How parking regulation affects the consumption of private cars – identification through a natural experiment

MANUSCRIPT IN PREPARATION

Guri Natalie Jordbakke, Institute of Transport Economics and University of Oslo.

Abstract

The supply of public parking in urban areas is often considerable – making parking prices and supply a possible regulation tool for car use and ownership in urban areas, affecting the level of related externalities.

This paper investigates the causal effect of parking regulation on car ownership, including type of car and car use, using the introduction of residential parking in Oslo as a natural experiment. From 2017 to 2021, several districts in Oslo introduced residential parking, where residents are now obligated to pay a minor annual fee for more available parking while visitors must pay an hourly fee. Variation in introduction timing between districts is observed, i.e., a case of staggered adoption where a staggered differences-in-differences framework is used for identification. Furthermore, a unique dataset with households as observational units and information regarding residential parking implementation is applied.

Results from this study show how residential parking, intended to make parking more available for residents, does so. The expected availability effect is significant through the increase in car use – regardless of whether it is a conventional or electric car. The increase in car use stems from both new ownerships, i.e., households that did not own a car before, and increased use of already car owners. Hence, for residents isolated, the externalities are expected to increase. Furthermore, not intentionally, the policy makes conventional cars preferable to electric cars in urban areas – as the number of electric cars reduces relative to a situation without residential parking. These findings have significant implications for policymakers and urban planners, giving them a deeper understanding of the unintended consequences of residential parking policies on car ownership and use patterns.

1 Introduction

Parking allocation and pricing directly impact car use and, in turn, car ownership decisions, as cars depend on parking space. Public parking is usually a significant supplier of parking space in urban areas, making pricing and supply of parking a possible regulation tool to affect both car ownership and use. In addition, regulating associated negative externalities of parking demand in urban areas where land is scarce often seems necessary. However, the under-researched causal effect between car ownership and parking regulations is a significant gap in the current literature (Albalate and Gragera 2020), a gap this paper will contribute to fill – answering the following question: **What is the causal effect of (residential) parking regulation on car ownership choice,** ***its extent of use, and the adoption of zero-emission cars?*** Where the causal effect is identified using the introduction of residential parking in Oslo as a natural experiment.

In 2012, the Oslo council decentralized the decision-making process, allowing each district to determine whether resident parking would be introduced in their neighborhood. This resulted in residential parking in several districts with varied introduction timing in the period 2017-2021. This context of locally decided implementation, with its staggered roll-out of residential parking, adds a unique dimension to the study.

The main purpose of such a policy was to reduce visitor parking and give residents better parking facilities i.e. increase parking availability. Motivated by this, residents were given the opportunity to buy a permit for a minor annual fee, while visitors were obligated to pay an (higher) hourly fee. As such, two groups of individuals were affected by such policy directly: (1) residents and (2) visitor parkers. This paper primarily focuses on residents.

Theoretically, I show that such a parking policy would give both a price effect as parking costs increase and an availability effect—which works through the alternative cost of time use and is provoked through price discrimination of visitors versus residents. However, theoretically, it is not clear if the availability or pricing effects will dominate, as they will work in opposite directions. Hence, the aggregated effect is an empirical question, answered in this paper by exploiting the staggered roll-out of residential parking and using a differences-in-difference framework for identification.

My findings show that residents respond by increasing their car use and ownership, which implies a significant availability effect - in line with the policy's intention. Moreover, this further implies that there is a significant price effect on the visitors, relative to the residents – which provokes an availability for the last.

The availability is presently looking at both conventional and electric cars. Although the policy stated ambition was to make parking more available – the significant increase in car use could be contrary to reducing the municipality's goal of reducing urban emissions. Furthermore, non-intentionally residential parking makes conventional cars preferable to electric cars in urban areas. Also, the results show a clear availability effect for separate estimation of inner- and outer city districts. As expected, the effect is larger for inner-city residents, typically more dependent on on-street parking than outer-city residents.

This study highlights the potential of local regulation as a tool for affecting traffic and related externalities. This strategy aligns with the increasing trend of local authorities making a political commitment to climate change adaptation (EEA 2021). In addition, the literature has focused on the transition to more sustainable car technologies, e.g., low—or zero-emission vehicles, even though private cars are found to be parked 95% of the time (Shoup 2011)[1].

The consequences of parking policies and their effect on household or individual travel behavior, including how they can distort land use and car usage (Inci 2015) and induce welfare losses (De Groote et al. 2016, Eliasson and Borjesson 2022), are not fully understood. At least not in a causal term (Albalate and Gragera 2020). In addition, knowledge about policy implications regarding residential parking is limited, as most studies focus on parking at the destination (Inci 2015). However, when such parking schemes are investigated, most studies conclude that residential parking availability positively correlates with car ownership and use (Russo et al., 2019). Furthermore, underpriced parking can induce car use and hence congestion directly through encouraging "cruising" for parking and indirectly inducing individuals to drive instead of taking other means of transport. Empirically, evidence shows that home parking is usually subsidized with cheap residential permits. This may distort parking demand, increase car ownership, and induce significant welfare losses (De Groote et al. 2016; Russo et al. 2019;

[1] Also, reducing the number of cars in cities can release space for the sustainable development of urban areas and possibly reduce emissions.

Van Ommeren et al. 2014). Based on surveys in the US, households with considerable access to off-street parking generally own more cars and use them more (Guo 2013a), i.e., conduct more car trips and drive longer distances (Guo 2013b). Furthermore, the same study shows how the availability of on-street parking can increase car ownership by up to 9% (Guo 2013a) and is associated with a 10% increase in driving distances (Guo 2013c). In Norway, individuals with access to private - owned or reserved parking - have about three times higher car ownership levels than others. In contrast, longer distances to home parking are associated with fewer car trips, more walking, and use of public transport (Christiansen et al. 2017). Commonly for this body of literature is that it explored the impact of parking and car ownership, mainly using cross-sectional data, although car ownership is a durable good and a household decision in the medium-term period.

A single study addresses insight into cases where one faces a potential resource allocation from non-resident to resident, i.e., parking is subsidized for non-residents and residents through free on-street parking – using panel data: Albalate and Gragera (2020). By studying the introduction of parking regulation policy city-wide – in Barcelona, observing neighborhoods from 2007 to 2014. Results show that paid curbside parking reduces visitor demand and positively affects residents' car ownership (ibid). Furthermore, they implicate that an increase in car use for residents can offset the decrease in car trips for visitors; however, with the given data, they cannot look at the extent of use.

Only some papers have investigated individual/household car ownership behavior with detailed register data, as transport behavior is first and foremost analyzed with survey data. Furthermore, applying the Differences-in-Differences (DiD) framework, widely employed in empirical economic research to assess the causal impact of policy implications, is less commonly used in transport studies. Of those, looking at car ownership and user behavior, including electric vehicle (EV) adoption using the introduction of differentiated road toll in Norway (Isaksen & Johansen, n.d.) or a large EV subsidy in California (Muehlegger & Rapson, 2018). In addition, Dio et al. (2017) use the introduction of a new Circle Line in Singapore to examine the effect on housing values using spatial differences-in-differences.

This paper contributes to this body of literature by using a suitable and new estimation method capturing the causal effect using the staggered difference-in-difference in a staggered roll-out setting. Furthermore, a rich and detailed dataset that observed households from 2015 to 2019 enables us to look at not only car ownership but also the type of car - conventional and electric cars, number of cars, and car use, i.e., kilometer-driven. The effect is also estimated on inner- and outer-city districts separately, showing how those effects differ between locations within an urban area. In addition, this paper also illustrated any dynamic effect over time associated with parking regulation on a durable good such as private car ownership.

The following parts of this paper are structured: Chapter 2 describes residential parking introduced in Oslo, Norway, from 2017 to 2020. Chapter 3 introduces the theoretical foundation and how to consider the price- and availability-effect - essential for the estimation results. An overview of the identification strategy is given in Chapter 4, which also discusses crucial identification assumptions. Data used for estimation is presented in Chapter 5, followed by the results in Chapter 6. Chapter 6 includes a descriptive analysis and estimation results primarily illustrated in the (cs) event plot. Lastly, some concluding remarks are given in chapter 7.

2 Context

Although parking regulation is primarily decided at the municipality level in Norway, in 2012 the council of Oslo, the largest city, municipality, and capital of Norway, gave each district the authority to determine whether resident parking would be introduced in their neighborhood. This authorization gave each district the chance to decide two things: (1) whether to introduce residential parking, and (2) in what area of the district.

The primary purpose of the regulation was to make parking more available for residents, i.e., reduce visitor parkers. Nonetheless, the official document encompassing the decision-making process for the introduction of resident parking shows tendencies that the general street environment is also considered. In addition, based on proposals from several districts, the regulation of residential parking is up for revision to include reducing car use in general.

Before the introduction of residential parking, on-street parking was free for visitors and residents in most districts. Some exceptions were a few areas close to the city center with zoning i.e. city center divided in different zones with heterogeneous parking prices.

As the implementation decision for residential parking was up to each district, this led to a variation in introduction time across and within some districts. From late 2017 to early 2021, 15 of 17 districts introduced resident parking in (parts of) their district. Oslo has 17 districts, including the city center and a greater area with woodlands. By January 2020, the number of residents per district ranged from approximately 27,000 to 62,000, and the municipality of Oslo had about 690,000 residents.

Table 1 summarizes the treatment timings when residential parking was introduced. By quarter, there are eight treated groups from the fourth quarter of 2017 to the fourth quarter of 2020. Furthermore, the table shows, by group, if the introduction happened in the outer- or inner city, if those district(s) introduced parking restrictions in selected or in their entire district, and how many districts the group contains.

Table 1. Implementation happened in the inner or outer city, if the introduction happened in the entire, parts or both entire and parts of the district and number of districts by group i.e. treatment timing.

Group i.e. treatment timing	*Inner/Outer city*	*Entire/ selected parts*	*Number of districts*
2017q4	Inner	Entire districts	2
2018q1	Inner	Entire districts	1
2018q2	Inner	Both	2
2018q3	Outer	Selected parts	4
2019q2	Inner	Entire districts	1
2019q3	Outer	Selected parts	1
2019q4	Outer	Selected parts	2
2020q4	Outer	Selected parts	1

With observation on quarter, treatment of residential parking is divided into eight groups, where the groups treated first (2017q4, 2018q1, and 2018q2) are in the inner city. In contrast, the last three groups (2019q3, 2019q4, and 2020q4) were in the outer city and introduced residential parking in selected parts of their districts. In addition, each group consists of a variated number of districts, where group 2018q3 consists of four districts – four districts introduced residential parking in the third quarter of 2018.

Resident parking entitles residents in the given area to buy an annual permit for 3000 NOK[2] (for a passenger car) for on-street parking. Such a permit gave the right to park in all permitted

[2] From 2017 – 2020, from 2020 the price increased to 5200 NOK a year.

streets in the given district. Hence, a district cannot be divided into several parking zones. Furthermore, all individuals registered as residents in the given area were entitled to purchase one permit only if they owned a vehicle. Thus, only one permit was given per individual per vehicle; there were no restrictions on the number of permits sold. In some cases, this led to more permits than available parking.

Other residents, such as students and commuters, could buy a permit condition on documentation that they lived in the given area. Visitors could still use on-street parking but to a given parking fee per hour or per day (maximum 167 NOK a day). Outside the hours of 8 p.m. to 8 a.m., parking is free for visitors.

In line with Norwegian policy and incentives to adopt electric vehicles, parking for electric vehicles was free of charge regardless of whether individuals were residents or not. However, this was changed in 2020 when electric vehicles were forced to pay a fee, although it was just a fraction of the parking fee for other types of vehicles.

When the district decided to implement resident parking, it could take up to a year before introducing the policy. However, the time between the decision-making and introduction did vary between districts, meaning that although decision-time might have led some individuals to adjust their car ownership prematurely, the introduction time does not necessarily do.

Residents were informed by covering parking signs in the given area with information that this street was becoming a part of the residential parking scheme approximately 14 days before the implementation. No information was given systematically prior to this. Nonetheless, in some districts, there were discussions in the local newspapers sometime before the introduction. In addition, it would not be unreasonable to assume that some residents had expectations regarding the implementation of residential parking, especially in districts with late implementation.

Public documents regarding resident parking in each district - documents such as identification of parking demand for residents and the overall decision-making process - exhibit great variation between districts regarding the reason for introduction. Some districts had more than one vote related to the decision to implement. Additionally, the political landscape shows a clear propensity of which party is and does not favor resident parking. All this indicates that introduction time across the district has not been systematic. However, the distribution of introduction times clearly shows that the inner-city districts typically introduce resident parking before the outer-city districts. In addition, all inner-city districts regulated the entire district, while outer-city districts consistently selected part of their district.

3 Theory

Investigating individuals/households' behavior regarding ownership and car use – the literature follows the neo-classical consumer behavior theory, where an agent will maximize utility under a given budget constraint (De Jong 1988). In such models, car ownership costs are split between fixed and variable. The utility function and the respective budget constraint can be written as

$$U = U(A, X), \qquad Y \geq X + vA + \mathbf{1}\{A > 0\}C$$

U is the utility function, depending on the consumption of automobile use A and other goods X. The measurement of A can reflect either the kilometer driven or the number of trips. The budget constraint is given by the inequality, where Y is the total consumption budget, v is the variable cost associated with car use (pr trip or km), and C is the constant (yearly) cost of holding a car. Notes that when the consumer does not drive, i.e. A=0, there is no cost associated with holding a car. This implies that consumers never own a car whenever they do not drive, represented by the index $\mathbf{1}\{A > 0\}$ in the budget constraint[3]. Note that this implicit assumes no car-sharing possibilities[4]. Furthermore, at a given level of car use A, the remaining income available and used is for consumption of X—without any car consumption, all income goes to consuming X, easily seen when letting A>0 and A=0, respectively:

$$Y = X + vA + C$$

$$Y = X$$

Graphically, this gives a partially straight-lined budget function that follows the axis of X as all income goes to X's consumption.

Figure 1 illustrates a state where consumers will be indifferent between owning a private car or not – this is seen as the indifferent curve tangent to the budget line and crosses the vertical axis at point Y – total income- i.e., indifferent between using all income on X or choosing to use a car. Note that the budget constraint is linear and parallel to the vertical axes from Y-C to Y,

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[3] A less restricted budget constraint will include the possibility to own a car even if you do not drive, where the index would be $\mathbf{1}\{A \geq 0\}$ i.e. budget constraint: $Y \geq X + vA + \mathbf{1}\{A \geq 0\}C$.

[4]. Including car sharing as an option would allow consumers to drive without owning a private car (both BP and PP) and allow other consumers to own cars without driving personally or with a total number of kilometers higher than personal use (PP).

which reflects the case where the consumer will choose 0 car (use) and only spend the income on commodity *X* – represented by the thicker line from *Y-C* and *C*.

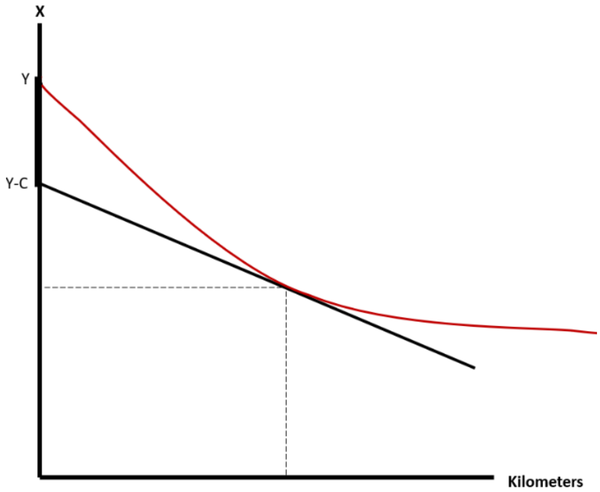

Figure 1. Utility function and budget constraint of car consumption versus consumption of other goods X.

The fixed cost of private car ownership reflects the cost that does not depend on the distance traveled, i.e., the cost needed to have the car ready for use. It usually includes the purchase price, depreciation, road or car tax, and insurance. Variable cost, on the other hand, depends on travel distance, e.g., fuel, maintenance, road toll, and parking fee.

Regarding the implementation of resident parking, residents will experience increasing costs related to parking. Increasing parking costs will raise the variable cost and influence private car use and ownership through budget constraints. However, I state that this cost will primarily be perceived as a fixed (yearly) cost, *C*, for residents in the case of residential parking, as they pay a yearly fee to the municipality for the parking permit. With the setup De Jong (1988), Figure 2, left panel, illustrates the expected effect of a higher parking fee for residents – an increase in *C*.

An increase in C will potentially reduce the income available for consumption of other goods – X – and the level of car use if one chooses to own a private car. As illustrated in the left panel of Figure 2, the budget function shifts downwards, and the level of consumption X will decrease when car ownership is chosen. However, it should be no surprise with the state of indifferent consumers; a cost increase will cause a maximizing consumer not to own a car —as they can reach a higher utility level (indifferent curve) if they choose to use total income on consumption of X. Hence total consumption *Y* is equal to the consumption of other goods *X*.

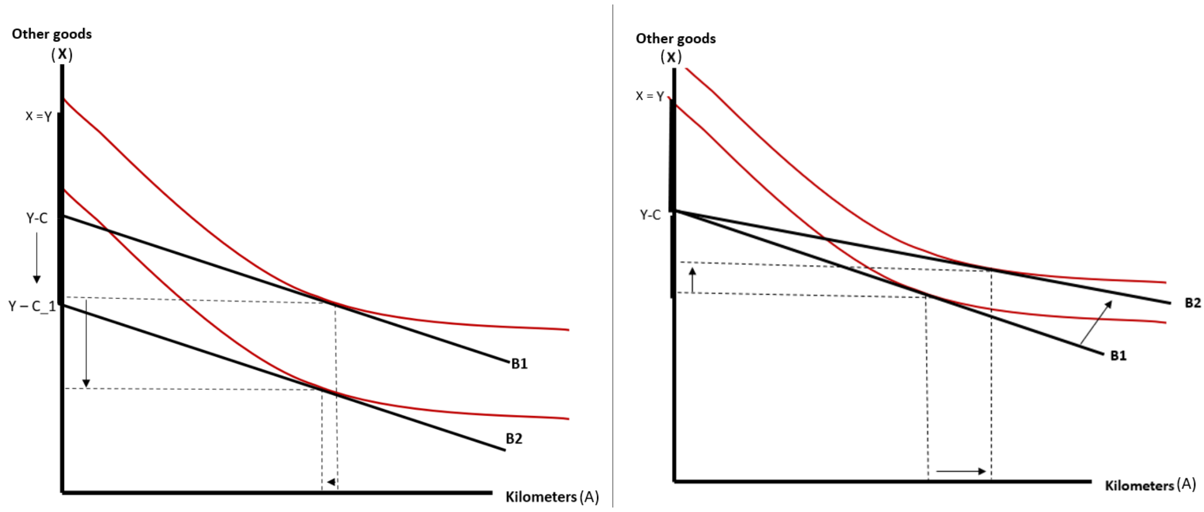

Figure 2. Effect on the consumption of car and X, other goods, when (i) C increases left panel, and (ii) when v decreases right panel.

