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Local Incentives and Electric Vehicle Adoption*

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Abstract

We study how the adoption of battery electric vehicles – a key technology for decarbonizing transportation – responds to two local privileges: road toll exemption and bus lane access. Combining rich Norwegian microdata with a quasi-experimental research design where we exploit household-level variations in incentives on work commutes, we find sizable and positive effects on electric vehicle ownership. The increase in electric vehicles from having road tolls and bus lanes on work commutes is offset by a similar decline in conventional vehicles. Road tolls also reduce brown driving, but lower CO_2 emissions are largely explained by the existence of fewer conventional vehicles.

Keywords: electric vehicles, local incentives, road tolls, bus lanes
JEL codes: H23, Q55, Q58, R41, R48

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1 Introduction

Transportation is responsible for almost one-quarter of global CO_2 emissions, and road vehicles are by far the most important source of transportation emissions (IEA, 2020). While rapid reductions in CO_2 emissions from vehicles are crucial to meet the mitigation goals implied by the Paris Agreement, current policies are not nearly enough to deliver the necessary emission cuts (Axsen et al., 2020). Policymakers largely agree that a shift from internal combustion engine vehicles (ICEVs) to battery electric vehicles (BEVs) will play a key role in decarbonizing road transportation (Archsmith et al., 2021), but they are still searching for effective policies that will boost the market share of BEVs.[1] Credible evidence on the effectiveness of policies that incentivize electric vehicle adoption is both scarce and hard to obtain because these policies rarely offer quasi-experimental variation that allows for causal effects identification (Muehlegger and Rapson, 2018). This challenge applies to incentives for both BEV purchase (Clinton and Steinberg, 2019; Yan and Eskeland, 2018) and use (Hardman, 2019), since variations in incentives could be due to strategic decisions by policymakers or local differences in preferences. Previous studies largely use aggregate data at the country, state, or municipality level (Münzel et al., 2019), with a large risk of confounding factors.[2]

In this paper, we exploit *individual*-level variations in exposure to BEV incentives and identify the effects on households' choices of car technology and driving. Households vary in their exposure to two key incentives, exemption from road tolls and access to bus lanes, because of having different commuting routes. Combining transportation network data with individual data on all Norwegian households, their location of residences and workplaces, as well as car ownership, we use a novel strategy for causal identification. We find that having road tolls and bus lanes on work commutes increases the demand for BEVs, lowers ICEV ownership, and reduces brown driving. The substitution of brown vehicles by green vehicles plays a more important role in reducing CO_2 emissions than does the impact on kilometers driven by each brown car.

By using data from Norway, where the market share of BEVs is higher than in any other country, we are able to study the behavior of a broad group of consumers, not only early adopters or targeted groups. Since the adoption of electric vehicles is picking up worldwide due to improved technology, our results can be informative for the choice of policies to accelerate the transition to low emission transportation in other countries. Most Western countries, China, and other emerging economies have introduced demand-side

[1] Previous studies often do not distinguish between BEVs and plug-in hybrid electric vehicles (PHEVs), despite the fact that PHEVs also use gasoline or diesel to power an internal combustion engine. In this study, we focus on incentives that apply to BEVs only. Throughout the paper we use brown cars/ICEVs interchangeably and green cars/BEVs interchangeably.

[2] Another strand of the literature relies on surveys where, often a small number of, respondents self-report on how important different incentives are for their purchase decisions, or state their choices under different hypothetical policy scenarios (*stated choice*) (Hardman, 2019).

policies for market adoption of BEVs and other low- and zero-emission vehicles. While incentives targeted at car purchase are most common (Münzel et al., 2019), these are often supplemented by incentives targeted at car use, also referred to as reoccurring incentives (Hardman, 2019) – like exemption from road tolls or parking fees; access to low-emission zones, bus lanes, or high occupancy vehicle (HOV) lanes; or publicly supported charging infrastructure.[3]

The two incentives we study in this paper, road toll exemption and bus lane access, make it more attractive to own and use a BEV. To what extent the policies lower total car ownership and overall driving is an empirical question and depends on the relative magnitude of the policies' effects on the ownership and use of green vs. brown vehicles. To date there are few ex-post empirical studies on the effects of road tolls combined with BEV exemptions. An exception is Mersky et al. (2016), where the authors find a non-significant effect of road tolls on BEV adoption using Norwegian data. However, the lack of a credible identification strategy and their use of municipality-level data call into question the causal interpretation of their findings.[4] Empirical studies on the effect of bus and HOV lane access on BEV and PHEV use are more common (Hardman, 2019). Most notably, Sheldon and DeShazo (2017) use cross-sectional census tract data to show that proximity to HOV lanes explains one quarter of BEV and PHEV registrations in California in 2010–2013. Although Jenn et al. (2018) corroborate these findings using US state-level panel data, the relatively coarse resolution of these data makes it difficult to account for omitted variables. These estimates also primarily apply to PHEVs which are closer substitutes for ICEVs than BEVs are.

We address these knowledge gaps in the literature by estimating the effect of road tolls and bus lanes on BEV ownership in Norway, where we combine exceptionally detailed data on car ownership and household characteristics from administrative registers for 2008–2017 (Fevang et al., 2021). These data are ideal for identifying behavioral responses to policies. First, they cover the whole stock of cars and not only sales of new cars. Second, they contain all households and vehicles in Norway, eliminating sample selection concerns and allowing us to compare results over time. Third, with individual-level information on residence and workplace locations, we observe variations in BEV incentives (exposure to road tolls and bus lanes) with a high level of precision. Finally, our data capture observed behavior rather than self-reported decisions or intentions.

We measure individual BEV incentives by the cost of road tolls and the length of bus

[3]BEVs are exempted from congestion charges in the UK and Sweden, from road tolls in Norway and Spain, and highway vignettes in Austria and Bulgaria (Münzel et al., 2019; Whitehead et al., 2014). BEVS have access to bus or HOV lanes in 10 of the 32 European countries reviewed by Münzel et al. (2019) and in 14 US states (Sheldon and DeShazo, 2017).

[4]See, for example, Whitehead et al. (2014) for evidence from an ex-ante analysis. The authors estimate a model of car choice and use the estimated model to simulate the impact of the exemption from congestion pricing in Stockholm for vehicles running on electricity, ethanol, and biogas. They find a 10.7 percent increase in the sales of alternative fuel vehicles due to the exemption.

lanes on the commuting trips of adult household members. Commuting trips account for about one third of kilometers driven by households that commute by car, making them an important determinant of car ownership. Road tolls paid on the commuting trip account for about one fifth of the annual costs of ICEV ownership and use on average, and significantly more for some commuters.[5] The commuting trip is defined as the quickest route between the neighborhoods where household members live and the neighborhoods where they work, using transportation network data. The average neighborhood in our study has fewer than 200 households, which is substantially smaller than neighborhoods in existing studies even compared with Muehlegger and Rapson (2018), who use zip code–level data to study the effect of purchase subsidies for BEVs and PHEVs.

By defining individual BEV incentives as exposure to road tolls and bus lanes on the trip between home and work, the identifying variation will not come from the home or work neighborhoods themselves, but from the combination of the two. Since we include home neighborhood and work neighborhood fixed effects, we control for unobserved characteristics that vary across neighborhoods, and that may affect car ownership decisions, such as differences in charging infrastructure (Li et al., 2017; Springel, 2021; Schulz and Rode, 2021) and differences in consumer preferences. In addition, we include several individual and household-specific controls, such as income, wealth, age, and the number of household members. We also include work commute-specific controls, like calculated travel time by car and public transit quality. In our estimations, we show that including home neighborhood and work neighborhood fixed effects is by far the most important, and additional controls at the individual, household, or work commute-level have minor consequences for our estimated coefficients.[6]

Unlike previous studies that use aggregate data (Mersky et al., 2016), we find a statistically significant and highly robust effect of road tolls on BEV ownership. In 2015–2017, an additional 10 NOK (about one dollar) of road tolls on the commuting trip one way increased the BEV ownership probability by 1.4 percentage points (or 37 percent) for two-adult households. The corresponding effect of an additional 0.5 kilometers of bus lane is 0.1 percentage points (or 2.7 percent).[7] As expected, we find negative effects of both policies on ICEV ownership. To assess the effect of the policies on CO_2 emissions, we consider both the effect on ICEV ownership and the effect on driving of existing brown cars, estimated using odometer data from periodic vehicle inspections. In the case of road tolls, we find that most of the reduced emissions are caused by having fewer ICEVs, while bus lanes also have a considerable negative effect on brown driving. Using estimates on

[5] See Section 3 for calculations of these numbers.

[6] In contrast to Isaksen and Johansen (2021), who use time variation in a panel data set-up to identify effects of congestion charges, our identification strategy relies on cross-sectional variation in combinations of residence and work locations.

[7] Ten NOK and 0.5 kilometers roughly correspond to the road toll and bus lane sample means, respectively, in 2015–2017.

both car ownership and driving, we find that toll (bus lane) exposure on the work commute reduced CO_2 emissions from driving by approximately 52,000 (31,000) tons in 2017. In total, the effect of road tolls and bus lanes corresponds to 2.2 percent of driving-related CO_2 emissions from working households.

Distributional effects of transportation policies depend on who are affected and how they respond. Therefore, we also examine heterogeneous effects across levels of household income and residential location. We find systematic differences in how households respond to road tolls: The negative effect of tolls on ICEV ownership is strongest for the first income quintile. The effect of tolls on BEV ownership increases monotonically in income, and is about eight times larger for the top quintile than for the bottom quintile. These findings imply that the poorest quintile reduces their overall car ownership as a result of road tolls, while the relatively high BEV adoption rate among the richest quintile of households causes their overall car ownership to increase. This systematic difference in how households respond to road tolls may suggest that financial barriers restrict poorer households from BEV adoption.

Our road-toll-effect estimates are derived from comparing households that differ in their exposure to work-commute road tolls. Because BEVs have been exempted from road tolls since the 1990s, our estimates are not capturing the isolated effect of the BEV exemption from road tolls, but rather the combined effect of having both road tolls and exemptions in place. However, with comparable data for years before BEVs were widely available, we shed light on the effects of the BEV privileges. When we compare our main estimates with those from an earlier period (2008–2010), we find that the negative effect of road tolls on ICEV ownership is substantially larger when BEVs are available. This finding suggests that the BEV exemption amplifies the negative effect of road tolls on brown-vehicle ownership. We also find that the negative effect of work-commute road tolls on households' total car ownership is weaker in recent years compared with their effect during the period before BEVs were widely available.

The insights from our study inform policymaking. First, we show that local privileges are powerful instruments to speed up the adoption of electric cars. A road toll exemption is more effective than bus lane access. Second, we find that road tolls combined with exemptions for BEVs have a close to zero effect on the total number of cars. However, our findings also suggest that the BEV exemptions themselves have led to more cars, and hence have come at a cost of increased congestion and other negative externalities. Third, the positive effect of work-commute road tolls on BEV ownership is strongest for high-income households, suggesting that the rich capture the largest gain from the BEV exemption policy. Our findings point to a trade-off whereby governments can effectively reduce CO_2 emissions, but at the cost of increased negative local externalities and a policy that disproportionately favors the rich.

Our paper makes contributions to the empirical literature on low- and zero-emission vehicles and on the role of different incentives, such as purchasing subsidies (Yan and Eskeland, 2018; Clinton and Steinberg, 2019), charging networks (Li et al., 2017; Springel, 2021), access to low-emission zones (Wolff, 2014; Barahona et al., 2020), access to HOV lanes (Bento et al., 2014; Sheldon and DeShazo, 2017; Jenn et al., 2018), and road tolls with BEV exemptions (Mersky et al., 2016). By calculating the implications for CO_2 emissions, we also add to the research on the environmental and climate benefits of policies to promote electric vehicle adoption (Holland et al., 2016; Xing et al., 2021; Camara et al., 2021). We present a novel identification strategy for studying the causal effects of transportation policies on individual behavior, a strategy that can also be applied to other policies and outcomes. Moreover, our paper is one of few studies with a focus on policies that exclusively promote BEVs. Most of the existing literature focuses on PHEVs, which are arguably a closer substitute for conventional vehicles than BEVs are. Finally, we study behavior when BEVs already have a substantial market share and when adoption covers a wider set of owners than just the early adopters of the electric-vehicle technology.

2 Data and institutional context

2.1 Institutional context

The large market share of BEVs in Norway compared with the market shares of BEVs in other countries is best explained by a wide set of incentives in the form of exemptions from taxes and fees, exemptions that lower the user price of electric vehicles compared with the user price of conventional vehicles. National purchase and ownership taxes for private vehicles are high compared with such taxes in other countries (Fridstrøm, 2019). Taxes are designed to favor cars with low emissions, particularly zero-emission cars. Most importantly, BEVs are exempt from purchase and value added taxes.[8] BEV owners also avoid other taxes and fees that apply to conventional cars, such as parking fees, ferry tickets and fuel taxes.

Our focus is on two local privileges: road toll exemption and bus lane access for BEVs. Road tolls are widely used in Norway; the first road projects financed by road tolls were almost 100 years ago. Revenues from road tolls have increased sharply over time (Odeck and Bråthen, 2002; Lauridsen, 2011) up to about 2100 NOK (or 210 USD) per capita in 2018 (Fridstrøm, 2019). Road tolls have traditionally been based on the idea that those who gain from new roads, tunnels, or bridges should cover some of their costs. More recently, road tolls in urban areas have evolved more in the direction of congestion pricing. The toll collected when passing a toll gate is typically around 10–30 NOK (about 1–3 USD), but more than 100 NOK in some cases.[9] BEVs have been exempted from road

[8]The VAT is 25 percent in Norway, while the purchase tax levied on conventional vehicles can be even higher. Typically, purchase taxes make up about half of the final consumer price of conventional vehicles.

[9]A map of all toll booths in Norway and corresponding toll charges can be found on the homepage of

tolls in Norway since 1997 (Figenbaum and Kolbenstvedt, 2013).[10]

Bus lanes are common in Norway on roads to and within the larger cities. HOV lanes giving access to private cars with at least one passenger are rare (Sandelien, 2017). BEVs were given access to bus and HOV lanes in 2005 (Figenbaum and Kolbenstvedt, 2013). Bus lanes in suburban areas can sometimes result from highway expansions, while bus lanes in urban areas are typically existing car lanes that have been converted. The capital (Oslo) established new bus lanes on several main roads in an around the city over the past decade (Ruter, 2011; Haga, 2017). Converting existing car lanes to bus lanes implies less capacity for ICEVs, which could result in higher and more variable travel times but also suppressed demand. Either way, BEVs become more attractive as an alternative to ICEVs. When bus lanes are established as part of road expansions, it is unclear whether the bus lane is a direct disincentive for ICEV ownership. However, there might be a positive effect on BEV ownership if the travel speed is higher in the bus lane.[11]

Notably, while PHEVs enjoy the tax benefits related to car purchase, PHEVs are not exempted from VAT or road tolls and do not have access to bus lanes. Hence, we would expect these policies to make BEVs more attractive than other low-emission vehicles.

