 %
Single (“Mar_S_Sing”)	48,673	14.9 %	34 %	25,697	15.1 %	18,554	14.8 %	4,422	14.3 %
Urban area									
Metropolitan (“Urb_Metr”)	47,251	14.5 %	22 %	25,015	14.7 %	17,703	14.1 %	4,533	14.7 %
100,000–999,999 inhabitants (“Urb_>100”)	52,223	16 %	9.8 %	27,376	16.1 %	20,061	16 %	4,786	15.5 %
50,000–99,999 inhabitants (“Urb_50_100”)	115,430	35.4 %	6 %	60,249	35.3 %	44,360	35.4 %	10,821	35.1 %
<49,999 inhabitants (“Urb_<50”)	111,478	34.2 %	62.2 %	57,772	33.9 %	43,009	34.4 %	10,697	34.7 %

Following Chipman et al. (2010), the standard BART model is extended to the probit model setup for binary classification problems (in our case, $Y = 1$ BEV owners, $Y = 0$ non-BEV owners):

$$Pr(Y_i = 1 \mid x_i) = \Phi(f(x_i)) \tag{2}$$

where Φ denotes the standard normal cumulative distribution function. In this setting, the probit model assumes that $\sigma^2 = 1$, meaning that only a prior on $(T_1, M_1), \dots (T_m, M_m)$ is needed, and the sum-of-trees model serves as an estimate of the conditional probit at *x*, which can be transformed into a conditional probability estimate of $Y = 1$ (Kapelner and Bleich, 2013; Chipman et al., 2010). By using the data augmentation approach of Albert and Chib (1993), Chipman et al., (2010 incorporate the latent variable *Z* into the Gibbs sampler (Geman and Geman, 1984), which replaces *Y* as a response vector:

$$Z_i | y_i = 1 \quad \max\left\{ N\left(\sum_{t=1}^{T} g(X; T_t, M_t) \right), 0 \right\}$$

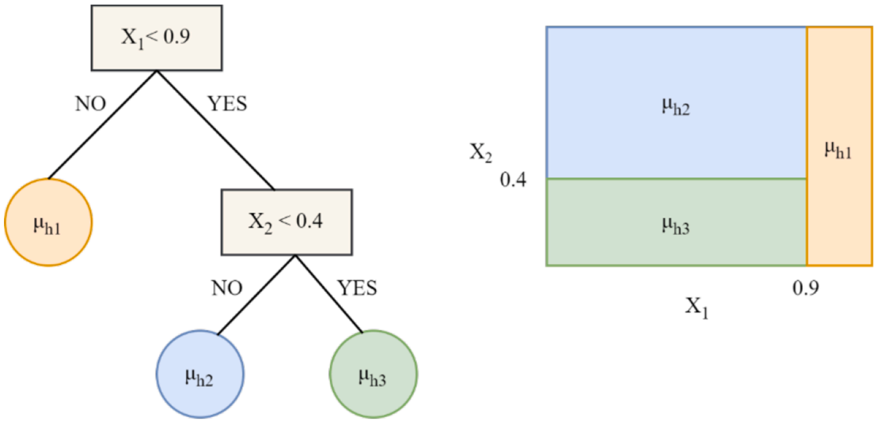

Fig. 1. An example of a subtree $\boldsymbol{g}$ (T_j, M_j) with the parameter values $\boldsymbol{\mu}$.

$$Z_i|y_i = 0 \quad \min\left\{N\left(\sum\nolimits_{t=1}^{T} g(X;T_t,M_t)\right),0\right\} \tag{3}$$

Inferences are made using the posterior distribution of conditional probabilities. The model learns the relationships between covariates and the response variable without requiring the covariates' functional relationship and their interaction terms to be prespecified (Sparapani et al., 2021). We use the recently released Rstudio packages "bartCause" (Dorie et al., 2020) and "bartMachine" (Kapelner et al., 2020) for the estimation of the treatment effects and predictors of BEV adoption, respectively. All the confusion matrix performance results and tests are shown and further discussed in the appendix (Tables A2-A6).