As the cost of parking rises for both residents and visitors—and is particularly high for visitors after the implementation of the parking policy—an availability effect is anticipated in addition to the price effect. This effect is expected to be primarily driven by visitors' response to the high parking cost—a significant price change. Consequently, less-price-sensitive visitors and residents will find more available parking.

More availability could reduce travel time – through reduced cruising for parking – and, in some cases, access time to an individual's private car, i.e., shorter walking distance from home to a parked car. Reducing the total time of each trip will increase the utility of each journey and, hence, private ownership. The travel time component can be implemented in the budget constraint through the variable cost *v*, as travel time represents an opportunity cost of time use. Expected reduced travel time will then be reflected through reduced *v*.

The right-side panel in Figure 2 illustrates the expected effect of an increase in availability, i.e., reduced travel time, hence reduction of *v*. With new budget constraints, consumers can reach a higher utility level (function) and respond by increasing both car use (*A)* and the consumption of other goods (*X)*. The consumer will no longer be indifferent to owning a car, as one can reach a higher utility level by consuming both car and other goods (*X)*.

From Figure 2, the total effect of higher cost and availability contributes in the opposite direction – in the case of residential parking, it is an empirical question of which effect dominates. In this paper, I exploit the natural experiment setting where parking fees change while other costs stay or change equally among the selected treatment and control groups to answer this question.

4 Identification strategy

This paper analyzes the implementation of resident parking using a counterfactual framework. The implantation is viewed as a natural experiment exploiting the variation of the introduction of residential parking, both in time and geographical location. Different groups of households receive the "treatment," i.e., they start paying parking fees and receiving more available street parking at different times. In literature called staggered roll-out. This allows for comparing the relevant outcome variables before and after the intervention and between groups – treatment and control - within an econometric Differences-in-Differences (DID) framework (Angrist and Pischke 2009).

Applying the DiD framework is largely used in empirical economic work related to evaluating the causal effect of policy implications, including studies of transport economics. However, recent literature shows that applying the standard TWFE[5] whenever we have multiple periods and treatment timing will likely give us biased estimates. See for example Chaisemartin and D Haultfæuille (2020), Goodman-Bacon (2021), Sun and Abraham (2020), Borusyak, Jaravel and Spiess (2022), Athey and Imbens (2021) and Callaway and Sant-Anna (2021). For this reason, using TWFE to analyze the staggered roll-out of residential parking might be inappropriate. This is especially the case whenever the effect is expected to be dynamic, i.e., change over time, which is expected with outcomes of durable goods such as car ownership. In addition, as an available effect depends on the change of parking use for visitors, this effect is expected to take some time to be fully utilized. Notes that when the treatment effect is expected to be homogenous and hit once at the outcome – one-time shock - then TWFE can appropriately be used. Even using an event study design, which accounts for dynamic effects, i.e., effects that are not constant over time, one cannot guarantee a parameter that can be interpreted as causal (Sun and Abraham, 2020).

Goodman-Bacon (2019) explains how TWFE is sensitive to the size of each group, the timing of treatment, and the total number of periods (Goodman-Bacon,2019; Callaway and Sant-Anna, 2021). When group size varies—as shown in Table 2, where early treated groups are somewhat

[5] Two-way fixed effect

bigger than those later treated—and the number of periods is relatively many, this could cause future challenges in using TWFE.

The core of this challenge lies within the method of OLS, which compares all variations, i.e., all groups (treated groups) if there is observed variation in the treatment status. Goodman-Bacon (2021) illustrates how one with different treatment timing compares three groups: (1) Treated (both early and late) with never-treated, (2) treated with not-yet treated, and (3) later treated with early treated. The third category is inappropriate – bad control – as we do not know the effect of early treatment over time[6]. For durable consumption goods such as car ownership, the effect is expected to take some time to adjust – implying that the shock is not a one-time effect. In such a case, comparing early treated with residential parking with later treated will give an incorrect estimate of ATT. Furthermore, once a household first gains access to residential parking, it will, in turn, stay treated, together with a staggered roll-out. This implies using a staggered adoption design when looking at the effect of residential parking.

For a reasonable estimate, one wants only to exploit the good variation—good control—that Callaway and Sant'anna (2021) suggest whenever one has a case with multiple time and treatment periods together with staggered treatment status. The building block they suggest for the estimation of the average treatment effect is a group-time average treatment effect $ATT_{g,t}$, formally defined as:

$$ATT_{g,t} = E\left[Y_t(g) - Y_t(0) \mid G_g = 1\right]$$

For the outcome of car ownership, the equation states that the average effect of residential parking on car ownership for group *g* at time *t* is given by the expectation of the differences between car ownership at time *t* if the group was treated vs. not have been treated. Using the setup with not-yet-treated as a control group and including covariates *X*, and without anticipation, the average treatment effect is formally defined as:

$$ATT_X\,(g,t) = E\left[Y_t - Y_{g-1} \mid X, G_g = 1\right] - E\left[Y_t - Y_{g-1} \mid D_t = 0, G_g = 0\right]$$

For estimation, they suggest a procedure to obtain the ATT(*g*,*t*) parameter where one first sub-sets the data to only contain observations at time *t* and *g-1* only for units in group *Gg=1* or *Ds=1*. With this given subset, one runs the population linear regression, with or without covariates, with the following model specification:

[6] As mentioned, if one expects the treatment effect to be homogenous and hit once at the outcome – one-time shock - then TWFE can appropriately be used.

$$Y = \tilde{a}_1^{g,t} + \tilde{a}_2^{g,t} \cdot G_g + \tilde{a}_3^{g,t} \cdot 1\{T = t\} + \tilde{\beta}^{g,t} \cdot (G_g \times 1\{T = 1\}) + \tilde{\gamma} \cdot X + \tilde{\epsilon}^{g,t}$$

The specification is quite common, with a constant a, a group effect a_2 , and a time effect a_3, potential control variables X with parameter(s) γ in addition to the standard error term ϵ. Finally, the treatment effect is represented by the parameter $\tilde{\beta}^{g,t}$ which in turn measures the average treatment effect for group g at time t.

This gives a set of group-specific treatment effects ATT(g,t), which is further used to find aggregated effects of both the general ATT (over time and group), which corresponds to the estimate given by the static version of TWFE, most reported in this paper an event study estimates.

4.1 Identification assumptions

Several essential assumptions must be satisfied in estimating the group-specific treatment effect ATT(g,t) for a causal interpretation. For instance, regarding design, one assumes that when treated with parking regulations, one stays treated. This can be interpreted as residents staying within a treated area or, more generally, being treated at some point.[7] Hence, you cannot remove that treatment experience, i.e., treatment is not irreversible. Irreversible treatment is often referred to as the staggered adoption design - and one often expects the effect to be different over time, hence dynamic effects. In addition, to measure such effects over time, it is necessary to access panel data – which is satisfying given the discussion in the data section.

In this paper, I have chosen to use not-yet-treated as a comparison group. Although many individuals in the greater Oslo area are not treated with the same parking policy, I expect them to differ in main characteristics regarding the outcome variables – as private car ownership and use are linked to residents' choices. The potential not-treated group is, for this reason, considered to be relatively small. Hence, the not-yet-treated group is a more valid comparison. This is in line with remark 2 of Callaway and Sant'Anna (2021) - one might not be comfortable using never-treated units as part of the comparison group because they behave very differently from the other "eventually treated" units. "In these cases, practitioners could drop all "never-treated" units from the analysis" (Callaway and Sant'Anna, 2021 p.6).

The third assumption gives restrictions regarding anticipation for all eventually treated groups – where this method has included the possibility for anticipation behavior whenever one has a

[7] In such cases, moving can be considered an outcome

good grasp of the time horizon. For the case of residential parking, the assumption states that any observed effect depends only on whether you live in a residential parking area or not - and not any expectation of any future implementation of residential parking (no-anticipation). With forward-looking and rational consumers, one will expect that information on parking regulations beforehand will contribute to the consumer's decision to own a private car prior to implementation. In such cases, any anticipation might be more present when studying later treated. This will, in turn, question the selection of not-yet-treated as a good control group.

A less strict interpretation would be that the effect of parking regulation on private car ownership (and car use) will ensure no anticipation whenever residents were unaware of the implementation before it happened, which means that making a decision and observing the decision might experience some lags, which can be shown as an immediate effect or an earlier effect than when the decision took place. However, any prior information on the implementation of residential, i.e., information on future treatment, would violate the assumption. In the case of residential parking, the main concern regarding anticipation would be later treated (districts) have some anticipation because they observe introduction in early treated (districts). Any homogenous anticipation over groups can be regarded directly in the analysis, while differences between groups would be more challenging.

However, as most districts decided to introduce residential parking simultaneously, i.e., same resolution timing, hence, some of the timing variation is due to the time variation from decision to implementation – the problem should not be extensive. In addition, we look at quarterly observations, which will absorb some anticipation effect. As private ownership of cars is considered a durable good, the decision will take some time – and the effect is expected to take some time.

The no-anticipation assumption underlines the importance of good controls; in addition, for the DiD framework to report causal effect, the crucial and stricter assumption regards the parallel trends – which is based on a not-yet-treated as a control group. The assumption regards the comparison of group g and groups that are “not-yet-treated” by $t + \delta$. This means that although the level of the outcome variable(s) could be different, the trend of the treated group at time t should equal to the trend of that not-yet. This means that private car ownership and use should have the same trend in treated groups as in not-yet-treated groups. If groups differ in car ownership and use characteristics, it could lead to different trends and violate the assumption. As mentioned, car ownership is expected to differ in inner and outer districts, which can challenge the parallel trend assumption. A common test for this is the pre-trend test, which tests whether the trend of the treatment and control group are parallel in periods before the treatment. The parallel trend assumption is discussed in greater detail in later chapters when looking at the development of outcome variables over time for each group. See also the appendix for the results of the pre-trend tests.

The final assumption states that each household has a positive probability of receiving each treatment level—meaning that a comparison group, a control group, can be used for estimation. Note that when all households eventually get treated, one can only identify the ATT (g,t) for periods before the last treated group starts their treatment. In this case, one cannot identify the last treated group's ATT(g,t).

1 Data

The dataset is a robust compilation of several registers, primarily sourced from Statistics Norway. This comprehensive dataset spans the period from 2015 to 2019 and encompasses the entire population of Norway. Each individual's data includes birthdate, gender, identification of mother and father, municipality/country of birth, yearly updates on their resident status (on census tract level), citizenship, civil status, and unique family identification – all with corresponding change dates[8]. Several things are worth empathizing with. First, one can identify parents, i.e., connect the different individuals in the dataset to construct a family composition. In addition, with a unique family identification, the dataset is aggregated to household units, with information regarding family composition giving, in turn, information regarding household composition – relevant to the choice of car ownership. Household as a unit of observation is derived as car ownership is generally considered a household decision.

Moreover, including socioeconomic characteristics such as education level from the education register gives information regarding individuals' higher started and finished education levels. When aggregated to the household level, the highest level is applied.

Furthermore, dates are used for disaggregation to a lower time dimension; this paper uses a year-quarter time unit. This is possible because most time-varying variables, including car ownership, are afflicted with dates. The Norwegian Central Motor Vehicle register provides

[8] For example, if the civil status changes, in a given year, the date for such change is provided. This enables us to disagree on the time dimension from year to for instant year-quarter observation.

information regarding car ownership and attributes, where each vehicle owned by a private individual will be registered to connect with the date of ownership. This unique feature allows for a comprehensive analysis of car ownership decisions at the household level.

For each vehicle, several dates are reported: first registration, re-registration (change of ownership), de-registration, and if and when the vehicle is scrapped. Also, one observes if a vehicle is either exported or stolen in addition to several features such as type of vehicle, model, fuel type, number of seats, and car size, either in cubic or net weight, Kw of the engine, and fuel per km. Lastly, particle, NOx, and C02 emissions are also reported but consist of many missing observations.

Information merged from the vehicle control register is applied when measuring car use. In Norway, each vehicle needs mandatory control every other year for vehicles older than four years, i.e., all cars driven by kilometer are reported in the fourth year and every other year after. Individuals' car use, i.e., kilometers for the period they own their car, is derived from this.

First, for each period between a control, the Average daily kilometer driven is calculated for each car. Furthermore, the number of days each individual owned the car in the given period is derived. Based on the average daily kilometer, individuals, and number of days with ownership, the total number of cars used by that individual in the given period was determined.

Finally, information on the implementation of resident parking is crucial for this research. It provides a key variable for investigating the effect of parking policies on car ownership and use. The municipality of Oslo has provided the introduction date for each treated regulated area, i.e., each (treated) district, enabling the identification of treatment status at the census tract level.

As car ownership choices are commonly viewed as a household decision, the data is analyzed at a household-quarter level, where the household is aggregated from individuals sharing the same family number, and the time dimension stems from the given date’s variable.

1.1 Treatment status and Sample selection

Contingent on the data described above, this paper can define treated individuals at a detailed level. Treated households are located in an area where residential parking is introduced. ***Treatment is defined as residents in a residential parking area one period before implementation.*** For instance, for a given household living in a district at the time of 2017q3 and this district implementing residential parking in 2017q4, the household is considered treated. Such a definition ensures that residents cannot change treatment status, i.e., move in and out of treatment; each household is only identified in one of the treatment groups.

As seen in the identification strategy, I use a version of DiD where not yet treated serve as the control group—for this reason, I only keep treated individuals. Subsequently, this paper studies the case of parking policy in Oslo municipality for treated households, i.e., the average treatment effect for treated (ATT).

Regarding the population of vehicles, the analysis is restricted to private-owned vehicles and vehicles defined as passenger cars based on the information regarding vehicle groups. In a further chapter, I therefore refer to it as cars. Household ownership of a car is defined by date. The number of cars owned is restricted to four cars per household, where the four newest cars are kept as these are most likely to be the cars used daily. This restriction is not considered rigorous in this analysis – especially since the focus is on the urban population. A similar restriction regarding cars per individual is done by Isaksen & Johansen (n.d.).

With these restrictions, the sample consists of 485 551 unique households for 2015 – 2019.

2 Results

2.1 Descriptive statistic

This paper operates with five outcome variables related to car ownership and use, e.g., independent and dependent on the type, conventional (diesel and gasoline) or electrical, and the number of private cars owned (per household). In addition, the number of kilometers driven is also an outcome variable.

The selected sample consists of treated households where the treatment status is defined as "living in a residential area the period before parking restrictions were implemented." In that way, households cannot move in and out of treatment, and once they are treated, they stay treated – which is in line with the method of staggered adoption.

The sample consists of 485 551 households; almost 36 percent own a car. The table below shows the number of households within the eight treated groups, the share that owns a car, and whether the group is in the inner or outer city.

Table 2. Number of households and the share of car owners - for each group.

Group (impl.date)	*Number of households*	*Share of car holders*	*Inner/Outer city*
2017q4	200 355	0.27	Inner
2018q1	77 105	0.29	Inner
2018q2	111 827	0.28	Inner
2018q3	47 298	0.44	Outer
2019q2	25 048	0.32	Inner
2019q3	11 828	0.38	Outer
2019q4	6 856	0.40	Outer
2020q4	5 234	0.16	Outer
Total treated	485 551	0.35	Both

Table 1 shows that early-treated groups are more extensive than the latest-treated group, which might affect the estimate's precision – especially several periods after the implementation of residential parking. In addition, the share of car ownership varies somewhat between groups – where earlier groups have a somewhat lower share of ownership than later groups. However, as discussed with the identification assumption, the crucial assumption is that the trend is parallel and not the level. The figure below illustrates car ownership development for all inner and outer city groups, separately for ownership in general and conventional and electric car ownership.

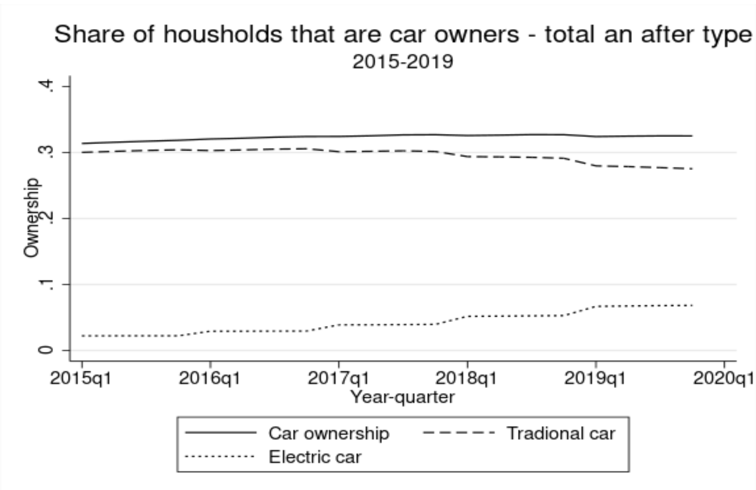

Figure 3. Share of households that own car, in general, conventional car and electric car – 2015-2019.

The general car ownership rate is consistently above 30 percent of households, slightly decreasing in 2018 and 2019. The share of conventional cars decreased over the entire period, implying that purchases of other types of cars do not offset the decrease in conventional cars. However, the decrease in conventional cars seems to be offset, to a certain degree, by an increase in electric cars in the periods before 2019.

As Table 1 shows, ownership differences depend on the inner or outer city location. The figure below illustrates the general car ownership over time for treated groups in the inner city. The red vertical line illustrates the implementation timing for each group – from left to right, respectively.