2.2 Data

We use national administrative data on all vehicles and individuals for the period 2008–2017 (Fevang et al., 2021), and for each household we match cars as well as local work commute incentives. All private cars have a record with the owner's national personal identification number in the motor vehicle register. Since adult household members typically share cars, we consider the household as the decision-making unit and study their car ownership regardless of the registered owner. Every person also has a household identifier which enables us to characterize the car portfolio of each household, which is defined at the end of each year. Since all registers use the same identifiers, we can match administrative data from several sources, enabling a detailed description of all Norwegian households in terms of family structure, income, wealth, educational attainment, and residence location.

By matching employees and employers, we identify the location of each individual's workplace. Residence and work locations are recorded at the level of basic statistical units (*grunnkretser*), which we will refer to as neighborhoods. There are about 14,000 Norwegian neighborhoods in total, with an average population of 450 individuals, or fewer

the toll road operator Ferde, ferde.no. In some urban areas, charges vary by time of day, and drivers do not have to pay more than once if passing multiple toll booths within a certain time interval.

[10] Some urban toll rings introduced tolls for BEVs in 2019 (i.e., after the period considered in the analysis in this paper). However, the charge cannot be higher than 50 percent of the toll on conventional vehicles and is typically considerably lower.

[11] As the number of BEVs has increased, their access to bus lanes has been restricted on a few selected roads with heavy traffic, starting with the main road (E18) going into Oslo from the west side in 2015 (Sandelien, 2017). During rush hours, BEVs are allowed to drive in the bus lane only if they have at least one passenger.

than 200 households.[12] Using individual residence and workplace locations, we calculate the travel time, distance, and road toll as well as bus lane distance associated with each work commute. These commute characteristics are based on a complete road network for Norway in 2015,[13] where we have identified the fastest route by car (according to the speed limit) between centroids of neighborhood combinations.

The road network data contain bus lane information and we add annual toll rates for the period 2008–2017. A few toll gates have differentiated rates by time of day (see, e.g., Isaksen and Johansen, 2021). Since our focus is on work trips, we use rush hour rates to calculate road toll exposure. These toll rates are upper bounds of the true toll exposure for two reasons: First, some cars enjoy discounts (e.g., if the car owner has mounted a chip for automatic toll payments) which we do not observe. Second, the data do not always include information on whether drivers are charged a toll in just one or both directions. Here, missing information is recoded as a road toll in both directions, which is most common.

Finally, we add information on expected cost and travel time by public transit between neighborhood pairs, information we obtained from the Norwegian regional transportation models (RTMs) (see, e.g., Kwong and Ævarsson, 2018, for more information).[14] As with the bus lane data, the information on public transit travel times is time-invariant, representing the year 2015.

Table 1 displays descriptives, focusing on the most recent years in our data (2015 to 2017). Since car portfolios of single-adult households and couples are very different, we present results by type of household throughout the analysis. Over a calendar year, many employees have multiple employers. We have chosen the workplace with the highest total annual wage. For the unemployed, the values for road tolls, kilometers of bus lanes, and travel time are set to zero. We exclude households without any adult employees. In 2015–2017, 7.4 percent of couples owned a BEV, compared to 1.7 percent among single-adult households. Most couples own at least one car, and the average number of cars per couple is about 1.65. Six in 10 single adults own a car, but few have more than one. Couples are wealthier, more educated, older, and less likely to live in a large city area than are singles. Note, however, that the dispersion is larger among single-adult households, partly because such households include more individuals in the tails of the age distribution.

For travel to work characteristics we use the average value across (1) the trip to and from work and across (2) the two adult members of the household (if applicable). The average commuting distance is about 15 km, giving a travel time by car of about 14

[12] By comparison, the average population of these neighborhoods is about 1/20 of that of a US zip code.

[13] An alternative approach would be to use a different network for each year. However, changes in the network data are often due to corrections of errors rather than to actual changes. In any case, there were not many major changes in the road network during the period considered.

[14] Specifically, we use data on travel cost, time on board, waiting time, transit time, and access/egress time from RTMs as control variables for public transit accessibility on the work route.

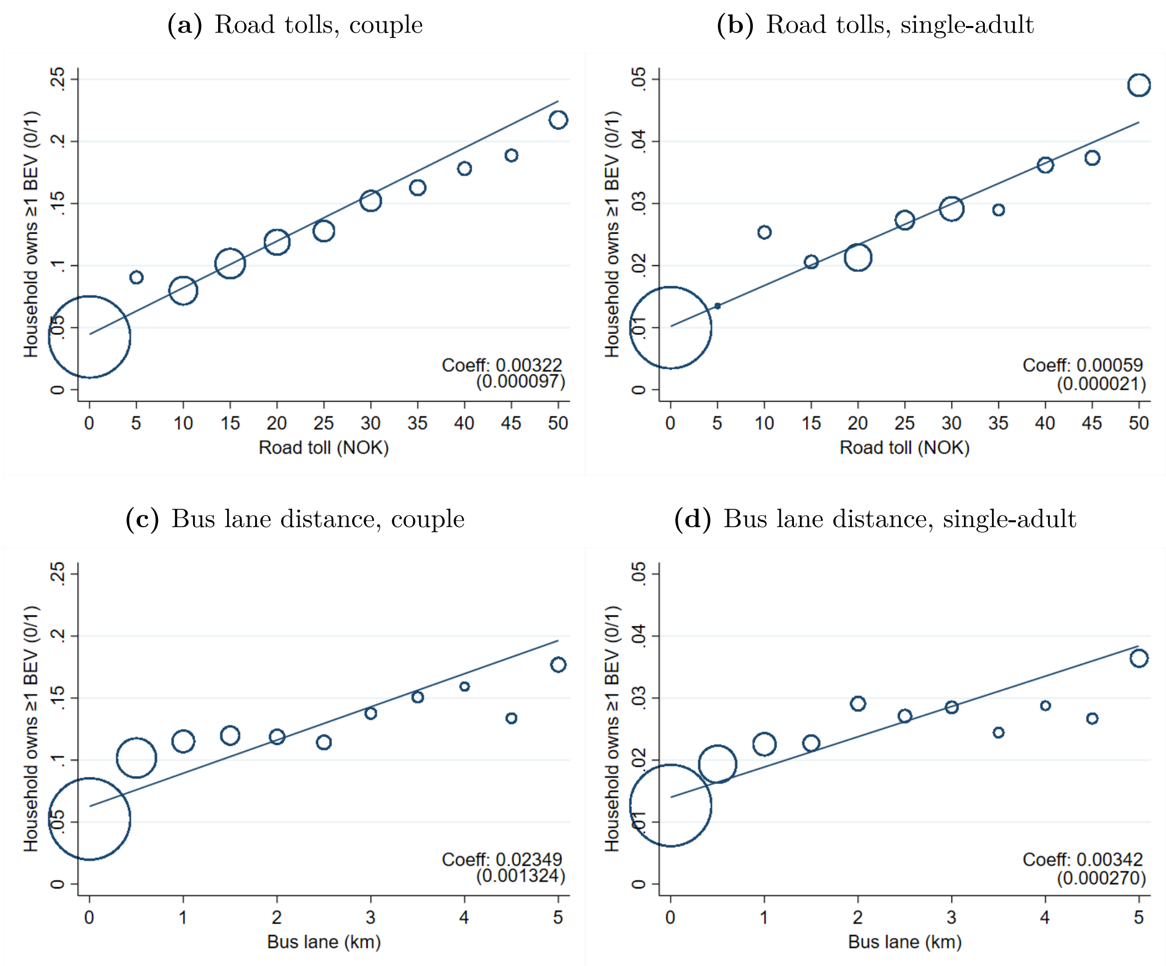
Table 1: Summary statistics by household type, 2015–2017.

	Couple		Single-adult	
	mean	sd	mean	sd
Panel A: Car ownership				
BEV (yes = 1)	0.074	0.261	0.016	0.127
Number of BEVs	0.077	0.280	0.017	0.131
Number of ICEVs	1.548	0.870	0.712	0.693
Number of cars	1.625	0.869	0.729	0.698
Car (yes = 1)	0.912	0.284	0.605	0.489
Panel B: Travel to work				
Road toll to work, mean (NOK)	9.49	16.57	9.30	18.54
Road toll to work, sum (NOK)	15.03	26.70	9.30	18.54
Road toll to work (yes = 1)	0.37	0.48	0.29	0.46
Bus lane, mean (km)	0.48	1.27	0.48	1.39
Bus lane, sum (km)	0.75	2.03	0.48	1.39
Bus lane (yes = 1)	0.26	0.44	0.32	0.47
Bus lane $\geq$ 500 metres (yes = 1)	0.20	0.40	0.17	0.38
Bus lane, share	0.03	0.07	0.04	0.09
Distance to work (km)	14.56	15.69	13.26	18.19
Time to work, driving (min)	13.75	12.92	12.58	14.98
Time to work, public transit (min)	61.02	114.79	70.53	176.21
Panel C: Household characteristics				
Number of household members	3.13	1.10	1.23	0.59
Children under age 18 (yes = 1)	0.51	0.50	0.14	0.34
Household income, mean (NOK)	419.16	389.70	400.10	448.64
Household income, sum (NOK)	838.31	779.40	400.10	448.64
Household wealth, mean (NOK)	1,553.71	7,345.75	1,300.45	12,855.81
Household wealth, sum (NOK)	3,107.41	14,691.50	1,300.45	12,855.81
Employment (yes = 1)	0.85	0.23	1.00	0.00
Retired (yes = 1)	0.07	0.20	0.04	0.19
Age	45.55	11.84	41.21	13.03
No high school	0.23	0.33	0.21	0.41
High school	0.32	0.35	0.32	0.47
University/College	0.41	0.41	0.40	0.49
Large city	0.37	0.48	0.46	0.50
Suburbs of large city	0.20	0.40	0.16	0.36
Small city	0.19	0.40	0.18	0.38
Observations	2,355,545		1,522,312	

Notes: Annual observations, 2015–2017. All Norwegian residents aged 18 or more. The sample is restricted to households with at least one identified work place location for employed adult members. The yearly location of the workplace is from the employment spell with the highest annual wage income, while the employment status is based on labor income in each year (employed if labor earnings > 1 social security basic amount (G)). Income, wealth, size, and location are measured at the household level, while employment, retirement, age, and educational attainment are individual characteristics of the adult members of the households. Panel B reflects values for employed individuals with a workplace location only. Note that in regressions, travel to work controls for unemployed adults in a two-adult household are assigned a value of 0. The mean household values in regressions reflect the average of both employed and unemployed individuals.

minutes. The expected travel time by public transit, including waiting time and walking to/from stations, is about 60 minutes. The average road tolls on the travel to work per adult are close to 10 NOK per trip and are similar for couples and single-adult households. The average bus lane distance on the commuting trip is about 0.5 km for both household types. The average bus lane distance accounts for only 3–4 percent of the average work distance, but 26 (32) percent of couples (single-adult households) have at least one road segment with a bus lane on their work trip. These fractions drop to 20 (17) percent if we include only bus lane distances longer than 0.5 km.

Figure 1: BEV share by local incentives and household type, 2015–2017.



(a) Road tolls, couple

(b) Road tolls, single-adult

(c) Bus lane distance, couple

(d) Bus lane distance, single-adult

Notes: Panels (a) and (b) show the average BEV ownership share for different intervals of road tolls per adult. Each circle reflects the average BEV share within a given interval. Circle size reflects the size of the population (i.e., number of households). The first circle to the far left reflects the average BEV share for households with 0 road tolls. The last circle to the far right reflects the average BEV share for toll road $\geq$ NOK 45. All circles in between reflect the average BEV share for 5 NOK intervals of road tolls. For example, the point at 5 NOK reflects the average BEV share for road tolls in the interval 0 to 5 NOK. The lines show linear fit. The coefficient is the slope of a linear curve, with standard errors clustered at the neighborhood level (residence and workplace) reported in parentheses. The sample is restricted to households where both adults are working. Panels (c) and (d) show the average BEV ownership for different intervals of bus lane distance to work per adult. The first circle to the far left reflects the average BEV share for households without a bus lane to work. The last circle to the far right reflects the average BEV share for bus lane distances $\geq$ 4.5 km. All circles in between reflect the average BEV share for 0.5 km bus lane intervals.

Figure 1 shows the unadjusted relationship between BEV ownership and road tolls (top panels) as well as bus lane distance (lower panels) to work. This figure also reveals considerable variation in incentives exposure across households. The plots show that the probability of BEV ownership is increasing in road tolls for couples as well as for single-adult households. For couples, an increase of 10 NOK in road tolls is associated with an increase in the probability of BEV ownership of 3.1 percentage points, compared with the mean BEV share in households without road tolls and bus lanes of 3.9 percent. For single-adult households, the association is weaker, mainly because the BEV share is much lower. There is a positive correlation between the BEV share and bus lanes, but it is not as strong as for road tolls. However, these plots cannot be given a causal interpretation, since both incentives are likely to correlate with other factors affecting car ownership. In Section 3, we explain how we identify the causal effects on car ownership of road tolls and bus lane distance to work.

3 Empirical strategy and identification

Our strategy is to exploit variation in *exposure* to BEV privileges across households in a quasi-experimental research design. While some neighbors cross toll gates and have bus lanes on their commuting routes, others do not. The gains from road toll exemption and bus lane access for BEVs vary across households due to the combined locations of homes and workplaces. The differential exposure implies that the incentives to buy and drive a BEV are much stronger for households with toll roads and bus lanes on their commutes to work. We estimate the effects of road tolls and bus lane distance on the work commute on household car ownership using linear regression models, where we control for the residential neighborhood of the household as well as the locations of workplaces by including three sets of fixed effects:[15]

$$Y_{ht} = \alpha_{rt} + \theta_{w_1t} + \theta_{w_2t} + \beta\text{Road Toll}_{rwt} + \lambda\text{Bus Lane}_{rwt} + \gamma X_{ht} + \delta Z_{rwt} + \varepsilon_{ht} \quad (1)$$

where Y_{ht} is the outcome (e.g., BEV ownership) of household h in year t.[16] Subscript r denotes the neighborhood of residence, while subscript $w = w_1, w_2$ denotes the neighborhood(s) of the workplace(s). α_{rt} are (year-specific) residential neighborhood fixed effects, θ_{w_1t} and θ_{w_2t} are (year-specific) workplace neighborhood fixed effects. Road Toll$_{rwt}$ is the road toll (in NOK) and Bus Lane$_{rwt}$ is the bus lane distance (in kilometers) on the trip from neighborhood r to w in year t (for couples, we use the average of both household members). X_{ht} is a vector of individual-/household-specific control variables, while Z_{rwt} controls for attributes of the work trips (travel distance and travel time by car, and access by public transit). The residual is ε_{ht}.

[15] It is infeasible to estimate a multi-outcome model (e.g., a multinominal logit) with the same specification due to the many fixed effects.

[16] We here focus on the effect on car ownership, while the effect on driving is estimated separately; see Section 5. The empirical specification for driving distance, conditional on car ownership, is slightly different from the specification in Equation 1, but is based on the same identification strategy. Ideally, we would like to estimate the car portfolio and driving distance simultaneously (see, e.g., Johansen and Munk-Nielsen, 2021), but this approach is unfeasible without strong, structural assumptions.