In addition, regarding the predictors of BEV adoption, we supplement our BART analysis with a standard discrete choice probit model framework using Eq. (2). Here, the classification probability is not obtained as a function of the sum-of-trees (as it is in the BART model) but as a nonlinear function of the binary response. Because of the nonlinear nature of the probit models, we estimate the average marginal effects (AMEs) to provide the probability of each covariate on BEV adoption.

4. Results and discussion

In the following, we first report and discuss the results of the impact of the change in the registration tax (and other policy changes) on BEV adoption. To this end, we compare the treatment group (newly registered cars between 2016 and 2018, registration tax at 20 % of the full registration tax rate) with control group I (newly registered cars between 2013 and 2015, registration tax exemption) and control group II (newly registered cars in 2019, registration tax exemption for BEVs priced at up to DKK 400,000). Thereafter, we analyze the determinants of adopting a BEV and the freerider effects.

4.1. *The effect of policy changes on BEV adoption*

Table 3 shows the average of the individual treatment effects estimates using the BART algorithm when comparing the treatment period (Period 2) with the two control periods. The average treatment effects of both models lie within posterior intervals that include zero. At face value, the point estimate in the left panel indicates that on average abolishing the registration tax exemption (and settling it at 20 %) reduced the adoption of BEVs by 0.6 percentage points. In other words, if no policy change had occurred between January 1, 2016, and December 31, 2018, BEV adoption – *ceteris paribus* – would have been 0.6 percentage points higher. Similarly, the right panel of Table 3 suggests that settling the registration tax at 20 % instead of applying a tax exemption for cars priced up to 400,000 DKK lowered the uptake of BEVs by 1.7 percentage points. Therefore, if the tax exemption for such cars had been implemented, the number of additional would be 1.7 percentage points higher.

Using the descriptive statistics from Table 2, we can translate our findings into absolute numbers. If the full tax exemption from Period 1 had been in place in Period 2, an additional 295,545*0.6/100 = 1,773 BEVs would have been registered. Similarly, if only the exemption for cars priced below 400,000 DKK from Period 3 had been effective in Period 2, an additional 155,970*1.7/100 = 2,651 BEVs would have been registered.

Beyond mean effects, the BART model allows us to closely analyze the distribution of the treatment effect estimates (Fig. 2). We detect notable heterogeneity in the treatment effects in both models across car owners, which vary from values close to zero to −0.20. Consequently, the policy changes had only a negligible bearing on the probability of purchasing a BEV for a large majority, while for a small group of individuals, they had a major impact.

To explain the treatment heterogeneity, we estimate an ordinary least squares (OLS) model and regress the individual treatment effects on the socioeconomic characteristics of car owners (Table 4). To provide a more intuitive interpretation of the results, we simply multiply the dependent variable by − 1, such that a larger value can be interpreted as a larger change in the probability of adopting a

Table 3
Average treatment effect of setting the registration tax at 20% (and other policy changes between January 1, 2016, and December 31, 2018) on BEV adoption during two different periods.

	Period 1 and Period 2(1.1.2013 – 31.12.2018)			Period 2 and Period 3(1.1.2016 – 31.12.2019)		
Method	ATE	95 % Credible Interval (lower limit)	95 % Credible Interval (upper limit)	ATE	95 % Credible Interval (lower limit)	95 % Credible Interval (upper limit)
BART	−0.006	−0.046	0.034	−0.017	−0.125	0.091