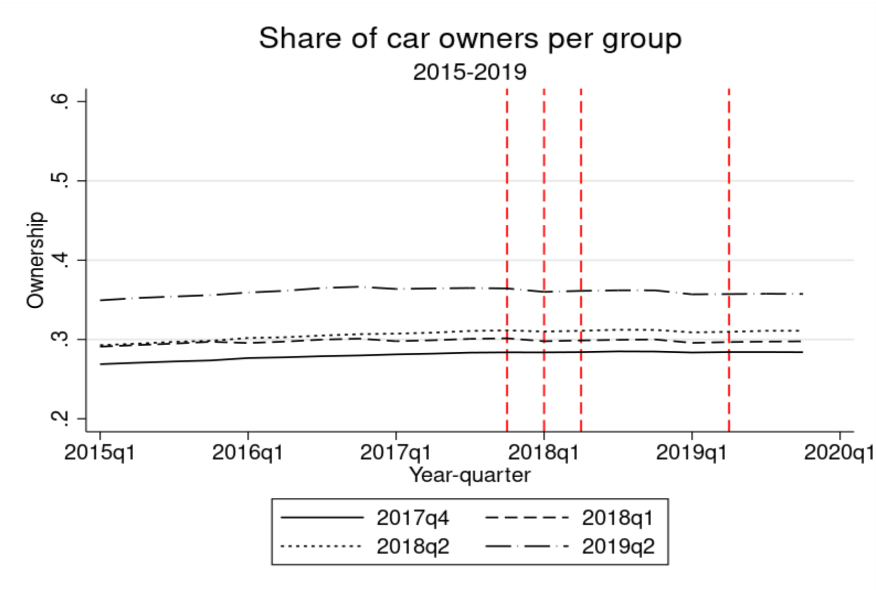

Figure 4. Share of households that own one or more cars for each treatment group located in the inner city.

For the four groups located in the inner city, the share of general car ownership seems to increase from 2016 to 2018, depending on the group. As with the total sample, a slight decrease was found in 2019. Figure 5 illustrates car ownership development for residents in the outer city. Generally, the owner's share is higher in the outer city. Groups 2018q3, 2019q4, and 2020q4 seem to follow the same trend, while the reduction in car ownership is more consistent throughout the entire period for group 2019q3.

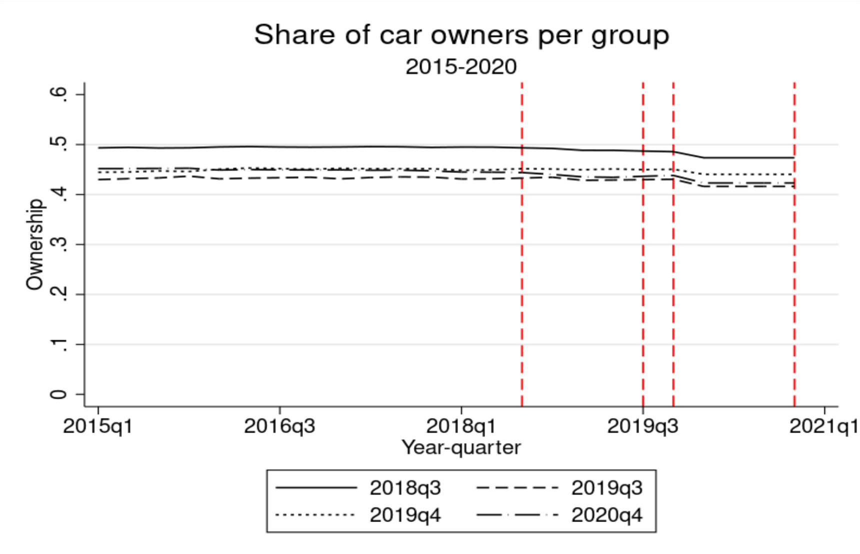

Figure 5. Share of households that own one or more cars for each treatment group located in the outer city.

Furthermore, more available parking might increase the probability of purchasing a second car. The figure below illustrates the development of the average number of cars per household over time. Both inner and outer city groups.

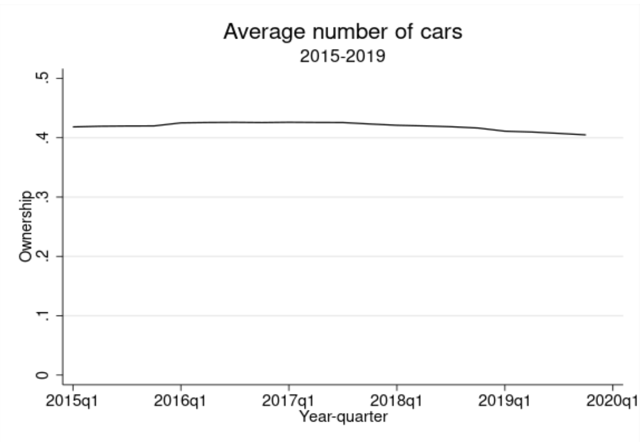

Figure 6. The average number of cars per household in the entire sample.

The average number of cars owned decreased throughout the period, while car ownership is more stable, implying a reduction in multiple-car households for the total sample. Looking at each group independently, the trend differs somewhat at the start of the period, but the trend seems quite similar over the entire period.

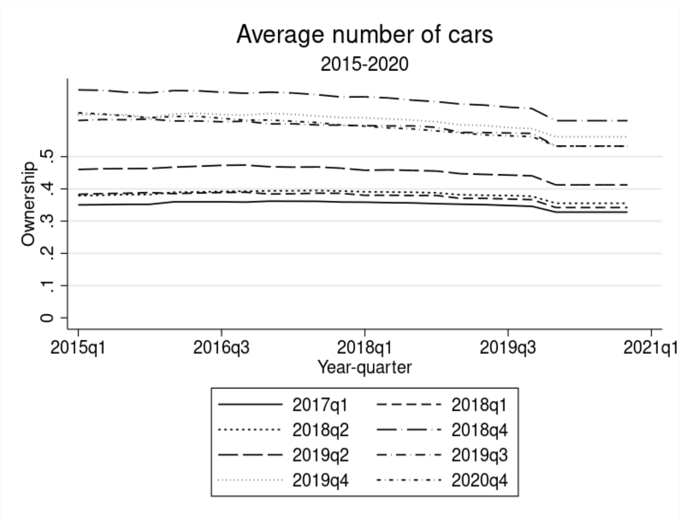

Figure 7. Average number of cars per household for each treatment group.

Furthermore, we look at the last outcome variable—the extent of use—the average kilometer driven for households. A reduction in car ownership is expected to affect the extent of use, measured as the average kilometer driven. The reduction seen in Figures 8 and 9 shows a decrease in the average kilometer driven, especially from early 2017.

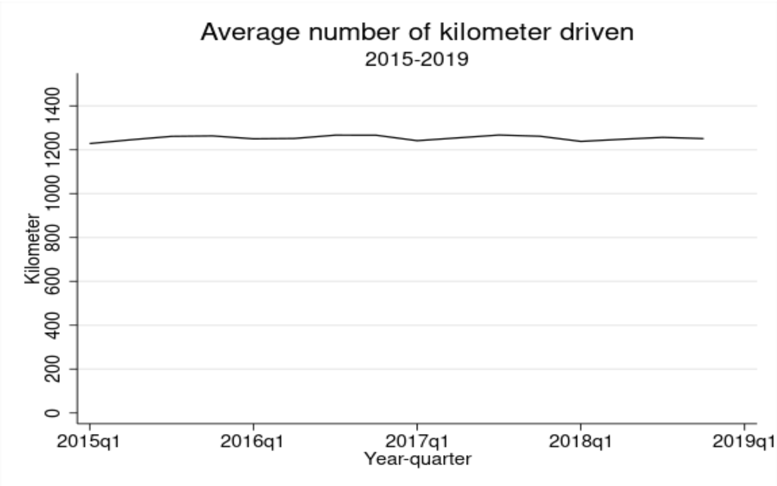

Figure 8. Average number of kilometers driven per household - all groups.

The development of each group shows apparent level differences. Many groups follow the same trend—both 2017q1, 2018q2, and 2019q4 seem to have a slight and smooth increase over the entire period. The average number of kilometers does vary somewhat more for other groups.

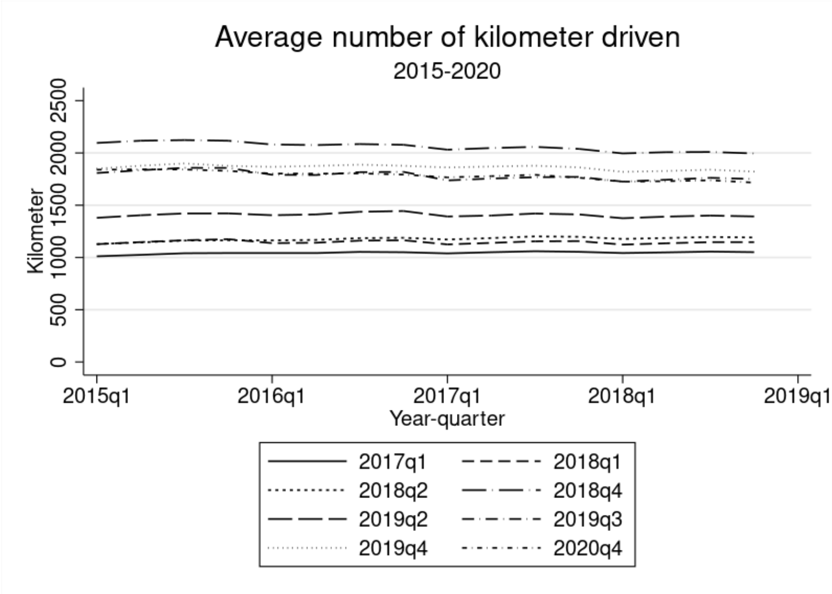

Figure 9. Average number of kilometers driven per household - per treated group.

2.2 CS event plot

As discussed earlier, private car ownership is a durable good; hence, consumer decisions can take some time. In addition, considering both a price and an availability effect - the availability effect is expected to come with lag, as it is conditioned on visitors responding to the policy. For this reason, the potential effect on private car ownership and its extent of use is expected to be dynamic over time. To capture any dynamic effect after treatment, we look at the effect over time in the (CS) event plot illustrated below for each outcome variable – for both inner and outer city – together and separately. All results are additionally given in tables in the appendix.

Figure 10 - 14 shows the event plot for the four outcome variables car ownership (binary), conventional car ownership (binary), Number of cars per household, and electric car ownership (binary) – from left to right.

Generally, residential parking contributes to increased car ownership over time, contrasting with the observed decrease or flat development in the total number of cars and car share in Figures 3 and 6. Hence, this implies that without residential parking, and all else equal, one would expect a larger reduction in car ownership and number of cars, i.e., the parking policy contributes to an increase in car ownership. As illustrated in Chapter Three, an increase in car ownership implies that the availability effect is more significant than the price effect for residents. The question would be to what degree this aligns with the initial policy agenda. The stated purpose was to make parking more available for residents, although the municipality of

Oslo has clear ambitions for reducing emissions related to transportation. In a case where the availability effect has dominated the price effect, hence more cars, the increase could be in line with the original purpose of the policy. However, such an effect is contrary to reducing urban emissions.

The ATT plot illustrates some lag of effects; as mentioned before, car ownership is a durable good, and any adjustment is, for this reason, expected to take some time. Looking at estimates of both car ownership and the number of cars for households, the increase in cars seems to come from an increase in the share of households previously without a car and an increase in multiple-car households. Illustrated by the sixth period after treatment, i.e. 1,5 years after, the effect on the number of cars is twice (0,01 percent) the effect on car ownership (0,005 percent).

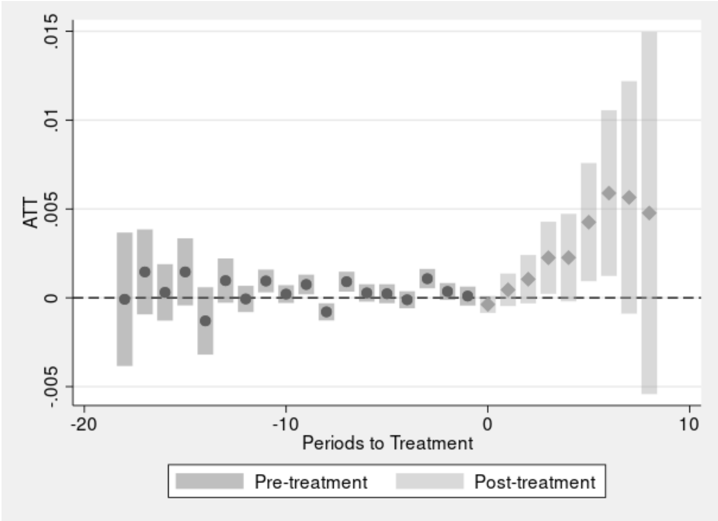

Figure 10. Event plot with outcome variable car ownership (binary)

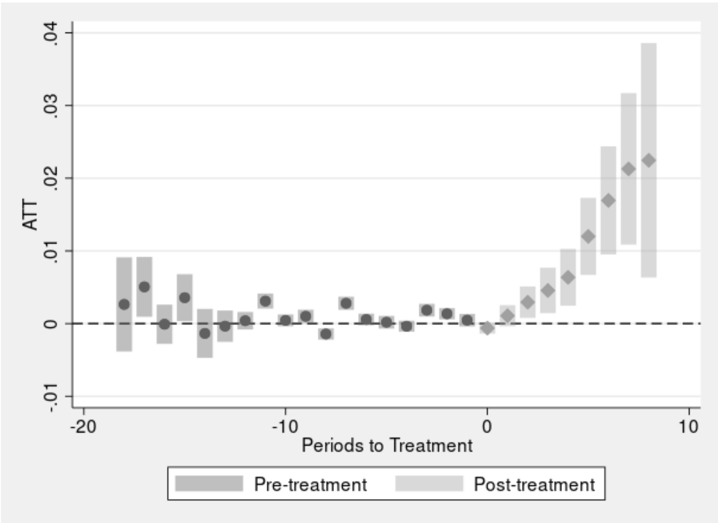

Figure 11. Event plot with outcome variable number of cars per household

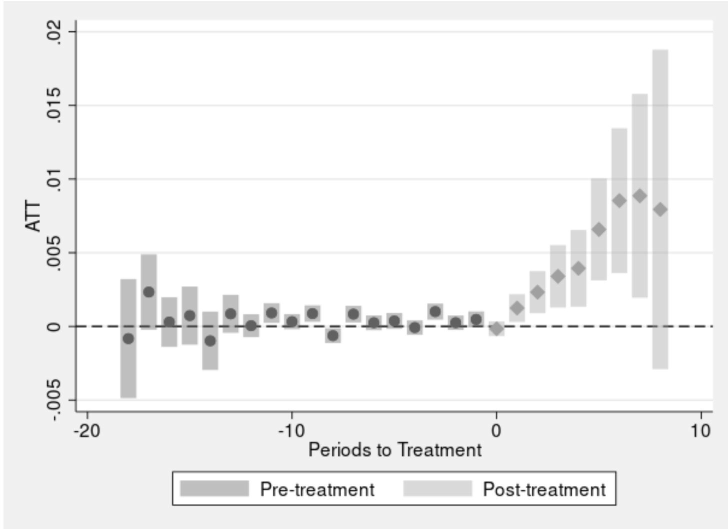

Figure 12. Event plot with outcome variable traditional car ownership (binary)

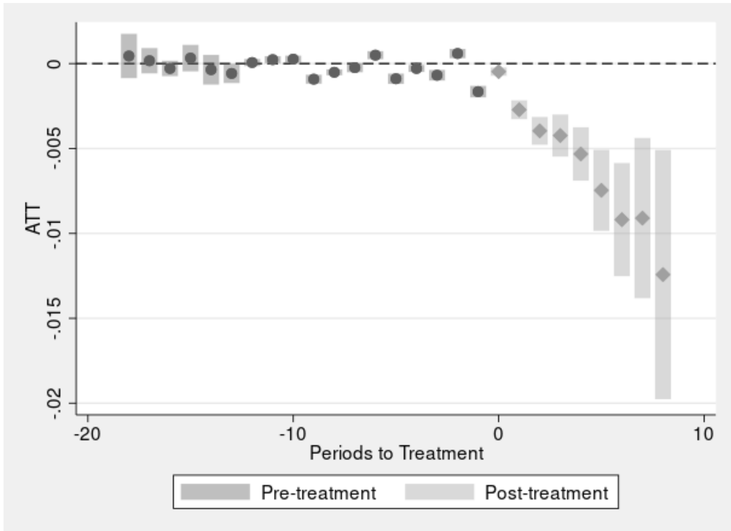

Figure 13. Event plot with outcome variable electrical car (binary)

Furthermore, looking at conventional and electric cars separately illustrates that the introduction of residential parking hits differently depending on the type of car. A conventional car faces a minor annual parking fee, whereas street parking was previously free. In addition, street parking becomes more available for residents as visitors need to pay a more substantial parking fee every time, they use the parking facilities. On the other hand, on-street parking was free for electric cars until 2021.

The effect of conventional car ownership follows the same pattern as ownership in general and seems to drive the main results as the level is somewhat higher. For residents, residential parking contributes to a significant increase in ownership of conventional cars two years (eight quarters) after treatment. In contrast, the impact on the ownership of electric cars happened immediately and was negative, i.e., there was a decrease in ownership of electric cars. Most likely, two processes contribute to this. Parking electric cars were free of charge for both residents and visitors. As some control groups will contain potential visitors, they will save relatively more using an electric car, and hence, compared to the control group, treated households increase the share of electric cars less than households in the control group. A second contribution to the negative effect on ownership of electric cars could be the lack of access to charging infrastructure for the given area – especially in the inner city, where residents most often do not have access to private charging infrastructure.

The policy has generally made conventional cars more attractive than electric cars as residential parking is implemented. This result is further strengthened when looking at the estimate of ATT for the number of conventional cars and the number of electric cars in Figures 5 and 6 below – where the average number of conventional cars held by households increases while the average of electrical cars decreases.

The average number of conventional cars in households is larger than the increase seen in conventional ownership, implying that multiple-car households also increase for conventional cars. Estimates related to electric cars: the average number of cars seems to be marginally higher than ownership over the entire period. A one-to-one relationship should be interpreted as when the number of electric cars decreases with one, there is one less household that no longer owns an electric car – either as a single-car household or a multiple-car household. In 2015 – 2019, there were limited households, being a multiple-electrical-car household, so the relationship between ownership and the number of electric cars is as expected.

Note that the policy can also affect those who would have bought an electric car without the introduction of parking regulations.