The parameters of interest, β and λ, are the marginal effects of road tolls and bus lane distance on car ownership. The detailed fixed effects imply that we identify the effects of road tolls and the bus lane distance through variation across households *within* each residential and work neighborhood. In addition, we control for travel distance and other key characteristics of the work commute. Arguably, our specification implies that we compare outcomes of very similar households.

Note that households are also exposed to tolls and bus lanes on leisure trips, but data on these traveling patterns are not available. However, conditional on detailed household characteristics, including residential neighborhood, it is reasonable to assume that leisure trip exposure to toll roads and bus lanes is uncorrelated with work-commute exposure. β and λ can therefore be interpreted as the isolated effects of work-commute road tolls and bus lane distance. It is reasonable to expect that road tolls and bus lanes on the commute have significant relevance for households' car ownership and driving decisions: For the average individual driving to work, the commute makes up about one third of total driving.[17] The average toll payments on the work commute will increase annual car ownership costs and fuel costs by roughly 25 percent for households that own a second-hand ICEV.[18] Furthermore, according to a survey of Norwegian BEV owners, exemption from road tolls (bus lane access) was stated to be "critical for purchase" for 49 (21) percent of the respondents (Bjerkan et al., 2016).

Local BEV incentives are particularly strong in urban areas and vary considerably across residential neighborhoods. Even so, there is substantial residual variation in road tolls and bus lane distance within neighborhoods, as illustrated by Figure 2.[19]

The identifying assumption is that road tolls and bus lane distance on work commutes are orthogonal to any unobserved household characteristic that affects car ownership, conditional on fixed effects and other controls. In the data, road tolls on work commutes correlate positively with economic resources of the household (i.e., income and wealth) and family size, and correlate negatively with age. These are all important predictors of demand for BEVs. However, when we include neighborhood fixed effects, these correlations largely disappear. In Figure 3, we display how the household income of couples correlates with BEV incentives. When we compare neighbors (in Panel b), there is basically no association between road toll exposure and household income. When we add other household

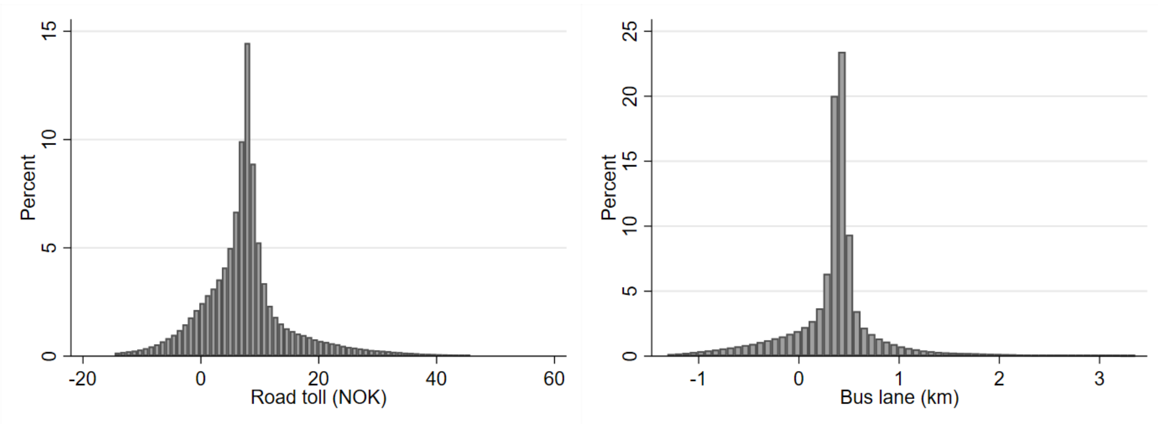
[17] More precisely, 33 percent, when considering that the average distance to workplaces is 9.5 kilometers (Table 1) and the average daily driving distance is 36 kilometers (Table 5), and assuming there are 230 work days per year. The Norwegian National Travel Survey reports driving patterns similar to those in our data (Grue et al., 2021).

[18] According to rough calculations in Isaksen and Johansen (2021, Table E.3), annual ownership and fuel expenses (not including insurance and maintenance costs) for a small, used ICEV are about 17,000 NOK. The average individual commuting by car is required to pay about 4370 NOK per year in commute-related tolls ($9.5 \times 2 \times 230$; see Table 1). Note that this value will be considerably higher for individuals that need to pass the most expensive toll gates.

[19] Figure A.10 shows the corresponding variation when using the data structure explained in Section A.4, with car and period of ownership as the units of observation.

Figure 2: Residualized road tolls and bus lane distance, 2015–2017.

(a) Road tolls **(b)** Bus lane distance



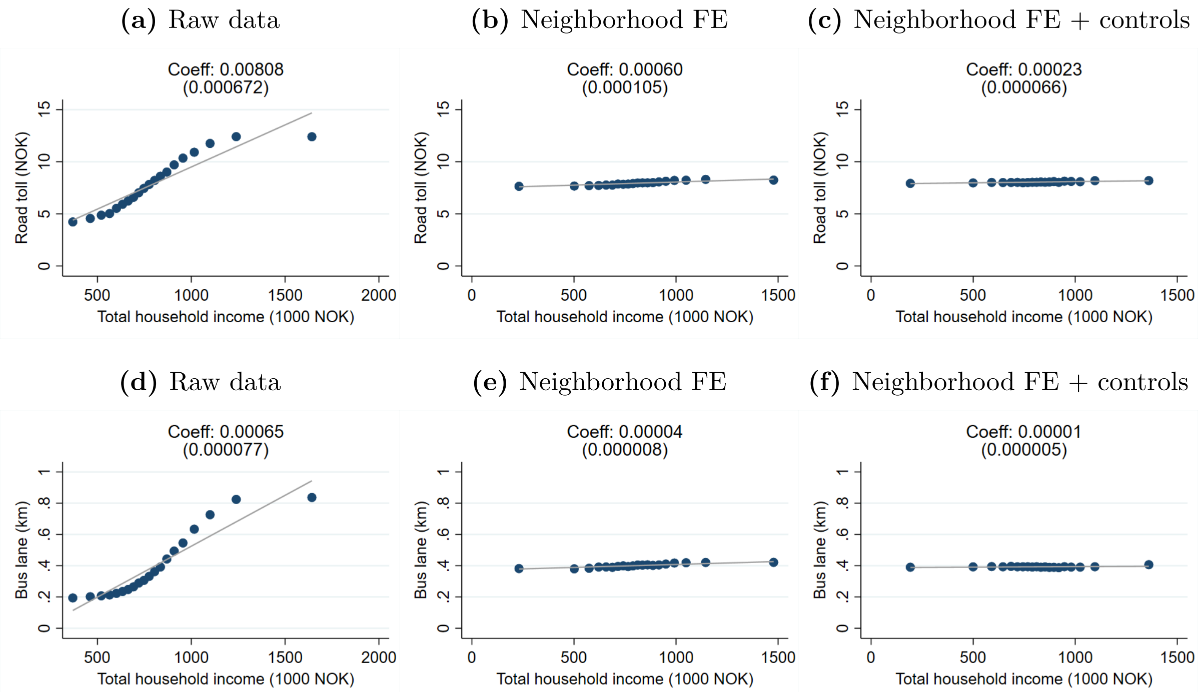
Notes: The figure shows histograms of road tolls (Panel a) and bus lane distance (Panel b). Both variables are residualized by absorbing neighborhood × year fixed effects (residence and work). The population mean is added to the residualized values. The sample is restricted to couple households where at least one of the adult members is employed.

and work trip controls (Panel c), the relationship is even weaker. The same holds for bus lane distance (in Panels e and f); the positive correlation between income and bus lane distance disappears when controlling for other household characteristics. In Appendix Figures A.1 and A.2, we also show that road tolls and bus lane distance are uncorrelated with other key household characteristics, such as wealth, household size, and the average age of adult members, as long as we condition on neighborhood fixed effects. While the concern for confounding characteristics never disappears completely, it is reassuring that core household characteristics are uncorrelated with road tolls and bus lane distance when including the three sets of fixed effects.

Several studies point to the importance of charging infrastructure for the adoption of electric vehicles (see, e.g., Li, 2017; Li et al., 2017; Narassimhan and Johnson, 2018; Schulz and Rode, 2021; Springel, 2021). Note that in our specification, the effect of charging stations located nearby the residence and workplace will largely be absorbed by the neighborhood fixed effects and therefore does not confound our estimates. Housing is also relatively similar within residential neighborhoods, offering similar opportunities to charge a BEV at home. Workplaces vary with respect to parking facilities, but this variation is typically across local areas. Private charging amenities at work or home can potentially be a confounding variable, but only if there is significant variation within neighborhoods. Moreover, if workplaces or housing communities respond to increased BEV ownership by investing in charging facilities, this response is part of the mechanism and not an omitted variable bias.

Because choices of home and work locations are choices made by the household, one might be concerned that families with a preference for BEVs (for whatever reason(s)) are less reluctant to choose a combination of locations that involve road tolls on work

Figure 3: Correlation between local BEV incentives and household income, 2015–2017.



Notes: The figure shows mean BEV incentives on the journey to work: road tolls (a–c) or lengths of bus lanes (d–f), within a given vigentile bin. The data set is divided into twenty equally sized bins based on household income. Panels (a) and (d) plot raw data. Panels (b) and (e) plot the residual (+ sample mean) from regressions of BEV incentives on yearly neighborhood fixed effects (residence and work) by income vigentile. Panels (c) and (f) display the residuals from regressions that also include household and work commute controls. The sample is restricted to couples where at least one is employed. The line shows linear fit over unbinned data. The coefficients are from regressions with standard errors three-way clustered at the neighborhood level.

commutes. Similarly, households with strong preferences for ICEVs may avoid home and workplace locations that involve road tolls on their work commutes. Both types of sorting will involve a bias that leads to overestimated effects of local BEV incentives. In Section 4.2, we examine potential sorting bias based on stayers and movers, and show that the effects of road tolls and bus lanes are not likely to be driven by geographical sorting.

Another potential threat to identification is road congestion; if local authorities implement road tolls and bus lanes on road sections where congestion is high initially, our estimated treatment effects might be biased. However, since road tolls in Norway are fairly common in both urban and rural areas, correlation between road tolls and road congestion is likely to be a minor concern. When establishing bus lanes, available space is often a more critical condition than congestion is. In our analysis of heterogeneous effects in Section 4.3, we also show that treatment effects are relatively similar across urban and rural areas, suggesting that congestion in urban areas is not driving our results.[20]

[20]Controlling directly for congestion would be problematic because road tolls and bus lanes are likely to affect travel time via their effect on car ownership and driving, making it a bad control. In our empirical specification, we therefore condition our estimates on free-flow travel time, calculated as the travel distance adjusted by the speed limits, without taking obstacles like queues into account. Our approach mitigates concerns that travel times during uncongested travel periods might confound our estimates, and avoids using endogenous variables as controls.

4 Results

4.1 Effects of local incentives on car ownership

Our main focus is on how local privileges influence the demand for BEVs. We first estimate the effects of road tolls and bus lanes on work commutes on BEV ownership using Equation 1. Since the car portfolios of single-adult households are very different from those of couples, we estimate the effects separately for the two household categories. Table 2 reports the effect estimates, using the three most recent years of our data (2015–2017), for different model specifications. The preferred estimates are in columns (3) and (6), for couples and single-adult households, respectively.

For couples, an additional 10 NOK (about 1 USD) in road tolls on work commutes increases the probability of owning a BEV by 1.4 percentage points (pp). Relative to the mean BEV ownership of couples without toll roads or bus lanes (3.9 percent), this amounts to an increase of 37 percent. The point estimate for single-adult households is much lower (0.3 pp), but the effect is of equal magnitude (38 percent) when evaluated relative to the mean (0.9 percent). The elasticity of BEV ownership with respect to road tolls is 0.16 and 0.20 for couples and single-adult households, respectively, evaluated at their respective means.

The effect of bus lane kilometers to work is also positive and significant for couples. Half a kilometer of bus lane leads to an increase in the probability of BEV ownership of 0.11 pp, or 2.7 percent of the mean. The elasticity of BEV ownership with respect to bus lane distance is 0.012. For single-adult households, the effect of bus lane distance is smaller and not statistically significant.

Our preferred estimated effects of local BEV incentives are substantially lower than the unadjusted correlations (Figure 1). For road tolls, the coefficient drops from 0.0031 to 0.0014. Neighborhood fixed effects are by far the most important controls, but the inclusion of travel distance and other work trip controls reduces the effect by an additional 10 to 20 percent (columns (2) vs. (1) and (5) vs. (4)). Adding household characteristics, however, does not alter the estimates (columns (3) and (6)), consistent with the evidence in Section 3, where road tolls and bus lane kilometers are uncorrelated with individual and household characteristics within neighborhoods.

The positive effects of local incentives on BEV ownership may arise from adjustments at different margins of the car portfolio. If households that otherwise had no car (e.g., due to environmental concerns/preferences, high user prices, or access to efficient public transit) were to decide to buy a BEV because of road tolls or bus lanes on their work commutes, the total number of cars would increase and more households would become car owners. On the other hand, if the BEVs are typically bought by households that would in any case own a car, the fraction of car owners is unaffected by BEV incentives. Even when the incentives trigger only existing car owners to buy a BEV, the car portfolio

Table 2: Effects of road tolls and bus lane distance on household BEV ownership, 2015–2017.

	Couple households			Single-adult households		
	(1)	(2)	(3)	(4)	(5)	(6)
Road toll (NOK)	0.00182***	0.00149***	0.00144***	0.00040***	0.00035***	0.00034***
	(0.00010)	(0.00009)	(0.00009)	(0.00002)	(0.00002)	(0.00002)
Bus lane (km)	0.00483***	0.00253***	0.00216***	0.00078***	0.00034	0.00038
	(0.00078)	(0.00079)	(0.00075)	(0.00024)	(0.00024)	(0.00024)
N	1,964,318	1,964,318	1,964,318	1,281,068	1,281,068	1,281,068
Year	2015–17	2015–17	2015–17	2015–17	2015–17	2015–17
Neighborhood residence FE	✓	✓	✓	✓	✓	✓
Neighborhood work FE	✓	✓	✓	✓	✓	✓
Ind-work controls		✓	✓		✓	✓
HH and ind controls			✓			✓
Public transit (minutes)			✓			✓
Mean outcome	0.0706	0.0706	0.0706	0.0160	0.0160	0.0160
Mean road toll (NOK)	8.054	8.054	8.054	9.247	9.247	9.247
Mean bus lane (km)	0.393	0.393	0.393	0.479	0.479	0.479

Notes: The estimates are OLS coefficients from linear probability models. Standard errors are three-way (couple) or two-way (single-adult) clustered at the neighborhood level. The average probability of BEV ownership among households without toll roads or bus lanes in their work commutes is 0.039 for couples and 0.009 for single-adult households.

can change in different ways. If the incentives induce households to add a BEV to their existing car fleet, the total number of cars will increase. If households replace the old ICEV with a BEV, the effect on the number of ICEVs will be negative. Road tolls and bus lanes on work commutes may also affect car demand among households that do not buy a BEV. For example, we expect that road tolls on work commutes lower demand for ICEVs since the relative price of alternative transportation is lower.