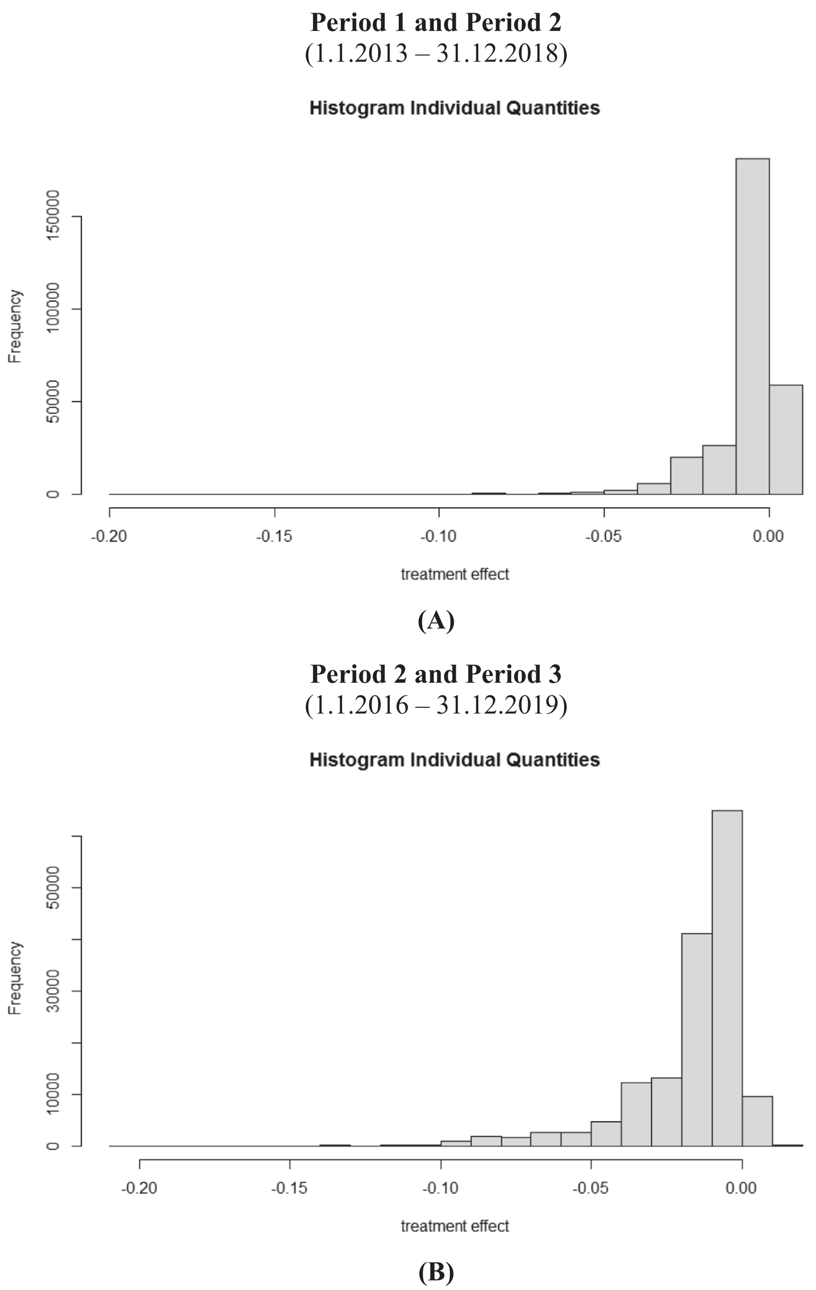

Fig. 2. Histogram of the distribution of the treatment effect (A: 2013–2018; B: 2016–2019).

Table 4
Heterogeneity of Treatment Effects (OLS-regression).