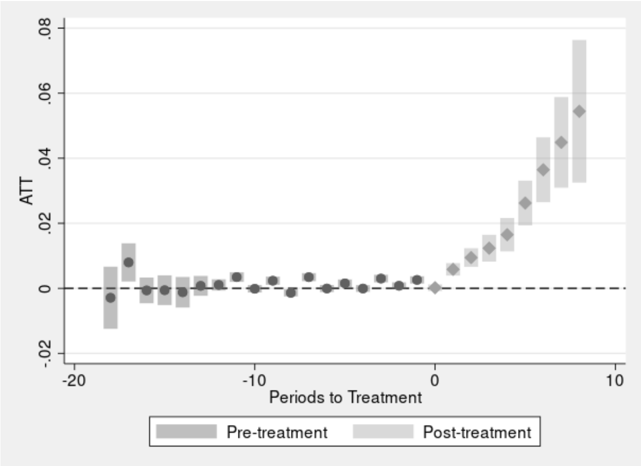

Figure 14. Number of traditional cars per household

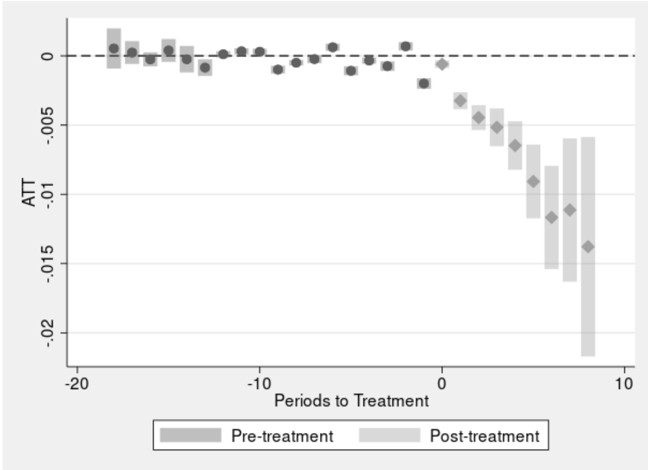

Figure 15. Number of electric cars per household

Furthermore, as the effect seems to change the preferences over conventional vs. electric cars and owning a car in general, do residents use their cars differently after such a policy? Figures 16 to 18 show the estimated ATT for average km driven for general, conventional, and electric cars. The average driven km increases regardless of the type of car – the average is measured in quarters, i.e., an increase of about 800 km (200 km/month) for both car ownership in general and conventional cars 2 years after parking policy implementation. This is a substantial increase in car use, as the average kilometer driven in Norway is 1000 km a month i.e. 12,000 a year. An increase in average driven kilometers is likely to be caused by the increased car ownership i.e. those who did not previously own a car shifted car use from 0, while the previous owner increased their use of their car(s).

Residents with electric cars generally also increase their car use, but to a lesser degree—almost 150 km 1,5 years after implementation. A smaller effect could be a reflection that an electric car in the multiple-car household is often considered to be the "second car", often related to the restriction to electric cars' kilometer range.

In total, it seems that the parking policy does affect the decision related to ownership of electric and conventional cars, in favor of conventional cars. In addition, the availability effect is expressed through the increase in both ownership of conventional cars and car use in general, the last one being both significant and considerable.

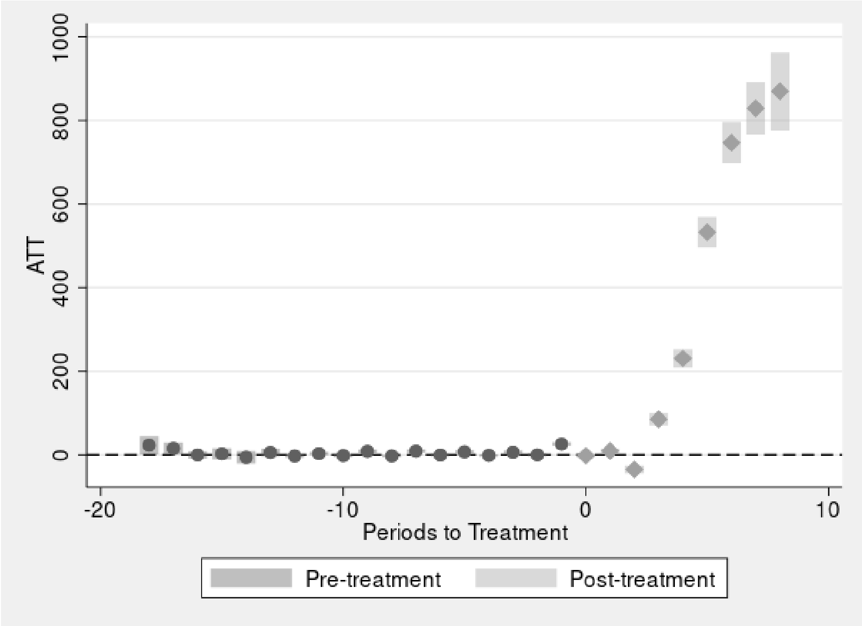

Figure 16. Event plot with outcome average driven km for all types of car.

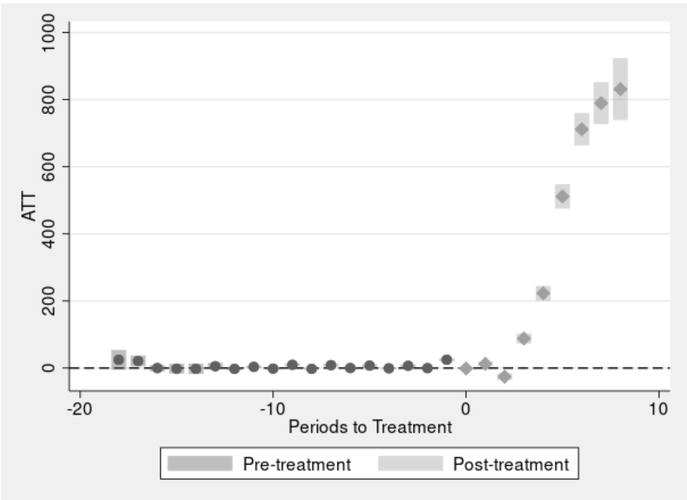

Figure 17. Event plot with outcome average-driven km for only traditional cars.

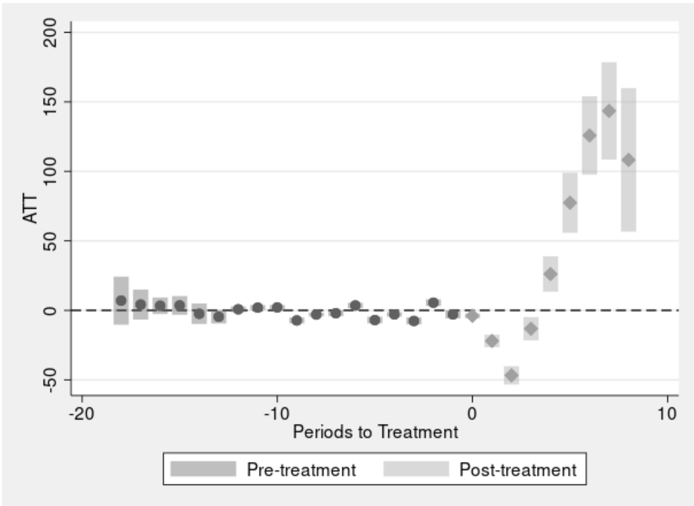

Figure 18. Event plot with outcome average-driven km for only electric cars.

Although the pre-trend test does not give suspicion of large differences between treatment and control groups that can drive the results, some models are conducted with control variables – mainly household composition and the highest education level of the household. Household composition is measured as the number of household members and the number of household members under 18 years. Three figures are reported below: (general) car ownership, number of cars, and kilometers driven. Respectively, figures 19, 20, and 21. Results divided by type of car i.e. conventional or electrical, are reported in the appendix.

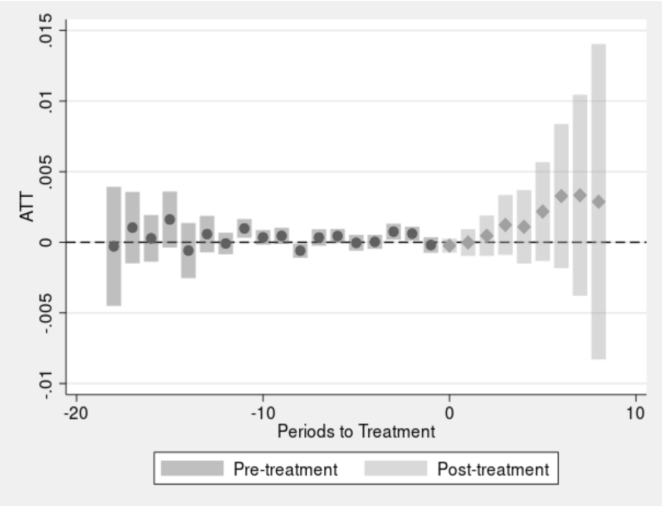

Figure 19. Event plot with outcome variable car ownership (binary)

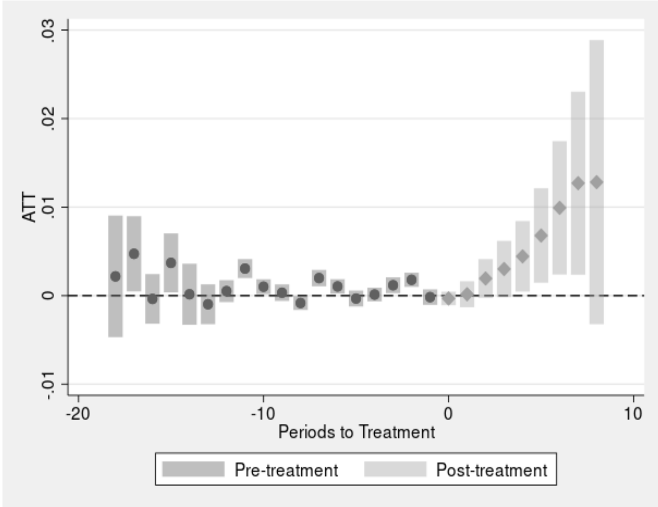

Figure 20. Event plot with outcome variable number of cars per household

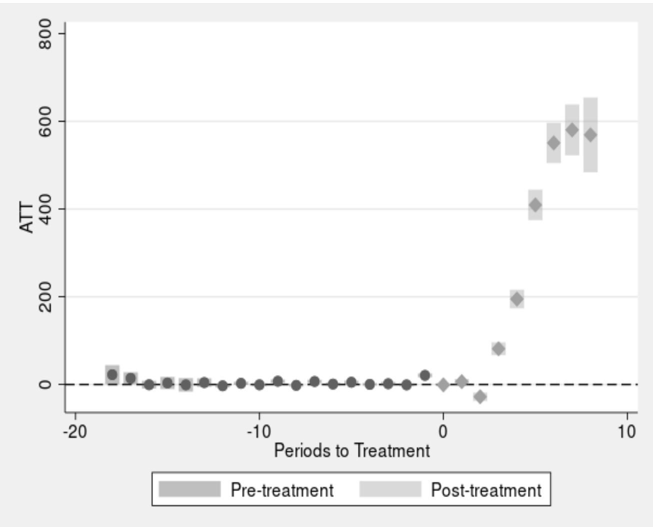

Figure 21. Event plot with outcome average driven km for all types of cars.

Controlling for household composition and education, the effect on car ownership in general is shown in Figure X, which shows that the level of the estimate is somewhat smaller. However, the pattern is similar, where one reaches the highest effect in the second year after treatment, which is twice the size of the number of cars per household –implying that the increase in the number of cars is both new ownership and an increase in the multiple-car household. In addition, the effect of availability is clear when it comes to car use. Although the level has gone from 800 to 600 km at the highest identified quarter effect, the effect is significant – both statistically and practical, i.e., a considerable increase in the number of kilometers driven.

2.3 CS event plot - inner and outer districts

Private parking and infrastructure for charging electric vehicles are less common in the inner city i.e. on-street parking is the most common parking facility in those areas. Also, the inner city is expected to have some differences in car ownership and use compared to outer city districts, i.e., general parking facilities, public transport, and car dependency. As residential parking was introduced in several parts of Oslo, these differences might also drive some results, as outer-city districts generally were treated after inner-city districts. Further analysis estimates the ATT for all outcome variables and divides the sample into inner and outer cities. Such separation could also give a more homogenous group, possibly a better-suited control group.

The following figures illustrate the effect of residential parking on inner-city and outer-city groups separately. As before, the results indicate a clear availability effect on several dimensions: ownership, number of cars, and car use. The effect is more present when looking at the number of cars compared to ownership in general, and to a larger extent in the inner city. The increase in new ownership can only explain about 25% of the increase in the number of cars in the inner city, while the same number for the outer city is about 40%. In addition, the increase in car use is larger in the inner city, maximum of about 1000 km increase in one quarter and 700 km for the outer-city district. A larger availability effect in the inner-city district is expected, as households are typically more dependent on on-street parking for car ownership in those areas.

The results regarding conventional cars vs. electrical seem to hold for both inner- and out-district, e.g., conventional cars become relatively more preferable.

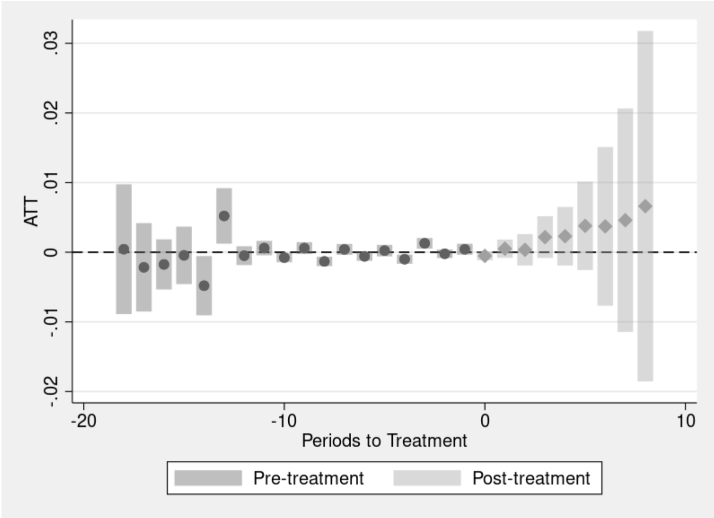

Figure 22. Event plot with outcome variable car ownership (binary) – inner-city districts.

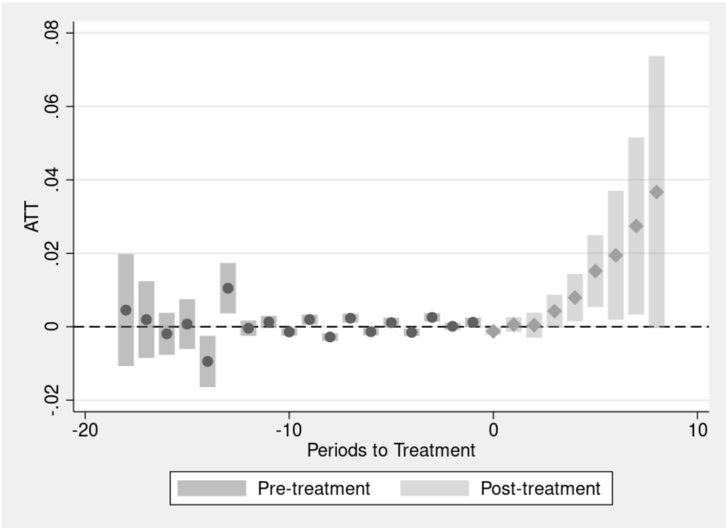

Figure 23. Event plot with outcome variable number of cars – inner-city districts.

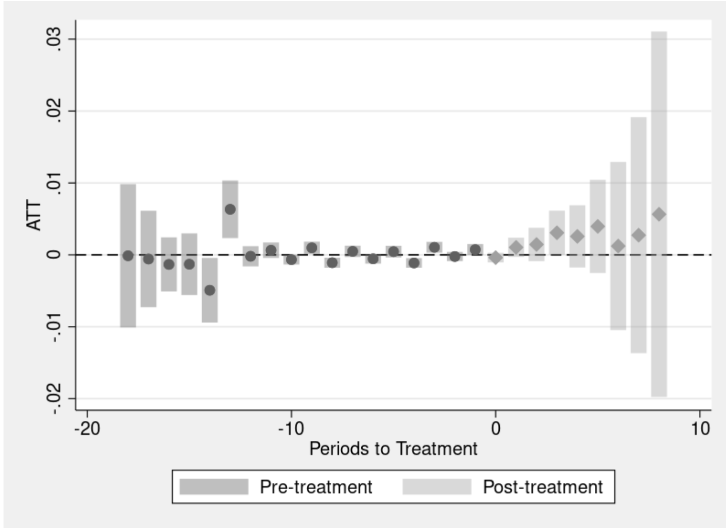

Figure 24. Event plot with outcome variable Traditional car (binary) – inner-city districts

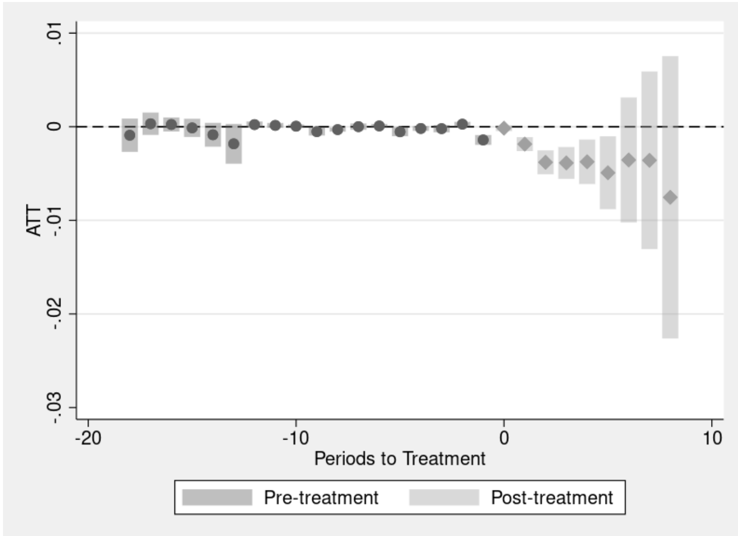

Figure25. Event plot with outcome variable electrical cars (binary) – inner-city districts.

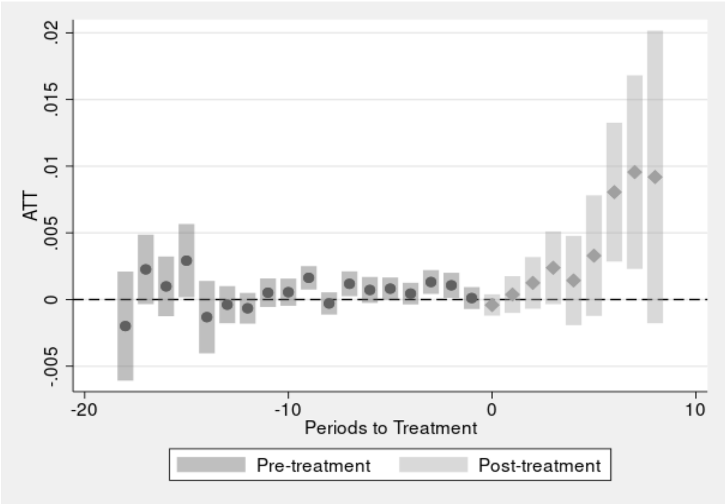

Figure 26. Event plot with outcome variable car ownership (binary) – outer-city districts.