In Table 3, we consider the effects of road tolls and bus lane distance on three outcomes; the number of ICEV cars, the total number of owned cars, and car ownership (yes or no). The results show that the effect of road tolls on the decision to own a car is negligible among couples (column (3)). An extra 10 NOK of road toll leads to an increase in car ownership of less than 0.1 pp. Single-adult households, however, are significantly less likely to own a car if they have to pay road tolls. Turning to total car ownership, we find a negative effect of road tolls on work commutes for both types of households (columns (2) and (5)). Thus, the stronger incentives to buy a BEV do not outweigh the negative effect of higher tolls on ICEV demand. If the road toll increases by 10 NOK, the total number of cars drops by just 0.003, for both types of households. Since the road toll boosts demand for BEVs, having fewer cars in total implies a significant reduction in ICEVs due to the increased road toll. As shown in column (1), an increase of 10 NOK leads to a reduction in the number of ICEVs by 0.018 (or 1 percent) for couples. For single-adult households (column (4)), the road toll effect is lower (-0.007), even in relative terms (0.8 percent).

Turning to the effects of bus lane distance in Table 3, we find that having more bus

Table 3: Effects of road tolls and bus lane distance on car ownership, 2015–2017.

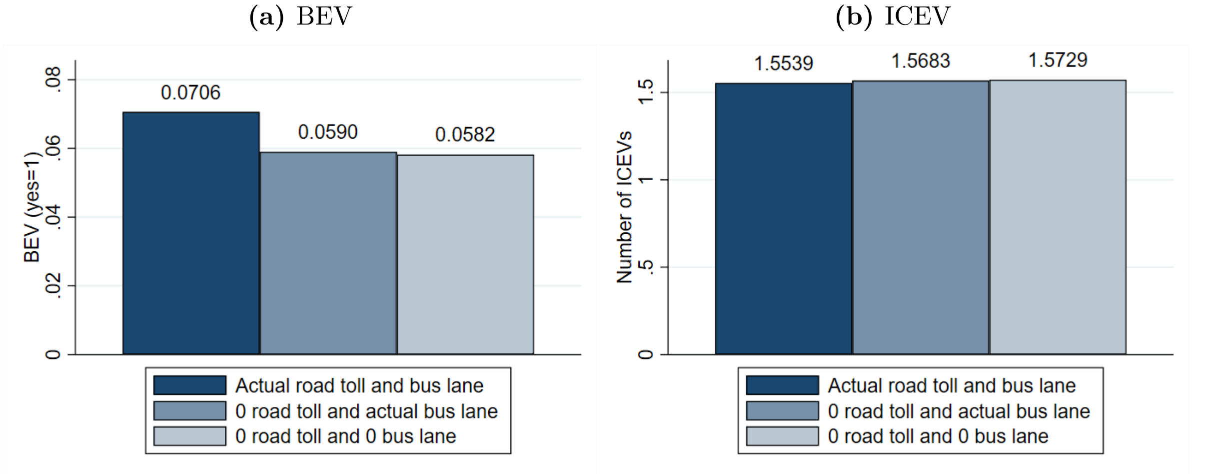
	Couple households			Single-adult households		
	(1) ICEVs	(2) Cars	(3) Car (yes = 1)	(4) ICEVs	(5) Cars	(6) Car (yes = 1)
Road toll (NOK)	-0.00179***	-0.00026***	0.00006**	-0.00065***	-0.00031***	-0.00017***
	(0.00010)	(0.00010)	(0.00003)	(0.00007)	(0.00007)	(0.00005)
Bus lane (km)	-0.01175***	-0.00901***	-0.00011	-0.00508***	-0.00465***	-0.00317***
	(0.00145)	(0.00150)	(0.00071)	(0.00090)	(0.00094)	(0.00073)
N	1,964,318	1,964,318	1,964,318	1,281,068	1,281,068	1,281,068
Year	2015–17	2015–17	2015–17	2015–17	2015–17	2015–17
Neighborhood residence FE	✓	✓	✓	✓	✓	✓
Neighborhood work FE	✓	✓	✓	✓	✓	✓
Ind-work controls	✓	✓	✓	✓	✓	✓
HH and ind controls	✓	✓	✓	✓	✓	✓
Public transit (minutes)	✓	✓	✓	✓	✓	✓
Mean outcome	1.554	1.628	0.914	0.722	0.738	0.615
Mean road toll (NOK)	8.054	8.054	8.054	9.247	9.247	9.247
Mean bus lane (km)	0.393	0.393	0.393	0.479	0.479	0.479

Notes: The estimates are OLS coefficients from linear probability models. Standard errors are three-way (couple) or two-way (single-adult) clustered at the neighborhood level.

lane kilometers is associated with lower car ownership, both in total (columns (2) and 5)) and for ICEVs (columns (1) and (4)). For single-adult households, there is also a negative effect on the probability of being a car owner (column (6)). The effects of bus lane distances are small, however. An increase of half a kilometer of bus lane leads to a reduction in the total number of cars owned by about 0.25 percent, for both household types. While the bus lane effect on BEV ownership is easily explained by the their access, it is less obvious why the number of ICEVs are affected. One channel is the substitution from ICEV to BEV. In addition, a bus lane will typically crowd out another lane, thereby reducing the capacity for handling regular ICEVs. The lower capacity will likely raise the actual travel time by car and hence lower the value of owning an ICEV. A work commute with a long bus lane distance may be associated with more congestion, even when we control for travel time by public transit.

What is the economic significance of the local incentives? In Figure 4, we display the average predicted BEV ownership probability (Panel a) and the average predicted number of ICEVs (Panel b) under three alternative sets of road toll and bus lane values. The first bar is the prediction based on actual values (and therefore is equal to the sample mean). Without toll roads on work commutes, the predicted BEV share drops by 1.2 percentage points. If we also set the bus lane distance to zero, the BEV rate is just marginally lower (0.1 pp). The smaller impact of bus lane distance reflects that road tolls are collected all over the country whereas bus lanes are limited to some urban areas. From Panel (b) in Figure 4, we see that without toll roads for work commutes, the average predicted number of ICEVs increases by 0.013. No bus lanes on work commutes add just 0.004 ICEVs per household.

Figure 4: Predicted BEV and ICEV ownership.



Notes: Panel (a) shows the predicted probability of owning at least 1 BEV for couples, 2015–2017. Panel (b) shows the predicted number of ICEVs in a household. The sample is restricted to couples where at least one is working.

4.2 Sensitivity to spatial sorting

The causal interpretation of our estimates of road tolls and bus lane distance effects is based on the assumption that the combined choice of residential and workplace locations is exogenous with respect to car portfolio preferences. Households do not randomly choose where to live and work, but we assume that location is not influenced by road tolls or bus lane distance on work commutes. To examine the potential influence of endogenous sorting on our effect estimates, we split the sample by residential and workplace mobility since 2011. The results are presented in Table 4.

Column (1) in Table 4 shows our baseline estimates when restricting the sample to households that are observed in 2011. These estimates are slightly different from our main estimates in Tables 2 and 3 due to the smaller sample size. To examine the potential influence of sorting, we start by restricting our sample to households that lived in the same neighborhood in 2015–2017 as they did in 2011; see column (2). While slightly smaller, these estimates are not statistically different from our baseline estimates. Conditioning on the same workplace for both adult members of the household reduces the sample size significantly, with minor changes to the estimated coefficients. Column (4) shows the estimates for "stayers" only, that is, couples where both lived and worked in the same neighborhoods in 2011 as they did in 2015–2017. Comparing these estimates with the baseline in column (1), where both stayers and movers are included, we find slightly smaller effects (toward zero) for stayers. The minor change in point estimates can be interpreted as endogenous sorting inflating our main estimates slightly, but the precision is weaker for stayers and the confidence intervals overlap with those of all households.

Hence, the results in Table 4 suggest that the effects of road tolls and bus lane distance in work commutes are not driven by geographical sorting of homes and workplaces.

Table 4: Effects of road tolls and bus lane distance on household car ownership, 2015–2017. Conditional on residential and work location in 2011.

	Couple households			
	Baseline	Same residence	Same workplace	Stayers only
	(1)	(2)	(3)	(4)
Panel A: BEV (yes = 1)				
Road toll (NOK)	0.00151***	0.00148***	0.00124***	0.00119***
	(0.0000941)	(0.0000994)	(0.000124)	(0.000130)
Bus lane (km)	0.00226**	0.00220**	0.00280**	0.00302**
	(0.000889)	(0.000959)	(0.00125)	(0.00147)
Panel B: Number of ICEVs				
Road toll (NOK)	-0.00163***	-0.00153***	-0.00178***	-0.00158***
	(0.000128)	(0.000149)	(0.000256)	(0.000303)
Bus lane (km)	-0.0109***	-0.0112***	-0.00976***	-0.00838**
	(0.00190)	(0.00224)	(0.00334)	(0.00367)
N	1,291,590	1,051,003	450,556	395,838
Year	2015–17	2015–17	2015–17	2015–17
Same residential location	✓	✓	✓	✓
Same work location	✓	✓	✓	✓
Different residential location	✓		✓	
Different work location	✓	✓		
Mean outcome, BEV	0.0767	0.0714	0.0606	0.0579
Mean outcome, ICEVs	1.662	1.715	1.697	1.728
Mean road toll (NOK)	8.184	7.836	7.081	6.877
Mean bus lane (km)	0.407	0.382	0.328	0.314

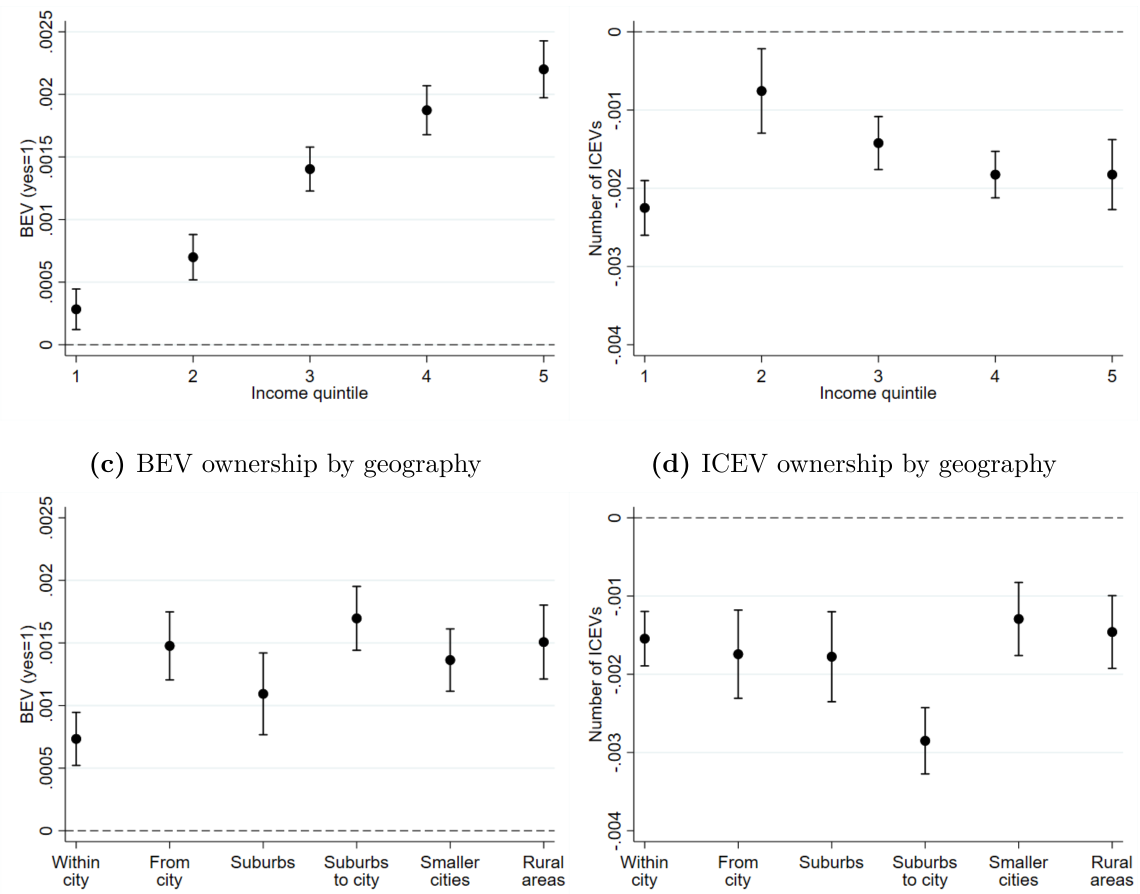
Notes: The coefficients presented in Column 1 in Panel A (Panel B) are estimated from the same regression as in Table 2, Column 3 (Table 3, Column 1), but the sample is restricted to households that are observed in 2011. Column 2 restricts the sample to households that did not change their residential location since 2011. Column 3 restricts the sample to households where neither of the household members changed their work location since 2011. Column 4 restricts the sample to households where both the residential and the workplace location are the same as in 2011. ** $p < 0.05$, *** $p < 0.01$. Standard errors are three-way clustered at the neighborhood level.

4.3 Heterogeneous effects of road toll and bus lane distance on car ownership

The effects of BEV incentives exposure are likely to differ across households. Car ownership depends on income and wealthy households are more likely to own a BEV. Road tolls and bus lanes are unevenly distributed across the country. Households living in the large cities, and particularly those who commute into the large cities for work, are likely to experience congestion and delays if they drive. To explore heterogeneous effects of road tolls and bus lane distance in work commutes, we estimate an extended model of Equation (1) where the effects of road tolls and bus lane distance differ by household income quintile and residential location. We split households into six regional groups.

First, we distinguish between large cities, large-city suburbs, small cities, and rural areas. For households in large cities, we split the sample in two based on whether the household members commute out of the city or not. For households in large-city suburbs, we similarly split the sample based on whether the household members commute into the city or not.

Figure 5: Heterogeneous effects of road tolls on car ownership.



(a) BEV ownership by income

(b) ICEV ownership by income

(c) BEV ownership by geography

(d) ICEV ownership by geography

Notes: The panels show heterogeneous treatment effects by income quintile and residential region, where the sample is restricted to couples where at least one is employed. Each panel plots coefficients from the same regression with two-way interactions between combinations of local incentives and income as well as resident region (see Appendix A.1 for the estimating equation). Income is measured as annual total household income in the years 2015–2017. The BEV shares in households without road tolls or bus lanes on their work commutes are for the five income intervals (from q1 to q5); 0.015/0.022/0.035/0.050/0.072. The BEV shares in the same sample across regions are 0.052 (4 largest cities within commute), 0.082 (4 largest cities with commute out), 0.056 (Suburbs without commute to large city), 0.096 (Suburbs with commute to large city), 0.035 (Smaller cities) and 0.024 (Rural). The average number of ICEVs in households without work-commute road tolls or bus lane for each of the five income intervals is (from q1 to q5); 1.41/1.79/1.85/1.83/1.77. Across regions, the number of ICEVs are 1.07 (4 largest cities within commute), 1.25 (4 largest cities with commute out), 1.64 (Suburbs without commute to large city), 1.65 (Suburbs with commute to large city), 1.68 (Smaller cities) and 1.90 (Rural). The confidence intervals are based on standard errors with three-way clustering at the neighborhood level.