Variables	Individual treatment effects (OLS) Period 1 and Period 2 (1.1.2013 – 31.12.2018)		Individual treatment effects (OLS) Period 2 and Period 3 (1.1.2016 – 31.12.2019)		F-Test on equality of coefficients	
	Coeff.	**Cluster-robust std. error**	**Coeff.**	**Cluster-robust std. error**	**F-Test**	**p-value**
(Ln) Electricity price	0.001	(0.016)	0.001	(0.025)	0.71	0.401
(Ln) Gasoline price	−0.007**	(0.003)	−0.001	(0.005)	121.19	0.000
Gender (Ref = Female)						
Male	0.001**	(0.000)	0.007***	(0.001)	45.64	0.000
Age (Ref = 18–28)						
29–39	−0.000	(0.001)	0.004	(0.002)	0.20	0.658
40–50	−0.001	(0.001)	0.008***	(0.002)	5.30	0.021
51–61	−0.001	(0.001)	−0.004*	(0.002)	0.23	0.628
≥ 62	−0.001	(0.001)	−0.008***	(0.002)	0.02	0.875
Education (Ref = Primary)						
Secondary	0.000	(0.000)	−0.004***	(0.001)	16.85	0.000
Tertiary	0.002***	(0.000)	0.002**	(0.001)	1.98	0.159
Household size (Ref = 1 member)						
2 members	0.000	(0.000)	−0.008***	(0.001)	27.21	0.000
3 members	−0.001	(0.001)	−0.007***	(0.001)	14.95	0.000
4 members	−0.001	(0.001)	−0.005***	(0.002)	1.38	0.240
≥ 5 members	−0.001	(0.001)	−0.007***	(0.002)	4.34	0.037
Household disposable income (Ref = Lowest 20 %)						
Quintile 2	−0.002***	(0.000)	−0.003***	(0.001)	0.20	0.651
Quintile 3	0.001	(0.000)	−0.003***	(0.001)	2.53	0.115
Quintile 4	0.001	(0.000)	−0.002*	(0.001)	0.48	0.490
Highest 20 %	0.015***	(0.001)	0.011***	(0.001)	68.03	0.000
Working status (Ref = Worker (skilled/unskilled))						
Self-employed	0.014***	(0.001)	0.014***	(0.002)	49.51	0.000
Routine nonmanual	−0.001**	(0.000)	0.005***	(0.001)	17.18	0.000
Manager	0.004***	(0.001)	0.018***	(0.001)	49.46	0.000
Outside workforce	0.001**	(0.000)	0.007***	(0.001)	14.57	0.000
Marital status (Ref = Married/Living with a partner)						
Separated/divorced/widowed	0.001	(0.000)	−0.0001	(0.001)	1.16	0.281
Single	0.000	(0.001)	−0.004***	(0.001)	4.12	0.042
Urban area (Ref = Metropolitan)						
100,000–999,999 inhabitants	−0.003***	(0.001)	−0.003***	(0.001)	1.81	0.179
50,000–99,999 inhabitants	−0.003***	(0.001)	−0.002**	(0.001)	12.69	0.000
<49,999 inhabitants	−0.003***	(0.001)	−0.001	(0.001)	15.26	0.000
Constant	0.0004	(0.018)	0.020	(0.031)		
R^2	0.011		0.015			
Number of observations	295,545		155,970			

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses, clustered at the individual level.
Note: The standard errors are calculated under the assumption of accurately measured ITEs variables obtained from the BART model and might be downward bias.

BEV. The results of both models suggest that men exhibit a somewhat larger treatment effect. Moreover, car owners with tertiary education and in the highest income quintile show a larger response to the policy changes. Furthermore, car owners living in metropolitan areas are more affected by the policy change. Taken together, these socioeconomic characteristics appear to be the typical determinants of BEV adoption that have been established in the literature (e.g., Gehrke and Reardon, 2021; Chen et al., 2020; Haustein and Jensen, 2018; Nayum et al., 2016).

In the last column of Table 4, we show the results of an F-test on the equality of the coefficients resulting from the two models. Comparing the magnitude of the coefficients reveals for instance that the negative effect of higher gasoline prices is much stronger in the first period. Moreover, the treatment effect for men is much more pronounced in the second model where we compare Period 2 and Period 3. Furthermore, we detect particularly strong differences across the models for the coefficients that reflect the working status of car owners. In each group, the effects on the adoption of an electric vehicle are higher when analyzing the policy change between Period 2 and Period 3 rather than between Period 1 and Period 2.