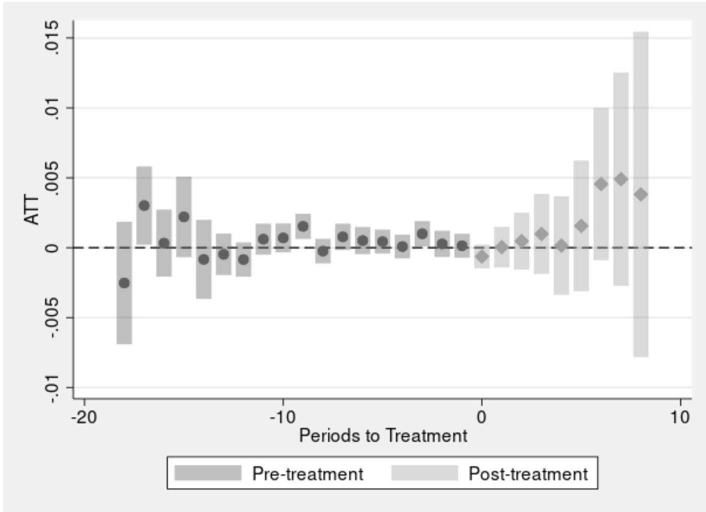

Figure 28. Event plot with outcome variable traditional cars (binary) - outer-city districts.

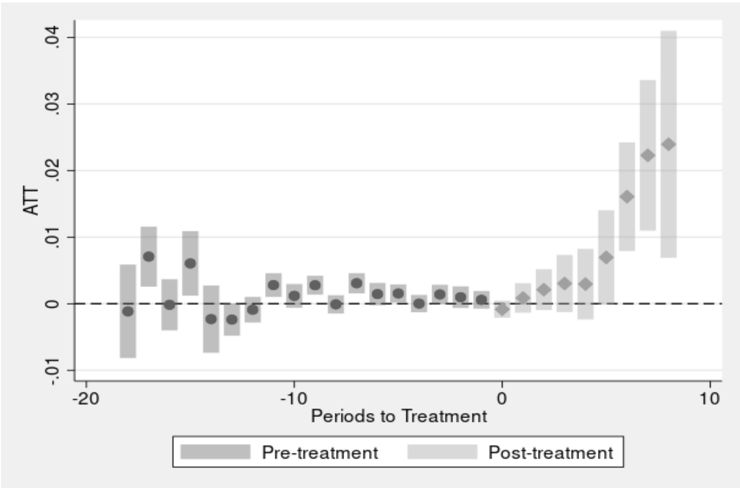

Figure 27. Event plot with outcome variable number of cars - outer-city districts.

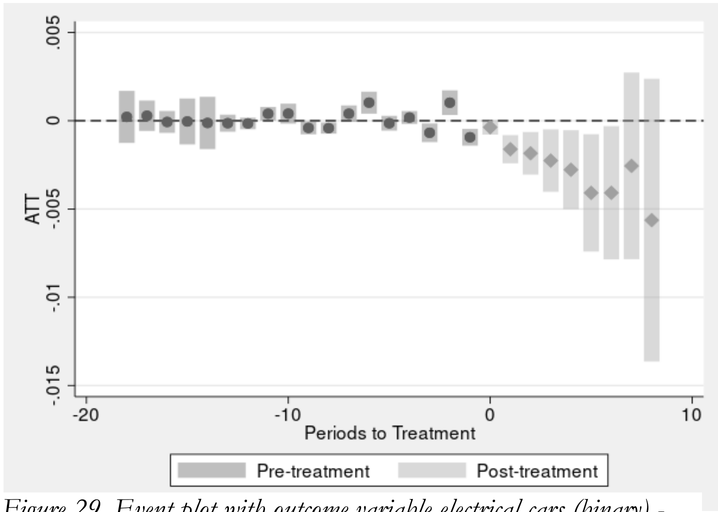

Figure 29. Event plot with outcome variable electrical cars (binary) - outer-city districts.

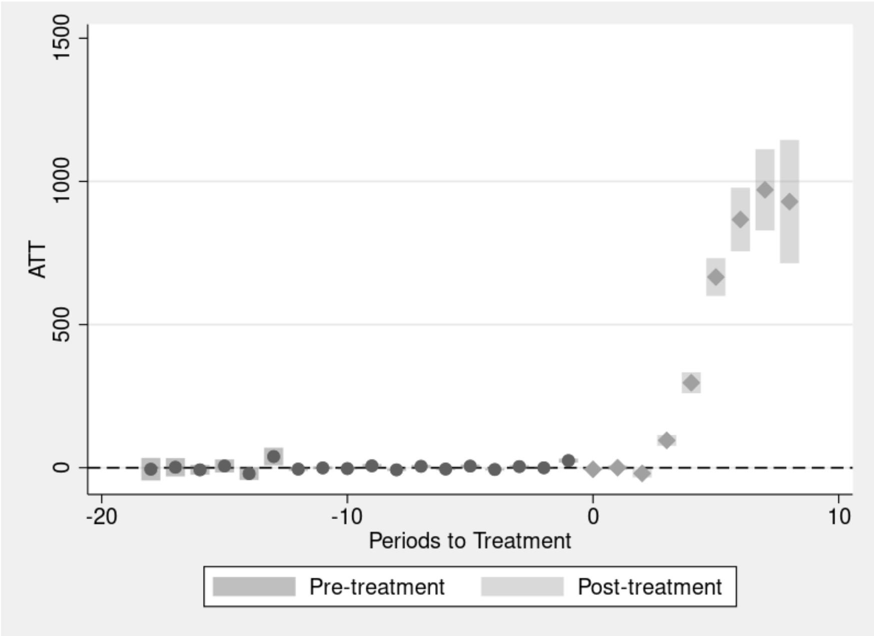

Figure 30. Event plot with outcome variable average driven km for all types of cars – inner-city districts.

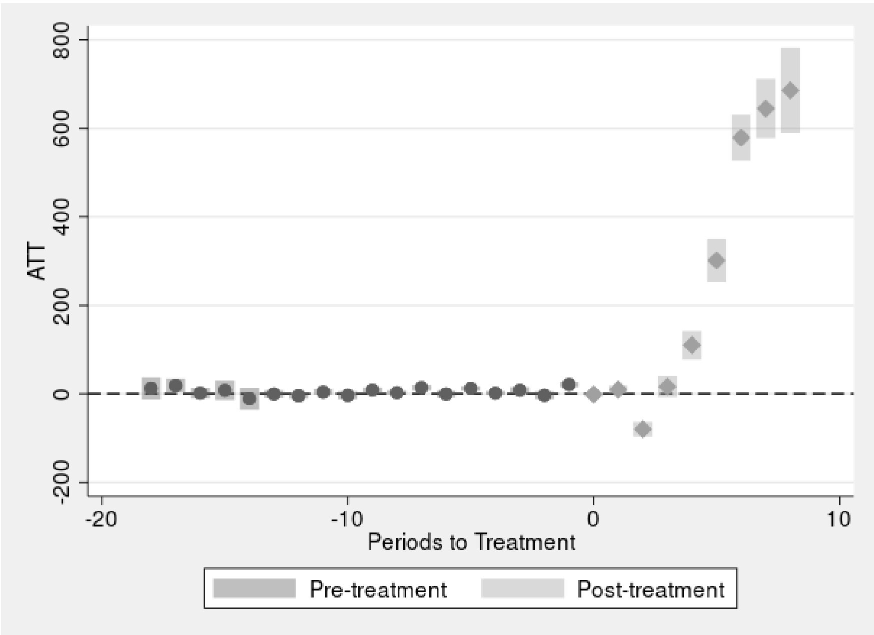

Figure 31. Event plot with outcome variable average driven km for all types of cars – outer-city districts.

3 Concluding remarks

This paper uses the introduction of residential parking in Oslo as a natural experiment to investigate the causal effect of parking regulation on car ownership and use. Resident parking entitles residents in the given area to buy an annual permit for 3000 NOK (for a passenger car) for on-street parking. Such a permit gave the right to park in all permitted streets in the given district. Visitors went from facing free on-street parking to a relatively high hourly fee. Regardless of residents, electric cars were free to park up to 2021.

To identify this effect, a unique dataset merged several administrative datasets with households as observational units and information regarding residential parking implementation. As the introduction varied over time between districts, a staggered differences-in-differences framework was used for identification.

The results show how residential parking, intended to make parking more available for residents, does so. This significant effect of more available parking is increasing car use – the increased car use stems from increased use of those who initially own a car and those who previously did not own a car, i.e., new ownership. Furthermore, the effect is somewhat higher for those who use conventional cars. In addition, the policy seems to make conventional cars preferable to electric cars in urban areas, as the number of electric cars reduces relative to the control group.

The effect is also present when analyzing inner and outer cities separately, however to a greater degree in the inner city, most likely because inner-city residents are more dependent on on-street parking infrastructure.

Parking regulation, including pricing and supply, is an important tool for urban traffic management. This paper shows how price discrimination between residents and visitors leads to a change in resource allocation, with residents allocated a larger share of the available parking space. However, more availability increases ownership and total driving for residents, when pricing is sustainably higher for visitors than residents. As pricing decreases the demand for parking (for visitors), more aggressive pricing for residents is expected to cancel out some of the availability effects and reduce ownership and car use.

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4 Appendix

4.1 Pre-trend test

Identification through a differences-in-differences framework crucially depends on the parallel trend assumption as it reflects the substitution of the randomized control one tries to mimic in natural experiments. Although not directly testable, the pre-trend test is a standard execution test. As the name indicates, it tests if the trend in all observed periods before the treatment is parallel when comparing the control and treated group(s). If those trends are parallel, the belief in parallel trends without treatment in the post-period is strengthened[9].

The null hypothesis states that every pre-period has the same trend; the differences in trend are equal to zero when comparing the different groups; hence, we have a parallel trend before intervention.[10] In the case of residential parking trends, all outcome variables are tested: car ownership, ownership of a conventional car, ownership of an electric car, number of cars, and driven kilometers. The null hypothesis states in those cases that the development in car ownership, type of car, number of cars, and kilometers driven is the same across treated and control groups but does not put any restriction regardless of the level.

As with most test statistics, the null hypothesis states that the differences between the two groups are equal to null, with the alternative hypothesis being different from null. A p-value below 0,05 means that one rejects the null hypothesis. Thus, we have no strengthened the belief that the parallel trend assumption holds. The result from a pre-trend test is reported in the tables below for each outcome variable, as well as the inner and outer cities together and separately. [11]

Table 3. Pre-trend test for models with car, conventional car, electric car, number of cars, and kilometer - without control variables.

	Without control variables				
	Car	Trad	El	Number of cars	Km
Chi2(X)	283.1	343.0	484.5	525.8	736.6
p-value	0.0000	0.0000	0.0000	0.0000	0.0000

[9] As the parallel trend assumption is conditioned on a counterfactual world i.e. in the post period with no treatment, the test only indicates if the parallel trend assumption holds.
[10] The Chi2(X) reports the test statistics and X represents the degree of freedom.
[11] I use the integrated package for pre-trend test in csdid.

X	97	97	97	97	94

Table 4. Pre-trend test for models with car, conventional car, electric car, number of cars, and kilometer - without control variables. For inner and outer separately.

	Inner city					***Outer city***				
	Car	Trad	El	Number of cars	Km	Car	Trad	El	Number of cars	Km
Chi2(X)	183.2	202.5	245.5	250.3	335.1	261.5	236.5	131.2	368.4	339.6
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0119	0.0000	0.0000
X	97	97	94	97	94	97	97	97	97	94

4.2 Sample results in table, total, inner- and outer city

Table 5. Estimation results (ATT) by event time, for outcome variable car ownership (binary). Base estimate for figure 10.

	Coefficient	Std. Err	z	P>|z|	[95% conf.interval]	
Pre_avg	.0003707	.0001527	2,43	0.015	.0000714	.0006699
Post_avg	.0029113	.0015056	1,93	0.053	-.0000397	.0058623
Tm18	-.0000838	.0019153	-0.04	0.965	-.0038377	.0036702
Tm17	.0014567	.0012194	1,19	0.232	-.0009334	.0038467
Tm16	.0003052	.0008101	0.38	0.706	-.0012827	.001893
Tm15	.0014574	.0009631	1,51	0.130	-.0004303	.003345
Tm14	-.001301	.0009677	-1.34	0.179	-.0031976	.0005957
Tm13	.0009669	.0006362	1,52	0.129	-.00028	.0022138
Tm12	-.0000644	.0003764	-0.17	0.864	-.0008022	.0006734
Tm11	.0009461	.0003275	2,89	0.004	.0003043	.001588
Tm10	.0002091	.0002567	0.81	0.415	-.000294	.0007122
Tm9	.0007477	.000283	2,64	0.008	.0001931	.0013024
Tm8	-.0007933	.0002469	-3.21	0.001	-.0012771	-.0003094
Tm7	.0009051	.0002863	3,16	0.002	.0003439	.0014662
Tm6	.000275	.0002493	1,10	0.270	-.0002137	.0007637
Tm5	.0002287	.0002732	0.84	0.403	-.0003067	.0007641
Tm4	-.000111	.0002438	-0.46	0.649	-.0005887	.0003668
Tm3	.0010767	.0002788	3,86	0.000	.0005303	.0016232
Tm2	.0003549	.0002431	1,46	0.144	-.0001215	.0008314
Tm1	.000096	.0002724	0.35	0.724	-.0004379	.0006299
Tp0	**-.0003763**	**.0002426**	**-1.55**	**0.121**	**-.0008518**	**.0000992**
Tp1	.0004502	.0004668	0.96	0.335	-.0004647	.0013651
Tp2	.0010474	.0006958	1,51	0.132	-.0003163	.002411
Tp3	.0022525	.0010342	2,18	0.029	.0002256	.0042795
Tp4	.002262	.0012581	1,80	0.072	-.0002039	.0047278
Tp5	.0042561	.0016968	2,51	0.012	.0009305	.0075817
Tp6	.0058903	.0023779	2,48	0.013	.0012298	.0105509
Tp7	.0056488	.0033379	1,69	0.091	-.0008933	.0121909
Tp8	.004771	.0051992	0.92	0.359	-.0054193	.0149613

Table 6. Estimation results (ATT) by event time, for outcome variable conventional car ownership (binary). Base estimate for figure 12.

	Coefficient	Std. Err	z	P>|z|	[95% conf.interval]	
Pre_avg	.0003924	.0001614	2,43	0.015	.000076	.0007087
Post_avg	.0047417	.0015936	2,98	0.003	.0016184	.007865
Tm18	-.0008258	.0020612	-0,40	0.689	-.0048657	.003214
Tm17	.0023344	.0013055	1,79	0.074	-.0002244	.0048932
Tm16	.0002967	.0008592	0,35	0.730	-.0013872	.0019807
Tm15	.0007349	.0010063	0,73	0.465	-.0012375	.0027073
Tm14	-.0009766	.0010114	-0,97	0.334	-.002959	.0010058
Tm13	.0008537	.0006575	1,30	0.194	-.000435	.0021425
Tm12	.0000488	.0003966	0,12	0.902	-.0007284	.0008261
Tm11	.0009119	.000341	2,67	0.007	.0002436	.0015803
Tm10	.0003229	.0002619	1,23	0.218	-.0001904	.0008362
Tm9	.0008708	.0002854	3,05	0.002	.0003115	.0014301
Tm8	-.0006242	.000255	-2,45	0.014	-.001124	-.0001243
Tm7	.0008346	.0002882	2,90	0.004	.0002698	.0013994
Tm6	.0002483	.000255	0,97	0.330	-.0002516	.0007482
Tm5	.0003721	.0002746	1,36	0.175	-.0001661	.0009103
Tm4	-.0000769	.0002504	-0,31	0.759	-.0005677	.0004138
Tm3	.0010069	.0002782	3,62	0.000	.0004616	.0015522
Tm2	.0002517	.0002505	1,00	0.315	-.0002394	.0007428
Tm1	.0004782	.0002746	1,74	0.082	-.00006	.0010164
Tp0	**-.0001574**	**.0002543**	**-0,62**	**0.536**	**-.0006559**	**.000341**
Tp1	.0012452	.0004813	2,59	0.010	.0003018	.0021886
Tp2	.0023238	.000729	3,19	0.001	.000895	.0037526
Tp3	.0034019	.0010801	3,15	0.002	.0012849	.0055189
Tp4	.0039412	.0013275	2,97	0.003	.0013393	.0065431
Tp5	.0065819	.0017631	3,73	0.000	.0031262	.0100376
Tp6	.0085351	.0025062	3,41	0.001	.0036231	.0134472
Tp7	.0088641	.0035278	2,51	0.012	.0019498	.0157784
Tp8	.0079396	.0055329	1,43	0.151	-.0029046	.0187838

Table 7. Estimation results (ATT) by event time, for outcome variable electrical car ownership (binary). Base estimate for figure 13.