In Figure 5 we report heterogeneous effects of road tolls on BEV as well as ICEV ownership.[21] Panel (a) reveals that the effect of road tolls on BEV ownership is mono-

[21] With two interaction terms, the marginal effect for one group, say income quintile, depends on the geographical region. We evaluate the effect for one dimension (say income) by the weighted average effect along the other dimension (say region), using total sample shares as weights.

tonically increasing in household income. The differential effects by income partly reflect that rich households are more likely to own a BEV. If we compare the elasticities rather than the marginal effect on the probability of BEV ownership, the effects are fairly similar throughout the household income distribution. In Panel (b) we report the effect of road tolls on ICEV ownership across income quintiles. The negative effect of road tolls is fairly similar across the income distribution. The elasticities, however, are largest at the two ends of the income distribution. The effect of road tolls on the total number of cars is approximately equal to the sum of the estimates in Panels (a) and (b), suggesting that work-commute road tolls increase the number of cars among the richest households. (Figure A.3 in the Appendix also reveals that this increase is significantly larger than zero.) For all other income quintiles, the negative effect on ownership of ICEVs exceeds the positive effect on BEV ownership.

The region-specific effects of road tolls are shown in Panels (c) and (d) in Figure 5. For BEV demand, the road toll effects are very similar across regions, except for weaker responses for large-city and suburban households that do not commute out of their region. Road tolls have a particularly large and negative effect on ICEV demand among households that commute from suburbs into the large cities.

There is no clear evidence of heterogeneity in the effect of bus lane distance, as shown in Appendix Tables A.4 and A.5, with one exception. The bus lane distance affects BEV ownership among only the richest 20 percent of the households.

5 Total effect on driving and emissions

Until now, we have considered how local incentives influence households' car demand. Local incentives can also influence how cars are used. To assess the climate benefits of road tolls and bus lanes, both the ownership and the driving channels must be considered. In this section, we will first consider the partial driving-distance effects, given car ownership. We then combine the ownership and driving-distance estimates to assess the total effect on CO_2 emissions, and focus on ICEV driving for two reasons. First, driving distance data of ICEVs are far better than for BEVs. Driving distance is based on odometer readings which take place within four years of the first registration date and then bi-annually after that. Since most BEVs in our data set are fairly new, we have few BEVs with valid driving distance information. Second, due to the relatively clean energy mix in Norway, BEVs have a very small carbon footprint.[22] From a climate perspective, the direct carbon emissions generated by ICEVs are hence the most important.

[22]The electricity supply in Norway is predominantly (96 percent) from hydropower plants. Indirect emissions from electricity generation based on fossil fuels are therefore less relevant than they are in many other countries – such as the US (Holland et al., 2016). Additionally, emissions from electricity production in Norway are covered by the EU Emissions Trading Scheme (EU ETS), while emissions from vehicle fuel consumption are not.

To estimate the effect of local incentives on kilometers driven per car, we use a slightly modified version of Equation (1) with log daily driving per car as the outcome.[23] The unit of observation is a driving period (∼2–4 years). The car identifier in the motor vehicle register enables us to map cars to owners on a daily basis. We calculate each car's average driving distance per day per driving period by taking the first difference between two subsequent odometer readings.

The dependent variable is the log of the average km driven per day (over a two- or four-year period), as in Gillingham and Munk-Nielsen (2019). Since we attach road tolls and bus lane distance to driving records via household ownership, we exclude the cars of owners who frequently switch their cars. Specifically, we include driving periods in which a household owned the car for more than 50 percent of the time interval and refer to this as the modal household.[24] All household-specific variables represent the modal household for each driving period. The controls are identical to those in the ownership model, with the exception of time and selection controls as well as fuel types and fuel prices.[25]

Results from the log driving regressions are reported in Table 5. With neighborhood, time, and selection controls only (first column), we find positive associations between ICEV driving and local incentives. However, households with road tolls and bus lanes on their work commutes typically live further away from work. When we add work distances, car attributes, and fuel prices as controls, we see from our preferred estimates in column (3) that increasing the road toll by 10 NOK is associated with a 0.34 percent reduction in ICEV kilometers. Similarly, increasing the bus lane distance to work by 0.5 kilometers reduces ICEV driving by 0.5 percent. A higher road toll gives incentives to choose other modes of transportation, which explains the fewer ICEV kilometers. For bus lane distance, we see two reasons why households drive their ICEVs less. First, a bus lane typically crowds out another lane, reduces the capacity for handling regular ICEVs, and raises the actual travel time. As a consequence of more congested roads, households drive less. Second, multi-car households with a BEV are more likely to drive it (and leave the ICEV parked) when they can save time by using the bus lane.

We can now calculate the effect on total kilometers driven, via the number of cars owned and the number of kilometers per car.[26] The marginal effect of a local incentive

[23]See Appendix A.4 for the exact empirical specification, and Appendix A.3 for a description of the data.

[24]Ideally, we would like to use the same time period (2015–2017) as for the car ownership regressions in Section 4. Due to the odometer reading intervals, driving periods covering 2015–2017 also include other years. Instead, we focus on driving periods overlapping with 2015. Appendix Table A.1 shows the distribution of the years covered.

[25]Time controls capture seasonality, and include one variable for each year and month, equal to the share of the driving period that is covered by that year/month. Selection controls capture the length of a driving period as well as the share of the period the car is owned by the modal household. Note that even though fuel prices are national, there is variation on the car level from the fact that each driving period covers a different time interval. Fuel prices mainly follow global oil prices, and should be exogenous to driving after conditioning on employment and income.

[26]Here we present back-of-the-envelope calculations based on partial estimates of the ownership and

Table 5: Effects of road tolls and bus lanes on the driving of ICEVs.

	(1)	(2)	(3)
Road toll (NOK)	0.00268***	-0.000353***	-0.000339***
	(0.000120)	(0.0000823)	(0.0000777)
Bus lane (km)	0.00773***	-0.0105***	-0.00977***
	(0.00145)	(0.00108)	(0.00104)
Year	2013–17	2013–17	2013–17
N	1,257,228	1,257,228	1,257,228
Neighborhood residence FE	✓	✓	✓
Neighborhood work FE	✓	✓	✓
Time and selection controls	✓	✓	✓
Commuting controls (car and PT)		✓	✓
Household and individual controls		✓	✓
Fuel type and price			✓
Mean km/day	36.05	36.05	36.05
Mean log(km/day)	3.439	3.439	3.439
Mean road toll (NOK)	7.049	7.049	7.049
Mean bus lane access (km)	0.356	0.356	0.356

Notes: The table shows the estimated effects of road tolls and bus lane distance on log driving. ** $p < 0.05$, *** $p < 0.01$. Standard errors are three-way clustered at the neighborhood level (residential and workplace for both household members).

on the total ICEV kilometers per household is given by the following (using road tolls as an example, but the effect of bus lane distance is equivalent):

$$\frac{\mathrm{d}ICEV km}{\mathrm{d}Toll} = \frac{\partial \# ICEVs}{\partial Toll} \times \overline{km\, per\, ICEV} + \frac{\partial km\, per\, ICEV}{\partial Toll} \times \overline{\# ICEVs} \tag{2}$$

The first term in Equation (2) represents the effect of road tolls on ICEV ownership. To get at the impact on ICEV kilometers, we multiply this ownership effect by the kilometers driven per car. The second term in Equation (2) captures the impact via daily driving decisions for a given car portfolio. Road tolls on work commutes are likely to reduce kilometers among ICEV owners since the relative price of driving increases. To calculate the impact on the average household's driving, we multiply driving per car by the number of ICEVs among households without road tolls or bus lanes on their work commutes.

In quantifying the effect on total driving per household in Equation (2), we evaluate the effect of changing the incentives from zero to the sample mean, which is 9.49 NOK (9.30 NOK) in road tolls for couples (single-adult households) and 0.48 km of bus lanes for both couples and singles (Table 1). While car ownership estimates are taken from Table 3, the driving distance effect is provided by Table 5. Note that we include only the effects related to work-commute exposure, and commuting amounts to about one third of total driving distance (see Section 3).

driving channels separately, ignoring any interaction between the two. We also ignore any impact on the composition of the stock of ICEVs.

Table 6: Total annual effect of road tolls and bus lane distance on driving and CO_2 emissions by household type, 2017.

		Source	Road tolls		Bus lanes	
			Couple	Single-adult	Couple	Single-adult
PARAMETERS						
A	Effect on ICEV ownership	Table 3	-0.00179	-0.00065	-0.01175	-0.00508
B	Toll and bus lane sample mean	Table 1	9.49	9.30	0.48	0.48
C	Kilometers per day per ICEV	Own calculations†	36.05	33.85	36.05	33.85
D	Effect on ICEV driving	Table 5	-0.000339	-0.000339	-0.00977	-0.00977
E	ICEV ownership per household	Table 1	1.548	0.712	1.548	0.712
F	Number of households	Own calculations‡	1,048,779	631,031	1,048,779	631,031
G	CO_2 intensity of ICEVs (g/km)	Rødseth et al. (2019)	141	141	141	141
CALCULATIONS: DRIVING AND CO_2 EMISSIONS						
H	Through car ownership (km/hh)	B × A × C × 365	-223.5	-74.7	-74.2	-30.1
I	Through driving of existing cars (km/hh)	B × D × C × E × 365	-65.5	-27.7	-95.5	-41.3
J	Total driving per household per year	H + I	-289.0	-102.4	-169.7	-71.4
K	Million ICEV kilometers per year	F × J / 1,000,000	-303.1	-64.6	-178.0	-45.0
L	CO_2 emissions, tons per year	K × G	-42,744	-9,113	-25,100	-6,351

Notes: This table presents parameter values and rough calculations for the effect of tolls and bus lanes on ICEV kilometers driven and associated CO_2 emissions. The source for each parameter value and the equations are presented in the second column.
†Average kilometers driven per day per car for singles and couples in our sample according to periodic vehicle inspections.
‡Number of households in register data where at least one adult member works.

Table 6 shows our calculation of the effect on total ICEV kilometers. We find that road tolls reduce household ICEV kilometers per year by 289.0 km for couples and 102.4 km for single-adult households. Extrapolating up to all households with at least one employed adult, the reduction is 303 million km/year for couples and 64.6 million km/year for single-adult households. For bus lanes, driving is reduced by 169.7 km/year for couples and 30.1 km/year for single-adult households. For all households with at least one employed adult, this amounts to 178 million km/year for couples and 45 million km/year for single-adult households.

The average emissions from ICEVs are 141 g of CO_2 per kilometer, when weighting by the composition of diesel, gasoline, and hybrid cars in the Norwegian car fleet (Rødseth et al., 2019, p. 32). By multiplying the total kilometers by the estimate of CO_2/km, we find that road tolls reduce total yearly CO_2 emissions from private car use by 42,744 tons (1.4 percent) for couples and 9113 tons (1.2 percent) among single-adult households.[27] For bus lanes, the yearly reduction is 25,100 tons of CO_2 for couples and 6,351 tons of CO_2 for single households, where both amount to 0.8 percent of the total emissions from private cars in the respective households. In total, the yearly CO_2 reduction from road tolls and bus lanes sums to 83,300 tons (51,850 from tolls and 31,450 from bus lanes), which is a 2.2 percent reduction in driving-related emissions of working households.

[27] Total yearly CO_2 emissions from private car transportation are calculated as: the total number of households × cars per household × km per car × CO_2 emissions per km × 365. The calculations are done separately for two-adult and single-adult households.

6 Discussion

How comparable are our results to those of previous studies? While evidence on the effect of road tolls on BEV ownership is scarce, we can compare our results with results regarding the estimated effects of other monetary incentives. Muehlegger and Rapson (2018) find that a 1000 USD one-time subsidy increases the sales of BEVs and PHEVs by 13 percent, which is large compared with the findings by Jenn et al. (2018) and Clinton and Steinberg (2019), which are based on state-level data and Sierzchula et al. (2014) and Münzel et al. (2019), which are based on country-level data. Our main estimate suggests a 37 percent increase in BEV ownership resulting from a daily incentive of about 2 USD (1 USD per trip). With plausible assumptions about how long car buyers expect to enjoy the road toll exemption, our estimate is comparable to, or even larger than, that of Muehlegger and Rapson (2018).[28] A possible explanation for this strong effect is that BEVs are relatively competitive in Norway due to other powerful incentives like the exemptions from the VAT and the vehicle registration tax.

Estimates of the effect of bus or HOV lanes are more difficult to compare across studies, because these studies use different measures of exposure. Sheldon and DeShazo (2017) estimate a non-linear relationship and find that a 10 percent increase in HOV lane density within a 30-mile radius leads to an increase in BEV and PHEV registrations of between 0.3 percent (Los Angeles) and 5.7 percent (Sacramento), while our main estimate implies an increase of 0.1 percent. However, HOV lane density in California metropolitan areas is relatively high, while large areas in our sample do not have bus lanes or HOV lanes at all.[29]

Our analysis shows that BEV ownership is increasing in road tolls and bus lane distance on the commute to work. For ICEVs, we find the opposite pattern. This evidence is consistent with significant impacts of local BEV privileges since the incentives to buy a BEV are much stronger for households with such amenities on their commutes to work. From a policy perspective, we would also like to provide direct evidence on the effects of road toll *exemption* and bus lane *access*. The ideal data for directly identifying the effects of these privileges would have existed if, at the outset of the BEV technology expansion, a randomly selected group of households had been given access to bus lanes and exemption from road tolls if they used a BEV. Since the privileges apply to all BEV drivers, such data do not exist. To get from our effects of road tolls and bus lane distance on the work

[28] Our point estimate is 2.85 times the estimate of Muehlegger and Rapson (2018), or 2850 if we multiply by 1000 USD. Assuming 230 work days per year and a 4 percent discount rate, it would take seven years to save 2850 USD in road tolls on the commuting trip. The road toll exemption has been partly reversed since the 2015–2017 period, but BEV drivers still enjoy a considerable discount as of 2021. However, one should have in mind that not all potential car buyers would choose to commute by car, and therefore would not enjoy the benefits of the road toll exemption.