4.2. Predictors of BEV adoption

Next, we investigate the predictors that explain BEV adoption using our BART model. As in our previous analysis, we include gender, age, energy prices, educational attainment, income, household size, residence, marital status, and working status. In addition, we include our treatment as a dummy variable ("z") to capture the policy changes during the period 2016–2018. Fig. 3 displays the inclusive proportion of all variables, which is the proportion of times each variable is chosen as a splitting rule out of all splitting rules

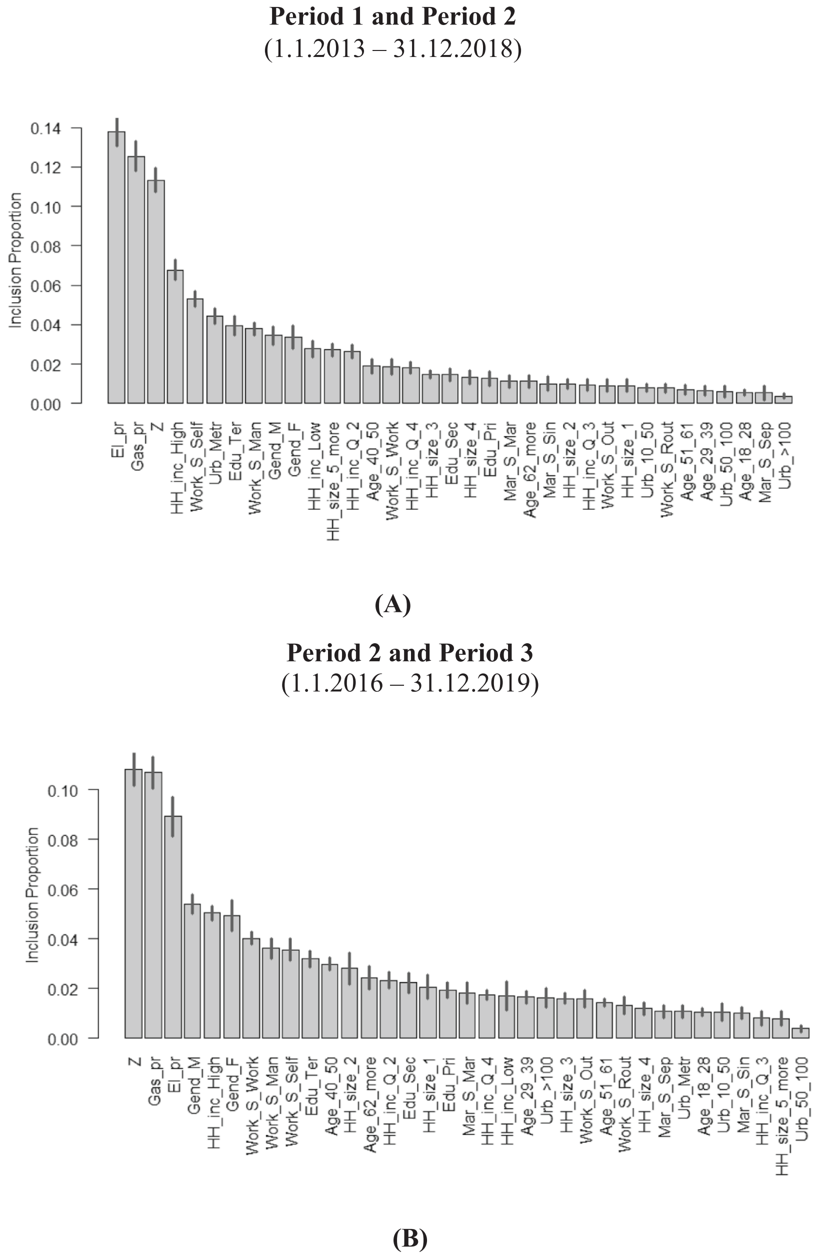

Fig. 3. Average variable inclusion proportions in the BART model (A: 2013–2018; B: 2016–2019).

among the posterior draws of the sum-of-trees model (Kapelner and Bleich, 2013).[9] The segments on the top of each bar indicate 95 % posterior intervals.