	Coefficient	Std. Err	z	P>|z|	[95% conf.interval]	
Pre_avg	-.0002125	.0000549	-3.87	0.000	-.0003201	-.0001049
Post_avg	-.0060984	.0010641	-5.73	0.000	-.008184	-.0040128
Tm18	.0004476	.0006659	0.67	0.501	-.0008575	.0017527
Tm17	.0001693	.0003793	0.45	0.655	-.0005742	.0009128
Tm16	-.0002856	.0002304	-1.24	0.215	-.0007372	.000166
Tm15	.0003231	.0003985	0.81	0.417	-.0004579	.0011042
Tm14	-.0003587	.0004465	-0.80	0.422	-.0012338	.0005164
Tm13	-.0005813	.0002875	-2.02	0.043	-.0011449	-.0000178
Tm12	.000063	.0001046	0.60	0.547	-.0001421	.0002681
Tm11	.0002323	.000103	2,26	0.024	.0000305	.0004342
Tm10	.0002619	.0001048	2,50	0.012	.0000565	.0004674
Tm9	-.0009186	.0001338	-6.86	0.000	-.0011809	-.0006562
Tm8	-.0005116	.000089	-5.75	0.000	-.000686	-.0003373
Tm7	-.0002382	.0001382	-1.72	0.085	-.000509	.0000326
Tm6	.0004956	.0001204	4,12	0.000	.0002596	.0007317
Tm5	-.0008915	.0001536	-5.80	0.000	-.0011925	-.0005904
Tm4	-.0002881	.000104	-2.77	0.006	-.0004919	-.0000843
Tm3	-.0006854	.0001603	-4.28	0.000	-.0009997	-.0003712
Tm2	.0005928	.0001382	4,29	0.000	.0003218	.0008637
Tm1	-.0016516	.0001736	-9.51	0.000	-.0019918	-.0013113
Tp0	**-.0004733**	**.0001244**	**-3.80**	**0.000**	**-.0007171**	**-.0002294**
Tp1	-.0027169	.0002825	-9.62	0.000	-.0032707	-.0021632
Tp2	-.003962	.0004159	-9.53	0.000	-.0047773	-.0031468
Tp3	-.0042359	.0006317	-6.71	0.000	-.005474	-.0029977
Tp4	-.0053218	.0008018	-6.64	0.000	-.0068933	-.0037504
Tp5	-.0074624	.0012161	-6.14	0.000	-.0098459	-.0050789
Tp6	-.0091885	.0016984	-5.41	0.000	-.0125173	-.0058598
Tp7	-.0090985	.0024071	-3.78	0.000	-.0138164	-.0043806
Tp8	-.012426	.0037433	-3.32	0.001	-.0197628	-.0050892

Table 8. Estimation results (ATT) by event time, for outcome variable number of cars. Base estimate for figure 11.

	Coefficient	Std. Err	z	P>|z|	[95% conf.interval]	
Pre_avg	.001105	.000248	4,46	0.000	.0006189	.001591
Post_avg	.0096706	.0023799	4,06	0.000	.005006	.0143351
Tm18	.0026423	.0033024	0.80	0.424	-.0038302	.0091149
Tm17	.0050577	.0021018	2,41	0.016	.0009382	.0091772
Tm16	-.0000859	.0013754	-0.06	0.950	-.0027817	.0026099
Tm15	.00357	.001644	2,17	0.030	.0003478	.0067922
Tm14	-.0013423	.0017162	-0.78	0.434	-.0047061	.0020215
Tm13	-.0003498	.0010999	-0.32	0.750	-.0025055	.001806
Tm12	.0003956	.0006122	0.65	0.518	-.0008043	.0015955
Tm11	.0030998	.0005289	5,86	0.000	.0020631	.0041365
Tm10	.000446	.0004163	1,07	0.284	-.0003698	.0012619
Tm9	.0010087	.0004601	2,19	0.028	.000107	.0019104
Tm8	-.0014284	.0003923	-3.64	0.000	-.0021973	-.0006595
Tm7	.0027971	.0004578	6,11	0.000	.0018997	.0036944
Tm6	.0005714	.0004046	1,41	0.158	-.0002215	.0013643
Tm5	.000188	.0004453	0.42	0.673	-.0006847	.0010607
Tm4	-.0003545	.0003818	-0.93	0.353	-.001103	.0003939
Tm3	.0018472	.0004457	4,14	0.000	.0009735	.0027208
Tm2	.0013535	.0003954	3,42	0.001	.0005784	.0021286
Tm1	.0004728	.0004387	1,08	0.281	-.000387	.0013325
Tp0	**-.0006221**	**.0003799**	**-1.64**	**0.102**	**-.0013666**	**.0001224**
Tp1	.0010838	.0007404	1,46	0.143	-.0003673	.002535
Tp2	.0029478	.0010988	2,68	0.007	.0007942	.0051014
Tp3	.0045671	.0015919	2,87	0.004	.001447	.0076872
Tp4	.0063683	.0019916	3,20	0.001	.0024648	.0102718
Tp5	.0119953	.0027051	4,43	0.000	.0066933	.0172972
Tp6	.016949	.0037944	4,47	0.000	.0095122	.0243858
Tp7	.021284	.0053129	4,01	0.000	.0108709	.0316971
Tp8	.022462	.0082284	2,73	0.006	.0063345	.0385894

Table 9. Estimation results (ATT) by event time, for outcome variable number of conventional cars. Base estimate for figure 14.

	Coefficient	Std. Err	z	P>|z|	[95% conf.interval]	
Pre_avg	.0011158	.0003528	3,16	0.002	.0004243	.0018072
Post_avg	.0229282	.0032021	7,16	0.000	.0166523	.0292042
Tm18	-.0028963	.0048707	-0.59	0.552	-.0124428	.0066502
Tm17	.0079724	.0029964	2,66	0.008	.0020995	.0138453
Tm16	-.0006316	.0020163	-0.31	0.754	-.0045835	.0033202
Tm15	-.0005684	.0023325	-0.24	0.807	-.00514	.0040033
Tm14	-.0011951	.0023946	-0.50	0.618	-.0058885	.0034983
Tm13	.0007701	.0015564	0.49	0.621	-.0022804	.0038207
Tm12	.0010545	.0008777	1,20	0.230	-.0006658	.0027747
Tm11	.0034588	.0007503	4,61	0.000	.0019881	.0049294
Tm10	-.0001301	.0005815	-0.22	0.823	-.0012698	.0010095
Tm9	.002344	.0006393	3,67	0.000	.001091	.0035969
Tm8	-.0013842	.0005525	-2.51	0.012	-.0024671	-.0003014
Tm7	.003442	.0006314	5,45	0.000	.0022045	.0046796
Tm6	-.0000438	.0005555	-0.08	0.937	-.0011326	.0010451
Tm5	.0015451	.0006049	2,55	0.011	.0003595	.0027308
Tm4	-.0000526	.0005278	-0.10	0.921	-.001087	.0009818
Tm3	.0030111	.0005972	5,04	0.000	.0018407	.0041815
Tm2	.0007949	.0005304	1,50	0.134	-.0002447	.0018344
Tm1	.002593	.0005753	4,51	0.000	.0014655	.0037205
Tp0	**.0001919**	**.0005137**	**0.37**	**0.709**	**-.0008148**	**.0011987**
Tp1	.0058455	.0009692	6,03	0.000	.0039458	.0077452
Tp2	.0094693	.0014562	6,50	0.000	.0066152	.0123234
Tp3	.0123571	.0021014	5,88	0.000	.0082384	.0164758
Tp4	.0164954	.0026191	6,30	0.000	.011362	.0216288
Tp5	.0262281	.003509	7,47	0.000	.0193506	.0331056
Tp6	.0364582	.0050797	7,18	0.000	.0265022	.0464141
Tp7	.0448754	.0071079	6,31	0.000	.0309441	.0588066
Tp8	.0544332	.0111782	4,87	0.000	.0325243	.0763421

Table 10. Estimation results (ATT) by event time, for outcome variable number of electrical cars. Base estimate for figure 15.

	Coefficient	Std. Err	z	P>|z|	[95% conf.interval]	
Pre_avg	-.0002261	.0000614	-3.68	0.000	-.0003464	-.0001058
Post_avg	-.0072888	.0011659	-6.25	0.000	-.009574	-.0050036
Tm18	.0005313	.0007396	0.72	0.472	-.0009182	.0019809
Tm17	.0002357	.0004202	0.56	0.575	-.0005878	.0010593
Tm16	-.0002559	.0002585	-0.99	0.322	-.0007625	.0002507
Tm15	.0003891	.0004201	0.93	0.354	-.0004343	.0012125
Tm14	-.0002471	.0004869	-0.51	0.612	-.0012013	.0007072
Tm13	-.0008497	.0003051	-2.78	0.005	-.0014477	-.0002517
Tm12	.0001131	.0001133	1.00	0.318	-.000109	.0003352
Tm11	.0003254	.0001128	2,89	0.004	.0001044	.0005465
Tm10	.0002947	.0001126	2,62	0.009	.000074	.0005155
Tm9	-.0009963	.0001429	-6.97	0.000	-.0012764	-.0007163
Tm8	-.0005017	.0000977	-5.14	0.000	-.0006931	-.0003103
Tm7	-.0002368	.0001481	-1.60	0.110	-.0005271	.0000535
Tm6	.0006182	.0001327	4,66	0.000	.0003582	.0008782
Tm5	-.0010823	.0001691	-6.40	0.000	-.0014138	-.0007509
Tm4	-.0003443	.0001144	-3.01	0.003	-.0005685	-.00012
Tm3	-.0007473	.0001764	-4.24	0.000	-.0010931	-.0004014
Tm2	.000686	.0001541	4,45	0.000	.000384	.0009879
Tm1	-.0020018	.0001933	-10.36	0.000	-.0023807	-.001623
Tp0	**-.0006039**	**.0001391**	**-4.34**	**0.000**	**-.0008766**	**-.0003313**
Tp1	-.0032405	.0003131	-10.35	0.000	-.0038541	-.0026268
Tp2	-.0044614	.0004571	-9.76	0.000	-.0053574	-.0035654
Tp3	-.0051621	.000697	-7.41	0.000	-.0065282	-.0037959
Tp4	-.0064765	.0008933	-7.25	0.000	-.0082273	-.0047256
Tp5	-.0090721	.0013589	-6.68	0.000	-.0117355	-.0064086
Tp6	-.0116705	.0018989	-6.15	0.000	-.0153922	-.0079488
Tp7	-.0111312	.0026391	-4.22	0.000	-.0163038	-.0059585
Tp8	-.0137812	.0040413	-3.41	0.001	-.021702	-.0058605

Table 11. Estimation results (ATT) by event time, for outcome variable number of driven kilometers. Base estimate for figure 16.

	Coefficient	Std. Err	z	P>|z|	[95% conf.interval]	
Pre_avg	5.011334	1.078062	4,65	0.000	2.898372	7.124297
Post_avg	362.981	14.45996	25,10	0.000	334.64	391.322
Tm18	22.89138	11.26385	2,03	0.042	.8146466	44.96812
Tm17	15.24923	7.137948	2,14	0.033	1.259112	29.23935
Tm16	-.2001205	4.391354	-0.05	0.964	-8.807016	8.406775
Tm15	2.494274	6.917823	0.36	0.718	-11.06441	16.05296
Tm14	-6.006754	7.590769	-0.79	0.429	-20.88439	8.870881
Tm13	5.820782	4.704844	1,24	0.216	-3.400543	15.04211
Tm12	-2.979876	1.97312	-1.51	0.131	-6.847119	.8873674
Tm11	2.989593	1.828988	1,63	0.102	-.5951572	6.574344
Tm10	-2.047527	1.712392	-1.20	0.232	-5.403755	1,3087
Tm9	8.552103	1.990802	4,30	0.000	4.650202	12.454
Tm8	-2.872792	1.472773	-1.95	0.051	-5.759374	.0137895
Tm7	8.965156	1.94699	4,60	0.000	5.149126	12.78119
Tm6	-.5710382	1.610797	-0.35	0.723	-3.728141	2.586065
Tm5	7.241897	1.884534	3,84	0.000	3.548278	10.93552
Tm4	-1.366663	1,4044	-0.97	0.330	-4.119237	1.38591
Tm3	6.314728	2.0176	3,13	0.002	2.360305	10.26915
Tm2	-.0207236	1.765882	-0.01	0.991	-3.481788	3.440341
Tm1	25.75036	2.189453	11,76	0.000	21.45911	30.04161
Tp0	**-2.072414**	**1.433182**	**-1.45**	**0.148**	**-4.881399**	**.7365714**
Tp1	9.237926	3.124146	2,96	0.003	3.114712	15.36114
Tp2	-34.85305	4.843078	-7.20	0.000	-44.34531	-25.36079
Tp3	85.12917	7.616087	11,18	0.000	70.20192	100.0564
Tp4	230.7655	11.22531	20.56	0.000	208.7643	252.7667
Tp5	532.7443	18.8405	28.28	0.000	495.8176	569.671
Tp6	746.8307	25.01107	29.86	0.000	697.8099	795.8515
Tp7	829.188	32.19221	25.76	0.000	766.0924	892.2836
Tp8	869.8592	47.64109	18.26	0.000	776.4844	963.234

Table 12. Estimation results (ATT) by event time, for outcome variable number of driven kilometers for conventional cars. Base estimate for figure 17.

	Coefficient	Std. Err	z	P>|z|	[95% conf.interval]	
Pre_avg	5.525515	1.288626	4,29	0.000	2.999855	8.051175
Post_avg	348.8819	14.30988	24.38	0.000	320.8351	376.9288
Tm18	24.48212	15.12824	1,62	0.106	-5.168681	54.13292
Tm17	21.1085	8.236004	2,56	0.010	4.96623	37.25077
Tm16	-.1875568	4.958519	-0.04	0.970	-9.906076	9.530962
Tm15	-1.879428	7.522871	-0.25	0.803	-16.62398	12.86513
Tm14	-2.102242	7.901903	-0.27	0.790	-17.58969	13.3852
Tm13	5.421798	4.892864	1,11	0.268	-4.168039	15.01164
Tm12	-2.443044	2.178925	-1.12	0.262	-6.713659	1.827571
Tm11	3.514121	1.970999	1,78	0.075	-.348967	7.377209
Tm10	-1.715839	1.776394	-0.97	0.334	-5.197508	1.765829
Tm9	9.57447	2.032686	4,71	0.000	5.590478	13.55846
Tm8	-2.365597	1.538247	-1.54	0.124	-5.380506	.6493122
Tm7	8.606396	1.982246	4,34	0.000	4.721266	12.49153
Tm6	.0564604	1.668579	0.03	0.973	-3.213895	3.326816
Tm5	7.10711	1.930962	3,68	0.000	3.322494	10.89172
Tm4	-.7914335	1.473283	-0.54	0.591	-3.679016	2.096149
Tm3	6.629092	2.061443	3,22	0.001	2.588738	10.66945
Tm2	-.3426073	1.823648	-0.19	0.851	-3.916891	3.231676
Tm1	24.78694	2.220317	11,16	0.000	20.4352	29.13868
Tp0	**-1.172503**	**1.560887**	**-0.75**	**0.453**	**-4.231786**	**1.88678**
Tp1	12.44738	3.272965	3,80	0.000	6.032486	18.86227
Tp2	-25.81839	5.024866	-5.14	0.000	-35.66695	-15.96984
Tp3	87.79416	7.747818	11,33	0.000	72.60871	102.9796
Tp4	222.8417	11,22	19.85	0.000	200.8425	244.841
Tp5	511.4798	18.54945	27.57	0.000	475.1235	547.8361
Tp6	711.559	24.64592	28.87	0.000	663.2539	759.8641
Tp7	789.4825	31.86343	24.78	0.000	727.0313	851.9337
Tp8	831.3237	47.14814	17.63	0.000	738.9151	923.7324

Table 13. Estimation results (ATT) by event time, for outcome variable number of driven kilometers for electrical cars. Base estimate for figure 18.

	Coefficient	Std. Err	z	P>|z|	[95% conf.interval]	
Pre_avg	-.4431732	.7843334	-0.57	0.572	-1.980438	1.094092
Post_avg	43.91362	8.104554	5,42	0.000	28.02899	59.79826
Tm18	6.980216	8.818222	0.79	0.429	-10.30318	24.26361
Tm17	4.179037	5.512053	0.76	0.448	-6.624387	14.98246
Tm16	3.312535	3.032233	1,09	0.275	-2.630532	9.255602
Tm15	3,53	3.420232	1,03	0.301	-3.169431	10.23763
Tm14	-2.446099	3.747385	-0.65	0.514	-9.790839	4.898642
Tm13	-4.617669	2.455941	-1.88	0.060	-9.431224	.1958858
Tm12	.7628259	1.012267	0.75	0.451	-1.221182	2.746833
Tm11	1.954253	.8878929	2,20	0.028	.2140154	3.694492
Tm10	2.107241	.8587299	2,45	0.014	.4241612	3.790321
Tm9	-7.265442	1.047875	-6.93	0.000	-9.319239	-5.211645
Tm8	-3.028514	.7091137	-4.27	0.000	-4.418351	-1.638676
Tm7	-2.046834	1.046934	-1.96	0.051	-4.098786	.0051191
Tm6	3.503359	.9776757	3,58	0.000	1.58715	5.419568
Tm5	-6.985701	1.187071	-5.88	0.000	-9.312318	-4.659085
Tm4	-2.899621	.7950522	-3.65	0.000	-4.457894	-1.341347
Tm3	-7.62541	1.272127	-5.99	0.000	-10.11873	-5.132087
Tm2	5.522605	1.202556	4,59	0.000	3.165639	7.879572
Tm1	-2.918002	1.468165	-1.99	0.047	-5.795552	-.0404506
Tp0	**-3.952696**	**.9773982**	**-4.04**	**0.000**	**-5.868361**	**-2.03703**
Tp1	-22.03176	2.279739	-9.66	0.000	-26.49997	-17.56356
Tp2	-46.7481	3.328654	-14.04	0.000	-53.27214	-40.22405
Tp3	-13.22359	4.258125	-3.11	0.002	-21.56936	-4.877817
Tp4	26.14711	6.49081	4,03	0.000	13.42536	38.86886
Tp5	77.44035	11.03558	7,02	0.000	55.81102	99.06968
Tp6	125.8381	14.38617	8,75	0.000	97.64171	154.0345
Tp7	143.4908	17.86298	8,03	0.000	108.48	178.5016
Tp8	108.2624	26.33685	4,11	0.000	56.6431	159.8816

4.3 Results with control variables – (cs) event plot

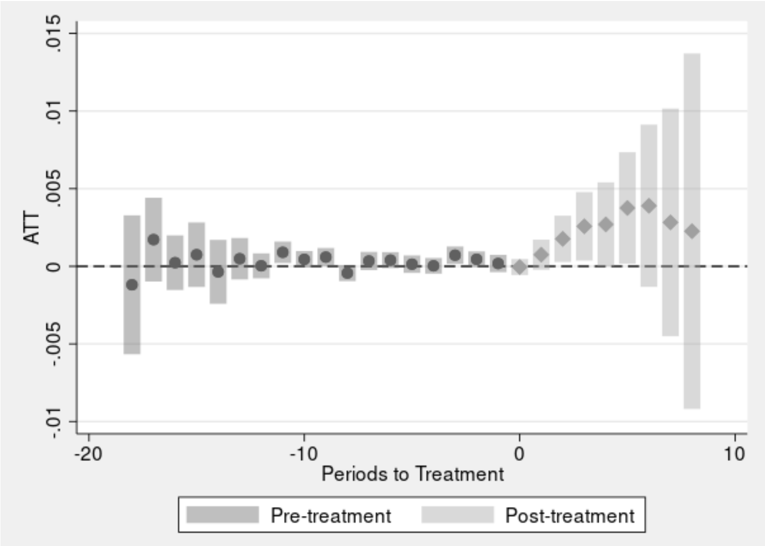

Figure 32. Conventional cars (binary).