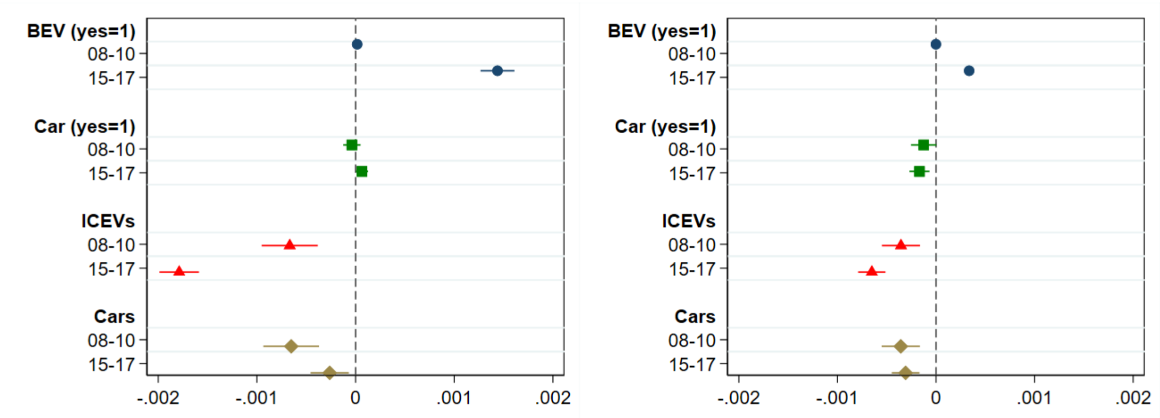
[29] The total of HOV lane kilometers within a 48-kilometer (30-mile) radius of Los Angeles and Sacramento is 419 and 62, respectively. According to our data, there are 136 kilometers of bus lanes in all of Norway.

commute to the effects of altering BEV privileges, there are several aspects to consider. Households with a toll road work commute face higher costs of car travel, independent of the BEV privileges. This is particularly important when we interpret our estimated effect of work-commute road toll on ICEV ownership. A road toll for work commutes raises the price of car transportation and (some) household members are likely to choose alternative transportation modes, resulting in a lower demand for cars. Even without BEV privileges, households without a toll road commute would be more likely to own an ICEV. This implies that our estimated road toll effect on ICEV ownership exaggerates the effect of the BEV exemption.

One could argue that the effects of road tolls before the expansion of the BEV market captures the effects unrelated to the road toll exemption for BEVs. In Figure 6, we present estimates from Tables (2) and (3) for 2015–2017 together with estimates for 2008–2010 with the same specification. The first period can be considered pre-BEV expansion, because 2011 was the first year BEVs from major car manufacturers were commercially available (e.g., Nissan Leaf). We see that the effect on ICEVs is substantially larger in 2015–2017 than in the pre-BEV years 2008–2010. The differential effect is about -0.001. For the total number of cars, the negative effect is reduced by a half of what it was in the pre-BEV years. All in all, the differential effects of road tolls over time clearly suggest that the road toll exemption is an important driver of the BEV expansion in Norway.

Figure 6: The effects of road tolls on car ownership, before and after the BEV expansion.

(a) Couple households **(b)** Single-adult households



Notes: The panels show effects of work-commute road tolls on car ownership in a given time period. Each coefficient within a panel is estimated from a separate regression, in total 8 regressions per panel. The confidence intervals are based on standard errors three-way (couples) or two-way (singles) clustered at the neighborhood level.

7 Conclusions

While the market penetration of BEVs depends on technical progress (e.g., an increase in battery capacity) and purchase taxes/subsidies, we show that local privileges, such as road toll exemptions and access to bus lanes for zero-emission cars, are powerful instruments to encourage households to replace conventional vehicles. With detailed information on the locations of workplaces and homes, we find that the probability that a household will own a BEV is larger the higher the road toll is and the longer the bus lane distance is on work commutes. In terms of elasticities, the effect of road tolls on BEV ownership is substantially larger than the effect of bus lane distance is. Further, we find that road tolls and bus lane distance both have negative effects on ICEV ownership and minor effects on the total number of cars. We also document negative effects of the local incentives on brown driving per car, but the increased share of green cars is by far the most important mechanism for explaining the policy-induced reduction in CO_2 emissions.

Our main results reflect the combined effect of road tolls and BEV privileges. By using data from a period before the BEV expansion, we show that the BEV privileges have likely strengthened the negative effect of road tolls on brown vehicles. At the same time, we find that the BEV privileges have also likely dampened the negative effect of road tolls on the number of cars. The latter implies that exempting BEVs from road tolls will lead to more cars and hence more congestion and other negative externalities from driving (Bento et al., 2014; Wangsness et al., 2020). When designing policies to promote electric vehicles, governments may therefore face a trade-off between reduced CO_2 emissions and increased negative local externalities.

In our paper, we exploit administrative microdata that allow us to measure variation in economic incentives for different modes of transportation and car ownership at an exceptionally detailed level. By using household-level variation, we are able to identify policy effects that are difficult to document with more aggregated data. While quasi-experimental studies using administrative data increasingly dominate empirical labor and education economics, the use of such data in transportation and environmental economics is still rare. We believe that there is a large and untapped potential for exploiting individual-level administrative data to examine effects of environmental, climate, and transportation policies, and that our paper showcases the potential of using such data to establish credible causal estimates.

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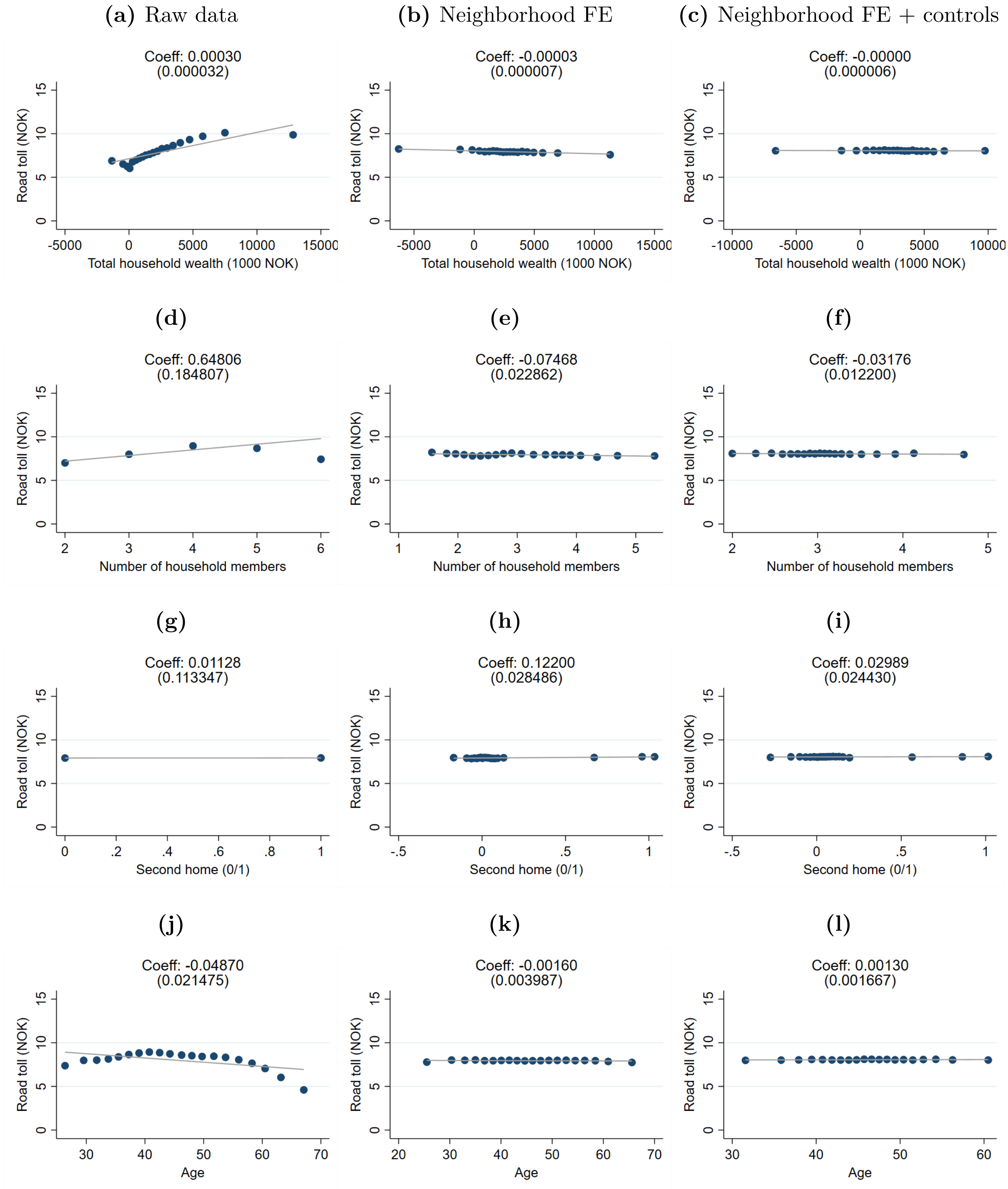
A Appendix

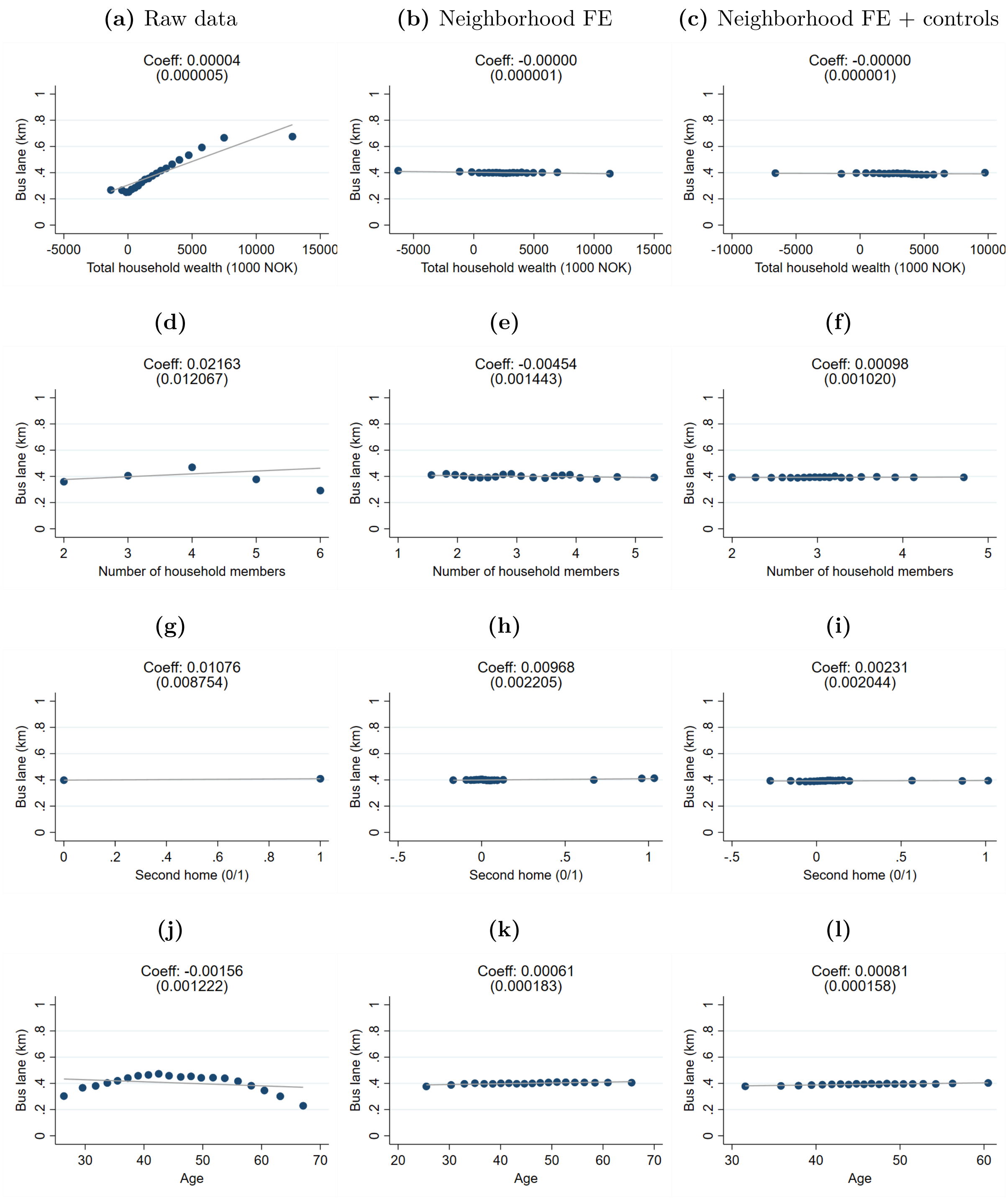
A.1 Supporting evidence, empirical strategy

Figure A.1: Correlation between road tolls and household characteristics, 2015–2017.



Notes: Panels (a), (d), (g), and (j) show average road tolls for equal-sized bins of different household characteristics. Panels (b), (e), (h), and (k) show residuals from regressions with neighborhood fixed effects (residential and workplace), while Panels (c), (f), (i), and (l) show residuals that are also conditional on household characteristics. The sample is restricted to couple households where at least one of the adult members is employed.

Figure A.2: Correlation between bus lane distance and household characteristics, 2015–2017.



Notes: Panels (a), (d), (g), and (j) show the average bus lane distances for equal-sized bins of different household characteristics. Panels (b), (e), (h), and (k) show residuals from regressions with neighborhood fixed effects (residential and workplace), while Panels (c), (f), (i), and (l) show residuals that are also conditional on household characteristics. The sample is restricted to couple households where at least one of the adult members is employed.

A.2 Additional results

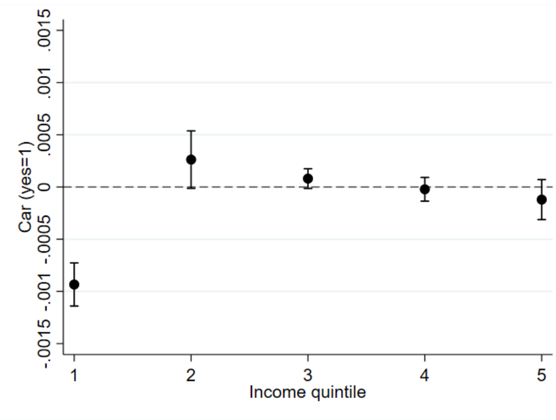
The estimating equation for heterogeneous effects has the following form:

$$\begin{aligned} Y_{ht} = & \left(\sum_{i \in \mathcal{I}} \beta_i \mathbb{1} \{ht \in i\} + \sum_{j \in \mathcal{J}} \beta_j \mathbb{1} \{rw \in j\} \right) \text{Road Toll}_{rwt} \\ & + \left(\sum_{i \in \mathcal{I}} \lambda_i \mathbb{1} \{ht \in i\} + \sum_{j \in \mathcal{J}} \lambda_j \mathbb{1} \{rw \in j\} \right) \text{Bus Lane}_{rwt} \\ & + \alpha_{rt} + \theta_{w_1 t} + \theta_{w_2 t} + \gamma X_{ht} + \delta Z_{rwt} + \varepsilon_{ht} \end{aligned} \tag{3}$$

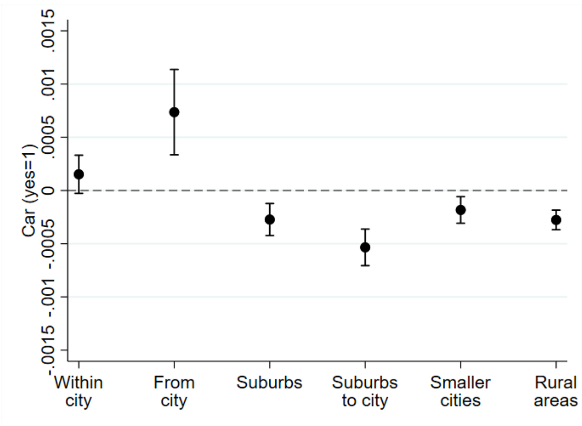
where i denotes one of $\mathcal{I}$ income groups; j denotes one of $\mathcal{J}$ geographic categories; $\mathbb{1} \{ht \in i\}$ is one if household h is in income group i in year t and zero otherwise; and similarly $\mathbb{1} \{rw \in j\}$ indicates whether the combination of residence-work neighborhoods for a certain household is contained in j or not. $\mathcal{I}$ contains income quintiles, while $\mathcal{J}$ covers the exhaustive categories "within city" (residence and workplace of both household members are in a large city); "from city" (residence in a large city, the workplace of at least one household member is outside a city); "suburbs" (residence in suburbs, the workplaces of both household members are outside a large city), "suburbs to city" (residence in suburbs, the workplace of at least one household member is in a large city); "smaller cities"; and "rural areas." The last two groups condition on place of residence independent of workplace location.