The larger the variable inclusion proportion is, the more likely a predictor variable is to be an important driver of response. During the period 2013–2018 (Fig. 3A), the top 10 predictors of BEV adoption were electricity and gasoline prices, followed by z (capturing the policy changes that occurred during 2016–2018), high levels of income and education, working status such as self-employed and manager, living in a metropolitan area, and gender (male). No significant differences emerge in the analysis of the top 10 predictors of BEV adoption during the period 2016–2019 (Fig. 3B); z, and electricity and gasoline prices have the highest proportions of splits in the posterior sum-of-trees model, followed by gender (male), high levels of income, working status such as worker (skilled/unskilled),

[9] The plots featuring the convergence diagnostics of the BART model, the confusion matrix visualizing the results of the BART classification model's predictions and performance results are shown in Tables A1–A4 (Appendix). In addition, the confusion matrix performance results using different decision thresholds are reported in appendix (Tables A2-A6) (Appendix).

manager, and self-employed, and high levels of education. Unlike the first two periods of analysis (2013–2018), living in a metropolitan area appears not to be an important predictor of BEV adoption. One possible explanation for this result might be related to a more even deployment of public charging infrastructure between metropolitan and less populated areas in 2019 compared to the period 2013–2015 (EA Energy Analyses, 2015). Overall, the results are in line with the majority of previous studies investigating the socioeconomic characteristics influencing early BEV adopters (e.g., Gehrke and Reardon, 2021; Chen et al., 2020; Haustein and Jensen, 2018; Nayum et al., 2016), although some contradictory findings exist (Bjerkan et al., 2016; Hidrue et al., 2011).

The results of the BART classification model are largely confirmed by the probit analysis (Table 5).[10] Both analyses (Period 1 and Period 2, Period 2 and Period 3) confirm the negative influence of policy changes during 2016–2018 ("z") on BEV adoption. Moreover, BEV adopters are more likely to be male and higher levels of income. The education factor suggests mixed results; higher levels of educational attainment are positively associated with BEV adoption during the period 2013–2018 but not during the period 2016–2019. Similar to the BART analysis, marital status and age do not seem to be important predictors of BEV adoption, whereas working status and residence are. Working status appears to be a more important factor of BEV adoption in the latest stages of BEV development. Finally, compared to single households, nonsingle households seem to be less likely to purchase a BEV. No clear evidence in this respect emerges from the BART analysis.

The combination of the results on BEV adoption (Table 5) and treatment heterogeneity (Table 4) can help us to identify freerider effects as BEV adopters share very similar traits with those who have been more affected by the changes in policy. In other words, this implies that the registration tax exemption (2013–2015) and the registration tax exemption for BEVs priced at up to DKK 400,000 (2019) primarily benefitted consumers who would have purchased a BEV in any case, indicating notable freerider effects. This result is in line with Chandra et al. (2010), who find that tax rebates mainly subsidized people who would have bought hybrids or fuel-efficient cars in any case. For instance, households in the highest income quintile have a 1.3 % higher probability to adopt an electric vehicle compared to households in the lowest income quintile (Table 5). In addition, Table 4 shows that within this group, the treatment effect is 1.5 percentage points larger compared to the lowest income quintile. Hence, not only have households with high incomes a higher propensity to purchase an electric vehicle, they also respond stronger to tax incentives.

4.3. Anticipation effects

As usual with policies changes, they are communicated in advance. In the case of the Danish registration tax for electric vehicles, the periods prior to effective policy changes differ notably though. Specifically, the Danish government announced the phasing out of the tax break for electric vehicles only in October 2015 for the period starting from 2016. Moreover, in April 2017, it announced to maintain the registration tax at 20 % instead of ramping it up to 100 % by 2020 as scheduled. On October 9, 2018, the Danish government announced the partial re-implementation of tax break for cars priced below 400,000 DKK as of 2019.

Fig. 4 illustrates the monthly adoption of electric vehicles of our observation period. Several points are worth mentioning: the registration of electric vehicles picks up momentum at the end of 2014 and remains high during 2015. We observe a slight increase after the announcement that the tax break phases out in 2016 and then expectedly a huge drop in uptake. Registration remains fairly low during the period in which the registration tax was introduced and only with the effective policy change in 2019, uptake picks up again. Importantly, adoption does not seem to decrease prior to the more generous exemption rules. Hence, looking at the data suggests that there are no significant anticipation effects.