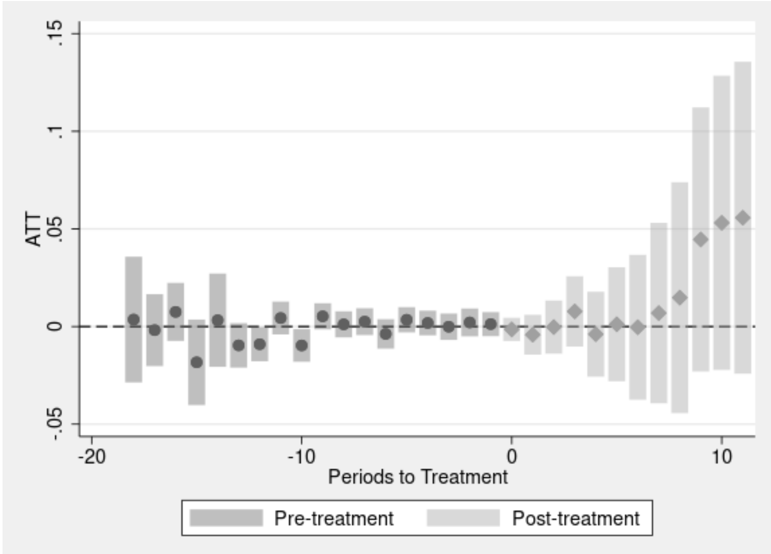

Figure 34. Number of conventional cars.

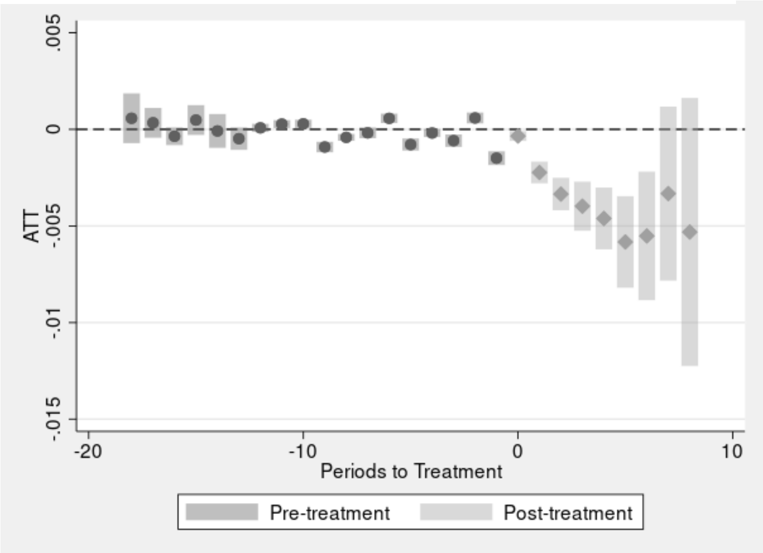

Figure. 33. Electrical cars (binary).

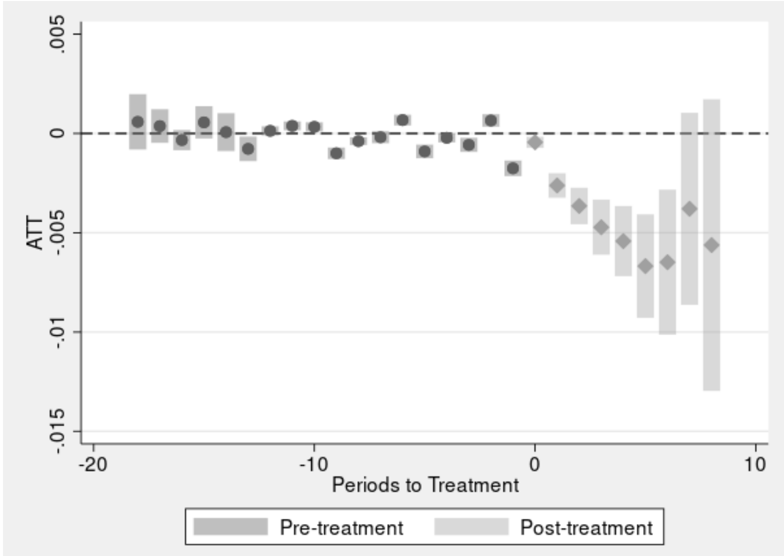

Figure 35. Number of electrical cars.

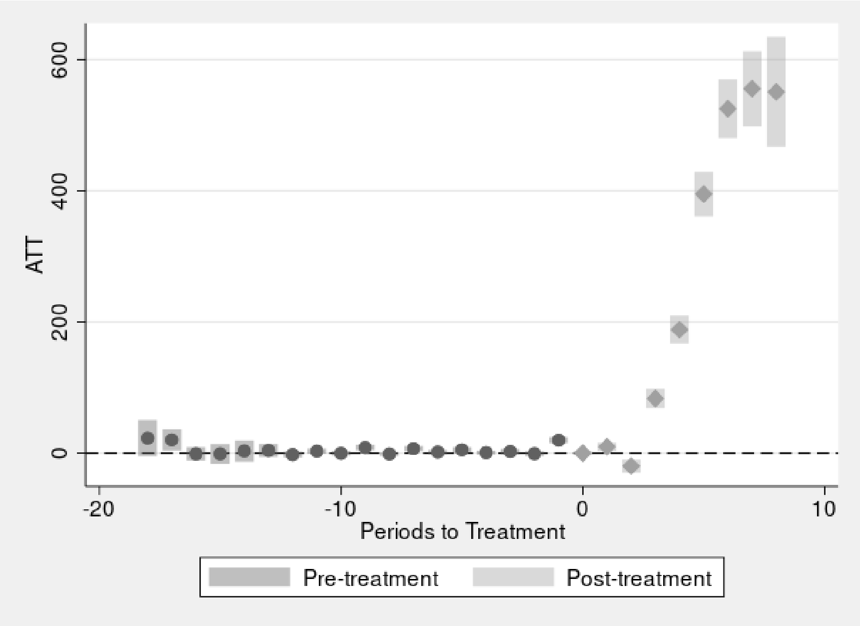

Figure 10. Number of kilometers for conventional cars.

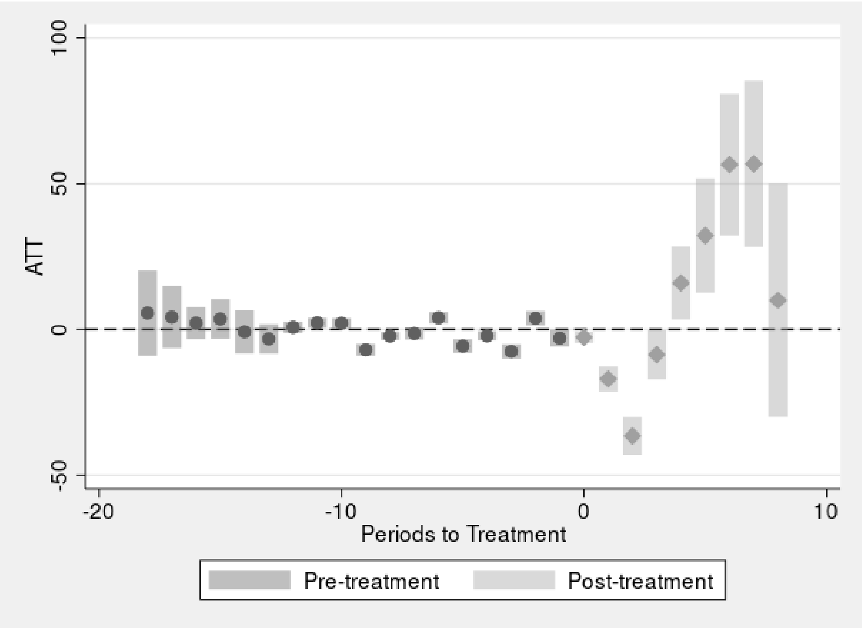

Figure 11. Number of kilometers for electrical cars.

4.4 Inner-City results

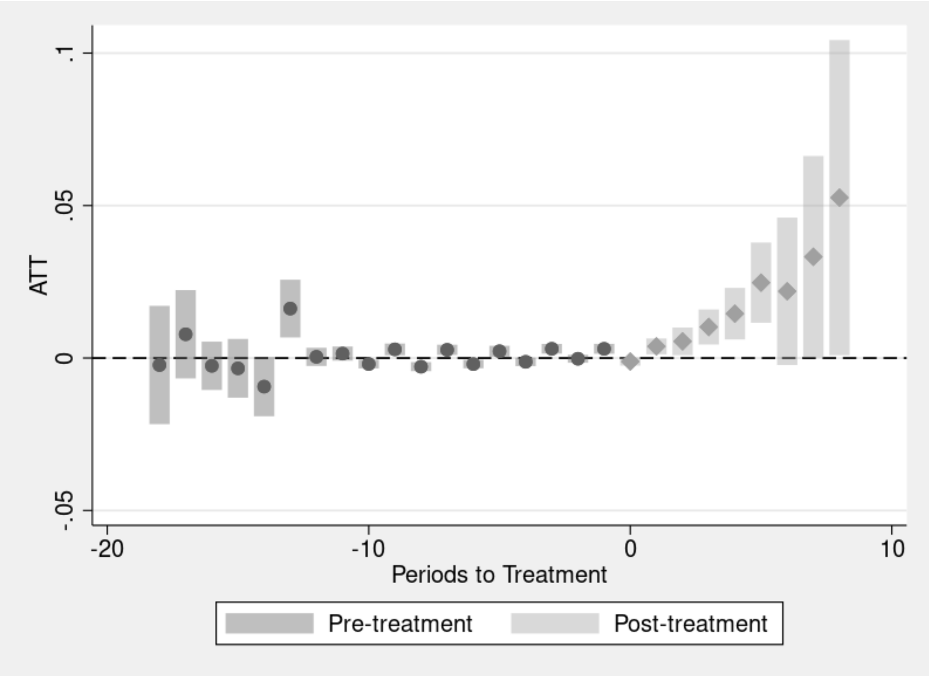

Figure 38. Number of conventional cars - inner city - without control variables.

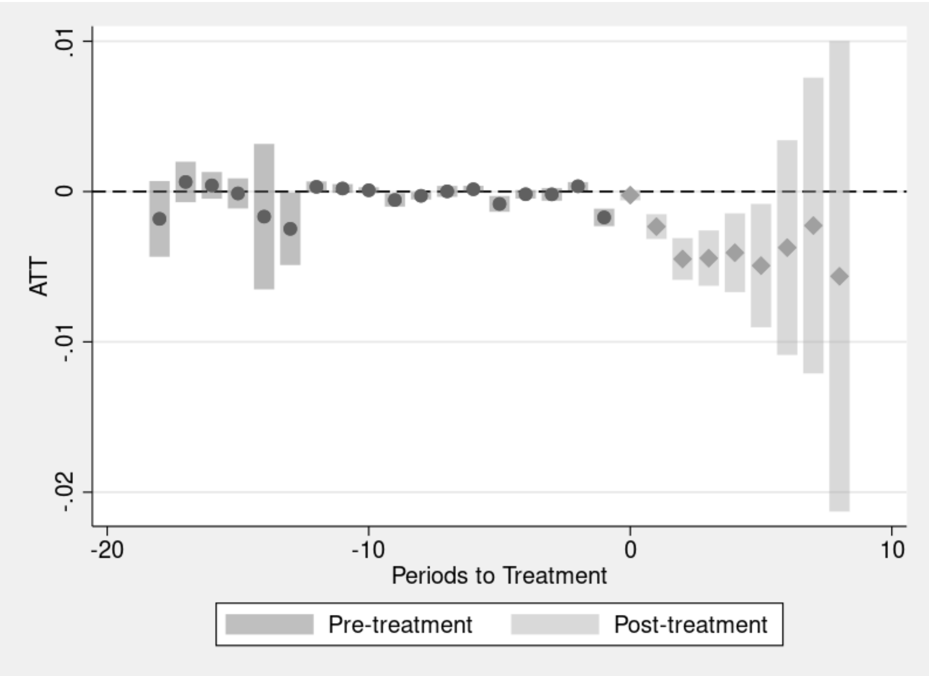

Figure 3912. The number of electrical cars - inner city - without control variables.

4.5 Outer-City results

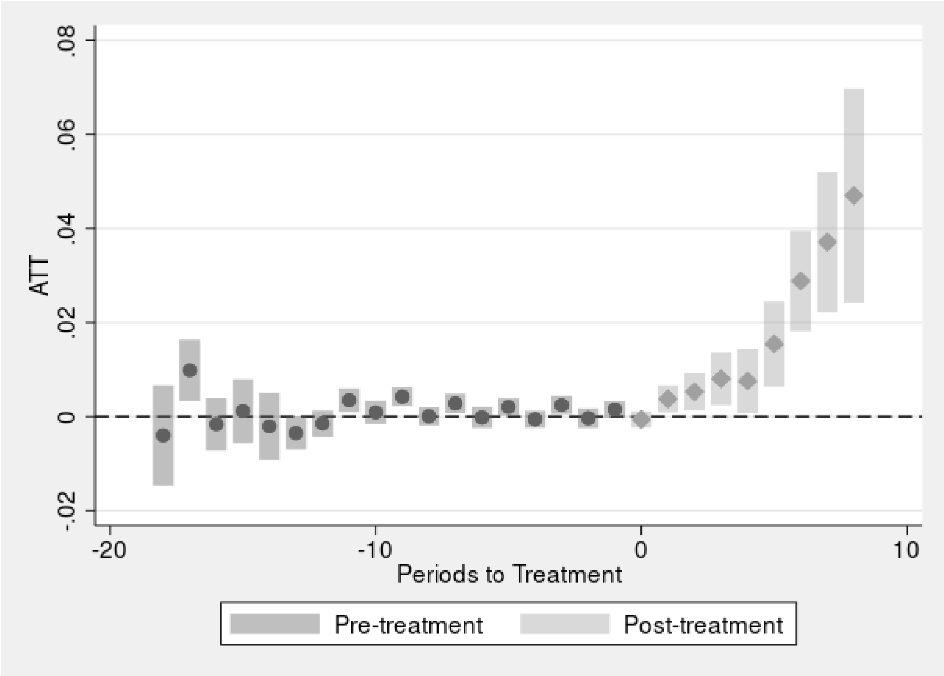

Figure 13. Number of conventional cars - outer city - without control variables.

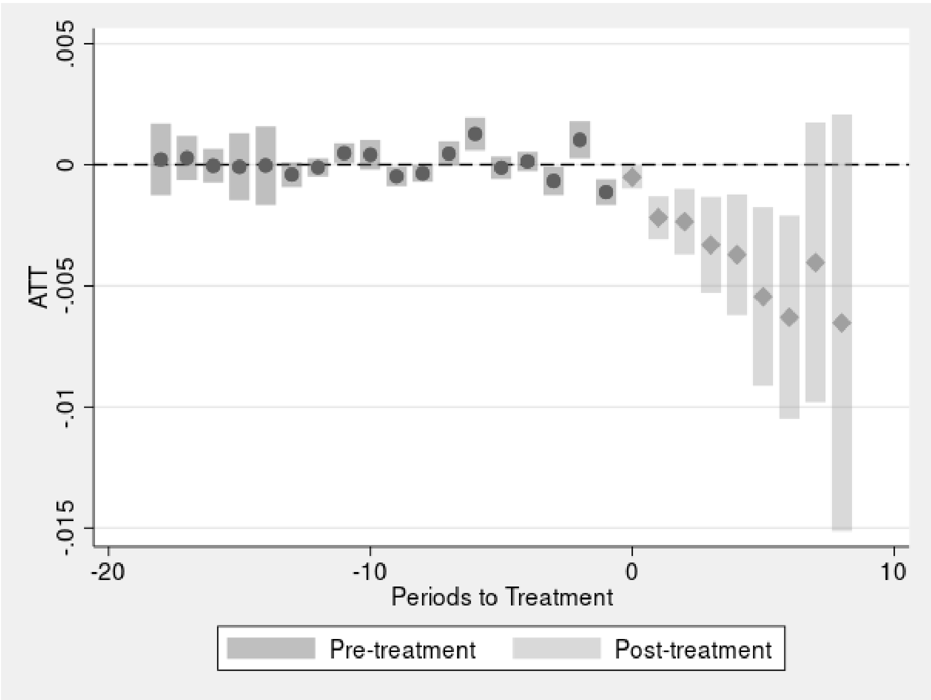

Figure 41. Number of electrical cars - outer city - without control variables.

4.6 Estimation results with clustered standard errors – cs event plot

The results reported earlier in the paper are, by default, clustered by ID, i.e., household. Additional clusters will, in turn, mean a two-way clustered standard. For further testing, the next pages show results when the standard error is also clustered with geographical location (resident), (1) census tract, and (2) district.