Figure A.3: Heterogeneous effects of road tolls on car ownership.

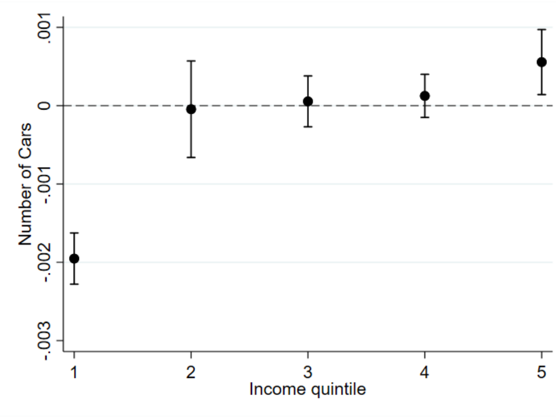
(a) Car ownership (1 = yes) by income



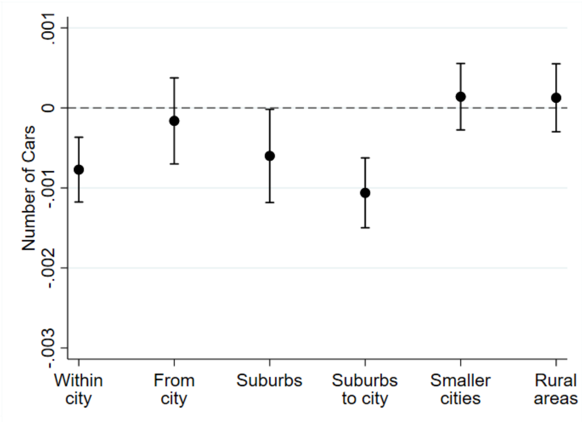
(b) Car ownership (1 = yes) by geography



(c) Number of cars by income



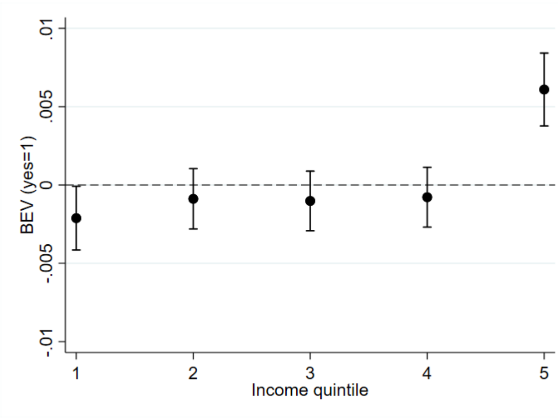
(d) Number of cars by geography



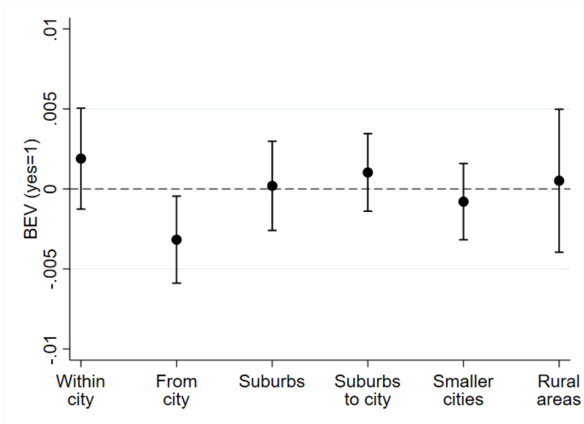
Notes: The panels show heterogeneous treatment effects by income quintile and residential region. Each panel plots coefficients from the same regression with two-way interactions between combinations of local incentives and income as well as resident region. See Equation 3 for the estimating equation. Income is measured as the annual total household income in the years 2015–2017. The confidence intervals are based on standard errors that are three-way clustered at the neighborhood level. The sample is restricted to couple households where at least one of the adult members is employed.

Figure A.4: Heterogeneous effects of bus lanes on car ownership.

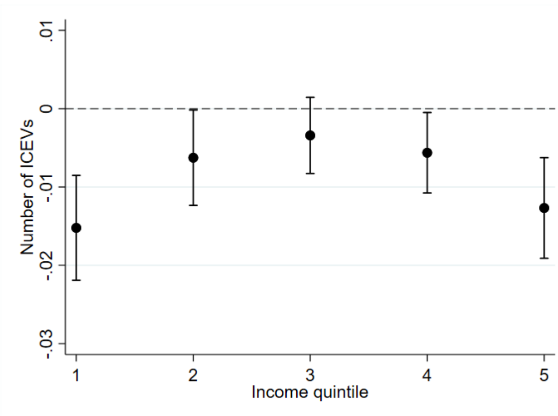
(a) BEV ownership by income



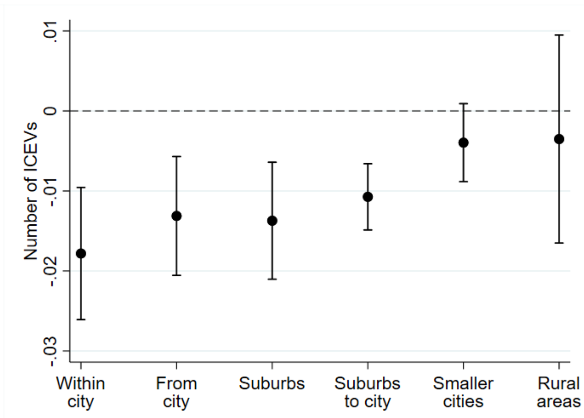
(b) BEV ownership by geography



(c) ICEV ownership by income

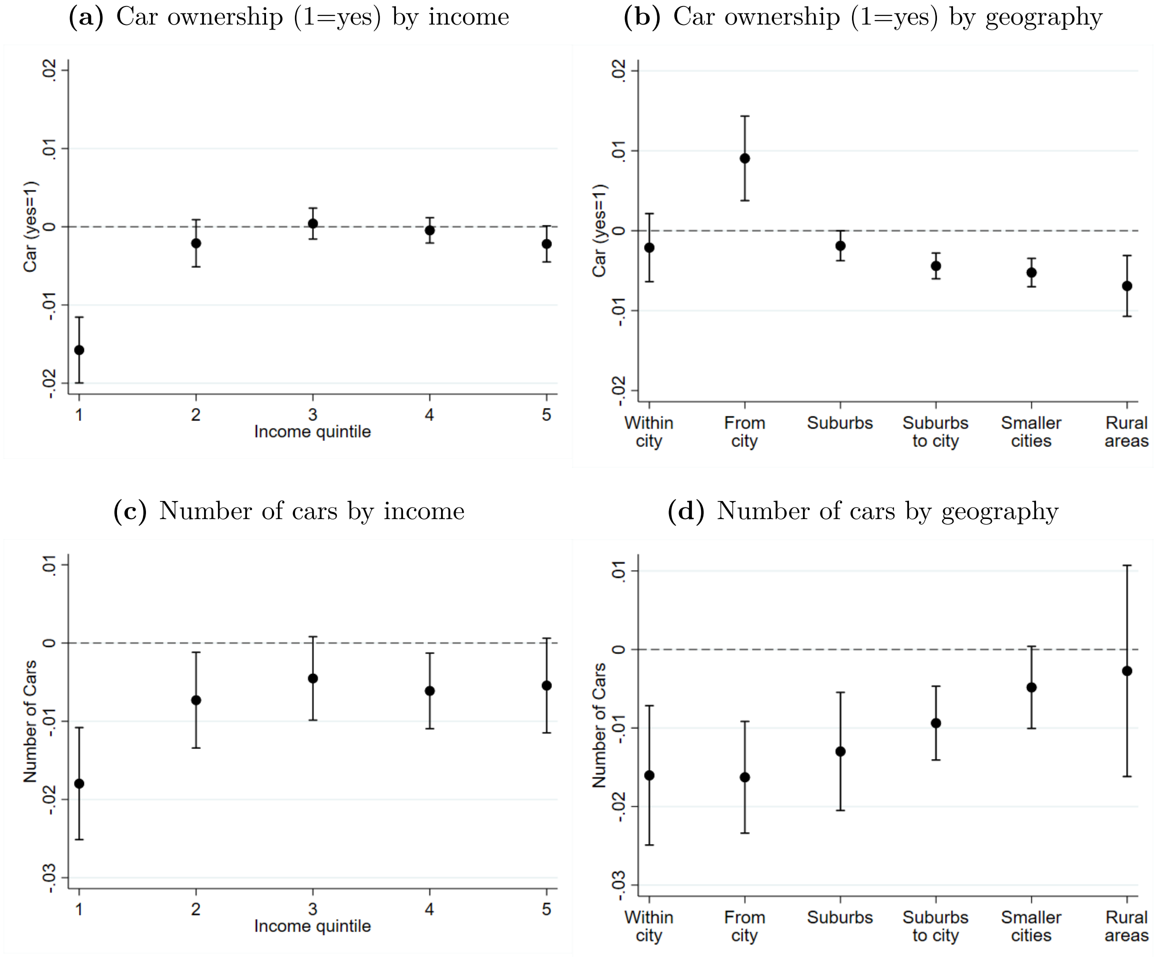


(d) ICEV ownership by geography



Notes: The panels show heterogeneous treatment effects by income quintile and residential region. Each panel plots coefficients from the same regression with two-way interactions between combinations of local incentives and income as well as resident region. See Equation 3 for the estimating equation. Income is measured as the annual total household income in the years 2015–2017. The confidence intervals are based on standard errors that are three-way clustered at the neighborhood level. The sample is restricted to couple households where at least one of the adult members is employed.

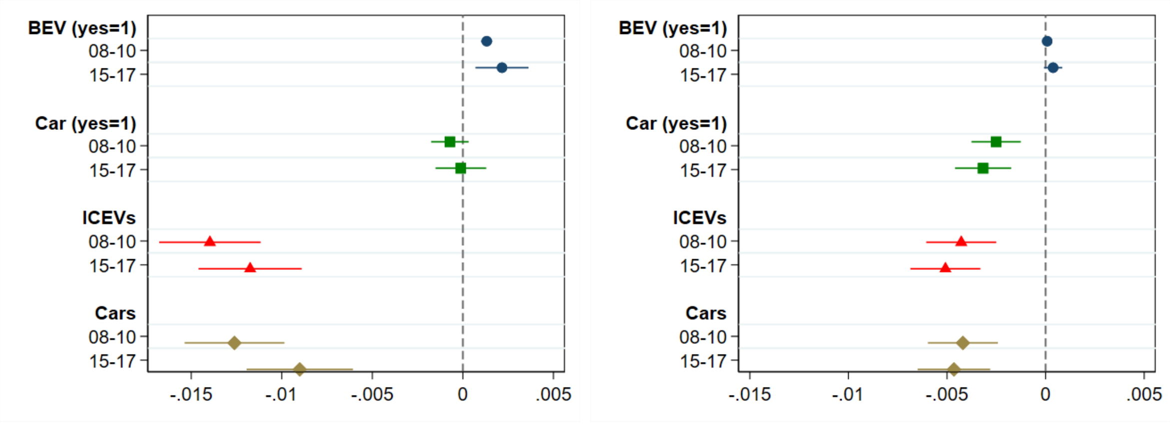
Figure A.5: Heterogeneous effects of bus lane distance on car ownership.



Notes: The panels show heterogeneous treatment effects by income quintile and residential region. Each panel plots coefficients from the same regression with two-way interactions between combinations of local incentives and income as well as resident region. See Equation 3 for the estimating equation. Income is measured as the annual total household income in the years 2015–2017. The confidence intervals are based on standard errors that are three-way clustered at the neighborhood level. The sample is restricted to couple households where at least one of the adult members is employed.

Figure A.6: Effect of bus lane distance on car ownership. Before and after the BEV expansion.

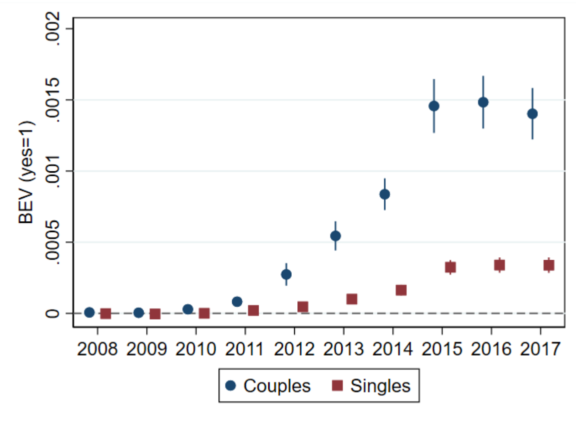
(a) Couple households **(b)** Single-adult households



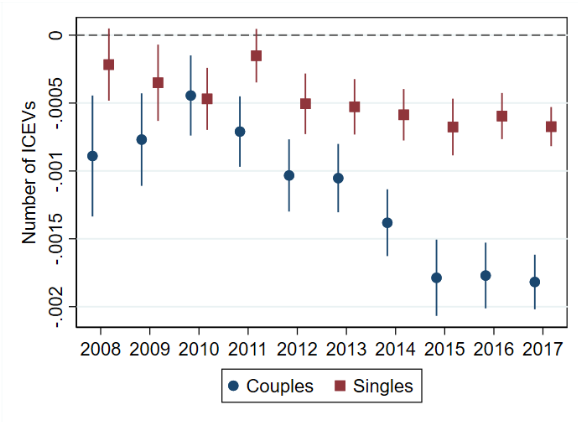
Notes: The panels show the effects of local incentives on car ownership in a given time period. Each coefficient within a panel is estimated from a separate regression, in total 8 regressions per panel. The confidence intervals are based on standard errors three-way (couples) or two-way (singles) clustered at the neighborhood level.

Figure A.7: Effects of road tolls and bus lane distance on BEV and ICEV ownership, by year and household type.