5. Conclusion and policy implications

Among policy makers, there is consensus on the importance of government policies in driving BEV adoption to reduce emissions. Despite the policy push, many countries have fallen short of developing a BEV market that matches climate ambitions. An ex post assessment of the effect of policies and the determinants of BEV adoption is therefore crucial for the design of future strategies that are more effective and reduce distortions in markets.

In this paper, by exploiting a car register database combined with population registers covering the period 2013 to 2019, we use a nonparametric Bayesian regression tree (BART) approach to (i) descriptively investigate the effect of the registration tax evolution on the adoption of BEVs in Denmark, (ii) identify the socioeconomic determinants of BEV adoption and (iii) assess the presence of freeriders diluting the power of the registration tax exemption.

We find that on average abolishing the registration tax exemption (and settling it at 20 %) reduced the adoption of BEVs by 0.6 percentage points. Similarly, settling the registration tax at 20 % instead of applying a tax exemption for cars priced up to 400,000 DKK lowered the uptake of BEVs by 1.7 percentage points. Using a simple back-of-the-envelope calculation, by multiplying our effect sizes by the stock of BEVs in the respective periods, we estimate that the additional uptake of BEVs amounts to approximately 4,500, which is roughly an 8.8 % increase compared to the existing stock as of December 2021.[11]

However, the average treatment effects of both models lie within posterior intervals that include zero. Therefore, we compute heterogenous treatment effects and find that the policy changes particularly affected men, middle-aged car owners, college graduates,

[10] The probit model results together with the McFadden pseudo R^2 and the percentage correctly predicted for the probit model are represented in the Appendix (Table A7). Moreover, to enhance the interpretability of the results, the odds ratio and confidence intervals from the logistic model (Hosmer et al., 2013) are represented in the Appendix (Table A8).

[11] https://www.statbank.dk/BIL52.

Table 5
Average marginal effects from probit estimations of BEV adoption.

Variables	BEV adoption (AMEs-probit)Period 1 and Period 2 (1.1.2013 – 31.12.2018)		BEV adoption (AMEs-probit)Period 2 and Period 3 (1.1.2016 – 31.12.2019)	
	Coeff.	**Cluster-robust std. error**	**Coeff.**	**Cluster-robust std. error**
Z	−0.011***	(0.00)	−0.034***	(0.00)
(Ln) Electricity price	0.543***	(0.02)	0.346***	(0.05)
(Ln) Gasoline price	−0.011***	(0.00)	0.135***	(0.01)
Gender (Ref = Female)				
Male	0.005***	(0.00)	0.010***	(0.00)
Age (Ref = 18–28)				
29–39	0.000	(0.00)	0.003	(0.01)
40–50	0.001	(0.00)	0.004	(0.01)
51–61	−0.001	(0.00)	0.000	(0.01)
≥ 62	−0.002	(0.00)	−0.004	(0.01)
Education (Ref = Primary)				
Secondary	0.000	(0.00)	−0.003***	(0.00)
Tertiary	0.002**	(0.00)	0.001	(0.00)
Household size (Ref = 1 member)				
2 members	−0.003***	(0.00)	−0.006***	(0.00)
3 members	−0.005***	(0.00)	−0.007***	(0.00)
4 members	−0.004***	(0.00)	−0.005***	(0.00)
≥ 5 members	−0.003**	(0.00)	−0.006***	(0.00)
Household disposable income (Ref = Lowest 20 %)				
Quintile 2	0.002**	(0.00)	−0.001	(0.00)
Quintile 3	0.006***	(0.00)	0.002	(0.00)
Quintile 4	0.008***	(0.00)	0.005***	(0.00)
Highest 20 %	0.013***	(0.00)	0.013***	(0.00)
Working status (Ref = Worker (skilled/unskilled))				
Self-employed	0.007***	(0.00)	0.012***	(0.00)
Routine nonmanual	0.001	(0.00)	0.005***	(0.00)
Manager	0.004***	(0.00)	0.011***	(0.00)
Outside workforce	0.004***	(0.00)	0.008***	(0.00)
Marital status (Ref = Married/Living with a partner)				
Separated/divorced/widowed	0.000	(0.00)	−0.001	(0.00)
Single	0.000	(0.00)	−0.002	(0.00)
Urban area (Ref = Metropolitan)				
100,000–999,999 inhabitants	−0.003***	(0.00)	−0.003*	(0.00)
50,000–99,999 inhabitants	−0.003***	(0.00)	−0.001	(0.00)
<49,999 inhabitants	−0.002***	(0.00)	0.000	(0.00)