4.6.1 Additional cluster with census tract level

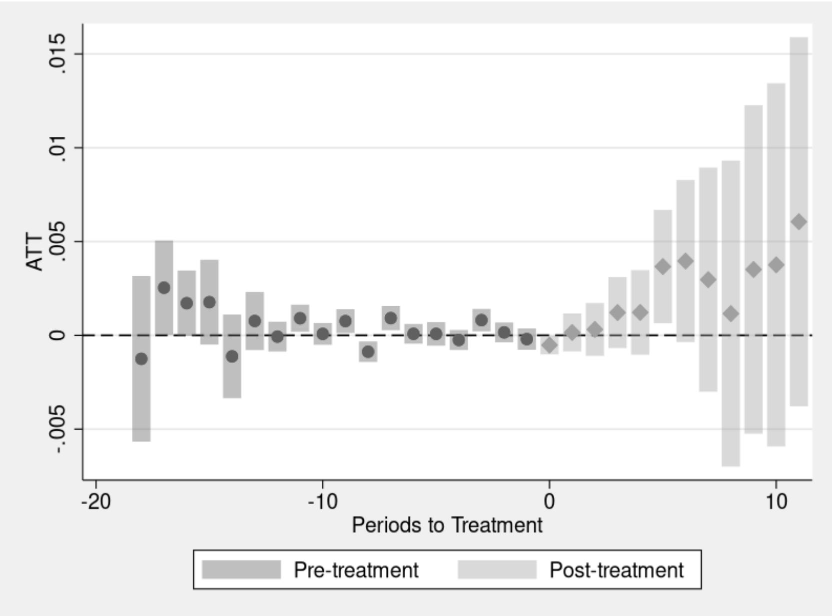

Figure 14. Event plot with outcome variable car ownership (binary)

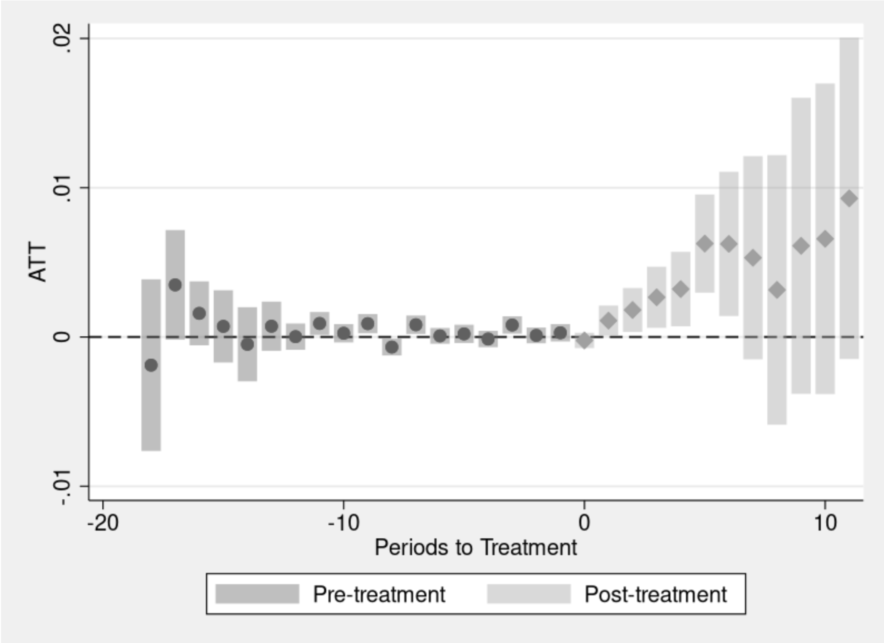

Figure 15. Event plot with outcome variable Conventional car ownership (binary)

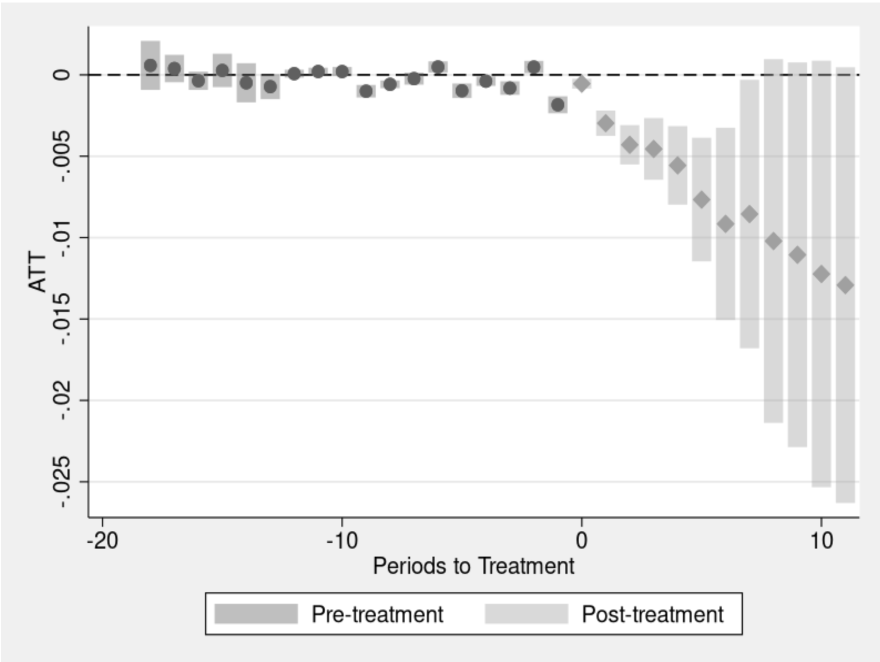

Figure 16. Event plot with outcome variable electrical car ownership (binary)

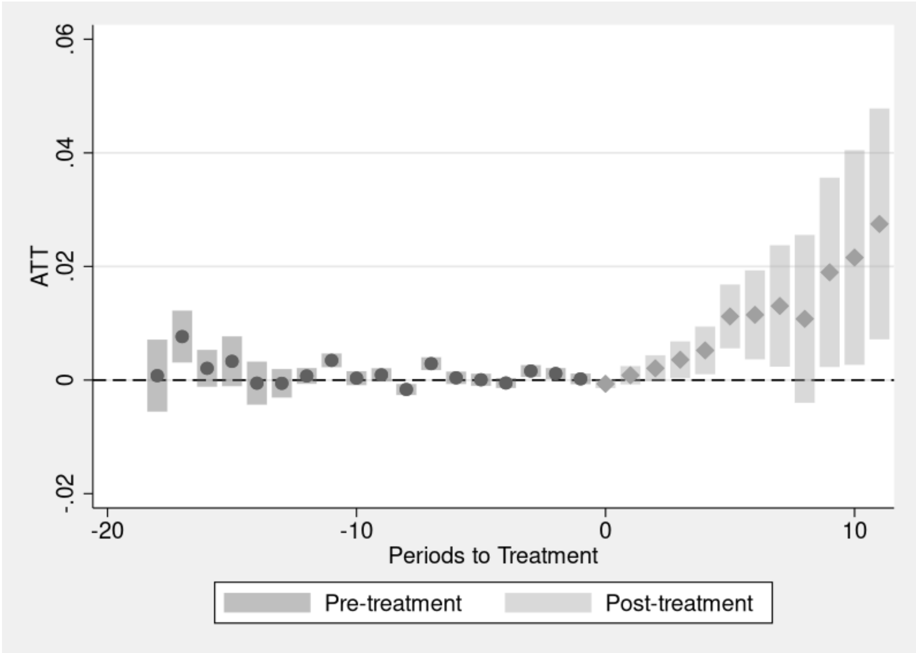

Figure 17. Event plot with outcome variable number of cars per household

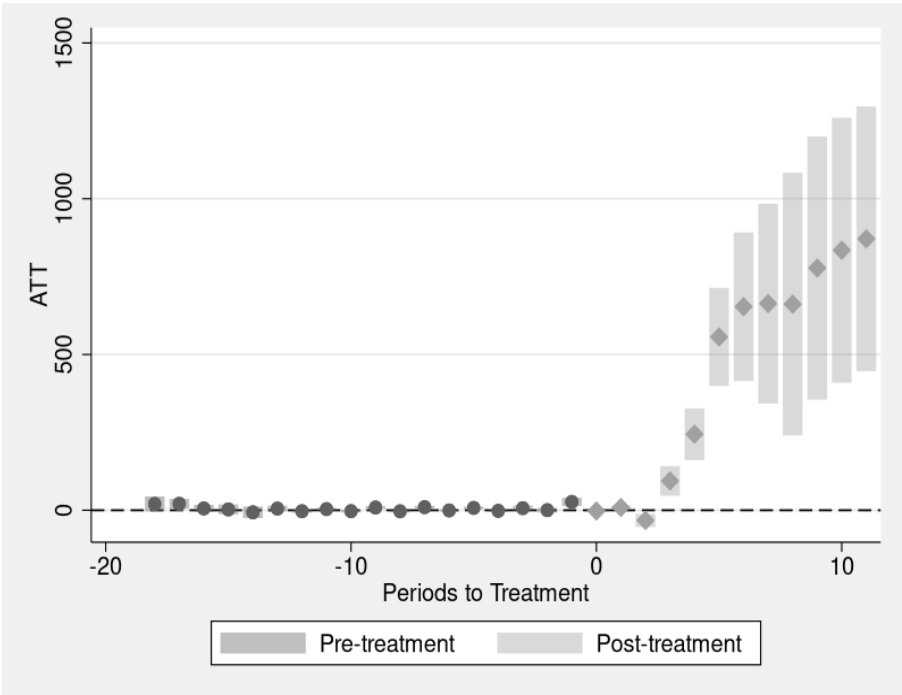

Figure 18. Event plot with outcome variable average driven km for all types of car

4.6.2 Additional cluster with district level

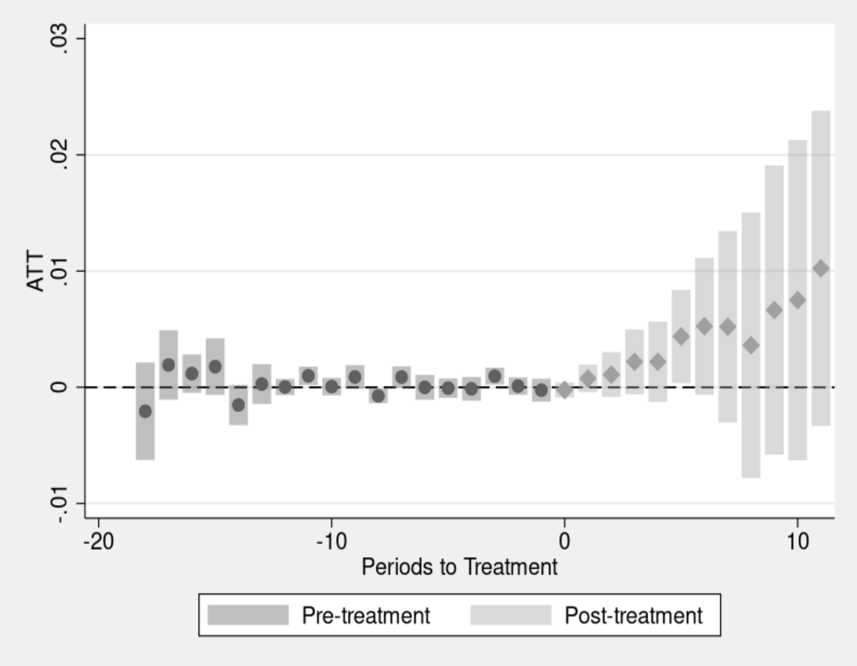

Figure 19. Event plot with outcome variable car ownership (binary)

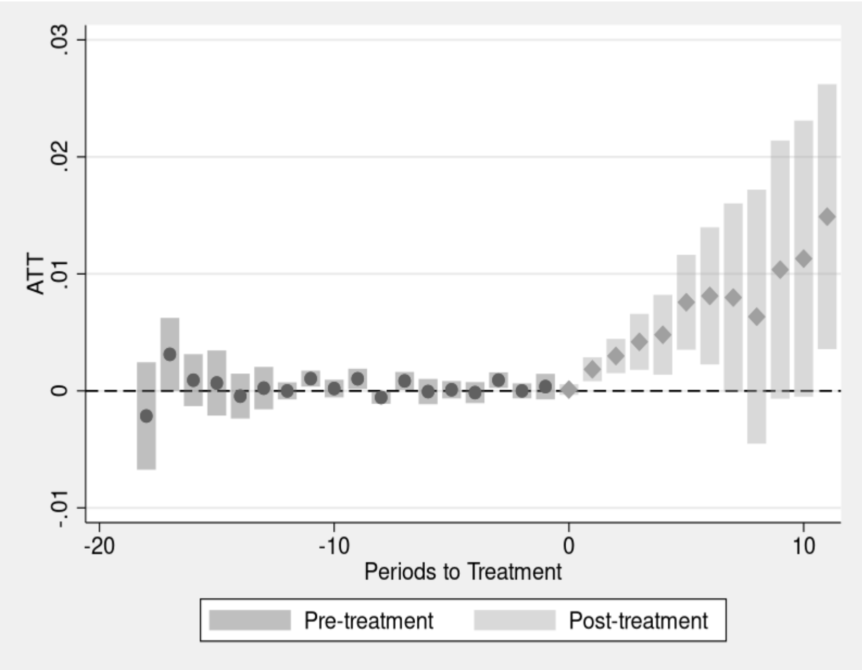

Figure 20. Event plot with outcome variable conventional car ownership (binary)

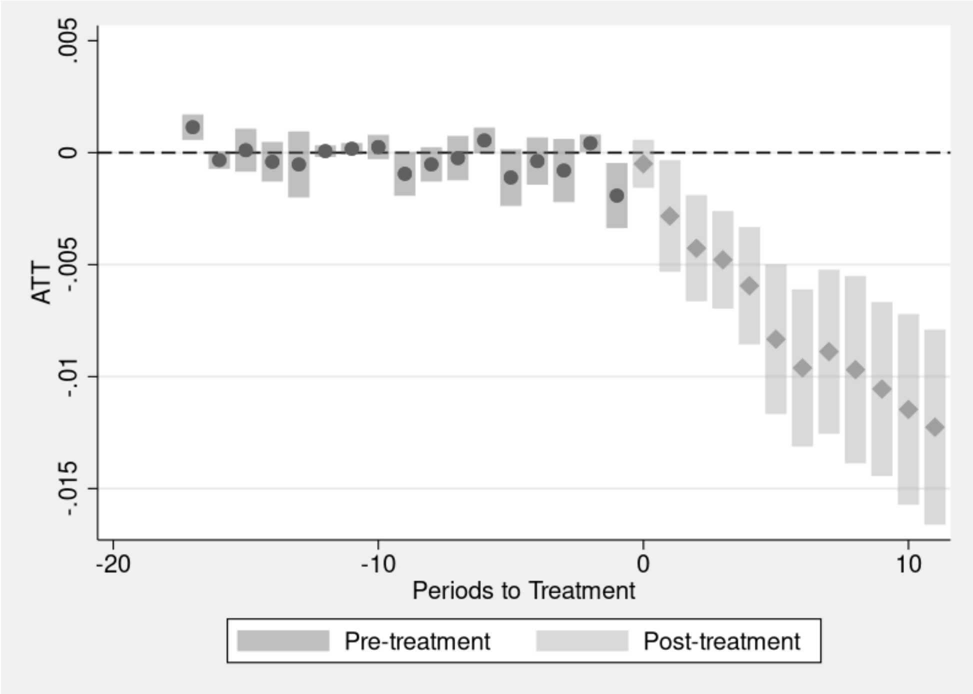

Figure 21. Event plot with outcome variable electrical car ownership (binary)

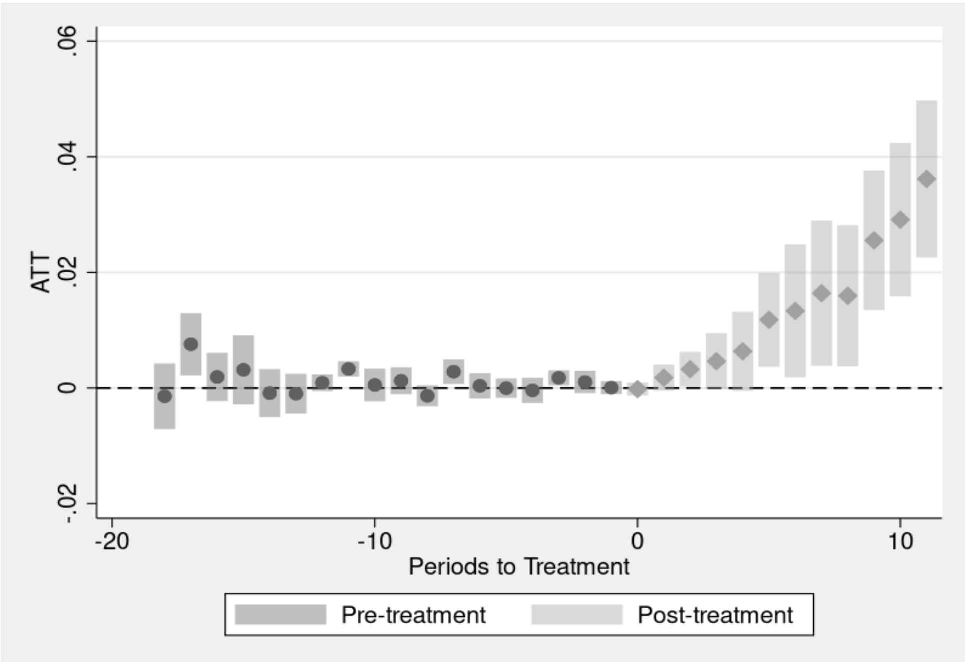

Figure 22. Event plot with outcome variable number of cars per household

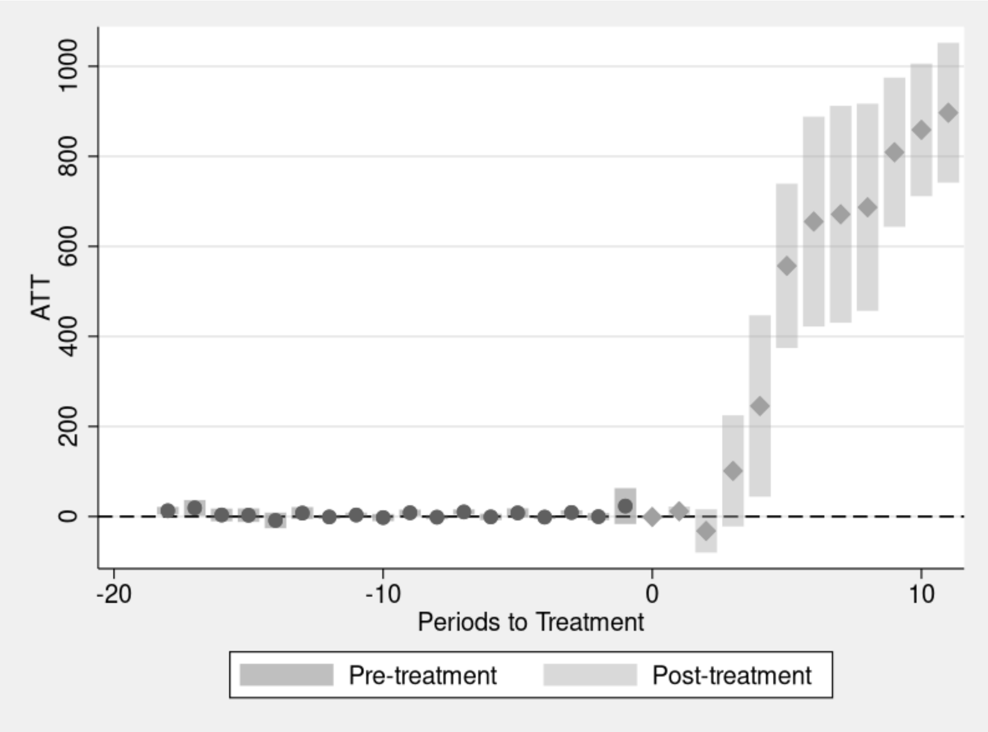

Figure 23. Event plot with outcome variable average driven km for all types of car