(a) Effect of road tolls on BEV ownership

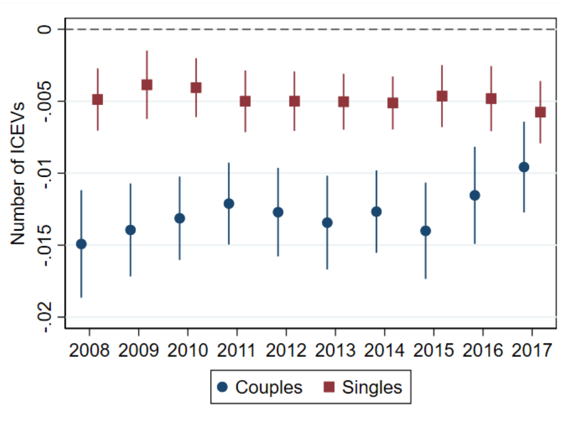


(b) Effect of road tolls on ICEV ownership



(c) Effect of bus lane distance on BEV ownership

(d) Effect of bus lane distance on ICEV ownership



Notes: The effect of local incentives on car ownership is estimated by year and each coefficient within a panel is estimated from a separate regression, in total 20 regressions per panel. Panels (a) and (c) plot coefficients of the preferred specification, that is, columns (3) and (6) in Table 2. Round (squared) markers indicate regressions restricted to two- (single-) adult households. Panels (b) and (d) plot coefficients from the same specification with the number of ICEVs as the outcome instead of the probability of BEV ownership. The confidence intervals are based on standard errors and are three-way (couples) or two-way (single-adult households) clustered at the neighborhood level.

A.3 Data set with car-level outcomes

Odometer readings in Norway are conducted at periodic safety inspections, within four years of the first registration date and then bi-annually. Our data set covers all safety inspections in the period 2005–2017. We will refer to the time intervals between the registration date and the first safety inspection as well as between two subsequent safety inspections as "driving periods." By taking the first difference of subsequent odometer readings, we can calculate the average driving per day per driving period for each car. This driving per day is an average over a two- or four-year period and the log is our dependent variable in the regressions. From the safety inspections, we know the identifier of the car, and from the motor vehicle register, we are able to map cars to owners on a daily level, since the transaction dates for ownership changes are recorded. Thus, we are able to trace ownership changes within each driving period.[30]

We restrict the sample in several ways. First, odometer readings are recorded manually and are therefore prone to errors. To remove extreme observations that are most likely due to errors, only driving periods where the daily driving is between 0 and 200 kilometers per day are kept (see Figure A.8 for how driving per day is distributed in the final sample). Second, to be able to relate a driving period to a specific household, we keep only driving periods in which one household owned the car for more than 50% of the time interval, and refer to this as the modal household. Each driving period is then assigned household-specific variables based on this household. The household-specific variables are weighted means of the annual values, where the weight is the share of the driving period that year covers.[31] Third, we keep only driving periods where the modal household is a couple, due to few single-household observations. Fourth, we keep only driving periods that overlap with 2015. Since driving periods are at most four years long and 2017 is the last year of our data, this will include driving periods that (partly) cover the time period 2013–2017.[32] Table A.1 displays selected summary statistics for all cars in our final sample, as well as for ICEVs and BEVs separately.

The first thing to note is the low number of observations for BEVs. The reason for this is that BEVs represent a new technology with an exponential growth in sales. Few BEVs with a valid driving period existed in 2013, which is necessary for a safety inspection to be conducted within 2017. In Panel A, we show that the average age of BEVs in the sample is just above two years. Therefore, when it comes to our analysis of driving kilometers, our current analyses will focus on ICEV driving.[33]

Panel B shows selected variables that are specific to the car-owning household. Note that this sample is conditional on selection into car types; therefore, demographics are not representative for the whole population. "Cars owned" is the number of cars weighted by the number of days, so that value 2 can mean owning either one other car the whole

[30]Ideally, we would want driving per day at the household level; however, this is not feasible without making several structural assumptions about the data generating process. First, driving is unobserved for a significant share of the cars, in particular the cars that were less than four years old at the end of 2017. Since car purchase decisions are endogenous to the policies in question, this would bias the sample of households with valid work distances. Second, driving periods for two cars owned by the same household will not necessarily cover the same time interval. Third, ownership changes occur frequently within driving periods, meaning that even though driving per car is observed, driving per household per car is not.

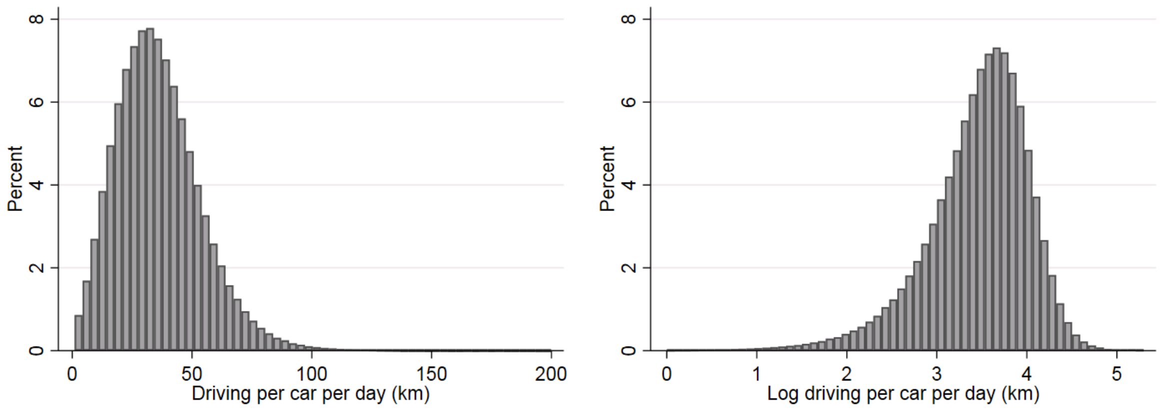
[31]If, for instance, a used car was bought by a household in the middle of 2014 and the next safety inspection was conducted in the middle of 2016, the 2015 demographics would get a weight of 0.5, while the 2014 and 2016 demographics would be weighted by 0.25 each.

[32]Ideally, we want to focus on the same time period as that for the ownership regressions (2015–2017). This is not possible, because driving periods are not recorded at the end of each year, but instead cover a longer time period.

[33]According to Table A.1, BEVs are driven slightly more than ICEVs are because BEVs are on average newer, and young cars are driven more than older cars. Conditional on car age, BEVs are driven approximately the same distance as gasoline cars are, and slightly less than diesel cars are.

Figure A.8: Distribution of driving, 2015.

(a) Driving per day (b) Log of driving per day



Notes: Panel (a) shows average driving per day per car for the cars in our sample that have driving periods overlapping with the year 2015. Panel (b) shows log of driving, which is what we use in our main regression specifications. We have removed all cars with registered driving above 200 km per day, and all cars with driving below 1 km per day. These removals ensure that log driving remains positive. The sample is restricted to couple households where at least one of the adult members is employed.

driving period or two other cars for half of the driving period. Panel C gives an indication of the time periods we are considering by focusing on driving periods that are overlapping with 2015. Values should sum to one and show the share of the driving period covered by each year.

Table A.2 shows selected summary statistics split by the car portfolio of the household. The first (last) two columns are households with less (more) than 1.5 cars during their ownership period. The last column is either two-car households where the car is a BEV or two-car households that owned another BEV for more than half of their ownership period. The main takeaway from this table is that conditional on the car portfolio, kilometers driven per car is relatively stable, independent of both drivetrain and the number of cars owned by the household.

Finally, Figure A.9 shows the unadjusted relationship between log driving per day per car for ICEVs, road tolls (left) and bus lanes (right), analogous to Figure 1. In isolation, we expect road tolls and bus lanes to work to reduce ICEV driving – having higher road tolls increases the generalized cost of car commutes, while having more bus lanes generally implies that public transit is more competitive. The positive association in the figure most likely comes from the fact that more driving, having higher road tolls, and having more bus lanes are positively correlated with longer work distances.

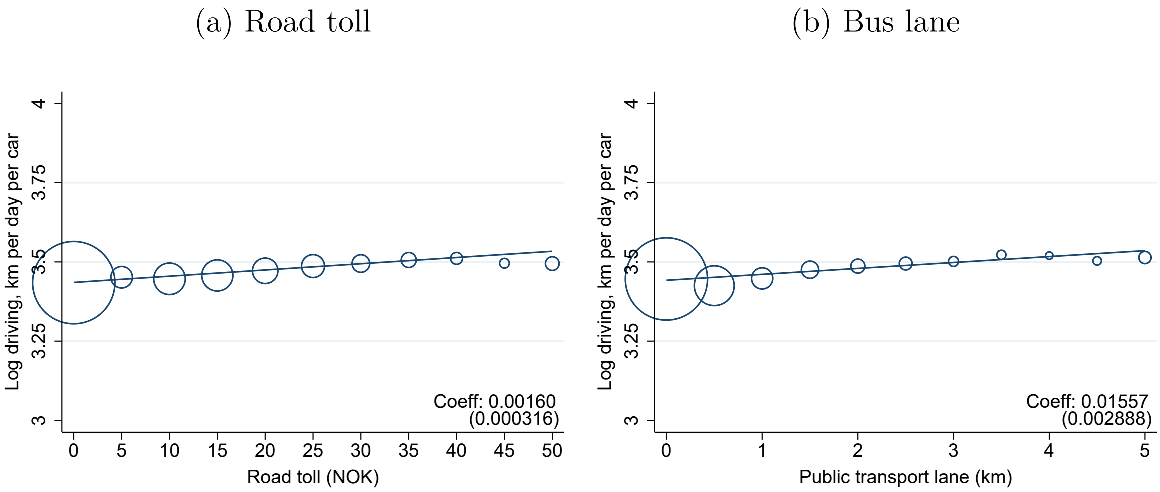
Table A.1: Summary statistics by car propulsion system, driving periods overlapping with 2015. Couples.

	All cars		ICEVs		BEVs	
	mean	sd	mean	sd	mean	sd
Panel A: Car-specific						
Driving (km per day per car)	36.23	18.44	36.22	18.45	38.01	16.40
Length of driving period (days)	804	218	801	214	1266	255
Diesel car (yes = 1)	0.577	0.494	0.581	0.495	-	-
Car age (years)	9.42	4.82	9.47	4.80	2.13	0.565
Panel B: Car-owner-specific						
Days owned by modal household	699	249	696	246	1113	349
Cars owned by modal household	2.04	0.706	2.04	0.706	2.13	0.565
Distance to work (km)	13.68	13.86	13.66	13.86	17.36	12.98
Time to work (min)	12.78	11.52	12.76	11.52	16.08	10.79
Toll to work (NOK)	6.85	11.92	6.78	11.84	17.26	17.91
Bus lane to work (km)	0.372	1.04	0.366	1.03	1.25	1.96
Panel C: Years of driving period						
2011	0.004	0.024	0.004	0.024	0.008	0.034
2012	0.015	0.055	0.015	0.055	0.049	0.086
2013	0.106	0.150	0.106	0.150	0.129	0.111
2014	0.262	0.207	0.262	0.208	0.220	0.101
2015	0.325	0.163	0.325	0.164	0.258	0.077
2016	0.224	0.214	0.224	0.215	0.240	0.149
2017	0.065	0.121	0.064	0.121	0.096	0.112
Observations	1,261,693		1,252,947		8,746	

Table A.2: Summary statistics by the car portfolio of the modal household, driving periods overlapping with 2015. Couples.

	One car		Two+ cars	
	ICEV only	BEV only	ICEV only	Incl. BEV
Driving, ICEV (km per day per car)	37.70	-	35.70	35.46
Driving, BEV (km per day per car)	-	36.81	-	38.20
Car age	8.56	2.31	9.81	7.61
Cars owned by the modal household	1.07	1.11	2.38	2.38
Distance to work (km)	10.80	14.33	14.48	17.28
Time to work (min)	10.29	13.32	13.56	16.03
Toll to work (NOK)	7.24	15.76	6.32	16.39
Bus lane to work (km)	0.443	1.24	0.324	0.903
Observations	324,878	1,222	900,088	35,505

Figure A.9: Driving by local incentives.



Notes: Panels show the average ICEV driving for different intervals of road tolls and bus lane access. Driving is measured as the logarithm of kilometers per day. Each circle reflects the average driving distance within a given interval. Circle size reflects the size of the population (i.e., number of cars). The first circle to the far left reflects the average driving distance for households with 0 road tolls/bus lane access. The last circle to the far right reflects the average BEV share for toll road $\geq$ NOK 45 (Panel a) and bus lane $\geq$ 4.5 km (Panel b). All circles in between reflect the average BEV share for 5 NOK intervals of road tolls/0.5 km intervals of bus lanes. The line shows the linear fit. The coefficient reports the slope of the linear curve. Standard errors are clustered at the neighborhood level (residence and workplace) and are reported in parentheses. The sample is restricted to couple households where at least one of the adult members is employed.

A.4 Identifying the effect on car use

To investigate the effect on car use, we use a similar identification strategy as that used in Section 3, but use a different data structure. Car use is measured at the periodic inspection and owners of cars may switch them between inspections. We therefore define the period each car is owned by a certain household as the unit of observation.

Formally, the model specification is as follows;

$$ln(Driving_{hv}) = \kappa_r + \tau_{w_1} + \tau_{w_2} + \beta \text{Road Toll}_{rwv} + \lambda \text{Bus lane}_{rwv} + \gamma X_{hv} + \delta Z_{rwv} + u_{hv} \quad (4)$$

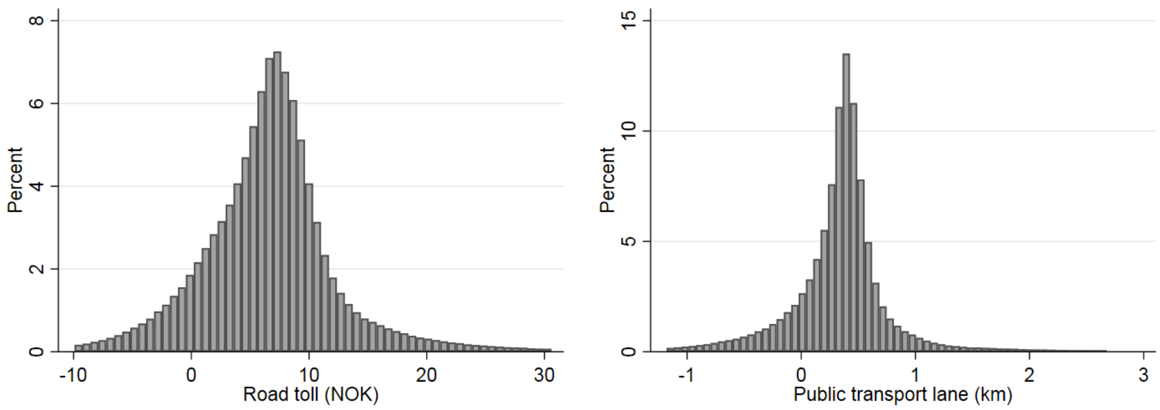
where v is the period that the car is owned by a certain household. Otherwise, the notation is the same as in Equation 1.

The estimated effects of road tolls and bus lanes on car use can be interpreted as the effects conditional on the household owning a particular car. If the household owns multiple cars, some of this effect might be driven by substituting driving from one car to another, for instance from a diesel or a gasoline car to an electric car.

Figure A.10 illustrates the residual variation in local incentives based on this data set and empirical strategy, analogous to Figure 2 based on the household-level data.

Figure A.10: Residualized road tolls and bus lane distance, driving data.

(a) Road toll (b) Bus lane



Notes: The figure shows histograms of road tolls (panel a) and bus lane distance (panel b). Both variables are residualized by absorbing demographic and commuting variables of owners and neighborhood fixed effects (residence and work). The population mean is added to the residualized values. The sample is restricted to couple households where at least one of the adult members is employed.