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses, clustered at the individual level.
Note: The standard errors are calculated under the assumption of accurately measured Z variables obtained from the BART model and might be downward bias.

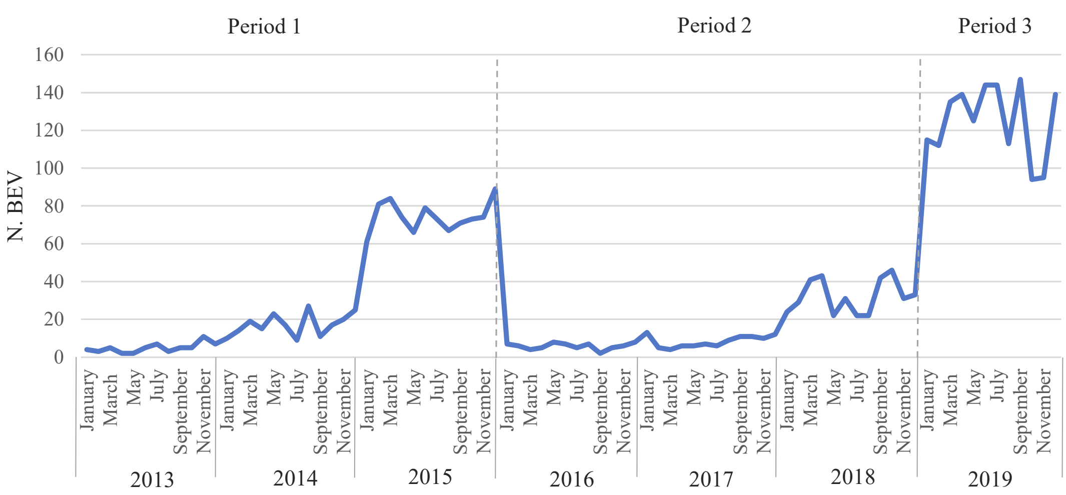

Fig. 4. Trend in newly registered BEV per month (2013–2019).

car owners in the highest income quintile, and car owners living in metropolitan areas. Moreover, coupling the heterogeneous treatment effects with the likelihood of adopting an electric vehicle allows us to confirm that there are likely to be substantial freerider effects in the promotion of electric vehicles via the tax system. Policy-makers could use detailed information on the predictors of BEV adoption and target information toward customers who are particularly likely to adopt BEVs.

This study has some limitations. Due to the lack of data on public charging infrastructure for the entire period of our investigation, our analyses do not include such information. We are only able to partially remedy this drawback by controlling for urban areas. Moreover, our analysis is limited to socioeconomic characteristics that influence BEV adoption and lacks information on vehicle attributes (e.g., ease of operation, purchase price, driving range, speed, battery costs), behavioral (e.g., usage satisfaction) and psychological factors (e.g., environmental concerns). Also, there might be other time-varying unobservable factors that contributed to influence the propensity to purchase a BEV that are not controlled by the model employed. Finally, although the study covers a period spanning 7 years, we acknowledge that the customer base might change over time. As BEVs mature and gain acceptance, the customer base expands beyond early adopters and they appeal to a broadening pool of consumers with heterogeneous socioeconomic characteristics.

CRediT authorship contribution statement

Gianluca Trotta: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Supervision, Validation, Writing – original draft, Writing – review & editing. **Stephan Sommer:** Conceptualization, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tra.2024.104117.

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